PERGAMON

Computers & Operations Research 30 (2003) 887–900

computers & operations research

www.elsevier.com/locate/dsw

A Bayesian vector error correction model for forecasting exchange rates

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Abstract

This paper develops a new method called Bayesian Vector Error Correction Model (BVECM), which is applied to forecast 1 month ahead changes of currency exchange rates for three major Asia Pacific economies. The study also compares out-of-sample forecasting performance with those of the random walk model and the Bayesian Vector Autoregression (BVAR), which has been shown in recent studies to outperform a variety competing of econometric techniques in exchange rate forecasting. Our experimental results indicate that both BVECM and BVAR are able to forecast the changes in exchange rates better than the random walk model. In terms of conventional forecast evaluation statistics, BVECM outperforms BVAR for all three currencies examined. In addition, the bias tests find that BVECM produces systematically less biased and more efficient out-of-sample forecasts than BVAR. Although the results of market timing tests indicate that both BVAR and BVECM have an economically significant value in predicting the directional change in two of the three exchange rates, BVECM is shown to produce equally or more economically significant directional change forecasts than BVAR.

Keywords: Forecasting; Currency exchange; Asia Pacific emerging economy; Bayesian vector autoregression; Error correction model

1. Introduction

With the advance of technologies in transportation and telecommunication, many corporations in these two decades often conduct business in different parts of the world and are characterized by rapid globalization of their operations. In order to gain a competitive advantage over their rivals, a lot of corporations have established and are extending their businesses in the fast growing emerging

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PII: S0305-0548(02)00041-2

markets, especially the ones in the Asia Pacific region. Although these multinational corporations have enjoyed many benefits from economic growth in the region, business operations in the Asian economies, unlike the ones in the developed countries, pose greater risks to the financial health of these foreign investors. The recent financial turmoil in Asia highlights the instability of these growing economies and stresses the firms' need to closer scrutinize the foreign exchange markets. For large multinational corporations which conduct substantial currency transfers in their course of business, being able to accurately forecast the movements of exchange rates can protect them from considerable loss or even improve the overall profitability. This notion has been echoed by many industrial leaders in both Asia and the United States to call for greater transparency of the foreign exchange markets and enhancing the predictability of the currency exchange movements.

In this study, we develop a new approach called Bayesian Vector Error Correction Model (BVECM) and use it to forecast currency exchange rates for three major Asia Pacific economies—Korea, Japan, and Australia. We select these foreign exchange markets because these economies not only have attracted substantial foreign investments but also are influential to the well-being of many countries in Asia and North America. The recent collapse of Korean economy and the prolong recession in Japan have underscored the direct relationship between their currencies to the financial performance of large corporations. The significant reduction of IBM's overall profitability in 1996–1997 provides a good example of the sufferings faced by many companies which had operations in the region. Although Australia is considered to be a relatively developed economy in the Asia–Pacific region, its indisputable connections to many emerging Asian economies has made Australia vulnerable to financial weakness in other Asian countries. In addition, forecasting the foreign exchange rates for the emerging or Asian markets is of great interest to academic researchers and practitioners. It is because the relatively higher volatility in these economies often poses a more difficult forecasting problem than the prediction on the more developed economies. Therefore, we apply our new approach to forecast the movements of the seemingly more unpredictable Asian currencies.

The difficulty in predicting currency exchange rates has been a long-standing problem in international finance. Despite various attempts to forecast exchange rates, it is still difficult for standard econometric forecasting models to outperform forecasts generated from a simple random walk model. The Bayesian vector autoregression (BVAR) model has been used in several recent studies to forecast exchange rates and has been shown to be able to generate forecasts that outperform the random walk forecast. Liu et al. [1], for example, compare the out-of-sample forecasting performance of various multivariate time series models in forecasting exchange rates using a variety of performance evaluation criteria. Their results indicate that, compared to the standard 'unrestricted' vector autoregression (VAR) models, restricted VAR models such as the BVAR provide superior forecasts and are able to outperform the naive or random walk forecasts. More recently, Sarantis and Stewart [2] compare the out-of-sample forecasting accuracy of a wide class of econometric models including BVARs, error correcting models (ECMs), structural models, unrestricted vector autoregressions (VARs), and the random walk model in forecasting quarterly exchange rates for major sterling exchange rates over different forecast horizons. Their results show that the BVAR model based on a version of the Uncovered Interest Parity (UIP) relationship is superior to the other models examined in their study, including the ECM extension of the VAR and the naive or random walk model, in forecasting short term (one-quarter-ahead) exchange rates.

