A Model of Analysing Long Memory with And Without Structural Breaks in Specific Reference to Indian Exchange Rate with Major Currencies

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Abstract

This paper investigates presence of long memory with and without structural breaks in exchange rate data. We propose to compare between standard GARCH and FIGARCH to find out suitable model for capturing volatility dynamics in case of INR versus USD, GBP, EURO and YEN over the sample period. We run two tests; GPH and Hurst exponent to detect presence of long memory before applying GARCH based models. Structural breaks were identified endogenously using Bai Perron test (BP) and optimum numbers of breakpoints were confirmed from log likelihood of BP test. We empirically examined daily return data from January 2000 through July 2018 and found presence of mild long memory in case of INR/USD and INR/YEN and strong memory in other two. Our result shows the evidence of parameter instability in case of INR/USD and INR/YEN while applying FIGARCH (1, d,1). We however found that volatility persistence significantly decreases in all the series except for INR/YEN after incorporating structural breaks in FIGARCH model. In case of INR/YEN, the value of long memory estimate has rather increased after adjusting for breaks. This study will have implications for investors and portfolio managers.

Keywords: long memory, structural break, volatility, persistence, exchange rate

1. Introduction

Economic liberalisation has a profound effect on the way the businesses are conducted. Globalisation causes resurgence of market forces which in turn has its tremendous impact on almost every aspect; technological, societal, economic, political. Asset prices in real economy are affected through variations in financial markets in terms of disruption in domestic economic activities [Gertler and Hubbard (1988)] and international assets flow [Goodhart (1988)]. Shiller (1988) attributed such variations in financial asset prices to ‘market psychology’.

Volatility is a common word that describes variations in asset prices over a time horizon. In finance, there exists a large number of studies that demonstrates presence of volatility persistence or long-lasting effects [Greene and Fielitz (1977); Andersen and Bollerslev (1997); Giraitis et al. (2003);Baillie and Morana (2009); Caporale et al. (2016); Charfeddine (2016)]. This means there is information built up into the asset prices which gets reflected slowly and steadily over a period of time. In other way, it is inferred that asset price can be predicted using past and current prices. This has provided contradicting result and of course a new perspective to notion of efficient market theory. Further, a number of previous studies have shown that financial asset returns show time varying volatility that are well captured by ARCH, GARCH and FIGARCH type models of Engle (1982); Bollerslev (1986);Baillie et al. (1996)respectively. These models explicitly assume the variance as a combination of conditional and unconditional, where the former to change over time while the latter remains constant.

Understanding dynamics of volatility and its persistence has clear implication. Volatility changes affect portfolio's exposure to risk. Therefore, investors should appropriately model volatility in order to achieve a profitable diversification and adopting an optimum hedging strategy [Mallikarjuna & Rao (2019);Salmanov et al. (2020)]. Volatility has significant information content about conditional variance and thus helps estimating VaR, thereby helping to price derivative contracts correctly [Giot (2003)].This apart, many literatures are available on volatility spill over between different markets [Malik and Ewing (2009);Clements et al. (2015);Fasanyaand Akinde (2019); Elsayed and Helmi (2021)]. This has been conjectured that financial market volatility often exhibits structural breaks and there is statistical inferences problem of ignoring such breaks. For instance, ignoring breaks in time series can result in spurious volatility persistence. Dieobold (1986), Lamoureux and Lastrapes (1990)were among the first to identify such phenomenon that may lead to existence of higher order moments like kurtosis in time series. In the similar lines, there were studies on different aspects such as equity premium and breaks [Pastor and Stambaugh (2001);Kim et al. (2005)], asset allocation and structural breaks [Petenuzzo and Timmermann (2011)] and structural change as a result of integration of emerging economies with developed markets [Garcia and Ghysels (1998)].

The exchange rate is an important economic variable that affects three principal activities of an economy; price level, interest rate and investment and therefore has significant impact on socio-economic condition of a country [Udoh and Egwaikhide (2008); Obansa et al. (2013); Fahlevi (2019)]. Volatility in exchange rate has always been a key concern due to the fact that it has substantial impact on primary economic variables mentioned above. Under such circumstances, there is a need to measure different stylized facts such as clustering, fat tails, asymmetry, long memory, variance evolution over time. To study such phenomenon, demand for new forecasting tools is inevitable that can capture these aspects. Based on random walk hypothesis, two set of studies are available. Some found that exchange rate behaviour follows a martingale process which is an unbiased random walk [Diebold and Nason (1990); Yang et al. (2008)]. However, studies by Liu and He (1991) and Bekaert and Hodrick (1992) found evidence against the martingale process. Continuous evolution of exchange rate with time entails risk which can best be modelled through conditional variance. In this context, a key question with respect to volatility modelling is whether presence of breaks affects long run estimates of exchange rate. This paper proposes to examine one important property of time series; long memory with and without structural breaks.

Exchange rate is considered to be the best candidate for testing such properties due to following reasons. First, exchange rate is affected mostly by global factors with timely intervention by respective central banking authorities. Therefore, it is interesting to see whether exchange rate possess both. At this point it can be hypothesized that exchange rate possesses long memory within a regime. In other words, its autocorrelation function is not integrable within a given regime. Regime change is induced by sudden and substantial shift in time series behaviour. It can be affected by central bank's intervention of buying or selling foreign currencies. Second, exchange rate acts as a linkage among several assets across different markets. This implies any transmission of shocks or volatilities between markets is possible through exchange rate. Therefore, all properties that are applicable to individual assets' volatilities traded in domestic market should somehow reflect in exchange rates. Third, being the largest financial market, significant volume of trading in forex market makes it possible to discover true value of currencies that in turn reflected in exchange rate. According to BIS Triennial Central Bank Survey conducted in April 2022, trading in OTC forex was around $7.5 trillion per day in April 2022[1]. Further FX swaps and spots continued to command a substantial bulk of trading volume. This can be inferred as exchange rate comprises of numerous daily short-term fluctuations due to large liquidity in the forex market.

