TESTING FOR LONG MEMORY IN THE ASIAN FOREIGN EXCHANGE RATES

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Abstract. In this paper, we use the plug-in and Whittle methods that are based on spectral regression analysis to test for the long memory property in 12 Asian/dollar daily exchange rates. The results according to the plug-in method show that with the exception of Chinese renminbi all series may have long memory properties. The results based on the Whittle method, on the other hand, show that only Japanese yen and Malaysian ringgit may have long memory properties.

It is well known that inference about the differencing parameter, \(d\), in presence of structural break in a series entails considerable difficulties. Therefore, given the financial crisis of 1997-1998 in Asia, further tests for unravelling of the memory property and presence of structural break in the exchange rate series are required.

Key words. Exchange rates, long memory, plug-in method, Whittle method.

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1 Introduction

Much of the analysis in financial economics is based on the assumption of efficient market hypothesis (EMH), which in its weak form implies that returns of financial time series (e.g., equity prices, interest rates, exchange rates) are white noise processes consisting of independent, identically distributed random variables\(^3\). These characteristics imply that the time series at the level follow random walks.

A time series that follows a random walk process has two important properties. First, the series has long memory in the sense that the effects of distant shocks are strongly felt at the present. Second, the first difference of the series is a white noise, short memory process [1].

A random walk model, however, is incapable of explaining a precipitous drop in many financial time series. For example, a major price change in the stock prices such as the fall of the New York markets in October 1987 can not be explained by a random walk process. Accordingly, in this study we seek to explore the nature of the data generating processes of certain Asian currencies by examining the memory properties of the series.

For a Gaussian process, the autocorrelation function or the spectral density describes the memory properties of the series. If a series exhibits long memory, there is persistent temporal dependence between distant observations. Such series are characterized by distinct but nonperiodic cyclical patterns [2]. In the time domain, this is characterized by autocorrelation function that decays hyperbolically. In the frequency domain, this is characterized by high power at low frequencies, especially near the origin. A broader definition of the long memory processes requires that the autocovariances are not summable or that the spectral density is unbounded.

In this study we use the plug-in and Whittle methods in testing for long memory properties of 12 Asian/dollar daily exchange rates. We are motivated to examine the dynamics of the exchange rates on the grounds of economic policy, statistical inference, and forecasting.

First, let us look at the policy implications of the long memory property of an exchange rate.

In the globally integrated economies of today, the behaviors of foreign exchange rates are of great importance to international investors as the volatility of the exchange rates is an important determinant of the degree of risks associated with the investment opportunities. Moreover, the

\(^3\)In spectral analysis, one comes across noises of various color: White, pink, brown, and black. Noise refers to the power spectra, or what is the same thing, squared magnitude of the Fourier transform of a time series. Noises follow a power law in the form of \(f^{-\beta}\), where \(f\) is frequency and \(\beta\) is a constant. White noise has a spectral exponent of \(\beta = 0\).
exchange rate plays a prominent role in international trade.

In a long memory process, the effects of shocks tend to persist. For example, establishing that shocks to an exchange rate persist, may give the Central Bank’s authorities additional incentives to intervene in the currency markets. These interventions would aim at steering the nominal exchange rate toward its long-run equilibrium path, for the cost of inaction on the part of the monetary authorities is further divergence of the nominal exchange rate from its long-run equilibrium value. Alternatively, if the monetary authorities believe that the prevailing nominal exchange rate is in the proximity of its long-run equilibrium, and that lack of intervention in the currency markets would cause divergence of nominal rate from its equilibrium rate, with possible dire consequences, then regular and frequent interventions in the currency markets would be justifiable.

For another example, consider gross domestic product (GDP). Persistence of shocks in the GDP series, would require corrective monetary and fiscal policies to force the nominal GDP towards its long-run equilibrium path (see Gil-Alana and Robinson [3] for a detailed discussion of testing for persistence of shocks and unit root in macroeconomic time series). In cases where shocks do not persist, policy activism is not required, since the series will automatically and eventually move towards its long-run equilibrium path.

Second, detecting long-memory in a time series has important implications for statistical inference and prediction. For example, the sample variance, \( s^2 \), as a biased estimator of population variance, \( \sigma^2 \), depends on the correlation structure of the series. If the observations are correlated, then the expected value of \( s^2 \) equals to \( \sigma^2 \). However, when the correlations are predominately positive, the sample variance tends to underestimate the population variance. By the same reasoning, \( s^2 \) would overestimate \( \sigma^2 \) when the correlations are predominately negative.

