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RESEARCH ARTICLE

Long Memory, Spurious Memory: Persistence in Range-Based Volatility of Exchange Rates

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Abstract

This study considers the long memory and fractional integration in the range-based volatilities across 30 currencies against USD. Graphical analysis of the autocorrelation function at long lags and pole near zero frequencies in the periodogram suggests the existence of fractional integration. We apply semi-parametric methods to measure long-range dependence. We find a decrease in the memory estimates with an increase in the bandwidth, which indicates the presence of spurious memory rather true long memory. The hypothesis of long memory against the alternative of spurious memory is also tested by applying the different semi-parametric methods. Empirical results confirm the presence of spurious memory that may be a result of some shocks to the volatility estimator. Furthermore, the reduced memory estimates obtained by utilising an estimator accounting for level shifts also explains the inconsistency of the Local Whittle estimator. We also estimate the number of breaks for each series.

Keywords Exchange rate · Volatility · Fractional integration · Long memory · Level shifts · Structural breaks

JEL Classification C14 · C22 · F31

1 Introduction

A persistent level of exchange rates in a country is important to reflect the stability of its currency, and it provides helpful information for policy implications in case of sudden shocks (Barros, Gil-Alana et al. 2011). Less developed countries are more

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prone to the phases of high exchange rate volatility owing to depreciation (appreciation) of the currency caused by either national or international shocks. Additionally, the exchange rate fluctuations have unlimited impacts on inflation predictability, international trade, and financial asset pricing. The exchange rate volatility has been described as an important factor of inflation in Turkey and Mexico (Mendoza 2012). Being a risk measure, an increase in the exchange rate volatility reduces trade by raising costs of the risk-averse investors and traders. Stock markets and foreign exchange rates are characterised by nonlinear and non-stationary behaviour in the literature. Taylor (2006) described the transaction costs, the collaboration of various agents in currency markets, and official interferences in these markets as three sources of nonlinear trends in the real exchange rates.

Volatility is persistent and predictable, whereas the asset returns are almost random (Choi et al. 2010). High persistence in different volatility measures of a financial time series is a common phenomenon and is analysed either by the significant correlations at long lags or by using the spectral density analysis. This characteristic is known as long memory and explains the long-lasting effects of shocks to volatility. Moreover, persistence in the exchange rates is important for policymakers to adopt the specific measures according to the persistence level in case of shocks (Barros, Gil-Alana et al. 2011). Long-range dependence is imperative and appealing, as it point towards the long-run effects of shocks. Along with the long-run effects, long memory is helpful in future predictions with an indication of some nonlinear dependence among observations (Charfeddine 2014). Analysis of the persistent trends has direct policy implications to help investors in avoiding any losses and to get benefits by following these trends (Ouyang et al. 2002). A unit root series is persistent to the shocks, whereas a stationary series is less persistent, and mean reverting with temporary effects of the shocks and strong policy actions are needed in this case to maintain higher levels of the positive shocks. With negative shocks, some strong measures are needed to converge a series back to its original trend in a unit root series, whereas a stationary series will return to its mean at some future point automatically (Gil-Alana et al. 2014).

Modelling and forecasting the volatility as a risk measurement has an interesting position in economics and finance literature, but it is not directly observable and needs to be measured (Molnár 2012). Frequently used measures of conventional volatility are based on either the squared or absolute returns using the daily closing prices. The idea of range-based volatility estimation by Parkinson (1980) was considered less noisy in comparison to the squared base estimators with 5 times' reduced variance. Although it is customary practice to present the candlestick plots based on the range in business newspapers, the range-based volatility is not practiced in general (Li and Hong 2011). The range-based proxy of volatility is more appropriate and efficient, being an unbiased estimator of the standard deviation and by using the two quantities (high and low), as compared to the returns-based volatility based only on the closing values (Chou and Liu 2010).

He and Wan (2009) analysed the highs, the lows, and the ranges of USD with an application of the error correction model. Okimoto and Shimotsu (2010) rejected the null hypothesis of no decline in persistence for the monthly real exchange rates across a sample of 9 out of 17 countries at the 10% level of significance. Lima and Tabak (2007) supported the random walk hypothesis in the emerging market exchange rates after adoption of the floating exchange rate regimes. Marques and Pesavento (2015) analysed an increase in the persistence of the real exchange rate for several countries after the liberalisation period. Gil-Alana and Sauci (2018) observed mean reversion in the real exchange rates of some Latin American countries with an application of parametric and semi-parametric methods. Gil-Alana and Toro (2002) used the ARFIMA technique to model the real effective exchange rates in five industrialised countries.

The hyperbolic decay of the autocorrelation function or an unbounded spectral density may also be a result of a short memory model with regime changes in the volatility. Theoretically, a true long memory process takes a long time to eliminate the effects of the financial shocks, but the autocorrelation function of the short memory process with level shifts should present an exponential decay after a few observations. Apparent persistent trends in a time series were criticised for the possibility of either structural breaks or regime switches, and this is known as spurious memory (Diebold and Inoue 2001; Granger and Hyung 2004). It is important to distinguish between the true long memory or spurious memory, as misspecification followed by the ignored structural breaks can destroy the results by overestimating the fractional integration (Charfeddine 2014).

Random shift model removes the spurious memory by taking into account the level shifts as it was observed in the five daily exchange rate series including JPY, DEM, CAD, GBP, EUR (Li et al. 2017). The existence of structural breaks in mean may cause persistence in the realized volatilities of three currencies pairs (Choi et al. 2010). Moreover, they proposed two different models with better predictive capability in case of known and unknown break points (Choi et al. 2010). Spurious memory was examined in the exchange rate volatility of Czech Kouna and Hungarian Forint while other four series were contaminated with level shifts and presented persistent behaviour of true long memory as well (Walther et al. 2017). Long memory trends in Latin American countries have been explored by (Holmes 2008; Karemera and Cole 2010; Gil-Alana and Sauci 2018).

Our study focuses on the possibility of either long memory or structural breaks in the spot exchange rates. Firstly, we study the long-range dependence in different exchange rates, including the developed, developing, and emerging countries, in a wider sense of long memory and fractional integration and considering the fact that the exchange rate volatility is persistent and can be modelled as a long memory process. Secondly, our analysis is based on the log-range volatility contrary to a conventional one approximated by closing values. Thirdly, we provide empirical evidence of long-range dependence and spurious memory by using different semi-parametric techniques. We use the semi-parametric Local Whittle (LW) method to estimate the long memory. To test the presence of either true long memory or spurious memory, we use the approaches by (Shimotsu 2006) and (Qu 2011) with the hypothesis of true long memory in the exchange rate volatilities. Our empirical results show either stationary or non-stationary long memory estimates in all series; however, later on, the hypothesis of long memory is rejected in favour of the spurious memory. Moreover, graphical analysis of the long memory parameters with different frequencies presents decreasing trends, which might be due to spurious memory. Decreased memory estimates by using the Modified Local Whittle (MLW) estimator, a consistent estimator in case of the random level shifts and low-frequency contaminations, may be caused by the structural breaks.