The remainder of the paper consists of the followings. Section 2 reviews literatures related to modelling of exchange rate volatility. Section 3 presents methodology. Section 4 describes data. Section 5 explains the empirical result. Finally, section 6 concludes the study by summarising results and section 7 presents practical implications for stakeholders.

2. Literature review

2.1 Volatility in exchange rate

Volatility is said to be persistent when asset returns are random [Choi et al. (2010)].Persistence in volatility makes it possible to predict which is generally known as long memory. Study of long memory helps to explain the reasons for shocks and its long-lasting impact on volatility. Analysis of long run effect of shocks is also directly helpful to investors to take appropriate strategies to minimise risk of loss. Presence of long memory indicates presence of nonlinear dependence in time series returns. This means it is possible to predict future return based on historical data fully contradicting weak form of market efficiency [Charfeddine (2014)].Cheung (1993)applied ARFIMA to five nominal dollar spot rates and found evidence in favour of presence of long memory. Bhar (1994)applied modified R/S statistic of Lo (1989) but found absence of long-term memory when the entire 10-year yen/dollar series was broken into components. However, when the entire data set is considered as a single period, it exhibits presence of long-term memory. Absence of long memory can possibly be due to increased sophistication of market participants which results in rapid reflection of information in prices, thereby no scope for carrying memories. Baillie et al. (1996)found long run volatility dependence in daily DM-USD data using FIGARCH method. Baum et al. (1999)examined the hypothesis of absolute PPP as a long run equilibrium concept post Bretton wood era of flexible exchange rate system by taking 17 CPI and 12 WPI based real exchange rates. They employed both fractional integration and structural breaks to study mean reversion and found real exchange rates are non-stationary thereby rejecting the notion of absolute PPP. Beine & Laurent (2001) applied Markov switching FIGARCH model to daily DEM-USD rates and found strong evidence of interaction between structural change and long memory. The result shows that significant decrease of long memory in exchange rate when adjusted for structural change. Similar results were obtained by Morana and Beltratti (2004). Cheung and Lai (2001)examined behaviour of real yen rates to shocks using fractional models and found presence of long memory dynamics. The study reveals that the rates move away from parity before reverting implying non-monotonic mean reversion. Nath and Reddy (2002) by employing R/S statistic and variance test ratio found mixed results. Variance test ratio indicates the INR-USD over a study period has mean reverting (tendency of long run persistence) characteristic except for 3-months window where returns follow a random walk. R/S statistic provides cue for presence of long memory with noise. Soofi et al. (2006) applied spectral regression analysis to examine long memory property to 12 Asian/dollar daily exchange rates and concluded that except Chinese renminbi, all other exhibit long run volatility. This means currencies at level are not mean reverting and accordingly demands intervention by central banks. Karemera and Cole (2010)examined nominal exchange rate of 13 emerging markets using ARFIMA process and found presence of fractionally integration process for most of the currencies implying rejection of random walk. In the similar line, Almudhaf (2014) tested the random walk behaviour of CIVETS countries exchange rates relative to USD over five-year time period using variance test ratio of Lo and Mackinlay (1988) suggests that except for Egyptian and Vietnamese exchange rates all other currencies show random walk behaviour. Chkili et al. (2012)tested the effects of asymmetry and long memory under both univariate and bivariate framework using three European stock markets and two US dollar exchange rates through GARCH-type models. Results were in favour of strong presence of both asymmetry and long-term dependence of conditional variances of all the series. Kumar & Maheswaran (2015) applied generalised Hurst exponent (GHE) to INR versus USD, Euro and yen and found evidence of presence of long-range dependence in all the cases. Gupta & Kashyap (2016)forecasted INR/USD and GBP/USD using past monthly data using GARCH family models and ANN. GARCH and EGARCH confirmed the presence of volatility and asymmetry. Tah (2018) examined the nature of US forex rate (in nominal terms) against its ten trading partners to test for mean reversion or random walk in the presence of structural breaks. Results support the presence of both sudden and gradual shifting towards mean in all the exchange rates. Afzal & Sibbertsen (2022) estimated long range dependence using range-based volatilities unlike absolute or squared returns using Local-Whittle estimator over different bandwidths. Results confirmed varying degrees of volatilities across different bandwidths indicating presence of structural breaks or central bank’s intervention.

2.2 Structural breaks

It is clearly evident from the above studies that volatility is persistent in exchange rates in most of the cases. Examining breaks in time series is important since it could affect signal transmission efficiency of currency market. Long memory in time series is characterised by slow decay of autocorrelation with increase in lag implying a momentum in a time series. Presence of structural breaks can cause a sudden and unexpected change to this momentum that are either exogenous or endogenousin nature. Garcia and Ghysels (1998)found economic events like liberalisation policies and global integration of equity markets can lead to structural change in the context of emerging markets. Bekaert et al. (2002)concluded that return and volatility of stock market increases after estimation of endogenous break dates. Kim et al. (2005) using a Bayesian marginal likelihood analysis found evidence of presence of one-time break in equity premium over the study period. They found a permanent decrease in volatility after the break. Logically it can be understood as inclusion of breaks can disrupt the series thereby causing randomness into the rally for a temporary period. This implies, previous values are no longer better representative of the new regime. Therefore, estimate of long memory should decrease after structural breaks. This particular behaviour was examined in many literatures. Ewing and Malik (2016)examined volatility spill over between oil price and stock market in the presence of structural breaks. They found evidence of increasing volatility spill over between two markets post introduction of breaks. However, they found a substantial decrease in volatility persistence after accounting for structural breaks for each of oil and stock market. Tsuji (2018) examined the impact of structural breaks on volatility of stock return of China and Japan using GARCH (1,1) and found evidence in decrease of volatility estimate after incorporating structural breaks as dummies. Similar results were found by Abakah et al. (2020); Yadav et al. (2021).

