Long Term Dynamics of Indian ADRs Market: The Case of Persistence and Irregular Cycles

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Abstract

The focus of this study is to understand the previously ignored return generating dynamics of American Depositary Receipts (ADR) markets. The main objective of this study is to investigate the nature of the return generating process of the Indian ADRs market. Specifically, the study addresses following interrelated research questions: Do returns series of Indian ADRs market exhibit random walk behavior or rather depict persistence and nonlinear dynamics? Is there any cyclicity in the returns series of Indian ADRs market? Rescaled Range (R/S) method on daily and weekly return series of Bank of the New York Mellon Indian ADR index (BKIN) from 2002 to 2016 has been applied to address the above questions. Empirical findings revealed that returns series of Indian ADRs market: (a) do not exhibit random walk behavior and rather depict both nonlinear behavior and persistence (long range dependence); (b) possess non-periodic cycles of 0.793, 2.38 and approximately 7 years. The findings can work as crucial inputs to forecasting, risk-management and market regulation processes. The knowledge of the average cycle length and persistence will enhance preparedness to handle the opportunities and risks at all levels in the market.

Keywords: ADRs, Persistence, R/S analysis, Nonlinearity, Irregular cycles

1. Introduction

Finance professionals need to decipher statistical processes which shape security prices because such understanding is crucial for forecasting security prices (Hinich & Patterson 1985). Extant empirical studies have confirmed the existence of nonlinearity and persistence in return series of equities, bonds and FX markets. However, such studies in Depositary Receipts (DRs) markets are almost non-existent. Notably, DRs are equity securities listed & traded on foreign markets, and therefore their returns are susceptible to the characteristics of host foreign markets (Choi and Kim 2000; Ely & Salehizadeh 2001). The additional factors of the host market make DRs different from the pure domestic equity securities, and quite logically, it is conjectured that return series of DR markets may possess some unique statistical attributes. With this view, this study focuses on investigating the nature of the return generating process of Indian American Depositary Receipts (ADRs) market. Specifically, following interrelated research questions are addressed: Do returns series of Indian ADRs market exhibit random walk behavior or rather depict persistence and nonlinear dynamics? Is there any cyclicity in the returns series of Indian ADRs market?

Numerous studies have used linear methods to assess the predictability of varied financial return series depending on whether they follow random walk or not (Malkei 2003; Kasman et al. 2009; Cevic & Emec 2013). If a return series doesn't follow a random walk, the inference drawn is that it contains predictable patterns, long memory or persistence (Note 1). Although the long memory can be generated by both linear and nonlinear (Note 2) processes, yet the stylized facts of financial time series data (Note 3) suggest that long memory is more likely to be generated by nonlinear stochastic processes rather than by linear processes (McKnzie 2001). Linear methods applied to nonlinear processes are prone to incorrectly accept the null hypothesis of random walk in security returns. Such erroneous conclusions result in wrong investment, policy and risk management decisions. In time series analysis, non-parametric methods have inherent advantages over parametric methods as the former class doesn't require any structural assumption about the underlying data generating process (Kreiss & Lahiri 2012). An observed time series can be generated by infinitely many processes, and the fact that non-parametric methods are not based on a specific set of assumptions about the underlying data generating process, make them flexible enough to identify the true dynamics of a process (Fan & Yao 2005). The Rescaled Range (R/S) method is a robust nonparametric method. This study used the R/S method to detect non-linearity and persistence in Indian ADRs market during the period 2001-2016. The superiority of the R/S method is that it not only detects persistence in the data series, but also identifies regular and irregular cyclic patterns in the underlying data generating process (Peters 1989; Yao & Tan 2000). The findings of our study revealed that returns series of Indian ADRs market: (a) does not exhibit random walk behavior and rather depicts both nonlinear deterministic behavior and persistence (long range dependence); (b) has non-periodic cycles of 0.793, 2.38, and approximately 7 years. The rest of the study is organized as follows: Section 2 discusses the existing literature; Section 3 documents methodology, data sources and sample; Section 4 contains the empirical findings and discussion; Section 5 has conclusions and recommendations.

2. Literature Review

2.1 Nonlinearity in Financial Asset Markets

The traditional linear methods used to validate Random Walk Hypothesis (RWH) assume that linear processes entirely shape the prices of financial securities. This assumption, however, fails to explain many phenomena observed in securities markets such as episodes of volatility clustering, extreme volatility, bubbles & crashes (Abreu & Brunnermeier 2003), profiting from simple technical strategies (Schulmeister 2009) etc., and leads to incorrect acceptance of the existence of random walk (Alharbi, 2009). DeBondt (1993) argues that market realities like institutional arrangements, human elements and investor heterogeneity in knowledge and information processing capabilities, possibilities of arbitrage, long-lived agents and competition etc. should not be ignored in financial market research. Deneckere and Pelikan (1986) suggests that the pervasiveness of market imperfections and human elements in financial markets can potentially give rise to non-linearity in returns series of these markets. Henry and Zaffaroni (2003) suggests the use of nonlinear methods like ARCH, two-shock nonlinear MA, GARCH etc. in studying financial time series. Such methods are capable of discerning linear as well as nonlinear relationships. Within the subset of nonlinear techniques, non-parametric methods provide a superior understanding of the true dynamics of the data generating process as they do not require restrictive assumption of normality of data (Fan 2005; Kukolj 2012). The R/S method is one such nonlinear, non-parametric approach, which can detect persistence and also reveal cyclicity in the returns series (McKnzie 2001). Hinich and Patterson (1985) in a pioneering study of nonlinear dynamics defines nonlinearity in terms of non-constant skewness. The study reports nonlinearity in returns of 15 common stocks listed at NYSE through the application of the bi-spectrum test. The stock market crash of 1987 provided further impetus to use of non-linear methods in financial research aimed at testing the validity of the random walk hypothesis (Lima 1998). In recent years, there has been spurt in studies which have refuted random walk and have documented nonlinear dynamics in a variety of financial return series (Ozer and Ertokatli, 2010; Mishra et al., 2011; Webel, 2012; Yilanci, 2012; Lim and Hooy, 2013; Madhavan 2014). However, existing literature provides mixed evidences on existence of non-linearity in financial return series.