Notwithstanding the difficulties associated with inference based on statistics estimated using a long-memory time series, slowly decaying correlations allow for more accurate predictions of the series. This is due to stronger dependency among the observations in a series (for details, see Beran [4], chapter 1).

The paper is arranged as follows. In section 2.1 we briefly discuss past empirical works on the long memory property of the exchange rates. In section 2.2, two methods for testing the long-memory property of a time series are presented. First, we proceed with a short discussion of GPH method and then examine the plug-in method based on the work of Hurvich and Deo [5] to estimate the differencing parameter of the ARFIMA model. Next, we discuss Whittle estimation method Fox and Taqqu [6]. In section 3.1, we discuss the data used here and present the empirical results
of the study. The final section gives the conclusions.

2 Literature Review and Methodologies

2.1 Literature Review

In empirical modelling of long memory processes the autoregressive fractionally integrated moving average (ARFIMA) model, proposed by Hosking [7] and Granger and Joyeux [8] is often used. There exist many empirical works that test for the presence of long memory in the financial and economic time series. These studies include, for example, Soofi [9] and Cheung [10] that test for the memory property of the exchange rate time series. Cheung first applied the ARFIMA model to foreign exchange rate series. In that study, using the weekly changes of US-Dollar spot rate of the British Pound, the Deutsche Mark, the Swiss Franc, the French Franc and the Japanese Yen for the period from January 1974 to December 1989, Cheung finds the statistical evidence for long memory using various estimation techniques. Soofi [9] tests for the presence of long memory in the black market exchange rates of a number of oil exporting countries.

Many of these studies of long memory are based on the estimation method by Geweke and Porter-Hudak [11] (GPH) which may involve less than robust estimates (see section 2.2.1 below). To avoid potential inefficiency of estimating the differencing parameter using the GPH method [12], we adopt plug-in method proposed by Hurvich and Deo [5], and the Whittle maximum-likelihood method in estimating the differencing parameter and testing for long memory in the exchange rate series.

2.2 Methodologies

An earlier method for detecting long memory in a time series is rescaled range analysis (R/S analysis) that was introduced by Hurst [13] and later refined by Mandelbrot [14, 15] and Mandelbrot and Wallis [16], and Lo [2]. The statistical inference about the estimates using this method is based on a null hypothesis of data exhibiting short memory. This method, however, does not provide correct statistical inference procedure, and is considered to be heuristic by some analysts Beran [4].

Later, Geweke and Porter-Hudak [11] (GPH) proposed a more robust estimation method based on spectral analysis. Due to its computational simplicity, the GPH method of estimation of the differencing parameter is used extensively. In this study, we will briefly discuss this method and focus on the recent developments of this and other estimation techniques. See a general survey on
ARFIMA estimation methods by Bhansali and Kokoszka [17]. Below we explain the two methods based on spectral analysis that we use in exploring the memory properties of the Asian exchange rates.

2.2.1 Plug-in Method

Consider a time series \( X = \{x_t\}_{t=1}^{N} \). It is said to be integrated of order \( d \), signified as \( I(d) \), if it has a stationary, invertible autoregressive moving average (ARMA) representation after applying differencing operator \( (1 - L)^d \), where \( L \) is the backward lag operator. The series is fractionally integrated when \( d \) is not an integer.

For \( 0 \leq d < 0.5 \), the autocorrelations of \( X \) decay at a hyperbolic rate that is proportional to \( k^{(2d-1)} \) for large \( k \), as compared to a faster, geometric decaying rate of a stationary ARMA process\(^4\).

According to the GPH method, given the periodogram \( I(\omega_j) \) of variable \( X \) one can estimate \( d \) by:

\[
\ln(I(\omega_j)) = c - d \ln(4\sin^2(\omega_j/2)) + \eta_j \quad (j = 1, \ldots, m),
\]

where \( \omega_j = \frac{2\pi j}{N} \) for \( (j = 1, \ldots, m) \) denote the harmonic ordinates, \( c = \log C - \theta \), \( \theta \) is Euler’s constant \( \theta = 0.5772\ldots \) and \( \eta_j = \log \{(4\sin^2(\omega_j/2))^d I(\omega_j)/C\} + \theta \). \( C \) is the constant assumed by Geweke and Porter-Hudak [11] to approximate the spectral density \( f(\omega) \) by \( C(4\sin^2(\omega/2))^{-d} \) in the neighborhood of zero frequency, so an asymptotic theory will require that \( m \) tend to infinity more slowly than \( N \).

