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Research Article

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Modeling the Exchange rate long-range dependence of some world emerging markets

Sanusi Alhaji Jibrin[1]*, Abdulhameed A. Osi[1], Aremu T. Adeyemi[2], Samaila Mohammed[2], Umar A. Zubair[3], Ahmed S. Saidu[3]

*[1]Department of Statistics, Kano University of Science and Technology, Wudil, Nigeria
[2]Department of Mathematics and Statistics, NuhuBamalli Polytechnic Zaria, Kaduna
[3]Department of Statistics, Central Bank of Nigeria

Abstract This research examined over ten years Chinese Yuan (CNY), Indian Rupees (INR), Nigerian Naira (NGN) and Malaysia Ringgits (MYR) daily to the U.S Dollar exchange rate using the conditional mean models namely: the Autoregressive Integrated Moving Average (ARIMA) and the Autoregressive Fractional Integrated Moving Average (ARFIMA) models. The best candidate modelswere selected using Akaike Information Criteria (AIC). Approaches used for testing and estimating long memory parameters are the rescaled range tests [1-3] and Local Whittle Estimator developed by Robinson [4]. The white noise, serial correlation and the heteroscedasticity test was carried out. Unit roots tests confirmed the nonstationary of all the four series while the inconsistency results obtained from the long memory parameters estimates guided the use of two modeling approaches. The findings revealed that the ARIMA model is the best to study CNY, INR and MYR to the U.S Dollar exchange rate while ARFIMA method is the suitable to model the NGN exchange rate.

Keywords Modeling, Exchange rate

1. Introduction

The increasing use of large time series data has initiated some competitive research work. Among other procedures that can be used to analyze a large data set is the long memory (LM) analysis. The behavior of businesses, economies, traffic flow and the walk of a drunkard are few simple examples of data with long-range dependence. LM represents a degree of dependence between observations or a situation where some figures persists or occurred in high frequency in a given data. The LM was first discovered in physical science data by Hurst (1951) and his effort was complimented by a lot of giant stride in the economies and financial data [5]. LM processes are stationary processes whose Autocorrelation Functions (ACF) decayed more slowly than a short memory process. Because the ACF die out slowly, the LM process displayed a type of long range dependence. The short memory process, ACF decayed to zero at a geometric rate while that of LM decayed at the hyperbolic rate [3]. Baillie and Beran introduced simple explanations to LM processes and also developed models to study the series characterized by this attribute [6-7]. Long range-dependence of two oil prices was studied and predicted for the possibility for a crude oil price to decline drastically in 2014 [8]. The research estimated two long memory models, the ARFIMA (1, 0.47, 2) and ARFIMA (2, 0.09, 0) using West Texas Intermediate (WTI) and Brent series respectively. Nezhad *et al* examined the fractional integration in Organization of Petroleum Exporting Countries (OPEC) prices and further confirmed that it is necessary to model the price using a fractional integration model [9]. The price in the option market is dominated by long memory characteristics and a fractional cointegrated relationship [10]. The fractional integration test may discriminate between spurious long memory and a true fractional integration parameter [11]. Jibrin *et al* studied the impact of Floating exchange rate regime introduced by the Nigerian government in 2016 using ARIMA intervention approach. The naira value witnessed a persistent depreciation against the United States dollar. The research findings further revealed that the currency and the economy will be affected by the devaluation for a long time except critical economics measures are taken by the authorities concerned [12].

It is paramount to note that considerable cautions are necessary whenever the nonparametric and semiparametric memory estimation procedures are used to explore the degree of long memory specifically when the series displayed the nonstationary, deterministic and liner trend. Phillips and Shimotsu emphasized on the need to take precautions when using LWE to determine the long-range dependence of a series that has trending attributes and deterministic trends. These characteristics of the time series sometime led to varying LM parameter estimate. Occasionally, for a particular series, some LM testing and estimation procedureconverge to unity indicating that the series is integrated of order one, I(1), while others said is fractional integrated, I(0<d<1). For I(1), it is clearly that the Autoregressive Integrated Moving Average (ARIMA) model could be suitable to study the series while if it is I(0<d<1), then Autoregressive Fractionally Integrated Moving Average (ARFIMA) model that is appropriate [13]. In view of these, the crucial issue for the analysis of data is making a decision on the best modeling approach. The use of single methodology (for example, the use of ARIMA or SARIMA or ARFIMA model) to study a series sometimes can lead to erroneous conclusions. Literature in the past indicated that the behaviors of the time series are not easily or graphically identified unless various formal tests are explored [8].

