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Editorial

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Exchange Rate Forecast: A Note

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The exchange rate forecast is an important topic in international finance especially after the breakdown of the Bretton Woods system in 1973. Firms that involve in international business need to know the future exchange rate for various and accurate decision making in firms such as financing, investing and hedging. An accurate exchange rate forecast is not only important to firms involved in international business but also to households, governments and international organisations engage in international transaction [1]. Nonetheless, exchange rate forecast is not an easy task. An accurate forecast is unlikely to be obtained. There is no single forecasting method that is superior for obtaining accurate exchange rate all the time and for different exchange rate. Generally, exchange rate forecast methods can be classified according to technical forecasting, fundamental forecasting, market-based forecasting, machine-learning based forecasting and mixed forecasting. Technical forecasting inspects the exchange rate history or studies the chart of exchange rate to find pattern that may recurrent in the future. Fundamental forecasting examines the relationship between exchange rate and other variable or investigates the intrinsic value of the exchange rate. Market-based forecasting explores the expectation of the market on the future exchange rate. Machine-learning based forecasting involves forecasting by using artificial neural network, which data are assumed to be non-linear [2]. Mixed forecasting is a composite of two or more methods. The same or different weight can be assigned to each method in mixed forecasting.

One issue in exchange rate forecast is to forecast exchange rate using high frequency data in shorter period such as in a day or a week. Meese and Rogoff [3] conclude that a random walk model, i.e. the future exchange rate is predicted by the spot exchange rate, surpasses a structural model such as the monetary model, the portfolio balance model and the Taylor exchange rate model [4] in terms of the out-of-sample forecasting performance. In other words, a random walk model is better than a structural or fundamental model. There are many studies in the literature, which displays the robustness of the conclusion that a random walk model outperforms a fundamental model using different econometric methods, exchange rate, time period and frequency data [5]. There are many studies that report the weak relationship between exchange rate and the economic fundamental, which is known as the exchange rate disconnect puzzle. The structural or fundamental model does not fit well the future exchange rate both in-sample and out-of-sample forecasting performance [5-7]. Evans and Lyons [7] reveal that the fundamental models of exchange rates perform poorly at higher frequency data more than one year. Nonetheless, there are a few studies, which demonstrate that the structural or fundamental models perform better than the random walk models [8,9].

One problem associated with the poor performance of the structural or fundamental model is the lack of economic data in high frequency, which are mostly available at monthly or quarterly basis. Andersen et al. [10,11] demonstrate the significant relationship between exchange rates and the economic fundamental in the short run. They show that economic announcement produces jumps in the conditional means of exchange rates using real time data. One solution to the unavailability of economic data in high frequency is to use data in the mixed frequencies. Bianco et al. [5] address the significance of economic data in explaining and predicting exchange rate using data with mixed frequencies, i.e. the study combines weekly data and monthly data. Monthly data are transformed into weekly data using an approximation of the geometric mean [12]. An exchange rate model based on the monetary approach to exchange rate is used to forecast. The model fits the in-sample weekly fluctuations of the euro against the United States Dollar (USD) exchange rate with an in-sample goodness of fit of about eighty percent. The out-of-sample forecasting performance is assessed by using the standard recursive regression approach. The results show that the model is better than the random walk model in terms of the out-of-sample performance based on mean absolute error or mean squared prediction error. Moreover, the result of the direction of change metric, which analyses the sign of future exchange rate returns, shows that the model performs better than the random walk model [5]. There are numerous measures of assessing the forecasting performance in the literature of exchange rate forecast such as the Diebold and Mariano [13] and West [14] (DMW) test and the Clark and West [15,16] (CW) test. The DMW test examines the equal predictability of two non-nested models. The null hypothesis of the DMW test is that the competing models have the same mean squared prediction errors, i.e. forecasting similarly well. The CW test analyses the null hypothesis of equal predictive ability of an econometric model, which could be linear or non-linear versus a martingale difference model. It is argued that the CW test is superior to the DMW test [17].

The failure of the economic fundamental in explaining and forecasting exchange rates has turned to the study of the microstructure of the exchange rate markets. The focus is to resolve behaviour of the exchange rate markets to predict exchange rates. One aspect of this literature is the study of the order flow in the exchange rate markets [5,18-20]. Rime et al. [21] report that order flow is a powerful predictor of the daily exchange rate movements of the USD against the Euro, British pound sterling and the Japanese yen, respectively in the out-of-sample forecasting performance. Savaser [19] finds that price contingent order flow contributes to the responses of the exchange rate to news. More specifically, stop loss order intensifies the reactions of the exchange rate to news. However, take profit order has no significant effect because of the absence of agents to intensify the placement of the order before the news. Evans [18] develops a theoretical model of the exchange rate determination that links the different between the microstructure and conventional models. The model analyses how economic information known to individual agents outside the foreign exchange market is aggregated and transmitted to dealers through transaction flows and how the information is transformed in the spot exchange rate. The results show the link between the economy, order flow and high frequency exchange rate returns. Moreover, the results show that between twenty to thirty percent of the variance in excess currency returns over a one-month horizon and two-month

