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INVESTIGATING THE EFFICIENCY OF THE INDIAN CURRENCY MARKET: A PERSISTENCE PERSPECTIVE

ABSTRACT

The presence of long range persistence and its impact on policy decisions are examined in the Indian Forex market during the period between 2000 and 2015. Hurst-Mandelbrot's Classical R/S Statistic, Lo Statistic, Robinson's Estimate have been computed. Long memory in volatility and absolute return series of each currency pair were evidenced but the logarithmic return series of all these currency pairs indicate proclivity towards the "random walk" hypothesis. Therefore, currencies are not systematically over- or under-valued, which provides justification for passive index investment in these currencies. However, possibilities of speculation/hedging activities could not be ruled out which may call Reserve Bank's intervention and interest smoothing behavior with potentials for impaired price discovery.

Key Words: long memory, volatility, rescaled range, Lo Statistic, spectral regression

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INTRODUCTION

With the growing economic importance of the Asian economies, the foreign exchange market of these economies have attracted global attention in the recent times. The burgeoning economic growth has also been reflected in the foreign exchange market in terms of increasing turnover. The foreign exchange markets of these countries have been gradually deregulated and have matured over the years. Most of the emerging economies have moved to a system known as the "managed float," whereby these countries allowed the value of the currencies to adjust according to market forces keeping monetary policy objectives in perspective. However, the volatility of exchange rates have often been cited as a major drawback of the floating rate system. Global trade and finance literature have repeatedly stressed the impact of exchange rate uncertainty on export pricing, international trade flows and foreign institutional investment. Although, short term forex risk can be mitigated by hedging, firms are exposed to medium and long term exchange rate volatility and the quantum of exposure can affect the investment decisions of firms. This is precisely why exploring predictability of exchange rates or presence of long range dependence in forex time series is one of the significant areas of research as implications of the same is enormous and calls for significant policy interventions to prevent speculative attacks.

The long memory property in a series means that the shocks to financial time series take a long time to disappear. The presence of long memory shadows the true dependence structure of a series (Mendes and Kolev, 2006) implying a potential predictable component in the returns and volatility that may provide benefits to speculators in the forex market. Derivative markets provide some cushion in terms of mitigating the exchange rate risks and derivative instruments are often effective to a limited extent of time period but long term fluctuations are generally more difficult to hedge, distorting relative prices. The sheer impact of exchange rate fluctuations in global business has grabbed the attention of researchers for long with respect to its univariate properties. However, with the Global Financial Crisis of 2008 in perspective, it is interesting to explore whether the effect of financial shocks on the exchange rates tend to decay quickly or over an extended period of time. Even statistically, long memory is a particularly interesting feature because its presence indicates evidence of nonlinear dependence in the first and second moments, and hence, evidence of a predictable component.

The presence of long memory in exchange rate of currency pairs raises the important question of its far reaching impact on the overall structure of the economy. The persistence of volatility leads to additional predictability resulting in increased speculation activities that may in turn adversely impact not only the true value of the currency but also the domestic economy as a whole. On a short time basis, the speculative activities might have the potential to adversely impact the value of the currency along with domestic interest rates similar to Latin American countries in 1999-2000 and East Asian countries in 1997. In a long time frame, export-oriented industries will be the worst affected by the erratic movements of the exchange rate. In the Indian context, a significant portion of GDP is contributed by service sector such as information technology and others whose business operations span across geographies and hence the relevance of long memory investigation in India.