The two popular semiparametric LM procedures are the log-periodogram regression discussed [14] and Gaussian semiparametric estimate also known as Local Whittle Estimate (LWE) proposed [15]. This research is motivated by the studies of [13, 17]. In their separate researches, they discussed the inconsistency of the various long memory estimation methods/tests. Robinson [4] and Velasco [17] both shows asymptotic normality, consistency and otherwise of the LWE for $d \in (-0.5,0.5)$ and $d \in [(-0.5,1),(-0.5,0.75)]$ respectively. This research want to determine the best conditional mean model that can be used to effectively study the exchange rate of some emerging world markets that exhibited long-range dependence. The remaining part paper consists of material and methods used in section 2, results and discussion in section 3 while the concluding remarks is discussed in section 4.

2. Materials and Methods

2.1. The dataset

The data for this research were obtained from the website of the Quandle database and include CNY, INR, NGN and MYR to the U.S dollar daily exchange rate for the period 01/01/2007 to 31/05/2017.

2.2. Methodology

Numerous real lifetime series is nonstationary. ARIMA model was introduced for such a time series [18] while Box Jenkins proposed that differencing up to an order d could render those series to be stationary [19]. Researchers contributed in designing models to study time series with long range dependence [6-7, 14, 20-21].

A data is called a fractionally integrated process if it can be represented as:

$$(1-\mathrm{B})^{d}\,\mathrm{X}_{t}=\varepsilon_{t}, \tag{1}$$

The expansion of (1) produced the following equation:

$$\mathrm{X}_{t}-d\mathrm{X}_{t-1}+\frac{d(d-1)}{2!}\mathrm{X}_{t-2}-\ldots=\varepsilon_{t}. \tag{2}$$

A general form of an ARFIMA model can be presented by

$$\Phi(\mathrm{B})(1-\mathrm{B})^{d}\,\mathrm{X}_{t}=\Theta(\mathrm{B})\varepsilon_{t},\ for 0<d<0.5 \tag{3}$$

where the parameter d is a fractional value, X_t is the original data at the time t, $\varepsilon_{t,}$ is normally distributed with mean 0 and variance σ^2. The $\phi(B)$ and $\theta(B)$ represents AR and MA polynomials with $lag\ B$, respectively. Furthermore, an ARIMA model can also be represented in a similar manner as the ARFIMA model in (3) if the "difference parameter", d, is allowed to take integer values. The best candidate for the ARIMA and ARFIMA model can be selected using Akaike Information Criteria (AIC). The stationarity tests employed in this study are

[22] and [23]. Approaches used for testing and estimating long memory parameters are the rescaled range tests [1-3] and Local Whittle Estimator suggested by Kunsch [15] and later developed by Robinson [4]. The white noise, serial correlation and the heteroscedasticity test was carried out using the residual normality test, the Portmanteau test and Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH-LM) test respectively.

2.3. Software used

The software used is Gretel version1.9.4 and G@RCH 7.0 and OxMatrics version 6.21.

