Trends in Stock Prices and Range to Standard Deviation Ratio

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Abstract
Hurst exponent (H) measured from R/S ratio, is being used as a measure to find predictability of a time series. The larger the H value, the stronger is the trending trait in the time series. In this paper, we estimated R/S ratio of several stock indexes of Indian market for 10 years. Though the overall Hurst exponent values for the selected series were close to 0.5, the value varied widely on period-to-period basis. The analysis of R/S ratio on a smaller window size of 30 trading day revealed a positive relationship between R/S ratio and performance of a moving average based trading rule.

Keywords: R/S ratio, Hurst exponent, Trading rule, Market trends, Indian stock market

1. Introduction
The Hurst exponent proposed by Hurst (1951) for use in hydrological studies has been applied to many research fields. The use of this exponent has also become popular in the financial studies largely due to work of Peters (1991, 1994). The Hurst exponent provides a measure for long-term memory and predictability of a time series. The objective of this paper is to develop some insights on price movements in financial markets by comparing Hurst exponent (H) and returns in Indian Stock market. The value of Hurst exponent can give some clue whether present value of the series depend on past values of the time series. H-value of 0.50 signals presence of Brownian motion. When the value of H lies between 0 < H < 0.5, it suggest trend reversing characteristics in the series. Conversely, value of H within the range of 0.5 < H < 1 suggest presence of trend in the series. The power of the trend increases until value of H reaches its upper ceiling value of one.

Hurst observed that the H-value directly depends on range to standard deviation ratio (R/S ratio). Thus R/S ratio can provide a method of classifying time series, which can be useful in identifying which markets have greater predictability. While forecasting a time series, we need to know whether the time series under study is predictable or not. If the time series is random, no forecasting method will be successful and therefore, we may focus only to those time series that have some degree of predictability. A time series with a large R/S ratio has trending characteristics and such series is more predictable than a series with a low R/S ratio.

The rest of the paper is organized as follows: Section-2 describes literature survey on application of Hurst exponent in financial markets. Section-3 deals with the estimation procedure of R/S ratio and Hurst exponent. Section-4 then describes various stock indexes used in the study. In Section-5, results of empirical tests in Indian market are tabulated and relationship between R/S ratio and Market returns are analyzed. Finally, the paper is concluded in Section 6.

2. Literature Survey
Application of Hurst exponent in financial time series has gained momentum with the work of Peters (1991, 1994) who estimated Hurst exponent for monthly returns on the S&P 500 from January 1950 to July 1988. From a sample of individual stocks, Peters noted that Hurst exponents varied from 0.54 for Consolidated Edison to 0.75 for Apple Computer. As the H-values are greater than 0.5, he found persistence among stock returns than would be expected if stock prices followed a Brownian motion.

Nath (2001) found that, the R/S analysis signaled of long-term memory for all-time lags in Indian stock market. With higher time lags of more than two years, there exists long memory. He inferred that movement of stock prices in India does not follow a random walk.

Corazza and Malliaris (2002) studied some foreign currency markets and found that Hurst exponent was statistically different from 0.5 in most of the samples. Besides, they also found that the Hurst exponent is not fixed but it changes dynamically overtime. They interpreted that foreign currency returns follow either a fractional Brownian motion or a Pareto-Levy stable distribution.
Lipka and Los (2002) measured the degrees of persistence of the daily returns of several European stock market indices. They found the global Hurst exponents, estimated from wavelet multi-resolution analysis, measured the long-term dependence of the data series quite well. They found the FTSE turns out to be an ultra-efficient market that exhibit abnormally fast mean-reversion, faster than theoretically postulated by a Geometric Brownian Motion (GBM).

Razdan (2002) studied Bombay stock exchange (BSE) index financial time series for fractal and multifractal behavior. He found that BSE index time series is mono-fractal and can be characterized by a fractional Brownian motion.

Carbone, Castelli and Stanley (2004) calculated the Hurst exponent of some time series by dynamic implementation of a scaling technique: the detrending moving average (DMA). The DMA algorithm allowed them calculation of the exponent without any prior assumption on the stochastic process and on the probability distribution function of the random variables.