Previous studies on long range dependence of currencies have been limited. Earlier studies have questioned the random walk properties of exchange rates. Hakkio (1986) indicated that exchange rates follow random walk under the specific condition if market is fundamental. While Embrechts, Cader, and Deboeck (1994) shows that most financial markets follow a biased random walk, Moody and Wu (1995) used re-scaled range and Hurst exponent analysis on tick-by-tick interbank foreign exchange rates, and suggested that they are mean-reverting. Cheung (1993) used Geweke and Porter-Hudak (1983) statistic to provide support to the existence of long memory in exchange rates, but evidences of weak long memory in the changes of US-dollar exchange rates are observed by Tschernig (1995). Cheung and Lai (2001) found long memory in yen-based real exchange rates while Barkoulas, Baum, Caglayan, and Chakraborty (2004) found less support for presence of long range dependence in 18 currency pairs. Inconclusive evidences on the presence of long memory in exchange rates were provided by Soofi, Wang and Y. Zhang (2006) using the plug-in and Whittle methods (spectral regression analysis). Floros (2008) found long term dependence in United States dollar (USD) returns against 17 exchange rates. Vats (2011) evidenced presence of long memory using integrated models for the Chinese yuan, Indonesian rupiah and Taiwanese dollar. In Indian context, Nath and Reddy (2002) used rescaled analysis and found long-term long memory in rupee-dollar exchange rate in India. However, rescaled analysis is often susceptible to noise and fails to differentiate between short and long memory. The present study is aimed to contribute to the present evidences on long memory of forex rates in Indian currency market by using Lo statistic which distinguishes long and short memory and additionally provides estimates of fractional differencing parameter using a semi-parametric method with improvements as proposed by Robinson (1995).

With the global integration and multinational organizations with operations spread all across the globe, managing foreign exchange risk has been on the top priority for them.

This has also created room for more vigilance and regulatory framework by the policy makers to ensure smooth and transparent market operations. Currency crisis has eroded the economic wealth of many organizations and economy in the history. Boosting export competitiveness to reap the benefits of currency depreciation has not been so fruitful for many, although the opinion might differ in terms of how and to what extent it might be warranted to promote depreciation to meet the domestic economic interests. Additionally, large depreciations also increase the burden of debt denominated in foreign currencies and raising of credit risk. All the scenarios above warrants an understanding of some level of efficiency and predictability of foreign exchange rates. The motivation for the paper stems from diverse findings on the existence of long memory in currencies across the globe. Long memory of Indian Rupee (INR) based exchange rates is limited which demands systematic investigation of the issue with comprehensive methodology. We cover a period 2000 to 2015 – a period that have witnessed many events that might have affected the Indian currency market like dot com bubble in stock market in India, Lehman Brother's collapse led to recession and its after affects, Chinese currency depreciation and its consequences. These led us to believe that there is a necessity to study the long memory property in Indian currency market especially in the awake of changing microstructure. During the last decade, structural reforms in the foreign exchange market had been carried out in view of more transparency and liquidity in capital flows across the globe. Moreover, it may be noted here that there remains always a natural need to vouch and verify the existing research findings. Unlike previous studies, this study considers absolute returns series which have more interesting statistical properties, thus further motivating the investigation in this study. For instance, absolute return modelling is more reliable than squared returns for the non-existence of a fourth moment commonly associated with financial returns (Mikosch and Starcia, 2000).

DEFINITION OF LONG MEMORY

Nowadays, the long memory in time series data describes the higher order correlation structure of a series. Suppose a series y_t is a long memory process, there is a persistent difference in observations separated in time. The presence of long memory can have some serious significance in the dynamics of the system; any shock at a point in time that leads to increased risk and uncertainty in the market doesn't elapse quickly if long memory is present. Rather, it persists and affects future outcomes. Mathematically, if $\lambda_s = \mathrm{cov}(y_t, y_{t+s})$, s=0, ±1, ±2, …., and there exist constants k and α, $\alpha \in (0,1)$ such that $\lim_{s\to\infty} \lambda_s s^{-\alpha} = 1$ then y_t is a long memory process. A long memory process can be regarded as a fractionally integrated process, between stationary and unit root process. But unlike an autoregressive stationary process, it shows a much slower hyperbolic rate of decay rather than exponential, and the process takes much larger time to adjust back to equilibrium. A stationary process is said to be I(0) process (integrated of order zero). Similarly, long memory process is I(d) process, where *d* lies between 0 and 1, i.e., a fraction. Long memory has also been called the "Joseph Effect" by Mandelbrot and Wallis (1968), a biblical reference to the Old Testament prophet who predicted seven years of plenty followed by the seven years of scarcity that Egypt was to experience.

