

Influence of Range to Standard Deviation Ratio on Results of a Trading Rule

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Abstract

This paper examines relationship between Range to Standard deviation ratio (R/S ratio) and the profitability of a trading rule using stock prices of Indian market. The R/S ratios are expected to detect long-term dependencies in a time series. If dependencies are found, the dependency can be used to develop strategies for profitable trades.

The larger the R/S ratio, the stronger is the trend and higher is the chance of technical trading rule giving profitable results. It was found that during the periods of high R/S ratios, a trend following trading rule could predict price movement of the series more accurately.

Keywords: Hurst exponent, R/S ratio, Trading rule, Technical analysis, Indian stock market

1. Introduction

Analysis involving Range to Standard deviation (R/S) ratio is found in the early work of the British hydrologist H. E. Hurst, who tried to find out the ideal features of reservoir design for the River Nile. An ideal reservoir should release needed amount of water without getting dry or overflowing. However, the inflow of the reservoir varies erratically because of climatic changes.

To analyze nature of water flow, Hurst developed a ratio by dividing high-low Range of the water flow by the Standard deviation of the data series. Hurst noted that many natural phenomena like, rainfall, river flow, temperatures, follow a biased random walk, which is a pure random walk mixed with trend and noise.

Similar to the study of natural phenomena, R/S ratio has found application in the study of price variations in financial markets. This ratio suggests dependence of the current value of the series on its past values. If the current value of a stock depends on its past values then it can be used to forecast future prices and take investment decisions.

The study compared R/S ratios of number of financial series involving stocks traded in Indian stock market in contiguous sub-periods and compared performance of a selected technical trading rule with the R/S ratios of those sub-periods.

2. Literature Review

In the investment parlors, trends in security prices are analyzed by studying past data of the series under the guise of Technical Analysis. Technical analysts believe that a security's price reflects all available information and therefore they focus at the price formation process to find out the trends in the series, rather than analyzing macroeconomic variables. They believe that price behavior repeat itself and therefore it is predictable by extrapolating past patterns.

A more general statement of technical analysis presented by Pinches (1970) is as follows: 1) The market value of a security solely depends on the supply and demand of the particular security. 2) Supply and demand forces at any moment depends on many reasons, both rational and irrational. Information, opinions, moods, guesses and blind needs integrate in the price discovery process. No individual can hope to grasp and weigh them all; market automatically performs this. 3) Excepting minor variations, prices move in trends that persist for some periods. 4) Changes in trend signal an important shift in the balance between supply and demand and the same are detectable eventually in the market prices.

The usefulness of technical analysis to make profits is the subject of a continuing debate. While many academic studies challenge usefulness of technical analysis and find little predictive power, some found it to produce excess returns.

Brock, Lakonishok and LeBaron (1992) examined moving average rules on daily data of the Dow-Jones Industrial Index from 1897 to 1986. They found that moving average based rules were able to yield excess returns compared to the buy-and-hold return. Consistently, buy (sell) signals produced returns which were higher (or lower) than 'normal' returns. They found that their results were consistent and concluded that technical rules do have predictive power. However, they cautioned that considerations of transactions costs are important before such signals are used. They remarked that, there are cases where the transaction costs are small, such as for pension funds and funds contributed by sponsors. Opportunities also might exist in the futures markets where transactions costs are small.

Hudson, Dempsey and Keasey (1996) repeated above study of Brock and others on the UK stock market for the period 1935 to 1994 and found profitable results with the moving averages. However, the profits vanished after considering transaction costs.

Bessembinder H. and Chan K (1998) also found that simple forms of technical analysis contain significant power for US stock index returns. However, they cautioned that transaction costs are main hindrance in profitable opportunity from technical trades. They commented it is unlikely that trade could have used technical rules evaluated by Brock and others to improve returns net of trading costs.

Mitra (2010) analyzed the profitability of moving average based trading rules in the Indian stock market using four stock index series. The study found that most technical trading rules are able to capture market movements in Indian stock market reasonably well and give significant positive returns. However, these returns are not exploitable fully because of real world transaction costs.

However, the methods of Technical Analysis are not free from criticism. The random walk theory insists that prices move in unpredictable and random manner and they do not follow any patterns or trends. Thus analysis of past price movements cannot predict future price movements. The random movement of asset prices can be traced to the doctoral dissertation titled 'The Theory of Speculation' of Louis Bachelier (1900). He discovered that the mathematical expectation of the speculator is zero and it is not possible to make profits using past prices.

