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Efficiency in BRICS Currency Markets Using Long-Spans of Data: Evidence from Model-Free Tests of Directional Predictability*

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Abstract: We analyze the directional predictability in foreign exchange markets of Brazil, Russia, India, China and South Africa (BRICS) using the quantilogram, based on long-spans of monthly historical data, at times covering over a century. We find that the efficient market hypothesis (EMH) holds at the extreme phases of the currency markets (and around the median for India and South Africa). Since predictability holds at certain parts of the unconditional distribution of exchange rate returns, we find support for the Adaptive Market Hypothesis (AMH). AMH, based on the idea of bounded rationality, suggests that currency return predictability will be intermittent, due to changing market conditions and institutional factors.

Keywords: *Correlogram, dependence, quantiles, efficiency, currency markets, BRICS.*

1. Introduction

The efficient market hypothesis (EMH) states that asset prices fully and instantaneously reflect all available and relevant information (as discussed in Plakandaras et al., (forthcoming), based on the seminal works of Samuelson, (1965) and Fama (1965)), hence, returns cannot be predicted. As a result, prices in an efficient market follow a random walk. Under the weak-form efficiency where the information set consists of past returns, future returns are purely unpredictable based on past price information. Hence, return predictability can be related to the weak-form of market efficiency. In this regard, the associated literature that tests the EMH in financial markets is huge (see, Aye et al., (2017a, b), Charfeddine et al., (2018), and Tiwari et al., (forthcoming) for detailed literature reviews in this regard). The foreign exchange rate market in the most popular and capitalized market with an average daily turnover in 2016 of 5.1 trillion U.S. dollars, as reported in the Triennial Survey of the Bank of International Settlements.

In light of the importance of currency markets, efficiency of the same has been examined extensively, since the seminal work of Meese and Rogoff, (1983), with the widespread acceptance that it is difficult to beat the random walk model in predicting the conditional mean dynamics of foreign exchange rate changes (see for example, Chung and Hong, (2007), Charles et al., (2012), Plakandaras et al., (2013, 2015a, b), Balcilar et al., (2016), Papadimitriou et al., (2016), Almail and Almudhaf (2017), and Christou et al., (forthcoming) for detailed reviews of this literature). However, the majority of these studies are based on the tests of some forecast models or forecast rules, i.e., these works examine the efficiency of models rather than data, and as a result, the conclusions are dependent on the model used. In this regard, Taylor (1995), and more recently Plakandaras et al. (forthcoming), points out that model-driven tests of foreign exchange market efficiency are likely to be elusive in the presence of risk premium and expectation errors. Understandably, it is desirable to evaluate the efficiency of currency markets using an econometric procedure that is independent of a model.

The objective of this paper, is to analyze the directional predictability in foreign exchange markets of Brazil, Russia, India, China and South Africa (i.e., the BRICS) using the correlogram of quantile hits (i.e., quantilogram) as proposed by Linton and Whang (2007), which in turn, is a model-free econometric procedure involving a simple diagnostic statistic based on a sample correlation. Our analysis uses the longest possible available monthly data set covering the periods of 1812M01-2018M05, 1814M01-2018M05, 1822M07-2018M05, 1948M08-2018M05, and 1844M01-2018M05, respectively for the dollar-based exchange rates of the BRICS countries. For the sake of comparison, we also look at the behavior of the British pound over 1791M01 to 2018M05, i.e., a developed market currency. Note that, while other tests of model-

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free directional predictability are available, we prefer the Linton and Whang, (2007) approach due to its advantages from a conceptual perspective, since using the quantile in connection with counts is preferable. From a different stance, using a fixed threshold (as in Hong and Chung (2006)) raise concerns over the proper determination of the threshold, is time-dependent and asymptotically correct. At this stage two questions arise: First, why look at the BRICS countries? In this regard, note that the decision to look at these five emerging market currencies is motivated by the emergence of the BRICS as a powerful economic force. In 2010, about 25 percent of global output emanated from the BRICS (Government of India, 2012). Also, the contribution to global output from this bloc is expected to surpass that of the G7 countries by 2050 (Wilson & Purushothaman, 2003; Cakan & Gupta, 2017; Plakandaras et al., forthcoming). In addition, trade by these economies with the rest of the world has been growing at a fast rate, with the strong economic performance of these countries linked to the high level of foreign direct investment in the private sector (Ruzima & Boachie, 2017). Naturally, unpredictable exchange rate movements are likely to affect the growth potential of these economies, and with them that of the world economy.

Hence, an investigation of predictability of exchange rates of the BRICS countries is highly warranted, which in turn, we aim to achieve, by looking at the longest possible spans of data available on the exchange rates of these economies to try and capture the entire historical evolution of the exchange rate dynamics. The second question deals with why we look at directional predictability instead of the conditional mean of the foreign exchange rate changes? The reasons behind this, as outlined in Chung and Hong (2007), and also in Plakandaras et al. (2013, 2015a, b), are: (a) From the perspective of a statistician, it is relatively easier to predict the direction of changes than the predictions of the conditional mean, as directional predictability depends on all conditional moments; (b) From an economist's point of view, the directional predictability of foreign exchange rate returns is more relevant as it is better able to capture a utility-based measure of predictability performance (such as economic profits). In addition, note that market timing (a form of active asset allocation management) is essentially the prediction of turning points in currency markets; (c) Direction of changes provide important insights to market practitioners and policymakers, Since technical trading rules widely used by foreign exchange dealers are heavily based on predictions of direction of changes, and central banks.

Under pegged exchange rate systems often intervene in the foreign exchange market when the domestic currency is expected either to appreciate or depreciate beyond a certain threshold; (d) Given the theory of the uncovered interest rate parity, the direction of changes can be an alternative instrument for the link between foreign exchange rates and interest rates, and; (e) Predicting the direction of large currency changes are likely to have information about possible future currency crises and also the likelihood of market contagion. The above five reasons thus make it more important to analyze directional predictability than just changes in the conditional mean of the dollar-based exchange rates of the BRICS. Two related studies dealing with efficiency in the BRICS dollar-based exchange rates are that of Kumar and Kamaiah, (2016) and Bhattacharya et al. (2018). While the former rejected the weak-form of efficient market hypothesis for nominal effective exchange rates of all the five countries, the latter indicated that dollar-based exchange rates of these economies all follow random-walk processes. Interestingly, Kumar and Kamaiah, (2016) found an underlying chaotic structure for all the five markets, but Bhattacharya et al. (2018) showed that the same holds true for Brazil, Russia, India, and China, but not South Africa. Combining the results on efficiency and chaotic dynamics, one can, in general, conclude that exchange rate returns are unpredictable in the BRICS using conditional mean-based model-dependent approaches adopted by these authors.

However, given the mixed evidence of weak-form of market efficiency, the scope of this paper is to answer whether BRICS exchange rates can be predicted, using the longest spans of data available, and hence, minimizing the likelihood of sample-specific results. Given that the model-free approach of quantilogram used in this paper is based on unconditional quantiles capturing the various phases of the currency market, the correlogram of quantile hits is inherently a time-varying approach detailing the market-situation under which directional predictability hold or does not hold. This in turn implies that the ability of the central banker aiming to stabilize currency market fluctuations could be limited to only certain parts of the unconditional distribution of exchange rate returns for which predictability holds, and might not always lead to the results the policymakers are striving for via the control of the exchange rate market, especially when exchange rates follow random-walk. To the best of our knowledge, this is the first paper to analyze model-free predictability in the BRICS (and the UK) dollar-based exchange rates using data, that in some cases spans more than two centuries. The remainder of the paper is organized as follows: Section 2 introduces the econometric methodology, while Section 3 presents the data and results, with Section 4 concluding the paper.