The seminal work in hydrology by Hurst (1951) pioneered the research related to long range dependence in various fields. He developed "Rescaled Range Analysis (R/S)" to quantify statistical long memory in time series. Mandelbrot (1963) was possibly one of the key developers who applied the concept of long memory in the area of finance when he concluded that the distributions of the asset price changes have heavier tails than those of standard econometric models. He also realized that heavy tail distribution can have long waiting times between events. This provided a platform for further studies carried out by Mandelbrot and Wallis (1969), Mandelbrot (1971, 1972), which suggested that the presence of long memory in financial markets may provide arbitrage opportunities arising out of the time required before new information is fully absorbed by the market. However, certain shortcomings in the classical Rescaled Range Analysis were documented by Lo (1991) who developed the "Modified Rescaled Range Analysis" and it is still contemporary in terms of predicting long memory of financial time series. In recent years, fractional differencing modelling and estimation has gained momentum for predicting and modelling long memory in financial time series. Geweke and Porter-Hudak (1983) suggested a semiparametric estimation of the fractional differencing estimator, d, that is based on a regression of the ordinates of the log spectral density on trigonometric function. Bhattacharya and Bhattacharya (2012, 2013) applied the above methodologies in equity markets of emerging and developed markets to examine the evidence of long memory in returns as well as squared and absolute returns data.

The presence of long memory in the exchange rate of currency pairs can have serious ramifications for global trade. It can lead to speculative profits and in turn affect investment decisions of organizations. In presence of long memory, returns do not follow random walk and are dependent to some extent on the historical data opening up room for predictability and scope for informed speculations rather than simple passive investments. As a result the past trends will be reinforced in the future values as well and the cycle of predictability will continue leading to systematic over-valuation or under-valuation of a currency. Hence, if long memory is shown to exist, it can be concluded that currency fluctuations will follow pre-determinable paths rather than just a "random walk" – thereby posing a considerable challenge to the proponents of efficient market hypothesis.

DATA AND METHODOLOGY

Determination of long memory of a time series empirically is difficult because strong autocorrelation of long memory processes make statistical fluctuations extremely large. This results in the requirement of a large amount of data for accurate statistical results. Foreign exchange markets are distinctively different from other financial markets primarily due to huge trading volume, dynamic involvement of financial institutions, high geographical dispersion and continuous operations. In this research, four currencies are considered for pairing with the Indian rupee (INR) are – United States dollar (USD), British Pound sterling (GBP), Euro (EURO) and Japanese yen (JPY), viz., (INR/USD), (INR/GBP), (INR/EURO) and (INR/JPY) for the period of 2000 to 2015 and the main source of data is Reserve Bank of India archives. The above mentioned four currencies are considered because currently, currency derivatives are available of these four currencies solely and hence the effect of derivatives trading, if any, on exchange rates is taken into consideration equally on all currency pairs. The daily exchange rates were considered for the above mentioned currencies and daily logarithmic return calculated using the relation: $R_t = \ln(\frac{P_t}{P_{t-1}})$ where, R_t is the return for the foreign currency on the t-th day, $\ln(P_t)$ and $\ln(P_{t-1})$ are the natural logarithm of the exchange rate on the t^{th} day and t-1 day respectively. We test for long memory on logarithmic return, absolute return and squared return series for the four exchange rate series mentioned above.

We have investigated the stationarity of all the data series using Phillips-Perron (PP) test and Augmented Dickey-Fuller (ADF) test. To correctly estimate the long memory property of financial data, we have estimated classical Hurst - Mandelbrot rescaled-range (R/S) statistic, modified rescaled-range (R/S) statistic introduced by Lo (1991) and the spectral regression parameters as suggested by Robinson (1995). The above mentioned tests were applied on logarithmic return, absolute and squared return series. The details of the methods are mentioned below.