Objective of our study is to explore the persistent trends in the exchange rates of emerging and developing countries by using different parametric and semi parametric methods. Moreover, we are interested in differentiating between true or spurious memory in these small and merging economies, where we expect long term effects of shocks and level shifts. We contribute in the existing literature by exploring the true or spurious memory trends by using broader aspect of fractional integration. On the other hand, our study comprises a more detailed data considering most of the small economies rather developed and more integrated economies. Additionally, our results will contribute in literature through a new aspect of trends in exchange rates by considering the effects of regional or international shocks on the small and developing economies.

The rest of this paper is structured as follows. Section 2 discusses the data and methodology of the study. The empirical results are discussed in the third section, and Sect. 4 concludes the paper with some future recommendations and limitations of this study.

2 Data and Methodology

We use the daily log range proxy of volatility in our empirical analysis. The difference between the highest and the lowest value in a fixed sampling interval (1 day for daily data) is defined as the range. We formulate the log range volatility as in Eq. 1

$$R_t = \ln\left(\ln(H_t\right) - \ln(L_t)). \tag{1}$$

where H_t, L_t, and R_t represent the highest, the lowest, and the range values, respectively. We use the data of daily highs and lows across 30 currencies against USD with a different number of observations depending on the availability of data on Eikon Thomson Reuter's database. The starting date is different for each country, and the end date is 6/18/2021. A detailed description of the currencies, with currency symbols, the starting date, and the number of observations, is presented in Table 1.

2.1 Fractional Integration or Long Memory

Fractional integration in x_t stationary process with an autocorrelation function ρ_k at lag k, with a finite constant c and a real number H is defined as in Eq. 2.

$$\rho_k = ck^{2(H-1)}ask \rightarrow \infty, \tag{2}$$

where H is the Hurst exponent to represent long-range dependence and relate to the fractional integration parameter d as $d = H - 1/2$ (Lim and Brooks 2011; Assaf 2015). The series is a long memory process for $H \in (\frac{1}{2}, 1)$, non-stationary for $H > 1$,

Table 1 currency symbols, start date, and total number of observations.

	Start date	Observations		Start date	observations
Japan(JPY)	1/2/1995	6286	Ukraine(UAH)	3/15/1996	5658
Brazil(BRL)	1/2/1995	6234	Kazakhstan(KZT)	1/17/1996	5839
Indonesia(IDR)	1/2/1995	6076	Philippines(PHP)	7/29/1997	5585
Mexico(MXN)	1/2/1995	6279	New Zealand(NZD)	3/5/2001	4679
Turkey(TRY)	1/2/1995	6262	UAE(AED)	8/3/1998	5327
Hong Kong(HKD)	1/2/1995	6281	Bahrain(BHD)	8/3/1998	5319
India(INR)	1/2/1995	6261	Kuwait(KWD)	8/3/1998	5353
South Africa(ZAR)	1/2/1995	6280	Saudi Arabia(SAR)	8/3/1998	5348
Thailand(THB)	1/2/1995	6276	Qatar(QAR)	8/3/1998	5292
Malaysia(MYR)	1/2/1995	5523	Oman(OMR)	8/3/1998	5301
Singapore(SGD)	1/2/1995	6282	Pakistan(PKR)	10/17/2001	4488
Hungary(HUF)	1/2/1995	6279	China(CNY)	9/28/2005	3315
Taiwan(TWD)	1/2/1995	6236	Sri Lanka(LKR)	5/24/2002	4129
South Korea(KRW)	1/2/1995	6211	Vietnam(VND)	8/4/2008	2677
Russia(RUB)	1/5/1996	5984	Bangladesh(BDT)	8/4/2008	2731

and anti-persistent if $H \in \left(0, \frac{1}{2}\right)$. A long memory process has an unbounded spectral density at the low frequencies. An integrated process of order d with a lag operator L and μ_t stationary and zero mean process can be

$$(1 - L)^d x_t = \mu_t \tag{3}$$

represented as.

The model in Eq. 3 is a short memory model and belongs to the class of ARMA models for $d = 0$ with exponential decay of autocorrelations. Another more general and flexible class of models, autoregressive fractionally integrated moving average (ARFIMA) models for $d\epsilon(-0.5, 1)$ was presented by (Granger and Joyeux 1980; Hosking 1981). (Diebold et al. 1991; Cheung and Lai 1993, 2001) used fractional models to find mean reversion and long memory dynamics in the exchange rates.

2.2 Local Whittle (LW) Estimator (1995)

There are plenty of methods to estimate the long memory, including parametric, semi-parametric, and non-parametric methods. Lack of reliable and good estimation methods for long memory may be a possible reason for such a wide range of methods (Aye et al. 2014). The LW estimator by (Robinson 1995), with λ_j frequency to compute the periodogram $I\left(\lambda_j\right)$, is

$$\hat{d} = argmin_d \left\{ \ln\left(\frac{1}{m} \sum\nolimits_{j=1}^{m} \frac{I\left(\lambda_j\right)}{\lambda_j^{-2d}} - \frac{2d}{m} \sum\nolimits_{j=1}^{m} \ln\lambda_j \right) \right\}. \tag{4}$$

This estimator is based on one researcher-specified truncation parameter, m. Moreover, the asymptotic distribution of the LW estimator is not effected by the conditional heteroskedasticity in μ_t. A short-term bias will be introduced with a too large value of the bandwidth parameter while an increased variance will result from a too small value (Okimoto and Shimotsu 2010).

2.3 Test of True Memory Against Structural Breaks (Shimotsu 2006)

(Shimotsu 2006) proposed two tests to explore either the true memory or spurious memory. The first test is the sample splitting test, which is based on the hypothesis that, in the case of a true long memory process, the memory parameter in the subsamples should be equal to the memory of a full sample. This test splits the sample length n into b subsamples of integer length n/b. The null hypothesis is written as

$$H_0 : d = d^{(1)} = \cdots = d^{(b)}, \tag{5}$$

where d is the true memory of the whole sample, and $d^{(i)}$ for $i \in (1, 2, \dots, b)$ are the memory parameters for b subsamples. The test static is given as

$$W_c = 4m\left(\frac{c_m/b}{m/b}\right)A\hat{d}_b\left(A\Omega A'\right)^{-1}\left(A\hat{d}_b\right)', \tag{6}$$

where $c_m = \sum_{j=1}^{m} v_j^2, v_j = \log\lambda_j - \frac{1}{m}\sum_{j=1}^{m}\log\lambda_j$ and

$$\hat{d}_b = \begin{pmatrix} \hat{d} - d \\ \hat{d}^{(1)} - d \\ \cdot \\ \cdot \\ \cdot \\ \hat{d}^{(b)} - d \end{pmatrix}, A = \begin{pmatrix} 1 & -1 \cdots & 0 \\ \vdots & \vdots \ddots & \vdots \\ 1 & 0 \cdots & -1 \end{pmatrix}, \Omega = \begin{pmatrix} 1 & \tau_b \\ \tau_b & b_{I_b} \end{pmatrix},$$

for $(b \times b)$ identity matrix I_b and τ_b is $(b \times 1)$ matrix of ones. The limiting distribution of W_c approaches to $\varkappa^2$ with $(b-1)$ degrees of freedom.

