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Exchange Rates Forecasting Model: An Alternative Estimation Procedure

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ABSTRAK

Kajian ini mengesyorkan suatu prosedur alternatif untuk memodel kelakuan pertukaran asing, melalui gabungan linear fungsi jangka masa panjang dan pendek. Di antara segala kombinasi kaedah-kaedah permodelan yang mungkin, kami mengesyorkan kombinasi yang paling ringkas, iaitu membentuk model jangka masa panjang berasaskan model Pariti Kuasa Beli (PPP) yang terkenal, diikuti dengan pembentukan model untuk fungsi jangka masa pendek berasaskan sifat-sifat siri masanya. Keputusan-keputusan yang diperolehi dalam kajian ini mencadangkan bahawa prosedur kami dapat menghasilkan model-model peramalan yang unggul kerana mereka meramal dengan lebih tepat lagi jika dibandingkan dengan model pergerakan rawak mudah (SRW) yang jarang diatasi secara keseluruhan oleh model-model peramalan pertukaran asing sebelum ini, dari segi peramalan luar sampel. Kajian ini memberikan kita suatu harapan yang cerah dalam penghasilan ramalan pertukaran asing negara-negara ASEAN dengan menggunakan model berasaskan kewangan dengan sedikit perubahan yang mudah.

ABSTRACT

This study proposes an alternative procedure for modelling exchange rates behaviour, which is a linear combination of a long-run function and a short-run function. Our procedure involves modelling of the long-run relationship and this is followed by the short-run function. Among all the possible combinations of modelling techniques, we proposed the simplest form, namely modelling the long-run function by the well established purchasing power parity (PPP) based model and setting up the short-run function based on its time series properties. Results of this study suggest that our procedure yields powerful forecasting models as they easily outperform the simple random walk model-which is rarely defeated in the literature of exchange rate forecasting-in terms of out-of-sample forecasting, for all the forecast horizons ranging from one to fourteen quarters. This study provides us with some hope of achieving a reasonable forecast for the ASEAN currencies using the fundamental monetary model just by a simple adaptation.

Keywords: Forecasting, exchange rate, purchasing power parity, interest rate differential, mean deviation, mean percentage error, Fisher's sign test

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INTRODUCTION

Most exchange rate markets in the floating exchange rate regime have experienced continuous and sometimes dramatic fluctuations and volatility. Mussa (1996) has summarized the broad features of exchange rate behaviour. Mussa noted that (i) exchange rates are extremely volatile, with deviation of about 3 percent per month for the US dollar-Japanese yen and US dollar-Deutschmark rates; (ii) changes in exchange rates are very persistent, and the exchange rate closely approximates a random walk; (iii) there is correlation of almost unity between real and nominal exchange rates on high frequency data; and (iv) the variability of real exchange rates increases dramatically when a country moves from fixed to floating exchange rates. All these suggest that exchange rates can be much more volatile than the apparent fundamentals, and in practice deviation from equilibrium value can be persistent. Thus, the researches of exchange rate behaviour and exchange rate forecasting have become perennial topics in international finance since the floating exchange rate regime was established in March 1973. As a result, many theories and models were developed.

The existing models of foreign exchange rates were developed using the linear and non-linear frameworks. Models based on the linear framework include the simple efficiency market approach (Fama 1965; Cornell 1977; Hsieh 1984), simple random walk approach (Giddy and Duffey 1975; Hakkio and Rush 1986), the linear fundamentals approach (for example, Dornbusch 1976; Frankel 1979; Meese and Rogoff 1983; Mark 1995; Clark and MacDonald 1998), the time series approach (for instance, Keller 1989; Cheung 1993; Palma and Chan 1997; Brooks 1997; Parikh and Williams 1998; Baharumshah and Liew 2003), the conditional heteroscedasticity approach (Engle 1982; Bollerslev 1986), among others.

There is a growing consensus among researchers that exchange rates and other financial variables are non-linear in nature (Brooks 1996; Taylor and Peel 2000; Liew *et al.* 2002) and so they are linearly unpredictable (Boothe and Glassman 1987; Plasmans *et al.* 1998). Hence the non-linear structural models are regarded more relevant in modelling these variables. Models in conjunction with this more recent view are commonly estimated through the non-linear fundamentals approach (see for example, Meese and Rose 1991; Lin and Chen 1998; Ma and Kanas 2000; Coakley and Fuertes 2001), the Exponential GARCH approach (Nelson 1991), the SETAR approach (Kräger and Kugler 1993), and the neural networks approach (Franses and Homelen 1998; Plasmans *et al.* 1998), among others.

Nevertheless, after three decades of research, exchange rate theory that provides a satisfactory and empirically consistent theory of the exchange rate remains to be uncovered (Hallwood and MacDonald 1994: p. 22). Like any other financial variables, exchange rates are difficult to forecast with any precision. The bulk of evidence has so far been proven illusive (Berkowitz and Giorgianni 1997; Lin and Chen 1998). In their survey on empirical work of exchange rate, Frankel and Rose (1995) make the following remark: We, like much of the profession, are doubtful of the value of further time series modelling of exchange rates at high or medium frequencies using macroeconomic models.' This observation has motivated us to search for an alternative approach to model exchange rates.

This study attempts to model exchange rates and the focus is on the ability of the model to yield reliable forecast in the short and intermediate run. The main focus is to construct a model that can capture the dynamics of exchange rates in the emerging economies. The model that we consider is a linear combination of long and short run functions. The long run component of the model is set to represent the relationship between any exchange rate and its fundamental variables (e.g. relative price, interest differential and money supply), whereas the short-run equation is based on time series model and is used to capture the deviations of the exchange rate from its long-run path[1]. Thus, the estimation procedure involves two stages: first, the long-run model is fitted to the data, and this is followed by the short-run function. To this end, we relied on the widely used linear structural model (purchasing power parity, PPP) hypothesis to trace the long-run relationship between exchange rate and its determinant[2]. To account for the inadequacy of the pure PPP model, we augmented the short-run component of the model based on statistical properties of the data[3]. In this article, our focus is on the PPP and interest differential models (IRD). We have no intention to identify a set of fundamental variables that is most appropriate to tract the movements of the exchange rates but simply to show that information contained in both domestic and foreign macroeconomic variables (prices and term structures of interest rates) may not be sufficient to tract the movement of exchanges rates. Intuitively, one may expect to gain efficiency in the forecasts, by adding more information to the