2. Methodology

Suppose that $y_1, y_2, \dots$ are random variables from a process without unit-roots with marginal distribution μ_α for $0 < \alpha < 1$ in quantiles. We test the null hypothesis that some conditional quantiles are time invariant, which can be written more formally as:
For some α:
$E[\psi_\alpha(y_t - \mu_\alpha)|\mathcal{F}_{t-1}] = 0\ a.s., where\ \psi_\alpha(x) = 1(x < 0) - \alpha$ (1),
denote the check function, while $\mathcal{F}_{t-1} = \sigma(y_{t-1}, y_{t-2}, \dots)$. Under this null hypothesis, if we exceed the unconditional α-quantile today, there is small la ikelihood that we will exceed this threshold α in the ext observation. This hypothesis can be further extended from a particular quantile to a set of quantiles and to the entire sample.

If we compare (1) with the usual weak form EMH that for some μ,
$E[y_t - \mu|\mathcal{F}_{t-1}] = 0$ (2),
We could infer that the median of the population is time-varying and the mean is invariant and vice versa. Under symmetry, there is a one to one relationship between (2) and (1), with $\alpha = 1/2$. Linton and Whang, (2007) suggest a formal procedure to examine the null hypothesis (1) by first estimating $\mu_\alpha$using quantile estimator $\hat{\mu}_\alpha$which is defined by:

$$\hat{\mu}_\alpha = arg \min_{\mu \in \mathbb{R}} \sum_{t=1}^{T} \rho_\alpha(y_t - \mu), where\ \rho_\alpha(x) = x[\alpha - 1(x < 0)]$$

Then letting:

$$\hat{\rho}_{\alpha k} = \frac{\frac{1}{T-k}\sum_{t=1}^{T-k} \psi_\alpha(y_t - \hat{\mu}_\alpha)\psi_\alpha(y_{t+k} - \hat{\mu}_\alpha)}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} \psi_\alpha^2(y_t - \hat{\mu}_\alpha)}\sqrt{\frac{1}{T-k}\sum_{t=1}^{T-k} \psi_\alpha^2(y_{t+k} - \hat{\mu}_\alpha)}}, k = 1,2, \dots,$$

for any $\alpha \in [0,1]$. Note that $-1 \leq \hat{\rho}_{\alpha k} \leq 1$ for any α, and$k$, given that this refers to the sample correlation on $\psi_\alpha(y_t - \hat{\mu}_\alpha)$. Under the null hypothesis (1) the population quantity is:
$E[\psi_\alpha(y_t - \mu_\alpha)\psi_\alpha(y_{t+k} - \mu_\alpha)] = E[\psi_\alpha(y_t - \mu_\alpha)E[\psi_\alpha(y_{t+k} - \mu_\alpha)|\mathcal{F}_{t+k-1}] = 0$ for all k. Thus, $\hat{\rho}_{\alpha k}$ should approximate zero.

3. Data and Empirical Results

We compile nominal exchange rates for the BRICS and the UK expressed as local currency to U.S. dollar obtained from the Global Financial Database, and work with log-returns in percentage, i.e., the first difference of the natural logarithm of the exchange rates times 100, as required by the model-free quantilogram-approach of predictability. The effective sample of monthly data thus covered for the BRICS and the UK is: 1812M02-2018M05, 1814M02-2018M05, 1822M08-2018M05, 1948M09-2018M05, and 1844M02-2018M05, and 1791M02- 2018M05 respectively, with us losing the first observation due to the computation of log-returns. The start- and end-points of our analysis are driven by data availability at the time of writing this paper. Recall the objective was to cover the longest possible samples of data, so that our test does not suffer from sample selection bias like other studies, since we are able to capture the complete evolution of the BRICS' dollar-based exchange rate across history. The descriptive statistics are reported in Table A1 of the Appendix, while, Figure A1 in the Appendix plots the data used. As can be seen from the Jarque-Bera test of normality in Table A1, the null is overwhelmingly rejected in all cases.

Due to positive skewness and excess kurtosis and in the process suggests heavy-tails in all the exchange rate returns. In Figures 1(a), 2(a), 3(a), 4(a), 5(a) and 6(a), we present the quantilogram for quantiles in the range 0.01 – 0.99 (specifically, α = 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, and 0.99) and out to 100 lags for the BRICS and the UK respectively. We also show the 95% confidence intervals (centred at 0) based on the lower and upper bound. There is evidence of predictability, but it depends on the quantiles we are looking at and the confidence interval (conservative or liberal) we use. The portmanteau tests reported in Figures 1(b), 2(b), 3(b), 4(b), 5(b) and 6(b), for the BRICS and the UK respectively, gives a clearer picture of the evidence of predictability. For Brazil and Russia, there is no evidence of predictability at α = 0.01, 0.05, and 0.99. When we look at China, besides α = 0.01, 0.05, 0.95 and 0.99, predictability holds for the remaining quantiles. In case of India, predictability is generally weak and just restricted to α = 0.25 and 0.75. For South Africa, predictability is restricted at α = 0.10, 0.25, 0.75, and 0.90 primarily, and around 40 lags quite strongly for α = 0.05, and weakly for α = 0.50.

Finally, for the UK, predictability is very pronounced at all the quantiles except for the most extreme ones (i.e., α = 0.01 and 0.99).[1] In other words, barring the extreme phases (appreciation and depreciation) of the currency market, and around the median for India and South Africa, we do find evidence of directional predictability, i.e., the EMH is rejected except for these quantiles.[2] In this regard, there is also comparability with the currency of a developed market, i.e., the UK pound relative to the dollar. Lack of predictability at the extremes is possibly due to herding by the agents participating in the market, whereby information from lags of returns does not necessarily matter (Balcilar et al., 2016). The fact that predictability holds at certain parts of the unconditional distribution of exchange rate returns, capturing stages of the currency markets, our results tend to support the so-called adaptive market hypothesis (AMH) of Lo (2004, 2005). Note that the AMH, based on the notion of bounded rationality, suggests that return predictability may arise from time to time, due to changing market conditions and institutional factors.[3]

[INSERT FIGURES 1 THROUGH 6]

4. Conclusion

In this paper, we analyze the directional predictability in foreign exchange markets of Brazil, Russia, India, China and South Africa (i.e., the BRICS) using the quantilogram, which in turn, is a model-free econometric procedure involving a simple diagnostic statistic based on a sample correlation. Our analysis uses the longest possible available monthly data set covering the periods of 1812M01-2018M05, 1814M01-2018M05, 1822M07-2018M05, 1948M08-2018M05, and 1844M01-2018M05, respectively for the dollar-based exchange rates of the BRICS countries. For the sake of comparison, we also look at the behavior of the British pound over 1791M01 to 2018M05, i.e., a developed market currency. We find that barring the extreme phases of the currency markets, and around the median for India and South Africa, we do observe directional predictability, i.e., the EMH is only accepted in these quantiles. In this regard, there is also a similarity with the results obtained for the UK pound. The fact that predictability holds at certain parts of the unconditional distribution of exchange rate returns, capturing stages of the currency market, tend to support the AMH, which suggests that return predictability may arise time to time.

