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Nonlinear prediction of Malaysian exchange rate with monetary fundamentals

Chun-Teck Lye
Multimedia University

Tze-Haw Chan
Universiti Sains Malaysia

Chee-Wooi Hooy
Universiti Sains Malaysia

Abstract

This paper compares one-step-ahead out-of-sample predictions on Malaysian Ringgit-US Dollar exchange rate using the generalized regression neural network for a range of forecasting horizons from 1991M3 to 2008M8. We find that the monetary fundamentals are significant in explaining the dynamics of Malaysian exchange rate in a longer forecast horizon as the performance of monetary exchange rate models outperformed the random walk benchmark model. The results also revealed that Malaysian exchange rate market provides profitable short-term arbitrage opportunities with lagged observations, and the integration of autoregressive terms into the monetary exchange rate models enhanced the out-of-sample forecasting performance.

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1. Introduction

Since the adoption of floating exchange rates in the 1970s, researchers have devoted immense efforts in developing fundamentally based empirical models and econometric models to explain the exchange rates movements seeing that it is universally acknowledged as an arduous task. Nonetheless, an influential paper by Meese and Rogoff (1983) has puzzled the creditability of most conventional linear econometric and monetary models in exchange rates predictions. In their study, the models failed to outperform the naïve random walk model in terms of out-of-sample forecast accuracy in short horizons. This has led to other studies progressing along this line to scrutinize Meese-Rogoff's finding using various samples and econometric specifications (e.g., Hsieh, 1988; Brooks, 1996; Soofi and Cao, 1999). These subsequent studies have reasonably conjectured that traditional linear models may be misspecified and hence are unable to adequately capture the complex nonlinear characteristics in exchange rates dynamics. The search for an alternative approach that is able to discern all essential characteristics of exchange rates without priori parametric restrictions has led to the adoption of modern technique, i.e. the artificial neural network (ANN), which is inspired by the structural and functional aspects of biological neural network.

Despite the fact that ANN is a well-recognized model that utilized in exchange rates predictions, owning to its competencies in nonstationary and nonlinear time series modeling (e.g., Panda and Narasimhan, 2007; Bissoondeeal *et al.*, 2008), its performance is significantly subjected to the structural designs of the network (see Zhang *et al.*, 1998). Therefore, in this study, we employed the Generalized Regression Neural Network (GRNN) as it has rather rigid architecture and consistency in noisy environments in a large sample size. The preference was also partly motivated by the findings of Leung, et al. (2000), that revealed the superiority of GRNN models over the widely-used multilayered feedforward network, multivariate transfer function, and random walk model in exchange rate forecasting.

In parallel, some later studies have reexamined the viability of the exchange rate-monetary fundamental relationships and provided convincing results (e.g., Rapach and Wohar, 2002; Cheung *et al.*, 2005; Cerra and Saxena, 2010). Baharumshah and Masih (2005), among others, disclosed cointegration between fundamental variables and exchange rates among the smaller economies in Asia, including Malaysia and Singapore. On the contrary, Azad (2009) argued that, in a short horizon, the Hong Kong and Malaysian foreign exchange markets are inefficient as a result of high regulations by the authorities. These foreign exchange markets may thereby provide profitable arbitrage opportunities with lagged time series observations. In other words, whether the fundamentals can better explain the currency of a small and open economy remains debatable.

Such argument leads to the interest to re-explore the Malaysian experience – a small and open developing economy in South-East Asia that greatly relies on external trade and global economic condition. For the past four decades, Malaysia has practiced various exchange rate regimes, but interventions from the authority are always evident even when floating regime is in place. Malaysia follows a managed-float system after the breakdown of the Bretton Wood fixed regime. During the Asian crisis, Malaysian ringgit was pegged at RM3.8/USD from September 1998 to July 2005. On July 21, 2005, the Central Bank of Malaysia discarded the fixed exchange rate and the floating regime was again in place.