2.2 Persistence in Financial Asset Markets

The RWH suggests that security prices follow a random walk, and don’t possess persistence (Osborne, 1959; Fama, 1965; Niederhoffer & Osborne, 1966; Fama et al., 1969; Fama, 1970). However, the available empirical literature provides mixed evidences on the applicability of RWH in security markets. Some studies support it (Godfrey et al., 1964; Fama, 1965; Fama, 1970; Fama, 1991; Alford & Guffey, 1996; Dow & Gorton, 1997; Barkoulas & Baum, 1997), and many others refute it (Grossman & Stiglitz, 1980; Shiller & Perron, 1985; Lo & MacKinlay, 1988; O’Brien & Srivastava, 1991; Barkoulas & Baum, 1996; Peress, 2010; Latif et al., 2011; Patel et al., 2012; Immonen, 2015). The rejection of the RWH infers existence of dependence and predictability in security returns. Granger and Joyeux (1980) suggests that security prices don’t follow RWH because future prices reflect investors’ opinions which are influenced by their past experiences, and introduces the concept of fractional differencing to identify persistence. Sowell (1992) argues that financial markets are predictable as investors are not always logical and often don’t consider the entire market information carefully in their investment decisions. Mandelbrot (1971) proposes the concept of time-lagged statistical dependence within time series to identify cases where strength of statistical dependence of asset prices decreased rather slowly, indicating presence of persistence. Ding, Granger and Engle (1993) finds significant autocorrelations between lagged observations in equity markets. Keim and Stambaugh (1986) empirically proves that equity returns show persistence and are forecast able. Fama and French (1988) shows that 25 to 40 percent of the variation in the longer-run holding period returns is predictable from past returns. Willinger et al. (1999) reports evidences of persistence in equity market of the USA. Similar results supporting the presence of persistence are reported by: Karp et al., 1972; Clark, 1973; Hsu et al., 1974; Greene & Fielitz, 1977; Kasman et al., 2007; Cevic & Emec, 2013; Ferreira & Dionisio, 2016. Several other studies have completely or partially negated the existence of persistence. Lee and Robinson (1996), using semi-parametric methods, reports that several stocks/index return series out of 26 stocks & 2 market indices don't possess persistence. Henry (2002) analyses 9 stock indices from developed markets using both parametric and semi-parametric methods, and reports existence of persistence only in 4 markets. Other studies which negate existence of persistence are: Aydogan & Booth, 1988; Lo, 1991; Cheung & Lai, 1995; Barkoulas & Baum, 1997; Lobato & Savin, 1998; Tolvi, 2003; Grau-Carles, 2005. The incomprehensiveness of literature in the area of persistence lies in the fact that the major focus of these studies is equity markets, and very few focus on other types of security viz. bonds, FX or DR markets (Malkei, 2003; Beine & Laurent, 2003; Oh, Kim & Eom, 2006; Kumar and Maheswaran, 2013; Madhavan, 2014; Anagnostidis and Emmanouilides, 2015; Ferreira & Dionisio, 2016; Sensoy & Tabak, 2016; and Masa and Diaz, 2017).

2.3 Nonlinearity & Persistence in DRs Markets

The field of literature in nonlinearity and persistence in DR markets is still very nascent, as evident from the following review. Rosenthal (1983) examines weak-form of efficiency in the ADRs market during 1974-1978 using serial correlation and finds it to be efficient. However, detection of persistence was not the objective of this study, it rather assessed the possibility of arbitrage created by short run dependencies. Wahab & Lashgari (1993) examines stationarity of co-movements of ADR & S&P 500 index returns for portfolio optimization, rather than for detecting persistence. Patro (2000) analyzes ADR returns to understand the risk exposure and not to detect persistence. Urrutia & Vu (2006) records presence of nonlinearity and chaotic structure in ADR returns by using BDS (Brock, Dechert, and Scheinkman) and EGARCH method. There exists a large gap in the existing literature which deal with nonlinearity and persistence in DR Markets. This study attempts to fill this void in literature.