The usefulness of technical analysis and various counter-arguments have produced many empirical studies trying to find out whether a certain price series is predictable or not. The efficient market hypothesis (EMH) developed by Fama affirmed that the prices quickly reflect all relevant information and therefore trend following methods cannot beat the market (Fama, 1970).

Though the debate on successes of technical analysis methods is unending, few studies analyzed circumstances when technical analysis tools can produce better results. This may help investors to be more selective in application of technical analysis.

Mandelbrot (1968) developed a rescaled range analysis procedure to measure Hurst's exponent and found that securities returns followed a fractal time series. The Brownian motion was not a satisfactory statistical description of the true stochastic process involved in securities returns. The deviations are prominent because of fat tails in the frequency distribution plots of stock returns. He observed that a series having Hurst exponent in the range $0.5 < H < 1$ exhibit presence of long memory in the series.

Peters (1994) estimated Hurst exponent for monthly returns on the S&P 500 from January 1950 to July 1988. While analyzing individual stocks, Peters noted that Hurst exponents varied from 0.54 for Consolidated Edison to 0.75 for Apple Computer. Most of the stock analyzed showed H-values that are greater than 0.50. Thus, he found persistence among stock returns than would a random series could produce.

Nath (2001) found presence of long-term memory while analyzing stocks traded in Indian stock market. He found that movement of stock prices in India does not follow a random movement.

Singh & Prabakaran (2008) studied the returns of the Indian stock markets using various statistical tests. They found the presence of dependencies and memory feedbacks in the returns of Indian stock market. They performed Rescaled range analysis to estimate Hurst's exponent and found that the Indian capital markets are not random. They confirmed that geometric Brownian motion could not accurately model the stock prices, because of significant memory effect. They detected significant departure from normal distribution while segregating observations into various clusters, particularly returns that fall in the tails of the distribution.

Few studies examined the Hurst exponent to identify financial market predictability. Lento (2009) tried to compare performance of trading rules and Hurst exponent values. He found that time series with high H resulted in higher profits in case of trend following trading rules and time series with low H resulted in higher profits from contrarian trading rules.

3. R/S Ratio and Hurst Exponent

Hurst worked in the Nile River Dam project in the early 20th century and he studied the Nile in such details that some Egyptians reportedly nicknamed him ‘the Father of the Nile’ (Peters, 1994). While designing the dam he confounded with the issue on how to find out the ideal storage capacity of the dam. The capacity of the dam will depend on various features like, rainfall, temperature, river overflows, water needed for irrigation purposes and so on. Hydrologists usually assume water flow to be a random process. When Hurst studied the 847-year record that the Egyptians had kept from 622 A.D. to 1469 A.D., he noted that water flows are not random and showed persistent behavior on several occasions. He found that larger than average overflows followed by larger overflows and then, the process suddenly changes to a lower than average overflows. He could find appearance of some cycles of an unpredictable order in the Nile River water flow.

Based on his analysis he developed a Range to Standard deviation (R/S) statistic that has the following property:

$\left(\frac{R}{S}\right)_n = C.n^H$. The R/S value in the equation is the range of fluctuations that is expressed by the standard deviation of the series. The ratio changes with time increment by a power exponent H. The H value is popularly known as Hurst exponent. If the observations from the series were independent of previous observations, then the expected value of H would be 0.5. However, while examining Nile River overflow, he found the value of H-exponent was much larger at 0.91. The higher value of H suggested a larger variation of water flow than could be possible from a random walk.

According to the original theory, $H = 0.5$ would mean an independent process, that is, current value of the series is independent of past values of the series. The process need not strictly follow a normal distribution; it could also include other non-Gaussian process.

When the value of H falls between the range $0 < H < 0.5$, the series is anti-persistent. Anti-persistent series are likely to be ‘mean-reverting’. If a value in the time series has been high in the previous period, it is more likely to come down in the next period towards the mean value. The strength of the anti-persistent behavior depends on how close the Hurst exponent is to zero. The closer it is to zero, the more negative short-term dependencies are present. Such series covers lesser range than an independent geometric Brownian motion. For the series to cover lesser range, it must reverse itself more often than a process with independent events.

When the range of H lies between $0.5 < H < 1$, the values of the series change in upward and downward direction in a wider range than possible by random walk. These series display clear trends for some time, but these seeming trends are unpredictably interrupted by sharp discontinuities. The strength of the trend-reinforcing behavior increases as the value of the Hurst exponent approaches near the value of one.

3.1 Estimation of R/S Ratio

An orderly procedure to calculate the R/S statistic of financial data series is available in Peters (1994). The study customized the following method based on the work of Peters.

