Time series forecast of Chinese Yuan through RMB reference currency basket

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Introduction

As RMB exchange rate dropped its peg to USD and reformed in 2005 to a managed floating exchange regime with the introduction of RMB reference currency basket, the composition of different currencies in the basket and their separate impact on RMB have been a hitting topic.

The history of RMB regime can be separated into two stages: 2005-2015 and 2015-present. During the first period, the RMB/USD bilateral rate became more flexible. In 2010, the People's Bank of China (PBoC) made a statement that the RMB exchange rate would transfer from a bilateral reference with USD to multilateral references, emphasizing the influencing power of other currencies on RMB, such as the Euro and the British Pound.

At the beginning of the second period, the PBoC for the first time announced the composition of the currency basket in Dec. 2015 (Appendix 1). Meanwhile, the PBoC also adopted a new mechanism to determine the RMB/USD which is based on the arithmetical average of the previous day's closing price and the current day's theoretical value of RMB/USD that can maintain the stability of the index of a given currency basket over the past 24 hours (Yu, 2018). This clarifies how the reference currency basket would participate in the RMB exchange rate changes.

At the end of 2016, the PBoC modified and published the composition of the currency basket again. The number of currencies in the basket was increased from 13 to 24, and 74% of China's total external trade was represented in the new currency basket, which was much higher than that in the old basket (HKEX, 2018). Looking at the new composition (Appendix 1), the weighting of USD fell from 26.4% to 22.4% and Korea Won was added to the basket.

Currency indices have important reference value for currency pricing; therefore, the composition of the currency basket are essential tools in determining the tradability and usability of RMB, especially considering China's trade relations with other countries and the liquidity of reference currencies in foreign markets. (HKEX, 2018). By analyzing the indices of currencies in the basket, we can infer the direction and degree of movement in the RMB exchange rate against other currencies, and further forecast the RMB exchange rate changes. This also adds value to the development of RMB risk-hedging or other related financial products.

To investigate the composition of the currency basket, numerous economists have conducted researches in this field. Frankel and Wei found a tight fit regression between RMB and the currency basket, and only USD (90%) and Malaysian ringgit (5%) received positive and statistically significant weights. The Euro and Yen, who are major non-dollar currencies presented zero weight in the basket (Frankel & Wei, 2007). Since new information was disclosed afterward, their conclusion should be extended to apply to current situations. Frankel released an individual paper in 2009 and revealed that by mid-2007, the RMB basket had switched a substantial part of the dollar's weight onto the Euro. This explained the appreciation of RMB against USD during that period, which was due to the appreciation of the Euro against USD. (Frankel, 2009). Cui provided a more recent analysis using data up 2012. His results illustrated that RMB did not perfectly peg to a basket of currencies during the period of January to November 2010. USD still had the most weighting in the basket and it showed a decreasing trend (Cui, 2012). McCauley and Shu studied how the determinants in the currency basket varied since the 2015 reform and the co-movements of RMB with regional and other emerging market currencies. They concluded that in the basket-management period, the co-movement with regional and Latin American currencies peaked and the RMB exchange rate was most predictable and multilateral. However, the co-movement effect declined in the countercyclical-management period between May and July 2017 (People's Bank of China and Bank for International Settlements, 2018).

Despite the thorough investigation into the composition of the currency basket, few pieces of research have been led to conduct forecast. Against the backdrop of the trade war between China and the US, we are as interested as in how the RMB exchange rate would fluctuate and how the currency basket would be adjusted in the near future. Would PBoC interfere in extreme circumstances, i.e. President Trump threatening to increase tariffs? If not, how the changes of the RMB exchange rate would affect the trade activities, the financial market, or other macroeconomic variables in China?

In the following part, this article tries to answer these questions. Specifically, in Section I we will introduce the data set and data selection. Section II will explain the economic methodology and define the economic model that would be applied in determining the fluctuations of the RMB exchange rate. In Section III, Vector Autoregressive (VAR) model would be adopted. Based on the magnitude of impulse responses, three currencies are chosen as significant representatives from the reference currency basket. Robustness check shows consistent results based on three numeraires. Section IV runs simple OLS test in each quarter from 2005 Q3 to 2019 Q1 to obtain the time series sample of weightings of different currencies. In section V, we adopt the ARMA model to look into the serial correlation among the time series of weightings. Section VI refers to the ARMA model built in section V, estimate the future values of weightings and provide a forecast about the RMB exchange rate in the next year.

Section I. Data Selection

We downloaded the last prices of daily currency exchange rate data from Bloomberg Terminal. Considering the fact that PBoC announced the new RMB exchange rate regime on Jul. 21st 2005, we set our time frame from Jul. 1st 2005 to May. 7th 2019. We further focused on the exchange rate between eight main currencies, including RMB, USD, EUR, JPY, AUD, MYR, GBP, SGD, and three base currencies, including CAD, RUB and THB. Therefore, there are 24 currency pairings in total. Comparing each list of the currency exchange rate in raw data, the number of observations in each list does not coincide with each other. To refine it, we picked out the date whose exchange rate disappeared in one currency pairing but existed in other currency pairings and then deleted this date. For example, JPYCAD does not have records on Jan. 2nd 2008 while other currency pairings have records on that day, thus we deleted the date Jan. 2nd 2008. Given the large sample base, our minor adjustments will not undermine the adequacy and characteristics of data. After data modification, under each base currency, we have 8 currency pairings with the same number of observations. The time series plot of exchange rate values of 8 currency pairings with CAD as the base currency and the summary statistics are shown in Appendix 2, 3, 4 and 5.

Section II. Methodology

We first define the daily fluctuation of RMB basket R over a base currency B as a summation of the lagged daily fluctuation of reference currencies C_i $(i = 1, 2, 3 \ldots)$ over the same base currency B with coefficients of p_i $(i = 1, 2, 3 \ldots)$ in the basket. We have:

$$Daily\ fluctuation\ S\left(\frac{R}{B}\right)_t = p_1 * daily\ fluctuation\ S\left(\frac{C_1}{B}\right)_{t-1} + p_2 * daily\ fluctuationS\left(\frac{C_2}{B}\right)_{t-1} + \cdots \quad (1)$$

where $S()$ determines the spot rate of the currency pair.

Since RMB is targeted to this basket, we assume that

$$S\left(\frac{R}{RMB}\right) = c$$

in which c is a constant.

If we run regression on log changes of $S\left(\frac{RMB}{B}\right)$ over log changes of $S\left(\frac{C_i}{B}\right)$ $(i = 1, 2, 3 \ldots)$ in below equation, we can obtain the estimates of the p_i in (1).

$$S\left(\frac{R}{B}\right) = S\left(\frac{R}{RMB}\right) \times S\left(\frac{RMB}{B}\right) = p_1 * S\left(\frac{C_1}{B}\right) + p_2 * S\left(\frac{C_2}{B}\right) + \cdots$$

To choose the reference currencies C_i for the RMB basket, we have referred to the disclose of the composition of the currency basket by PBoC in 2016 (Appendix 1). We chose seven currencies, that are with the highest weightings, including USD, EUR, JPY, AUD, MYR, GBP, SGD[1]. We then picked CAD, RUB, and THB as the base currencies as they were not chosen as reference currencies but have relatively high weightings. As RMB was not pegged to the reference basket until July 2005, we then set the sample range of the foreign exchange data as to from July 1st 2005 to May 7th 2019.

However, running a model with 8 currencies can be redundant, we thus wish to rely on the VAR model to help simplify the basket composition.