One thing is clear from above studies. Most studies confirmed a decrease in volatility persistence due to breaks. It is therefore important to test long memory behaviour due to structural breaks for correct estimation of volatility and its persistence. There appears to be lack of empirical evidences on study of long memory in exchange rates in Indian context. This paper contributes to existing literatures in the following way. It examines volatility persistence with and without structural breaks in Indian nominal exchange rate with four major currencies; USD, GBP, Euro and Yen with a broader data set ranging from 2000 till 2018. Such period covers both the periods of ups and downs. Ups are considered as normal periods whereas downs comprising of external shocks in terms of crisis, macroeconomic shocks and voluntary act of RBI to stabilise INR's external value.

3. Methodology

We use two models; standard GARCH model and the FIGARCH model. Both the models are intended to capture auto regressive nature of volatility. Under GARCH framework as developed by Bollerslev (1986), the conditional variance is a function of both its own lagged values and past squared errors. This is described as

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$$

where $\alpha \geq 0$, $\beta \geq 0$ guarantees non-negativity of ARCH and GARCH parameters and $\alpha+\beta<1$ indicates stationarity of conditional variance.

GARCH assumes the impact of past errors on current volatility to be constant over time. Though asset returns are assumed to follow i.i.d. process in a speculative market, but returns tend to be dependent through time due to temporal bursts of volatility. Following development of ARCH by Engle (1982) there were notable works about presence of extreme degree of volatility persistence. Baillie et al., (1996) propose the fractionally integrated GARCH model in the similar line. This model can effectively capture long memory in time series since it models impact of past shocks on current volatility to decay at hyperbolic rate.

The FIGARCH (p, d,q) modelcan be written as

$$[1-\alpha(L)-\beta(L)](1-L)^d \varepsilon^2_t = \omega + [1-\beta(L)]v_t$$

L denotes the lag operator, $(1-L)^d$ is the fractional differencing operator, d is fraction which lies between 0 and 1. v_t is innovations in conditional variance. FIGARCH model is stationary if value of d is $0 < d < 1$

4. Data

The study of volatility of four major exchange rates, i.e., INR versus the American dollar (USD), the British Pound (GBP), the euro (Euro) and the Japanese yen (Yen) were obtained from database of RBI. RBI calculates these spot rates on a daily basis by taking the average of bid-ask rates. The same is used as reference rates for settlement of currency derivatives at NSE and MCXSX. Apart from this, corporates use this rate for fixing transfer pricing of goods in case of international transaction. All data are converted into log returns which are used as inputs for further calculation. Following figure (Fig.-1) present original (left) and return (right) data for all the four series. The return is calculated as follows.