Let us begin with a time series having M observation. Many financial time series display high degree of non-stationarity but the impact of non-stationarity comes down in first differenced value of the series. In a financial series, non-stationarity is reduced by converting the original series to a returns series taking logarithm returns from consecutive values of the series.

$$x_t = \log\left(\frac{M_t}{M_{t-1}}\right) \quad (1)$$

The entire data series was divided into ‘A’ contiguous sub-periods each having n-observations and defined each sub-period as I_a . For each I_a of length n, the average value of the sub-period can be determined as:

$$\mu_a = \frac{1}{n} \sum_{k=1}^n x_k.$$

π_a is the mean return of the sub-period I_a . A nonzero mean marks presence of a trend in the series. The returns are de-trended by subtracting mean return of the sub-period: $r_{t,a} = x_{t,a} - \mu_a$

In the next step, a cumulative trend adjusted return series was created for each sub-period I_a : $c_{t,a} = \sum_{i=1}^t r_{(t,a),i}$

The range of variation of the cumulative trend adjusted return series for each sub-period I_a , was estimated by taking differences of maximum and minimum values of $c_{t,a}$:

$$R_{t,a} = \max(c_{1,a}, c_{2,a} \dots c_{t,a}) - \min(c_{1,a}, c_{2,a} \dots c_{t,a})$$

The standard deviation (S) of the sub-period is: $S_{t,a} = \sqrt{\frac{1}{t} \sum_{i=1}^t (x_{t,a} - \mu_a)^2}$

Finally, the rescaled range of each sub-period was calculated by taking the ratio:

$$\left(\frac{R}{S}\right)_{t,a} = \frac{R_{t,a}}{S_{t,a}} \quad (2)$$

As there are 'A' contiguous sub-periods, the average R/S value of full series can be calculated by estimating average R/S values of all individual sub-periods.

$$\left(\frac{R}{S}\right)_t = \frac{1}{A} \sum_{a=1}^A \left(\frac{R}{S}\right)_{t,a} \quad (3)$$

After determination of $\left(\frac{R}{S}\right)_t$ value of the series, H-value can be obtained by solving the equation

$\left(\frac{R}{S}\right)_t = C.n^H$. By taking logarithm of both sides, the Hurst exponent can be transformed from a power exponent to a linear form:

$$\log\left[\left(\frac{R}{S}\right)_t\right] = \log[C] + H \cdot \log[t] \quad (4)$$

An easier way to find the H-value is to plot $\left\{\log\left[\frac{R}{S}\right]_t\right\}$ versus $\log[t]$ and fit a straight regression line on it.

The slope of the regression line is the H-value for the series.

3.2 Expected value of R/S Ratio

The R/S ratio will naturally depend on the length of the series. The longer is the length of the series, the larger is the expected range between highest and lowest values in the series. Hurst (1951) estimated expected $\left(\frac{R}{S}\right)_n$ for a random walk to be:

$$\left(\frac{R}{S}\right)_n = \left(n \frac{\pi}{2}\right)^{0.5} \quad (5)$$

However, this equation was not suitable for smaller number of observations (n). Estimating standard deviation (S) with small number of observations is likely to lead to inaccurate conclusion. Empirical studies confirmed that R/S statistic differs from the value that results from above equation when number of observations is low. To circumvent the problem associated with small sample size, Anis and Lloyd (1976) developed the following equation to get better estimations of expected R/S statistic.

$$E\left(\frac{R}{S}\right)_n = \left[\Gamma\{0.5 * (n-1)\} / (\sqrt{\pi} * \Gamma(0.5 * n)) \right] * \sum_{r=1}^{n-1} \sqrt{\frac{(n-r)}{r}} \quad (6)$$

Estimating above equation is difficult because of complexities involved in solving Gamma function of the equation, at higher values of n . The formula can however be approximated by using Sterling's function:

$$E\left(\frac{R}{S}\right)_n = \left(n \frac{\pi}{2}\right)^{-0.5} * \sum_{r=1}^{n-1} \sqrt{\frac{(n-r)}{r}} \quad (7)$$

Peters (1994) carried out Monte Carlo Simulations with a pseudo-random number series from a large number of empirical simulations from S&P 500 monthly returns and found that expected $\left(\frac{R}{S}\right)_n$ converges to the values found from above equation. Nevertheless, the expected values created by simulating random numbers are lower than the expected values of both Hurst (1951) and Anis & Lloyd (1976) method, when the number of observations (n) was less than 20. To create an estimate that gives expected value closer to simulation results he adjusted the formula by adding a correcting factor of $\left(\frac{n-0.5}{n}\right)$. The formula as used by Peters (1994) after the correction is:

$$E\left(\frac{R}{S}\right)_n = \left(\frac{n-0.5}{n}\right) * \left(n \frac{\pi}{2}\right)^{-0.5} * \sum_{r=1}^{n-1} \sqrt{\frac{(n-r)}{r}} \quad (8)$$

The expected $\left(\frac{R}{S}\right)_n$ values using various formulas for a random walk model are produced in Table 1 below:

Insert Table 1 here

The table reveals that for higher number of observations, expected R/S ratio of all the methods are close to the values found from the simulated values. However, when the number of observation is low, expected R/S values using Peters (1994) equation is better than Hurst (1951) and Anis & Lloyd (1976) equations.