The fact that the time-domain property of the fractionally integrated process, a stationary process integrated of order zero (i.e., $I(0)$) can be obtained by differencing an $I(d)$ process d times, is the main point in the difference test of (Shimotsu 2006). This property may not hold for some spurious memory processes. The $\hat{\mu}$, as purposed by (Shimotsu 2006), is used to demean the data as

$$\hat{\mu}\left(\hat{d}\right) = \frac{w(d)}{N}\sum_{n=1}^{N} Y_n + (1 - w(d))Y_1, \tag{7}$$

where

$$w(d) = \begin{cases} 1 \; if \; d \le 0.5 \\ 0 \; if \; d \ge 0.75 \end{cases}.$$

The KPSS test for the null hypothesis of stationary series and the Z_n test including an intercept term for the null hypothesis of unit root are applied to the d^{th} differenced series. Now, the critical values for KPSS and Z_n are different, and they are described in table 1 and 2 of (Shimotsu 2006).

2.4 Semiparametric Test of True Against Spurious Memory (Qu 2011)

We also apply the semi-parametric test of (Qu 2011) for the null hypothesis of true long memory against the alternative of structural break process. The test statistic is given as follows:

$$W_{Qu} = sup_{r\epsilon[\varepsilon.1]}\left(\sum_{j=1}^{m} v_j^2\right)^{-0.5}\left|\sum_{j=1}^{[mr]}\left\{\frac{I_j}{G(\hat{d})\lambda_j^{-2\hat{d}}} - 1\right\}\right|, \tag{8}$$

with bandwidth parameter m; v_j, described as in the splitting test above; the LW estimator $\hat{d}$; and a trimming parameter ε.

Table 2 Descriptive statistics

	Mean	SD	Skewness	Kurtosis	ADF		Mean	SD	Skewness	Kurtosis	ADF
JPY	0.010	0.006	3.522	31.143	0.01	**UAH**	0.009	0.016	6.854	101.691	0.010
BRL	0.012	0.011	3.195	26.296	0.01	**KZT**	0.002	0.006	20.882	617.244	0.010
IDR	0.012	0.025	6.507	62.943	0.01	**PHP**	0.008	0.009	5.371	55.160	0.010
MXN	0.010	0.010	6.613	75.615	0.01	**NZD**	0.013	0.007	2.625	16.875	0.010
TRY	0.014	0.016	6.956	81.516	0.01	**AED**	0.000	0.000	5.039	52.580	0.010
HKD	0.000	0.000	7.915	137.724	0.01	**BHD**	0.001	0.002	4.765	41.813	0.010
INR	0.006	0.004	2.150	11.442	0.01	**KWD**	0.004	0.004	4.765	51.583	0.010
ZAR	0.017	0.011	2.452	21.278	0.01	**SAR**	0.000	0.001	8.523	111.893	0.010
THB	0.011	0.020	4.047	20.661	0.01	**QAR**	0.001	0.004	8.969	101.914	0.010
MYR	0.005	0.007	5.332	45.744	0.01	**OMR**	0.002	0.003	4.852	36.218	0.013
SGD	0.005	0.004	3.774	32.655	0.01	**PKR**	0.004	0.005	4.041	32.708	0.010
HUF	0.013	0.008	2.202	11.942	0.01	**CNY**	0.002	0.001	2.310	11.458	0.010
TWD	0.005	0.003	2.568	18.925	0.01	**LKR**	0.003	0.003	3.534	27.205	0.010
KRW	0.008	0.010	9.795	197.872	0.01	**VND**	0.003	0.004	6.198	63.141	0.010
RUB	0.010	0.020	12.238	248.952	0.01	**BDT**	0.004	0.005	2.604	14.881	0.010

2.5 Estimation of Long Memory in Presence of Structural Breaks (Hou and Perron 2014)

In the case of spurious memory in the range-based volatilities, memory estimates measured by the LW estimator are not applicable and are inconsistent. The long memory estimator by (Hou and Perron 2014), the MLW estimator, provides consistent estimates with the smallest bias and mean square errors compared to most other estimators in the case of low-frequency contaminations, random level shifts, and deterministic trends. The asymptotic variance of this estimator is equivalent to the LW with an absence of low-frequency contamination and does not require the underlying process to be Gaussian (Hou and Perron 2014). The estimator is based on the short or long memory process z_t, with a constant term c, a stationary process y_t and u_t low- frequency contaminations as

$$z_t = c + y_t + u_t. \tag{9}$$

The estimator is

$$\hat{d} = argmin_{d,\theta} R(d, \theta), \tag{10}$$

which is based on the pseudo spectral density obtained by adding one new term $(G_u/T)\lambda_k^{-2}$ in the spectral density of the stationary process to control the low-frequency contaminations.

$$f_z(\lambda_k) = G_0 \lambda_k^{-2d} + \left(\frac{G_u}{T}\right)\lambda_k^{-2}. \tag{11}$$

3 Empirical Results

3.1 Graphical Analysis

As the first step of the empirical work, we perform a graphical analysis of the autocorrelation function and periodogram to detect the persistence in the range series. All series show significance and a hyperbolic decay of the autocorrelations up to lag 100, which is perhaps an indication of the long-range dependence and fractional integration. Moreover, a pole near zero frequencies in the periodogram specifies the need of differencing to obtain stationary series. An analysis of the periodogram for differenced series may suggest the over-differenced series by displaying values around zero at small frequencies (Gil-Alana and Toro 2002). The graphs of ACF and periodograms in levels and differenced series for JPY are provided in Fig. 1. Graphs of the other volatility series present similar trends.

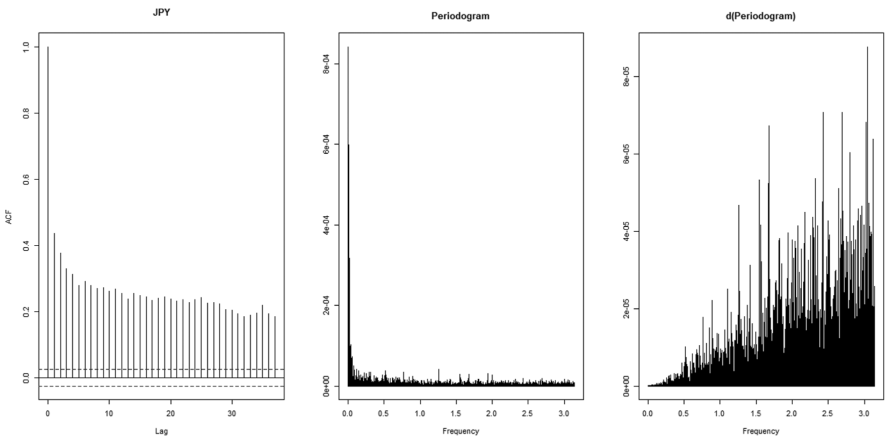


Fig. 1 ACF, periodogram and differenced periodogram of JPY

3.2 Descriptive Statistics

The descriptive statistics are presented in Table 2, with the first four moments and the unit root test. We find the positive mean for all the range volatilities, and the skewness measure is greater than 0 in all cases presenting non-symmetrical and right-skewed distributions. High values of the kurtosis show the non-normal (leptokurtic) distribution of the range volatilities in all cases. Moreover, the hypothesis of non-stationary series is rejected in all cases with the Augmented Dickey–Fuller (ADF) by (Dickey and Fuller 1979) test at the 5% level of significance. Graphical analysis suggests the use of long memory methods to model trends in the log ranges of the spot exchange rates.