3. Methodology, Data Sources and Sample

This study applied R/S method to daily and weekly adjusted closing return series of Bank of New York Mellon India ADR Index (BKIN) (Note 4) from January 2002 to July 2016 to detect persistence and nonlinearity. The data used are collected from *Bloomberg Database*. R/S method is probably the best-known test to assess persistence in financial time series (Zivot and Wang, 2007). Application of R/S method is justified as follows. *First*, its application doesn't warrant any prior assumption about data series and it is also superior to spectral analysis as it can detect non-periodic cycles (Mandelbrot, 1972). *Second*, it provides reliable results even for series with large skewness and kurtosis, which are common features of financial time series (Jacobsen, 1996). In contrast, conventional methods, such as analysis of autocorrelations etc. are not robust to such features. *Third*, as noted by Mandelbrot (1972), R/S method can be used even for stochastic processes with infinite variances, i.e. stable Paretian (Note 5) distribution suggested by Fama & French (1965). It doesn't rule out the possibility of such distributions in advance, which lends higher flexibility. As evident from Table 1, non-normality, high skewness and excess kurtosis of Indian ADR return series make the R/S method highly suitable for analyzing underlying return generating process. With $P_t \; and \; P_{t-1}$ as closing index values on two consecutive days (or weeks), we use the following formula to calculate the daily and weekly returns series

$$R_t = (\log_{10} P_t - \log_{10} P_{t-1}) * 100 \quad (1)$$

The R/S method requires one to calculate Hurst exponents, which governs the behaviour of a process. The first step is to pre-whiten the return series using an Autoregressive (AR) model. This was done to reduce short term dependencies in the residual or pre-whitened series, which otherwise would have emerged as an unwanted output in the process of detection long run dependencies (Brock et al. 1996; Jacobsen 1996). The pre-whitened series, each having N data points, are split into k non-overlapping sub-samples (shorter time series) of length n, which is chosen in a way that k = N/n is always an integer. The number of data points is considered to maximize the number of sub-samples and each sub-sample must contain at least 10 data points. Our study considers 3600 and 760 daily and weekly data points respectively. The R/S statistic is calculated as the range of partial sums of deviations of a time series from its mean, rescaled by its standard deviation (Jacobsen, 1996). For a sub-sample with data points as $X_1, X_2, X_3 \dots \dots \dots X_n$, the range is calculated as:

$$R_n = max\left(Z_{1,}Z_2, Z_3, \dots \dots \dots, Z_n\right) - min\left(Z_{1,}Z_2, Z_3, \dots \dots \dots, Z_n\right) \quad (2)$$

Here Z_j represents a cumulative deviate series calculated from the mean adjusted series of deviations. The *R/S* statistic for each subsample is calculated by dividing the range by their respective standard deviations. The R/S statistics of k sub-samples corresponding to a set value of n are then averaged to calculate $(R/S)_n$ for a given *n*. In order to detect departure of $(R/S)_n$ from random walk, we compare them with their corresponding expected values, a random number calculated through an empirically proven formula provided below, which was initially developed by Anis and Lloyd (1976) and later on modified by Peters (1994) by adding a correction factor:

$$\mathrm{E(R/S)_n} = \left(\frac{\mathrm{n-0.5}}{\mathrm{n}}\right) * \sqrt{\frac{2}{\mathrm{n\pi}}} * \sum_{\mathrm{r=1}}^{\mathrm{n-1}} \sqrt{\frac{\mathrm{n-r}}{\mathrm{r}}} \quad (3)$$

For a non-random process, $(R/S)_n$ values will deviate from $\mathrm{E(R/S)_n}$ values. To detect such deviations, values of $Log(R/S)_n$ and $Log(E(R/S)_n)$ are plotted against $Log(n)$. This plot also indicates the presence of cyclicity in the underlying return series by revealing break points (Note 6), where slope of $Log(R/S)_n$ becomes positive from negative. Shortcoming of this approach is that it may miss some cycles due to potential superimposition of a large number of cycles of different frequencies (Peters, 1994). V-statistics are calculated to overcome this inadequacy. The V statistic V_n is $(R/S)_n$ normalized with $\sqrt{n}$:

$$V_n = \frac{\left(\frac{R}{S}\right)_n}{\sqrt{n}}, for\ sample\ of\ size\ n \quad (4)$$

V statistics for $\mathrm{(R/S)_n}$ and $\mathrm{E(R/S)_n}$ and plotted against $Log(n)$. If $\mathrm{(R/S)}_n$ scales at a rate $= \sqrt{n}$, (which signifies a random process), the V_n line should be a horizontal line and deviations implies non-randomness. Cycles are identified and starting of a cycle is marked at points where the slope of the V_n line for $\mathrm{(R/S)}_n$ becomes positive from negative. Values of the Hurst exponents *H* are estimated for various intervals which are constructed to cover a complete cycle. Values of *H* for various intervals are calculated by fitting the following OLS equation:

$$\mathrm{Log}_{10}(R/S)_n = \mathrm{Log}_{10}\, C + H\, \mathrm{Log}_{10}\, n + \varepsilon \quad (5)$$

For a value of $H = 0$, the underlying process implies a random and independent process. In the range $0.5 < H \leq 1$, *H* implies a persistent process, and for such a process what happens today impacts the future forever (Peters, 1994). In the range $0 \leq \mathrm{H} < 0.5$, *H* signifies a mean reverting process. In order to assess statistical significance of estimated *H* we use two approaches: 1) the usual t-test of linear regression where p-value indicates how significantly values of *H* were different from zero 2) a confidence test of R/S Analysis proposed by Peters (1994) to observe the deviation of *H* from $E(H)$, an IID random variable obtained by regressing another independent random variable $E(R/S)_n$ on *n* as follows:

$$\mathrm{Log}_{10}\, E(R/S)_n = \log_{10} C + E(H)\, \mathrm{Log}_{10}\, n + \varepsilon \quad (6)$$

If the values of the estimated *H* are approximately two standard deviations (Note 7) greater than $E(H)$ values for same *n*, then *H* values represent processes which are significantly different from random.