These values are just expected R/S values from a random walk model. When R/S value in a period differs from the expected value, it signals a deviation from random behavior. The series with a higher than expected value of R/S ratio may present a trend reinforcing behavior and may be a suitable candidate for application of trend following trading rule.

4. Trading Rules using Technical Analysis

There are many approaches and methods used in technical analysis. In the graphical approach, it plots the price data in a graph to find patterns in price formation. However, trading decisions taken on visual pattern recognition by the analyst also include biases and prejudices of the analyst. It is also not easy to express such visual judgments into automatic trading decisions.

In another approach, some mathematical modeling is set up based on past price movements. These models try to identify underlying trends in the price series by detecting whether the market is moving upwards or downwards. It gives a 'buy' signal when market moves in upward direction and a 'sell' signal when market moves down. In addition, there are models on contrarian strategies. Users of the contrarian strategies believe that the prices revert to the mean values in time. That is an upward movement is likely to face a downward correction soon. These models produce sell signal after a jump in prices and create buy signal after a sharp fall in prices.

The debate on which method is likely to work better is endless, but to limit the scope of the study, the study analyzed impact of a trend following rule based on moving averages.

4.1 Moving Averages (MA)

Moving averages are among the popular technical indicators used to identify the trend in financial series. It calculates average of past prices on a moving window size and this makes moving averages an orderly way to find out the current trend of a market. There are several variants of moving averages. In the study, a simpler version of moving averages, namely Simple Moving Averages (SMA) was used.

A simple moving average is the arithmetic 'mean' or average of a price series over a moving time window. As the time passes, the oldest price is removed from average calculation and latest price is added. This allows the moving average to keep pace with changing prices with time. The simple moving average for past n-day prices are arithmetic averages of past 'n' period's data.

$$MA_t = \frac{1}{n} \sum_{i=t-n}^t x_i$$

Trends in the price series is identified by comparing current prices with the moving average values. When current price at time 't' is higher than simple moving average value of the same period, it is a sign of uptrend and a buy signal is produced. Conversely, when current price is less than its simple moving average, a sell signal is produced considering it as a sign of downtrend. In a trend following market, signals following moving averages work well but the results are unsatisfactory when prices move in a random fashion or shows mean reverting tendencies.

One of the critical deciding features in the analysis based on moving averages is the size of moving window. The window size controls how many past observations are to be used to estimate the average value. If the window size is small then the moving average values will move close to the current prices and will produce trading signals often. Such averages have the power to detect trends of shorter duration as well. However, signals based on shorter moving averages often produce false signals that results in unprofitable trades. It also increases number of trades and by it increases transaction cost.

Moving average signals based on longer-term moving averages, on the other hand, will produce fewer trading signals and will save on trading costs but these signals cannot capture short-term trends in the price series. The decision on window size of moving average is usually determined by judgment or by experimenting with past data. The choice of the window size is the most critical in discovering success of the trading model, as different window size will give different profits. The paper produced results using moving window size of 20 days that nearly matches to trading duration of one month.

5. Data

The study used two types of datasets. From Indian stock market, it selected three stock index series and five individual stocks with high market capitalization.

5.1 Stock Index series

The study analyzed the daily closing price of following stock indices reported by National Stock Exchange, India.

- S&P CNX Nifty
- CNX Nifty Junior
- S&P CNX 500

It collected the daily closing values of the indices from the website of the stock exchange from the start of the current century that is from January 2000 to April 2010. Brief descriptions of these indexes are given below (source: website of National Stock Exchange, www.nseindia.com)

5.1.1 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. Nifty is the most popular index in India for trading in derivatives.

- 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 around 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%

5.1.2 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 coordinated so that the two indices will always be disjoint sets; that is 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 roughly 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%

5.1.3 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 namely 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 a near representation of 5% in the index.

5.2 Individual Stocks

The study had chosen individual stocks based on their free float market capitalization in April 2010. The five largest stocks traded in Indian stock market based on their free float market capitalization are presented in Table 2.