3. Analysis and Results

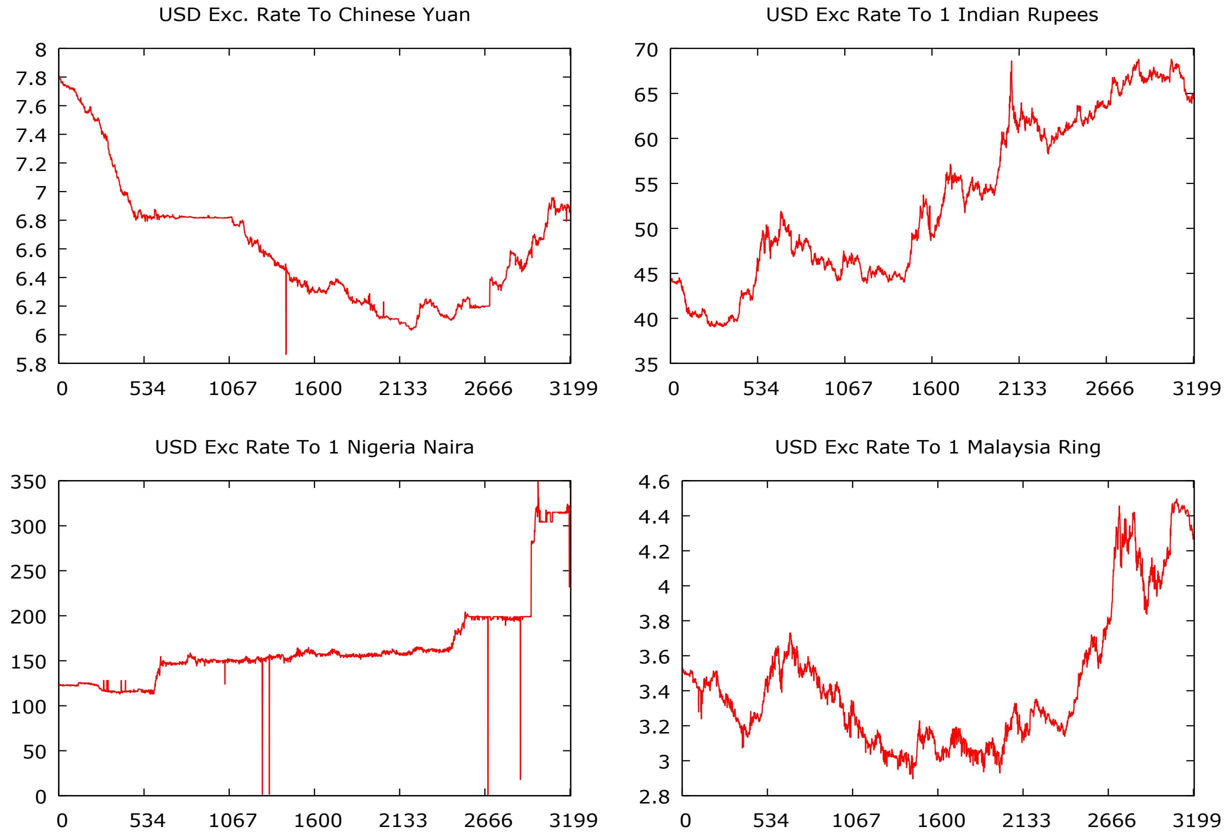

Figure 1: A time plots of daily CNY, INR, NGN and MYR to the U.S dollar exchange rate

The CNY, INR, NGN and MYRto the U.S dollar daily exchange rate are displayed in Figure 1. Three of the graphs exhibited deterministic trends, namely: Chinese Yuan, Indian Rupees and Malaysian Ringgits. The Nigeria Naira exchange rate is dominated by stable movements and regimes switching. Overall, the four series are not stationary.

Table 1: The long memory tests, the stationary test and long memory estimates

Currencies	HM/RS	Lo/RS	KPSS	SP	GPH	LWE
USD/CNY	22.97	16.25	62.97	-3.77	1.00048	0.94137
USD/INR	25.32	17.91	98.38	-6.09	1.00070	0.94136
USD/NGN	18.34	13.04	64.11	-38.87	0.80550	1.00287
USD/MYR	20.21	14.29	38.58	-5.85	1.00009	0.93600

Hurst-Mandelbrot Rescaled Range =HM/RS, Lo Rescaled Range= Lo/RS, Geweke Porter-Hudak=GPH, Local Whittle Estimator= LWE, Kwiatkowski Phillips Schmidt and Shin=KPSS and Schmidt Phillips =SP.