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[1] Given that the results could be susceptible to data-frequency (Linton and Whang, 2007), we use daily data on the pound-dollar exchange rate, which is available (from the Global Financial Database) for a long-span of 3rd January, 1900 to 31st, May 2018, and repeated our analysis. The results for the quantilogram and the portmanteau test are reported in Figures A2(a) and A2(b) respectively. As can be seen, when compared to Figures 6(a) and 6(b), our results continue to be qualitatively similar to the monthly data, except now that lack of predictability is also observed for α = 0.05 and 0.95.

[2] We also estimated the Hurst (1951) exponent (H) for long-range dependence using the detrended fluctuation analysis (DFA) as proposed by Peng et al. (1994). In all cases the, the value of H>0.50 (), highlighting the predictability of the exchange rate returns series, especially for Brazil (H =0.96), Russia (H =0.93), and China (H=0.97), and to some extent South Africa (H=0.60). For India (H=0.56) and the UK (H 0.51), the predictability was relatively weak. A rolling-window analysis however showed increased persistence in the post-Bretton Woods era. While, we cannot draw one-to-one correspondence with our directional predictability results based on the quantilogram, there is indeed some evidence of predictability also provided by the Hurst exponent. Complete details of these results are available upon request from the authors.

[3] The AMH hypothesis for the British pound in short and long-spans of data has also been confirmed by Charles et al. (2012) and Almail and Almudhaf, (2017) respectively.

Our results imply that, practitioners would need to devise state-specific trading strategies aiming to exploit temporary inefficiencies in the currency markets. Similarly, policy makers must realize that their possible attempts to control exchange rate fluctuations and reduce the vulnerability of the domestic economy, would also be contingent on market phases. Finally, given that exchange rate returns of the BRICS countries tend to be unpredictable at the extreme ends of their respective distributions, implies that the global economy, given the dominance of the BRICS bloc, is most vulnerable to exchange rate risks in the face of massive appreciations and depreciation of these currencies. Naturally, these episodes of possible bubbles in the currency market resulting in massive appreciation and depreciation, is what the policymakers in countries that have close trading links need to be aware of and design appropriate monetary and fiscal, as well as foreign trade policies, to ensure that their domestic economy does not get into a recession. As part of future research, given that in-sample predictability does not guarantee the same over an out-of-sample period (Christou et al., 2018), one can conduct a forecasting exercise to see if our results continue to hold.

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Figure 1(a): Values of $\hat{\rho}_{\alpha k}$Along With Liberal and Conservative 95% Confidence Intervals for the Returns on Brazilian Real Relative to the US Dollar

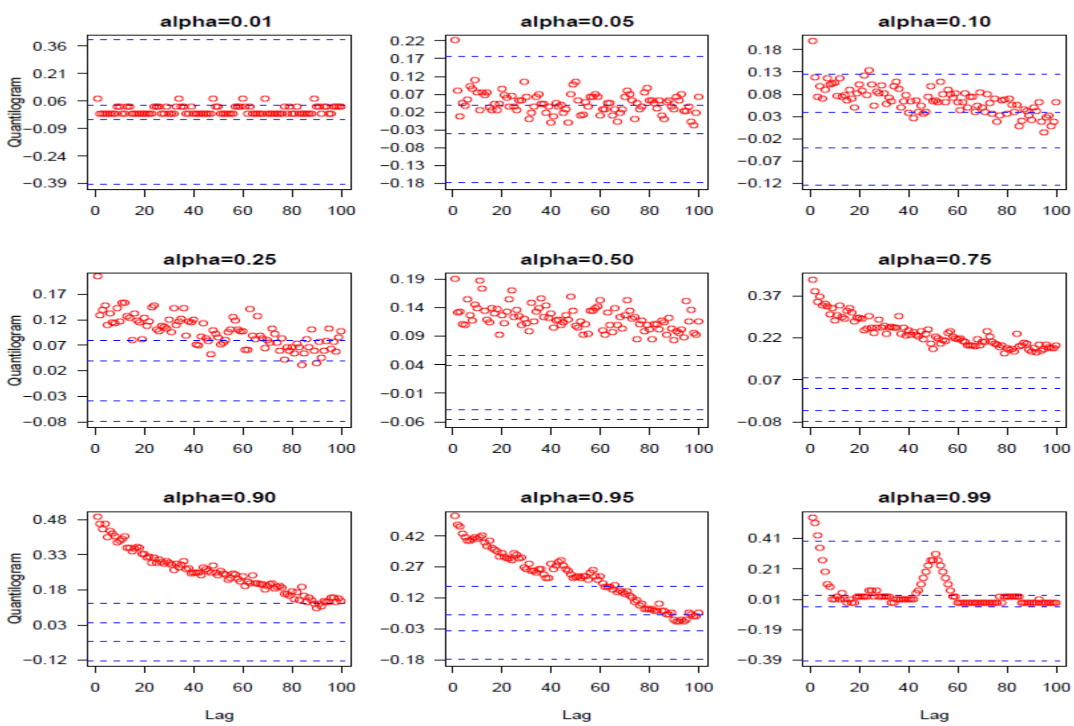


Figure 1(b): Portmanteau Test With 95% Critical Values for the Returns on Brazilian Real Relative to the Us Dollar

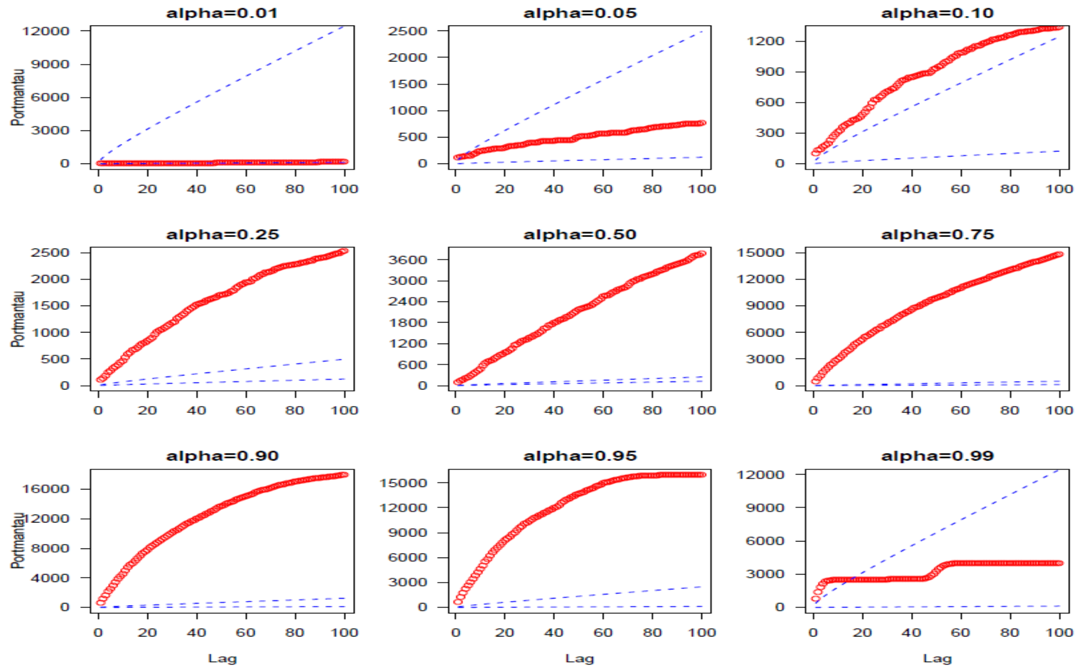


Figure 2(a): Values of $\hat{\rho}_{\alpha k}$ Along With Liberal and Conservative 95% Confidence Intervals for the Returns on Russia Real Relative to the US Dollar