Brief descriptions of the selected companies whose share prices are used for analysis are as follows (source: websites of respective companies).

Insert Table 2 here

5.2.1 Reliance Industries Ltd.

The Reliance Group is India's largest private enterprise; with annual revenues more than US\$ 28 billion. The flagship company, Reliance Industries Limited, is a Fortune Global 500 company and is the largest private company in India. The Group's business span exploration and production of oil and gas, petroleum refining and marketing, petrochemicals (polyester, fiber intermediates, plastics and chemicals), textiles, retail and special economic zones. The company has a 26% share of the total refining capacity in India and with its subsidiary, IPCL, controls over 70% of the country's domestic polymer capacity.

5.2.2 Infosys Technologies Ltd.

Infosys was started in 1981 by seven people with US\$ 250. Today, Infosys is a global leader in the 'next generation' of IT and consulting with revenues of over US\$ 4.8 billion and is recognized globally for its excellent management practices and work ethics. It offers services like software development, maintenance, consulting, testing and packaging implementation. Infosys offers all these services through its integrated and globally recognized delivery model. The company's revenues and profits have grown at compounded rates of 35% each during the period FY03 to FY09. Infosys has a global presence with over 50 offices and development centers in India, China, Australia, the Czech Republic, Poland, the UK, Canada and Japan.

5.2.3 ICICI Bank Ltd.

ICICI Bank is India's second-largest bank with total assets of US\$ 81 billion at March 31, 2010. The Bank has a network of 2,000 branches and about 5,219 ATMs in India and presence in 18 countries. ICICI Bank offers a wide range of banking products and financial services to corporate and retail customers through various delivery channels. The bank has specialized subsidiaries in the areas of investment banking, life and nonlife insurance, venture capital and asset management. The Bank currently has subsidiaries in the United Kingdom, Russia and Canada, branches in United States, Singapore, Bahrain, Hong Kong, Sri Lanka, Qatar and Dubai International Finance Center. It has representative offices in United Arab Emirates, China, South Africa, Bangladesh, Thailand, Malaysia and Indonesia.

5.2.4 Larsen & Toubro Ltd.

Larsen & Toubro (L&T) is India's largest engineering company with expertise in wide areas like infrastructure, oil and gas, power and process. The company has broadly separated its business into three key areas - Engineering and Construction (E&C), Electrical & Electronics (E&E) and Machinery & Industrial Products (MIP). L&T provides its global clients with the winning edge through the development of optimal solutions. L&T's e-engineering services leverage the Company's own engineering heritage and experience. The Embedded Systems unit provides technological assistance across a broad spectrum - design, maintenance, reengineering, testing, prototyping and industrial design.

5.2.5 Housing Development Finance Corporation Ltd. (HDFC)

HDFC is India's largest housing finance company with strong brand value and market share of around 19%. Apart from housing loans, HDFC has also been benefiting from the retail reach of its banking subsidiary (HDFC Bank). Over the years, HDFC has emerged as a financial conglomerate by not restricting its ambitions to just housing finance but also venturing into new businesses like insurance, banking and asset management (mutual funds).

6. Empirical Analysis

To find relationship between R/S ratio of the series and profits from a trading rule, both of these measures are estimated first. As all the series studied in the paper have increased in their values by several times, stationarity of the series were tested. Some authors have argued that evidence of long-term memory could be spuriously caused by non-stationarity of the time series itself.

6.1 Stationarity Tests

The result of Augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests to detect stationarity of the series both at levels and at their first differences are produced in Table 3.

Insert Table 3 here

As trends in the original series were obvious, expectedly, null hypothesis of non-stationarity at the level data could not be rejected with both ADF and PP tests. p-values of most of the series were above 90% in both the tests. However, with first difference of data, p-values were almost zero, which proves that, first differences of all the series are stationary. Accordingly, the original series was transformed into returns series for further analysis.

6.2 Splitting into Sub-periods

The original series contain data for 2563 trading days, from 3rd January 2000 to 12th April 2010 for all the series except for L&T. The website of National Stock Exchange provides data for L&T from 23rd June 2004 onwards and therefore it studied the data for the stock for this period of 1440 days. To find R/S ratios in smaller sub-periods, it further divided the series into contiguous sub-periods of 20-periods each. A 20-trading period nearly matches to one months trading. The study deliberately avoided breaking the series into calendar months, as different trading months will have different number of trading days. Uniformity in number of observations in each sub-period is a necessity to make R/S ratios of various sub-periods comparable.