In light of the past studies reviewed, we have decided to use GRNN to examine the validity of monetary fundamentals in explaining the movement of MYR/USD during 1991:M3 to 2008:M8. Despite the conventional Meese-Rogoff monetary models, we also employed the modified uncovered interest parity model proposed by Sarantis and Stewart (1995), which has not been applied to the Malaysia-US case. Considering the fact that the US has been Malaysia's major trading partner, all the US variables were treated as foreign variables in the exchange rate models. Additionally, we also investigate if the inclusion of autoregressive (AR) terms into the monetary exchange rate models would enhance the out-of-sample prediction accuracy of the forecasting models.

2. Data and Methods

In this study, we used the monetary exchange rate model employed in the work of Meese and Rogoff (1983). The model embraces the Frenkel-Bilson's flexible-price monetary model (FPMM) which strictly follows the purchasing power parity (PPP) rule, Dornbusch-Frankel's stickey-price monetary model (SPMM) that allows deviations from PPP, and Hooper-Morton's stickey-price asset model (SPAM) which allows changes in the real exchange rate in the long-run. The quasi-reduced form of the three models is subsumed under the general specification:

$$y = \beta_0 + \beta_1\left(m - m^*\right) - \beta_2\left(i - i^*\right) + \beta_3\left(r - r^*\right) + \beta_4\left(\pi - \pi^*\right) + \beta_5 b + \beta_6 b^* + \varepsilon \qquad (1)$$

where y is the log of exchange rate, m is the log of money supply, i is the log of real income, r is the short-term interest rate, π is the rate of inflation, b is the cumulated trade balance, and ε is the disturbance term. In all cases, all foreign variables are denoted by an asterisk. The FPMM sets $\beta_4 = \beta_5 = \beta_6 = 0$, SPMM sets $\beta_5 = \beta_6 = 0$ while the SPAM does not constrained any of the coefficients to zero. Additionally, we also examined the modified uncovered interest parity model (MUIP) proposed by Sarantis and Stewart (1995):

$$y = \alpha_0 + \alpha_1\left(r - r^*\right) - \alpha_2\left(\pi - \pi^*\right) + \alpha_3\left(p - p^*\right) + \alpha_4\chi \qquad (2)$$

where foreign variables are denoted by an asterisk, y is the nominal exchange rate, $r - r^*$ is the nominal interest differential, $\pi - \pi^*$ is the expected inflation differential, p is the relative price, and χ is risk premium which is proxy by the domestic and foreign ratios of current account to gross domestic product.

Out of all the 210 historical data, we reserved the most recent 12 observations for out-of-sample test whereas the remaining data for model building and validation. All monthly data (1991:M3 to 2008:M8) prior to the global financial crisis in September 2008 were sourced from the International Financial Statistics, IMF. However, since the data for current account and gross domestic product are only available quarterly, we used interpolation technique to convert the data into monthly frequency. All series were transformed into natural logarithm forms and the lagged differences, $\Delta y_t = \ln y_t - \ln y_{t-1}$ for each period were computed. In line with previous studies, we used the naïve random walk (RW) without drift as our benchmark model. The RW forecast was acquired by replacing the exchange rate for month t, Δy_t with the preceding month observation, Δy_{t-1}. Endeavored for a rational comparative study, we performed one-step-ahead predictions in the GRNN forecasting models, as comparable to RW.

The GRNN, which was first proposed by Specht (1991), is a class of neural network that is conceptually analogous to the kernel regression. The GRNN adopts the multivariate Gaussian function, and the output of the network is defined as:

$$\hat{y}(X) = \sum_{i=1}^{n} w_i \exp\left(-d_i^T d_i / 2s^2\right) \Big/ \sum_{i=1}^{n} \exp\left(-d_i^T d_i / 2s^2\right) \tag{3}$$

where $d_i = (X - P_i)$ is the distance between the point of prediction and the training sample, w_i is the weight of the point of prediction, and s is the smoothing parameter. As shown in Equation (3), the performance of GRNN greatly depends on the value of its only parameter, i.e. the smoothing parameter, s. Unlike previous studies which had used random generator or trial and error (see Kim *et al.*, 2004; Celikoglu, 2006), we used a more rational method to attain the optimal smoothing parameter to retain the generalization of the model and to avoid overfitting issues. Our optimal parameter was obtained based on the random validation set formed from random selection of an observation from successive equal-width intervals. The procedure in attaining the optimal network is shown in Table 1. For each random validation set, the entire process summarized in Table 1 was repeated.