Rescaled-range (R/S) analysis

R/S analysis provides an estimation of long range dependence on the basis of evaluation of the Hurst's exponent of stationary time series first introduced by H.E Hurst in 1951. The Hurst exponent was built on the study of Einstein regarding Brownian motion of physical particles and is often used to test for long memory in time series. R/S analysis in economy was introduced by Mandelbrot (1971, 1972 and 1997) who argued its superiority to autocorrelation, the variance analysis and spectral analysis. Let R_t be the return for the foreign currency on the t^{th} day, ln (P_t) and ln (P_{t-1}) be the natural logarithm of the exchange rate on the t^{th} day and t-1 day respectively, then the logarithmic return will be denoted by $R_t = \ln(\frac{P_t}{P_{t-1}})$. Under the null hypothesis of absence of long memory in the data series, classical R/S analysis is performed by calculating the confidence intervals under generally accepted significance level. The R/S statistic is the range of partial sums of deviations of time series from its mean, rescaled by its standard deviation. Hence if R_1, R_2, R_3,….. R_n denotes returns for a particular exchange rate and $\overline{R(n)}$ represents the mean return given by $R\ (n) = \frac{1}{n}\sum_{t=1}^{n} R_t$, where 'n' is the time span considered, the rescaled range statistic is given by:

$$\left(\frac{R}{S}\right)_n = \frac{1}{\sigma_n}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(R_t - \overline{R(n)}\,) - \min_{1\le k\le n}\sum_{t=1}^{k}(R_t - \overline{R(n)}\,)\right] \qquad (1)$$

where σ_n is the maximum likelihood estimate of simple standard deviation:

$\sigma_n = \frac{1}{n}\sum_{t=1}^{k}(R_t - \overline{R(n)})^2$. The first term in the parenthesis in equation (1) is the maximum of the partial sums of the first k deviations of R_t from the sample mean. It is non-negative since sum of all n deviations of R_t's from their mean is zero, thus the maximum by varying k from 1 to n has to be zero or a positive number. The second term in the parenthesis in equation (1) is the minimum of the same sequence of partial sums and is non-positive. The difference of these two terms is called "range" and is always non-negative. This makes $\left(\frac{R}{S}\right)_n \geq 0$. The advantage of the classical R/S analysis is the fact that the normality of underlying series is not a requirement making its findings reliable whether the distribution is known or unknown. Classical R/S statistic is often debated for its inability to distinguish between short memory and long memory present in financial data. This drawback was removed by modified R/S statistic proposed by Lo (1991).

Modified rescaled-range (R/S) analysis

The modified R/S analysis was suggested by Lo (1991) and was tested for long memory that examined the null hypothesis of no long range dependence at varying significance levels. Lo's modified R/S statistic, denoted by Q_n is defined as:

$$Q_n = \frac{1}{(\sigma_n)^2(q)}\left[\max_{1\leq k\leq n} \sum_{t=1}^{k}(R_t - \overline{R(n)}) - \min_{1\leq k\leq n} \sum_{t=1}^{k}(R_t - \overline{R(n)})\right]. \quad (2)$$

where $(\sigma_n)^2(q)$is the Newey and West (1987) estimate of long run variance of the series defined as:

$$(\sigma_n)^2(q) = \frac{1}{n}\sum_{t=1}^{n}(R_t - \overline{R(n)})^2 + 2\sum_{j=1}^{q}\omega_j(q)\gamma_j \quad (3)$$

where γ_j represents the sample auto-covariance of order j, and $\omega_j(q)$ represents the weights applied to the sample auto-covariance at lag j (1, 2, 3, …q). $\omega_j(q)$ is defined as: $\omega_j(q) = 1 - \frac{j}{q+1}$. The second term in the long run variance equation is intended to capture the short term dependence. Henceforth, the estimate of $(\sigma_n)^2(q)$ involves not only sums of squared deviations of R_t but also its weighted auto-covariances upto lag q. The weights $\omega_j(q)$ are the correction factors that help to distinguish between long and short memory. The lag length q obtained from the bandwidth selection procedures suggested by Andrew (1991) has been used to estimate the heteroscedasticity and autocorrelation corrected (HAC) standard deviation and is extremely crucial for modified R/S test for long memory.