Return (R_t) $= ln\left(\frac{Pt}{Pt-1}\right)$

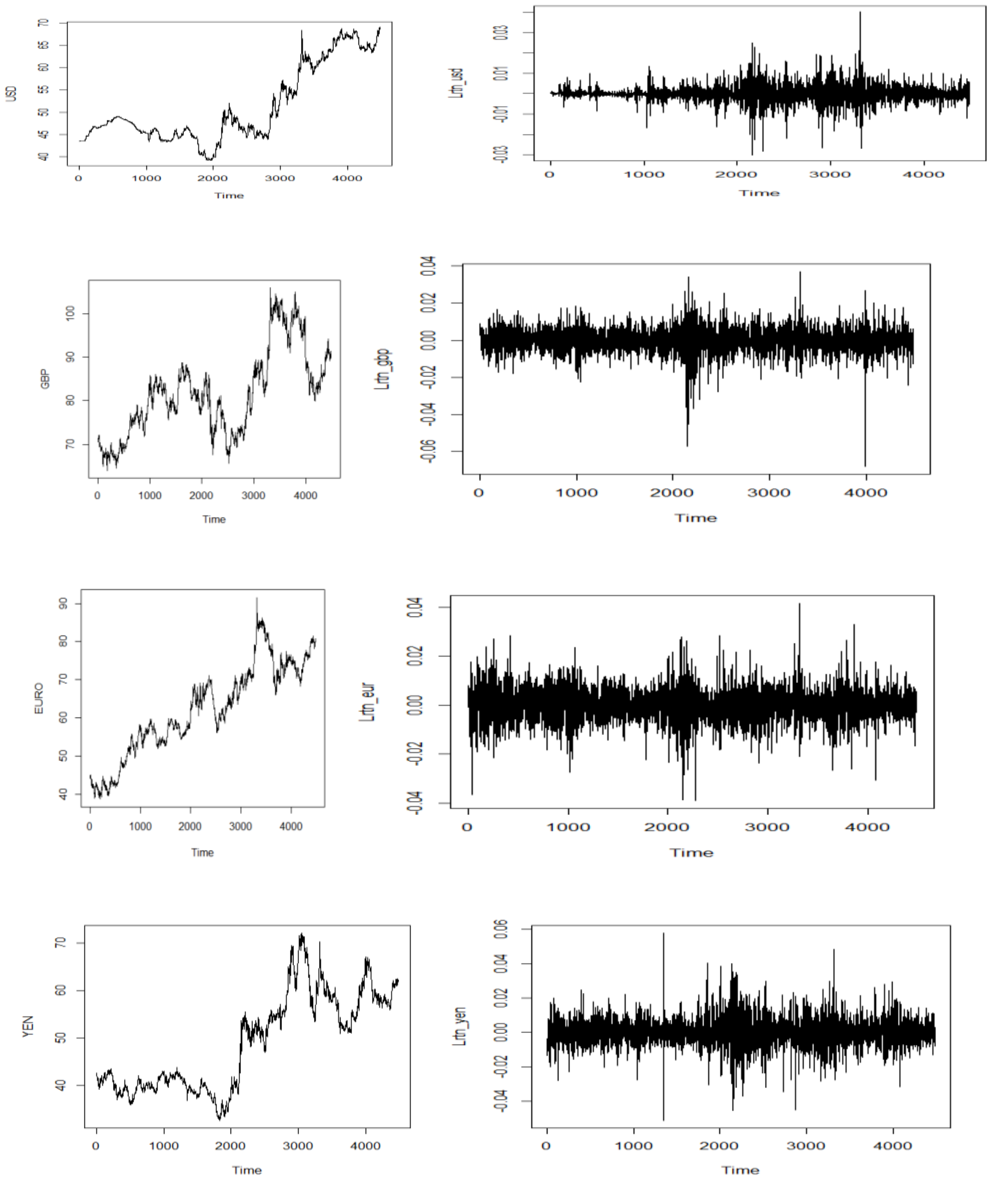

Fig.-1 Exchange rates from4.1.2000 to 24.7.2018 (number of observations is 4488)

Preliminary plotting of raw exchange rates data (series to the left) indicates presence of disruptions across time indicating breaks. The figures (series to the right) show pooling (clustering) of return in all the four series which justifies application of GARCH type models to describe the volatility dynamics. All data are tested for stationarity using ADF, PP, KPSS tests, ARCH effect and JB test for normality along with descriptive statistics.

Table 1: Descriptive Statistics and Unit root tests

Panel A: Descriptive Statistics

Parameters	INR/USD	INR/GBP	INR/EURO	INR/YEN
Mean	0.000103	0.000055	0.000134	0.000083
St. Deviation	0.004174	0.006332	0.006589	0.007925
Skewness	0.236523	-0.604588	-0.015643	0.206657
Kurtosis	7.891008	6.887165	2.393631	3.872144
JB	11700[0.000]	9154.9[0.000]	1073.7[0.000]	2840.2[0.000]
ARCH	855.4[0.000]	420.16[0.000]	277.15[0.000]	608.54[0.0000]

JB is Jarque-Bera test of normality, p values are in brackets.

Panel B: Unit root tests

Parameters	INR/USD	INR/GBP	INR/EURO	INR/YEN
ADF	-15.432[0.000]	-16.116[0.000]	-16.49[0.000]	-15.303[0.000]
PP	-4619.1[0.000]	-4401.4[0.000]	-4601.9[0.000]	-4520.9[0.000]
KPSS	0.18307[0.1]	0.041506[0.1]	0.032955[0.1]	0.087526[0.1]

In KPSS, null hypothesis is “data does not have unit root”.

The mean of all series is positive, highest in case of INR/EURO and the standard deviation representing daily unconditional volatility is highest for INR/YEN (0.007925) and lowest for INR/USD (0.004174). Skewness of INR/EURO appears to be symmetrical with a slight negative deviation. Skewness of, INR/GBP is also negative. This may be interpreted as trading in GBP results in frequent gains with few heavy losses. Skewness of both INR/USD and INR/YEN are positive. All the series are found to be leptokurtic except INR/EURO. None of the series are normal as evident from JB statistic which is significant a 1%. ARCH test is significant suggesting that variance is heteroscedastic. This confirms application of GARCH type models. It is proposed to use student’s t distribution in modelling exchange rate data as it appears to fit all the above characteristics like leptokurtic feature and volatility clustering. Further it is most parsimonious to use t distribution in case of financial data [Afuecheta et al. (2020)].Panel B shows results of unit roots test of stationarity. The statistic of ADF and PP tests is significant at 1% significance level, hence we can reject null hypothesis of presence of unit root. KPSS test shows acceptance of null hypothesis which confirms that all series are stationary hence suitable for further analysis.

5. Empirical result

We first verify presence of conditional volatility persistence by applying a non-parametric GPH test (named after Geweke and Porter-Hudak) based on a log periodogram regression previously used inliteratures [Aloui and Mabouk (2010);Chkili et al. (2014)]. This test is applied to both absolute and squared return of all the four series at a different bandwidth m. The estimated value of fractional parameter ‘d’ is presented in Table 2.

Table 2: GPH test

	INR/USD		INR/GBP		INR/EURO		INR/YEN	
	Absolute Return	Squared Return	Absolute Return	Squared Return	Absolute Return	Squared Return	Absolute Return	Squared Return
$m=T^{0.5}$	0.099(0.09)	0.406(0.07)	-0.085(0.09)	0.474(0.07)	-0.053(0.07)	0.449(0.09)	0.085(0.07)	0.414(0.1)
$m=T^{0.6}$	0.034(0.05)	0.385(0.04)	-0.041(0.06)	0.427(0.05)	0.032(0.05)	0.292(0.05)	0.105(0.05)	0.389(0.05)

Figures in brackets are standard error

On analysing the above table, it is observed that fractional parameter'd' from squared return of all the four series shows the existence of mild or weak long memory in conditional variances. The same can be interpreted as all the series are more or less stationary and any change in variances is short lived and dissipate quickly. Further, the value of d computed using absolute return is negative for INR/GBP and INR/EURO. A negative fractional estimate can be interpreted as mean reversion behaviour or anti-persistence indicating a tendency of return series to reverse the direction after a positive or negative shock[Shah et al. (2020)].In addition to GPH test, Hurst exponent is used further to confirm the presence of volatility persistence in exchange rates. Using rescaled range, all the four series show value of H as more than 0.50, implying that there is a tendency of the series to have a deviation from the mean. A careful observation of H estimate (presented below in Table 3) shows that all the values are in between 0.50 to 0.60 (H of 0.50 indicates absence of persistence) suggesting that series might be having mild level of long memory. Therefore, fractionally integrated GARCH (FIGARCH) model is proposed to be used to capture presence of long memory, if any.