Table 1: The GRNN modeling

Step 1:	Form validation set by randomly select one data from each of the 15 successive equal-width intervals.
Step 2:	Construct GRNN using the remaining 183 data and smoothing parameter, s (initial s=0.005).
Step 3:	Simulate the validation set to evaluate the mean square error (MSE) of the GRNN.
Step 4:	Increase s by +0.005. Repeat steps 2 to 3 (do until s=10).
Step 5:	Select the optimal smoothing parameter, s_b that yielded the smallest MSE.
Step 6:	Reconstruct the optimal GRNN with the optimal smoothing parameter s_b. Forecast the out-of-sample value, y_{t+a} (a = 1, 2, …).
Step 7:	Rebuild the optimal network with y_{t+a} to forecast y_{t+a+1}.
Step 8:	Repeat steps 6 to 7 until all the out-of-sample data are tested.

Table 2 lists the forecasting models considered in this paper. For each of the forecasting models that was incorporated with autoregressive terms, step 1 to step 5 in Table 1 was repeated for each lag order, q. We limited the lag length from 1 month to 12 months in this study. Consequently, the optimal values of s and q that yielded the least MSE were utilized in the forecasting model for out-of-sample tests.

Table 2: The forecasting model specifications

AR(*q*):	$\Delta y_t = G(\Delta y_{t-1},..., \Delta y_{t-p})$
FPMM(1):	$\Delta y_t = G(\Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1})$
SPMM(1):	$\Delta y_t = G(\Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1})$
SPAM(1):	$\Delta y_t = G(\Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1}, \Delta b_{t-1}, \Delta b^*_{t-1})$
MUIP(1):	$\Delta y_t = G(\Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1}, \Delta(p-p^*)_{t-1}, \Delta\chi_{t-1}, \Delta\chi^*_{t-1})$
AR(*q*)-FPMM(1):	$\Delta y_t = G(\Delta y_{t-1},..., \Delta y_{t-p}, \Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1})$
AR(*q*)-SPMM(1):	$\Delta y_t = G(\Delta y_{t-1},..., \Delta y_{t-p}, \Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1})$
AR(*q*)-SPAM(1):	$\Delta y_t = G(\Delta y_{t-1},..., \Delta y_{t-p}, \Delta(m-m^*)_{t-1}, \Delta(i-i^*)_{t-1}, \Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1}, \Delta b_{t-1}, \Delta b^*_{t-1})$
AR(*q*)-MUIP(1):	$\Delta y_t = G(\Delta y_{t-1},..., \Delta y_{t-p}, \Delta(r-r^*)_{t-1}, \Delta(\pi-\pi^*)_{t-1}, \Delta(p-p^*)_{t-1}, \Delta\chi_{t-1}, \Delta\chi^*_{t-1})$

We used four performance criteria, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Directional Symmetry (DS) and Theil's Inequality Coefficient (U) to evaluate the in-sample fits and out-of-sample predictions forecasting performance:

$$\mathrm{RMSE} = \sqrt{(1/T)\sum_{t=1}^{T}(\hat{y}_t - y_t)^2} \tag{4}$$

$$\mathrm{MAE} = (1/T)\sum_{t=1}^{T}\left|\hat{y}_t - y_t\right| \tag{5}$$

$$\mathrm{DS} = (100/T)\sum_{t=1}^{T} D_t\,, \quad D_t = \begin{cases} 1 \;\; ; & (y_t - y_{t-1})(\hat{y}_t - \hat{y}_{t-1}) \geq 0 \\ 0 \;\; ; & \textit{otherwise} \end{cases} \tag{6}$$

$$\mathrm{U} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - y_t)^2} \Bigg/ \left(\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t)^2}\right) \tag{7}$$

where y_t is the actual observation, $\hat{y}_t$ is the forecasted value, and T is the number of predictions. When evaluating the model's forecast performance, a smaller value in RMSE, MAE or U was preferred as it implied lower prediction errors, while a larger value in DS was favoured as it showed the parallels in the fluctuations between the actual and predicted observations.