[1] Many theoretical models suggest that exchange rates should be jointly determined with macroeconomic variables such as foreign ad domestic money supplies, real growth rates, interest rates, price levels, and balance of payments. However, as mentioned earlier the empirical performance of these models has been very poor. In fact, Meese (1990) concludes that '*the proportions of (monthly or quarterly) exchange rate changes that current models can explain is essentially zero.*"

[2] A hallmark of the conventional model of real exchange rate is that it follows a PPP benchmark in the long run. Briefly, the PPP doctrine states that the price of a basket of goods should equate across countries when evaluated in common currency. For the empirical work on PPP, see Nagayasu (1998), Coakley and Fuertes (1997), and M-Azali et al. (2001), to name a few. The work by Nagayasu found support for a "semi-strong' version of the long-run PPP hypothesis in a sample of 16 African countries. M-Azali et al. also found evidence that PPP holds between the developing Asian countries and Japan.

[3] This is in line with the view that PPP is a long run relationship and overtime prices adjust and PPP is re-established.

model. For this purpose, we compare the performance of the simple PPP model with that of the interest rate differential (IRD) model[4].

The rest of this paper is organized as follows: In the section that follows, we construct the proposed model. Section 3 describes the method used in the analysis and Section 4 interprets the results of the empirical investigation. The last section concludes this paper.

Derivation of the Model

The estimation of model is based on a two-step procedure. First, the long-run component of the model is considered and second, the deviation of the actual observations from its long-run equilibrium path is considered to model the short-run component of the model. In this way, our forecasting model will not only trace the long-run movement, but is also capable of capturing misalignment in the exchange rate series that may occur in the short-run. This strategy is also in line with the argument that exchange rates can be more volatile than the fundamentals; in our case it is the relative price and/or interest rate differential. Consider the model

$$X_t = f_t(l_1, l_2, \ldots, l_l) + g_t(s_1, s_2, \ldots, s_s) \tag{1}$$

where X_t is exchange rate defined as domestic currency, per unit foreign currency; $f_t(l_1, l_2, \ldots, l_l)$ is a set of long-run determinants $\{l_1, l_2, \ldots, l_l\}$ that explained the long-run movement of the exchange rate; and $g_t(s_1, s_2, \ldots, s_s)$ is a function of a set of short-run determinants $\{s_1, s_2, \ldots, s_s\}$ that may cause exchange rate to deviate from its long-run equilibrium path.

Let the expected value of f_t be given by $\hat{X}_t$, which is determined by the fundamental variables. By subtracting the value of $\hat{X}_t$ on both sides of (1) we obtained

$$X_t - \hat{X}_t = f_t - \hat{X}_t + g_t \tag{2}$$

If $\hat{X}_t$ is an unbiased predictor of f_t, then the term $(f_t - \hat{X}_t)$ on the RHS of (2) vanishes to random error term, ε_t with mean zero and variance σ^2_ε. Thus, we have

$$X_t - \hat{X}_t = \varepsilon_t + g_t \qquad \text{where } \varepsilon_t \sim \text{WN } (0, \sigma^2_\varepsilon) \tag{3}$$

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[4] The literature has not provided conclusive evidence on the long-run determinants of exchange rate. Frankel (1979) sets the long-run determinants as the relative interest rates. Dornbusch (1976) and Chin dan Meese (1995) identify the long-run determinants based on the standard monetary model (money supply, income and inflation rate). Clark and MacDonald (1998) include interest rates, government debt ratio, terms of trade, price levels and net foreign assets to model the exchange rates.

or equivalently

$$X_t = \hat{X}_t + g_t + \varepsilon_t \quad (4)$$

Modelling short-run function g_t is even more complicated as the subsets of short-run determinants may change over time due to either internal or external events (e.g. policy change, capital reversal and regional financial crises). One way out of this dilemma is to think of g_t as generated by time series mechanism, whatever the underlying macroeconomic determinants may be. For instance, one may think of g_t as represented by the ARIMA, ARFIMA or GARCH processes. It is worth noting that the GARCH process involves modelling the square of residuals, and in our case, g_t. However, authors like McKenzie (1999) have pointed out that by squaring the residuals, one effectively imposes a structure on the data, which has the potential of reducing the forecasting performance of the model. In the present study, we assume that g_t as proportionate to its most recent available value, g_{t-1}, to avoid the problem of complexity, i.e.

$$g_t = \alpha\ g_{t-1} + v_t \text{ where } v_t \sim \text{WN }(0, \sigma^2_\varepsilon) \quad (5)$$

with $\alpha < 1$ if g_t is stationary and $\alpha \geq 1$ if g_t is non-stationary.

By simply substituting (5) into (4) and upon simplification, we obtained the final model that is

$$X_t = \hat{X}_t + \alpha\ (X_{t-1} - \hat{X}_{t-1}) + \mu_t \quad \text{where } \mu_t = \varepsilon_t + v_t \quad (6)$$

Clearly, the estimation of Equation (6) also involves procedures to solve for $\hat{X}_t$ and searching for optimal value of α.

METHODOLOGY

In this study we attempt to model the Malaysia ringgit (MYR), the Singapore dollar (SGD), and Thailand baht (THB) against the US dollar (USD) and Japanese yen (JPY), all of which have received little attention in the exchange rate literature. The base currencies chosen are based on the importance of trade to these ASEAN countries. According to the International Monetary Fund (IMF)'s classification, these countries pegged their currency to a basket of currencies (the US dollar received that highest weight). Our sample period covers the first quarter of the year 1980 to the fourth quarter of the year 2000 (1980:1 to 2000:4). Bilateral rates used in the analysis are the end of period market rate specified as line ae in *International Financial Statistics* published by the IMF, except for the MYR/USD rate. For the case of MYR/USD rate, we choose the series from line aa, which is calculated on the basis of SDR rate. This is to avoid the problem of zero denominators that may arise during the assessment of the performance of the forecasting exercises.