Table 3: Hurst exponent

H estimate	**INR/USD**	**INR/GBP**	**INR/EURO**	**INR/YEN**
	0.600	0.517	0.521	0.543

Table 5 shows output of GARCH (p,q) and FIGARCH (p,d,q) without breaks in two parts; first part shows estimation results and second part shows diagnostic tests. FIGARCH allows for impact of past shocks on current volatility to decay at hyperbolic rate, whereas GARCH assumes such impact to remain constant over time.

Multiple breaks were identified separately for each series with Bai perron test (BP) and optimum number of breaks were finally confirmed with the help of log likelihood of BP test (Table 4). Breakpoints presented below were determined endogenously from data points without any precision of coincidence with real world events. Our purpose here is to examine volatility dynamics of chosen series in the presence of breaks and not to identify the real causes of such breaks that are affected mostly by exogenous events. We do believe identifying exact date of break points is impossible since market represents collective reflection of investors sentiment therefore some events may get accounted for in asset price in advance and some in late.

Table 4: Structural breaks of exchange rates

Series	**Break points**	**Time periods**
Lrtn_Usd	5	January4,2000–October18, 2002 October21,2002 – July 11, 2005 July 12, 2005 – April 11,2008 April 15,2008 – April 21,2011 April 25,2011 – July 4,2014 July 7,2014 – July 24,2018
Lrtn_Gbp	4	January4,2000 -September 1,2003 September2,2003 – August 4,2006 August 7, 2006 – May 13,2010 May 14,2010 – August 26,2013 August 27,2013 –July 24,2018
Lrtn_Eur	5	January4,2000-September 16,2002 September17,2002–July11,2005 July 12, 2005 – September23,2008 September24,2008–September 19, 2011 September20,2011-March 10,2015 March 11,2015 –July 24,2018

Lrtn_Yen	4	January4,2000 -October 20,2003 October 21,2003 – August 8,2006 August 9, 2006 – August 23,2011 August 24,2011 – May 20,2014 May 21,2014 –July 24,2018

We use dummy variables for including the effect of structural breaks as external regressors in FIGARCH model.Lrtn (.) denotes log returns of four different series. For example, in case of Lrtn_Usd, we assign one from the first structural break point (October 21, 2002 to July 11, 2005) and zero elsewhere. Similarly, one is assigned for each time period with zero otherwise for each of the series during the study period. Accordingly, five dummies (d1, d2, d3, d4, d5) for each USD and EUR series and four dummies (d1, d2, d3, d4) for each GBP and YEN series were used along with return series to estimate fractional differencing parameter. Table 6 shows output of FIGARCH (p,d,q) with structural breaks in two parts; first part shows estimation results and second part show diagnostic tests.

Table 5: output of GARCH and FIGARCH models (without breaks)

Panel A: estimation results

Coefficients	INR/USD		INR/GBP		INR/EURO		INR/YEN	
	GARCH (1,1)	FIGARCH (2,d,2)	GARCH (1,1)	FIGARCH (1,d,1)	GARCH (1,1)	FIGARCH (1,d,1)	GARCH (1,1)	FIGARCH (2,d,2)
μ	-0.00[0.073]	-0.00[0.000]	0.00[0.223]	-0.00[0.222]	0.00[0.184]	0.00[0.193]	-0.00[0.139]	-0.00[0.000]
ω	0.00[0.978]	0.00[0.984]	0.00[0.114]	0.00[0.000]	0.00[0.010]	0.00[0.000]	0.00[0.039]	0.00[0.911]
α	0.14[0.000]	0.008(α_1) 0.020(α_2)	0.05[0.000]	0.08[0.034]	0.04[0.000]	0.08[0.031]	0.07[0.000]	0.043(α_1) 0.056(α_2)
β	0.85[0.000]	0.232(β_1) 0.443(β_2)	0.92[0.000]	0.89[0.000]	0.94[0.000]	0.90[0.000]	0.90[0.000]	0.407(β_1) 0.277(β_2)
d	NA	0.52[0.000]	NA	0.87[0.000]	NA	0.88[0.000]	NA	0.50[0.000]
Shape	6.10[0.000]	4.24[0.000]	8.34[0.000]	7.14[0.000]	9.11[0.000]	8.18[0.000]	6.54[0.000]	6.35[0.000]

Figures in parenthesis are *p* values. NA: Not Applicable

Panel B: diagnostic tests

Parameters	**INR/USD**		**INR/GBP**		**INR/EURO**		**INR/YEN**	
	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH
Log-likelihood	20057.2	19711.24	16768.74	16755.84	16482.42	16475.07	15921.65	15872.64
AIC	-8.93	-8.78	-7.47	-7.46	-7.34	-7.34	-7.09	-7.06
BIC	-8.92	-8.76	-7.46	-7.45	-7.33	-7.33	-7.08	-7.05
SIC	-8.93	-8.78	-7.47	-7.46	-7.34	-7.34	-7.09	-7.06
HQIC	-8.93	-8.77	-7.46	-7.46	-7.34	-7.33	-7.09	-7.06
t value of Joint effect of	6.45[0.091]	1.87[0.598]	3.02[0.387]	3.00[0.391]	9.09[0.028]	5.92[0.115]	6.86[0.076]	5.55[0.135]

sign bias test								
Ljung-Box test statistic on standardised 1151esidual*	25.04[0.000]	6.49[0.068]	3.07[0.393]	3.04[0.399]	2.13[0.587]	2.15[0.582]	1.39[0.765]	0.91[0.879]