Qian and Rasheed (2004) analyzed the Hurst exponent for all trading-day periods of the Dow-Jones index from January 1930 to May 2004. They found that the periods with large Hurst exponents could be predicted more accurately. This suggests that stock markets do not show random walk in all periods. Some periods have strong trend structure and this structure can be learned to benefit forecasting. They classified financial data series of different periods and experimented with back-propagation neural networks to show that series with large H can be predicted more accurately. The authors inferred that the H provides a measure for predictability.

Glenn (2007) analyzed of the NASDAQ Composite index in the 36-year period since its beginning in 1971. He found that the probability density function of 1-day return is highly leptokurtotic; the maximum 1-day loss is more than nine standard deviations from the mean. To assess whether long-term dependence is present in the NASDAQ time series, rescaled range-statistic calculations were carried out to find out the Hurst exponent. It was found that H was 0.59 for 1-day returns and increased monotonically to a value of 0.87 for 250-day (annual) returns.

Los & Bing (2008) identified lack of ergodicity, stationarity, and independence, and it identified the degree of early persistence of the Chinese stock markets when they were more regulated. They used index series are from the Shanghai (SHI) stock market and Shenzhen A-shares (SZI) and B-shares (SZBI), before and after the various deregulations and reregulations. By computing the Hurst exponents, they identified the markets' later degrees of persistence. The empirical evidence revealed that SHI, SZI, and SZBI are moderately persistent with Hurst exponents slightly greater than the Fickian 0.5 of the Geometric Brownian Motion. It also shows that these stock markets were more persistent before the deregulations, but that they now move like geometric Brownian motions, i.e. the markets have become more efficient in recent times.

Singh & Prabakaran (2008) examined the various features of the logarithmic return spectrum of the Indian stock markets using various statistical tests for the normality of data. They performed rescaled range analysis and carried on to estimate the Hurst’s exponent. They inferred that the Indian capital markets are not random and therefore, do not form a population that is normally distributed. Further, geometric Brownian motion cannot accurately model the stock prices, because of significant memory effect found by lumping observations into some sort of clusters, particularly for returns that are found in the tails of the distribution.

Lento (2009) tried to find synthesis between technical analysis and fractal geometry. He argued that Hurst exponent (H) was developed from the field of fractal geometry and provides a statistical technique to identify the nature of any dependencies in a time series. Moreover, Technical analysis has developed various trading rules that are premised on the belief that past price data reveals patterns that can be used to predict future prices. Based on this logic, and further empirical analysis he found that time series with high H resulted in higher profits in case of trending trading rules and time series with low H resulted in higher profits from contrarian trading rules. However, according to some authors, the R/S test is biased toward finding long-term memory. Stock market returns may follow time paths that are biased and the standard statistical tests cannot distinguish it from random behavior. Though R/S ratio can be used to detect long-term, nonperiodic cycles in stock market returns, if this technique is not applied correctly, then it can be influenced by short-term biases. These biases can lead to the inaccurate conclusion that the stock market has long-term memory. Lo (1991) tested R/S statistic, for daily, weekly, monthly, and annual stock returns indexes over several different time-periods. Contrary to previous findings, he found no evidence of long-range dependence in any of the indexes over any sample period or sub period once short-term autocorrelations are considered. His Monte Carlo experiments suggested that the modified R/S test had power against at least two specific models of long-run memory, suggesting that stochastic models of short-range dependence may adequately capture the time series behavior of stock returns.
3. R/S Ratio and Hurst Exponent

Hurst was a hydrologist and worked on the Nile River Dam project for about 40 years during the early years of the last century. He tried to find out the ideal features for reservoir design. An ideal reservoir should discharge a certain amount of water every year and should never overflow. However, the inflow of the reservoir varies due to changes in the climatic conditions. If the inflow of the reservoir is too low then releasing fixed amount of water will make reservoir dry. Thus, he was confounded with the problem of fixing the water discharge policy, such that the reservoir will never be emptied nor it will overflow.