Besides the bilateral exchange rate series, data on relative price and interest differential are also utilized in this study. The price variable is constructed as the ratio of domestic price to foreign price. We use consumer price indices (CPI 1995 = 100) as the proxy for prices. Interest rate differential is computed by dividing the domestic market rate over the foreign market rate. All the data series are taken from various monthly issues of IMF/IFS. The full sample period is divided into two periods. The first sub-period that begins in 1980:1 and ends in 1997:2 is used for the purpose of estimation and the remaining observations (1997:2-2000:4) are kept for assessing the out-of-sample forecast performance of the model. Following the work of García-Ferrer *et al.* (1997), our data are purposely treated in such a way that they showed a break in the trend (due to the 1997 Asian financial crisis) during the forecasting period, making the prediction exercise more difficult. Specifically, the large depreciation in the post currency crisis period makes the post-sample prediction more stringent [5].

For each country, we first examine the time series properties of three variables used in the analysis. We applied the augmented Dickey Fuller (ADF) and the Philips-Perron (PP) unit root tests to the level and first differences of the data. Results of unit root test are summarized in Table 1.

Overwhelmingly, the results of the unit root tests suggest that we cannot reject the hypothesis of nonstationarity in levels and reject it in first differences in all the series, except in one case (SGD/JPY)[6]. Since exchange rates, relative price and interest rate differential exhibit the same order of integration, this allows us to proceed with the co-integration test. To this end we utilise the Johansen and Juselius (1990) multivariate cointegration test that is based on statistics: trace test and the maximum eigenvalue tests.

For each country we ran the vector autoregressive (VAR) system in levels with one to five lags. The primary goal was to eliminate serial correlation while avoiding power-draining due to the presence of too many lags. We also check for serial correlation using the Bruesch-Godfrey asymptotic test before deciding on the optimal lag for the VAR model. The results of the Johansen-Juselius co-integration test are tabulated in Table 2. Table 2 reveals that all the exchange rates (except THB/USD) are co-integrated with their corresponding relative prices at the 5% significance level or better. This finding suggests that long-run relationship between exchange rate and relative price exists in the studied countries. Hence, the co-integration test results are consistent with the PPP hypothesis at least for the five exchange rates (MYR/USD, SGD/USD, MYR/JPY, THB/JPY and SGD/JPY).

Similarly, we found that for all the countries exchange rates, relative price and interest differential variables for all cases (except SGD/JPY and THB/

[5] Visual inspection of the data reveals that up to the middle of 1997 volatility is less pronounced, whilst thereafter it rises substantially.

[6] Because of the low power of the classical unit root tests, we continue with the analysis by assuming that all the exchange rate series are I(1) variable.

TABLE 1
Results unit root tests

Countries	Intercept Without Trend						Intercept With Trend					
	X	ΔX	P	ΔP	I	ΔI	X	ΔX	P	ΔP	I	ΔI
Augmented Dickey - Fuller Test												
Malaysia - US	-0.658	-5.079*	-1.445	-5.170*	-2.001	-3.923*	-2.763	-5.088*	-0.780	-5.434*	-1.980	-4.043*
Thailand - US	-0.562	-5.377*	-0.479	-3.866*	-2.131	-4.801*	-1.691	-5.377*	-1.482	-3.971*	-2.782	-4.802*
Singapore - US	-1.000	-5.114*	-2.492	-6.148*	-3.104#	-4.768*	-0.544	-5.131*	-1.729	-6.583*	-3.142	-4.738*
Malaysia - Japan	-0.362	-4.958*	1.989	-5.537*	-2.148	-4.815*	-2.696	-4.953*	-0.040	-6.260*	-2.802	-4.657*
Thailand - Japan	0.179	-6.336*	1.237	-3.541*	-1.758	-5.566*	-2.489	-6.482*	-0.985	-3.920*	-2.494	-5.533*
Singapore - Japan	-0.211	-3.712*	0.054	-5.551*	-3.633#	-3.076*	-0.575	-3.989*	-1.172	-5.744*	-4.066#	-2.721
Philips - Perron Test												
Malaysia - US	-0.661	-10.70*	-1.948	-10.83*	-2.448	-7.097*	-2.973	-10.09*	-1.152	-11.19*	-2.251	-7.106*
Thailand - US	-0.731	-9.827*	-0.414	-7.479*	-2.084	-7.227*	-2.161	-9.828*	-1.351	-7.572*	-2.354	-7.171*
Singapore - US	-1.370	-9.930*	-3.626#	-8.823*	-3.072#	-6.957*	-0.987	-9.930*	-1.817	-9.906*	-3.117	-6.903*
Malaysia - Japan	-0.528	-8.653*	3.726	-11.67*	-2.998	-11.54*	-2.987	-8.653*	0.233	-12.86*	-3.726#	-11.44*
Thailand - Japan	-0.576	-11.10*	-1.360	-9.811*	-1.787	-7.014*	-3.107	-11.10*	-0.757	-10.13*	-2.541	-6.948*
Singapore - Japan	0.240	-5.811*	0.991	-11.18*	-3.439#	-10.79*	-0.832	-5.811*	-0.842	-11.43*	-4.042#	-10.70*

Notes:X, P and I denote exchange rate, relative price and interest differential respectively. Δ denotes first difference. Optimum lag length is automatically given by E-views based on Newey and West (1987).
Critical values are given by McKinnon (1991). Test-statistics with * and # denote reject null hypothesis of unit-root at 1% and 5% level respectively.