The primary objective of this study is to assess whether an error correcting extension of the BVAR may be able to improve upon the forecasting performance of the BVAR. To do this, we develop a Bayesian vector error correction model (BVECM) and compare its out-of-sample forecasting performance with the BVAR. Another objective of the present study is to examine the out-of-sample forecastability of several Asian currencies, complementing the existing exchange rate forecasting literature which mainly focuses on major Western currencies. In Section 2, we present a literature review of the relevant studies in this area. Then, various forecasting models used in this paper as well as a brief summary of the underlying forecasting techniques are described. It is followed by an explanation of the statistical testing and the findings of the empirical experiment. The paper is then concluded.

2. Related literature

There are several theories of exchange rate determination normally used in empirical studies: the flexible price monetary model, the sticky price monetary model, the Hooper–Morton model, the portfolio balance model, and the uncovered interest parity model. The flexible price monetary model, the sticky price monetary model, and the Hooper–Morton model are essentially different versions of the monetary approach. Of these three monetary approaches, the Hooper–Morton model is the more general model and nests the other two models. Meese and Rogoff [3], Alexander and Thomas [4], Schinasi and Swamy [5], and Meese and Rose [6] are examples of studies which use the monetary approach and the Hooper–Morton model. A detailed discussion of these theories and the derivation of the relevant equations are given in Baillie and McMahon [7]. Sarantis and Stewart [8] provide a more recent review of the main theoretical exchange rate models and a detailed econometric evaluation of these models using the cointegration-error correction methodology. Further evidence on variants of the monetary exchange rate model is also provided in Sarantis [9].

According to Baillie and Selover [10], however, the exchange rate equations derived from the alternative theoretical models are essentially long-run equilibrium relationships, implying that if we fail to find the existence of long-run equilibrium relationships consistent with the respective theoretical models, the development of short-run structural equations based on such models will be inappropriate for forecasting purposes. Using cointegration tests, Baillie and Selover [10] reject, for five bilateral exchange rates against the US Dollar, the existence of a long-run equilibrium relationship consistent with the monetary models. Similarly, Sarantis and Stewart [8] provide a detailed econometric evaluation of the main theoretical exchange rate models mentioned above for sterling exchange rates over the period 1973Q1–1990Q3 using the cointegration-error correction methodology and reject overwhelmingly the existence of a long-run equilibrium relationship consistent with the monetary models. These studies provide evidence which casts doubt on the validity of monetary models used in exchange rate forecasting.

Sarantis and Stewart [8], on the other hand, using the Johansen [11] maximum likelihood cointegration tests, found long-run equilibrium relationships consistent with the portfolio balance (PB) model and a version of the uncovered interest parity relationship (UIP). In a related study, Sarantis and Stewart [2] show that the exchange rate forecasting models based on the UIP produce more accurate out-of-sample forecasts than the portfolio balance model at all forecast horizons and that the BVAR model based on the UIP produces the best short-term (one quarter ahead) forecasts which were also superior to the naive or random walk forecasts.

In light of previous literature, in this study, we will use the UIP relationship as the theoretical basis and the BVAR as the 'benchmark' statistical model for exchange rate forecasting analysis. The

UIP relationship can be recast in the following forecasting form:

$$\Delta e_{t+1} = f(\Delta e_t, \Delta e_{t-1}, \ldots, \Delta(r_t^* - r_t), \Delta(r_{t-1}^* - r_{t-1}), \ldots, \Delta(\pi_t^* - \pi_t), \Delta(\pi_{t-1}^* - \pi_{t-1}), \ldots, \Delta(p_t^* - p_t), \Delta(p_{t-1}^* - p_{t-1}), \ldots,), \quad (1)$$

where e is the natural logarithm of the exchange rate, defined as the foreign currency price of domestic currency. r, π, and p represent the logarithm of nominal short-term interest rate, expected price inflation rate, and the logarithm of the price level, respectively. [1] Asterisks denote the corresponding foreign variables.