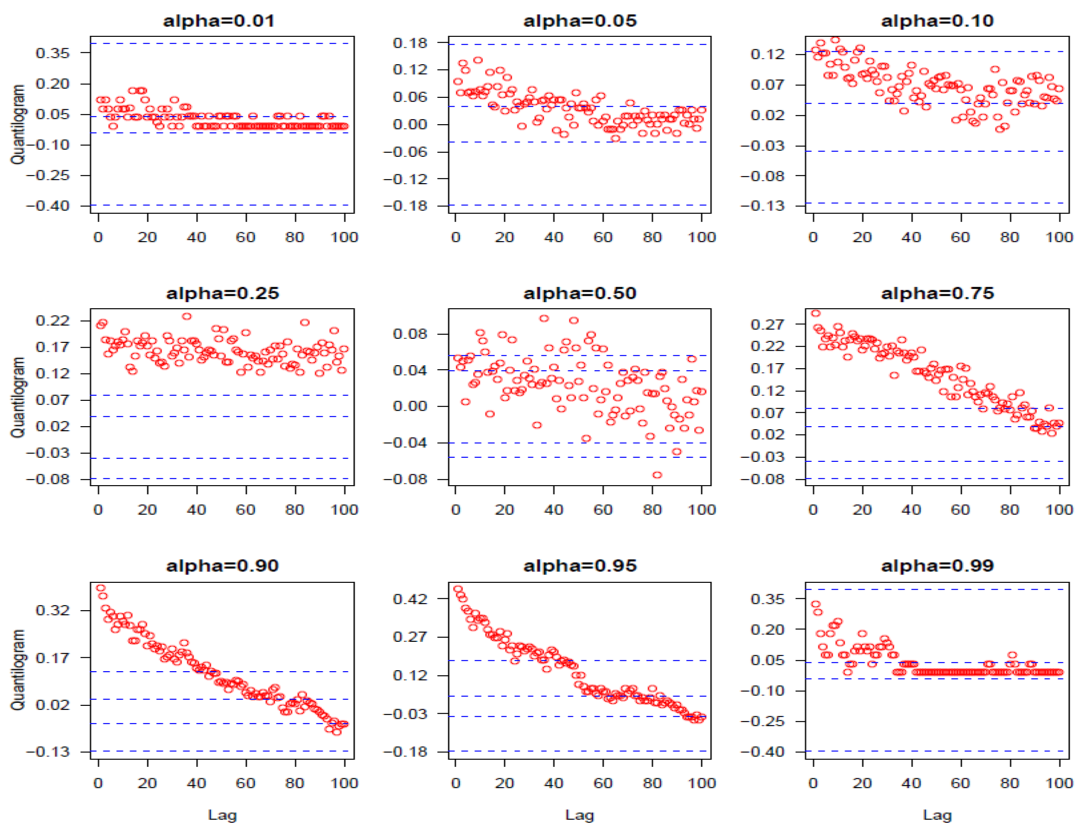


Figure 2(b): Portmanteau Test With 95% Critical Values for the Returns on Russian Ruble Relative to the Us Dollar

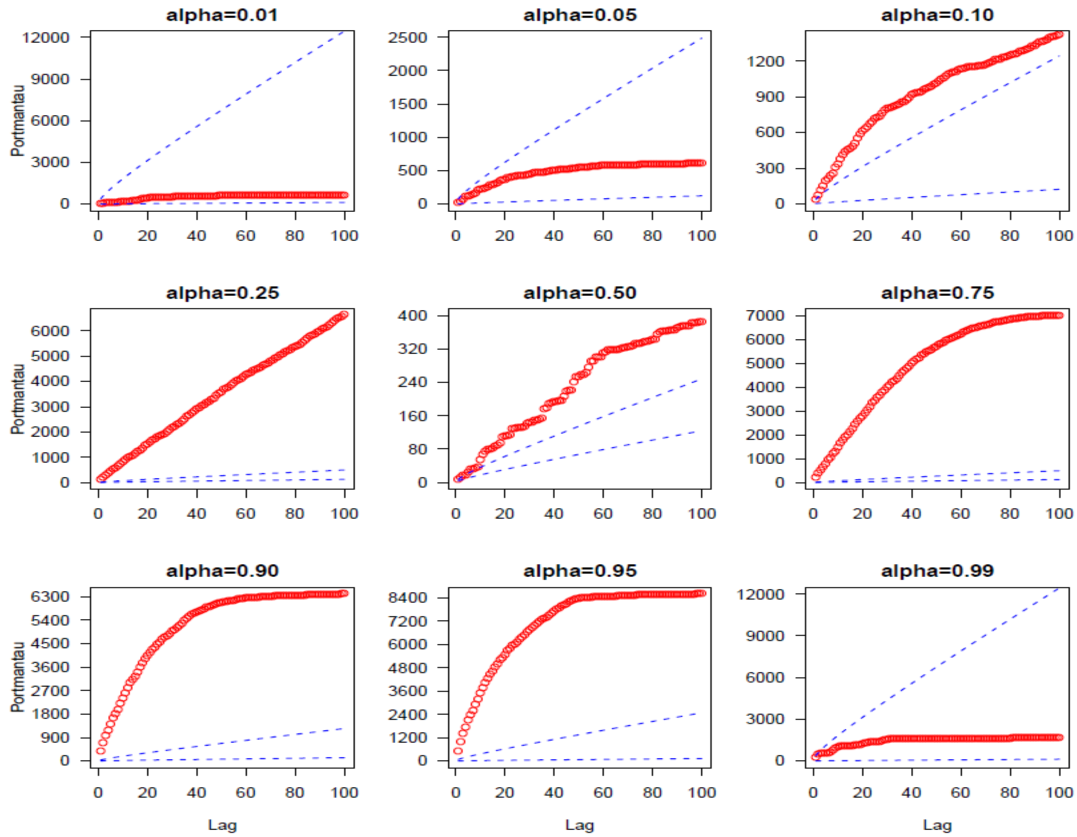


Figure 3(a): Values of $\widehat{\rho}_{\alpha k}$Along With Liberal and Conservative 95% Confidence Intervals for the Returns on Indian Rupee Real Relative to the US Dollar