In developing such a model, Hurst studied the inflow of water from rainfall. He measured how reservoir level rises and falls around its average and recorded range of the variations. If the series were random, the range would increase with the square root of time. To standardize the analysis Hurst created a dimensionless ratio by dividing high-low Range of the reservoir by the Standard deviation of the time series (R/S ratio). Hurst watched that many natural phenomena like, rainfall, temperatures, river flow follow a biased random walk, which is a combination of random walk, trend and noise. Following Hurst, many authors have also used R/S analysis to analyze data on hydrological parameters such as river flow, precipitation, temperature, etc.

3.1 Estimation of R/S Ratio

R/S analysis was established by Hurst in 1951 and the same was further developed by Mandelbrot and Van Ness (1968). This concept has found application in a diverse area. It has also been applied to economic price analysis by many authors. The R/S value is referred to as the rescaled range analysis because the series is converted to a zero mean series and is expressed in terms of sample standard deviation. The rescaled series is created by first rescaling or normalizing the data by subtracting the sample-mean: \( Z_t = X_t - \mu \). The rescaled range, or R/S statistic, is estimated by measuring the range between the maximum and minimum values of the cumulative sum of the variable Zt and then dividing this range by the standard deviation of the series.

Hurst drew up a null hypothesis on Binomial distribution and developed the following equation:
\[
\left( \frac{R}{S} \right)^n = \left( n, \frac{\pi}{2} \right)^H
\]
where \( n \) = number of observations and \( H \) is characteristic constant of the series.

According to the theory of Brownian motion, \( H = 0.5 \) implies an independent innovation process i.e. the events are mutually independent throughout time, where past values do not influence the present values. A persistent market return series is characterized by presence of a long memory. In a persistent market, a positive (negative) change in a period is likely to be continued in the same direction in the following period. The strength of the trend-reinforcing behavior increases as the value of the Hurst exponent approaches unity. The closer the Hurst exponent is to 0.5, the price movement will appear as random and become unpredictable.

Anti-persistent processes are mean-reverting, which means that if the market has been in a particular direction in the previous period, it is more likely to move in the reverse direction in the following period. The strength of this mean reverting behavior depends on how close the Hurst exponent is to zero.

4. Data

The data used for this study are the daily closing price of various stock indices reported by National Stock Exchange, India. The stocks are classified into various major indices and the following indices are analyzed in the study.

- S&P CNX Nifty
- CNX Nifty Junior
- S&P CNX Defty
- S&P CNX 500
- CNX IT Index
- CNX Bank Index

The daily closing values of the above indices were collected from the website of the exchange for a period of ten years, i.e. from January 2000 to April 2010. Brief description of these indexes are given below (based on information collected from the website of National Stock Exchange, www.nseindia.com)
4.1 S&P CNX Nifty
S&P CNX Nifty is a diversified 50 stock index accounting for 22 sectors of the Indian economy. It is managed by India Index Services and Products Ltd. (IISL), which is a joint venture between NSE and CRISIL.

- Nifty stocks represent about 63% of the Free Float Market Capitalization as on Dec 31, 2009.
- The total traded value for the last six months of all Nifty stocks is about 52% of the traded value of all stocks on the NSE
- Impact cost of the S&P CNX Nifty for a portfolio size of Rs. 2 crore is 0.10%

4.2 CNX Nifty Junior
The next rung of liquid securities after S&P CNX Nifty is the CNX Nifty Junior, which is also, formed using 50 stocks. It may be useful to think of the S&P CNX Nifty and the CNX Nifty Junior as making up the 100 most liquid stocks in India. The maintenance of the S&P CNX Nifty and the CNX Nifty Junior are synchronized so that the two indices will always be disjoint sets; i.e. a stock will never appear in both indices at the same time. Therefore, it is always meaningful to pool the S&P CNX Nifty and the CNX Nifty Junior into a composite 100 stock index or portfolio.