4. Empirical Findings and Discussion

Table 1 reports the descriptive statistics of the daily and weekly ADR return series. The series possess negative skewness, leptokurtic, and exhibit non-normality. Presence of leptokurtosis supports the existence of systematic bias in the return series (McKenzie 2001), which could be revealed by R/S Analysis.

Table 1. Descriptive Statistics of the Daily and Weekly ADR Return Series

Particulars	Daily Return Series	Weekly Return Series
No. of Observations	3600	760
Mean	0.0004987	0.002105
Standard Deviation	0.021427	0.044015
Skewness	-0.1899589	-0.6582007
Kurtosis (Excess)	8.95617	4.31066
JB Statistic	12071	648.79

4.1 R/S Analysis of Daily Return Series of BKIN Index

Table 2 and Figure 1 depict results of R/S Analysis of daily return series of BKIN Index. Figure 1 depicts that $Log(R/S)$ values were greater than $Log(E(R/S))$ values for all the sub-periods. Till the point 1.3979 (n=25), both the lines move parallel to each other, and beyond this point systematic deviations appear. The dispersion becomes more prominent from the point 2.352 (n=225) and subsequent breaks are observed at points 2.477 (n=300), 2.778 (n=600), and 2.954 (n=900). The presence of these breaks indicates the possibility of existence of multiple cycles.

Table 2. R/S Analysis of Daily Return Series of BKIN Index: Results of R/S analysis of the residual of AR model fitted to daily return series of the BKIN index from 13 May 2002 to 22 July 2016. The daily series containing a total of 3600 data points was split into non-overlapping sub-samples.

n	R/S	E(R/S)	Log(n)	Log(R/S)	log(E(R/S))
10	3.0775	2.6503	1	0.4882	0.4233
12	3.4482	3.0374	1.0792	0.5376	0.4825
15	3.9493	3.5605	1.1761	0.5965	0.5515
16	4.1382	3.7228	1.2041	0.6168	0.5709
18	4.4117	4.0323	1.2553	0.6446	0.6056
20	4.6648	4.3247	1.3010	0.6688	0.6359
24	5.0718	4.8677	1.3802	0.7052	0.6873
25	5.1186	4.9961	1.3979	0.7092	0.6986
30	5.7802	5.6018	1.4771	0.7619	0.7483
36	6.3219	6.2642	1.5563	0.8008	0.7969
40	6.7049	6.6749	1.6020	0.8264	0.8244
45	7.2698	7.1599	1.6532	0.8615	0.8549
48	7.4284	7.4379	1.6812	0.8709	0.8715
50	7.6789	7.6186	1.6989	0.8853	0.8819
60	8.2719	8.4704	1.7782	0.9176	0.9279
72	9.0681	9.4026	1.8573	0.9575	0.9732
75	9.5828	9.6231	1.8751	0.9815	0.9833
80	9.8425	9.9809	1.9031	0.9931	0.9992
90	10.2943	10.6642	1.9542	1.0126	1.0279
100	11.1496	11.3103	2	1.0473	1.0535
120	12.1433	12.5111	2.0792	1.0843	1.0973
144	12.6157	13.8258	2.1584	1.1009	1.1407
150	13.7797	14.1369	2.1761	1.1392	1.1504
180	14.9234	15.6058	2.2553	1.1739	1.1933
200	16.1534	16.5175	2.3010	1.2083	1.2179
225	17.0763	17.5949	2.3522	1.2324	1.2454
240	16.7091	18.2127	2.3802	1.2229	1.2604
300	20.2179	20.5083	2.4771	1.3057	1.3119
360	20.2206	22.5831	2.5563	1.3058	1.3538
400	23.3353	23.8710	2.6021	1.3680	1.3779
450	26.0891	25.3932	2.6532	1.4165	1.4047
600	30.4884	29.5099	2.7782	1.4841	1.4699
720	32.3628	32.4421	2.8573	1.5100	1.5111
900	38.3789	36.4139	2.9542	1.5841	1.5613
1200	41.6190	42.2332	3.0792	1.6193	1.6257
1800	51.2993	51.9939	3.2553	1.7101	1.7159
3600	69.1445	74.0233	3.5563	1.8398	1.8694