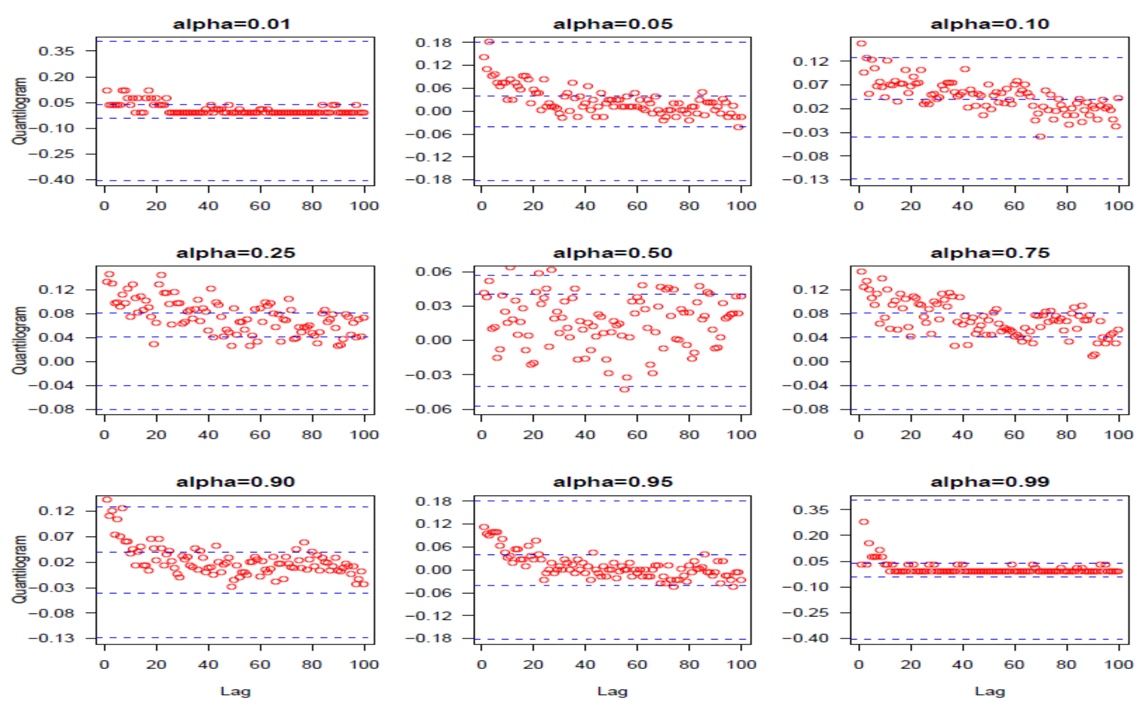


Figure 3(b): Portmanteau Test With 95% Critical Values for the Returns on Indian Rupee Relative to the Us Dollar

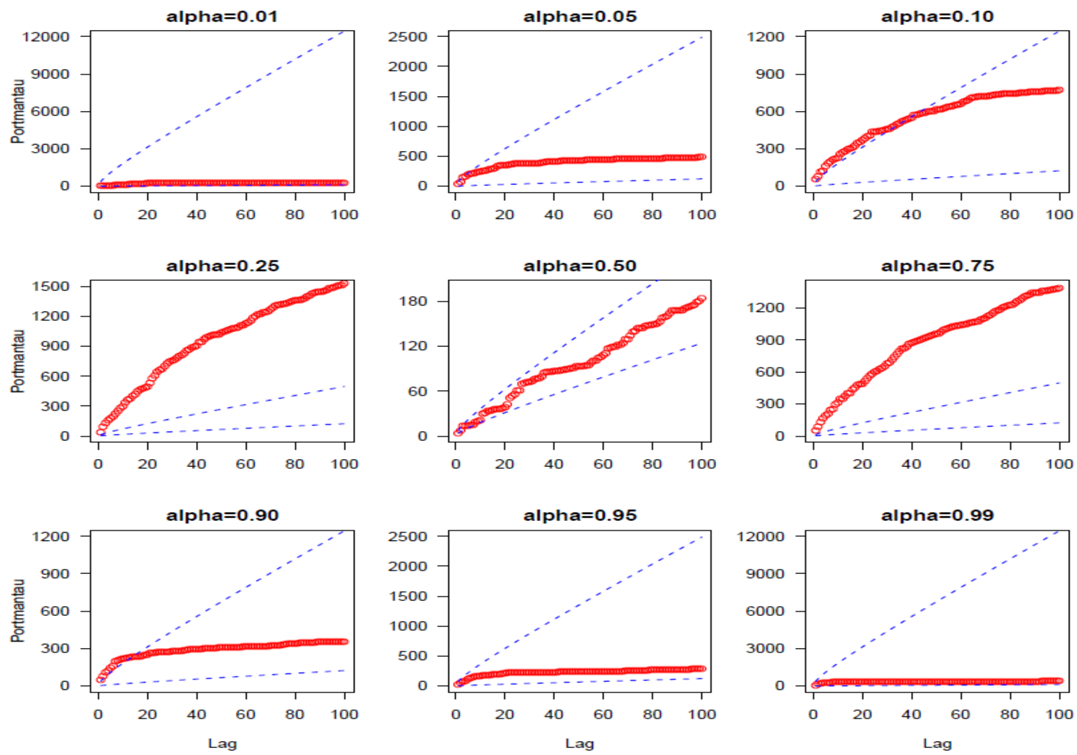


Figure 4(a): Values of $\hat{\rho}_{\alpha k}$Along With Liberal and Conservative 95% Confidence Intervals for the Returns on Chinese Yuan Relative to the US Dollar

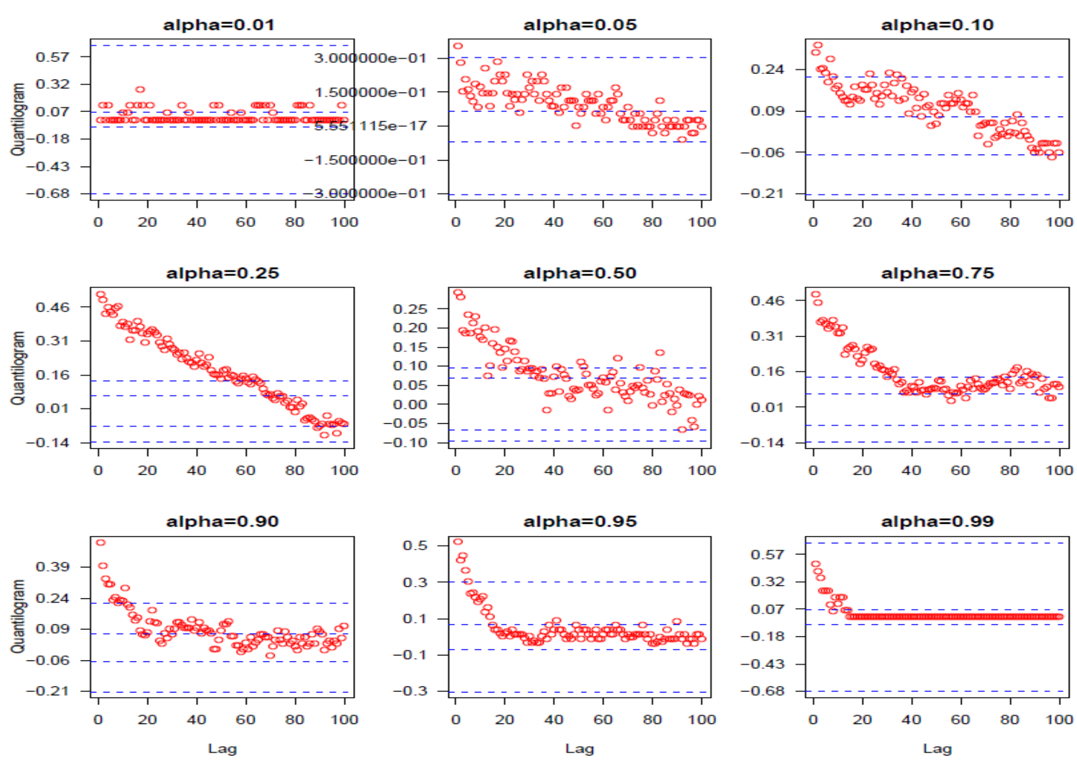


Figure 4(b): Portmanteau Test With 95% Critical Values for the Returns on Chinese Yuan Relative to the Us Dollar