3. Data and forecasting strategy

In the present study, we examine the Australia Dollar/US Dollar, Japanese Yen/US Dollar, and Korea Won/US Dollar exchange rates. The data used in our empirical experiment are collected from various sources. The relevant data for Japan and Korea are obtained from the PACAP database, maintained by the University of Rhode Island, whereas the data for Australia and USA are obtained from the AREMOS database, maintained by the Department of Education of Taiwan. Monthly data are used and the entire sample covers the period from January, 1980 to December, 1994. To evaluate the relative performances of the various forecasting models, we partition the data into two periods: the in-sample estimation period (from 1980:1 through 1990:12) and the out-of-sample forecast comparison period (from 1991:01 through 1994:12). This represents approximately a $\frac{3}{4}$–$\frac{1}{4}$ split, a standard validation split ratio in forecasting evaluation literature.

The in-sample period is devoted to estimating the initial model parameters and the out-of-sample period is restricted to testing the models' forecasting performance. Information from the out-of-sample period is not allowed to be used in the estimation of the initial model parameters. Specifically, data from the in-sample estimation period, that is from 1980:01 to 1990:12, is used to estimate the initial parameter estimates of the forecasting models and generate the first 'true' out-of-sample forecast for 1991:01. As new data becomes observable, they are added to the sample while the oldest observation is removed. Parameters of the forecasting models are then re-estimated and the forecast for the next month is generated using the re-estimated model parameters. This process continues through the last period in the out-of-sample forecasting period (1994:12). Out-of-sample forecasts are, thus, generated for each month in the reserved out-of-sample forecast comparison period. In short, at any point in time, only information that is observable up to that point in time is used to estimate the model parameters. At no time is future unobservable information used to estimate the model parameters.

The input variables that are required by the forecasting models described in this study are constructed so that they are all observable on or before the last day of the month preceding the month to be forecast. For example, if you are interested in forecasting the change in exchange rate for 1991:01, then the input variables that you will use to produce your model forecasts are constructed so that they are all observable on or before the last day of 1990:12. Constructing the data set in this manner ensures that when out-of-sample forecasts are made after the models are estimated, the

[1] Following Sarantis and Stewart [2,8], this study uses the long-term interest rate as a proxy for unobservable expected price inflation rate. Similar approaches were used by Meese and Rogoff [3], Baillie and Selover [10], and Frankel [12] among others.

out-of-sample forecasts will be similar to forecasts made in the real world in that only observable data is used as inputs to the forecasting model and that future, unobservable data are not used as inputs.

4. Bayesian vector autoregression (BVAR) model

The BVAR model is first described in Litterman [13]. Other papers which provide more detailed discussions of the BVAR include Doan, Litterman, and Sims [14], Todd [15], Litterman [16], and Spencer [17]. The BVAR model is essentially a 'restricted' version of the vector autoregression (VAR) model. The VAR model with a lag length of p can be represented as

$$\boldsymbol{Z}_t = \sum_{s=1}^{p} \phi(s)\boldsymbol{Z}_{t-s} + \boldsymbol{\mu}_t, \tag{2a}$$

$$E(\boldsymbol{\mu}_t, \boldsymbol{\mu}_t') = \Sigma, \tag{2b}$$

where $\boldsymbol{Z}_t$ is an $(n \times 1)$ vector of variables measured at time period t, $\phi(s)$ is an $(n \times n)$ matrix of the coefficients, p is the lag length of the variables, and $\boldsymbol{\mu}_t$ is an $(n \times 1)$ vector of random disturbances. There are a total of n^2L free coefficients in this model. A serious problem associated with VAR models, even in small systems, is the number of insignificant parameters (over-parameterization), which can lead to poor out-of-sample forecasting performance. The BVAR model overcomes the problem of over-parameterization associated with VAR models by imposing 'fuzzy' restrictions on the coefficients. Following the restrictions proposed in Litterman [16] and used in Sarantis and Stewart [2] for exchange rate forecasting, the BVAR model used in this study assumes that each coefficient has an independent and normal distribution with zero mean, except for the coefficient on the first lag of the own variable which has a mean of one. These restrictions are also referred to as the 'Minnesota prior' due to its development at the Federal Reserve Bank of Minneapolis and the University of Minnesota. The standard deviations of the prior distributions are given by