The spectral regression method

A stationary long memory process can be characterized by the behaviour of the spectral density f(λ) function. The function is of the form f(λ): c|1-$e^{-i\lambda}$ |$^{-2d}$, as λ-> 0 with d ≠0, c≠0, d is the long memory parameter (or fractional differencing parameter) and 0<|d|<0.5. In order to estimate the fractional differencing estimator d, Geweke and Porter-Hudak (1983) proposed a semi-parametric method of long memory parameter d which can capture the slope of the sample spectral density through a simple OLS regression based on the periodogram, as follows: log I(λ) = β_0 - d log {4 $sin^2\,(\frac{\lambda_j}{2})\} + v_j, j = 1, \dots M; where\; I(\lambda)$ is the jth periodogram point; $\lambda_j = 2\Pi j/T$; T is the number of observations; β_0 is a constant; and v_j is an error term, asymptotically i.i.d, across harmonic frequencies with zero mean and variance known to be equal to $\Pi^2/6$. M= g(T) $= T^{\mu}$ with 0< μ<1 is the number of Fourier frequencies included in the spectral regression and is an increasing function of T. The estimator is known as a semi-parametric estimator because it yields an estimate of the fractional integration parameter, d, without specification of the short-term dynamics, the autoregressive and moving-average parameters. This is a considerable advantage over maximum likelihood based methods because a) misspecification of the short-term dynamics does not bias or otherwise impact the estimate of the fractional integration parameter; and b) a closed-form solution for the fractional integration parameter can be obtained, avoiding numerical optimization of a likelihood function. While estimating, a choice must be made of the number of harmonic ordinates to be included in the spectral regression. Robinson (1995) highlighted that the GPH estimator does not have ideal finite sample properties due to the dependence of the periodogram ordinates at low frequencies and proposed a semi-parametric average periodogram estimator and suggests to exclude a few periodogram ordinates at low frequencies. One of the innovations of Robinson's estimator is that it is not restricted to using a small fraction of the ordinates of the empirical periodogram of the series. The estimator also allows for the removal of one or more initial ordinates and for the averaging of the periodogram over adjacent frequencies. To achieve the optimal choice of T, several choices are established in terms of the bandwidth parameter M= $T^{0.50}$, $T^{0.55}$,…….. $T^{0.80}$.

EMPIRICAL FINDINGS

Descriptive statistics

The statistical summaries of logarithmic return, absolute return and squared return series for all the four currencies are presented in Table 1. The average logarithmic return of all four currencies are positive. The return series of two currencies, namely GBP and JPY are negatively skewed while other two, namely USD and EURO are positively skewed and all four return series are leptokurtic. The high values of Jarque-Bera statistic along with the leptokurtic nature helps explain the non-normal distribution of the return series. The squared return series and the absolute return series are positively skewed and leptokurtic in nature indicating non-normal distribution, which is also reaffirmed by the very high values of the Jarque- Bera statistic.

Table1. Descriptive statistics

Currency		Mean	Median	Std. Dev	Skewness	Ex. Kurtosis	Jarque-Bera
USD	RET	0.00011112	-0.00014893	0.004589	0.23125	6.7031	6453.96
	ABS	0.0029913	0.0017493	0.003482	2.6926	12.134	25192.80
	SQR	2.11E-05	3.06E-06	6.22E-05	10.355	178.31	4606660.00
GBP	RET	0.00010351	0.00022691	0.006596	-0.41603	4.3239	2771.72
	ABS	0.004885	0.0037672	0.004433	2.4662	13.152	28207.70
	SQR	4.35E-05	1.42E-05	0.000109	12.761	279.16	11234100.00
EURO	RET	0.00013937	0.00017679	0.00709	-0.024326	2.091	625.38
	ABS	0.0053559	0.0041747	0.004647	1.8959	6.1114	7394.86
	SQR	5.03E-05	1.74E-05	0.000102	6.585	70.665	738658.00
JPY	RET	5.42E-05	-0.00025638	0.008533	0.17013	3.551	1819.18
	ABS	0.0061313	0.0043662	0.005933	2.2689	8.1085	12343.10
	SQR	7.28E-05	1.91E-05	0.000172	7.2374	83.983	1038250.00