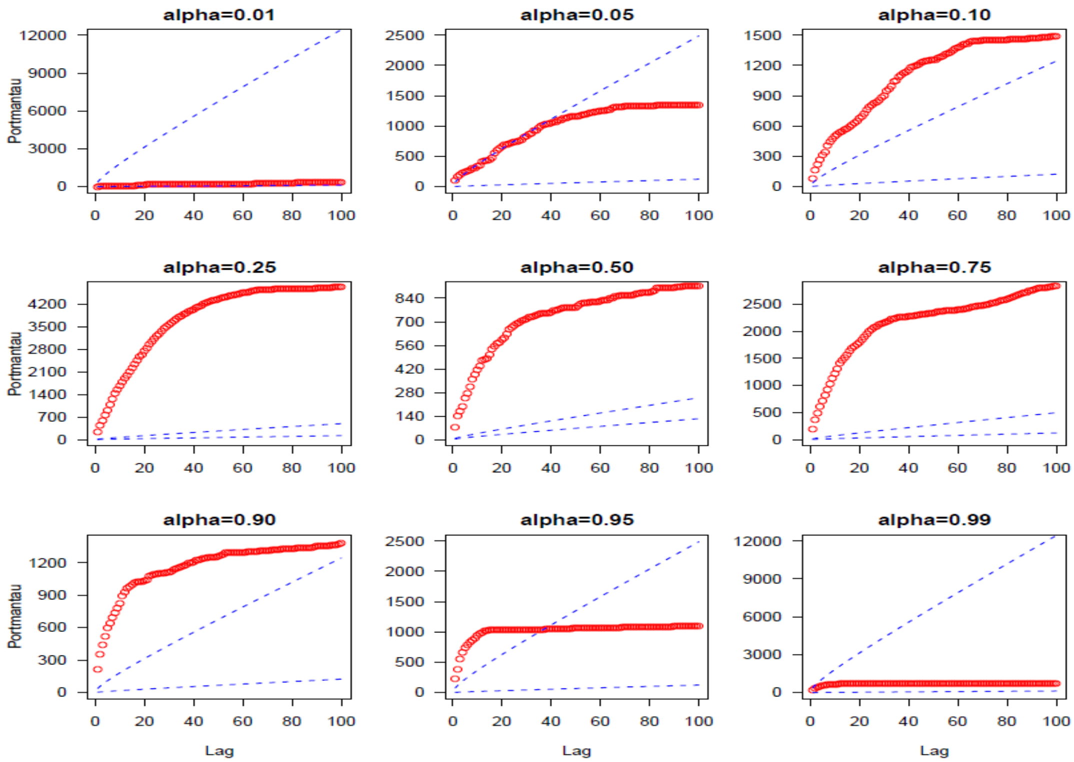


Figure 5(a): Values of $\hat{\rho}_{\alpha k}$ Along With Liberal and Conservative 95% Confidence Intervals for the Returns on South African Rand Relative to the US Dollar

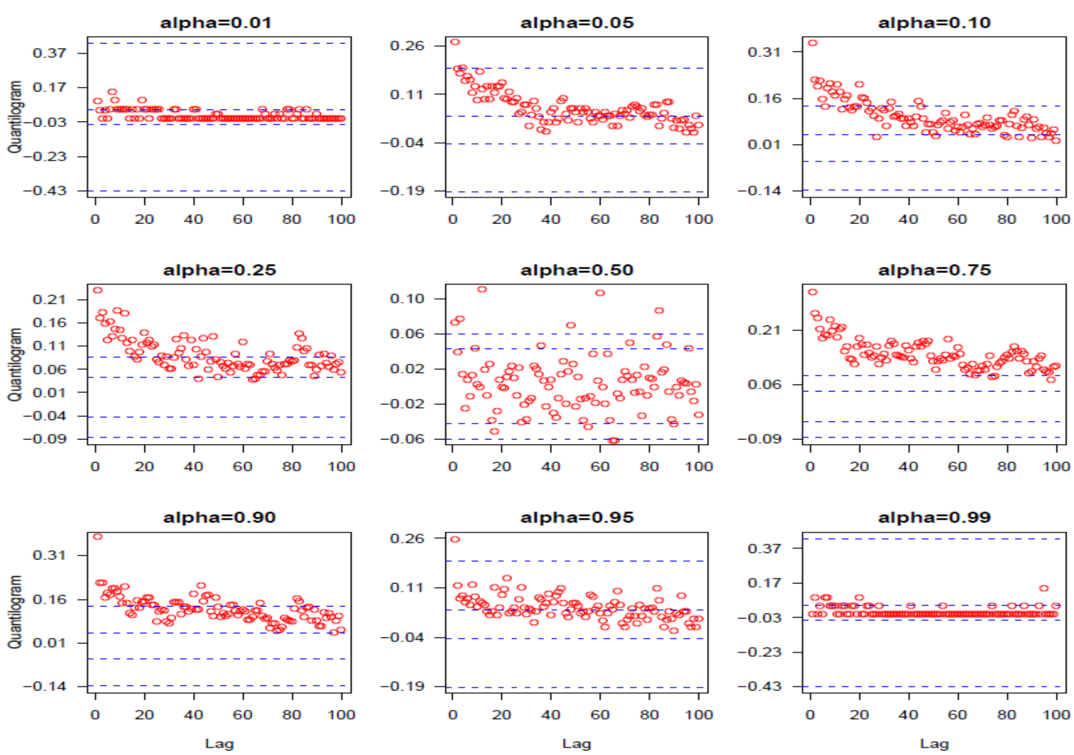


Figure 5(b): Portmanteau Test With 95% Critical Values for the Returns on South African Rand Relative to the Us Dollar