3.3 Results of Long Memory Estimates

Long memory estimates obtained by using the LW estimator for different bandwidths are reported in Table 3. These estimates change with different bandwidths within stationary and non-stationary regions. The values of d move between 0.2304 and 0.8104, with $m = T^{0.6}$, between 0.2393 to 0.8468, with $m = T^{0.7}$, and between 0.2662 to 0.8862, with $m = T^{0.8}$. Overall results of the long memory estimates in the exchange rate volatilities exhibit either stationary or non-stationary long memory depending on the truncation parameter. Generally, results of the semi-parametric estimates show mean reversion in the stationary region ($d \leq 0.5$) for nine series while non-stationary ($d \geq 0.5$) in others with the memory estimates greater than 0.8 in 2 volatilities.

We observe that d tends to decrease with an increase in the bandwidth parameter m for JPY, IDR, MXN, TRY, INR, THB, MYR, SGD, HUF, TWD, UAH, PHP, NZD, AED, BHD, KWD, OMR, and CNY. This decrease in the memory estimates may suggest the existence of level shifts or low-frequency contaminations in the

Table 3 LW results (point estimates)

	$m^{0.6}$	$m^{0.7}$	$m^{0.8}$		$m^{0.6}$	$m^{0.7}$	$m^{0.8}$
JPY	0.41	0.39	0.34	**UAH**	0.56	0.35	0.36
BRL	0.52	0.58	0.54	**KZT**	0.24	0.24	0.27
IDR	0.61	0.56	0.57	**PHP**	0.58	0.51	0.43
MXN	0.50	0.46	0.47	**NZD**	0.52	0.46	0.43
TRY	0.48	0.48	0.44	**AED**	0.49	0.46	0.48
HKD	0.40	0.46	0.48	**BHD**	0.50	0.45	0.42
INR	0.52	0.50	0.47	**KWD**	0.50	0.49	0.44
ZAR	0.51	0.51	0.49	**SAR**	0.62	0.55	0.60
THB	0.83	0.76	0.64	**QAR**	0.88	0.85	0.89
MYR	0.58	0.57	0.56	**OMR**	0.70	0.56	0.50
SGD	0.50	0.46	0.42	**PKR**	0.51	0.52	0.48
HUF	0.52	0.50	0.45	**CNY**	0.45	0.43	0.40
TWD	0.52	0.47	0.41	**LKR**	0.50	0.43	0.42
KRW	0.66	0.68	0.60	**VND**	0.49	0.51	0.52
RUB	0.52	0.61	0.57	**BDT**	0.60	0.60	0.55

exchange rate volatilities (Sibbertsen et al. 2018). One other reason for such a trend may be the failure of the semi-parametric method to deal satisfactorily with the short memory components (Chatzikonstanti and Venetis 2015). This tendency in the series may be explained by the structural breaks (Perron and Qu 2010).

We also investigate the changing behaviour of the long memory estimates, with the graphs of d against the truncation parameters ranging from $m = T^{0.4}$ to $m = T^{0.8}$ in Fig. 2. This recursive estimation of long memory parameters by using range of bandwidths may be a good alternative of detecting structural break points. These graphs of the long memory estimates against a range of truncation parameters reveal the changing behaviour of persistence in the exchange rates. The memory parameters in the cases of IDR, THB, MYR, SGD, KRW, KWD, QAR, and PKR are greater than 0.7 at the smaller bandwidths, with a memory parameter greater than one for OMR and PHP presenting non-stationary but mean reverting behaviour in the volatilities. The memory estimates for the remaining exchange rate volatilities are in the vicinity of 0.5 at the lower bandwidths while we observe a declining trend with an increase in the bandwidth.

The graphs of memory estimates in Fig. 2 for JPY, BRL, IDR, INR, ZAR, THB, MYR, SGD, HUF, TWD, PHP, NZD, AED, BHD, KWD, OMR, PKR, CNY, LKR, and BDT present an upward trend at the start of the series for almost the first 50 frequencies, after which a constant decline in the graph is visible with an increase in the bandwidth parameter. (Perron and Qu 2010) observed that the memory parameter decreases as the bandwidth parameter increases in the case of short memory series with breaks. The importance of the short memory components increases with an increase in bandwidth parameter in comparison to the level shift components, resulting in a decline in the memory parameter (Chatzikonstanti and Venetis 2015). The memory estimates in a true long memory process are independent from the

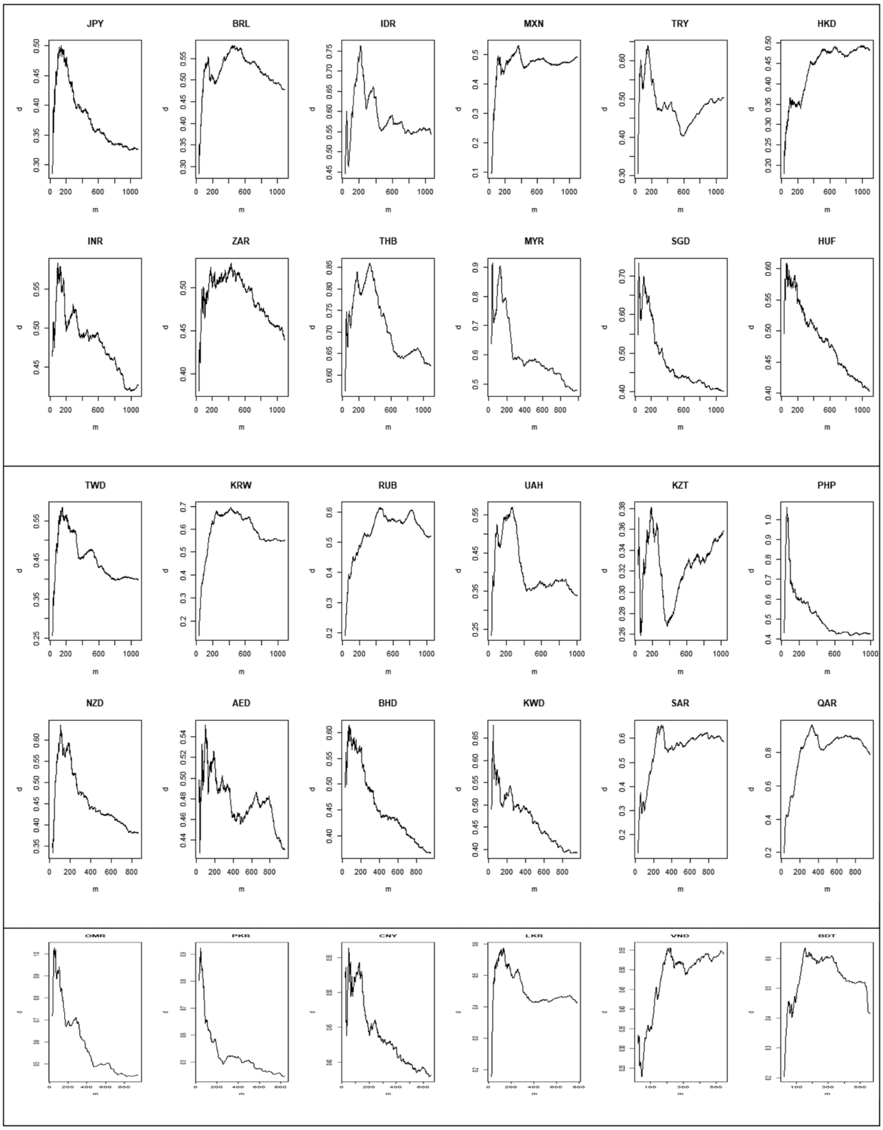


Fig. 2 Graphs of *d* against range of frequencies

values of the truncation parameter (McMillan and Ruiz 2009). Therefore, the visual inspection of these graphs with an increase in the bandwidth parameter suggests the presence of spurious memory in the form of the level shifts or structural breaks in these spot exchange rates' volatilities.