6.3 Relationship between R/S Ratio and Returns from a Trading Rule

The study applied 20-period moving average to take trading decisions and produced trading signal whenever current price of the series crossed its moving average value. It then produced a buy signal when prices were higher than the moving average values and conversely, produced a sell signal when series value was lower than the moving average value. To make analysis simpler, the analysis did not consider transaction costs in estimating profit. Chart 1 illustrates price plots of the original series and profit gained from using 20-period moving average trading rule.

Insert Chart 1 here

As the series were divided into contiguous sub-period of 20-trading periods, R/S values of each sub-period was estimated according to the steps listed in Section 3.1 and compared this value with returns gained in that sub-period using 20-period moving averages. These results are presented graphically in Chart 2 by taking R/S ratios on x-axis and return values in y-axis.

Insert Chart 2 here

A trend-line to find any linear relationship between these two measures were also fitted. Interestingly, all the data series presented a positive slope confirming that trading rule profits are positively correlated to R/S ratios. Thus, the trend following trading rule has given better performance when R/S ratio in the period is high.

6.4 Analysis of Trend-lines

All the trend lines presented in Chart 2, involving R/S ratio in x-axis and returns in y-axis have shown positive slope. This is a clear signal that 20-period moving average rule has yielded higher profits in those sub-periods that showed high R/S ratio. The slope and intercept measures of the fitted trend-lines and their significance values are given in Table 4.

Insert Table 4 here

It can be noted from the table that the slope coefficients are not only positive in value but all of them are also significant at 1% levels.

7. Conclusion

Range to Standard deviation ratio, which was originally used to study natural phenomena are now extended to study behavior of stock prices. The study used daily data of eight stock series for past ten years and divided data into smaller sub-periods, each containing 20 data. For each sub-period, it estimated R/S ratio and compared the ratio with the results gained from a 20-period moving average trading rule. The study found that periods that showed higher R/S values gave better profits in contrast to the periods of low R/S ratio. The observation is similar across all the eight financial series studied. In case of HDFC stock, the overall profit from moving average based trading rule was negative. Nevertheless, even in that series, profit versus R/S ratio showed positive upward slope.

From the observations, it can be summarized that R/S value may form an important indicator of return formation process and therefore, it can find use in taking trading decisions using Technical Analysis. R/S ratios themselves may not have any power to decide direction of trend but trend-detecting rules produce better results during the periods of high R/S ratio.

It must be mentioned here that the profits using 20-period moving averages were estimated without considering transaction cost. If transaction costs are included, the profits will come down and can even become negative. This study is not intended to confirm benefits using technical analysis; it merely states that investors can be more selective in application of technical analysis. In a financial time series, periods having high R/S ratio are likely to give better results with a trend following rule than the periods of low R/S ratio.

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Table 1. Expected R/S ratio from Random Walk

No of Data Points	Hurst (1951)	Anis & Lloyd (1976)	Monte Carlo Simulations*	Peters*
10	3.9633	3.0234	2.8688	2.8721
20	5.6050	4.6111	4.4978	4.4957
25	6.2666	5.2578	5.1558	5.2143
50	8.8623	7.8127	7.7464	7.7357
100	12.5331	11.4525	11.4209	11.3972
250	19.8166	18.7068	18.6638	18.6681
500	28.0250	26.8596	26.8658	26.8349
1000	39.6333	38.4680	38.6278	38.4503
2500	62.6657	61.5035	60.7995	61.4894

*Adapted from Peters (1994)

Table 2. Market Capitalization of Selected Indian Stocks

Sl.	Security Name	Free Float Market Cap*.	Weightage % in S&P CNX Nifty
1	Reliance Industries Ltd.	174808	11.43
2	Infosys Technologies Ltd.	131895	8.62
3	ICICI Bank Ltd.	106074	6.94
4	Larsen & Toubro Ltd.	97258	6.36
5	Housing Development Finance Corporation Ltd.	71344	4.67

* Free Float Market Capitalization in Rupees Crores for April 2010

Table 3. p-values of ADF and PP Test Results of the Financial Series

Series	ADF* test results		Phillips-Perron* test results	
	Level Data	First Difference	Level Data	First Difference
Nifty	0.9264	0.0000	0.9376	0.0001
JrNifty	0.9384	0.0001	0.9515	0.0001
CNX500	0.9237	0.0000	0.9241	0.0000
Relience	0.9209	0.0001	0.8793	0.0001
Infosys	0.9573	0.0000	0.9773	0.0001
ICICI Bank	0.7929	0.0000	0.7298	0.0001
L&T	0.4303	0.0000	0.4434	0.0000
HDFC	0.9234	0.0001	0.9173	0.0001