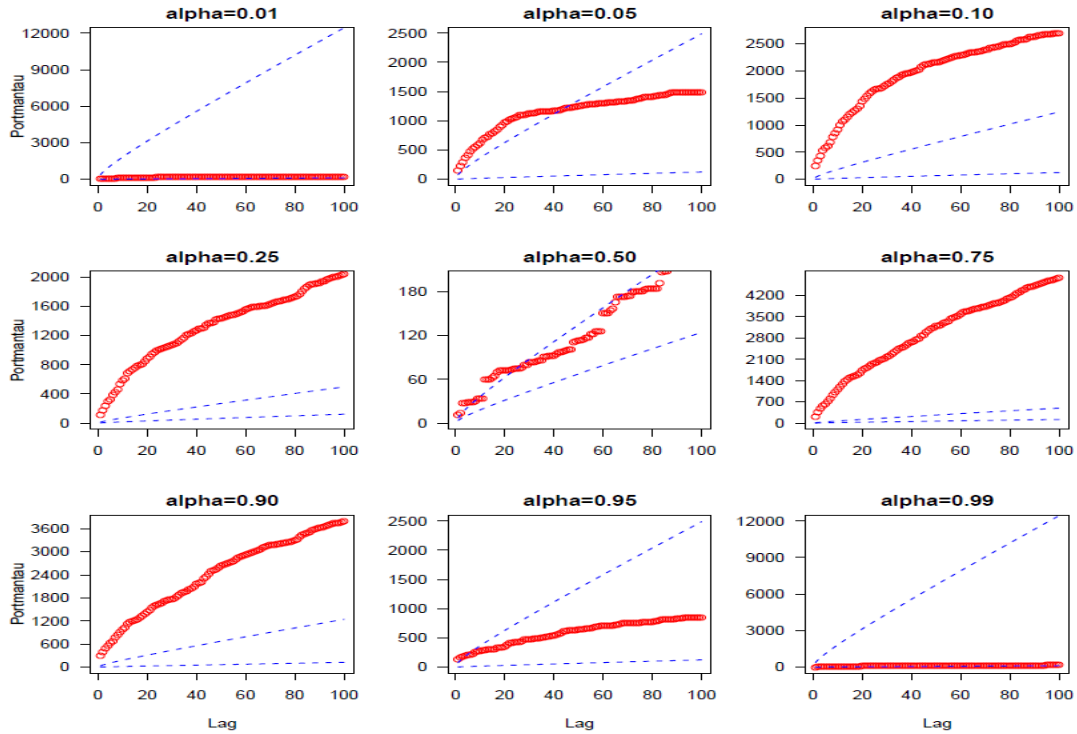


Figure 6(a): Values of $\hat{\rho}_{\alpha k}$Along With Liberal and Conservative 95% Confidence Intervals for the Returns on UK Pound Relative to the US Dollar

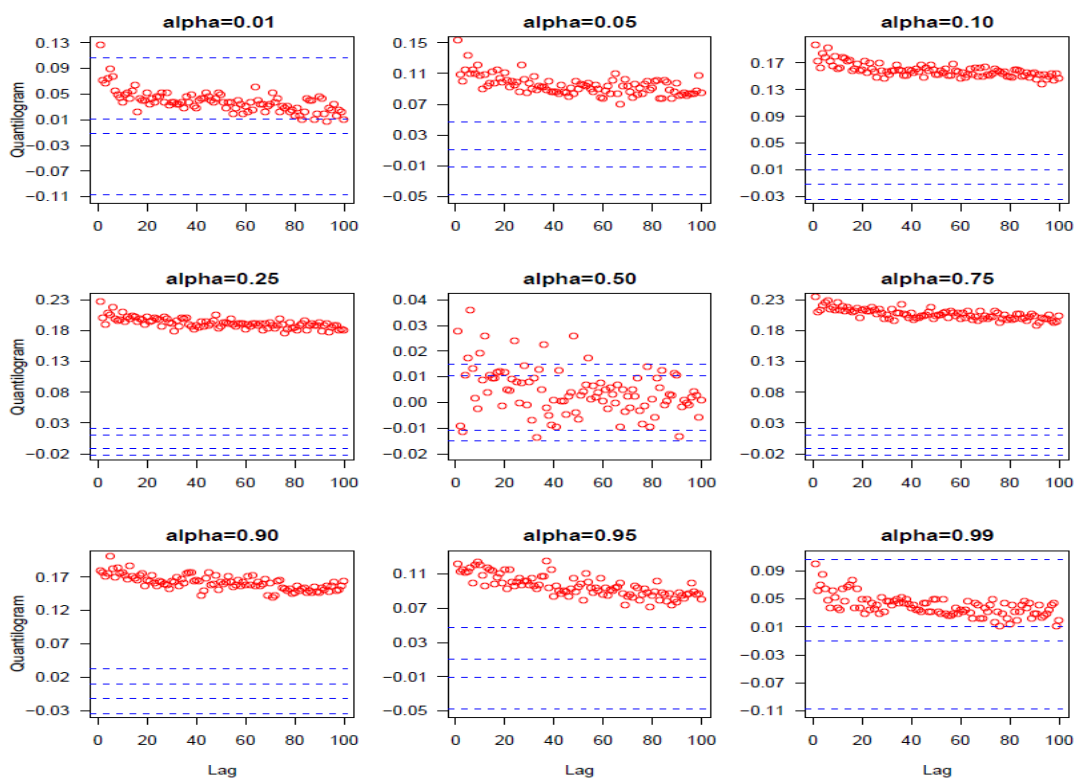
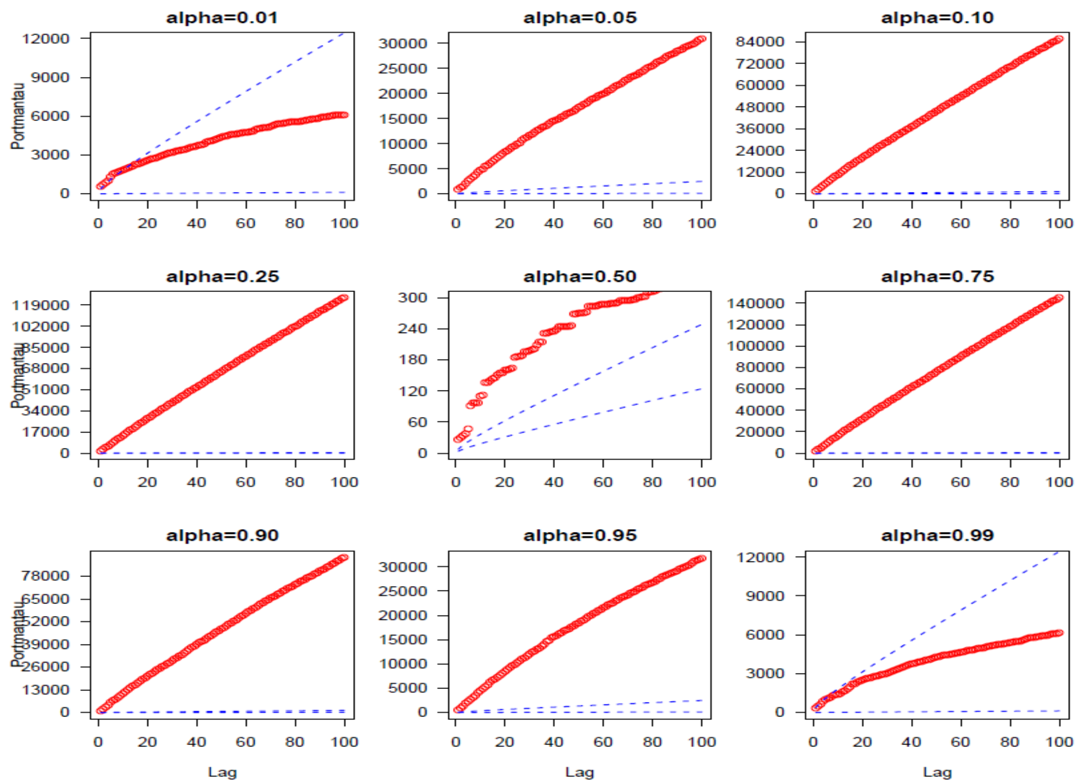


Figure 6(b): Portmanteau Test With 95% Critical Values for the Returns on UK Pound Relative to the Us Dollar



Appendix

Table A1: Summary Statistics

	Country					
Statistic	**BRAZIL**	**RUSSIA**	**INDIA**	**CHINA**	**SOUTH AFRICA**	**UK**
Mean	1.52	1.05	0.15	0.77	0.16	0.04
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	83.94	277.79	84.34	113.25	36.35	61.11
Minimum	-34.05	-127.69	-31.63	-10.34	-27.39	-60.43
Std. Dev.	6.45	11.28	3.14	6.49	2.71	2.58
Skewness	3.41	11.61	10.05	11.53	1.96	0.42
Kurtosis	25.92	258.39	255.54	162.67	42.16	234.57
Jarque-Bera	59019.26	6718544.00	6284248.00	907638.80	135022.30	6095249.00
p-value	0.00	0.00	0.00	0.00	0.00	0.00
N	2476	2452	2350	837	2092	2728

Note: Std. Dev. symbolizes the Standard Deviation; *p*-value corresponds to the null of normality based on the Jarque-Bera test; *N* is number of observations.