3. Results and Discussion

In this empirical study, we utilized five different random validation sets to ensure no preconception on the model's performance was concluded based on a particular validation set. Table 3 exhibits the optimal values obtained in the forecasting models for different validation sets. It was evident that the smallest and largest range of the spread constants in the forecasting models was given by AR (0.015) and MUIP (0.270), respectively.

Table 3: The optimal value of spread constant *s* and lag order *q* in the forecasting models

Validation Set	Parameter	AR	FPMM	SPMM	SPAM	MUIP	AR-FPMM	AR-SPMM	AR-SPAM	AR-MUIP
1	*s*	0.005	0.065	0.070	0.125	0.285	0.055	0.010	0.035	0.120
	q	2	-	-	-	-	8	12	6	5
2	*s*	0.020	0.030	0.020	0.095	0.070	0.030	0.040	0.055	0.140
	q	12	-	-	-	-	11	10	2	6
3	*s*	0.015	0.050	0.220	0.080	0.015	0.050	0.015	0.040	0.020
	q	12	-	-	-	-	10	4	5	6
4	*s*	0.015	0.055	0.040	0.075	0.140	0.025	0.015	0.035	0.050
	q	2	-	-	-	-	6	5	9	3
5	*s*	0.005	0.015	0.075	0.100	0.040	0.075	0.035	0.050	0.045
	q	1	-	-	-	-	9	5	5	2

The overall forecasting performance of the prediction models was summarized in Table 4. Our in-sample results revealed that the all the models outperformed the benchmark RW model, in which the AR was the best in-sample fit model. Alternatively, the results of the out-of-sample predictions revealed that the monetary fundamentals became more significant at a longer forecast horizon and the observation was in line with earlier literatures (e.g., Rapach and Wohar, 2002; Chen and Chou, 2010). Specifically, the FPMM turned out to be the best monetary forecasting model in a 12-month forecast horizon. This implied that the changes in money supply, real income and interest rate were significant in the dynamic of MYR/USD. Although Sarantis and Stewart (1995) showed that interest rate was one of the main determinants in their MUIP model, our findings were in contrary in the context of risk premium and expected inflation differentials in exchange rate determination.

As for the forecasting models that were incorporated with autoregressive terms, the results demonstrated that the forecasting accuracy of the integrated models was comparatively enhanced. Plasmans *et al.* (1998) also found the same evidence in supporting the lagged observations and changes in interest rate differential as the two main underlying determinants in monthly exchange rate changes. Additionally, the results also attested the findings of Azad (2009) which argued that the Malaysian foreign exchange market was predictable and inefficient in short horizon but efficient in the long horizon as can be seen in its superior performance of AR over the RW in 6-month and 9-month forecast horizons. Further examinations on the null hypothesis of difference in the forecasting accuracy between the forecasting models and the benchmark model via *t*-tests revealed that the differences between the forecasting models and the RW were not statistically significant except for SPAM, underperformed at 6-month forecasting horizon at 5% level of significance, with *t*-statistic and *p*-value of 2.23 and 0.030, respectively.