Note that selection of a large sample size leads to estimator’s sensitivity to short memory, and an inadequate sample size will result in an imprecise estimation. As suggested by GPH [11], one should use \( m \) observations, where \( m = g(N) \ll N \).

The critical values for the GPH test are non-standard, and critical evaluation of estimated \( d \) requires computation of empirical values\(^5\). The choice of \( m = T^{0.5} \) is widely used in the literature. This choice, however, yields suboptimal convergence rate. Moreover, the notion of long memory in the GPH test is an asymptotic one, and the proportionality of the spectral density to \( \omega^{1-2H} \) (where \( H \) is the Hurst exponent), i.e. \( f(\omega) \sim c_f \|\omega\|^{1-2H} \), is observed in the neighborhood of zero. Assum-

\(^4\)For a comparison of the rates of decay of autocorrelations for AR(1) and ARFIMA(0,d,0) models, see Diebold and Rudebusch [18].

\(^5\)For the quantiles of Monte Carlo distribution of GPH standardized t-statistics which are based on \( GPHT = \frac{d - \hat{d}}{SD(d)} \), where \( \hat{d} \) is estimate of \( d \), and \( SD(d) \) is the asymptotic standard error of \( \hat{d} \), see Soofi [9].
ing that the proportionality holds in the whole interval \([-\pi, \pi]\), the estimate of \(H\) (and therefore \(d\)) can be severely biased [4].

In addressing these problems, Robinson [19] proposed a Gaussian semiparametric estimator (GSE). Since GSE is defined implicitly, derivation of a formula for asymptotically optimal \(m\) is rather problematic. Moreover, the estimation method rests on a theory of optimal selection of \(m\) yielding a formula which includes both \(m\) and \(d\). To deal with this problem, Delgado and Robinson [20] proposed an iterative method of estimating \(d\) and \(m\) in alternating cycles.

To resolve some of these problems, Hurvich and Deo [5] proposed a plug-in method of selecting \(m\) as follows\(^6\). Let \(X\) consists of \(N\) observations such that \(\{x_t\}_{t=1}^N\) are both normal and stationary. Hurvich and Deo [5] suggests using \(\hat{C}\) to construct estimators \(\hat{d}_m\) of \(d\) where,

\[
\hat{m} = \hat{C} N^{4/5}\tag{2}
\]

\(\hat{C}\) is consistently estimated by

\[
\hat{C} = \left( \frac{27}{128\pi^2} \right)^{1/5} \hat{K}^{-2/5}
\]

and,

\[
\hat{K} = \sum_{j=1}^H b_j \log I_j.
\]

In this model \(b_j\) is the third row of matrix \((Y'Y)^{-1}Y'\), where matrix \(Y\) has the columns \((1, \log |2 \sin(\omega_j/2)|, \omega_j^2/2), (j = 1, 2, ..., L), L = AN^\delta\), for some arbitrary constant \(A\), and \(0 < \delta < 1\). To minimize the mean square error, we set \(\delta = 6/7\) as suggested by Hurvich and Deo [5]. \(I_j\) is the periodogram of the \(j\)-th Fourier frequency given by

\[
I_j = \frac{1}{2\pi N} \left| \sum_{t=1}^N x_t e^{-i\omega_j t} \right|^2
\]

The regression estimator of \(d\) is given by

\[
\hat{d}_m = -0.5 \frac{\sum_{j=1}^{\hat{m}} (a_j - \bar{a}) \log I_j}{\sum_{j=1}^{\hat{m}} (a_j - \bar{a})^2}
\]

where \(a_j = \log |2 \sin(\omega_j/2)|\), \(\bar{a} = \frac{1}{\hat{m}} \sum_{j=1}^{\hat{m}} a_j\), and \(\hat{m}\) is the Fourier frequencies obtained in formula (2). We find the estimates of \(d\) are sensitive to the constant \(A\) occurring in \(L = AN^\delta\). \(A = 0.2, 0.25, \) and \(0.3\) which are based on an initial simulation study by Hurvich and Deo [5] are also used in this study.