- CNX Nifty Junior represents about 12% of the Free Float Market Capitalization as on Dec 31, 2009.
- The traded value for the last six months of all Junior Nifty stocks is about 15% of the traded value of all stocks on the NSE
- Impact cost for CNX Nifty Junior for a portfolio size of Rs. 50 lakhs is 0.13%

4.3 S&P CNX Defty
Institutional investor and offshore fund enterprise with an equity exposure in India would like to have an instrument for measuring returns on their equity investment in dollar terms. To facilitate this, a new index the S&P CNX Defty-Dollar Denominated S&P CNX Nifty has been developed. S&P CNX Defty is S&P CNX Nifty, measured in dollars.

Salient Features of S&P CNX Defty are as follows:
- Performance indicator to foreign institutional investors, offshore funds, etc.
- Provides an effective tool for hedging Indian equity exposure.
- Impact cost of the S&P CNX Nifty for a portfolio size of Rs. 2 crore is 0.16%
- Provides fund managers an instrument for measuring returns on their equity investment in dollar terms.

4.4 S&P CNX 500
The S&P CNX 500 is India’s first broad based benchmark of the Indian capital market. The S&P CNX 500 represents about 92.57% of total market capitalization and about 91.17% of the total turnover on the NSE as on Sept 30, 2009. The S&P CNX 500 companies are disaggregated into 72 industry indices viz. S&P CNX Industry Indices. Industry weightages in the index reflect the industry weightages in the market. For example if the banking sector has a 5% weightage in the universe of stocks traded on NSE, banking stocks in the index would also have an approximate representation of 5% in the index.

4.5 CNX IT Index
Information Technology (IT) industry has been playing a major role in the Indian economy since last decade. A number of large, profitable Indian companies today belong to the IT sector and a great deal of investment interest is now focused on the IT sector. To have a good benchmark of the Indian IT sector, IISL has developed the CNX IT sector index. The total traded value for the last six months of CNX IT Index stocks is around 83.39% of the traded value of the IT sector. CNX IT Index stocks represent about 80.33% of the total market capitalization of the IT sector as on March 31, 2009. The total traded value for the last six months of all CNX IT Index constituents is nearly 8.59% of the traded value of all stocks on the NSE. CNX IT Index constituents represent about 6.97% of the total market capitalization as on March 31, 2009.

4.6 CNX Bank Index
CNX Bank Index is an index comprised of the highly liquid and large capitalized Indian Banking stocks. It provides investors and market intermediaries with a benchmark that captures the capital market performance of Indian Banks. The index has 12 stocks from the banking sector which trade on the National Stock Exchange. The total traded value for the last six months of CNX Bank Index stocks is approximately 96.46% of the traded value.
of the banking sector. CNX Bank Index stocks represent about 87.24% of the total market capitalization of the banking sector as on March 31, 2009. The total traded value for the last six months of all the CNX Bank Index constituents is approximately 15.26% of the traded value of all stocks on the NSE. CNX Bank Index constituents represent about 7.74% of the total market capitalization as on March 31, 2009.

5. Empirical Analysis

Some standard descriptive statistics applicable to the selected data series are produced in Table-I and Table-II. The figures reported in Table-I show means, medians, maximum and minimum values of the original series. Table-II reports means, medians, standard deviations, skewness, and kurtosis of the daily returns obtained from the first difference of the original index series.

Insert Table-I and Table-II here

All daily return series reported in Table-II, qualitatively show to some degree of departure from normal distribution. This is evidenced by the difference between mean returns from their corresponding medians, negative skewness values, and higher kurtosis values. The price charts of these time series are given in Chart-I

Insert Chart-I here

5.1 Stationarity Tests

From Chart-I, it can be observed that all selected series have displayed some kind of trending behavior during last 10 years. It was therefore needed to find out stationarity of the series. According to some authors, evidence of long-term memory could be spuriously caused by non-stationarity in the time series itself. We therefore, performed augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests to find stationarity of the data series both at levels and at their first differences. The results of ADF and PP tests are produced in Table-III.