The graphs for MXN, KRW, SAR, QAR, and VND in Fig. 2 show some decreases; however, they then maintain an almost constant level of persistence with increasing values of *m*. In the case of TRY and KZT, an upward trend is visible after a constant decline, whereas a continuous increasing trend in the persistence of HKD and RUB is obvious. Overall, the graphical analysis suggests that the memory is not constant and decreases with a range of truncation parameters in most of the cases.

3.4 Results for Test of True Memory Against Structural Breaks (Shimotsu 2006)

As the next step of the empirical analysis, we apply three tests, as described in the previous section, to distinguish between the true and spurious long memory in the exchange rate volatilities. The results of all these tests are reported in Table 4.

The split Wald test also rejects the null hypothesis of equal memory for the whole sample and subsample for 10 series, with $b = 2, 4$ and $m = T^{0.6}$. The number of rejections increases to 14 series, with $m = T^{0.7}$. The Z_n test, based on the assumption that an $I(d)$ series will be $I(0)$ after differencing d times, cannot reject the hypothesis of $I(d)$ series in 24 cases at $m = T^{0.6}$. These results support the hypothesis of true memory in the remaining six series. There is evidence of true memory only for Russia, with $m = T^{0.6}$. The KPSS test for the null hypothesis of $I(0)$ series cannot be rejected on the basis of calculated values using both bandwidths, and these results support the hypothesis of true memory in all range series. Al-Shboul and Anwar (2016) obtained similar results with application of the difference test for sectoral returns of Jordan's Amman stock exchange. Based on the results of a Phillips Perron test (Phillips and Perron 1988), a Split Wald test (Shimotsu 2006), and a Qu test (Qu 2008), there is evidence of spurious memory or level shifts in the exchange rate range volatilities across different countries.

3.5 Semiparametric Test of True Against Spurious Memory (Qu 2011)

The first column in Table 4 reports the results of the (Qu 2011) test for the null of true memory against the spurious memory. The results are described for $\varepsilon = 0.05$ and bandwidth parameter 0.7. The critical values at the 10%, 5%, and 1% levels of significance are 1.022, 1.15, and 1.426. All series, except for Brazil, India, South Africa, Kazakhstan, and Bangladesh, reject the hypothesis of true long memory at the 5% level of significance. Overall, 25 range series out of 30 reject the null hypothesis of true long memory, indicating that the visual memory is not true but spurious.

3.6 Estimation of Long Memory in Presence of Structural Breaks (Hou and Perron 2014)

Estimates of the LW are inconsistent with evidence of spurious memory in the range-based volatilities, so we estimate fractional integration by applying the MLW. The estimates are provided for the bandwidth parameters $m = T^{0.65}, T^{0.7}, T^{0.75}$, as Hou and Perron (2014) recommend using bandwidth parameters greater than $m = T^{5/9}$. These results are reported in Table 5; reduction in the memory estimates in most of the cases may be caused by the low-frequency contaminations. The

Table 4 True memory versus spurious memory (bold values stand for hypothesis rejection at 5% level of significance)

word	W_{Qu}	W_c				Z_n		KPSS	
		$m = T^{0.6}$		$m = T^{0.7}$					
		$b = 2$	$b = 4$	$b = 2$	$b = 4$	$m = T^{0.6}$	$m = T^{0.7}$	$m = T^{0.6}$	$m = T^{0.7}$
JPY	**1.68**	0.10	1.41	0.04	1.92	**-2.10**	**-1.08**	0.11	0.26
BRL	0.82	2.26	3.36	2.29	**18.59**	**-1.72**	**-2.13**	0.09	0.04
IDR	**2.91**	**8.19**	**11.02**	**5.58**	**7.87**	-3.79	**-1.46**	0.04	0.14
MXN	**1.69**	0.46	5.22	3.29	**21.95**	**-2.23**	**-2.40**	0.06	0.05
TRY	**1.93**	2.07	1.12	2.56	11.70	-3.18	**-2.03**	0.03	0.06
HKD	**1.16**	2.81	3.55	0.34	5.73	**-1.66**	**-2.70**	0.10	0.03
INR	1.04	2.13	1.39	0.32	1.63	**-1.34**	**-1.28**	0.15	0.17
ZAR	0.69	0.58	1.38	0.95	**23.23**	**-1.26**	**-1.28**	0.16	0.15
THB	**2.20**	**16.58**	**38.42**	**39.62**	**92.81**	-3.80	**-2.94**	0.03	0.04
MYR	**3.73**	**26.33**	**21.44**	1.39	**8.13**	-5.15	**-1.90**	0.02	0.09
SGD	**3.19**	1.19	**16.80**	0.23	3.36	-3.20	**-1.69**	0.05	0.10
HUF	**1.89**	**7.29**	**11.25**	**9.41**	**13.81**	**-1.62**	**-1.11**	0.11	0.24
TWD	**1.44**	0.24	0.75	0.37	1.11	-3.01	**-1.89**	0.04	0.10
KRW	**1.41**	0.03	1.52	13.13	**22.95**	-3.71	-4.47	0.02	0.02
RUB	**1.61**	0.57	0.30	14.74	**12.36**	**-2.10**	-3.68	0.07	0.02
UAH	**3.77**	**7.85**	6.20	11.48	**9.30**	-3.61	**-1.65**	0.02	0.10
KZT	0.51	0.12	0.94	2.19	2.44	**-1.55**	**-1.62**	0.17	0.16
PHP	**3.79**	1.05	**8.34**	0.47	9.22	**-1.42**	**-1.02**	0.05	0.22
NZD	**2.05**	**3.96**	5.48	0.46	4.03	**-2.48**	**-1.20**	0.07	0.22
AED	**1.35**	**4.36**	4.88	**19.23**	**20.36**	**-1.56**	**-1.21**	0.11	0.19
BHD	**2.64**	2.38	**12.78**	**30.44**	**55.14**	**-2.31**	**-1.26**	0.06	0.18
KWD	**1.74**	0.07	2.74	**6.25**	3.18	**-1.54**	**-1.32**	0.12	0.16
SAR	**1.44**	0.00	1.64	0.33	**7.99**	**-2.04**	**-2.89**	0.07	0.03
QAR	**1.86**	**22.38**	**32.76**	**135.72**	**101.89**	**-2.75**	-5.13	0.04	0.01
OMR	**5.11**	**4.10**	**15.13**	3.36	5.66	**-2.54**	**-1.29**	0.09	0.21
PKR	**2.68**	0.47	**8.38**	0.03	6.90	**-1.38**	**-0.93**	0.18	0.28
CNY	**1.54**	0.01	5.48	0.27	3.97	**-0.27**	**1.21**	0.36	1.03
LKR	**2.25**	**7.52**	7.19	0.56	0.72	**-2.38**	**-1.33**	0.06	0.18
VND	**1.46**	1.05	3.97	0.02	2.36	**-0.60**	**-1.75**	0.42	0.11
BDT	1.11	1.11	2.16	2.08	5.64	**-1.40**	**-2.18**	0.16	0.06

memory estimates are equivalent to the LW results for BRL, MXN, HKD, THB, KRW, RUB, KZT, SAR, QAR, VND, and BDT. Overall, we get mixed results, and it is necessary to analyse these series in more detail to better understand the structural breaks.