The Table 1 displayed above contains the LM rescaled range tests, unit root tests, and long memory parameter estimates. Both the Hurst-Mandelbrot and Lo rescaled range tests statistic rejected the null hypothesis of no autocorrelation and long-term dependence respectively at 5% significance levels for all the four exchange rate series. In addition, the two unit root tests confirmed the nonstationary of the four series. However, the GPH and LWE estimates converges to unity and shows that the CNY, INR, MYR and NGN are respectively integrated of order one, I(1). Therefore, the ARIMA model is a candidate model to study the series. Another point is that GPH and LWE also indicated that NGN and CNY, INR, MYR respectively are of integrated order I(0<d<1) and therefore can be study using the ARFIMA model.

Table 2: ARIMA candidate models for CNY, INR, NGN and MYR

Currencies	ARIMA(p,1,q)	AIC	Norm. of Resi.	Portm. Test	ARCH-LM test
USD/CNY	ARIMA(1,1,2)	-17371.50	(0,1.0160)	89.36(0.0104)	488.05(0.0000)
USD/INR	ARIMA(2,1,0)	882.08	(0,1.0277)	92.72(0.0893)	635.57(0.0000)
USD/NGN	ARIMA(0,1,2)	22228.75	(0,7.7774)	1.84(0.9855)	124.16(0.0000)
USD/MYR	ARIMA(0,1,2)	-14722.68	(0,1.0243)	80.93(0.0000)	329.36(0.0000)

Table 3: ARFIMA candidate models for CNY, INR, NGN and MYR

Currencies	ARFIMA(p, fd, q)	AIC	Norm. of Resi.	Portm. Test	ARCH-LM test
USD/CNY	ARFIMA(2, 0.941, 0)	-3904.05	(0.0036,0.2254)	80.96(0.0000)	122.72(0.0000)
USD/INR	ARFIMA(1, 0.941, 1)	7795.11	(0.0149,0.1609)	77.99(0.0000)	131.06(0.0000)
USD/NGN	ARFIMA(0, 0.806, 2)	22641.31	(0.0002,1.2881)	10.11(0.2574)	167.08(0.0000)
USD/MYR	ARFIMA(1, 0.936, 2)	-8287.27	(0.0000,0.0917)	64.59(0.0000)	222.43(0.0000)

fd=fractional difference.

The ARIMA and ARFIMA candidate's models for the four currency exchange rate together with the accuracy measure and various residual tests are displayed in the Table 2 and Table 3 respectively. Seven different models were identified for all the four series and the best model was selected based on the minimum AIC and residual analysis. A comparison between the results of ARIMA and ARFIMA modeling shows that ARIMAis the best model to study CNY, INR and MYR series because they all possesses minimum AIC, white noise residuals and less serial correlation while ARFIMA approach is the suitable to model the NGN exchange rate.

4. Conclusion

The study examined the CNY, INR, NGN and MYR to the U.S Dollar daily exchange rate. The inconsistency results obtained from long memory tests and parameter estimates guided the use of two modeling approaches, the ARIMA and ARFIMA models. After models identified and estimation, the best model was selected based on the minimum AIC and residual analysis tests results. The ARIMA model is the best to study CNY, INR and MYR to the U.S Dollar daily exchange rate due to minimum AIC, white noise and less serial correlation in the residuals while ARFIMA method is the suitable to model the NGN exchange rate. One of the assumptions of conditional mean models is the homoscedastic residuals and the two models, ARIMA and ARFIMA considered here violate such assumption. The ARCH-LM test results displayed in the Table 3 and 4 for the identified and estimated models show the presence of heteroscedasticity in the model's residuals. Therefore, further research can be conducted out using LM conditional volatility models to account for the effects of some stylized facts.

References

[1]. Mandelbrot, B. B. (1972): Statistical methodology for non periodic cycles: From the covariance to R/S analysis. *Annals of Economic and Social Measurement*, 1**:** 259-290.

[2]. Lo, A.W. (1991): Long term memory in Stock market prices, *Econometrica*, 59: 1279-1313.