Figure A1: Data Plots

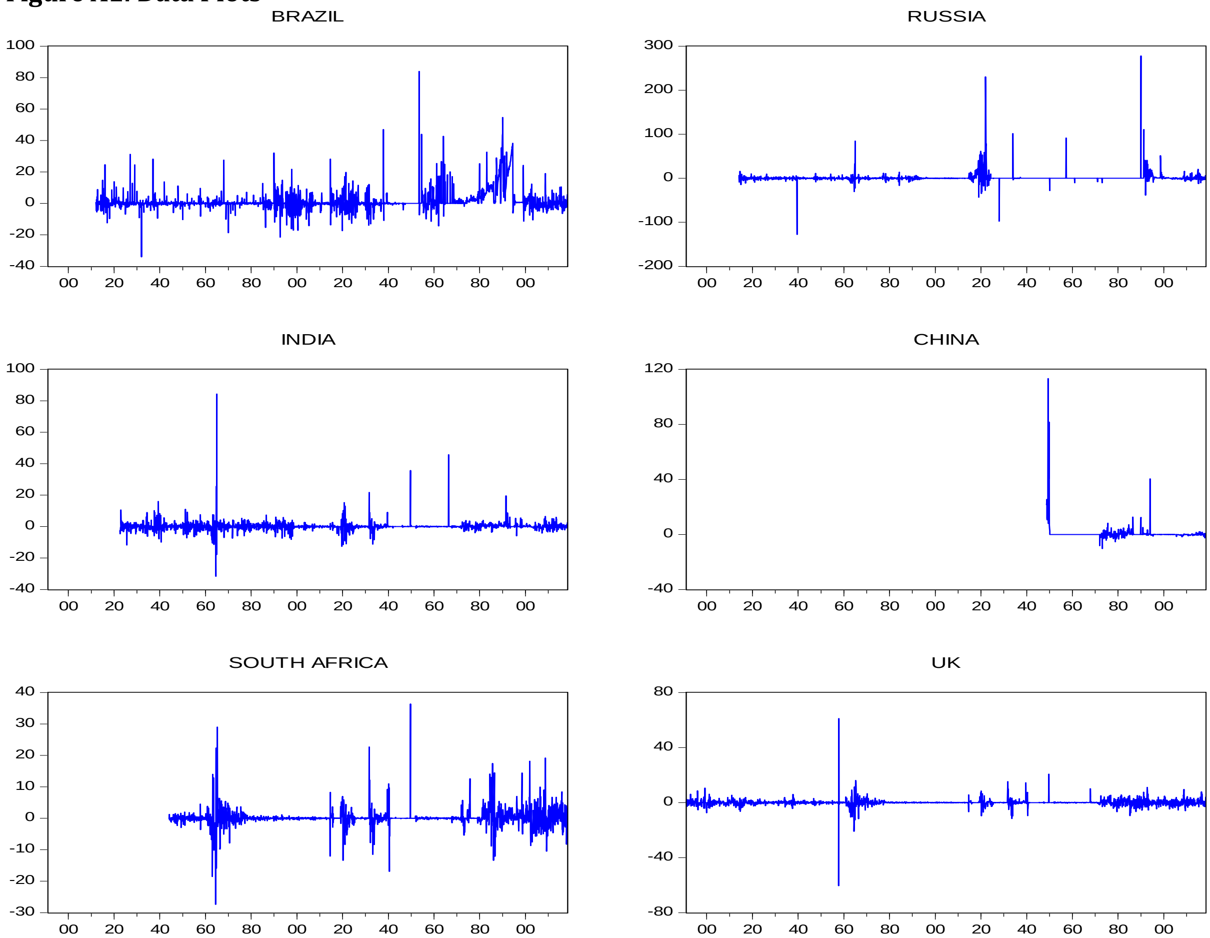


Figure A2(a): Values of $\hat{\rho}_{\alpha k}$ Along With Liberal and Conservative 95% Confidence Intervals for the Returns on UK Pound Relative to the US Dollar: Daily Frequency

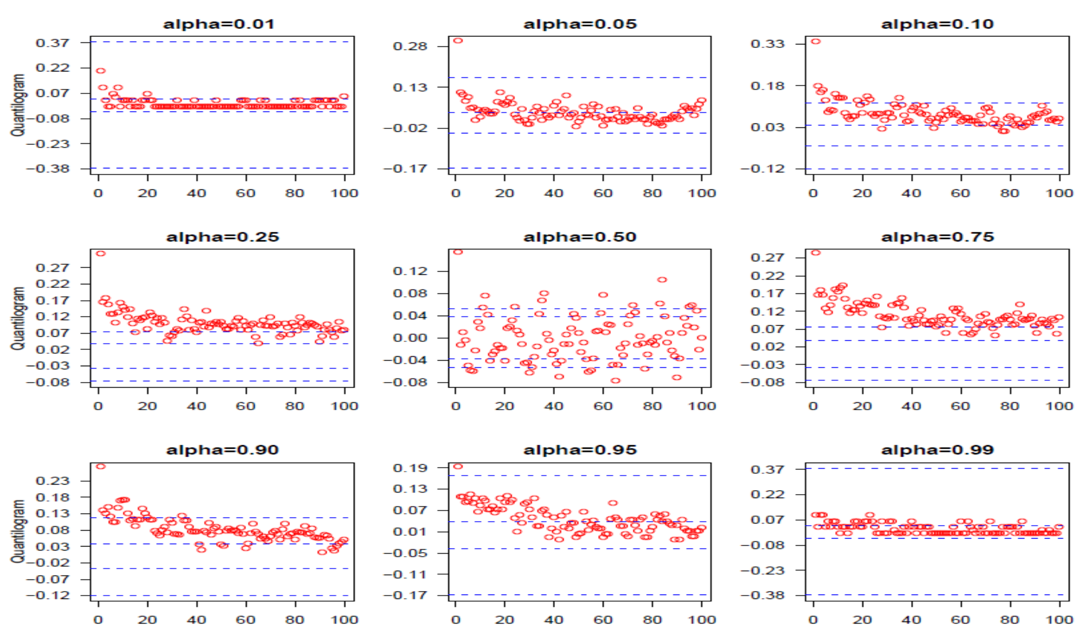


Figure A2(b): Portmanteau Test With 95% Critical Values for the Returns on UK Pound Relative to the Us Dollar: Daily Frequency