TABLE 2
Co-integration test results

Pairwise Variables	Exchange Rate and Relative Price			Exchange Rate, Relative Price and Interest Differential[a]			
		Likelihood Ratio[b]			Likelihood Ratio[b]		
Countries	Lag[c]	r = 0	r ≤ 1	Lag[c]	r = 0	r ≤ 1	r ≤ 2
Based Country: United States							
Malaysia	8	21.646#	8.189	6	33.576#	11.412	1.363
Thailand	10	12.573	4.765	3	28.346	13.435	4.066
Singapore	12	38.982*	8.871	2	33.610#	10.058	0.568
Based Country: Japan							
Malaysia	10	24.369#	5 061	12	89.299*	21.391*	1.359
Thailand	11	23.884#	9.080	12	36.579*	13.122	2.106
Singapore	12	24.559#	2.817	—	—	—	—
Critical Values							
5%		19.90	9.24		29.68	15.41	3.76
1%		24.60	12.97		36.65	20.04	6.65

Note: [a]For SGD/JPY, the three variables are not integrated of the same order, hence cointegration does not exist by definition.
[b] r denotes the hypothesized number of co-integrating equation.
[c] Optimum lag-length is determined by the AIC statistics.
* and # denote rejection of hypothesis at 1% and 5% significance level respectively.

USD) are co-integrated (see Table 2). All in all, there exists at least one co-integrating vector in the exchange rates based on conventional significance levels.

Our next task is to proceed with the forecasting model as given in Equation (6). The estimation involves two steps. In step one, we estimate the PPP model by regressing the exchange rate (X_t) on CPI (or IPI) ratios (P_t). For the case of SGD/USD, for instance, the PPP model is estimated by running SGD/USD on PS/PU, where PS and PU are CPI (1995=100) of Singapore and CPI (1995=100) of US respectively. Then we compute the values of $\hat{X}_t$, which is the predictor of the spot exchange rate, g_t. The deviation from the long-run model, g_t is obtained as

$$g_t = Xt - \hat{X}_t \tag{7}$$

In step two, we estimate the function as suggested in Equation (5). In this study, we employ a search algorithm to determine the optimum value of α such that the in-sample forecasting error is the minimum with respect to the selected criteria (e.g. Mean Square Forecast Error (MSE) and the Mean Square Percentage

Error (MSPE), Mean Absolute Percentage Error (MAPE) and Theils' *U*). We chose to minimise the MAPE of the in-sample forecasts as we found that it is more reliable in the sense that the selected optimum for the in-sample period is a better estimator for the optimum value of the out-of-sample period (results not shown here but are available upon request).

The optimum model is then subjected to a battery of diagnostic tests. We emphasized two important aspects, namely the efficiency of the forecasts and the stationarity of the residuals, μ_t. If the model is capable of capturing the long run and short run movements of the actual exchange rate behaviour, the residuals must be random errors and hence stationary. Besides that, since we utilize time series data it is important that we eliminate serial correlation. We checked for serial correlation by using the standard Durbin-Watson (*d*) and Bruesch-Godfey Lagrange Multiplier (LM) test for autocorrelation.

To sum up, the selection process for the "optimum" model can be summarized by the follow steps:

Step One: (1) Regress sample exchange rate, X_t on sample relative price, P_t; (2) Obtain $\hat{X}_t$ from the regression; and (3) Compute $g_t = X_t - \hat{X}_t$.

Step Two: (1) Search for optimum with based on selected criteria; (2) Check for serial correlation on the residuals and efficiency of model; and (3) proceed with forecasting.

In order to forecast X_{t+n} where the number of quarter, $n = 1, ..., 14$ for the out-of-sample period (1997:3 to 2000:4), we need to have the values of P_{t+n}. As P_{t+n} is also not available, the fastest way of obtaining reliable estimator for it is to do forecasting using the ARIMA methodology. The reason why we chose not to forecast directly using the ARIMA methodology is that although this method could provide better forecasts (see for examples, Montogomery *et al.* 1990; Lupoletti and Webb 1986 and Litterman 1986), it is not capable of significantly outperforming the simple naïve model for the case of ASEAN currencies; see Baharumshah and Liew (2003).

The performance of our forecasting models over the forecast horizon of $n = 1$, then $n = 2$ and so forth until $n = 14$ quarters are evaluated by taking the naïve models of predicting no change as the benchmark. The criteria involved are the minimum of the Mean Square Forecast Error (*MSE*) and the Mean Square Percentage Error (*MSPE*) and the Mean Absolute Percentage Error (*MAPE*) ratios of the two competing models, with the appropriate error criterion of the naïve model as denominator. If the ratio is greater than one, it implies the naïve model is better. If the ratio is less than one, it means the forecasting model has defeated the naïve model and the researchers' effort is at least paid-off. It is worth noting that the closer the ratio to zero, the better is the forecast. We also provide the statistical significance of the MSE ratio using Meese and Rogoff (1988) (MR) test statistics defined as:

$$MR = \frac{\bar{s}_{UV}}{\sqrt{\frac{1}{n^2}\sum_{j=1}^{n} u_j^2 v_j^2}} \overset{asy}{\sim} N(0,1) \tag{8}$$

where $\bar{s}_{UV}$ is the sample covariance of means of U and V (transformed functions of forecast errors of two rival models) and is approximated by $\frac{1}{n}\sum_{j=1}^{n}\left(u_j - \bar{u}\right)\left(v_j - \bar{v}\right)$ where $\bar{u} = \frac{1}{n}\sum_{j=1}^{n} u_j$ and $\bar{v} = \frac{1}{n}\sum_{j=1}^{n} v_j$ with $u_j = e_{1j} - e_{2j}$ and $u_j = e_{1j} + e_{2j}$ in which e_{ij}, $i = 1, 2$ is the j^{th} forecast error of model i; and n is the number of forecasts.

Following Wu and Chen (2001), we also applied the Fisher's sign test (FS). Briefly, the FS test compares the forecast accuracy of two competing models term by term on the basis of loss differential, whereby the accuracy criterion could be based on MSE, MSPE, MAPE, among others. The Fisher's sign test is the total number of negative loss differential (d_j) observations in a sample size n. Under the null hypothesis of "equal accuracy of two competing forecasts", FS has a binomial distribution with parameter n and 0.5. The significance of test is assessed using a table of the cumulative binomial distribution.

In this study we also estimated our model by using the same procedure as described above but a different long-run fundamental model that is the interest rate differential (IRD) model. This is achieved by adding the interest rate differential to the pure PPP model as an additional explanatory variable. The purpose is to study whether by adding extra information, the forecasting performance of the model could be improved or not.