$$S(i,j,l) = \gamma f(i,j) g(l) s_j / s_i, \tag{3}$$

where s_i is the standard error of a univariate autoregression for variable i. The ratio s_i/s_j scales the variables to account for differences in units of measurement and thus enables specification of the prior without consideration of the magnitudes of the variables. The parameter γ is the overall tightness of the prior and is also the standard deviation on the first own lag in each equation. The function f gives the tightness of the prior for variable j in equation i relative to the tightness on the own lags. This function is assumed to symmetric and has the form, $f(i,j) = w$. The function g describes the lag pattern and is assumed to have a harmonic shape $(g(l) = l^{-d})$ with decay factor d. The BVAR model is estimated using Theil's mixed-estimation technique. The vector of variables, $\boldsymbol{Z}_t$, is

$$\boldsymbol{Z}_t = [\Delta e_t, \Delta(r_t^* - r_t), \Delta(\pi_t^* - \pi_t), \Delta(p_t^* - p_t)]'. \tag{4}$$

In estimating the BVAR model, the hyperparameters w and γ must be prespecified a priori. Numerical specification of the values for the hyperparameters is based on suggestions from previous studies (e.g. Litterman [16], Bessler and King [18], Kaylen [19], Doan [20]). This study sets the BVAR hyperparameter specifications equal to those recommended by Doan [20]. Specifically, the overall tightness parameter, γ, and harmonic lag decay, d, is set to 0.2 and 1.0, respectively. The symmetric interaction function, w, is set to 0.5. Other recent studies which use these BVAR hyperparameter specifications include Liu et al. [1] and Dua and Smyth [21] among others.

5. Bayesian vector error correction (BVECM) model

According to the UIP theory, the long-run equilibrium relationship between the nominal exchange rate, the nominal interest rate differential, and the expected inflation differential can be written in the following semi-reduced form: [2]

$$e_t = \alpha_0 + \alpha_1(r_t^* - r_t) + \alpha_2(\pi_t^* - \pi_t) + \alpha_3(p_t^* - p_t) + \boldsymbol{\mu}_t, \tag{5}$$

where the variables in (5) have been described previously. This suggests that it is possible that the forecasting performance of the BVAR may be enhanced if information from the long-run UIP relationship could somehow be captured within the BVAR model framework. In this study we introduce a BVECM specification which modifies the BVAR to capture information from the long-run UIP relationship. The vector $\boldsymbol{Z}$ of input variables of the BVECM is specified as follows:

$$\boldsymbol{Z}_t = [\Delta e_t, \Delta(r_t^* - r_t), \Delta(\pi_t^* - \pi_t), \Delta(p_t^* - p_t), \mathrm{RES}_t]', \tag{6}$$

where

$$\mathrm{RES}_t = e_t - \alpha_1(r_t^* - r_t) - \alpha_t(\pi_t^* - \pi_t) - \alpha_3(p_t^* - p_t). \tag{7}$$

It can be seen that the RES_t term represents deviations from the long-run equilibrium theoretical UIP relationship of Eq. (5). In estimating the BVECM, the parameters of Eq. (5) are estimated using the method of ordinary least squares (OLS), and are recursively re-estimated and updated at each forecast point, as the data for the latest month becomes observable and are, thus, added to the sample.

6. Random walk (naive) model

It is also of interest to compare the results of the naive forecast or the random walk model with the forecasts generated from the other models described in this study. The random walk forecast is just a forecast of no change in the independent variable. For example, the random walk model forecast of next month's change in exchange rate is just this month's change in exchange rate:

$$\Delta\hat{e}_{t+1}^{\mathrm{au}} = \Delta e_t^{\mathrm{au}}, \tag{8a}$$

$$\Delta\hat{e}_{t+1}^{\mathrm{ja}} = \Delta e_t^{\mathrm{ja}}, \tag{8b}$$

$$\Delta\hat{e}_{t+1}^{\mathrm{ko}} = \Delta e_t^{\mathrm{ko}}, \tag{8c}$$

[2] Details concerning the derivation of the UIP relationship can be found in Hall [22]. A similar treatment and a detailed econometric evaluation for the UIP can be found in Fisher et al. [23]. Sarantis and Stewart [8] provide additional evidence supporting various specifications of the UIP using the cointegration-error correction methodology.