Section III. Vector Autoregression (VAR) model

VAR model is a multivariate time series model that captures the linear interdependencies among multiple variables' time series and is usually employed to describe the simultaneity between them. As the currencies we have here are used by countries that are having multilateral trading relationships with each other, and that the daily fluctuation of RMB may depend

[1] KRW was excluded as it was not included in the reference RMB basket until 2016.
HKD was excluded to avoid perfect multicollinearity as it is strictly pegged to USD.

on the current values as well as the lagged values of the reference currencies, we consider it as an appropriate model to use here.

Furthermore, the VAR model allows us to obtain the impulse responses of fluctuation in each variable and their lagged terms, which indicate the effect of one unit positive shocks in each currency or its lagged term on the value of RMB. By examining the magnitudes of impulse responses, we then picked three reference currencies that are with the highest value of impulse response to form the simplified model of RMB basket.

To construct the most adequate model, we first went through lag selection for the VAR model. By running VAR lag selection test on gretl, we chose the lag orders via Schwarz Bayesian criterion (BIC), for we have large sample size of the foreign exchange data (3608 observations). As shown in Appendix 6, 7 and 8, BIC results suggest running VAR model on lag order 1 no matter the base currency is CAD, RUB or THB. We then run VAR(1) model on 8 variables, with CNY listed as the last variable.

The F-test of the VAR(1) model (CAD as the base currency) (Appendix 9) indicates that USD has the most significant Granger causality on the daily fluctuation of CNY, this is similar when RUB (Appendix 10) or THB is used as base currency (Appendix 11). However, we are more interested in the magnitudes of impulse responses of CNY to shocks in lagged fluctuation of reference currency. By running impulse response analysis on the model with 3 periods, we obtained responses in daily fluctuation of CNY to one-standard error shock in daily fluctuations of the reference currencies (Appendix 12, CAD as base; Appendix 13, RUB as base; Appendix 14, THB as base). After comparing the absolute values of each response, USD, EUR, and MYR are picked as the composition of the simplified basket for having the highest values among all the currencies. The model then becomes:

$$S\left(\frac{R}{B}\right) = p_{USD} * S\left(\frac{USD}{B}\right) + p_{EUR} * S\left(\frac{EUR}{B}\right) + p_{MYR} * S\left(\frac{MYR}{B}\right)$$

After obtaining the quarterly time series data of p_{USD}, p_{EUR}, and p_{MYR}, we then wish to forecast their future behavior based on the available data, assuming that there is some correlation between the data in the time series

Section IV. Ordinary Least Squares (OLS)

To further investigate the values and characteristics of p_{USD}, p_{EUR}, and p_{MYR}, we intend to obtain the time series data of p_i by (1).

In a linear regression model, OLS is adopted to estimate the unknown parameters by the principle of least squares. Since time series effect is unlikely to reveal within one quarter, taking advantage of its simplicity, we choose the OLS model to track the values of $\mathrm{p_{ij}}$. However, if within one quarter there exists time series effect, for instance, structural break or serial correlation, the OLS model cannot capture this effect.

The economic model employed in the OLS test is as follows:

$$Daily\ fluctuation\ S\left(\frac{RMB}{B}\right)_t = p_{USDj} * daily\ fluctuation\ S\left(\frac{USD}{B}\right)_{t-1} + p_{EURj} * daily\ fluctuationS\left(\frac{EUR}{B}\right)_{t-1} + p_{MYRj} * daily\ fluctuationS\left(\frac{MYR}{B}\right)_{t-1},$$

where $j = 1,2,3, \dots 55$ (from 2005 Q3 to 2019 Q1, 55 quarters in total), and $daily\ fluctuation\ S\left(\frac{C_i}{B}\right)_{t-1} = \log(\frac{S\left(\frac{C_i}{B}\right)_{t-1}}{S\left(\frac{C_i}{B}\right)_{t-2}}), i = 1, 2, 3.$

Under each numeraire, by running the above model in gretl 55 times, we receive three time series lists of p_i with quarterly frequency. The time series plot and the summary statistics of p_i against three numeraires are presented in Appendix 15, 16, 17, 18, 19 and 20. It is indicated by the time series plot that p_{USD} have been decreasing between 2015 and 2016 no matter the numeraire is. This suggested two possible reasons: the bilateral dependence relationship of RMB and USD declined since 2015 or RMB started to flow more independently of the reference currency basket. To determine which statement explains more of the fact, we further looked into the standard error of the regression in each quarter.

The standard error of the regression (SER) stands for the average distance that the observed value falls from the regression line. SER estimates the precision of the model and suggests how the model fits the data. In our case, SER estimates the changes of RMB value that cannot be captured by changes of the currency basket and how closely RMB move alongside with the basket. We recorded the SER of each OLS model and linked them in the time series plot as shown in Appendix 21.

The time series plot of SER showed two significant jumps, one in 2010 and the other in 2016. Firstly, in 2010, we considered the PBoC made the statement that RMB exchange rate regime would evolve from a bilateral reference with USD to multilateral references, emphasizing the influencing power of other currencies in the reference currency basket. This explained the sudden decline in SER and suggested that since 2010, RMB moved more closely with the basket. Secondly, in 2016, PBoC disclosed a new composition of the currency basket and the weighting of USD fell from 26.4% to 22.4%. What's more, as indicated in the jump of SER, we regarded the p_{USD}'s decreasing trend between 2015 and 2016 as a joint consequence of less weighting of USD and RMB's moving more independently of the reference currency basket.

After obtaining the value of p_{USD}, p_{EUR}, and p_{MYR}, we wanted to investigate their serial correlation and to make a forecast for the next year. In order to do so, we implemented the ARMA (p, q) model in the next section.

Section V. ARMA(p, q) Model

ARMA(p, q) refers to autoregressive moving average model that contains p autoregressive terms and q moving-average terms. Such model represents the correlation in the time series. Here we have assumed that p_{USD}, p_{EUR}, and p_{MYR} are correlated with their past data, and in order to best forecast their future behavior, the important lags (the value p and q) need to be found to construct the best-fit model.

Firstly, we looked at the ACF and PACF correlogram for p_{USD}, p_{EUR} and p_{MYR}[2] (Appendix 22, 23, 24). The correlograms of them all have tendency to demonstrate AR model characteristics, with PACF almost equal to zero after certain lags and ACF slowly decaying to zero. We can also observe from the Q-stat that PACF shows 5% significance at lag 5 for p_{USD}; 10% significance at lag 5 for p_{EUR}; 1% significance at lag 2 for p_{MYR}; thus we will need to try the AR model of those orders for the respective currency.

The results of AR(5) model for p_{USD}, AR(5) model for p_{EUR}, and AR(2) model for p_{MYR} are shown in Appendix 25, 26 and 27. The AR model results had shown significance for lag 4 of p_{USD} instead of lag 5. For p_{EUR} and p_{MYR}, the AR model results indicated significance at lag 5 and lag 2 respectively as expected. To see if AR(4) or AR(5) will be a better fit for p_{USD}, we select the model by considering residual correlogram, information criteria and the robustness of in-sample forecast.

Residual correlogram can be used to see if white noise residuals are presented, which makes the model good to be used to do forecast (Appendix 28, 29, 30). We compared the residual correlograms of AR(4) and AR(5) for p_{USD}, and have found that both demonstrated white noise residuals at 5% significant level. However, AR(5) performs slightly better in providing white noise residuals if 10%

[2] For the following models, CAD is used as based currency for simplification.

significance level is used. For p_{EUR} and p_{MYR} , both of their residual correlograms of model AR(5) and AR(2) respectively had indicated white noise residuals, and thus these two models are chosen for them.

As the sample size here is 56, which is not very large, Akaike's Information Criteria (AIC) shall be used to select the model. By comparing the AR(4) and AR(5) for p_{USD} in Appendix 25, we can see that the AIC of AR(4) is 3.514074, which is considerably smaller than the 4.3297 of AR(5). In this case, AR(4) should be chosen.