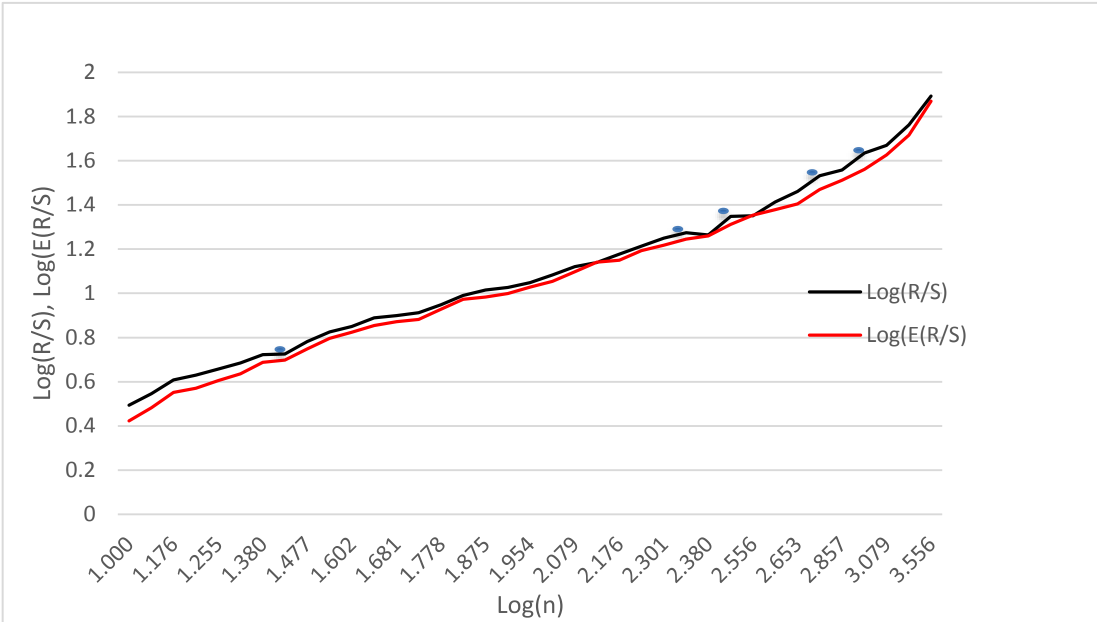

Figure 1. Plots of $Log\ (R/S)$ & $Log(E(R/S))$ against $Log(n)$

V statistics V_n for $(R/S)_n$ and $E(R/S)_n$ for sub-periods are calculated (Table 3) and plotted against $Log(n)$ (Figure 2). Figure 2 shows that till the point 1.398(n=25), both the V_n lines are smooth. In between $n \geq 25$ and $n \leq 300$, the lines deviate from each other, and breaks appear. After 2.477(n=300), breaks become more prominent, and beyond 3.255(n=1800) the two lines converge. Figure 2 indicates presence of multiple cycles at break points: 1.398(25), 2.477(300), 2.778(600), 2.857(720), 2.954(900), 3.255(1800).

Table 3. V_n for $(R/S)_n$ and $E(R/S)_n$ for Various Sub-Periods

n	Log(n)	V_n for (R/S)	V_n for E(R/S)
10	1	0.9732	0.8381
12	1.0792	0.9954	0.8768
15	1.1761	1.0197	0.9193
16	1.2041	1.0345	0.9307
18	1.2553	1.0399	0.9504
20	1.3010	1.0431	0.9670
24	1.3802	1.0353	0.9936
25	1.3979	1.0237	0.9992
30	1.4771	1.0553	1.0227
36	1.5563	1.0537	1.0440
40	1.6021	1.0601	1.0554
45	1.6532	1.0837	1.0673
48	1.6812	1.0722	1.0736
50	1.6989	1.0859	1.0774
60	1.7782	1.0679	1.0935
72	1.8573	1.0687	1.1081
75	1.8751	1.1065	1.1112
80	1.9031	1.1004	1.1159
90	1.9542	1.0851	1.1241
100	2.0000	1.1149	1.1310
120	2.0792	1.1085	1.1421
144	2.1584	1.0513	1.1522
150	2.1761	1.1251	1.1542
180	2.2553	1.1123	1.1632
200	2.3010	1.1422	1.1679
225	2.3522	1.1384	1.1729
240	2.3802	1.0786	1.1756
300	2.4771	1.1673	1.1840
360	2.5563	1.0657	1.1902
400	2.6021	1.1668	1.1936
450	2.6532	1.2299	1.1970
600	2.7782	1.2447	1.2047
720	2.8573	1.2061	1.2090
900	2.9542	1.2793	1.2138
1200	3.0792	1.2014	1.2192
1800	3.2553	1.2091	1.2255
3600	3.5563	1.1524	1.2337

Based on identified break points in Figure 2, five intervals are constructed and are shown in column 1 of Table 4. The Hurst exponents and their corresponding expected values are calculated using equations (5) and (6)

