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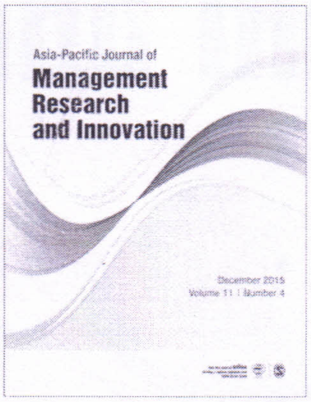

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We Shape Futures

Stock Market Reaction during the Global Financial Crisis in India: Fractal Analysis

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Abstract

The Bombay Stock Exchange is the most popular and also the oldest stock exchange in Asia. It has the major number of listed companies in the world. In September 2008, the Sensex experienced huge falls, along with other markets around the world. Financial markets have become ever larger and financial crises have become more threatening to society. The devastating consequences of these crises stimulated the development of methods for predicting financial turmoil. New approaches to stock market prediction are considered on the basis of the intensity of stock index fluctuations estimated by fractal analysis techniques. Fractal analysis is used to analyse the financial time series. This article examined the fractal dimension in S&P BSE Sensex for pre- and post-recession periods—2004–2008 and 2008–2012 respectively.

Keywords
Fractal dimension, global financial crisis, long range dependence, S&P BSE Sensex, R/S Analysis

Introduction

The Global Financial Crisis 2008 is believed by many economists to be the most horrible financial crisis. It resulted in the falling down of prices in large financial institutions, national governments bailouts to banks and a recession in stock markets around the world (Atanda & Idowu, 2012). In many parts of the world, the housing market also suffered. The crisis played an important task in the failure of businesses; a turn down in consumer wealth estimated in trillions of USD and a downturn in the economic movement leading to the 2008–2012 global recession (http://en.wikipedia.org/wiki/financial crisis).

The Bombay Stock Exchange (BSE) is the tenth largest stock exchange in the world in terms of market capitalisation and one of India's leading exchanges. The growth of the Indian corporate sector, by giving a resourceful capital-raising platform, has been facilitated by BSE over the past 137 years. In 1986, the BSE developed the BSE Sensex to measure the overall performance of the Indian economy. The BSE is weighted on the basis of free-float market capitalisation. The 30 components of companies represent the various sectors of industries of the Indian economy. It is considered the largest and has most actively traded stocks (www.wikipedia.org/BSE Sensex).

Fractal analysis is a tool that studies the repeating patterns of price over long periods of time that are created by a common driver of price that can be isolated. In essence, fractal development is the means by which the main fundamental variable that drives a market's price creates repeating patterns of price growth at an ever higher degree over time due to repetitive market psychology (www.goldrunnerfractalanalysis.com). By measuring the fractal dimension of index, the investors may identify the price return patterns and subsequently the investors may regulate their pricing strategies to buy or sell their stock accordingly in the market (Thiele, 2007).

Review of Literature

Earlier studies which explored the fractal dimension and market predictions in stock markets are briefly summarised as follows.

Gayathri and Selvam (2011b) examined the long range dependence of daily returns of Nifty in the stock market. This study identified that the time series data from Indian Stock Market were not random and the result indicated the rejection of Efficient Market Hypothesis for Indian Stock Markets.

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Gayathri Mahalingam et al. (2012) evidences the long memory in the returns of BSE. The study found that the investors reacted to the information received from past news and there was high degree of persistence in BSE Sensex returns. Besides, the study confirmed the persistent behaviour of Sensex returns.

Kumar and Maheswaran (2013) tested the presence of long memory in daily index returns of S&P CNX Nifty, CNX 100, S&P CNX 500, CNX Nifty Junior, Nifty Midcap 50 and CNX SMALLCAP from the Indian stock market. The study found that long range dependence existed in the Indian stock market of six index returns of NSE.