Figures in parenthesis are *p* values.**at lag 5*

μ representing long run conditional mean of the series which appears to be zero for all the series. ω is constant term in conditional mean equation. The parameters α, β and d are all significant. This implies that the conditional volatility of exchange rates is significantly influenced by its past conditional volatility and shocks (residuals). The coefficient of alpha and beta is less than/equal to one indicating that the models are stable. Finally, a high value of β for all the series shows that volatility is persistence over the sample period. Long memory parameter (d) lies between 0 and 1. In case of INR/GBP and INR/EURO, value of d is close to 1 suggesting that there exists a strong memory in their conditional volatility. For INR/USD and INR/YEN, d value is close to 0.50 indicating presence of mild memory. P-value of shape parameter is significant for all indicating the data fit well into student's t distribution. Diagnostic test results in panel B, contains log-likelihood and information criteria. Log likelihood results suggest that GARCH (1,1) is marginally better than FIGARCH except for INR/USD. Information criteria of GARCH(1,1) and FIGARCH models are nearly same implying that both fit data equally well. Results of sign bias test of FIGARCH confirm that there is no leverage effect for all the series. Ljung-Box test applied to standardised residuals suggest, except for GARCH(1,1) on INR/USD series, no autocorrelation in short-term indicating good fit to data. Overall, the test result is in line with previous literatures [Beine et al. (1999);Amiri (2016);Segnon and Bekiros (2019)].Both the models are stable at lags of p=1 and q=1 except in case of INR/USD and INR/YEN, where results of FIGARCH (2, d,2) are presented due to instability of parameters of FIGARCH (1, d,1) model.

Table 6: output of FIGARCH (1, d,1) (with breaks)

Panel A: estimation results

Coefficients	INR/USD	INR/GBP	INR/EURO	INR/YEN
μ	0.00008[0.000]	-0.0005[0.000]	0.0001[0.0000]	-0.0000[0.0000]
ω	0.0000[0.9477]	0.0000[0.9566]	0.0000[0.9479]	0.0000[0.8363]
α	0.0421[0.0000]	0.0514[0.0000]	0.0465[0.0000]	0.0687[0.0000]
β	0.9023[0.0000]	0.8906[0.0000]	0.8980[0.0000]	0.8515[0.0000]
d	0.3935[0.0000]	0.4817[0.0000]	0.4033[0.0000]	0.5924[0.0000]
Shape	2.9255[0.0000]	4.4498[0.0000]	4.0844[0.0000]	4.5954[0.0000]

Figures in parenthesis are *p* values.

Panel B: diagnostic tests

Parameters	INR/USD	INR/GBP	INR/EURO	INR/YEN
Log likelihood	19095.9	16082.95	15590.79	15548.51
AIC	-8.5044	-7.1631	-6.9438	-6.9249
BIC	-8.4873	-7.1502	-6.9309	-6.9121
SIC	-8.5044	-7.1631	-6.9438	-6.9249
HQIC	-8.4984	-7.1585	-6.9392	-6.9204
t value of Joint	13.267[0.004] ***	15.040[0.001] ***	14.467[0.002] ***	92.355[0.000] ***

effect of sign bias test				
Ljung-Box test statistic on standardised squared residuals^	1.30853[0.9697]	2.054[0.8985]	2.645[0.8158]	40.31[0.0000]

Figures in parenthesis are *p* values. ***, ** and * refers to significance at 1%, 5% and 10% respectively. ^at lag 9

First part of Table 6 shows results of coefficient estimates with structural breaks included as dummy variables. Since the purpose is to examine the long memory in presence of structural breaks, it can give important insights on correct modelling of volatility having implications for asset pricing, risk hedging and evaluation. Arouri et al. (2012) examined both long memory and structural breaks in oil spot and futures using three GARCH based models and found significant decrease of memory after incorporating breaks in FIGARCH. Mensi et al.(2019) compared different models to test the impact of breaks on volatility persistence and show that after incorporating structural breaks in return and volatility equations, their persistence level decreases. They concluded that FIGARCH with structural breaks provides a better accuracy in forecasting performance. Panel A of Table 6 shows except for INR/YEN, long memory has decreased for other three exchange rates thus confirming to previous literatures. In case of INR/YEN, estimate of long memory parameter (d) has increased to around 0.60 after including structural breaks. This suggests that post break dates, shocks to the INR/YEN exchange rate have a long-lasting effect on future volatility. Dua and Suri (2019)in their study confirmed that though volatility has increased significantly for all the exchange rates but INR/YEN was the worst hit due to sub-prime crisis of 2007-2009 and eurozone debt crisis of 2010-2012.

6. Conclusion

In this paper, we attempt to estimate long memory in exchange rates using FIGARCH model. We compare standard GARCH with FIGARCH to determine the suitable model that describe volatility properties of exchange rate over sample period. We run two tests to detect presence of long memory before applying FIGARCH model. We show that presence of real market events such as shocks in the form of structural breaks can impact long memory estimate and so also the volatility dynamics. On the basis of log likelihood and information criteria we found similar volatility estimate from both the models with slightly better performance of standard GARCH over FIGARCH. Following this, we can infer that there exists mild level of long memory in conditional volatilities in case of INR/USD and INR/YEN but a strong memory in INR/GBP and INR/EURO. After incorporation of structural breaks in FIGARCH model, long memory however, has significantly decreased in all the three series except for INR/YEN exchange rate.