In-sample forecast allows us to see how well the prediction of a model fits the actual data points. We set the forecast range from the second quarter of 2010 to the second quarter of 2019, and the reports of forecast using AR(4) and AR(5) are listed in Appendix 31. By comparison, the mean error and root mean squared error of the in-sample forecast using AR(4) and AR(5) are very close, with AR(5) performing slightly better than AR(4). By taking the outcome of the aforementioned criterion into consideration, we chose AR(4) for p_{USD} for it is simpler and its ability to bring robust results.

Forecasting

The objective here is to generate a quarterly forecast for RMB against CAD. This goal shall be achieved by firstly acquiring the quarterly forecast for p_{USD}, p_{EUR}, and p_{MYR}, and next combining them with the log changes of the market quarterly forecast of USD, EUR and MYR against CAD to produce the forecast for RMB against CAD. As the foreign exchange market is a non-stop rapid changing market, we chose the horizon of one year – four quarters – to make the forecast more meaningful.

By applying model AR(4) on p_{USD}, AR(5) on p_{EUR} and AR(2) on p_{MYR}, we used gretl to conduct automatic forecast (dynamic out of sample) for $p_{USD,}$ p_{EUR} and p_{MYR} from the second quarter of 2019 to the second quarter of 2020. The results are as shown in Appendix 32.

From the forecast of $p_{USD,}$ p_{EUR} and p_{MYR}, we can observe that the fluctuation of Malaysian Ringgit plays the most significant role in the fluctuation of RMB, while the fluctuation of US dollars and Euros have less impact. With the market forecast of quarterly fluctuation of USD, EUR and MYR against CAD (Appendix 33), we can thus eventually obtain the forecast of RMB against CAD in the next four quarters (Appendix 34).

According to the results from our models, Canadian dollars is expected to depreciate against Chinese RMB in the next four quarters, which means that Chinese RMB is expected to appreciate against CAD.

Structural break

To possibly strengthen the accuracy of our models, we used Quandt Likelihood Ratio (QLR) Test to look for possible structural breaks at unknown break date, which means the change of coefficients for lags of p_{USD}, p_{EUR} and p_{MYR} before and after this date. However, the weakness of this test includes that it is conducted with 15% trimming data, and thus some possible structural breaks that happen in the data that got trimmed may not be spotted.

The outcome of QLR test for p_{USD} (Appendix 35) shows that the only statistically significant (5% significance level) structural break happened in the first quarter of 2016. For p_{EUR}, the QLR results (Appendix 36) indicates that the only structural break took place in the second quarter of 2008, while there is no statistically significant structural break for p_{MYR}.

Conclusion

This article intends to investigate the evolution of RMB exchange regime and make a forecast of RMB value in the next year. By running VAR, OLS, and ARMA(p,q) model respectively, we found four major results:

Firstly, the changes of value of USD, EUR and MYR have different influencing power on value of RMB over time, as suggested by the different lag selection in the ARMA(p,q) model. More specifically, MYR has the most short-term effect and EUR has the most long-term effect on RMB;

Secondly, MYR is playing a more important role in determining RMB value than expected. Comparing the magnitude of quarterly forecast for p_{USD}, p_{EUR}, and p_{MYR}, we observed that most of RMB variation is induced by MYR, other than USD;

Thirdly, the RMB exchange rate regime experienced a major reform between 2015 and 2016. We found evidence from the decline in value of p_{USD}, jump of the standard error of regression of the OLS model and one significant structural break of p_{USD}, all of which happened from 2015 to 2016;

Fourthly, we estimate that RMB is going to appreciate, which has a profound impact on the trade balance of China. Macroeconomic theory suggests that a real depreciation has a positive impact on net export. If RMB was going to appreciate in the following four quarters, we may foresee a boom in sectors exporting final goods to China and a decrease in China's net export, taking consideration of price stickiness effect. Given high tariffs imposed by President Trump, there are more chances that China's trade balance would experience a downward trend.

For simplicity, we only select three currencies out of the basket, therefore, it is highly likely that some variation of RMB that is captured by other currencies, i.e. JPY and KRW, cannot be reflected in our result. What's more, in view of the reform of the RMB exchange rate regime in 2016, future studies could focus on the new multilateral dependence relationship between RMB and currencies in the basket using data starting from 2016. By including more currencies in the analysis, the forecast about value of RMB could be more precise and informative.

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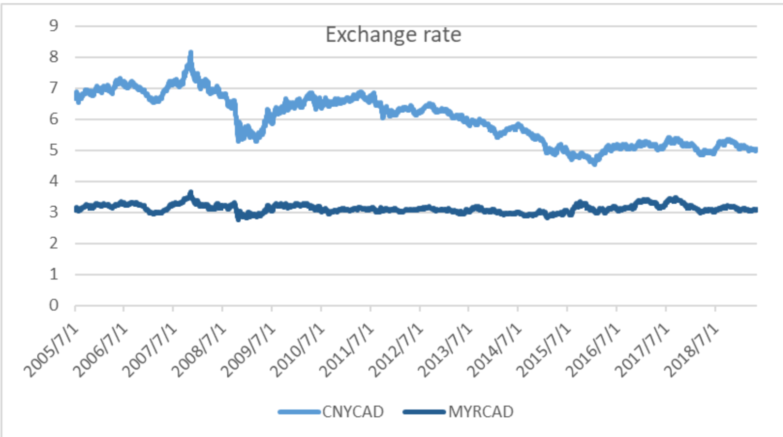
Appendix

Appendix 1 – Comparison of RMB Index composition in 2015 and 2016

Location	Currency	Index weighting（2015）	Index weighting（2016）	Weighting adjustment
US	USD	26.40%	22.40%	-4.0%
Eurozone	EUR	21.39%	16.34%	-5.1%
Japan	JPY	14.68%	11.53%	-3.2%
Korea	KRW	—	10.77%	+10.8%
Australia	AUD	6.27%	4.40%	-1.9%
Hong Kong	HKD	6.55%	4.28%	-2.3%
Malaysia	MYR	4.67%	3.75%	-0.9%
UK	GBP	3.86%	3.21%	-0.7%
Singapore	SGD	3.82%	3.16%	-0.6%
Thailand	THB	3.33%	2.91%	-0.4%
Russia	RUB	4.36%	2.63%	-1.7%
Canada	CAD	2.53%	2.15%	-0.4%
Saudi Arabia	SAR	—	1.99%	+2.0%
United Arab Emirates	AED	—	1.87%	+1.9%
South Africa	ZAR	—	1.78%	+1.8%
Switzerland	CHF	1.51%	1.71%	+0.2%
Mexico	MXN	—	1.69%	+1.7%
Turkey	TRY	—	0.83%	+0.8%
Poland	PLN	—	0.66%	+0.7%