RESULTS AND INTERPRETATION

The empirical results from the estimated PPP model and its adapted form are summarized in Table 3. As expected, the true PPP model only managed to capture the long-run movement of the actual exchange rate, but the adapted model has been adapted (or trained) to trace the short-run deviation of the actual exchange rate from its long-run course (*Fig.* 1). The R^2 suggests that relative price, P_t could account for 58.52 to 68.35% of the variation in bilateral rates of the ASEAN currencies (Table 3). The adapted model for the five ASEAN currencies tabulated is selected based on MAPE criterion. Notice that the R^2 value for the Singapore-yen rate (SGD/JPY) rate is unacceptably low (17.96)! Because of the poor performance base on the R^2, we did not pursue further and dropped it from the analysis[7].

[7] We found that the optimum model selected through this criterion (and in fact, other criteria e.g. MSE and Theil-U) may not necessary pass all the diagnostic tests. These results based on other criteria are not shown here but are available upon request from the authors.

TABLE 3
Estimated models

Exchange Rates	Estimated Coefficients[a]			R^2 Values	Optimal α Values[b]
	Intercept	Relative Price	Interest Differential		
		PPP Model[c]			
MYR/USD	12.283 (13.54)*	-8.881 (-9.94)*	—	0.585	0.929
SGD/USD	-0.529 (-2.62)#	2.177 (11.96)*	—	0.678	0.900
MYR/JPY	-0.010 (-3.12)*	0.028 (7.467)*	—	0.451	0.935
THB/JPY	-0.178 (-6.14)*	0.448 (12.12)*	—	0.684	0.940
SGD/JPY	0.020 (6.97)*	-0.011 (3.564)*	—	0.180	—
		IRD Model			
MYR/USD	12.030 (11.17)*	-8.669 (8.51)*	0.038 (0.44)	0.352	0.929
SGD/USD	-1.468 (-5.52)*	3.113 (13.24)*	-0.048 (-0.40)	0.755	0.900
MYR/JPY	-0.029 (-5.55)*	0.054 (8.38)*	-0.001 (-4.66)*	0.549	0.995
THB/JPY	-0.295 (-6.69)*	0.659 (9.12)*	-0.022 (-3.35)*	0.729	0.700

Notes: [a] t-statistics are given in parenthesis. * and # stand for significantly different from zero at 1% and 5% level respectively.

[b] The adapted model is of the form $\hat{\hat{X}} = \hat{X}_t + \alpha\,(X_{t-1} - \hat{X}_{t-1})$ where $\hat{\hat{X}}$ and $\hat{X}_t$ denote exchange rate (X_t) predicted by the adapted model and PPP Model or IRD Model respectively, and the optimal value for each adapted model is obtained by a computer search algorithm.

[c] Estimated PPP Model for SGD/JPY has very low R^2 value and hence we do not attempt to adapt it.

We subjected the selected model to a battery of diagnostic checking before the model is used to generate the in-sample and post-sample forecasts. Results of diagnostic tests performed on both the pure and adapted models' are depicted in Table 4. A striking feature of the results shown in Table 4 is that the pure PPP model proved incapable of completely attaining the serial correlation standard. The PPP model is contaminated with series correlation problem (positively correlated) as it has low Durbin-Watson *d* statistic[8]. This finding is further supported by the large values of Breusch-Godfrey Lagrange Multiplier (*LM*) statistics, which indicate that there exists serial correlation up to 12-lag length. On the other hand, the adapted PPP model easily passed the serial correlation tests. We consider these results as indication that the standard

[8] In our study, we have 70 in-sample observations and hence the actual decision region for the Durbin-Watson autocorrelation test of no autocorrelation in our model is $1.485 \leq d \leq 2.571$, at 1% significance level.

TABLE 4
Diagnostic test for PPP model and the adapted form

PPP Model		Adapted PPP Model	
1. MYR/USD			
$X_t = -0.163 + 1.032\ \hat{X}_t + \varepsilon_t$		$X_t = 0.039 + 0.987\ \hat{\hat{X}} + \mu_t$	
(0.217) (0.064)		(0.108) (0.033)	
$R^2 = 0.793$	$\varepsilon_t \sim I(1)$	$R^2 = 0.932$	$\mu_t \sim I(0)$
$d = 0.361$	$LM\ (12) = 48.226$	$d = 2.385$	$LM\ (12) = 11.839$
$\chi^2_2 = 4.039$	$\chi^2_1 = 0.250$	$\chi^2_2 = 0.200$	$\chi^2_1 = 0.154$
2. SGD/USD			
$X_t = -0.761 + 1.446\ \hat{X}_t + \varepsilon_t$		$X_t = -0.204 + 1.115\ \hat{\hat{X}}_t + \mu_t$	
(0.200) (0.116)		(0.047) (0.026)	
$R^2 = 0.752$	$\varepsilon_t \sim I(1)$	$R^2 = 0.971$	$\mu_t \sim I(0)$
$d = 0.141$	$LM\ (12) = 60.232$	$d = 2.23$	$LM\ (12) = 11.655$
$\chi^2_2 = 0.951$	$\chi^2_1 = 0.358$	$\chi^2_2 = 4.389$	$\chi^2_1 = 3.402$
3. MYR/JPY			
$X_t = 0.000 + 0.977\ \hat{X}_t + \varepsilon_t$		$X_t = 0.001 + 0.933\ \hat{\hat{X}}_t + \mu_t$	
(0.001) (0.144)		(0.006) (0.037)	
$R^2 = 0.423$	$\varepsilon_t \sim I(1)$	$R^2 = 0.905$	$\mu_t \sim I(0)$
$d = 0.145$	$LM\ (12) = 0.767$	$d = 1.728$	$LM\ (12) = 13.821$
$\chi^2_2 = 5.516$	$\chi^2_1 = 5.160$	$\chi^2_2 = 3.913$	$\chi^2_1 = 3.242$
4. THB/JPY			
$X_t = 0.002 + 0.989\ \hat{X}_t + \varepsilon_t$		$X_t = 0.006 + 0.959\ \hat{\hat{X}}_t + \mu_t$	
(0.013) (0.085)		(0.005) (0.026)	
$R^2 = 0.664$	$\varepsilon_t \sim I(1)$	$R^2 = 0.953$	$\mu_t \sim I(0)$
$d = 0.145$	$LM\ (12) = 60.414$	$d = 1.706$	$LM\ (12) = 13.965$
$\chi^2_2 = 0.023$	$\chi^2_1 = 2.868$	$\chi^2_2 = 2.877$	$\chi^2_1 = 2.528$