7. Practical implications

Though the property of long memory has been examined several times in the past, this study has important implications for risk managers, investors and portfolio managers particularly having exposure to international market. Financial time series modelling and forecasting such as stock and asset prices require trend study which in turn depends on ability to quantify risk. Risk in case of time series can be studied through a statistical property yet a non traditional one; the long memory which examines dependence between two points in time. This property of time series can be tested with different models, the suitability of which, once again depends on other stylised facts. For instance, ARFIMA can best capture long memory in linear series but it failed to do so in non-linear ones. In the similar lines, models based on GARCH (in this case, FIGARCH) also captures long memory with application of long memory operator being applied on squared errors unlike constancy of unconditional mean under ARFIMA model. Risk managers can use this property to quantify risk which helps them to attract investment suiting to risk. Knowing risk related to investment, can help investors to precisely measure value of assets and accordingly then can diversify their existing portfolio particularly by including forex currency in their portfolio. Yield and liquidity are two primary features of foreign currencies which is why they should be included in portfolios. This apart, internationally diversified fund houses can take more effective trading or hedging strategies by estimating volatility of their portfolios. Finally, analysts can consider certain other stylized facts such as pool, persistence and breaks in conditional volatility to properly forecast asset prices.

References

1) Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in crypto currency markets under structural breaks. *International Review of Economics & Finance*, *69*, 680-691.
2) Afuecheta, E., Semeyutin, A., Chan, S., Nadarajah, S., & Andrés Pérez Ruiz, D. (2020). Compound distributions for financial returns. *Plos one*, *15*(10), e0239652.
3) Afzal, A., & Sibbertsen, P. (2022). Long Memory, Spurious Memory: Persistence in Range-Based Volatility of Exchange Rates. *Open Economies Review*, 1-23.
4) Almudhaf, F. (2014). Testing for random walk behaviour in CIVETS exchange rates. *Applied Economics Letters*, *21*(1), 60-63.
5) Aloui, C., & Mabrouk, S. (2010). Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed GARCH models. *Energy Policy*, *38*(5), 2326-2339.
6) Amiri, E. (2016). Comparison of forecasting performance of long memory GARCH models and Markov switching GARCH models.
7) Andersen, T. G., & Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of empirical finance*, *4*(2-3), 115-158.
8) Arouri, M. E. H., Lahiani, A., Lévy, A., & Nguyen, D. K. (2012). Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long memory models. *Energy Economics*, *34*(1), 283-293.
9) Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *74*(1), 3-30.
10) Baillie, R. T., & Morana, C. (2009). Modelling long memory and structural breaks in conditional variances: An adaptive FIGARCH approach. *Journal of Economic Dynamics and Control*, *33*(8), 1577-1592.
11) Baum, C. F., Barkoulas, J. T., & Caglayan, M. (1999). Long memory or structural breaks: can either explain non stationary real exchange rates under the current float?. *Journal of International Financial Markets, Institutions and Money*, *9*(4), 359-376.
12) Beine, M., Bénassy-Quéré, A., & Lecourt, C. (1999). The impact of foreign exchange interventions: new evidence from FIGARCH estimations.
13) Beine, M., & Laurent, S. (2001). Structural change and long memory in volatility: new evidence from daily exchange rates. *Developments in forecast combination and portfolio choice, Wiley series in quantitative analysis*, 145-157.
14) Bekaert, G., Harvey, C. R., &Lumsdaine, R. L. (2002). Dating the integration of world equity markets. *Journal of Financial Economics*, *65*(2), 203-247.
15) Bekaert, G., & Hodrick, R. J. (1992). Characterizing predictable components in excess returns on equity and foreign exchange markets. *The Journal of Finance*, *47*(2), 467-509.
16) Bhar, R. (1994). Testing for long-term memory in yen/dollar exchange rate. *Financial Engineering and the Japanese Markets*, *1*, 101-109.
17) Caporale, G. M., Gil-Alana, L., Plastun, A., & Makarenko, I. (2016). Long memory in the Ukrainian stock market and financial crises. *Journal of Economics and Finance*, *40*, 235-257.
18) Charfeddine, L. (2014). True or spurious long memory in volatility: Further evidence on the energy futures markets. *Energy policy*, *71*, 76-93.
19) Charfeddine, L. (2016). Breaks or long-range dependence in the energy futures volatility: Out-of-sample forecasting and VaR analysis. *Economic Modelling*, *53*, 354-374.
20) Cheung, Y. W. (1993). Long memory in foreign-exchange rates. *Journal of Business & Economic Statistics*, *11*(1), 93-101.