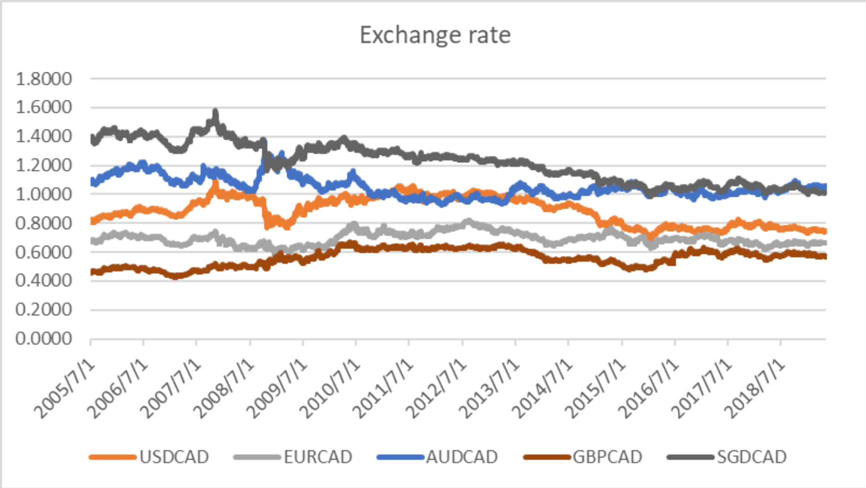
Appendix 2

CNYCAD and MYRCAD



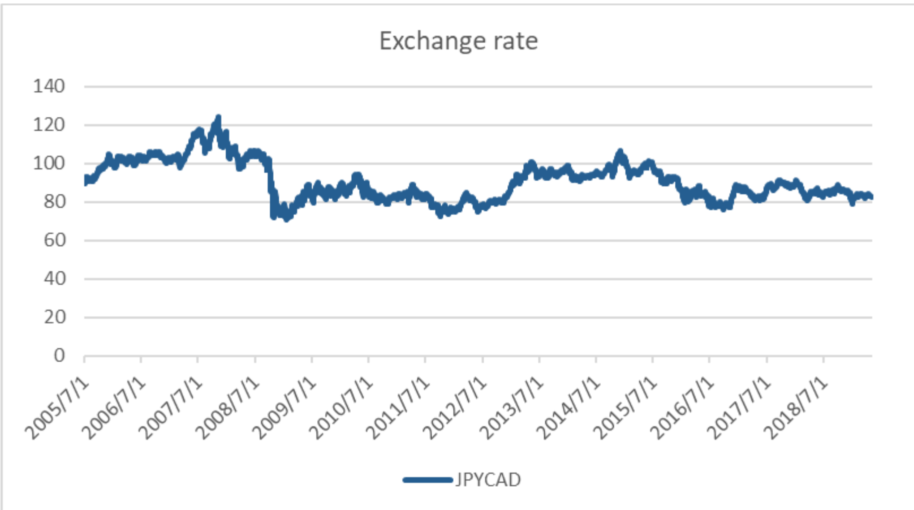
Appendix 3

USDCAD, EURCAD, AUDCAD, GBPCAD, and SGDCAD



Appendix 4

JPYCAD



Appendix 5

Summary statistics of exchange rate

	CNYCAD	USDCAD	EURCAD	JPYCAD	AUDCAD	MYRCAD	GBPCAD	SGDCAD
Mean	6.002	0.886	0.694	90.589	1.051	3.125	0.561	1.221
Standard Error	0.013	0.002	0.001	0.167	0.001	0.002	0.001	0.002
Median	6.114	0.895	0.693	88.438	1.037	3.110	0.567	1.234
Mode	4.916	1.001	0.666	83.703	1.050	3.067	0.623	1.225
Standard Deviation	0.786	0.096	0.044	10.048	0.071	0.128	0.059	0.138
Sample Variance	0.618	0.009	0.002	100.962	0.005	0.016	0.004	0.019
Kurtosis	-1.247	-1.384	-0.293	-0.314	0.105	-0.023	-1.069	-1.184
Skewness	0.036	-0.110	0.299	0.559	0.797	0.332	-0.279	0.047
Range	3.643	0.415	0.251	53.806	0.439	0.898	0.246	0.600
Minimum	4.531	0.683	0.572	70.671	0.928	2.762	0.427	0.983
Maximum	8.174	1.098	0.824	124.477	1.366	3.660	0.673	1.583

Appendix 6

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VAR system, maximum lag order 10

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1  139651.64127            -77.565791   -77.441989*  -77.521670
   2  139814.65150  0.00000  -77.620812   -77.386963   -77.537472*
   3  139885.36848  0.00000  -77.624545*  -77.280649   -77.501986
   4  139943.08285  0.00009  -77.621052   -77.167109   -77.459275
   5  140001.58469  0.00006  -77.617996   -77.054007   -77.417001
   6  140033.53003  0.48034  -77.600183   -76.926147   -77.359969
   7  140079.84821  0.01112  -77.590357   -76.806274   -77.310924
   8  140118.52451  0.12203  -77.576285   -76.682155   -77.257633
   9  140175.88226  0.00010  -77.572594   -76.568417   -77.214723
  10  140235.84747  0.00003  -77.570351   -76.456128   -77.173262
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Appendix 7

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VAR system, maximum lag order 10

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1  136108.10524            -75.617624   -75.493792*  -75.573492
   2  136367.02516  0.00000  -75.725973   -75.492069   -75.642612
   3  136509.28841  0.00000  -75.769477   -75.425500   -75.646888*
   4  136599.64909  0.00000  -75.784130   -75.330081   -75.622312
   5  136711.69339  0.00000  -75.810836   -75.246715   -75.609790
   6  136771.74545  0.00003  -75.808641   -75.134448   -75.568367
   7  136870.21315  0.00000  -75.827801   -75.043535   -75.548298
   8  136939.22761  0.00000  -75.830588   -74.936250   -75.511857
   9  137015.98873  0.00000  -75.837681   -74.833271   -75.479722
  10  137104.06531  0.00000  -75.851065*  -74.736581   -75.453877
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Appendix 8

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VAR system, maximum lag order 10

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1  140846.24011           -78.491352*  -78.367202*  -78.447100*
   2  140902.38578  0.00018  -78.486973   -78.252468   -78.403385
   3  140970.62132  0.00000  -78.489334   -78.144474   -78.366411
   4  141016.83509  0.01155  -78.479417   -78.024202   -78.317159
   5  141079.33655  0.00001  -78.478582   -77.913011   -78.276988
   6  141115.72313  0.21159  -78.463185   -77.787259   -78.222256
   7  141154.39578  0.12215  -78.449064   -77.662782   -78.168799
   8  141187.16584  0.42313  -78.431651   -77.535014   -78.112051
   9  141224.53396  0.16885  -78.416802   -77.409809   -78.057867
  10  141285.39585  0.00002  -78.415052   -77.297704   -78.016782
```

Appendix 9

```
F-tests of zero restrictions:

All lags of logUSDRUB      F(1, 3598) =   94.617 [0.0000]
All lags of logEURRUB      F(1, 3598) =   9.1799 [0.0025]
All lags of logAUDRUB      F(1, 3598) =   4.7531 [0.0293]
All lags of logMYRRUB      F(1, 3598) = 4.3073e-05 [0.9948]
All lags of logGBPRUB      F(1, 3598) =   31.942 [0.0000]
All lags of logSGDRUB      F(1, 3598) =   4.2217 [0.0400]
All lags of logJPYRUB      F(1, 3598) =   1.6643 [0.1971]
All lags of logCNYRUB      F(1, 3598) =   121.31 [0.0000]
```

Appendix 10

```
F-tests of zero restrictions:

All lags of logUSDCAD      F(1, 3599) =   35.759 [0.0000]
All lags of logEURCAD      F(1, 3599) =   2.4974 [0.1141]
All lags of logJPYCAD      F(1, 3599) =   1.0414 [0.3076]
All lags of logAUDCAD      F(1, 3599) =  0.20415 [0.6514]
All lags of logMYRCAD      F(1, 3599) =  0.54031 [0.4624]
All lags of logGBPCAD      F(1, 3599) =   4.4419 [0.0351]
All lags of logSGDCAD      F(1, 3599) =   5.5532 [0.0185]
All lags of logCNYCAD      F(1, 3599) =   22.981 [0.0000]
```

Appendix 11

```
F-tests of zero restrictions:

All lags of logUSDTHB      F(1, 3587) =   9.1802 [0.0025]
All lags of logEURTHB      F(1, 3587) = 0.039563 [0.8423]
All lags of logJPYTHB      F(1, 3587) =  0.10989 [0.7403]
All lags of logAUDTHB      F(1, 3587) =   1.1006 [0.2942]
All lags of logMYRTHB      F(1, 3587) =  0.86488 [0.3524]
All lags of logGBPTHB      F(1, 3587) =   1.3952 [0.2376]
All lags of logSGDTHB      F(1, 3587) =   1.3607 [0.2435]
All lags of logCNYTHB      F(1, 3587) =   7.3212 [0.0068]
```

***Appendix 12** – Responses of log(CNYCAD) to a one-standard error shock in log(XCAD) in period 1*

X	USD	EUR	AUD	MYR	GBP	SGD	JPY
Impulse Responses	**0.0018984**	**0.0012123**	6.2559e-05	**0.00032642**	0.00011928	0.00020421	0.00017621

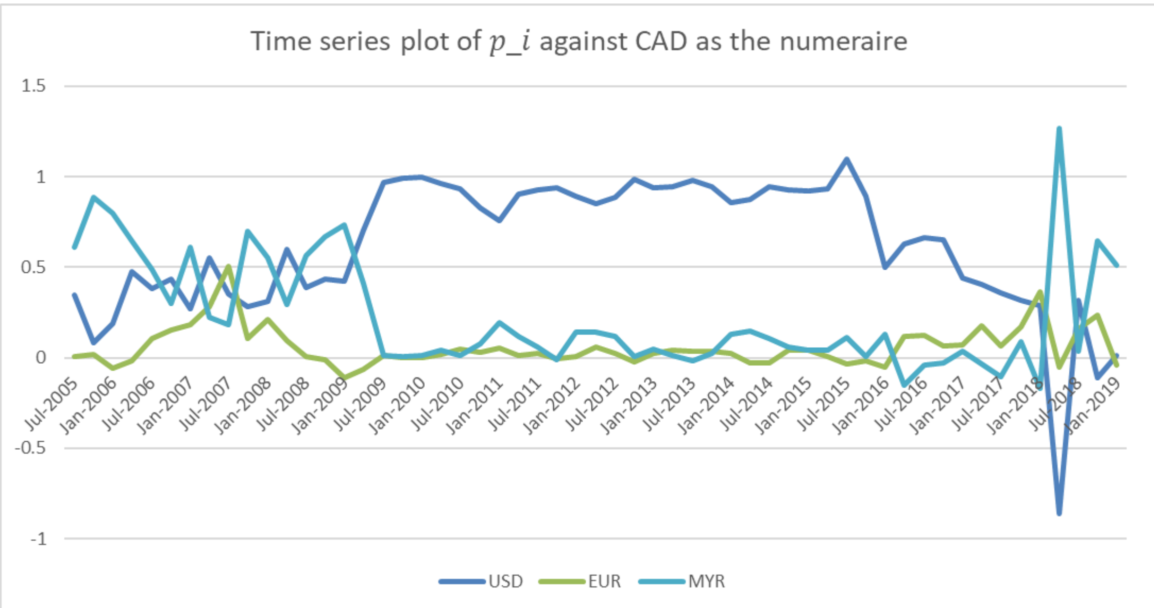
***Appendix 13** – Responses of log(CNYRUB) to a one-standard error shock in log(XRUB) in period 1*

X	USD	EUR	AUD	MYR	GBP	SGD	JPY
Impulse responses	**0.0021818**	**0.0026440**	0.00015445	**0.00031911**	0.00012153	5.8691e-005	0.00028653

***Appendix 14** – Responses of log(CNYTHB) to a one-standard error shock in log(XTHB) in period 1*

X	USD	EUR	AUD	MYR	GBP	SGD	JPY
Impulse responses	**0.00104**	**0.00049091**	0.00019101	**0.00050114**	0.00016837	-0.00021694	0.00029524

Appendix 15

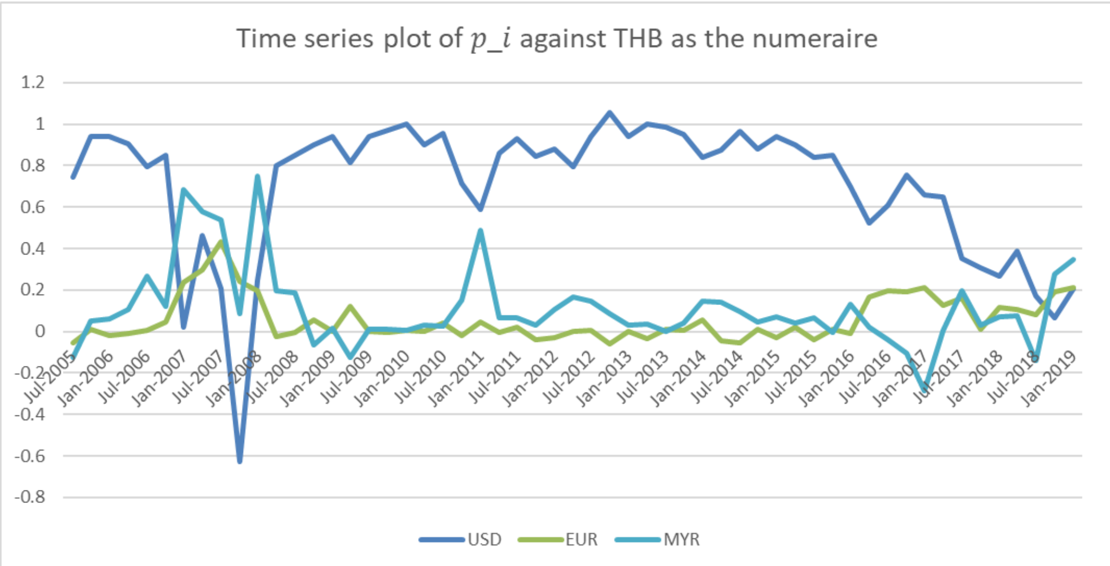


Appendix 16

Summary statistics of p_i against CAD as the numeraire

CAD					
USD		*EUR*		*MYR*	
Mean	0.617	Mean	0.059	Mean	0.227
Standard Error	0.050	Standard Error	0.015	Standard Error	0.041
Median	0.666	Median	0.026	Median	0.112
Standard Deviation	0.368	Standard Deviation	0.110	Standard Deviation	0.307
Sample Variance	0.135	Sample Variance	0.012	Sample Variance	0.094
Kurtosis	3.277	Kurtosis	4.797	Kurtosis	1.190
Skewness	-1.359	Skewness	1.881	Skewness	1.279
Range	1.962	Range	0.617	Range	1.436
Minimum	-0.862	Minimum	-0.110	Minimum	-0.169
Maximum	1.100	Maximum	0.507	Maximum	1.267

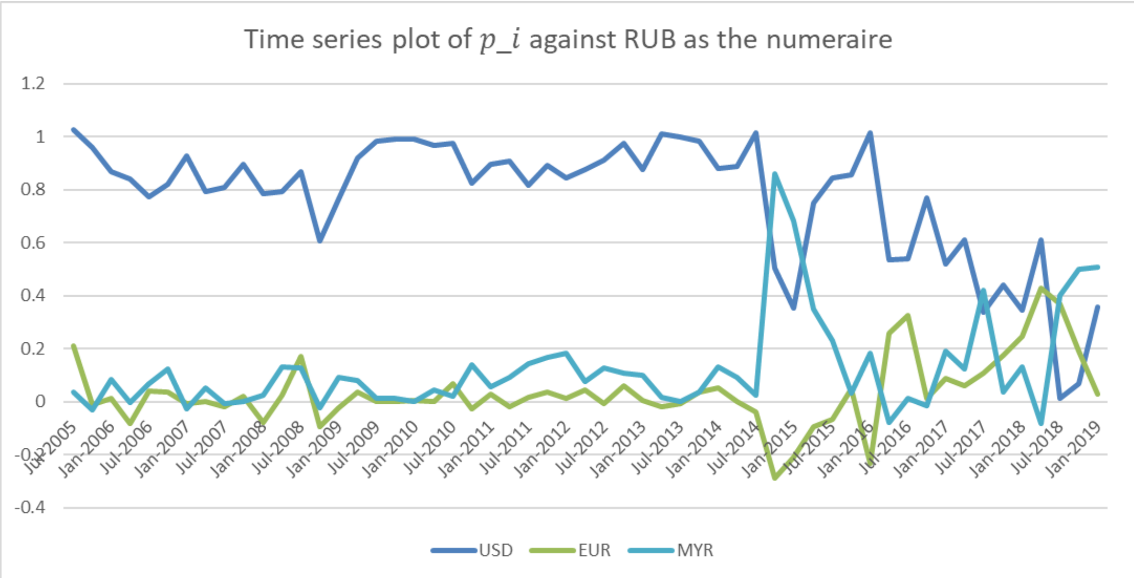
Appendix 17



Appendix 18

THB					
USD		*EUR*		*MYR*	
Mean	0.705	Mean	0.058	Mean	0.109
Standard Error	0.044	Standard Error	0.014	Standard Error	0.026
Median	0.842	Median	0.011	Median	0.067