Cajuerio and Tabak (2005) analysed the long-range dependence for mean returns and volatility for banking sector indices for 41 different countries. The study found that there was strong long-term dependence for banking sector indices around the world for volatility. Kasman and Torun (2007) investigated the long-memory properties of the returns and the volatility of the Turkish stock market. The study found that the returns series showed evidence of long memory in the Turkish stock market. Cajueiro and Tabak (2008) tested the long-range dependence in equity returns and volatility using R/S and V/S methodologies for 41 equity indices for different countries. The study found that the world equity indices possessed long range dependence in volatility and there was less evidence of long range dependence in equity returns. Danilenko (2009) examined the long-term memory in Baltic sector indices. The Hurst exponent value was greater than 0.5 for the 10 sample indices and therefore, the long-term memory effect found in stock indices of different sample periods. Barkoulas et al. (2000) studied the monthly stock returns series of 30 most heavily traded stocks on the Athens Stock Exchange (ASE30) over longer forecasting horizons. It was found that the fractional model was a more flexible and parsimonious way of modelling both short-term and long-term properties of the ASE30 stock returns series. Henry (2002) tested the long memory in the monthly stock index returns of German, Japanese, South Korean and Taiwanese markets using parametric and semi-parametric estimators. The study found that the semi-parametric approaches provided strong evidence of long memory in the South Korean returns and some evidences for long memory in German, Japanese and Taiwanese returns. The remaining sample returns series were broadly consistent with short memory processes. Gayathri and Selvam (2011a) analysed the efficiency of stock markets in India using fractal analysis. The research study found that the short-term time series follow technical information and long-term time series follow fundamental information. A study on fractal analysis in the Indian stock market has been carried out by Selvam, Jayapal and Saranya (2011). The study investigated the fractal dimension in returns of the Sensex and found that the price series occasionally followed a random walk.

It is understood from the above review that in the Indian stock markets, there is no inclusive study examining the current circumstances using the R/S analysis. Therefore, this study plans to inspect the long-term memory in daily returns of the Indian stock market.

Statement of the Problem

Loss of confidence among the investing public is the reason for stock market crashes. Regarding securities, the recent announcement about the stock prices arrives in to the market in an unsystematic manner. One announcement is normally independent of another from time to time and the security prices quickly reflect the effect of recent information. If the time horizon of all investors were to become exclusive, the market would turn out to be uneven because everyone would react to the same information in a unique way.

It is to understand that there was lack of quantitative evidence to predict market prices in the Indian stock market. Hence, an attempt has been made to predict the market price returns in the Indian stock market by analysing the fractal dimension.

Need of the Study

Time series forecasting is important in financial markets. Traditionally, forecasting research and practice was dominated by statistical methods. To know the dynamic nature of financial markets, traditional methods are inadequate. In the last few years, research has focused on understanding the nature of financial markets before applying methods of forecasting in domains like stock markets, financial indices, bonds, currencies and varying types of investments. The time series of the data computed by using R/S analysis to find out the persistence, long-range dependence, randomness and mean reversion in time series data of financial markets, characterised by non-periodic cycles.

Objectives of the Study

The main objective of this study is to find out the normality by testing the presence of short-term dependence and to examine long memory in daily Sensex returns.

Hypotheses

The following two null hypotheses were tested.

NH1—There is no normality in the daily Sensex returns during the pre- and post-global financial crisis.

NH2—There is no long-range dependence in the daily Sensex returns during the pre-global financial crisis.

NH3—There is no long-range dependence in the daily Sensex returns during the post-global financial crisis.

Methodology

Data and Computational Details

The oldest stock exchange in Asia is BSE. As on January 2013, USD 1.32 was the market capitalisation of the companies listed on the BSE. Hence, the BSE Sensex daily returns were used to check the evidence of long-range dependence. The necessary data were collected from the official website of BSE (www.bseindia.com). The other relevant information was retrieved from research articles and websites.

Study Period

There are two sets of sample periods covered in this study (from 1 May 2004 to 29 August 2008, that is, the pre-global financial crisis period and the other period from 1 September 2008 to 31 December 2012, that is, the post-global financial crisis period).

Tools Used for the Study

The investigation employed the following statistical tools.

Descriptive Analysis

The descriptive analysis includes mean, median, standard deviation, skewness and kurtosis.

Normal Q–Q plot, Kolmogorov–Smirnov and Shapiro–Wilk Tests

In statistics, for comparing two probability distributions, the Q–Q plot graphical method is used. The Kolmogorov–Smirnov test statistic is defined as

$$D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right) \quad (1)$$

Autocorrelation

An autoregressive (AR) model is a sign of a type of random process and it explains time-varying processes in nature, economics, etc. The model states that the outcome variable depends linearly on its own preceding values.

The autoregressive model of order p is referred as AR(p) and it is written as

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t. \quad (2)$$

R/S Analysis

R/S is described as follows:

$$R/S = (a*N)^H \quad (3)$$

where, R/S = rescaled range; a = constant (number of intervals); N = number of observations; H = Hurst exponent.

The V-statistic takes the following format:

$$V_n = \frac{R_n/S_n}{\sqrt{n}} \quad (4)$$

where, V_n = V-statistic; R/S = rescaled range; n = increment time

$$H = \frac{\text{In}(R_n/S_n) - \text{In}(c)}{\text{In}(c)} \quad (5)$$

where, R/S = rescaled range, c = constant (number of intervals), n = time increment, H = Hurst exponent

$$\text{Fractal Dimension} = 2 - H \quad (6)$$

where, H = Hurst

Analysis of Normality, Short-term Dependence and Fractal Dimension in the S&P BSE Sensex

The analysis of the study was arranged as below.