Table 1
Out-of-sample forecasting results of the BVAR and BVECM, 1991:01–1994:12

	RMSE		U	
	BVAR	BVECM	BVAR	BVECM
Australian \$/US \$	0.018602	0.018291	0.813894	0.800272
Japanese Yen/US \$	0.025496	0.025411	0.733925	0.731474
Korean Won/US \$	0.003601	0.003594	0.910987	0.909317

Note: BVAR is the Bayesian Vector Autoregression model. BVECM is the Bayesian Vector Error Correction model. The RMSE is defined as $\text{RMSE} = [1/N \sum_{p=1}^{N} (\text{actual}_p - \text{forecast}_p)^2]^{1/2}$ where actual_p is the actual change in the exchange rate for month p. N is the number of months in the out-of-sample forecast comparison period. The Theil's U-statistic is the ratio of the RMSE of the model forecast to the RMSE of the 'naive' forecast of no change in the dependent variable. A U-statistic of less than 1 implies that the model forecast outperforms the naive model during the out-of-sample forecast comparison period. Likewise, a U-statistic in excess of 1 implies the forecasting model did worse than the naive model.

where $\Delta\hat{e}^{\text{au}}_{t+1}$, $\Delta\hat{e}^{\text{ja}}_{t+1}$, and $\Delta\hat{e}^{\text{ko}}_{t+1}$, are the random walk forecasts for the change in the Australian Dollar/US Dollar, Japanese Yen/US Dollar, and Korean Won/US Dollar exchange rates for month $(t+1)$.

7. Out-of-sample forecast results

The out-of-sample forecasting results of the BVAR and BVECM for 1 month ahead changes in the exchange rates are summarized on Table 1. Two descriptive statistics on forecast accuracy are reported in the table. They are root mean square error (RMSE) and Theil's U. The RMSE is defined as

$$\text{RMSE} = \left[\frac{1}{N}\sum_{p=1}^{N}(\text{actual}_p - \text{forecast}_p)^2\right]^{1/2}, \tag{9}$$

where actual_p is the actual change in the exchange rate for month p and forecast_p is the forecasted change in the exchange rate for month p. N is the number of months in the out-of-sample forecast comparison period. The Theil's U-statistic is the ratio of the RMSE of the model forecast to the RMSE of the 'naive' forecast of no change in the dependent variable. A U-statistic of less than 1 implies that the model forecast outperforms the naive model during the out-of-sample forecast comparison period. Likewise, a U-statistic in excess of 1 implies the forecasting model did worse than the naive model. The Theil's U-statistic has several advantages over the RMSE when comparing forecasting models. It is a unit-free measurement. Therefore, it is often easier to work with than the unit-bound RMSE. The magnitude of the RMSE will vary depending upon the type of variable being forecasted. Finally, examination of the U-statistic provides an immediate comparison of the model forecasts with those of the naive scheme of forecasting no change in the dependent variable over time.

In terms of the forecast evaluation statistics shown on Table 1, the BVECM is able to improve upon the BVAR forecasts for every exchange rate examined in this study. It can be seen that the magnitude of the out-of-sample forecast improvement is small, but, nevertheless, improvement occurs in every exchange rate examined in terms of both RMSE and U-statistics. The U-statistics indicate that both the BVECM and the BVAR outperform the naive model forecasts for every exchange rate examined.

To summarize, the results on Table 1 provide evidence to support the use of the UIP relationship in forecasting exchange rate changes. Both the BVECM and the BVAR based on the UIP are able to forecast the 1 month ahead changes in exchange rates better than the naive model. The out-of-sample forecasting results further show that the BVECM is able to improve upon the forecasting performance of the BVAR and by extracting additional information from the long-run UIP relationship.