Standard Deviation	0.329	Standard Deviation	0.105	Standard Deviation	0.192
Sample Variance	0.108	Sample Variance	0.011	Sample Variance	0.037
Kurtosis	3.848	Kurtosis	1.747	Kurtosis	3.218
Skewness	-1.800	Skewness	1.395	Skewness	1.562
Range	1.687	Range	0.489	Range	1.033
Minimum	-0.629	Minimum	-0.058	Minimum	-0.284
Maximum	1.057	Maximum	0.431	Maximum	0.749

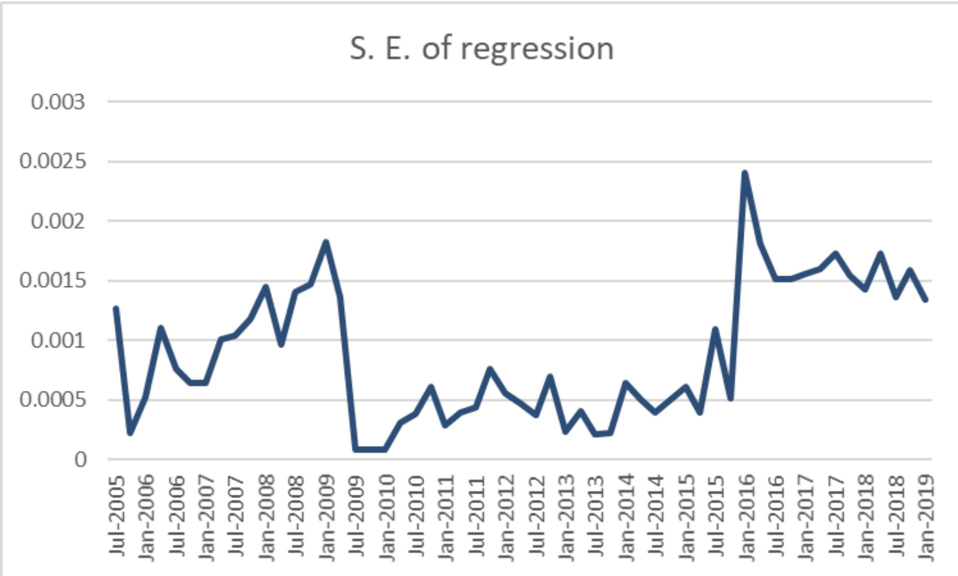
Appendix 19



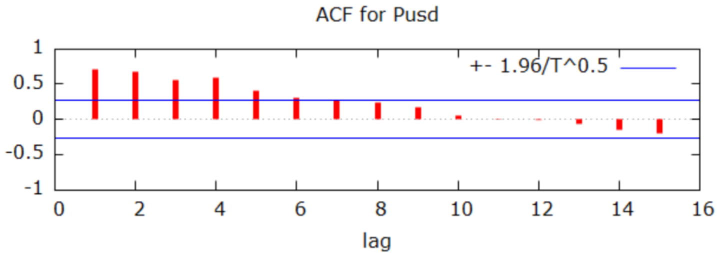
Appendix 20

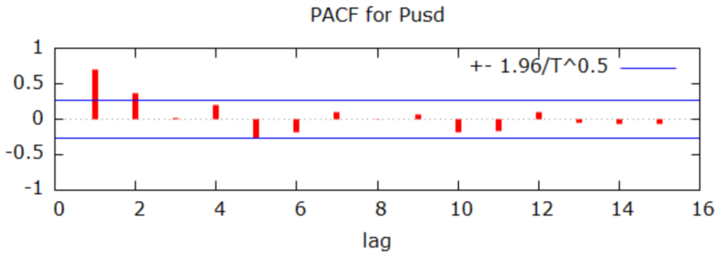
RUB					
USD		*EUR*		*MYR*	
Mean	0.771	Mean	0.035	Mean	0.124
Standard Error	0.032	Standard Error	0.017	Standard Error	0.024
Median	0.845	Median	0.014	Median	0.080
Standard Deviation	0.239	Standard Deviation	0.129	Standard Deviation	0.181
Sample Variance	0.057	Sample Variance	0.017	Sample Variance	0.033
Kurtosis	1.700	Kurtosis	2.204	Kurtosis	5.650
Skewness	-1.447	Skewness	0.724	Skewness	2.243
Range	1.015	Range	0.716	Range	0.943
Minimum	0.012	Minimum	-0.288	Minimum	-0.082
Maximum	1.027	Maximum	0.429	Maximum	0.861

Appendix 21



Appendix 22 – ACF and PACF of USD

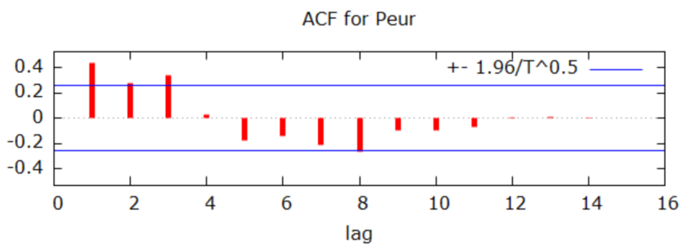


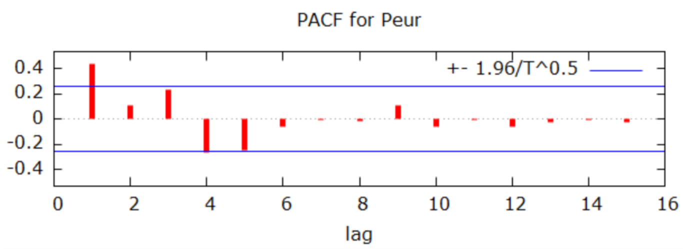


Autocorrelation function for Pusd
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

LAG	ACF		PACF		Q-stat.	[p-value]
1	0.6999	***	0.6999	***	28.9319	[0.000]
2	0.6754	***	0.3636	***	56.3683	[0.000]
3	0.5638	***	0.0190		75.8452	[0.000]
4	0.5877	***	0.1974		97.4191	[0.000]
5	0.3971	***	-0.2624	**	107.4634	[0.000]
6	0.3096	**	-0.1805		113.6904	[0.000]
7	0.2649	**	0.0963		118.3427	[0.000]
8	0.2296	*	0.0047		121.9106	[0.000]
9	0.1757		0.0710		124.0448	[0.000]
10	0.0447		-0.1928		124.1858	[0.000]
11	-0.0055		-0.1662		124.1880	[0.000]
12	-0.0118		0.1070		124.1984	[0.000]
13	-0.0658		-0.0472		124.5251	[0.000]
14	-0.1550		-0.0599		126.3824	[0.000]
15	-0.2067		-0.0647		129.7684	[0.000]

Appendix 23 – ACF and PACF of EUR



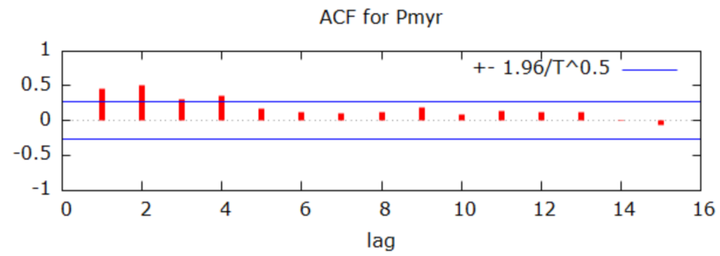


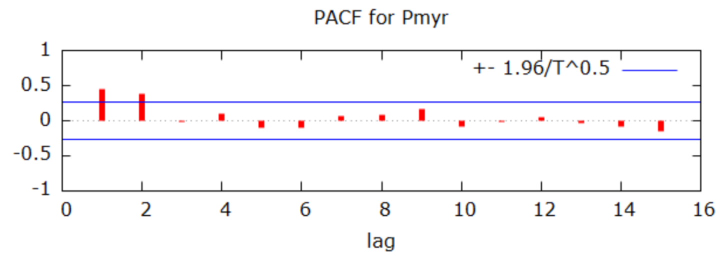
```
Autocorrelation function for Peur
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