\(^6\)This discussion is heavily drawn from Soofi and Payesteh [21].
According to Theorem 2 of Hurvich and Deo [5], \( \text{Var}(\hat{d}_m) = \frac{x^2}{2m} \). Hence, the asymptotic standard errors are given by \( SD(\hat{d}_m) = \frac{\pi}{\sqrt{2m}} \).

For the differences between the empirical results based on the GPH and the plug-in methods, see Soofi and Payesteh [21].

Since in practice, the exact form of the correlation structure of the form \( \rho(k) = c_\rho k^{2H-2} \) can not be known, one may estimate the whole correlation structure using a flexible parametric model such as the maximum likelihood estimation of the parameter vector, \( \theta^0 \).

We now turn to a short discussion of Whittle estimator.

### 2.2.2 Whittle Method

The log-likelihood function, \( L_N(x; \theta^0) \), for a stationary, Gaussian process \( \{x_t\}_{t=1}^N \) is given by

\[
L_N(x; \theta^0) = -\frac{N}{2} \log 2\pi - \frac{1}{2} \log |\Sigma_N(\theta^0)| - \frac{1}{2} x^t \Sigma_N^{-1}(\theta^0)x,
\]

where \( \Sigma(\theta^0) \) is the covariance matrix of \( x \) and \( |\Sigma_N| \) is the determinant of \( \Sigma_N \). The maximum likelihood estimators (MLE) of \( \theta^0 \) is obtained by maximizing (7). Because of computational difficulties of maximizing (7), in practice, an approximate MLE of \( \theta^0 \) is obtained by minimizing

\[
L_W(\theta) = \frac{1}{2\pi} \int_{-\pi}^\pi \log f(\omega; \theta) \, d\omega + \frac{x^t A(\theta)x}{N}
\]

with respect to \( \theta \), where \( A(\theta) = [\alpha(j-l)]_{j,l=1,...,n} \) is the \( (n \times n) \) matrix with elements

\[
\alpha(j-l) = (2\pi)^{-2} \int_{-\pi}^\pi \frac{1}{f(\omega; \theta)} e^{i(j-l)\omega} d\omega.
\]

Matrix \( A \) is asymptotically the inverse of \( \Sigma_N \) (see Beran [4], Chapter 5).

According to Hosking [7], when \( 0 < d < 0.5 \), the series is a long memory process, and when \( -0.5 < d < 0 \), it is short memory and 'antipersistent' in the terminology of Mandelbrot [22]. When \( d = 0 \), the series is white noise, with zero correlations and constant spectral density. For \( d = \pm 0.5 \), the series will be either stationary or invertible but not both. For the case \( d \notin [-0.5, 0.5] \), the process can be reduced to case \( -0.5 \leq d \leq 0.5 \) by taking appropriate differences or summing.
3 Data and the Empirical Results

3.1 The Data

In this study, 12 Asian daily dollar exchange rates series\textsuperscript{7} are included: Chinese Renminbi (CNY), Hong Kong Dollar (HKD), Indonesia Rupiah (IDR), Indian Rupees (INR), Japanese Yen (JPY), South Korean Won (KRW), Malaysian Ringgit (MYR), Philippines Pesos (PHP), Pakistani Rupees (PKR), Singapore Dollar (SGD), Thai Baht (THB), and Taiwan Dollar (TWD). The sampling time periods for these series are indicated in the second column of Table 1.

The unit root tests confirm that the series are nonstationary, even though we do not report the results in this paper. Therefore, before estimating the differencing parameters $d$, we first preprocess the data by taking the first difference of the log of the series.

We use both plug-in method and the aggregate Whittle method to test for the memory property of the data.

3.2 The empirical results

3.2.1 Results Based on the Plug-in Method

Table 1 reports the estimated differencing parameter $d$ based on the plug-in method, the optimal $ms$, and the 95\% confidence intervals for the estimates.

We postulate the null hypothesis $H_o : d = 0$ and the alternative hypothesis $H_a : d \neq 0$.