1. Descriptive Statistics of S&P BSE Sensex
2. Analysis of Normality of S&P BSE Sensex using Normal Q-Q Plot and Kolmogorov–Smirnov and Shapiro-Wilk Test
3. Analysis of Short-term Dependence using Autocorrelation
4. Estimating Rescaled Range Analysis of BSE Sensex and
5. Analysis of Fractal Dimension of S&P Sensex during Pre- and Post-global financial crisis.

Descriptive Statistics of S&P BSE Sensex

Table 1 discloses the outcome of risk–return analysis for the BSE Sensex for the pre- and post-global financial crisis period from May 2004 to December 2012. Table 1 evidently shows that the Sensex had earned 0.0009 and 0.0003 positive average returns during the pre- and post-global

Table 1. Descriptive Statistics for Sensex Returns during Pre- and Post-Crisis Period

Descriptive Variables	Pre-Crisis Period (May 2004–Aug 2008)	Post-Crisis Period (Sep 2008–Dec 2012)
Mean	0.0009	0.0003
Maximum	0.0793	0.1599
Minimum	–0.1181	–0.1160
Standard Deviation	0.0165	0.0171
Skewness	–0.6278	0.4494
Kurtosis	4.9780	10.9029
Number of observations	1088	1073

Source: Computed from yahoofinance website using SPSS 16.0.

financial crisis period respectively. It is observed that the Sensex recorded a standard deviation of 0.0165 during the pre-crisis period. The value of 0.0171 was recorded during the post-crisis period, which reveals high risk in the market during the post-crisis period. The negative skewness (that is, −0.6278) for the pre-crisis period indicates that the series was not normally distributed, with an asymmetrical leaning towards low values, while a positive skewness value (0.4494) was recorded during the post-crisis period. This implies that the return data points were at the high end of the scale of measurement. The positive return distribution of kurtosis was categorised by peakedness of the data, whose values during the pre- and post-crisis periods were at 4.9780 and 10.9029 respectively. The kurtosis values were greater than three under both periods and therefore the chance of data distribution was leptokurtic. However, the more peaked distribution was found during the post-crisis period. This means that the probability of extreme returns was higher during the post-global financial crisis period rather than during the pre-global financial crisis period.

Analysis of Normality of S&P BSE Sensex Returns Using Normal Q–Q Plot, and Kolmogorov–Smirnov and Shapiro–Wilk Tests

The analysis of descriptive statistics indicates that the returns of BSE Sensex did not perfectly correspond to the shape of a normal distribution. In order to make a conclusive statement about the distribution shape of the empirical data sets, the normality test was applied (Thiele, 2007). Figure 1 exhibits the Q–Q plot for the pre-global financial crisis period, while Figure 2 shows the Q–Q plot for the post-global financial crisis period for the S&P BSE Sensex. It is to be understood that the straight line indicates the reference line for the normal distribution. According to Figure 1, the empirical values depart from the reference line at both ends and also in between the region. This indicates a distribution which is different from the normal distribution. From the Figure 2, it is understood that the empirical values depart from the reference line at both ends and this indicates a distribution which is similar to the normal distribution.

The Kolmogorov–Smirnov and Shapiro–Wilk statistics for the S&P BSE Sensex for the pre- and post-global

Figure 1. Pre-Global Financial Crisis May 2004–Aug 2008

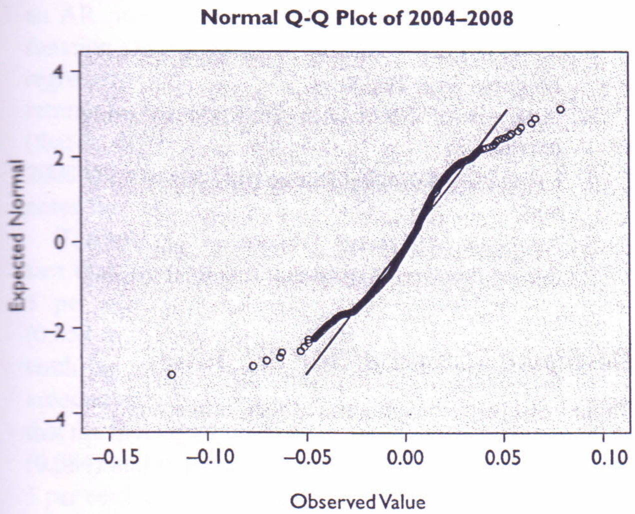
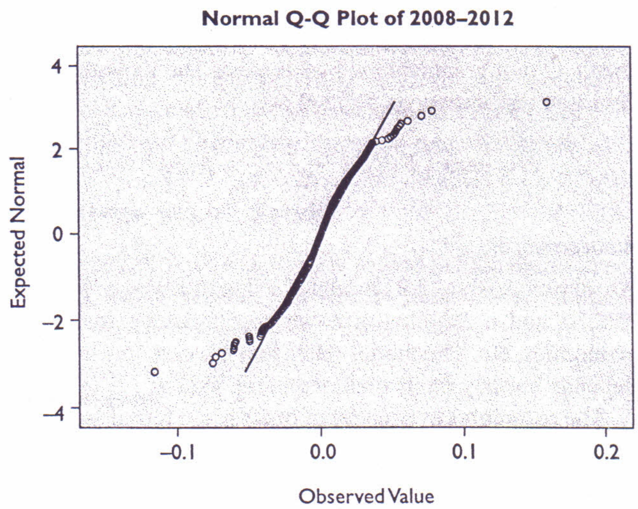