  LAG       ACF          PACF         Q-stat. [p-value]

    1   0.4390  ***   0.4390 ***     11.3804  [0.001]
    2   0.2807  **    0.1090         16.1186  [0.000]
    3   0.3415  **    0.2305 *       23.2659  [0.000]
    4   0.0287       -0.2685 **      23.3172  [0.000]
    5  -0.1808       -0.2506 *       25.3991  [0.000]
    6  -0.1439       -0.0622         26.7449  [0.000]
    7  -0.2096       -0.0131         29.6561  [0.000]
    8  -0.2646  **   -0.0174         34.3937  [0.000]
    9  -0.0995        0.1050         35.0784  [0.000]
   10  -0.0951       -0.0617         35.7175  [0.000]
   11  -0.0737       -0.0115         36.1091  [0.000]
   12   0.0058       -0.0638         36.1116  [0.000]
   13   0.0102       -0.0281         36.1195  [0.001]
   14  -0.0039       -0.0092         36.1207  [0.001]
   15  -0.0004       -0.0282         36.1207  [0.002]
```

Appendix 24 – ACF and PACF of MYR






```
Autocorrelation function for Pmyr
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

  LAG       ACF          PACF         Q-stat. [p-value]

    1   0.4472  ***   0.4472 ***     11.8092  [0.001]
    2   0.5104  ***   0.3880 ***     27.4790  [0.000]
    3   0.3015  **   -0.0172         33.0505  [0.000]
    4   0.3459  ***   0.1010         40.5250  [0.000]
    5   0.1620       -0.0951         42.1964  [0.000]
    6   0.1247       -0.0935         43.2063  [0.000]
    7   0.1033        0.0639         43.9139  [0.000]
    8   0.1223        0.0772         44.9268  [0.000]
    9   0.1850        0.1633         47.2915  [0.000]
   10   0.0819       -0.0807         47.7647  [0.000]
   11   0.1290       -0.0216         48.9668  [0.000]
   12   0.1192        0.0509         50.0158  [0.000]
   13   0.1112       -0.0336         50.9497  [0.000]
   14   0.0084       -0.0885         50.9551  [0.000]
   15  -0.0682       -0.1432         51.3235  [0.000]
```

Appendix 25 – AR(4) and AR(5) model for p_{USD}

```
Function evaluations: 56
Evaluations of gradient: 20

Model 1: ARMA, using observations 2005:3-2019:2 (T = 56)
Estimated using AS 197 (exact ML)
Dependent variable: Pusd
Standard errors based on Hessian

             coefficient   std. error     z      p-value
  ------------------------------------------------------
  const       0.339665      0.317942    1.068    0.2854
  phi_1       0.348731      0.132177    2.638    0.0083   ***
  phi_2       0.336275      0.140512    2.393    0.0167   **
  phi_3       0.0364232     0.141759    0.2569   0.7972
  phi_4       0.206085      0.136474    1.510    0.1310

Mean dependent var   0.600459   S.D. dependent var   0.384966
Mean of innovations  0.004049   S.D. of innovations  0.220816
Log-likelihood       4.242963   Akaike criterion     3.514074
Schwarz criterion    15.66618   Hannan-Quinn         8.225421
```

```
Function evaluations: 37
Evaluations of gradient: 13

Model 1: ARMA, using observations 2005:3-2019:2 (T = 56)
Estimated using AS 197 (exact ML)
Dependent variable: Pusd
Standard errors based on Hessian

             coefficient   std. error     z      p-value
  ------------------------------------------------------
  const       0.410290      0.279158    1.470    0.1416
  phi_1       0.367074      0.131195    2.798    0.0051   ***
  phi_2       0.346345      0.138044    2.509    0.0121   **
  phi_3       0.0884811     0.147362    0.6004   0.5482
  phi_4       0.293516      0.155126    1.892    0.0585   *
  phi_5      -0.189542      0.173642   -1.092    0.2750

Mean dependent var   0.600459   S.D. dependent var   0.384966
Mean of innovations  0.006919   S.D. of innovations  0.218222
Log-likelihood       4.835352   Akaike criterion     4.329296
Schwarz criterion    18.50676   Hannan-Quinn         9.825868
```

Appendix 26 – AR(5) model for p_{EUR}

```
Function evaluations: 38
Evaluations of gradient: 10

Model 2: ARMA, using observations 2005:3-2019:2 (T = 56)
Estimated using AS 197 (exact ML)
Dependent variable: Peur
Standard errors based on Hessian

             coefficient   std. error     z      p-value
  -------------------------------------------------------
  const       0.0526253    0.0183279     2.871   0.0041   ***
  phi_1       0.306940     0.131409      2.336   0.0195   **
  phi_2       0.168820     0.134127      1.259   0.2082
  phi_3       0.407990     0.129655      3.147   0.0017   ***
  phi_4      -0.163328     0.139902     -1.167   0.2430
  phi_5      -0.357621     0.139423     -2.565   0.0103   **

Mean dependent var    0.055404   S.D. dependent var   0.111564
Mean of innovations -0.000080   S.D. of innovations  0.085511
Log-likelihood        57.45060   Akaike criterion    -100.9012
Schwarz criterion    -86.72374   Hannan-Quinn        -95.40463
```

Appendix 27 – AR(2) for p_{MYR}

```
Function evaluations: 32
Evaluations of gradient: 10

Model 3: ARMA, using observations 2005:3-2019:2 (T = 56)
Estimated using AS 197 (exact ML)
Dependent variable: Pmyr
Standard errors based on Hessian

             coefficient   std. error     z     p-value
  ------------------------------------------------------
  const       0.308929      0.128861     2.397   0.0165   **
  phi_1       0.281338      0.118201     2.380   0.0173   **
  phi_2       0.472751      0.123607     3.825   0.0001   ***