Insert Table-III here

Both ADF and PP tests reveal that null hypothesis of non-stationarity cannot be rejected at the level data as p-values of most of the series were above 90%. However, p-values are close to zero, when first difference of data is analyzed. The index series at levels are therefore transformed into daily returns series by taking (logarithm) differences. The series comprising of daily stock returns are therefore stationary.

5.2 R/S and H Values

Given the index level \( X_1, X_2, \ldots, X_t \), the rate of return at time \( t \) is estimated by taking differences of the consecutive logarithm values: \( \Delta x_t = \ln(X_t) - \ln(X_{t-1}) \). To remove any secular trends from the series the daily returns series are first de-trended by subtracting mean return from daily log returns. Sample mean is calculated by averaging return of the sample period: \( \mu = \frac{1}{n} \sum_{i=1}^{n} x_i \). The trend adjusted return for period \( t \) is thus:

\[
r_t = x_t - \mu.
\]

In the next stage, a cumulative trend adjusted return series is formed: \( c_t = \sum_{i=1}^{t} r_i \). The rescaled range (\( R/S \)) of this cumulative series is calculated taking differences of maximum and minimum values of \( c_t \):

\[
R_t = \max(c_1, c_2, \ldots, c_t) - \min(c_1, c_2, \ldots, c_t)
\]

The standard deviation (\( S \)) of the series is calculated: \( S_t = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (x_i - \mu)^2} \) and finally, the rescaled R/S ratio of the series is obtained by taking ratio:

\[
\left( \frac{R}{S} \right) = \frac{R_t}{S_t}
\]

It has been noted that the rescaled \( \frac{R}{S} \) is proportional to \( t^H \cdot \left( \frac{R}{S} \right) = C_t t^H \). The letter exponent \( H \) was coined by Mandelbrot in honor of Harold Edwin Hurst. He also suggested a method of measuring the strength of long-range dependence of a series. By taking logarithm, the Hurst exponent can be transformed from a power
exponent to a linear form: \[ \log \left( \frac{R}{S} \right) = \log(C) + H \cdot \log(t) \] When we plot \( \{ \log \left( \frac{R}{S} \right) \} \) versus \( \log(t) \) and fit a straight regression line, the slope of the regression line will give the value of H. The plot and regression line for all the selected series are produced in Chart-II. The slope coefficient in the equation of trend line is the overall Hurst exponent value of the corresponding series.

5.3 Relationship between R/S Ratio and Returns

In Chart-II, overall H-values were estimated using entire 10 years daily data and it might be noted that the H values varied between 0.42 and 0.55 in line with the expected value of 0.5 for a random walk model. Thus on a overall basis, all the studied series closely followed a random walk and therefore prediction of trend in these series are not easy.

However, most of the stock market predictions are done analyzing short term fluctuations of the market. Though a market may remain efficient, in general, in a short intervening period, the market returns may deviate from normal distribution due to various reasons. To analyze the variations of R/S ratio in short term, the full data set is split into smaller series; each contains data of 30 consecutive trading days. We estimated R/S ratios separately for each of these smaller periods and found that R/S ratio fluctuated widely from period to period. The dispersion of R/S ratio generally remained within the range of 4 to 14, barring few outliers. We therefore, classified each 30-period smaller series based on their R/S values and presented the classification in Table-IV.

It is believed that a series having higher R/S ratio shows evidence of trending behavior. When trends are present in a series, the same can be captured using a trend detecting rule. To evaluate trending characteristic, we used a trading rule using 10-period moving average. We produced a buy signal when index value was higher than its moving average value and conversely, produced a sell signal when index value was lower than its moving average value. We estimated theoretical profits based on these buy and sell trading signals. However, to make analysis simpler, we did not consider transaction costs in estimating profits. We present the results of comparison between estimated R/S values with returns gained in each sub-period in Table -IV.

We also present the results of our analysis in Chart-III taking R/S ratio on x-axis and return value in y-axis. It is apparent from the charts that higher returns are associated with higher R/S ratios as all the trend-lines displayed upward slope. To analyze significance of slope values, we compared coefficient values with its standard errors and obtained p-values. The observations are tabulated in Table-V.