Figure 2. Post-Global Financial Crisis Sep 2008–Dec 2012



Sources: Collected from www.bseindia.com computed using SPSS 16.0

Table 2. Tests of Normality of BSE Sensex Returns during Pre- and Post-Crisis Period

	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
Period	Statistic	Df	Sig.	Statistic	Df	Sig.
Pre-Crisis Period (May 2004 to Aug 2008)	.086	1,088	.000	.936	1,088	.000
Post-Crisis Period (Sep 2008–Dec 2012)	.081	1,073	.000	.911	1,073	.000

Sources: Collected from www.bseindia.com computed using SPSS 16.0.
Note: [a]Lilliefors Significance Correction.

financial crisis are displayed in Table 2. It is observed that the significant values of the Kolmogorov–Smirnov and Shapiro–Wilk statistics were below the 5 per cent significant level. In other words, the returns have been considerably different from those of a normal distribution. The probabilities were less than 0.05 (the typical alpha level) and therefore, the data returns were normally distributed and hence the null hypothesis (NH1) is rejected. The findings of the Kolmogorov–Smirnov test strongly support the findings of the descriptive statistics of excessive kurtosis.

Analysis of Short-term Dependence Using Autocorrelation

The auto-correlation function can be used to detect periodicity in a signal. This study has employed the autocorrelation function to examine the short-term autoregression.

The rescaled range can be biased under the circumstances of a short-memory process (Peters, 1996). An autoregressive process (AR) represents a time series where change in time n is related to the change in one or more previous periods (Thiele, 2007). To test the presence of an AR process, this study examined the autocorrelation function (ACF) up to an order of 20. The results of the regression function for daily returns of BSE Sensex returns for the pre- and post-global financial crisis period (that is, from May 2004 to August 2008 and September 2008 to December 2012) are presented in Table 3. It is to be noted that totally 20 lags were used for the analysis.

The analysis of autocorrelation coefficients reveals the fact that pre-global financial crisis was significant at the 5 per cent level of significance, with positive values (0.052 at the first lag, 0.055 at the ninth lag, 0.081 at the tenth lag and 0.054 at the fourteenth lag). The results of autocorrelation during post-global financial crisis indicate that the first lag (0.081), eighth lag (0.092), seventeenth lag (0.084) and nineteenth lag (0.008) were significant at the 5 per cent level of significance. Further, it can be seen that the values of the post-global financial crisis period were negative for lower lags and positive for higher lags. But there was no autocorrelation which was significantly different from zero for lags beyond 20. The number of significant autocorrelations is the same for both sample periods. The negative autocorrelations indicate the fact that in the long run, the increase of the stock prices might be followed by a decrease rather than an increase. In other words, the autocorrelations indicate the possibility of long-run mean reverting tendencies of the Indian stock market. From this analysis, the study found the presence of autoregressive processes under both the periods (pre- and post-crisis periods). The findings were significant at the 5 per cent level.

Table 3. Autoregressive Function of BSE Sensex Returns during Pre- and Post-Crisis Period

Lag	Before Crisis (May 2004–August 2008)	After Crisis (September 2008–December 2012)
1	0.052*	0.081*
2	–0.033	–0.061
3	–0.011	–0.009
4	0.003	–0.014
5	–0.051	–0.024
6	–0.057	–0.034
7	–0.015	0.039
8	0.019	0.092*
9	0.055*	–0.009
10	0.081*	–0.013
11	–0.042	0.021
12	–0.022	0.006
13	0.026	0.040
14	0.054*	0.031
15	0.027	–0.024
16	–0.008	0.025
17	0.012	0.084*
18	–0.005	–0.040
19	–0.035	0.008*
20	–0.060	–0.037

Sources: Collected from www.bseindia.com computed using E-Views 6.
Note: *Significant at 5% level of significance.