RET-Logarithmic Return series, SQR-Squared Return Series, ABS-Absolute Return Series

Unit root tests

The results of unit root tests are displayed in Table 2. The null hypothesis of presence of unit root in ADF test and PP test is rejected at 1% level of significance for logarithmic return, absolute return and squared return series of all four currencies indicating all the data series are stationary.

Table 2. Unit root tests

Indices	Data	ADF	PP
USD	RET	-58.4466***	-58.4466***
	SQR	-8.523606***	-85.55018***
	ABS	-9.817221***	-46.90206***
GBP	RET	-57.66244***	-57.66244***
	SQR	-10.10378***	-116.2255***
	ABS	-8.315543***	-125.8380***
EURO	RET	-59.08341***	-59.08341***
	SQR	-15.99559***	-65.75947***
	ABS	-14.10651***	-72.28443***
JPY	RET	-61.61182***	-61.61182***
	SQR	-9.178946***	-75.82116***
	ABS	-8.523941***	-89.18452***

Note: a) The critical values are those of Mackinnon (1991). b) *** represent the rejection of null hypothesis at 1% level of significance.

Rescaled-range (R/S) analysis: Hurst-Mandelbrot's classical R/S Statistic and Lo Statistic

The results of Rescaled-Range (R/S) analysis is presented in Table 3. The estimated values of Hurst-Mandelbrot's Classical R/S statistic suggests that the null hypothesis of no long range dependence in case of logarithmic return series of all four currencies cannot be rejected at a generally acceptable level of significance as estimated values of the statistic fall within the acceptable region. However, for both absolute and squared return series, the null hypothesis is rejected at 1% level of significance. The critical values of the statistic are obtained from Table 2 from Lo (1991). The results clearly depict that whereas logarithmic returns show no signs of long memory, absolute returns as well as volatility as measured by squared returns shows existence of long range dependence in the series. Now, since Classical R/S statistic is often sensitive to short range dependence, heterogeneities and non-stationary series, we have computed Lo's statistic to overcome these shortcomings. The Lo statistic computed in Table 3 shows that the null hypothesis of no long range dependence in case of logarithmic return series cannot be rejected at a generally accepted level of significance for all currencies as the estimated value of the statistic falls within the acceptance region. However, both for the squared return and absolute return series, the null hypothesis can be rejected at 1% level of significance for all currencies. The results of both tests indicate the existence of long memory for absolute and squared return series in general for all currencies under observation.

Table 3. Hurst-Mandelbrot's classical R/S statistic and Lo statistic

Currency	Data	Hurst-Mandelbrot's classical R/S statistic	Lo statistic
USD	RET	1.52	1.52
	ABS	12.3	4.86
	SQR	7.82	4.16
GBP	RET	1.06	1.06
	ABS	4.78	3.3
	SQR	4.48	3.37
EURO	RET	1.12	1.12
	ABS	3.72	2.75
	SQR	3.11	2.45
JPY	RET	1.46	1.46
	ABS	7.46	4.21
	SQR	5.74	3.27

Note: Critical values:

90%	[0.861, 1.747]
95%	[0.809, 1.862]
99%	[0.721, 2.098]

The spectral regression method (Robinson's estimates)