8. Regression tests

A well established regression test can be used to test whether model forecasts are systematically higher or lower than actual exchange rates. Shastri and Tandon [24], Canina and Figlewski [25], Liu et al. [1], and Jorion [26] are examples of related studies which use regression tests for this purpose. Following the methodology used in Liu et al. [1], a regression of the following type is used to compare the various exchange rate forecasting models:

$$\boldsymbol{Z}_{t+1} - \boldsymbol{Z}_t = \alpha + \beta(\boldsymbol{Z}^{\mathrm{e}}_{t,t+1} - \boldsymbol{Z}_t) + \boldsymbol{\mu}_t. \tag{10}$$

Here, $\boldsymbol{Z}_{t+1}$ is the actual exchange rate at month $(t+1)$, $\boldsymbol{Z}_t$ is the actual exchange rate at time t, and $\boldsymbol{Z}^{\mathrm{e}}_{t,t+1}$ is the 1 month ahead exchange rate forecast made at time t. Using this framework, the regression R^2 would give an indication of the explanatory power of the alternative models. A better forecast should produce a higher R^2. Further, if the forecast is the true expected value of the exchange rate conditional on the currently available information at time t, regressing $(\boldsymbol{Z}_{t+1} - \boldsymbol{Z}_t)$ on $(\boldsymbol{Z}_{t,t+1} - \boldsymbol{Z}_t)$ as in Eq. (10) should produce regression estimates of 0.0 and 1.0 for α and β, respectively. Deviation from those values is evidence of bias and inefficiency in the forecasts. The F-test can be used to test the joint hypothesis that $(\alpha, \beta) = (0, 1)$.

The results from the regression tests are shown in Table 2. Similar to the results for the RMSE and U-statistics, the R^2 statistic also shows that the BVECM produces better out-of-sample forecasts than the BVAR in that the BVECM produces a higher R^2 than the BVAR for every exchange rate examined. In other words, the R^2 results indicate that for all countries examined, the BVECM provides more explanatory power than the BVAR.

The F-test results show that the joint hypothesis that $(\alpha, \beta) = (0, 1)$ was not rejected for all cases, indicating that all of the forecasts generated by the models used in this study are statistically unbiased. In each case, however, the F-statistic computed for the BVECM is better than the F-statistic computed for the BVAR, indicating that the BVECM produces out-of-sample forecasts that are systematically less biased and more efficient than those produced by the BVAR.

9. Henriksson–Merton market timing test

Statistical evaluation measures, such as those considered previously, may not always yield results consistent with the actual trading profits generated by exchange rate forecasting models. Boothe

Table 2
Regression test results, 1991:01–1994:12

Exchange rate	Model	α	$t(\alpha)^a$	β	$t(\beta)^b$	R^2	F^c
Australian $/US $	BVAR	− 0.00103	0.37976	0.45075	− 1.61141	0.03662	1.61392
Australian $/US $	BVECM	− 0.00013	0.05141	0.50756	− 1.60108	0.05589	1.28183
Japanese Yen/US $	BVAR	− 0.00441	1.01375	0.38497	− 1.25282	0.01319	0.86911
Japanese Yen/US $	BVECM	− 0.00432	1.02100	0.43582	− 1.16783	0.01738	0.81211
Korean Won/US $	BVAR	0.00006	0.10443	0.88956	− 0.62079	0.35213	0.24560
Korean Won/US $	BVECM	0.00014	0.23109	0.88842	− 0.62991	0.35355	0.21104

Note: The regression is specified as follows:

$$\boldsymbol{Z}_{t+1} - \boldsymbol{Z}_t = \alpha + \beta(\boldsymbol{Z}^e_{t,t+1} - \boldsymbol{Z}_t) + \boldsymbol{\mu}_t,$$

where $\boldsymbol{Z}_{t+1}$ is the actual exchange rate at month $(t+1)$, $\boldsymbol{Z}_t$ is the actual exchange rate at time t, and $\boldsymbol{Z}^e_{t,t+1}$ is the 1 month ahead exchange rate forecast made at time t. BVAR is the Bayesian vector autoregression model. BVECM is the Bayesian vector error correction model.

[a]The t-values in parentheses are calculated for the null hypothesis that $\alpha = 0$.

[b]The t-values in parentheses are calculated for the null hypothesis that $\beta = 1$.

[c]F-statistics are calculated to test the null hypothesis of $(\alpha, \beta) = (0, 1)$. None of the statistics reported the table are statistically significant at the usual levels indicating that all of the forecasts generated by the models used in this study are statistically unbiased.