Based on the data in Table 1, we classify the currencies into three categories. First, the series with a confidence interval that contains zero. Second, the series with the confidence intervals that both include and exclude zero, depending on the parameter $A$. Third, the series with confidence intervals that exclude zero regardless of the value of the $A$ parameter.

The only currency that falls in the first category is Chinese renminbi. This result implies that the first difference of the log of renminbi/dollar exchange rate appears to be white noise with zero correlations. Furthermore, this finding implies that the series at the level has a unit root and may follow a random walk process.

If the RMB/USD series at the level follows a random walk process, then currency market interventions by Chinese monetary authorities become imperative. In the absence of such interventions, the spot RMB/USD exchange rate may diverge from its long-run equilibrium value. To steer

\textsuperscript{7}These data are retrieved from: http://fx.sauder.ubc.ca/.
the exchange rate towards its equilibrium value, currency market interventions might be pivotally important and urgently required.

It is important to note that nonstationarity of a series does not necessarily imply long-run divergence of the series from its mean value. It is well-known that a series with $0.5 < d < 1$, is mean reverting even though it is non-stationary [23].

Next, the series in the second category includes Korean won, Malaysian ringgit, and Singapore dollar. In the Korean won case, for the log of the returns for $A = 0.20$, the confidence interval contains zero, implying that we can not reject the null hypothesis. However, for $A = 0.25, 0.30$ the confidence intervals do not contain zero. Finally, the estimate for Singapore dollar for $A = 0.20, 0.25$, the intervals contain zero also. However, since for these currencies certain intervals exclude zero for $d$ estimate also, we have mixed results that are not robust.

Finally, for the remaining currencies, the point estimates of $d$ parameter and the confidence intervals all fall below interval $0.5 < d < 1$, implying that the first differenced log series may not be short memory. Alternatively, since all interval estimates for the first differenced log currencies fall in the intervals $0 < d < 0.5$ we conclude that the series may be long memory processes.

### 3.2.2 Results Based on Whittle Method

We present the estimation results by Whittle method\(^8\) in Table 2. From this table, we see that only Malaysian ringgit, and Japanese yen have estimated $d$ and 95% confidence intervals that do not include zero value. Again since these d-estimates and the corresponding confidence intervals for the log of first difference of these currencies fall in the interval $0 < d < 0.5$, we conclude that these series may be long memory processes.

### 4 Conclusions

Testing for the long memory property in the daily dollar exchange rates of the Asian currencies has important policy implications. Two methods based on spectral regression analysis are used to test for the long memory property in the Asian dollar exchange markets. Based on the results provided in the tables, we find the evidence of the long memory for Japanese yen and Malaysian ringgit. For all the other series, we cannot reject the hypothesis that the returns of the series are generated

\(^8\)We estimated the differencing parameter $d$ using the software SELFIS provided by Karagiannis, Faloutsos, and Mølle [24].
from the short memory process.

The latter finding implies that these currencies at the level may not have mean-reverting property. Accordingly, currency market interventions become necessary for all major currencies that fall in this category.

It is well known that inference about the differencing parameter, $d$, in presence of structural break in a series entails considerable difficulties. Therefore, given the financial crisis of 1997-1998 in Asia that may have caused structural breaks in the time series under study, further tests for unravelling of the memory property and presence of structural break in the exchange rate series may shed additional light on true memory characteristic of the series.

References


Table 1: Estimated Differencing Parameters with 95% Confidence Intervals for the first differenced log data by plug-in method