Lima and Tabak (2007) did not reject the random walk hypothesis in the exchange rates of Indonesia, Malaysia, The Philippines, South Korea, Thailand, Brazil, Mexico, and Russia. Li et al. (2017) rejected the hypothesis of true long memory for the

Table 5 Modified Local Whittle estimator (d values)

	$m = T^{0.65}$	$m = T^{0.7}$	$m = T^{0.75}$		$m = T^{0.65}$	$m = T^{0.7}$	$m = T^{0.75}$
JPY	0.3040	0.2931	0.2260	UAH	0.5728	-0.4999	0.2076
BRL	0.5276	0.5799	0.5434	KZT	0.2462	0.2439	0.2687
IDR	0.5869	-0.3907	0.5434	PHP	0.1235	0.1394	0.0772
MXN	0.5049	0.4640	0.4767	NZD	0.4843	0.1944	0.2403
TRY	0.1380	0.3378	0.3256	AED	0.4370	0.3932	0.4479
HKD	0.4057	0.4695	0.4805	BHD	0.2772	0.2156	0.2516
INR	0.4886	0.4570	0.4225	KWD	0.3855	0.4161	0.3232
ZAR	0.5021	0.4943	0.4605	SAR	0.6372	0.5568	0.6023
THB	0.8382	0.7590	-0.3892	QAR	0.8965	0.8521	0.8888
MYR	-0.4999	0.0259	0.2799	OMR	0.2324	-0.0566	0.0576
SGD	0.0562	0.1507	0.2083	PKR	-0.0174	0.2693	0.2940
HUF	0.3869	0.3791	0.3007	CNY	0.2603	0.2849	0.2777
TWD	0.5166	0.4003	0.2581	LKR	0.3476	0.1234	0.2743
KRW	0.6726	0.6822	0.6059	VND	0.5032	0.5217	0.5210
RUB	0.5292	0.6202	0.5751	BDT	0.6209	0.6067	0.5315

daily exchange rates of JPY/USD, CAD/USD, GBP/USD, EUR/USD and applied the random level shift model to specify the short memory plus level shift. Gil-Alana and Sauci (2018) found a lack of purchasing power parity in the real exchange rates of some Latin American countries through using parametric and semi-parametric techniques. Gogas et al. (2013) used Detrended Fluctuation Analysis and rolling window analysis to analyse the persistence in the exchange rates of 23 OECD countries.

3.7 Estimation of Breakpoints

The indicated spurious memory in exchange rate volatilities may be caused by some level shifts or structural breaks. As the next step of our analysis, we try to locate the breakpoints by using a method proposed by (Bai and Perron 1998, 2003). The multiple mean break model in the range volatilities to test the null hypothesis of constant unconditional mean against the multiple breaks is

$$R_t = c_j + \mu_t, t = T_{j-1} + 1, \dots, T_j, j = 1, \dots, m + 1. \tag{12}$$

where T is the sample size, $T_0 = 0, T_{m+1} = T$, and c_j is the mean of the range volatility. The number of breaks is considered unknown, and the least squares methods are used in estimation. This is a sequential test to estimate the consecutive number of breaks. The procedure of this test divides the sample into two parts after the estimation of the first break point. Further division of the sample depends on the failure of the constancy parameter hypothesis. Hence, this methodology includes l breaks and $l + 1$ regimes, and it tests the hypothesis of $l + 1$ against l breaks. Choi et al. (2010)

found that the persistence in Deutsche Mark/Dollar, Yen/Dollar, and Yen/Deutsche Mark can be explained somewhat by the structural breaks in mean.

Our results present the different number of breaks in each series. A list of the total number of breakpoints in all 30 series is provided in Table 6. We find a minimum of 2 breaks in Kazakhstan and a maximum of 7 breaks in the volatilities of Brazil, Hong Kong, South Africa, Taiwan, Ukraine, Kuwait, and China. We notice that these structural breaks are related to some specific events, such as the financial crisis faced by several Asian countries, including Thailand, Indonesia, Malaysia, South Korea, and The Philippines during 1997–1998; the Russian crisis in August 1998; the Brazilian crisis in 1999; the recession crisis during 2007–2008; and the European crisis in 2010.

The Asian crisis of 1997–1998 began in Thailand, and the most-affected countries, Thailand, Malaysia, South Korea, Hong Kong, and Indonesia, show a structural break during 1997. The less-affected countries of Singapore and Taiwan also show a break in 1997. This crisis was a result of large external deficits and frequent fluctuations in exchange rates. The depreciation of the Japanese yen against the USD during 1996–1997, combined with some insignificant effects of the Asian crisis, is reflected at the breakpoint in 1997, and the captured break in 2000 is also a result of the financial crisis of 1997–2002 (Fukao 2009). The depreciation in the Yen during 2013 was related to some policies, known as 'Abenomics', to expand the Japanese economy and to encourage private investment. The first break point in RUB is related to the Russian crisis of 1998, which demolished Russia's trade because of the decreased oil prices accompanying the Asian crisis and instability in the balance of payments (Chiodo and Owyang 2002). The aftershocks of the Asian crisis caused the Brazilian crisis in 1998–1999, and the situation became worse with the Russian crisis in August 1998, resulting in a break point in 1999. Food inflation related to weather shocks in Brazil may have affected the exchange rate volatility which is reflected as 2014 break point. The Tequila Crisis, which began in 1994–995 with the devaluation of the Mexican currency and resulted in the country's worst banking crisis in 1995–1997, reveals the level shift in Mexican volatility. One other great crisis that caused the structural breaks in the volatilities of almost every country is the great recession of 2008. It started with the sub-prime crisis in the USA during 2007 and spread worldwide, including the emerging markets. The breakpoints in 2007, 2008, or, in some cases, in 2009 are the result of this global financial crisis (GFC).

Breakpoints in the Gulf Cooperation Council (GCC) countries in 2001 were triggered by USD depreciation. All GCC currencies were pegged to the USD, excluding the Kuwaiti dinar, and the USD lost value due to the terrorist attacks of 11th September 2001. Currency appreciation is believed to have occurred in oil-exporting countries with positive oil price shocks, whereas oil importing countries experienced depreciation (Amin and El-Sakka 2016). The other breaks may relate to some oil price fluctuations, as GCC countries are the major exporters of oil. The financial crisis of 2000–2001 caused by a currency collapse was mirrored by the break point at 2001 in Turkey. The break in the Hungarian volatility series in 2011 may have been caused by the European crisis of 2010.