Table 3
Market timing test results, 1991:01–1994:12

Exchange rate	Model	β	$t(\beta)$
Australian $/US $	BVAR	0.009238	1.75235*
Australian $/US $	BVECM	0.011687	2.24712**
Japanese Yen/US $	BVAR	−0.00033	− 0.03917
Japanese Yen/US $	BVECM	0.00335	0.40190
Korean Won/US $	BVAR	0.00462	3.52922***
Korean Won/US $	BVECM	0.00462	3.52922***

Note: H_0: $\beta = 0$ is the null hypothesis that the forecasting model has no ability to predict directional changes. If the model is able to forecast directional changes, then β will be greater than zero in absolute value. BVAR is the Bayesian vector autoregression model. BVECM is the Bayesian vector error correction model.

*Indicates significance at the 10% level.

**Indicates significance at the 5% level.

***Indicates significance at the 1% level.

and Glassman [27], Gerlow and Irwin [28], and Liu et al. [1] are examples. It is, therefore, useful to consider a methodology which will provide us a measure of the economic value of a forecasting model. In this study, we will employ the market timing testing methodology first proposed by Henriksson and Merton [29] to measure the economic value of the forecasting models.

The Henriksson–Merton market timing test is essentially a test of the directional forecasting accuracy of a model. Directional accuracy has been shown to be highly correlated with actual trading profits. Leitch and Tanner [30], for example, compare directional accuracy measures with conventional error measures and find directional accuracy to be highly correlated with actual trading profits and a better indicator of the economic value of a forecasting model then conventional error measures.

Cumby and Modest [31] reformulated the Henriksson–Merton test in a regression framework which is more intuitive than the original method proposed by Henriksson and Merton [29]. In this study, we will compute the Henriksson–Merton test statistic using the regression framework proposed by Cumby and Modest [31].

To implement the Henriksson–Merton test in a regression framework, let $x_t = 1$ if the forecast change for a series is non-negative and $x_t = 0$ if the forecast change is negative. The test is based on the following regression:

$$\boldsymbol{Z}_t = \gamma + \beta X_t + \varepsilon_t, \tag{11}$$

where $\boldsymbol{Z}_t$ represents the actual change in the variable. Under the null hypothesis that the forecasting model has no ability to predict directional changes, β is equal to zero. If the model is able to forecast directional changes in a variable, then β is greater than zero. It should be noted that this regression test is a two tailed test, meaning that a null hypothesis would be rejected for β significantly less than zero as well. This implies that forecasts which are consistently wrong also would have informational value.

The results of the regression test of market timing are given in Table 3. The table presents the estimated slope coefficients of Eq. (11) along with the t-statistics. The market timing results indicate

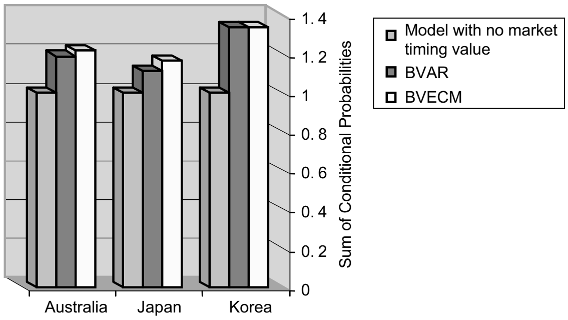

Fig. 1. Market timing value for BVAR and BVECM forecasts, 1991:01-1994:12 Note: The sum of conditional probabilities (SCP) measures the conditional probabilities of correctly forecasting the directional movements of exchange rate. SCP has to exceed 1 for a forecasting model to exhibit market timing value.

that the BVAR and the BVECM have an economically significant value in predicting the directional change in two of the three exchange rates. The BVAR forecasts exhibit statistically significant market timing ability for the Australian Dollar/US Dollar exchange rate at the 10% significance or less and for the Korean Won/US Dollar exchange rate at the 1% significance or less. The BVECM forecasts exhibit statistically significant market timing ability for the Australian Dollar/US Dollar exchange rate at the 5% significance or less and for the Korean Won/US Dollar exchange rate at the 1% significance or less.