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horizons can be linked to developments in the economy. Zhang et al. [20] investigate the exchange rate in China by using a market-microstructure approach. An index of order flow is constructed to capture excess demand pressure in the exchange rate market. The results of the vector autoregressive modelling show that there is long-run cointegration between the USD against Reminbi (RMB) exchange rate and its determinants, namely the order flow, the proxy for economy influences and the country risk premium. Moreover, unidirectional causality is found from order flow to exchange rate. The estimated results reveal that order flow not only Granger causes the exchange rate movements but also is a significant determinant of the exchange rate in the short run. The order flow explains approximately nineteen percent of the exchange rate movements for one $0.1 million the USD against RMB exchange rate purchase.

There is abundance of effort focused on the accuracy of exchange rate forecast [2]. There are two broad efforts in this direction namely exchange rate forecast by using the Markov-switching model and artificial neural network. The use of the ordinary least squares estimator to estimate the exchange rate with the assumption that there is only one state is not appropriate if there are two states appear in the series. Nikolsko-Rzhevskyy and Prodan [17] examine the out-of-sample forecasting performance of the two-state Markov-Switching Random Walk (MS-RW) with drift model. The model allows both the constant term and the variance of innovations to take two specific values during times of appreciation and depreciation. Moreover, the exchange rate is allowed to follow persistent swings, switching between an upward and a downward drift. The study examines monthly exchange rate series for twelve Organizations for Economic Co-operation and Development countries against the USD over the period from March 1973 to January 2008. The study uses a rolling window forecasting and the results show both short-run and long-run predictability that is robust across different samples and test statistics. The out-of-sample predictability of the MS-RW with drift model versus the random walk model is evaluated by using the CW test. The results show that at the one-month period, the MS-RW with drift model outperforms the random walk model for nine out of twelve countries at the 10 percent significance level. Moreover, there is evidence of long-horizon predictability, more than one month period at the three month period for seven countries and at the twelve month period for three countries. The long-run predictability declines with the forecast period increases. Yuan [22] uses a multi-state Markov-switching model with smoothing and reports that the model outperforms a random walk in the short run over different sample periods.

There are plenty studies of exchange rate forecast by using artificial neural network, which can be in many forms [1,2]. A standard neural network has three layers. The first layer is called the input layer, the second layer is called the hidden layer and the last layer is called the output layer. The hidden layer consists of nodes. Each node represents a weight factor. The information reaches a single hidden layer node as the weighted sum of its inputs. Each node of the hidden layer passes the information through a nonlinear function to the output layer [2]. The training of the network begins with randomly chosen weights and proceeds by applying a learning algorithm called the back propagation of errors. The learning algorithm tries to find the weights that minimise an error function. However, there are several weaknesses and contradictory empirical evidence of the forecasting power by using artificial neural network. This can be due to the fact that the selection of the inputs is based more on trial and error and the experience of the researcher rather than based on some scientific methods [23]. Sermpinis et al. [2] investigate the trading and statistical performance of the Euro against the USD European Central Bank fixing series over the period from 2002 to 2010 with the last two years for the out-of-sample forecasting testing by using an Auto Regressive Moving Average (ARMA) model, a Multi-Layer Perceptron (MLP), a Recurrent Neural (RN) network and the Psi Sigma Neural (PSN) network. Moreover, the study compares the performance of a Kalman filter with the simple average, the Bayesian average, the Granger-Ramanathan Regression (GRR) approach and the Least Absolute Shrinkage and Selection Operator (LASSO). The results show that the PSN network beats the other models in terms of statistical accuracy and trading performance. The simple average, the Bayesian average and the GRR approach do not outperform the PSN network but are better than MLP and RN network whilst LASSO and Kalman filter present the best results. All models except ARMA show an increase in their trading performance and a striking reduction in maximum drawdowns after applying time varying leverage with a Kalman filter.

In a summary, there is an extensive literature in exchange rate forecast. One issue in exchange rate forecast is the poor performance of the use of the exchange rate fundamental models in exchange rate forecast especially in the short run. In the future, more economic data shall be available at higher frequency perhaps real time data for the evaluation of the predicting performance of the structural or fundamental models in the short run. One direction to solve the exchange rate disconnect puzzle is to the study of the microstructure of the exchange rate markets. There are plenty methods used in exchange rate forecast such as the Markov-switching model and artificial neural network with the aim to obtain the accurate exchange rate forecast. However, there is no single exchange rate forecast method outperforms others all the time and for different exchange rate. The exchange rate forecast is still remaining as a challenging topic for research in international finance.

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