6. Conclusion

All the stock indices studied in this paper show a Hurst exponent that is close to 0.5, which reconfirms random behavior of market returns and market efficiency. However, the R/S ratio in the intermediate 30-period trading window is found to vary dynamically overtime, within a wide range of 4 to 14. It is also found from the analysis that whenever the R/S values were high, the average returns obtained from a moving average based trading rule were also high and vice versa. These observations lead to the conclusion that R/S ratios are related to the return generating process in the Indian stock market.

Since R/S ratio provided a measure of predictability of a financial series, this ratio can be used as a guide for data selection while analyzing trend and deciding a trade. Some aspects might have influenced the results of the study. The data is subdivided in smaller block period of 30 trading days. Change in block size may have some
impact on the results. Besides, we used only one trading rule based on moving average, using other trading rules may present more insights into the issue.

References


Table 1. Descriptive Statistics of the Data Series

<table>
<thead>
<tr>
<th>Series</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nifty</td>
<td>2581</td>
<td>2000</td>
<td>6288</td>
<td>854</td>
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<td>Junior Nifty</td>
<td>4688</td>
<td>4185</td>
<td>13069</td>
<td>1047</td>
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<tr>
<td>Defty</td>
<td>2007</td>
<td>1589</td>
<td>5549</td>
<td>617</td>
</tr>
<tr>
<td>CNX 500</td>
<td>2095</td>
<td>1753</td>
<td>5503</td>
<td>546</td>
</tr>
<tr>
<td>CNX IT</td>
<td>3248</td>
<td>3027</td>
<td>9550</td>
<td>961</td>
</tr>
<tr>
<td>BANK Index</td>
<td>3748</td>
<td>3373</td>
<td>10698</td>
<td>744</td>
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</table>
Table 2. Descriptive Statistics of the Daily Return Series

<table>
<thead>
<tr>
<th>Series</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
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<tbody>
<tr>
<td>Nifty</td>
<td>0.047%</td>
<td>0.143%</td>
<td>1.750%</td>
<td>-0.302</td>
<td>10.122</td>
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<tr>
<td>Junior Nifty</td>
<td>0.037%</td>
<td>0.204%</td>
<td>2.053%</td>
<td>-0.666</td>
<td>7.625</td>
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<tr>
<td>Defty</td>
<td>0.046%</td>
<td>0.149%</td>
<td>1.883%</td>
<td>-0.198</td>
<td>11.004</td>
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<tr>
<td>CNX 500</td>
<td>0.048%</td>
<td>0.188%</td>
<td>1.775%</td>
<td>-0.539</td>
<td>9.040</td>
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<tr>
<td>CNX IT</td>
<td>0.012%</td>
<td>0.066%</td>
<td>2.770%</td>
<td>-0.411</td>
<td>8.138</td>
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<td>BANK Index</td>
<td>0.086%</td>
<td>0.084%</td>
<td>2.189%</td>
<td>-0.205</td>
<td>8.035</td>
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</table>

Table 3. Stationarity test of data series (p-values of ADF and PP test)

<table>
<thead>
<tr>
<th>Series</th>
<th>ADF test results</th>
<th>Phillips-Perron test results</th>
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<tr>
<td></td>
<td>Level Data</td>
<td>First Difference</td>
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<tr>
<td>Nifty</td>
<td>0.9264</td>
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<td>0.9384</td>
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</tr>
<tr>
<td>BANK Index</td>
<td>0.9008</td>
<td>0.0000</td>
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Table 4. R/S Ratio and Average 30-period Return*