Notes: X_t is the actual exchange rate, $\hat{X}_t$ and $\hat{\hat{X}}$ are the predictors of X_t with the former from the PPP model and the latter from the adapted model. The standard error for each estimated coefficient is given in parenthesis. The Wald tests for the null hypotheses of strong (β=0 and β_1=1) and weak (β_1=1) form efficiency of the predictors are reported as χ^2_2 and χ^2_1 respectively. The 5% critical values for the chi-square concerned are in that order, 5.99 and 3.84. Both d and LM(12) are the Durbin-Watson statistic and Lagrange Multiplier statistic for serial correlation. The 5% critical value for LM(12) statistic (chi-squared distributed) is 21.03.

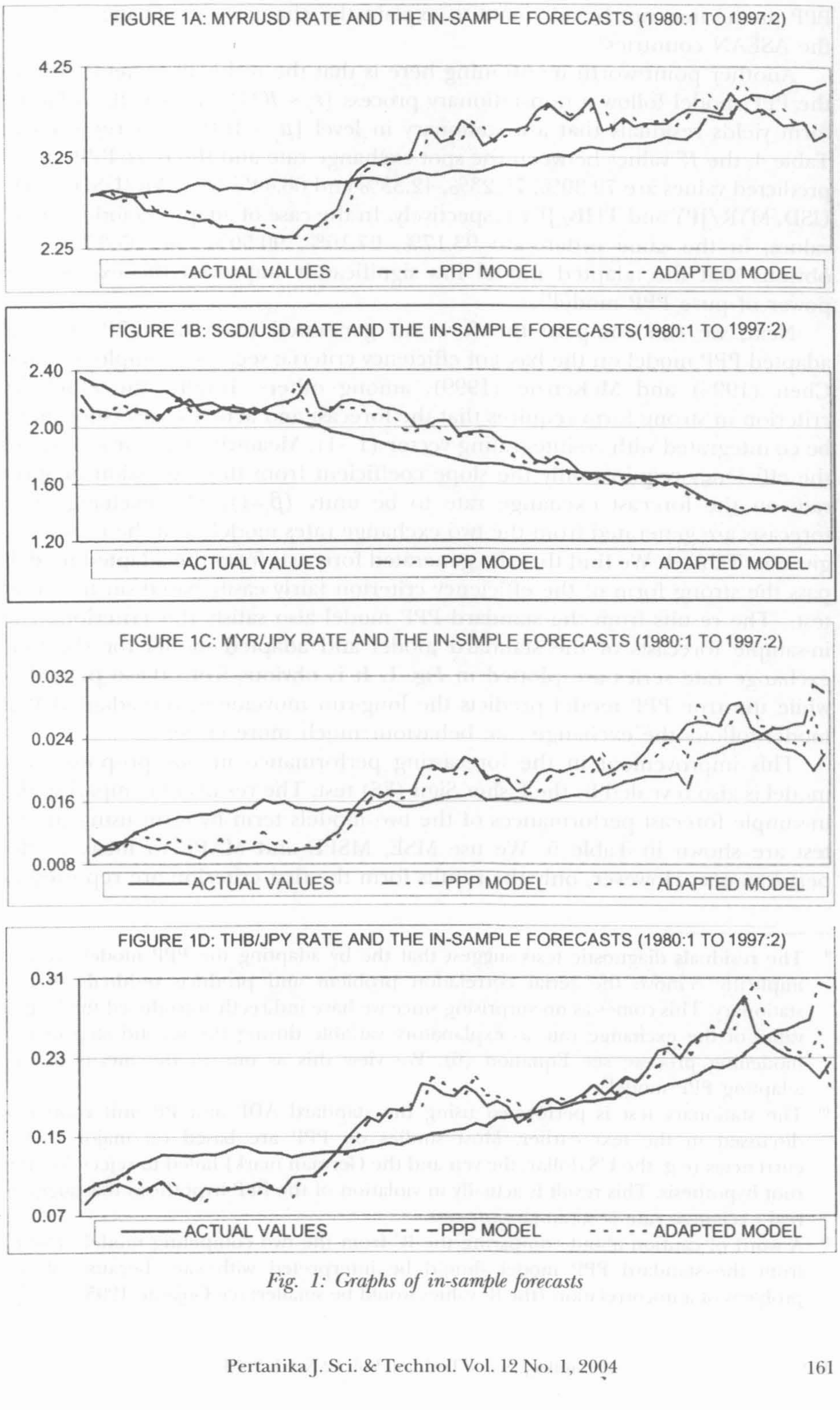

Fig. 1: Graphs of in-sample forecasts

PPP model may not be adequate to explain the changes in exchange rates of the ASEAN countries[9].

Another point worth mentioning here is that the residuals generated from the PPP model follow a nonstationary process [$\varepsilon_t \sim I(1)$] whereas the adapted form yields residuals that are stationary in level [$\mu_t \sim I(0)$].[10] As reported in Table 4, the R^2 values between the spot exchange rate and the pure PPP model predicted values are 79.30%, 75.23%, 42.33% and 66.44% for MYR/USD, SGD/USD, MYR/JPY and THB/JPY respectively. In the case of adapted model, the R^2 values, in the same order, are 93.17%, 97.10%, 90.50% and 95.33%. It is obvious that the adapted model has significantly improved the explanatory power of pure PPP model[11].