For the Japanese Yen/US Dollar exchange rate, both the BVAR and BVECM did not exhibit statistically significant market timing ability. However, the slope coefficient of the BVECM, though not statistically significant, is slightly more significant than that of the BVAR. Moreover, it is of the correct sign. On the contrary, the slope coefficient of the BVAR is of the wrong sign (negative), indicating that the model tends to forecast price changes opposite to actual changes, though not significantly so. These observations seem to suggest that the Japanese market may be more efficient than the other two foreign exchange markets. In fact, a comparison between the Australian and Korean markets shows that the Australian dollar market, which is believed to be more efficient and exhibits greater transparency, provides a less certain (smaller t-statistics for the β's) trading profit than the less efficient Korean won market. This finding is also consistent with many political and business leaders' call for greater transparency and openness for the emerging markets.

Fig. 1 presents a chart comparing the market timing results of the BVAR and BVECM to a model with no market timing value for the three exchange rates using the sum of conditional probabilities (SCP) measure. The SCP is defined as the conditional probability of correctly forecasting that the exchange rate will decrease plus the conditional probability of correctly forecasting that the exchange rate will increase or stay constant. Merton [32] shows that the SCP must exceed 1 for forecasts to exhibit market timing value and a forecasting model with no market timing value would produce a SCP equal to 1. The SCPs shown in the figure are all in excess of 1, confirming the Henriksson–Merton test results shown on Table 3. Fig. 1 shows that both the BVAR and BVECM provides market timing value and that the market timing value of the BVECM is greater than or equal to that of the corresponding BVAR for all three exchange rates. Of the three exchange rates analyzed, the models provide the greatest market timing value for Korean Won/US Dollar exchange rates, then the Australian Dollar/US Dollar exchange rates, and, lastly, the Japanese Yen/US Dollar exchange rates.

To summarize, for all three exchange rates, the market timing results indicate that the BVECM produces market timing regression slope coefficients that are of the correct sign and are equally significant or more significant than the corresponding slope coefficients produced by the BVAR. In other words, for all three exchange rates, the BVECM provides directional change forecasts that are equally or more economically significant than the corresponding BVAR.

10. Conclusions

This study introduces an error correcting extension (BVECM) of the BVAR to forecast 1 month ahead changes of three Asian currency exchange rates and compares BVECM's out-of-sample forecasting performance with those produced by the BVAR and the random walk models. In terms of the conventional forecast evaluation statistics of RMSE and U, the BVECM is able to improve upon the BVAR forecasts for every exchange rate examined in this study. The results of the regression tests (both R^2 and F-statistic) also show that the BVECM produces out-of-sample forecasts that are systematically less biased and more efficient than those produced by the BVAR. Finally, the results of the market timing tests indicate that both the BVAR and the BVECM have an economically significant value in predicting the directional change in two of the three exchange rates. However, the BVECM is shown to be able to provide directional change forecasts that are equally or more economically significant than the corresponding BVAR. Moreover, the results of this study provides additional evidence to support the use of the UIP relationship in forecasting exchange rate changes. Both the BVECM and the BVAR based on the UIP are able to forecast the 1 month ahead changes in exchange rates better than the naive model.

Given these findings, the current study should be of great interest to many practitioners and managers of multinational corporations as it provides a better tool to forecast the exchange rates for the more volatile Asian economies, which exhibit a lesser degree of financial predictability than the markets in more developed countries. This notion is also in general agreement with our observation that the trading profit from Japanese yen market, which is believed to be more efficient than Australian dollar and Korean won markets, is less certain than the profits obtained from the trading of the other two currencies. Likewise, the Australian dollar market has a less-certain yield than the less efficient Korean won market. Nevertheless, given the well performance of the proposed BVECM models relative to the others, corporations can devise more effective business strategies to improve their financial positions and efficacious precautionary measures to reduce potential currency risk.

Directions for future research include: extending this study by incorporating more (non-Asian) bilateral exchange rates vis-a-vis the US Dollar to try to obtain more general conclusions; and developing dynamic trading tests to see if trading profits can be obtained from using the various forecasting models used in this study. Comparisons with the predictability of exchange rates for those emerging markets in other continents and, especially, the major developed economies should shed some light on the differences among the infrastructures of the foreign currency markets, thus guiding the managers more effective ways to hedge against the volatility found in many emerging economies.

Acknowledgements

The authors are grateful for the helpful comments from the two anonymous referees and Li D. Xu, the guest editor of this issue.

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