Mean dependent var    0.237760   S.D. dependent var   0.314222
Mean of innovations -0.012512   S.D. of innovations  0.244623
Log-likelihood       -1.030910   Akaike criterion     10.06182
Schwarz criterion     18.16323   Hannan-Quinn         13.20272
```

Appendix 28 – Residual correlogram of AR(4) and AR(5) for p_{USD}

```
Residual autocorrelation function
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

  LAG      ACF          PACF         Q-stat. [p-value]

    1   0.0332       0.0332
    2   0.0679       0.0669
    3   0.0855       0.0816
    4   0.1785       0.1713
    5   0.0894       0.0749          3.2878  [0.070]
    6  -0.0150      -0.0458          3.3023  [0.192]
    7   0.0518       0.0157          3.4804  [0.323]
    8   0.1480       0.1132          4.9619  [0.291]
    9   0.1939       0.1768          7.5601  [0.182]
   10  -0.0753      -0.0966          7.9606  [0.241]
   11  -0.0732      -0.1336          8.3478  [0.303]
   12   0.0999       0.0396          9.0839  [0.335]
   13   0.0937       0.0601          9.7467  [0.371]
   14   0.0041       0.0257          9.7480  [0.463]
   15  -0.0518      -0.0367          9.9606  [0.534]
   16  -0.0040      -0.0727          9.9619  [0.619]
   17  -0.0256      -0.1089         10.0165  [0.693]
   18  -0.0747      -0.0788         10.4930  [0.725]
   19  -0.0710       0.0195         10.9353  [0.757]
   20   0.0389       0.0986         11.0719  [0.805]
```

```
Residual autocorrelation function
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

  LAG      ACF          PACF         Q-stat. [p-value]

    1  -0.0192      -0.0192
    2   0.0427       0.0423
    3   0.0200       0.0216
    4   0.0878       0.0870
    5   0.0567       0.0591
    6  -0.0317      -0.0371          0.9072  [0.341]
    7   0.0532       0.0439          1.0947  [0.578]
    8   0.1268       0.1237          2.1818  [0.536]
    9   0.1806       0.1800          4.4355  [0.350]
   10  -0.0986      -0.1004          5.1219  [0.401]
   11  -0.0959      -0.1358          5.7857  [0.448]
   12   0.0736       0.0447          6.1850  [0.518]
   13   0.0762       0.0682          6.6239  [0.578]
   14   0.0046       0.0140          6.6256  [0.676]
   15  -0.0489      -0.0411          6.8151  [0.743]
   16  -0.0184      -0.0739          6.8426  [0.812]
   17  -0.0430      -0.1081          6.9968  [0.858]
   18  -0.0689      -0.0689          7.4024  [0.880]
   19  -0.0643       0.0157          7.7650  [0.901]
   20   0.0401       0.0802          7.9103  [0.927]
```

Appendix 29 – Residual correlogram of AR(5) for p_{EUR}

```
Residual autocorrelation function
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5
```

LAG	ACF	PACF	Q-stat.	[p-value]
1	-0.0032	-0.0032		
2	0.0044	0.0044		
3	-0.0098	-0.0098		
4	-0.0008	-0.0009		
5	0.0374	0.0375		
6	-0.0356	-0.0355	0.1790	[0.672]
7	0.0029	0.0024	0.1795	[0.914]
8	-0.1358	-0.1351	1.4276	[0.699]
9	0.0583	0.0584	1.6625	[0.798]
10	0.0035	0.0025	1.6634	[0.893]
11	0.0282	0.0295	1.7210	[0.943]
12	0.0101	0.0088	1.7285	[0.973]
13	-0.0917	-0.0835	2.3632	[0.968]
14	-0.0713	-0.0866	2.7560	[0.973]
15	-0.0191	-0.0146	2.7849	[0.986]
16	0.0272	0.0072	2.8449	[0.993]
17	-0.0206	-0.0033	2.8803	[0.996]
18	-0.0732	-0.0718	3.3383	[0.996]
19	-0.0135	-0.0085	3.3543	[0.998]
20	-0.0139	-0.0208	3.3718	[0.999]

Appendix 30 – Residual correlogram of AR(2) for p_{MYR}

```
Residual autocorrelation function
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5
```

LAG	ACF	PACF	Q-stat.	[p-value]
1	-0.0313	-0.0313		
2	-0.0898	-0.0909		
3	-0.0072	-0.0132	0.5459	[0.460]
4	0.1199	0.1121	1.4443	[0.486]
5	-0.0008	0.0055	1.4443	[0.695]
6	-0.0774	-0.0588	1.8333	[0.766]
7	-0.0982	-0.1032	2.4728	[0.781]
8	0.0100	-0.0221	2.4795	[0.871]
9	0.1147	0.1016	3.3886	[0.847]
10	-0.0886	-0.0686	3.9423	[0.862]
11	0.0021	0.0356	3.9426	[0.915]
12	0.0950	0.0846	4.6095	[0.916]
13	0.1051	0.0809	5.4443	[0.908]
14	-0.0280	-0.0011	5.5047	[0.939]
15	-0.1072	-0.0952	6.4148	[0.930]
16	-0.0566	-0.0802	6.6749	[0.947]
17	-0.0060	-0.0570	6.6779	[0.966]
18	-0.0386	-0.0464	6.8054	[0.977]
19	-0.0602	-0.0026	7.1238	[0.982]
20	0.0167	0.0341	7.1491	[0.989]

Appendix 31 – In-sample forecast using AR(4) and AR(5) for p_{USD}

Forecast evaluation statistics

Mean Error	-0.03409
Root Mean Squared Error	0.23599
Mean Absolute Error	0.12604
Mean Percentage Error	-25.929
Mean Absolute Percentage Error	51.578
Theil's U	0.43322
Bias proportion, UM	0.020867
Regression proportion, UR	0.030816
Disturbance proportion, UD	0.94832

```
Forecast evaluation statistics

Mean Error                              -0.022853
Root Mean Squared Error                  0.23449
Mean Absolute Error                      0.12166
Mean Percentage Error                   -8.1348
Mean Absolute Percentage Error           32.514
Theil's U                                0.16379
Bias proportion, UM                      0.0094981
Regression proportion, UR                0.0093275
Disturbance proportion, UD               0.98117
```

Appendix 32 – Quarterly forecast for p_{USD}, p_{EUR} and p_{MYR}

Quarter	Pusd	Peur	Pmyr
2019Q2	-0.175429	0.056978	0.524003
2019Q3	-0.017242	0.118114	0.547891
2019Q4	-0.107359	0.031359	0.61801
2019Q5	-0.027767	-0.067783	0.508855

Appendix 33 – Quarterly forecast for USD, EUR, MYR against CAD

Quarter	USDCAD	EURCAD	MYRCAD
2019Q2	0.7429200	0.6657790	3.0771002
2019Q3	0.7390273	0.6656903	3.0682935
2019Q4	0.7350995	0.6655131	3.0593372
2019Q5	0.7312133	0.6653803	3.0504025

(Source: Trading Economics)

Appendix 34 – Forecast for RMB against CAD

Quarter	CNYCAD
2019Q2	5.03439464
2019Q3	5.03112599
2019Q4	5.02841114
2019Q5	5.02551285

Appendix 35 – QLR test for p_{USD}

```
Quandt likelihood ratio test for structural break at an unknown point,
with 15 percent trimming:
The maximum F(5, 42) = 4.64781 occurs at observation 2016:1
Asymptotic p-value = 0.0074848 for chi-square(5) = 23.2391
```

Appendix 36 – QLR test for p_{EUR}

```
Quandt likelihood ratio test for structural break at an unknown point,
with 15 percent trimming:
The maximum F(6, 39) = 4.4725 occurs at observation 2008:2
Asymptotic p-value = 0.00405453 for chi-square(6) = 26.835
```