Next, we can compare the forecasts generated from the PPP and the adapted PPP model on the basis of efficiency criteria; see, for example, Lin and Chen (1998) and McKenzie (1999), among others. Briefly, the efficiency criterion in strong form requires that the forecast and actual series (spot rates) be co-integrated with co-integrating vector (1, -1). Meanwhile the weak form of the efficiency requires only the slope coefficient from the regression of sport rate on the forecast exchange rate to be unity (β_1=1). The exchange rate forecasts are generated from the two exchange rates models and the results are given in Table 4. We find that the generated forecasts form the adapted models pass the strong form of the efficiency criterion fairly easily based on the Wald test. The results from the standard PPP model also satisfy this criterion. The in-sample forecasts of the standard model and adapted model for the four exchange rate series are plotted in *Fig.* 1. It is obvious from these plots that while the true PPP model predicts the long-run movement, the adapted PPP model follows the exchange rate behaviour much more closely.

This improvement in the forecasting performance in our proposed mix model is also revealed by the Fisher Sign (FS) test. The results of comparing the in-sample forecast performances of the two models term by term using the FS test are shown in Table 5. We use MSE, MSPE and MAPE to measure the performance. However, only the results form the first criterion are reported as

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9 The residuals diagnostic tests suggest that the by adapting the PPP model, we can implicitly remove the serial correlation problem and produce residuals that is stationary. This comes as no surprising since we have indirectly introduced the lagged value of the exchange rate as explanatory variable during the second step of our modelling process; see Equation (6). We view this as one of the merits of our adapting PPP model.

10 The stationary test is performed using the standard ADF and PP unit root tests discussed in the text earlier. Most studies on PPP are based on major traded currencies (e.g. the US dollar, the yen and the German mark) failed to reject the unit root hypothesis. This result is actually in violation of the PPP hypothesis that suggests real exchange rate is stationary process.

11 A word of caution about comparing the R^2 from the two competing models The R^2 from the standard PPP model should be interpreted with care because of the problem of autocorrelation (the R^2 values would be smaller; see Gujarati 1995, p. 411).

the other two criteria produce the same outcome qualitatively. It appears that adapting the PPP model increased the total loss differentials from 15, 9, 7 and 10 to 32, 24, 24 and 33 out of a total of 65 forecasts for MYR/USD, SGD/USD, MYR/JPY and THB/JPY correspondingly. This finding implies that the adapted model is at least twice as good as the original PPP model. It is worth mentioning that the improvement is realised not only in the in-sample but also out-of-sample forecasts. We will discuss the out-of-sample forecasts in greater detail later.

A consensus has emerged among economists that exchange rate misalignments over an extended period of time may trigger a currency or economic crisis. Indeed, a number of studies have provided the evidence that overvaluation is a key factor in predicting forthcoming financial crises; see Kaminsky and Reinhart (1999) and Goldfajn and Valdes (1999), among others. We used the adapted PPP model to compute the equilibrium exchange rates and compared these values with the actual or observed rates. The period chosen is 8 quarters just prior to the outbreak of the Asian Financial Crisis. To accomplish this task, we calculate the mean deviation (*MD*) of the observed rate from its equilibrium value. A negative *MD* by definition implies overvaluation while a positive value means otherwise. Meanwhile, *MD*=0 means no deviation and the observed rate is effectively in equilibrium. Mean percentage error (*MPE*) is also constructed so that the magnitude of overvaluation (or undervaluation) can easily be compared across currencies. Interpretation of the sign of *MPE* is similar to that of *MD*. Simply reporting the point estimates may not provide a complete picture of the misalignment experienced by the crisis-affected countries. We supplement the point estimates by the Fisher's sign (FS) test to indicate whether the point estimates are statistically significant. These test results are presented in Table 6.

It is obvious from Table 6 that both the *MD* and *MPE* values are all in the negative range for the four exchange rates. This suggests that all four currencies were overvalued in several quarters prior to the crisis. In addition, the MPE values reveal that baht-yen rate (THB/JPY, -7.6889%) is the most overvalued currency, followed by MYR/JPY (-4.9811%), SGD/USD (-0.6966%) and MYR/USD (-0.1348%). It appears that the most overvalued currency (Thai baht) was the currency most susceptible to crisis. This result coincided with the historical events surrounding the recent financial crisis. The baht, which was initially pegged to the US dollar, was the first currency in the region that was forced to devalue. The pressures then quickly spread to neighbouring countries. Another interesting observation present in Table 6 is that the values of FS statistic suggest that the overvaluation is statistically significant at 5% level in the yen-based currencies (MYR and THB) but not for dollar-based currencies (MYR and SGD). In a nutshell, although the *FS* test indicates not all currencies were statistically significanly misaligned, the model offers some support for the

TABLE 5
Forecasting performance of PPP models and adapted PPP models by Fisher's sign (FS) test[a]

PPP Model Vs. Random Walk[b]				Adapted PPP Model Vs. Random Walk[c]			
MYR/USD	SGD/USD	MYR/JPY	THB/JPY	MYR/USD	SGD/USD	MYR/JPY	THB/JPY
In-sample (Forecast Horizon = 65 Quarters)							
15 (0.000)	9 (0.000)	7 (0.000)	10 (0.000)	32 (0.098)	24 (0.011)	24 (0.010)	33 (0.098)
Out-of-sample (Forecast Horizon = 14 Quarters)							
0 (0.000)	3 (0.022)	4 (0.061)	5 (0.122)	8 (0.183)	10 (0.061)	8 (0.183)	6 (0.183)

Notes: [a] Total numbers of negative loss differential are reported with marginal significance value (msv) given in parenthesis. The null hypothesis of FS test is 2 forecasting models have equal accuracy.
[b] Loss differential = $SE_{PPP,j} - SE_{RW,j}$; $j = 1, ..., n$, where n is the forecast horizon. SE_{PPP} and SE_{RW} stand for Square Error of PPP model and Random Walk model respectively.
[c] Loss differential = $SE_{ADPPP,j} - SE_{RW,j}$; j = 1, ..., n, where n is the forecast horizon. SE_{ADPPP} and SE_{RW} stand for Square Error of Adapted PPP model and Random Walk model respectively.