*Automatic selection of lags was based on SIC values: 1 to 12

Table 4. Slope and Intercept Parameters of the fitted trend-line on R/S ratio versus Profit

Series	Slope			Intercept		
	Value	Std. Error	p-value	Value	Std. Error	p-value
Nifty	50.01	9.85	0.0000	-271.62	67.61	0.0001
JrNifty	70.67	15.78	0.0000	-291.22	123.03	0.0194
CNX500	36.24	6.32	0.0000	-188.90	46.69	0.0001
Relience	13.55	2.41	0.0000	-72.92	15.50	0.0000
Infosys	37.55	5.32	0.0000	-209.98	31.87	0.0000
ICICI Bank	12.69	2.43	0.0000	-69.48	15.86	0.0000
L&T	24.11	6.91	0.0007	-115.40	45.89	0.0132
HDFC	36.35	8.34	0.0000	-218.53	48.47	0.0000

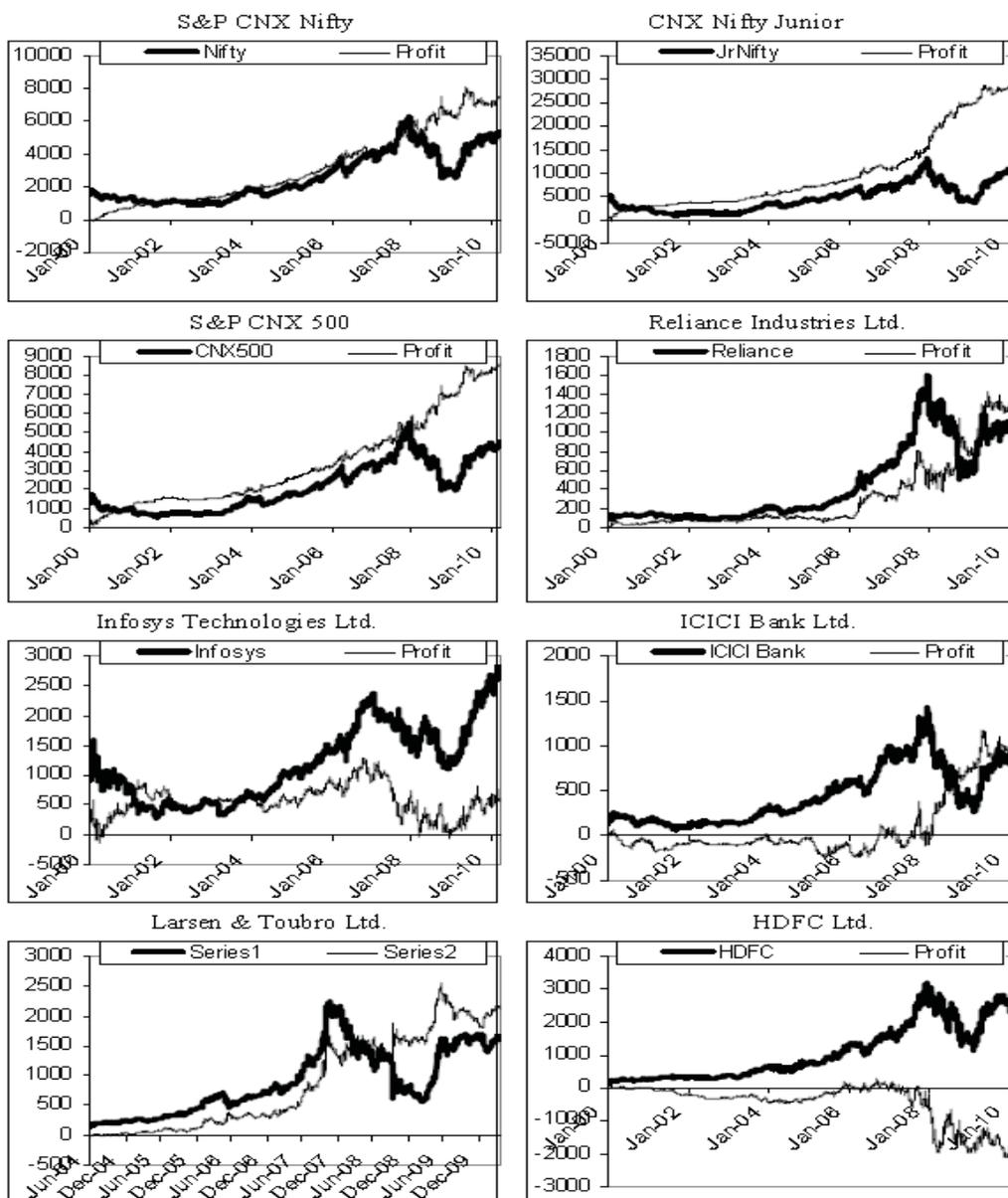


Chart 1. Time Series Plots and Trading Profits from a Trading Rule

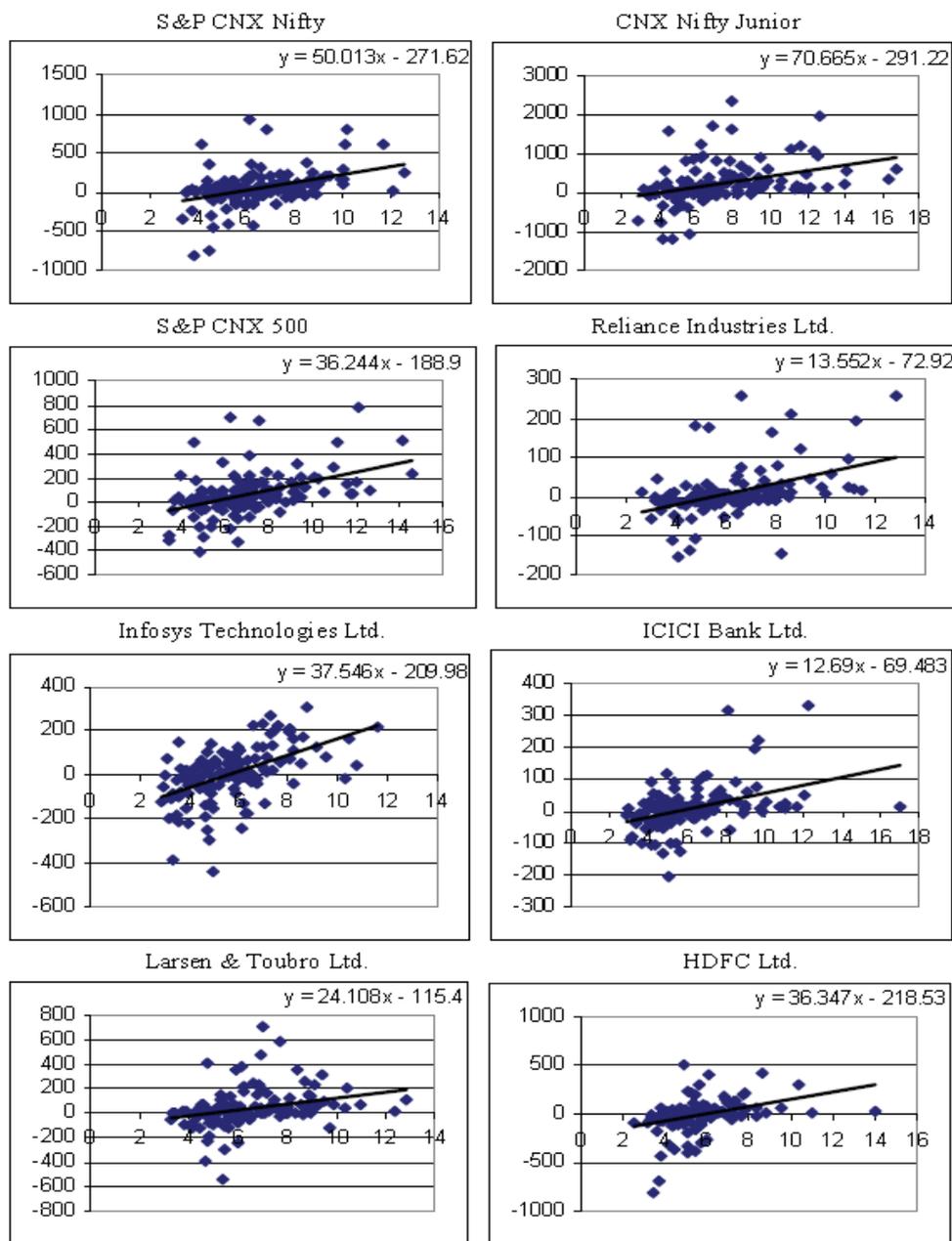


Chart 2. Return from a Trading Rule versus R/S Ratio

Each data series is sub-grouped by taking contiguous observations of 20 periods. For each sub-period, the R/S ratio and trading profit (using a 20-period simple moving average rule) were estimated. The results are plotted by taking R/S ratios in x-axis and trading profit in y-axis. The chart also includes fitted trend-line for each series and regression equation for the respective trend-lines.