Table 4: The overall in-sample and out-of-sample forecasting performance

	Forecast horizons	RW	AR	FPMM	SPMM	SPAM	MUIP	AR-FPMM	AR-SPMM	AR-SPAM	AR-MUIP
RMSE	In-sample	0.0372	0.0113	0.0213	0.0208	0.0232	0.0244	0.0158	0.0315	0.0331	0.0232
	6	0.0156	0.0142	0.0159	0.0184	0.0217	0.0204	0.0152	0.0151	0.0175	0.0181
	9	0.0189	0.0155	0.0158	0.0184	0.0206	0.0196	0.0159	0.0164	0.0178	0.0179
	12	0.0207	0.0221	0.0178	0.0204	0.0222	0.0218	0.0184	0.0189	0.0198	0.0208
MAE	In-sample	0.0131	0.0046	0.0086	0.0076	0.0091	0.0097	0.0066	0.0108	0.0113	0.0098
	6	0.0129	0.0124	0.0135	0.0157	0.0187	0.0169	0.0132	0.0132	0.0135	0.0151
	9	0.0158	0.0133	0.0132	0.0161	0.0180	0.0166	0.0137	0.0145	0.0145	0.0152
	12	0.0173	0.0160	0.0143	0.0171	0.0188	0.0178	0.0151	0.0158	0.0158	0.0169
DS	In-sample	19.01	38.67	32.87	41.89	38.45	39.53	31.15	19.98	19.12	21.91
	6	60.00	32.00	44.00	12.00	8.00	28.00	44.00	52.00	64.00	20.00
	9	37.50	40.00	35.00	17.50	17.50	35.00	32.50	50.00	52.50	27.50
	12	36.36	32.73	43.64	18.18	20.00	30.91	27.27	49.09	56.36	20.00
U	In-sample	0.6793	0.2187	0.5218	0.4942	0.6408	0.6590	0.3311	0.6720	0.6799	0.5614
	6	0.4575	0.7396	0.9310	0.9567	0.9875	0.9494	0.9137	0.8464	0.7973	0.9055
	9	0.5593	0.7505	0.8624	0.9366	0.9602	0.9198	0.9341	0.8417	0.8254	0.9034
	12	0.5501	0.6015	0.8419	0.9349	0.9481	0.9277	0.9398	0.8739	0.8485	0.9331

Notes: The in-sample data size evaluated is the product of the number of validation sets and the training and validation data size. The out-of-sample data size evaluated is the product of the number of validation sets and the forecasting horizons.

We conducted additional test to investigate the consistency of the GRNN forecasting models with different random validation sets employed in this study. Table 5 presents the *p*-value of the analysis of variance test for the validation sets, and the results showed no significant (statistically) differences between the out-of-sample forecasts acquired from different random validation sets in most of the assessed models. Thus, the results validated the robustness and generalization of the GRNN forecasting models built based on the random validation sets and justified its utilization in this study.

Table 5: The analysis of variance test for the validation sets

Forecast horizons	AR	FPMM	SPMM	SPAM	MUIP	AR-FPMM	AR-SPMM	AR-SPAM	AR-MUIP
6	0.289	0.287	0.209	0.859	0.349	0.731	0.995	0.991	0.980
9	0.970	0.783	0.123	0.933	0.739	0.994	0.998	0.989	0.994
12	0.742	0.875	0.336	0.974	0.971	0.996	1.000	0.992	0.994

4. Conclusion

This empirical study investigated the predictability of Malaysian exchange rate with monetary fundamentals by using the generalized regression neural network. The results found evidence of superior performance in monetary exchange rate models over random walk benchmark in longer forecast horizons. This enlightened the significance of monetary fundamentals in explaining the MYR/USD exchange rate. Thus, from the policy perspective, the monetary fundamentals are able to function as the benchmark indicators for the Malaysian foreign exchange formulation. Potential misalignments are temporal and can be corrected by monetary adjustments. In addition, both foreign price and monetary mechanism have affected the planning and implementation of domestic monetary policy, at least in a long run. The findings also revealed that the Malaysian exchange rate was predictable in the short horizon with lagged time series observations and hence could provide arbitrage opportunities for short-term investors. However, investors should carefully evaluate the associate risks, the relevant financial policies and exchange rate regime in Malaysia as compared to the US. Finally, the results also showed that the forecasting accuracy of the monetary exchange rate models in the short forecast horizon was improved by incorporating the autoregressive observations into the forecasting models.

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