TABLE 6
Evaluation of the position of exchange rates before Asian crisis

	For 8 Quarterly Forecasted Values			
CRITERIA	MYR/USD	SGD/USD	MYR/JPY	THB/JPY
MD[a]	-0.0079	-0.0097	-0.0008	-0.0177
MPE[b]	-0.1348	-0.6966	-4.9811	-7.6889
FS[c]	5 (0.2188)	5(0.2188)	7 (0.0313)	7 (0.0313)

Notes: [a]*MD* = Mean deviation. Negative value implies overvaluation is detected.
[b]*MPE* = Mean percentage error. Negative value implies overvaluation is detected.
[c]*FS* = Fisher's sign test. Total numbers of overvaluation are reported with marginal significance value (msv) given in parenthesis. The null hypothesis of FS test is the exchange rate is in equilibrium before crisis.

notion that the Asian Financial Crisis may be due to overvaluation of the some of the regional currencies[12].

The estimated IRD models together with their adapted versions are tabulated in Table 3, and the related diagnostic test results are given in Table 7. Several interesting observations emerged from these tables. The Wald (χ^2_2) statistics in Table 7 suggest that both models meet the strongly efficient criteria, since β_0 and β_1 are not significantly different from zero and one respectively for each model. As previously observed in the PPP models, the standard IRD model is contaminated with autocorrelation problem as indicated by both the Durbin-Watson and Lagrange Multiplier test results. The problem, however, disappeared in the adapted IRD models. Notice that the R^2 values of the adapted IRD models are generally lower than the corresponding adapted PPP models (Table 3). This comes as a surprise since we expect the adapted IRD models to have higher explanatory power given that we have added interest rate differential to adapted PPP models[13].

Both the adapted PPP and IRD models are used to generate the forecasted values of the exchange rate in the out-of-sample period. The out-of-sample forecasts form these models are compared with the simple random walk model based on *MSE*, *MSPE* and *MAPE* ratios. Our preliminary results showed that all

[12] Alternatively, one may interpret that overvaluation is necessary but not sufficient condition for a currency crisis.

[13] In this study, we find that interest rates do not enter in the long-run relationship for ringgit-US dollar and Singapore dollar-US dollar rates. They may suggest that exchange rate dynamics are affected by other factors that are not in the interest rate dynamics. We are also aware that short-term interests (Treasury bills of 3-month rate) may not be appropriate to the model. Some authors have used long-term rates and obtained more favourable results. With the usual caveat, we are in debted to one of the referees for pointing this out.

quarters. In particular, the forecasting models for SGD/USD and THB/JPY rates statistically outperformed the random walk model at 1% significance level regardless of wheter we are comparing on the basis of one forecast value, two forecast values or more. Meanwhile, the ratio for the MYR/USD and MYR/JPY rates are statistically significant at 10% or better up to at least 6 quarters. It is interesting to note that our forecasting models have defeated the random walk model, even in the presence of more stringent forecasting period and also over the short forecasting horizon.

Turning to the adapted IRD model, all the MSE ratios for the MYR/USD (significant up to 9 quarters), SGD/USD (significant up to 7 quarters) and THB/JPY (significant for all 14 quarters) rates are less than one (Table 8B). Hence, the adapted IRD model could also outperform the random walk for these three rates. The ratio for MYR/JPY rate shows mixed results but the MR statistics suggest that adapted IRD is only comparable with the random walk with a minor exception that the former is significantly beaten.

The forecast accuracy of the adapted PPP and IRD models are compared and the results are also depicted in Table 8C. Overall, the weight of the evidence is against the adapted RID model. The adapted PPP models have smaller MSE values when compared to the adapted IRD models. As shown in the table, the ratios are smaller than one for the MYR/USD, SGD/USD and MYR/JPY rates across all forecasting horizons. Statistically, the adapted PPP model is better than the adapted IRD up to all the 14 quarters in MYR/USD, 2 quarters in SGD/USD and 6 quarters in MYR/JPY. However, the adapted PPP model for SGD/USD rate is statistically better than the adapted IRD model only for forecast up to 2 quarters ahead and for the rest of the forecasting horizon, the latter is statistically better. Generally, these results suggest that the adapted IRD model, which is incorporated with more information, does not necessarily out-perform the adapted PPP model. Thus, we have shown that the simple PPP model can adequately represent the movements in exchange rate series by adapting the model to include information from the deviation form equilibrium value.

CONCLUSION

Numerous studies have compared the forecasting performance of the exchange rate models against the random walk model. The consensus that emerged from these studies is that it is extremely difficult to out-predict a random walk using structural or non-structural models. In this article, we consider alternative procedures to model exchange rates in the ASEAN countries. Specifically, the proposed model is a linear combination of long run and short-run functions. We exploit the long-run information from the well-known PPP hypothesis in estimating the model, whereas the time series properties of the temporary deviations from equilibrium PPP is incorporated in our estimating procedure to capture the unusual feature of the data generating process. Our results show that even if the model includes the right set of fundamentals, they still could not explain movements of exchange rates well. Meese (1990) and Frankel and Rose (1995), among others have highlighted this point.

Our forecasting models are purposely set to allow the model to forecast in the post-crisis period, to make the task much more difficult. The empirical results based on the bilateral exchange rates of three ASEAN countries suggest that our approach has improved significantly the explanatory power of the pure PPP model. In other words, we found that the adapted model is capable of capturing the salient features of currencies that experienced speculative attacks and severe deprecation. Furthermore, the out-of-sample forecasts of our model out-predict the simple random walk, even during the post-crisis period. The adapted PPP model outperformed the rarely beaten naïve model, for the forecast horizons ranging from one to fourteen quarters.

Giddy and Duffey (1975) pointed out that successful forecasting has its premise in the satisfaction of at least one of the following criteria: (a) has used a superior forecasting model; (b) has consistent access to information; (c) is able to exploit small, temporary deviations from equilibrium; and (d) can predict the nature of government intervention in the foreign exchange market. Based on our empirical results, we showed that our procedure is capable of producing models that satisfy the above criteria. Specifically, the model is able to incorporate the long-run information based on macroeconomic theory, and our procedure is able to exploit small and temporary deviations from equilibrium and thereby yield a forecasting model much superior to the naïve model. Therefore, a reasonable conclusion that can be drawn from this study is that it provides some hope of achieving a reasonable forecast for the ASEAN currencies. Finally, the model could easily include other determinants as suggested by monetary models and may be used to forecast other financial variables and we reserve this for future research.

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