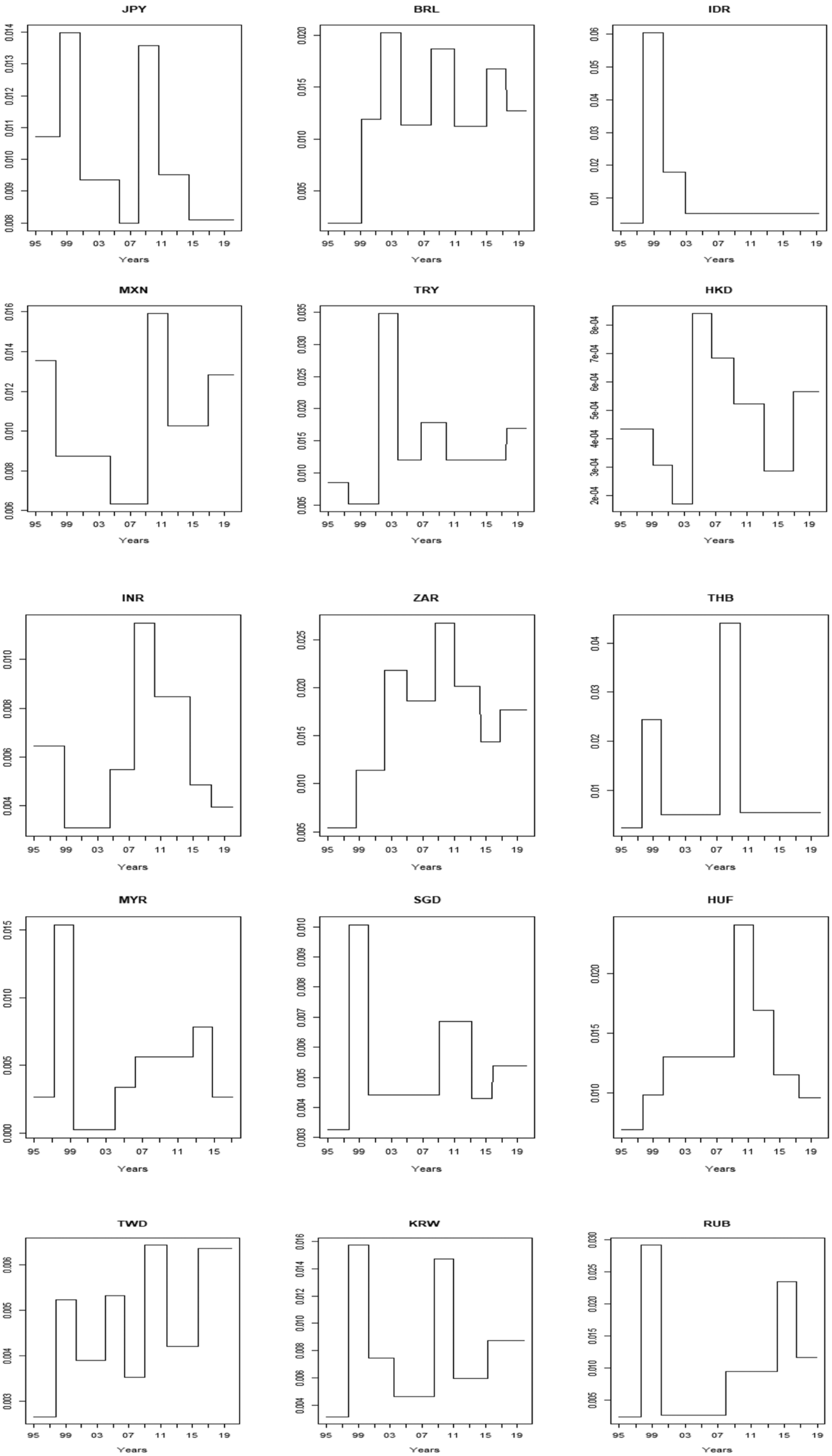
China depreciated its currency against the USD, the EUR, the JPY, and the KRW, reaching its lowest value over a four-year period in August 2015 and resulting in a

Table 6 Number of breaks with break dates

	JPY	BRL	IDR	MXN	TRY	HKD	INR	ZAR
No. breaks	6	7	3	5	6	7	6	7
Break dates	12/16/1997 6/6/2000 2/24/2005 7/25/2007 12/21/2009 9/19/2013	1/12/1999 6/15/2001 11/13/2003 7/23/2007 6/10/2010 4/24/2014 9/15/2016	8/12/1997 12/15/1999 8/2/2002	5/30/1997 2/11/2004 9/3/2008 1/28/2011 1/5/2016	6/16/1997 2/21/2001 7/22/2003 5/8/2006 6/24/2009 9/23/2016	11/17/1998 4/18/2001 9/19/2003 2/16/2006 10/28/2008 6/4/2012 1/6/2016	8/27/1998 3/22/2004 3/19/2007 9/1/2009 12/20/2013 7/1/2016	5/21/1998 11/28/2001 8/27/2004 1/14/2008 6/10/2010 7/11/2013 12/8/2015
	THB	**MYR**	**SGD**	**HUF**	**TWD**	**KRW**	**RUB**	**UAH**
No. breaks	4	6	5	6	7	6	5	7
Break dates	6/2/1997 10/29/1999 12/15/2006 5/18/2009	2/14/1997 4/5/1999 12/2/2005 3/5/2008 8/8/2014 11/2/2016	7/2/1997 12/2/1999 8/4/2008 7/13/2012 1/1/2015	7/9/1997 12/31/1999 8/25/2008 1/21/2011 6/24/2013 6/30/2016	10/16/1997 3/14/2000 10/6/2003 3/7/2006 8/6/2008 4/14/2011 1/14/2015	10/14/1997 3/15/2000 4/29/2003 3/6/2008 7/30/2010 10/7/2014	8/10/1998 12/1/2000 8/4/2008 7/15/2014 10/31/2016	8/14/1998 11/24/2000 4/16/2004 9/20/2007 12/7/2009 1/15/2014 5/20/2016
	KZT	**PHP**	**NZD**	**AED**	**BHD**	**KWD**	**SAR**	**QAR**
No. breaks	2	4	5	5	5	7	5	3
Break dates	2/14/2000 8/18/2015	9/24/1999 11/19/2001 5/15/2007 12/17/2010	7/25/2007 6/25/2009 12/21/2011 9/24/2014 9/15/2016	6/19/2001 7/9/2003 7/26/2005 11/12/2007 2/16/2010	9/6/2001 1/22/2004 5/4/2007 5/19/2009 6/18/2015	8/22/2000 1/21/2004 11/9/2006 11/28/2008 12/17/2010 12/12/2013 3/1/2016	8/18/2000 9/19/2007 1/28/2010 1/1/2015 1/31/2017	11/19/2007 3/14/2011 2/6/2017

Table 6 (continued)