Estimating Rescaled Range Analysis for BSE Sensex Returns

Estimation of Rescaled Range Value for BSE Sensex Returns during Pre-Global Financial Crisis

The data of daily returns for the BSE Sensex for the first set of samples from 1 May 2004 to 29 August 2008, giving a total of 1,087 observations, and the second set of samples from 1 September 2008 to 31 December 2012, giving a total of 1,073 observations, were used. Rescaled range analysis was used to study the fractal dimension of the S&P BSE Sensex returns. In the first step, the sample period was divided in to two sub-periods. Then the returns data were split into 340 contiguous sub-periods for the first set of samples of 1087 observations and also for a second set of samples of 1,073 observations (refer to the Appendix).

Table 4 depicts the outcome of rescaled range value for the returns during the pre-global financial crisis period from May, 2004 to August, 2008. The highest value (1.3484) of log R/S was registered on the 330th day while the lowest value (0.4632) of log R/S was recorded on the starting period (N = 10). It is to be noted from the Table 4 that the log R/S and log E(R/S) values (from N = 10) were closer to N = 130. Later, values diverged from the value (N = 140) (1.1379) up to N = 300 (1.3137). After that, the log R/S value did not diverge from E(R/S) throughout the study period. In the case of V-Statistics, the highest value of 1.4067 was witnessed on the 190th day period and the lowest value of 0.9188 was found on the starting period (N = 10). It implies the interesting fact that the index returns tended to decrease in future.

The overall analysis shows the fact that the Sensex returns during the study period were influenced by the past data. In other words, there was a long-memory effect in the Sensex returns because there was strong support of long memory in the daily index returns of S&P BSE Sensex during the period of study.

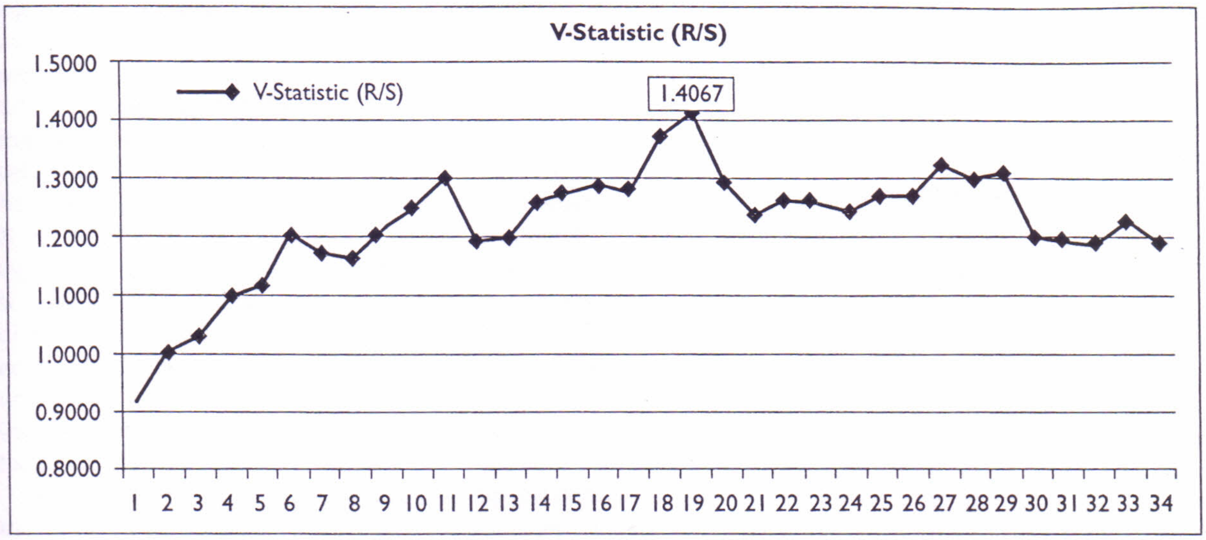
The results of the V-statistic plot for the Sensex against log (N) during the pre global financial crisis are shown in Figure 3. The V-statistic plot records the deviation of the R/S series. According to the analysis of the figure, there was an increase in the plot of the V-statistic value (1.2002) at point 6. After that, there was an increase in the trend of the V-statistic slope during point 11, with a value of 1.2958. The highest value of V-statistics (1.4067) was recorded at point 19. It is significant to note that the growth movement of the V-statistic for Sensex returns declined after point 19. From this, the investors may infer that the market return value was increased in the previous period and it is obvious that the value will be increased in the subsequent period also. It implies that the index returns would tend to increase in the future. It establishes that there was evidence of long-term effect during the study period. Based on the