Table 4 depicts Robinson's (1995) estimates of the fractional differencing parameter (d) for the logarithmic return, absolute and squared return series for all four currencies under observation. This test examines the null hypothesis of short memory (H0: d =0) against alternate hypothesis (H1: d≠0) for a range of bandwidth (M = T0.50, T0.55, T0.60,……, T0.80). The estimates of d are statistically significant for all currencies in the absolute and squared return series, which rejects the null hypothesis of absence of long memory. Henceforth, the findings indicate the presence of long memory in absolute and squared return series for all four currencies. However, in case of logarithmic return series, the estimate of differencing parameter (d) is found to be significant in two chosen bandwidths for United States Dollar. Thus, existence of long range dependence in return series may not be, but it exists in case of absolute and squared returns for the four currencies under study.

Table 4. Robinson's estimates of fractional differencing parameter (d)

Currency	Data	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$	$M=T^{0.75}$	$M=T^{0.80}$
USD	RET	0.0498	0.0501	0.0854	0.1076**	0.0644	0.0720**	0.0335
		(0.0895)	(0.0684)	(0.0609)	(0.0491)	(0.0382)	(0.0303)	(0.0243)
		[0.5567]	[0.7328]	[1.4009]	[2.1939]	[1.6837]	[2.3793]	[1.3789]
	ABS	0.5351***	0.5095***	0.4372***	0.3861***	0.4083***	0.3921***	0.3296***
		(0.0755)	(0.0638)	(0.0491)	(0.0402)	(0.0347)	(0.0291)	(0.0249)
		[7.0907]	[7.9897]	[8.9002]	[9.5872]	[11.7552]	[13.4708]	[13.2042]
	SQR	0.3653***	0.3913***	0.4104***	0.3941***	0.3861***	0.4030***	0.2974***
		(0.0814)	(0.0690)	(0.0609)	(0.0477)	(0.0383)	(0.0311)	(0.0261)
		[4.4895]	[5.6688]	[6.7327]	[8.269]	[10.0943]	[12.9448]	[11.4122]
GBP	RET	-0.0835	-0.1110	-0.0642	-0.0217	0.0033	0.0202	-0.0169
		(0.0867)	(0.0678)	(0.0538)	(0.0415)	(0.0350)	(0.0282)	(0.0239)
		[-0.9630]	[-1.6383]	[-1.1957]	[-0.5225]	[0.0957]	[0.7162]	[-0.7044]
	ABS	0.6089***	0.4735***	0.4973***	0.4138***	0.3324***	0.2813***	0.2137***
		(0.0948)	(0.0714)	(0.0558)	(0.0453)	(0.0386)	(0.0311)	(0.0258)
		[6.4211]	[6.6238]	[8.9114]	[9.1358]	[8.6209]	[9.0312]	[8.2858]
	SQR	0.5668***	0.5093***	0.5474***	0.4600***	0.4462***	0.2826***	0.1960***
		(0.0968)	(0.0785)	(0.0616)	(0.0473)	(0.0382)	(0.0321)	(0.0266)
		[5.8554]	[6.4846]	[8.8811]	[9.7184]	[11.681]	[8.8145]	[7.3601]
EURO	RET	-0.0533	-0.0410	-0.0108	-0.0355	-0.0011	0.0201	-0.0009
		(0.0900)	(0.0795)	(0.0575)	(0.0447)	(0.0353)	(0.0309)	(0.0249)
		[-0.5920]	[-0.5164]	[-0.1894]	[-0.7940]	[0.0310]	[0.6487]	[-0.0354]
	ABS	0.5141***	0.4357***	0.3593***	0.2903***	0.2421***	0.2012***	0.1598***
		(0.1002)	(0.0936)	(0.0694)	(0.0536)	(0.0422)	(0.0338)	(0.0279)
		[5.1276]	[4.6520]	[5.1727]	[5.4094]	[5.7371]	[5.9480]	[5.7149]
	SQR	0.3795***	0.3096***	0.2786***	0.2624***	0.2382***	0.2148***	0.1552***
		(0.0913)	(0.0694)	(0.0549)	(0.0475)	(0.0386)	(0.0316)	(0.0263)
		[4.1559]	[4.4617]	[5.0697]	[5.5235]	[6.1711]	[6.7800]	[5.8861]
JPY	RET	0.1229	0.0617	0.0947	0.0601	0.0364	0.0005	-0.0147
		(0.0859)	(0.0677)	(0.0604)	(0.0484)	(0.0421)	(0.0324)	(0.0260)
		[1.4316]	[0.9118]	[1.5677]	[1.2417]	[0.8654]	[0.0167]	[-0.5661]
	ABS	0.5580***	0.4852***	0.4073***	0.3642***	0.3021***	0.2668***	0.2121***
		(0.1244)	(0.0885)	(0.0651)	(0.0515)	(0.0404)	(0.0346)	(0.0269)
		[4.4859]	[5.4807]	[6.2498]	[7.0699]	[7.4735]	[7.6999]	[7.8765]
	SQR	0.4195***	0.4045***	0.3742***	0.3299***	0.2643***	0.2405***	0.2228***