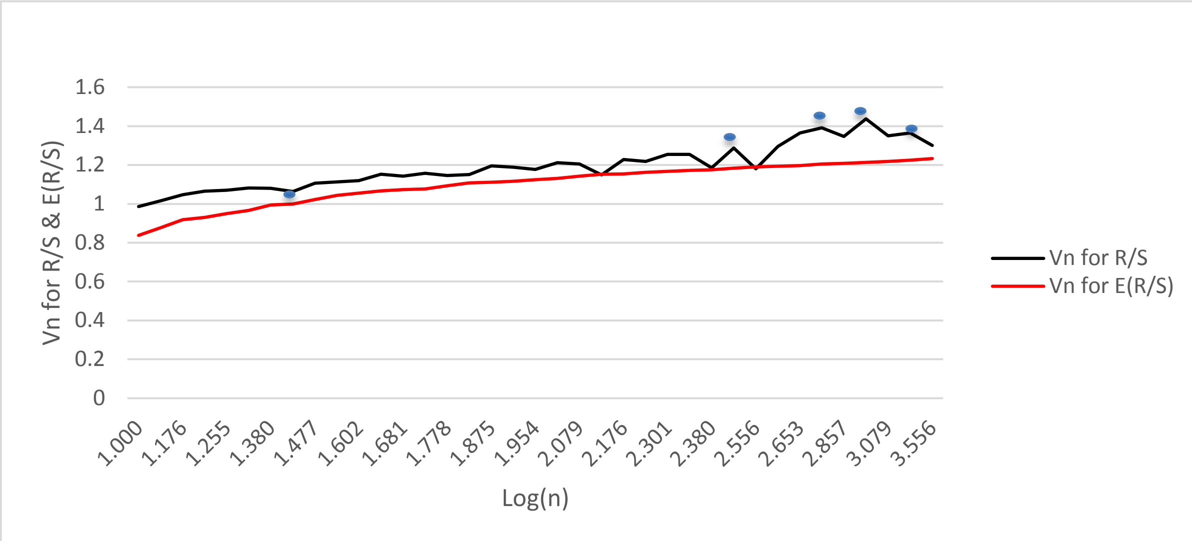

Figure 2. Plot of values of V_n for R/S & E(R/S) against $Log(n)$

Table 4. Identification of Cycles: *H* & E(*H*) are calculated as slopes of the least square lines between (R/S) & Log(n), & between E(R/S) & Log(n), respectively. The bracketed terms in *H* & E(*H*) column represent the standard errors. In P-value column, ***, ** & * represent significance at 0, 0.001, & 0.01 respectively.

Interval	H	t stat.	P-Value	Adj. R^2	E(H)	t stat.	P-Value	Adj. R^2
(25, 1800)	0.561 (0.005)	111	0.000***	0.998	0.5457 (0.003)	190	0.000***	0.999
(25, 900)	0.5661 (0.006)	96	0.000***	0.997	0.5512 (0.003)	191	0.000***	0.999
(25, 300)	0.5571 (0.007)	83	0.000***	0.997	0.5651 (0.003)	184	0.000***	0.999
(360, 600)	0.7848 (0.121)	6.5	0.023*	0.952	0.5235 (0.001)	791	0.000***	1
(720,1800)	0.4877 (0.054)	0.1	0.012*	0.965	0.5147 (0.001)	692	0.000***	1

For all intervals, *H* values are found to be significant. High R^2 values along with low standard error estimates illustrate the goodness of fit of the regression model used for estimation. For the intervals except for (720, 1800), *H* values are greater than 0.5 which signifies presence of persistence in the return series. For this particular interval, the return series is mean reverting. Applying Peter's confidence test, we calculate the standard deviation of $E(H)$ as 0.0167. The estimated *H* values are significant for intervals (360, 600) and (720, 1800), as *H* estimates in these two intervals are 15.67 and 1.62 standard deviations greater than the $E(H)$. We conclude that these *H* values represent processes significantly different from an independent & random process. Thus the daily return series is found to exhibit significant persistence and anti-persistence at two occasions, viz. (360, 600) and (720, 1800). For the other three intervals, the estimated *H* values are greater than 0.5, indicating non-randomness. However, Peter's test doesn't conclude them to be significant. Table 3 also confirms the presence of cycles in the return generating process. Statistically significant breaks are identified at points $n = 600$ and 1800. Considering 252 trading days in a year, these breaks correspond to periods of 2.38 and 7.14 years respectively. Thus, it can be concluded that the Indian ADR market exhibits nonlinear dynamics with irregular cycles of 2.38 and 7.14 years.

4.2 R/S Analysis of Weekly Return Series of BKIN Index

Table 5 and Figure 3 present the results of R/S Analysis of weekly return series. In Figure 3, the plots of R/S and E(R/S) move parallel to each other till 1.279(n=19). Beyond this point both the plots deviate from each other and these deviations are more pronounced beyond 1.580(n=38). At n=38 the first break point is observed, which marks the end of a cycle. Beyond this point the R/S plot kept altering directions till the point n=380, indicating the presence of multiple cycles in the return series. After the point n=380, the two plots converge. Additional breaks are observed at 2.182(n=152) and 2.580(n=380).

Table 5. R/S Analysis of Weekly Return Series of BKIN Index: Results of R/S analysis for Weekly return series of the BKIN index from 4 January 2002 to 22 July 2016. There are 760 observations which are split into non-overlapping sub-samples.

n	R/S	E(R/S)	Log(n)	Log(R/S)	Log(E(R/S))
10	3.0398	2.6503	1.0000	0.4828	0.4233
19	4.3445	4.1805	1.2788	0.6379	0.6212
20	4.5496	4.3247	1.3010	0.6579	0.6359
38	6.1469	6.4723	1.5798	0.7887	0.8110
40	7.0392	6.6749	1.6020	0.8475	0.8244
76	9.2468	9.6956	1.8808	0.9659	0.9866
95	10.9660	10.9916	1.9777	1.0400	1.0411
152	14.9488	14.2392	2.1818	1.1746	1.1535
190	18.5335	16.0677	2.2788	1.2679	1.2059
380	26.8845	23.2356	2.5798	1.4295	1.3662
760	32.6328	33.3642	2.8808	1.5137	1.5233