Table 4. Rescaled Range Analysis for BSE Sensex Returns during Pre-Global Financial Crisis Period (May 2004–Aug 2008)

N	log N	log R/S	log E(R/S)	V-Stat (R/S)
10	1.0000	0.4632	0.4805	0.9188
20	1.3010	0.6517	0.6638	1.0028
30	1.4771	0.7514	0.7667	1.0300
40	1.6021	0.8411	0.8382	1.0965
50	1.6990	0.8970	0.8928	1.1157
60	1.7782	0.9683	0.9370	1.2002
70	1.8451	0.9908	0.9741	1.1702
80	1.9031	1.0176	1.0060	1.1642
90	1.9542	1.0614	1.0340	1.2142
100	2.0000	1.0953	1.0589	1.2453
110	2.0414	1.1332	1.0814	1.2958
120	2.0792	1.1168	1.1018	1.1945
130	2.1139	1.1359	1.1206	1.1994
140	2.1461	1.1740	1.1379	1.2617
150	2.1761	1.1934	1.1540	1.2745
160	2.2041	1.2119	1.1690	1.2877
170	2.2304	1.2196	1.1831	1.2718
180	2.2553	1.2649	1.1963	1.3719
190	2.2788	1.2876	1.2088	**1.4067**
200	2.3010	1.2598	1.2207	1.2862
210	2.3222	1.2532	1.2319	1.2362
220	2.3424	1.2729	1.2426	1.2637
230	2.3617	1.2815	1.2529	1.2607
240	2.3802	1.2854	1.2626	1.2453
250	2.3979	1.3017	1.2720	1.2668
260	2.4150	1.3106	1.2810	1.2679
270	2.4314	1.3359	1.2896	1.3190
280	2.4472	1.3374	1.2980	1.2998
290	2.4624	1.3479	1.3060	1.3082
300	2.4771	1.3184	1.3137	1.2019
310	2.4914	1.3215	1.3212	1.1908
320	2.5051	1.3281	1.3285	1.1899
330	2.5185	1.3484	1.3355	1.2279
340	2.5315	1.3412	1.3423	1.1899

Source: Computed from yahoo finance website using MATLAB R2012a.

Figure 3. Chart Showing V-Statistic for Sensex Returns for Log N Period during Pre-Global Financial Crisis (May 2004–Aug 2008)



Source: Computed from Table 4 using Microsoft Excel 2007.

analysis of the study, the forecasting of share price is possible in the case of Sensex during the pre-global financial crisis period.

Estimation of Rescaled Range Value for BSE Sensex Returns during the Post-global Financial Crisis

Table 5 depicts the outcome of the rescaled range value for the post-global financial crisis period from September

Table 5. Rescaled Range Analysis for Sensex Returns during Post-Global Financial Crisis Period (September 2008–December 2012)

N	log N	log R/S	log E(R/S)	V-Stat R/S
10	1	0.4735	0.4805	0.9407
20	1.3010	0.6669	0.6638	1.0384
30	1.4771	0.7703	0.7667	1.0758
40	1.6021	0.8497	0.8382	1.1186
50	1.6990	0.9206	0.8928	1.1779
60	1.7782	0.9409	0.9370	1.1267
70	1.8451	1.0102	0.9741	1.2235
80	1.9031	1.0579	1.0060	1.2776
90	1.9542	1.0729	1.0340	1.2467
100	2	1.0792	1.0589	1.2000
110	2.0414	1.0946	1.0814	1.1856
120	2.0792	1.1031	1.1018	1.1575
130	2.1139	1.1295	1.1206	1.1817
140	2.1461	1.1358	1.1379	1.1554
150	2.1761	1.1617	1.1540	1.1849
160	2.2041	1.1682	1.1690	1.1644
170	2.2304	1.1828	1.1831	1.1684
180	2.2553	1.2118	1.1963	1.2137
190	2.2788	1.2190	1.2088	1.2012
200	2.3010	1.2501	1.2207	1.2578
210	2.3222	1.2512	1.2319	1.2304
220	2.3424	1.2418	1.2426	1.1766
230	2.3617	1.2417	1.2529	1.1503
240	2.3802	1.2429	1.2626	1.1294
250	2.3979	1.2429	1.2720	1.1063
260	2.4150	1.2668	1.2810	1.1463
270	2.4314	1.2841	1.2896	1.1705
280	2.4472	1.2949	1.2980	1.1786
290	2.4624	1.3122	1.3060	1.2050
300	2.4771	1.3464	1.3137	**1.2818**
310	2.4914	1.3387	1.3212	1.2389
320	2.5051	1.3302	1.3285	1.1957
330	2.5185	1.3465	1.3355	1.2225
340	2.5315	1.3609	1.3423	1.2451

Source: Computed from yahoo finance website using MATLAB R2012a.