	JPY	**BRL**	**IDR**	**MXN**	**TRY**	**HKD**	**INR**	**ZAR**
	OMR	**PKR**	**CNY**	**LKR**	**VND**	**BDT**		
No. breaks	5	6	7	5	4	4		
Break dates	3/7/2001	11/10/2004	7/26/2007	9/3/2009	11/23/2009	2/10/2010		
	3/21/2003	4/14/2008	4/24/2009	2/3/2012	11/30/2010	2/19/2014		
	9/5/2007	1/6/2010	8/11/2010	10/2/2013	6/28/2012	5/9/2016		
	6/30/2011	9/26/2011	4/17/2012	9/3/2015	7/17/2017	9/4/2017		
	7/11/2013	2/26/2015	2/24/2014	6/9/2017				
		5/23/2017	8/10/2015					
			8/7/2017					


JPY
BRL
IDR
MXN
TRY
HKD
INR
ZAR
THB
MYR
SGD
HUF
TWD
KRW
RUB
Years

◂ **Fig. 3** Graphs for structural changes

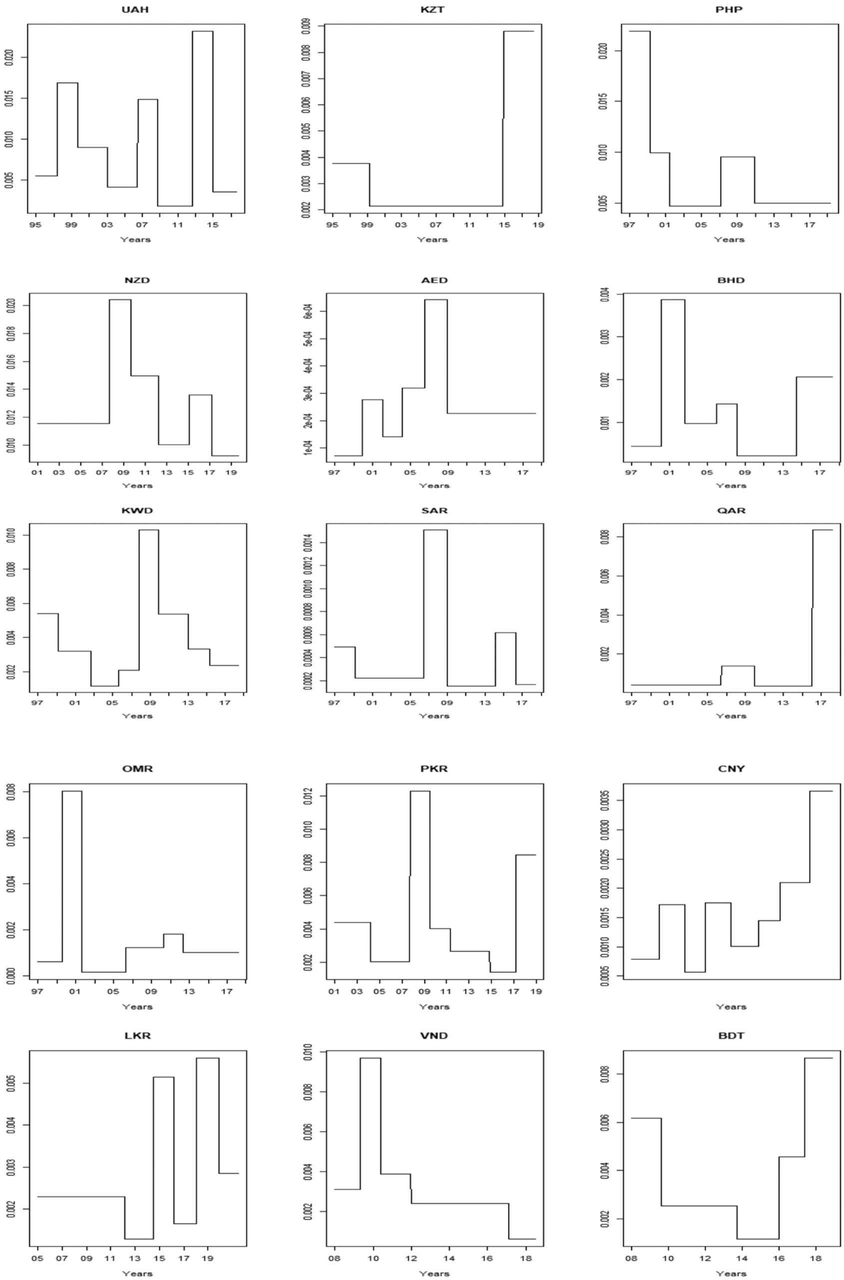


Fig. 3 (continued)

break. Due to this devaluation of the Yuan against the USD, many other currencies had to depreciate against the USD. The reported breakpoints during 2014–2015 in some countries may be caused by the decline in oil prices due to surplus supply and weak demands. The currency depreciation of INR against USD in 2013, result of the US Federal Reserve's policy of Quantitative easing, has been presented by a breakpoint in 2013.

Not only India's currency but most Asian currencies, except for China and Bangladesh, went through devaluation in this regard. The breakpoints in the PKR volatility series in 2010 and 2011 are the result of a bad economic situation resulting from destruction of fertile lands by terrible flooding during 2010. KZT fluctuations in 2015 occurred following an announcement by the government that it was going to convert the Tenge into a floating currency. The graphs for the structural changes in Table 6 are presented in Fig. 3 with years on the x-axis.

4 Conclusion

We analyse the long-range dependence in daily spot exchange rates across 30 different countries. Our results are based on the range-based volatility contrary to either the absolute returns or the squared returns. We use semi-parametric methods to estimate the long-range dependence. The Local Whittle (LW) estimator is used to estimate the memory for different bandwidths. The results of the memory estimates are in both the stationary and the non-stationary regions for considered bandwidths. We were motivated to test for the hypothesis of true long memory versus spurious memory because of a decrease in the value of the memory parameter with an increase in the bandwidth parameter. We tested the true memory hypothesis through application of two tests by (Shimotsu 2006) and a more powerful test by (Qu 2011). We obtained mixed results in favour of true memory and spurious memory. Graphical analysis of the memory estimates against a range of truncation parameters shows that the persistence level decreases with the increase in bandwidth for most of the volatilities. Due to inconsistency of the LW estimator in the case of either level shifts or low-frequency contaminations, we estimate the long-range dependence by using the Modified LW (MLW) estimator of (Hou and Perron 2014). With the MLW, we find reduced memory estimates in 18 cases. We estimate the number of breaks in the volatility series and find a different number of breaks by using the method of (Bai and Perron 2003), with a minimum number of 2 breaks and a maximum of 7. Most of the breakpoints are related to important disasters, such as the Asian crisis, the global financial crisis, the Russian crisis, and the Brazilian crisis, and some of the economic strategies involved.

Our results seem to suggest that the phenomenon of varying fractional integration in range-based volatilities through different bandwidths may be caused by either structural breaks or level shifts. Along with structural breaks, some other economic factors, such as central bank interventions and speculative effects, may cause fluctuations in exchange rates. Our findings are important for modelling and forecasting the exchange rate volatilities. It is important to distinguish between true and spurious memory to specify the volatility process correctly (Zhou 2011). Furthermore, exchange rate modelling can be performed by taking into account the structural breaks and using a random level shifts model. Our results are helpful for policymakers to develop better policies for persistence in exchange rates with consideration of level shifts. In fact, different policy measures can be based on the volatility persistence in exchange rates while studying the true nature of the process underlying the data.

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