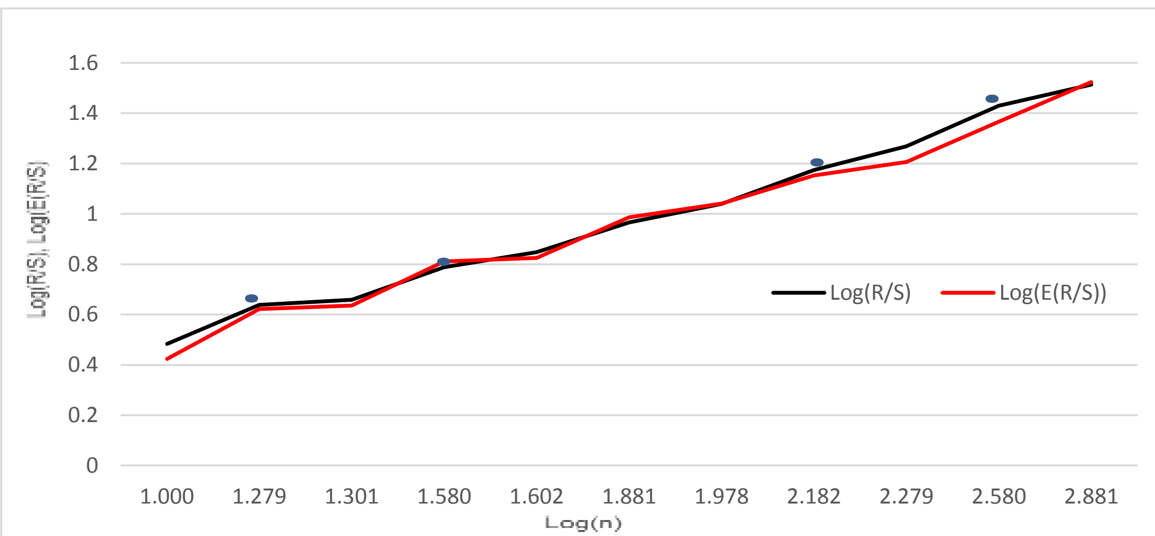

Figure 3. Plots of $Log\ (R/S)$ & $Log(E(R/S))$ against $Log(n)$

V statistic, V_n for R/S and E(R/S) are calculated (Table 6) and plotted them against $Log(n)$ (Figure 4). Evident from figure 4 is that the V_n plots move coherently till the point 1.279(n=19), indicating that both the plots represent random movements. Beyond n=19, the V_n plot for R/S contrasts the movements of the plot for E(R/S) and completes a cycle at 1.6020(n=40). This trend reverses soon and a new cycle starts at 1.8808(n=76), which continues roughly to 2.2787 (n=190) and ends at 2.5797(n=380). Breaks are observed at: 1.2787(19), 1.6020(40), 1.8808(76) and 2.5797(380). Presence of these break points clearly indicates the presence of irregular cycles in the weekly return series.

Table 6. Values of V_n for $(R/S)_n$ and $E(R/S)_n$

n	Log(n)	V_n for (R/S)	V_n for E(R/S)
10	1	0.9613	0.8381
19	1.2788	0.9967	0.9591
20	1.3010	1.0173	0.9670
38	1.5798	0.9972	1.0499
40	1.6021	1.1130	1.0554
76	1.8808	1.0607	1.1122
95	1.9777	1.1250	1.1277
152	2.1818	1.2125	1.1549
190	2.2788	1.3446	1.1657
380	2.5798	1.3791	1.1919
760	2.8808	1.1837	1.2102