2008 to December 2012. The highest value (1.3609) of log R/S was registered on the 340th day, while the lowest value (0.4735) of log R/S was recorded on the starting period (N = 10). It is to be noted from Table 5 that the log R/S values and log E(R/S) values were closer to N = 60 from the starting period. Later, values diverged from the value of N = 70 (1.0102) to the value of N = 90 (1.0729). After that, log R/S values were closer from the period of N = 100 to N = 220. The log (R/S) value diverged from log E(R/S) during the period of N = 230 (1.2417) to N = 260 (1.2668) and during N = 300 (1.3464). In the case of V-statistics, the highest value of 1.2818 was witnessed on the 300th day period and the lowest value of 0.9407 was found in the starting period (N = 10). It implies the interesting fact that the index returns tended to decrease in the future.

The V-statistic plot of the Sensex against log (N) during the post-global financial crisis was used to record the variation of the log R/S and E(R/S) series. According to Figure 4, there was an increase in the plot of V-statistic values (1.1779) on point 5 and (1.2776) on point 8. After that, there was an increase in the trend of the V-statistic slope during point 20, with a value of 1.2578. The highest value of V-statistics (1.2818) was recorded on point 30. It is significant to note that the growth movement of V-statistic for Sensex declined after the point 20 up to the point 25, with a value of 1.1063. There was no decline at the end of the study period.

It implies that the Sensex returns would tend to increase in the future. It was established from the evidence that there was a long-term effect during the study period. Based on the results of the Sensex, the forecasting of share prices is possible to some extent in the case of the Sensex during the post-global financial crisis.

Analysis of Fractal Dimension of the S&P Sensex during the Pre- and Post-Global Financial Crisis

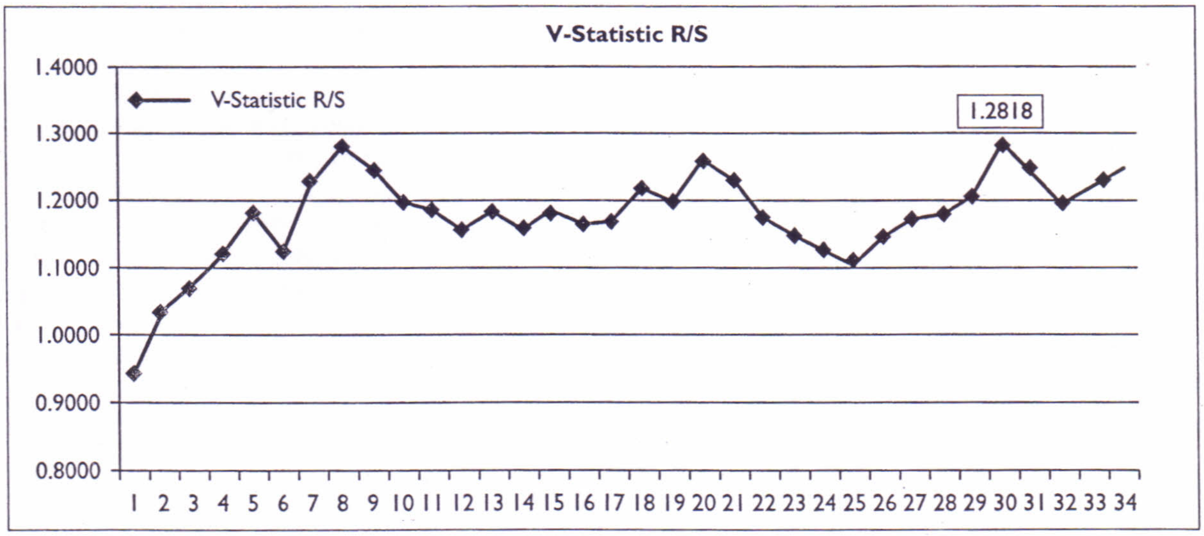
The Hurst exponent outputs, computed using Equation (5) for the periods from May 2004 to August 2008 and September 2008 to December 2012 regarding the S&P Sensex, are depicted in Table 6. The values of the Hurst exponent (0.5466) and (0.6269) were found for the S&P Sensex during pre- and post-global financial crisis periods respectively. From this analysis, it is to be understood that the post-global financial crisis period recorded a higher Hurst value than during the pre-global financial crisis period, indicating more persistent behaviour. Thus the

Table 6. Fractal Dimension for S&P BSE Sensex during Pre- and Post-Global Financial Crisis

Statistic	Pre-Crisis Period (May 2004–August 2008)	Post-Crisis Period (Sep 2008–December 2012)
Hurst Values	0.6269	0.5466
Fractal Dimension	1.3731	1.4534

Source: Computed from yahoo finance website using Equations (5) and (6).