21) Cheung, Y. W., & Lai, K. S. (2001). Long memory and nonlinear mean reversion in Japanese yen-based real exchange rates. *Journal of International Money and Finance*, *20*(1), 115-132.
22) Chkili, W., Aloui, C., & Nguyen, D. K. (2012). Asymmetric effects and long memory in dynamic volatility relationships between stock returns and exchange rates. *Journal of International Financial Markets, Institutions and Money*, *22*(4), 738-757.
23) Chkili, W., Aloui, C., & Nguyen, D. K. (2014). Instabilities in the relationships and hedging strategies between crude oil and US stock markets: do long memory and asymmetry matter?. *Journal of International Financial Markets, Institutions and Money*, *33*, 354-366.
24) Choi, K., Yu, W. C., &Zivot, E. (2010). Long memory versus structural breaks in modeling and forecasting realized volatility. *Journal of International Money and Finance*, *29*(5), 857-875.
25) Clements, A. E., Hurn, A. S., & Volkov, V. V. (2015). Volatility transmission in global financial markets. *Journal of Empirical Finance*, *32*, 3-18.
26) Dieobold, F. X. (1986). Modeling the persistence of conditional variances: A comment. *Econometric Reviews*, *5*(1), 51-56.
27) Diebold, F. X., & Nason, J. A. (1990). Nonparametric exchange rate prediction?. *Journal of international Economics*, *28*(3-4), 315-332.
28) Dua, P., & Suri, R. (2019). Interlinkages between USD–INR, EUR–INR, GBP–INR and JPY–INR exchange rate markets and the impact of RBI intervention. *Journal of Emerging Market Finance*, *18*(1_suppl), S102-S136.
29) Elsayed, A. H., & Helmi, M. H. (2021). Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. *Annals of Operations Research*, *305*(1-2), 1-22.
30) Ewing, B. T., & Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal*, *29*, 12-23.
31) Fahlevi, M. (2019, August). The influence of exchange rate, interest rate and inflation on stock price of LQ45 index in Indonesia. In *First International Conference on Administration Science (ICAS 2019)* (pp. 157-163). Atlantis Press.
32) Fasanya, I. O., & Akinde, M. A. (2019). Volatility transmission in the Nigerian financial market. *The Journal of Finance and Data Science*, *5*(2), 99-115.
33) Garcia, R., & Ghysels, E. (1998). Structural change and asset pricing in emerging markets. *Journal of International Money and Finance*, *17*(3), 455-473.
34) Gertler, M., & Hubbard, R. G. (1988). Financial factors in business fluctuations.
35) Giot, P. (2003). The information content of implied volatility in agricultural commodity markets. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *23*(5), 441-454.
36) Giraitis, L., Kokoszka, P., Leipus, R., &Teyssière, G. (2003). Rescaled variance and related tests for long memory in volatility and levels. *Journal of econometrics*, *112*(2), 265-294.
37) Goodhart, C. (1988). The international transmission of asset price volatility. *Financial market volatility*, 79-120.
38) Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. *Journal of Financial Economics*, *4*(3), 339-349.
39) Gupta, S., & Kashyap, S. (2016). Modelling volatility and forecasting of exchange rate of British pound sterling and Indian rupee. *Journal of Modelling in Management*, *11*(2), 389-404.
40) Karemera, D., & Cole, J. (2010). ARFIMA tests for random walks in exchange rates in Asian, Latin American and African-Middle Eastern markets. *Review of Pacific Basin Financial Markets and Policies*, *13*(01), 1-18.
41) Kim, C. J., Morley, J. C., & Nelson, C. R. (2005). The structural break in the equity premium. *Journal of Business & Economic Statistics*, *23*(2), 181-191.
42) Kumar, D., & Maheswaran, S. (2015). Long memory in Indian exchange rates: an application of power-law scaling analysis. *Macroeconomics and Finance in Emerging Market Economies*, *8*(1-2), 90-107.

43) Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, *8*(2), 225-234.
44) Liu, C. Y., & He, J. (1991). A variance-ratio test of random walks in foreign exchange rates. *The Journal of Finance*, *46*(2), 773-785.
45) Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*, *18*(3), 95-100.
46) Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Financial Innovation*, *5*(1), 1-16.
47) Mensi, W., Al-Yahyaee, K. H., & Kang, S. H. (2019). Structural breaks and double long memory of cryptocurrency prices: A comparative analysis from Bitcoin and Ethereum. *Finance Research Letters*, *29*, 222-230.
48) Morana, C., &Beltratti, A. (2004). Structural change and long-range dependence in volatility of exchange rates: either, neither or both?. *Journal of Empirical Finance*, *11*(5), 629-658.
49) Nath, G. C., & Reddy, Y. V. (2002, December). Long memory in rupee-dollar exchange rate: An empirical study. In *Capital Market Conference*.
50) Obansa, S. A. J., Okoroafor, O. K. D., Aluko, O. O., & Eze, M. (2013). Perceived relationship between exchange rate, interest rate and economic growth in Nigeria: 1970-2010. *American journal of humanities and social sciences*, *1*(3), 116-124.
51) Pástor, Ľ., & Stambaugh, R. F. (2001). The equity premium and structural breaks. *The Journal of Finance*, *56*(4), 1207-1239.
52) Pettenuzzo, D., & Timmermann, A. (2011). Predictability of stock returns and asset allocation under structural breaks. *Journal of Econometrics*, *164*(1), 60-78.
53) Saha, K., Madhavan, V., & G. R., C. (2020). *Pitfalls in long memory research. Cogent Economics & Finance, 8(1), 1733280.* doi:10.1080/23322039.2020.1733280
54) Salmanov, O. N., Babina, N. V., Samoshkina, M. V., Drachena, I. P., & Salmanova, I. P. (2020). The effects of volatility and changes in conditional correlations in the stock markets of Russia and developed countries. *Economic Annals*, *65*(227), 67-94.
55) Segnon, M., &Bekiros, S. (2019). Forecasting Volatility in Cryptocurrency Markets. *Center for Quantitative Econmics*, *79*(1), 1-37.
56) Shiller, R. J. (1988). Causes of changing financial market volatility. *Proceedings, Federal Reserve Bank of Kansas City*, 1-32.
57) Soofi, A. S., Wang, S., & Zhang, Y. (2006). Testing for long memory in the Asian foreign exchange rates. *Journal of Systems Science and Complexity*, *19*, 182-190.
58) Tah, K. A. (2018). Random walk and structural break in exchange rates. *International Journal of Monetary Economics and Finance*, *11*(4), 384-393.
59) Tsuji, C. (2018). How Are Structural Breaks Related to Stock Return Volatility Persistence? Evidence from China and Japan. *Modern Economy*, *9*(10), 1635-1643.
60) Udoh, E., &Egwaikhide, F. O. (2008). Exchange rate volatility, inflation uncertainty and foreign direct investment in Nigeria. *Botswana Journal of Economics*, *5*(7), 14-31.
61) Yadav, A. K., Irfan, M., Singh, R., & Shaikh, Z. H. (2021). Effect of Structural Breaks on Volatility Regime: Lessons from Leading European and Indian Indices. *NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal| NVEO*, 10683-10692.
62) Yang, J., Su, X., & Kolari, J. W. (2008). Do Euro exchange rates follow a martingale? Some out-of-sample evidence. *Journal of Banking & Finance*, *32*(5), 729-740. https://www.bis.org/statistics/rpfx22_fx.htm