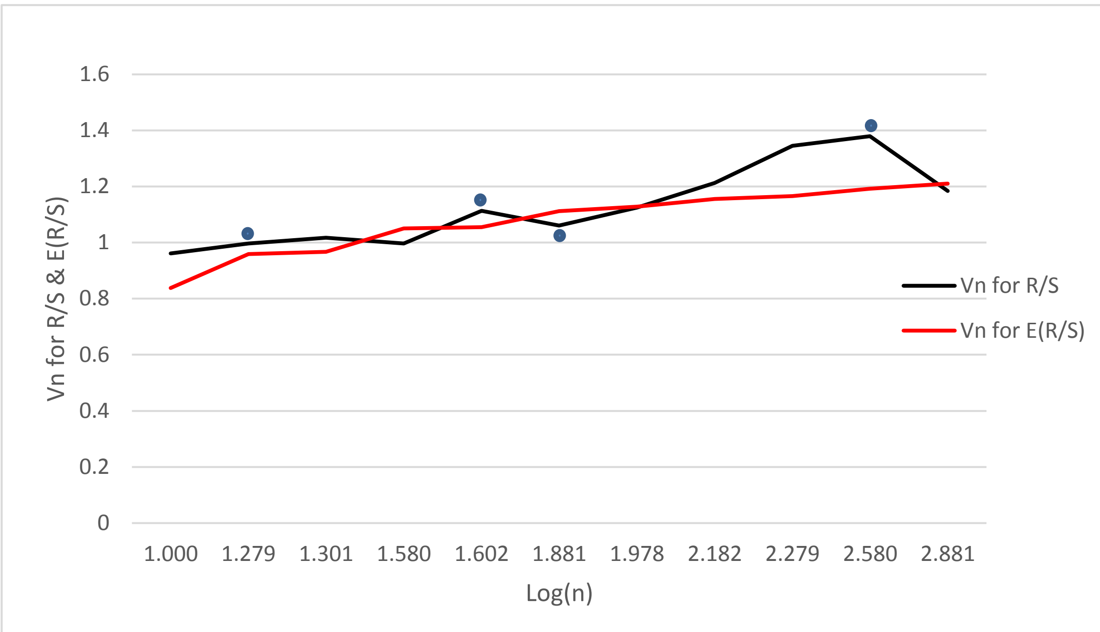

Figure 4. Plot of Values of V_n for R/S & E(R/S) against $Log(n)$

Based on identified break points in Figure 4, three intervals are constructed (presented in column 1 of Table 7), and Hurst exponents and their corresponding expected values are calculated using equations (5) and (6).

Table 7. Identification of Cycles: *H* & E(*H*) ae calculated as the slopes of the least square lines between (R/S) & Log(n), & between E(R/S) & Log(n), respectively. The bracketed terms in H & $E(H)$ column represent the Standard Error values. . In P-value column, ***, ** & * represent significance at 0, 0.001, & 0.01 respectively.

Intervals	H	t stat	P-Value	Adj. R^2	$E(H)$	t-stat .	p-value	Adj. R^2
(19, 380)	0.610 (0.017)	35	0.000***	0.997	0.574 (0.007)	79	0.000***	1
(19, 40)	0.5718 (0.078)	7	0.018*	0.967	0.528 (0.002)	397	0.000***	1
(76, 380)	0.669 (0.033)	20	0.000***	0.996	0.543 (0.004)	153	0.000***	1

For all the three intervals, H values exhibit high statistical significance, as indicated by p-values. Applying Petr's significance test in the intervals (19, 40) and (76, 380), the estimated values of H are found to be 1.2 and 3.4 standard deviations greater than the $E(H)$ value (standard deviation is 0.0362). For these two intervals, H values represent a process significantly different from a random and independent process. Based on significance levels, cycles are discerned at n=40 and n=380 for these two intervals. These two values correspond to approximately 0.793 and 7.54 years, respectively (considering 252 trading days in a year). The overall empirical findings suggest that the ADR market in India exhibits persistence and nonlinear dynamics with non-periodic cycles of 0.793 and 7.54 years respectively. The cycle of 7.54 years discerned from weekly data roughly matches the cycle of 7.14 years discerned from the daily data, and this is possibly the average cycle length.

5. Conclusion and Recommendations

Existence of nonlinearity and underlying deterministic processes in equity markets has been posited and tested by many empirical studies and theoretical frameworks. However, in Depositary Receipts markets such research studies are rare. This paper attempted to fill this void by applying Rescaled Range Analysis to the return series of Depositary Receipts market index of India, BKIN, to affirm the existence of persistence and nonlinearity. The results affirmed that the Indian ADR market possesses non-linear dynamics and persistence. The study also identified non-periodic cycles of length 0.793, 2.38 and approximately 7 years, using Daily and Weekly return series of BKIN. An average cycle of 7 to 8 years in the Indian equity market may be considered for comparison purpose. Detection of persistence or long memory and identification of irregular cycles have important implications for research in modeling prices of Depositary Receipts, and also for market participants for exploiting earning benefits, risk managements and policy framing etc. An important inference that can be made based on the results of this study is that if linear models applied to BKIN return series provide evidences of random behavior, such evidences should be considered carefully. This is because linear models can't adequately capture the dynamics of complex deterministic underlying processes as exhibited by BKIN index. This study has the following limitations. ***Firstly***, due to availability of limited data, we could identify only four cycles. If abundant data would have been there, we could have possibly identified more cycles using weekly data and possibly also conducted an analysis based on monthly data too. The later analysis would have further increased the robustness of our study results. ***Secondly***, this study has only focused on the dynamics of ADRs issued by the Indian firms. In the future, researchers can better understand the dynamics of other Depositary Receipts markets by performing multi-country studies. This possibly will highlight the impact of country specific factors on the dynamics of DR markets.

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Notes

Note 1. A security market exhibits persistence or long memory if information at large lags are correlated to each other, and correlation between lagged variables show hyperbolic decay (Robinson, 2003).

Note 2. Any time series process which can't be modelled using linear ARIMA model is termed as nonlinear (Ammermman & Patterson, 2003).

Note 3. Few well documented stylized facts of financial markets are: clustered volatility, positive kurtosis, low starting and slow-decaying autocorrelation function of squared returns and Taylor effect etc. (Sewell, 2011; Terasvirta & Zhao, 2011).

Note 4. BKIN index tracks the performance of the Indian ADRs and is maintained by the Bank of New York Mellon.

Note 5. A class of distribution for which variance does not exist or is infinite if exists.

Note 6. The points where an existing trend changes is termed as break points, and a cycle is a region between two break points, where the graph resumes similar trend.

Note 7. The standard deviation of $E(H)$ is $\sqrt{1/\mathrm{N}}$ for sample size N & it is independent of both N & H (Peters, 1994). For our Daily return series, total number of observations is 3600. Hence standard deviation of $E(H)$ for this series is $\sqrt{1/3600}$.