Figure 4. Chart Showing V-Statistic for Sensex Returns for Log N Period during Post-Global Financial Crisis (September 2008–December 2013)



Source: Computed from Table 5 using Microsoft Excel 2007.

actual value for Hurst Exponent was greater than 0.5, and it indicates that the return prices showed persistence and the value of returns would increase in the future.

Table 6 also denotes the fractal dimension values for both the samples. It was observed from Table 6 that the post-global financial crisis period registered the highest fractal dimension (1.4534) while the pre-global financial crisis period recorded the lowest fractal dimension (1.3731), computed from Equation (6). Therefore, it is inferred that the pre-global financial crisis period was less risky than the post-global financial crisis period. Since the value of fractal dimension for the pre-global financial crisis period was closer to one, there was evidence of persistent behaviour, with fractal dimension at $1 < D < 1.5$. It is to be noted that during the post-global financial crisis, the value was closer to 1.5. It reveals the fact that if the share price had been increasing during the current period, it was expected to continue into the subsequent period also. The Sensex return was predictable in one direction for both the sample periods. Therefore, under both the sample periods of Sensex, the fractal dimension did exist.

Conclusion and Implications

This study has investigated the long range dependence by using daily data of the BSE Sensex returns of the Indian stock market. The results from this study evidenced the presence of fractal structure, with long memory in the Sensex returns. Long memory was found for both the sample periods. The daily returns of the Sensex displayed a persistent behaviour. From the above analysis, it is inferred that the persistence of samples indicated upward trends for the next period as the value of the Hurst exponent was greater than 0.5. It is also evident that for both the sample periods of Sensex returns; more than 90 per cent of the data were influenced by past values. It is to be noted that some previous studies using R/S analysis did find evidence of fractals in various financial markets.

Authors like Barkoulas et al., 2000; Cajuerio and Tabak (2005, 2008), Danilenko (2009), Henry (2002); Kasman and Torun (2007), Selvam et al. (2011) examined long-term memory using R/S Analysis by calculating the Hurst exponent. The returns showed the investors' sentiment was strongly influenced. The returns series of Sensex returns exhibit a fractal structure and these returns are predictable in the long term period.

Appendix

MATLAB Algorithm for Computing the Rescaled Ranges

```
function [out]=RSA(x)
%Syntax: [out]=RSA(x)
%Output format: 1st column=N; 2nd column=logarithm of n [log (n)]; 3rd column =
% logarithm of empirical rescaled ranges [log (R/S)]; 4th column = logarithm of
% expected rescaled ranges [log E(R/S)] (random process); 5th column =
% V-statistic (R/S); 6th column = V-Statistic E(R/S).
%This function performs the classical rescaled range analysis to a time
% series. The algorithm computes the rescaled ranges (R/S), the expected rescaled
% ranges of a random process E(R/S) according Anis and
%Lloyd (1976).
% This algorithm is based on earlier work by Thomas A. Thiele (2007).
if nargin<1 || isempty(x)==1
   error('Please enter a time series');
else
if min(size(x))>1
   error('Invalid time series');
end
   x=x(:);
   N=length(x);
end
   n=10:10:340
for i=1:length(n)
   % Calculate the subperiods
   a=floor(N/n(i));
   % Make the subperiods' matrixes
   X=reshape(x(1:a*n(i)),n(i),a);
   % Estimate the mean of each subperiod
   ave=mean(X);
   % Remove the mean from each subperiod
   cumdev =X-ones(n(i),1)*ave;
   % Estimate the cumulative deviation from the mean
   cumdev =cumsum(cumdev);
   % Estimate the standard deviation
   stdev =std(X);
   % Estimate the rescaled range
   rs=(max(cumdev)-min(cumdev))./stdev;
   clear stdev
   % Take the logarithm of the mean rescaled ranges
   logRS(i,1)=log10(mean(rs));
   % The estimation of log(E(R/S))
   j=1:n(i)-1;
   s=sqrt((n(i)-j)./j);
   s=sum(s);
   % Using the formula provided by Anis and Lloyd (1976)
   logERS(i,1)=log10((gamma(0.5*(n(i)-1))/(sqrt(pi)*gamma(.5*n(i))))*s);
   % The estimation of the V-statistics
   V-Statistic(R/S)(i,1)=mean(rs)/sqrt(n(i));
   V-Statistic E(R/S)(i,1)=10^ logERS(i,1)/sqrt(n(i));
```

```
logn(i,1)=log10(n(i));
nrange(i,1)=n(i);
out=[nrange,logn,logRS,logERS,V-Statistic(R/S),
V-Statistic E(R/S)];
end
end
```

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