Predicting Exchange Rate Direction with Leading Indicators via Neural Network Model

Fu-Ming Lee[1*] Li-Hua Li[1] Chia-Yang Lin[1]

[1] Department of Information Management, Chaoyang University of Technology,
168, JiFong E. Rd., Wufeng Township, Taichung County 41349, Taiwan(R.O.C.)
* Corresponding author, E-mail: fmlee@cyut.edu.tw ; TEL: 886-4-23323000 ext. 4286

Abstract

This paper attempts to predict exchange rate direction at the short horizon (1-, 6-, and 12-month) to provide the market-timing information. We presume that the leading indicators of a specific country could appropriately represent its future macroeconomic conditions, and the relative variations of two countries' macroeconomic conditions would therefore lead to exchange rate moving. Neural network model is employed to describe the relationship between the leading indicators of two countries and the direction of their exchange rate in the future. We find empirical evidence that our model outperforms the random walk model and appears to be more accurate at 6- and 12-month horizons.

Keywords: Exchange rate forecasting; Leading indicators; Neural network model.

1. Introduction

Predicting exchange rate and its corresponding direction is an important and beneficial task in terms of theoretical and practical aspects. Literature states, unfortunately, that most forecasting methods hardly beat the random walk (RW) model. Meese and Rogoff [10] report that linear models do not perform well in out-of-sample forecast. After Meese and Rogoff, numerous researchers devote themselves to exploring nonlinear models. Some studies provide support for the long-horizon forecast [9], but find weak support at short horizon [6].

Most of the works mentioned above focus on the exchange rate forecast. However, some studies show that it is even more important to predict the direction of exchange rate. Leitch and Tanner [7] suggest that the numerical accuracy measures (RMSE, MAE, etc.) for exchange rate forecast have little relevance for users of forecasts in business enterprises, who are most concerned with the direction indicated by the forecasts. Also, EI Shazly [1] points the importance of correct prediction on the exchange rate direction for hedging or speculative activities. Finally, for firms which conduct substantial currency transfers in the course of business, being able to accurately forecast exchange rate direction can result in considerable improvement in the overall profitability of the firm [8].

Because neural network (NN) model is a universal approximator which can approximate a large class of nonlinear functions with a high degree of accuracy, there are numerous researches applying NN model to predict exchange rate and its corresponding direction. Qi and Wu [12] use some monetary fundamentals as input to predict four exchange rate directions via NN model. Jasic and Wood [5] improve the performance of daily exchange rate forecast. Furthermore, in the study of El Shazly [1], currency price forecast shows that it is easier for NN model to predict the direction and turning points than actual prices.

In this study, we aim at predicting exchange rate direction at short (i.e. 1-, 6-, and 12-month) horizons under the flexible exchange rate regime. A 3-layer NN model with the leading indicators as inputs is used to forecast the four main exchange rate directions as the same ones considered in the work of Qi and Wu. Our model outstands the RW model across all examinant currencies. In addition, these findings outperform the results of Qi and Wu. We may say that, in our NN model, the leading indicators could probably represent macroeconomic conditions, and the trend of exchange rate depends deeply on macroeconomic conditions.

The remaining sections of the paper are organized as follows. Section 2 provides the concept why we adopt the leading indicators. Section 3 describes our proposed NN model and statistic methods. In Section 4, the data sets are introduced in terms of its origins. Section 5 demonstrates our results. Finally, Section 6 gives conclusions of our research.

2. Why we adopt the leading indicators?

The most popular model of exchange rate, the monetary model, concerns the economic fundamentals which focus on the demand and supply of money and the price level. Many researches about predicting exchange rate are based on monetary model [12]. But Hopper [4] concludes that the monetary model do not provide a satisfactory account of the exchange rate. Faust et al. [3] empirically examine Mark's [9] monetary model and find weak evidence of predictability.

We find that most studies only considered the parameters that would affect currency supply and demand directly. There may be additional parameters that will affect the exchange rate. Without these potential factors, satisfactory forecast performance will not be obtained. In order to overcome the problem, we extend the monetary model into the ideal of macroeconomic model. That is to say, macroeconomic conditions of different countries are utilized to predict the flow of the money. Therefore, various kinds of leading indicators which have the ability to predict the macroeconomic conditions in the future are used as the parameters for verifying this relationship. In out study, we will only use standard leading indicators provided by the considered countries.

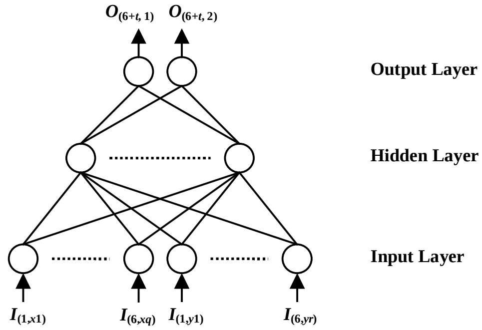
3. Empirical design and statistics

Foreign exchange is the exchange of the currency of one country for currency of another. For this concept, we should consider both countries' macroeconomic conditions. Therefore, we divided our input nodes into two parts, each of which contains one country's leading indicators for six consecutive months. In contrast to the prior works using the same parameters in common, the leading indicators of a specific country are usually different from those of the other in terms of amount and definition. As mentioned in Section 2, it would not make sense to concern fewer and the same leading indicators for different countries. Our policy is to adopt more and suitable leading indicators (may not be all the same) for effective forecasting. This is the novel part of our NN model.