<table>
<thead>
<tr>
<th>FX</th>
<th>Sample Period</th>
<th>A</th>
<th>$m_{op}$</th>
<th>$\hat{d}$</th>
<th>$\hat{d} - 1.65\sigma$</th>
<th>$\hat{d} + 1.65\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNY</td>
<td>1-4-1993</td>
<td>0.20</td>
<td>822</td>
<td>-0.0040</td>
<td>-0.0409</td>
<td>0.0329</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>248</td>
<td>-0.0016</td>
<td>-0.0688</td>
<td>0.0656</td>
</tr>
<tr>
<td>HKD</td>
<td>1-2-1981</td>
<td>0.20</td>
<td>253</td>
<td>0.0764</td>
<td>0.0098</td>
<td>0.1429</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>123</td>
<td>0.1273</td>
<td>0.0319</td>
<td>0.2227</td>
</tr>
<tr>
<td>IDR</td>
<td>11-16-1995</td>
<td>0.20</td>
<td>92</td>
<td>0.1585</td>
<td>0.0482</td>
<td>0.2689</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>92</td>
<td>0.1585</td>
<td>0.0482</td>
<td>0.2689</td>
</tr>
<tr>
<td>JPY</td>
<td>1-4-1971</td>
<td>0.20</td>
<td>381</td>
<td>0.0798</td>
<td>0.0255</td>
<td>0.1340</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>297</td>
<td>0.0740</td>
<td>0.0126</td>
<td>0.1354</td>
</tr>
<tr>
<td>KRW</td>
<td>4-13-1981</td>
<td>0.20</td>
<td>84</td>
<td>0.0461</td>
<td>-0.0694</td>
<td>0.1615</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>119</td>
<td>0.1224</td>
<td>0.0254</td>
<td>0.2194</td>
</tr>
<tr>
<td>MYR</td>
<td>1-4-1993</td>
<td>0.20</td>
<td>93</td>
<td>0.1999</td>
<td>0.0901</td>
<td>0.3096</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>217</td>
<td>0.0690</td>
<td>-0.0028</td>
<td>0.1409</td>
</tr>
<tr>
<td>PHP</td>
<td>11-16-1995</td>
<td>0.20</td>
<td>53</td>
<td>0.1624</td>
<td>0.0170</td>
<td>0.3077</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>68</td>
<td>0.1370</td>
<td>0.0087</td>
<td>0.2653</td>
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<tr>
<td>PKR</td>
<td>11-16-1995</td>
<td>0.20</td>
<td>48</td>
<td>0.3308</td>
<td>0.1781</td>
<td>0.4835</td>
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<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>47</td>
<td>0.3213</td>
<td>0.1669</td>
<td>0.4756</td>
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<tr>
<td>SGD</td>
<td>1-2-1981</td>
<td>0.20</td>
<td>144</td>
<td>0.0287</td>
<td>-0.0595</td>
<td>0.1168</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>184</td>
<td>0.0389</td>
<td>-0.0392</td>
<td>0.1169</td>
</tr>
<tr>
<td>THB</td>
<td>1-4-1993</td>
<td>0.20</td>
<td>85</td>
<td>0.1849</td>
<td>0.0702</td>
<td>0.2997</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>92</td>
<td>0.2103</td>
<td>0.1000</td>
<td>0.3206</td>
</tr>
<tr>
<td>TWD</td>
<td>10-3-1983</td>
<td>0.20</td>
<td>133</td>
<td>0.1456</td>
<td>0.0538</td>
<td>0.2373</td>
</tr>
<tr>
<td></td>
<td>2-1-2005</td>
<td>0.25</td>
<td>252</td>
<td>0.1749</td>
<td>0.1082</td>
<td>0.2415</td>
</tr>
</tbody>
</table>

11
Table 2: Estimated Differencing Parameters with 95% Confidence Intervals for the first differenced log data by Whittle method

<table>
<thead>
<tr>
<th>FX</th>
<th>CNY</th>
<th>HKD</th>
<th>IDR</th>
<th>INR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>0</td>
<td>0</td>
<td>0.024</td>
<td>0</td>
</tr>
<tr>
<td>CI</td>
<td>[-0.020,0.019]</td>
<td>[-0.020,0.019]</td>
<td>[-0.004,0.027]</td>
<td>[-0.028,0.027]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FX</th>
<th>JPY</th>
<th>KRW</th>
<th>MYR</th>
<th>PHP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>0.025</td>
<td>0</td>
<td>0.047</td>
<td>0.015</td>
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<tr>
<td>CI</td>
<td>[0.012,0.039]</td>
<td>[-0.020, 0.019]</td>
<td>[0.019,0.074]</td>
<td>[-0.013,0.042]</td>
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<table>
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<tr>
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<th>PKR</th>
<th>SGD</th>
<th>THB</th>
<th>TWD</th>
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<tr>
<td>$d$</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>CI</td>
<td>[-0.020,0.019]</td>
<td>[-0.020,0.019]</td>
<td>[-0.020,0.019]</td>
<td>[-0.020,0.019]</td>
</tr>
</tbody>
</table>

$CI$ indicates the 95% confidence intervals.