<table>
<thead>
<tr>
<th>R/S ratio</th>
<th>S&amp;P CNX Nifty</th>
<th>CNX Nifty Junior</th>
<th>S&amp;P CNX Defty</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of Periods</td>
<td>Average 30-period return</td>
<td>No. of Periods</td>
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<tr>
<td>0-4</td>
<td>2</td>
<td>-2.74%</td>
<td>1</td>
</tr>
<tr>
<td>4-6</td>
<td>14</td>
<td>1.23%</td>
<td>10</td>
</tr>
<tr>
<td>6-8</td>
<td>23</td>
<td>5.01%</td>
<td>23</td>
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<td>8-10</td>
<td>29</td>
<td>3.40%</td>
<td>23</td>
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<td>10-12</td>
<td>7</td>
<td>5.78%</td>
<td>16</td>
</tr>
<tr>
<td>12-14</td>
<td>6</td>
<td>9.59%</td>
<td>8</td>
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<tr>
<td>14+</td>
<td>4</td>
<td>13.03%</td>
<td>4</td>
</tr>
<tr>
<td>S&amp;P CNX 500</td>
<td></td>
<td></td>
<td>CNX IT Index</td>
</tr>
<tr>
<td></td>
<td>No. of Periods</td>
<td>Average 30-period return</td>
<td>No. of Periods</td>
</tr>
<tr>
<td>0-4</td>
<td>1</td>
<td>3.13%</td>
<td>1</td>
</tr>
<tr>
<td>4-6</td>
<td>7</td>
<td>1.28%</td>
<td>23</td>
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<td>6-8</td>
<td>30</td>
<td>2.97%</td>
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<td>8-10</td>
<td>26</td>
<td>5.32%</td>
<td>12</td>
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<tr>
<td>10-12</td>
<td>9</td>
<td>11.34%</td>
<td>16</td>
</tr>
<tr>
<td>12-14</td>
<td>6</td>
<td>14.77%</td>
<td>2</td>
</tr>
<tr>
<td>14+</td>
<td>6</td>
<td>15.92%</td>
<td>3</td>
</tr>
</tbody>
</table>

*The entire data series is broken into small window size containing returns of 30 consecutive trading days. The returns are classified based on the R/S ratio of the respective windows. For example, while analyzing R/S ratios of S&P CNX Nifty, we found that in 23 windows the R/S value were within 6-8 and the average 30-period returns (following a moving average based trading rule) of those 23 windows were 5.01%.

Table 5. Coefficient, Standard Error and p-value of trend line parameters

<table>
<thead>
<tr>
<th>Series</th>
<th>Slope Value</th>
<th>Std. Error</th>
<th>p-value</th>
<th>Constant Value</th>
<th>Std. Error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nifty</td>
<td>0.0095</td>
<td>0.0026</td>
<td>0.0004</td>
<td>-0.0361</td>
<td>0.0227</td>
<td>0.1155</td>
</tr>
<tr>
<td>Junior Nifty</td>
<td>0.0175</td>
<td>0.0029</td>
<td>0.0000</td>
<td>-0.0896</td>
<td>0.0280</td>
<td>0.0019</td>
</tr>
<tr>
<td>Defty</td>
<td>0.0102</td>
<td>0.0026</td>
<td>0.0002</td>
<td>-0.0336</td>
<td>0.0237</td>
<td>0.1604</td>
</tr>
<tr>
<td>CNX500</td>
<td>0.0145</td>
<td>0.0024</td>
<td>0.0000</td>
<td>-0.0685</td>
<td>0.0223</td>
<td>0.0029</td>
</tr>
<tr>
<td>CNX IT</td>
<td>0.0431</td>
<td>0.0041</td>
<td>0.0000</td>
<td>-0.3139</td>
<td>0.0348</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bank Index</td>
<td>0.0243</td>
<td>0.0034</td>
<td>0.0000</td>
<td>-0.1629</td>
<td>0.0294</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
* Plot depict daily closing value of respective index from January 2000 to April 2010

Chart 1. Time Series Plots of the Index*
* A trend line is fitted amongst the log(n) versus log(R/S) plots of each series and the equation of the trend line is included. The slope coefficient of the equation is the Hurst exponent value of the corresponding time series.

Chart II. Log R/S versus Log (n) Plots*
* All index series are split into a number of smaller series; each contains daily returns of 30 consecutive trading days. For each 30-period series, we estimated the R/S ratio and trading return using a moving average rule. A fitted trend-line and regression equation for the same are also added.

Chart III. R/S ratio versus Average 30-period Return*