[3]. Box, G. E. P., Jenkins, G. M. and Reinsel, G. C. (2008): Time Series Analysis: Forecasting and Control. 4th ed. Hoboken, NJ: Wiley.

[4]. Robinson, P. M.(1995): Gaussian Semiparametric Estimation of Long Range Dependence. *The Annals of Statistics*,23**:** 1630-1661.

[5]. Hurst, H. E. (1951): Long-term storage capacity of reserviors. *Transactions of the American Society of Civil Engineers* 116**:** 770-799.

[6]. Baillie, R. T.(1996): Long memory processes and fractional integration in econometrics. Journal of Econometrics 73**:** 5-59.

[7]. Beran, J. (1994): Statistics for Long-Memory Processes. Baca Raton: Chapman and Hall/CRC

[8]. Sanusi, A. J., Musa, Y., Umar, A. Z., & Ahmed, S. S. (2015): ARFIMA Modelling and Investigation of Structural Breaks in West Texas Intermediate and Brent Series. *CBN Journal of Applied Statistics*, *6*(2), 59-79.

[9]. Nezhad, M. Z., Raoofi, A. and Akbarzdeh, M. H. (2016): The Existence of Long Memory Property in OPEC Oil Prices. *Asian Journal of Economic Modelling*, *4*(3), 142–152.

[10]. Huang, Z., Liu, H., and Wang, T. (2016): Modeling long memory volatility using realized measures of volatility: A realized HAR GARCH model. *Economic Modelling*, *52*, *Part B*, 812–821.

[11]. Hassler, U., Rodrigues, P. M. M. and Rubia, A. (2014): Persistence in the banking industry: Fractional integration and breaks in memory. *Journal of Empirical Finance* 29**:** 95-112.

[12]. Jibrin, S. A., Yakubu, M., Olanrewaju, I. S., Maimuna, A. A., Samaila M. and Kabir, L. (2017): The Impact of Floating Exchange Rate Market to Nigeria Naira: Time-series Intervention Analysis. *Journal of Scientific and Engineering Research.* 4(4): 152-156.

[13]. Phillips, P. C. B., and Shimotsu, K. (2004): Local Whittle Estimation In Nonstationary And Unit Root Cases. *The Annals of Statistics*, 32**:** 656–692.

[14]. Geweke, J. and Porter-Hudak, S. (1983): The Estimation and Application of Long Memory Time Series Models. *Journal of Time Series Analysis* 4**:** 221-238.

[15]. Kunsch, H. R.(1987): Statistical aspects of self-similar processes. 67-74 in *Proceeding of the First Word Congress of the Bernoulli Society*. VNU Sciences Press, Tashkent.

[16]. Kim, C. S. and Phillips, P. C. B. (1999): Log periodogram regression: The nonstationary case. Mimeographed, Cowles Foundation, Yale Univ.

[17]. Velasco, C. (1999): Non-stationary log-periodogram regression. *Journal of Econometrics*, 91: 325-371.

[18]. Norbert, W., Paley, R. and Zygmund, A. (1940): Notes on random functions. MathematischeZeitschrift 37**:** 647-668.

[19]. Box, G. E. P. and Jenkins, G. M. (1976): *Time Series Analysis, Forecasting and Control*. *Holden-Day*, San Francisco. Holden-Day, California, USA.

[20]. Hosking, J. R. M.(1981): Fractional differencing. *Biometrika* 68**:** 165-176.

[21]. Granger, C. W. J. and Joyeux, R. (1980): An introduction to long memory time series models and fractional differencing, . *Journal of Time Series Analysis* 1**:** 15-39.

[22]. Kwiatkowski, D., Phillips, P. C.B., Schmidt, P. and Shin, Y. (1992): Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root, *Journal of Econometrics*, 54: 159-178.

[23]. Schmidt, P. and Phillips, P. C. B. (1992): LM Tests for a Unit Root in the Presence of Deterministic Trends, *Oxford Bulletin of Economics and Statistics,* 54, 257-287.