	(0.0953)	(0.0711)	(0.0565)	(0.0439)	(0.0351)	(0.0287)	(0.0248)
	[4.4002]	[5.6872]	[6.6159]	[7.5068]	[7.5153]	[8.3648]	[8.9765]

Note: a) ***, ** and * represents the rejection of null hypothesis at 1%, 5% and 10% level of significance respectively. b) Standard errors in ( ) and t-statistics in [ ].

CONCLUSION

Our findings indicate that long memory is present in the absolute and volatility series in all the four currency pairs. However, the logarithmic return series for all currency pairs do not exhibit the presence of long memory. The findings are consistent across all currency pairs. In the current scenario, when international markets are getting increasingly dependent on one another leading to seamless inflow and outflow of capital, the findings bear additional significance. An absence of long memory in logarithmic return series of the forex rates show no evidence against the weak form of market efficiency in currency returns. Apparent past exchange rates are not predictive for future prices leaving little scope for profitable arbitrage opportunities. Consequently, although an investor can design a model to make investments on currency based on the amplitude of fluctuations in past data, he cannot predict the direction in which the fluctuations may occur in future. Therefore, we can expect less headroom for hedge fund activity as far as the logarithmic returns in the Indian currency market are concerned.

The presence of long memory in squared returns indicates volatility of currency returns can be modelled using returns from the recent as well as remote past and hence derivative instruments can now be more efficiently priced. This can provide a leverage for increased speculative investment activities. In the short term, these activities may give rise to speculative attacks, similar to what happened to some Latin American and Asian countries in the 1990s that have the potential to adversely impact the value of the currency along with domestic interest rates. In the long term, it can amplify the normal appreciation-depreciation cycles of the currency and have negative impacts on macro-economic parameters, especially those related to export-import industries. Also identifying the presence of long memory will help in application of risk analysis models like Value at Risk (VaR) to estimate potential losses with more conservative and precise estimation. Furthermore, with little support for speculation over a considerably large period of time, the currency's tendency to attain true value will be favoured.

With increased chances of predictive volatility in INR based exchange rates, monetary policy measures may additionally try to prevent sudden large fluctuations and aim to restrict the capital flows – more specifically, outflows when the market is bearish. One way of achieving this is through alternative channels of fiscal restrictions on specific imports/exports. Another way can be to issue directives to domestic firms (especially financial entities) on their permissible limits of borrowing foreign money. The Central Bank should intervene wherever required in order to eliminate excessive speculation and inject further randomness in the fluctuation of currency rates to prevent consistent profit making strategies. While the bank should perform its necessary function of maintaining the value of the domestic currency as a tool for imparting economic stability, it must not become too rigid while defending the exchange rate of the currency - since an effort to keep the currency value absolutely stable runs the risk of making the exchange rate too predictable. Thus, our findings support the recent steps of partial market intervention by the Indian Central Bank to prevent rupee depreciation and limit the chances of making profit from market.

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