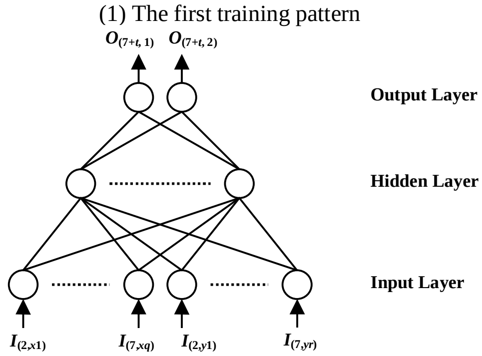
Suppose we have two countries, namely x and y, and we design a 3-layers NN model whose structure is depicted in Fig. 1. The input vector is

$$\mathbf{I} = (I_{(n\text{-}5,\, x1)},\ldots, I_{(n\text{-}5,\, xq)}, I_{(n\text{-}4,\, x1)},\ldots, I_{(n,\, xq)}, I_{(n\text{-}5,\, y1)},\ldots, I_{(n\text{-}5,\, yr)}, I_{(n\text{-}4,\, y1)},\ldots, I_{(n,\, yr)})^{T}, \quad (1)$$

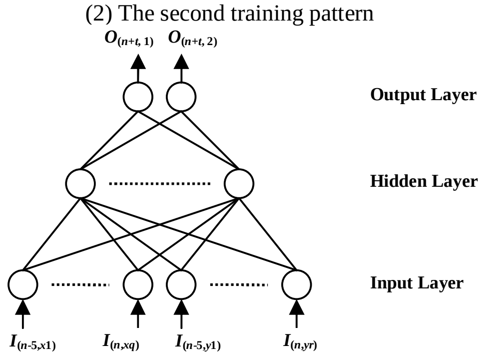
where n denotes the last month, country x has q kinds of leading indicators ($x1,\ldots, xq$), and country y has r kinds of leading indicators ($y1,\ldots, yr$). The output vector is $(O_{(n+t,\,1)}, O_{(n+t,\,2)})^{T}$. If the exchange rate on month $n+t$ is higher than or equal to the one on month n, we set $(O_{(n+t,\,1)}, O_{(n+t,\,2)})^{T}$ to $(0, 1)^{T}$. Otherwise, we set $(O_{(n+t,\,1)}, O_{(n+t,\,2)})^{T}$ to $(1, 0)^{T}$. The number of hidden nodes will be set from 1 to 10 to compare with the work of Qi and Wu. We will study the forecast of 1-, 6- and 12-month horizon exchange rate direction.



(1) The first training pattern



(2) The second training pattern



(3) The last training pattern

Fig. 1: Data representation in training a neural network

Two criteria are used to judge the correctness of our out-of-sample forecasts. One is the direction accuracy (DA), measured by the proportion of correct forecasts. The other is Pesaran and Timmermann (PT) test [11], testing the significance of predicted signs of direction. We set RW model as 50% direction accuracy and use the PT to test the relation of our model and random walk model.

4. The Data

We choose four major currency exchange rates: British pound/US dollar, Canadian dollar/US dollar, Deutsche mark/US dollar, and Japanese yen/US dollar, all of which come from PACIFIC [13]. The monthly exchange rate is calculated as average daily rate of the last week of that month. The leading indicators of the U.S., the U.K., and Germany are obtained from the U.S. Conference Board [14] (the index of the U.S. consumer confidence is obtained from the University of Michigan). The leading indicators of Canada are obtained from CASIM [15]. ESRI, Cabinet Office, Government of Japan [16] provides the data of Japan leading indicators. Because the ranges of different leading indicators are greatly different from one another, all data will be transformed into percentage form. The form of transformation function is

$$I_{\text{new}} = \frac{(I_{\text{ori}} - I_{(2000,\text{ average})})}{\left|I_{(2000,\text{average})}\right|}, \qquad (2)$$

where I_{ori} means the original value of the indicator, $I_{(2000,\text{ average})}$ means the average value of the indicator in year 2000, and I_{new} is the transformed value of the indicator that will be used to train NN model.

Our data sets cover from the horizon from January 1978 to July 1997 and are divided into two periods. The first period running from January 1978 to December 1989 is used for model training and validation. The second period covering the remaining years from January 1990 to July 1997, the same horizon as considered in the work of Qi and Wu, is reserved for out-of-sample evaluation and is used to compare forecasting performance for different models.

5. Empirical results

Here we present the results from our out-of-sample experiment. Table 1 provides forecasting performance for British pound. In most situations, our model demonstrates a strong market-timing ability at the 6- and 12-month horizons. Comparing to Engel‘s [2] work whose DA is 52% on average, our results outperforms Engel‘s work. Even at the 1-month horizon, the DA is well above 60% at some nodes, but not all significant at 5% or 1% level.

The results of Table 2 for Canadian dollar are similar to Table 1. At the 12-month horizon, DA is over 80% for both node 3 and node 4. At the 1-month horizon, our model still has the market-timing ability. Table 3 draws the performance for predicting Deutsche mark. It is glad to see that these data show the market-timing ability at the 1-, 6-, and 12-month horizon. The last currency, Japanese yen in Table 4, performs significant market-timing ability and gets DA all over 80% at the 12-month horizon. In addition, these findings outperform the results of Qi and Wu.

Overall, leading indicators are suitable to simulating macroeconomic conditions and, then, to predicting market-timing ability for exchange rate direction. The NN model with macroeconomic fundamentals as explicative variables outstands the RW model across all examinant currencies.

Table 1. Performance for the British pound

	1 month		**6 month**		**12 month**	
Hidden node	DA (%)	PT	DA (%)	PT	DA (%)	PT
1	54.95	0.08	52.75	0.71	57.14	0.92
2	58.24	0.37	57.14	0.94	69.23**	1.00
3	59.34	0.83	63.74**	1.00	69.23**	1.00
4	60.44	0.92	62.64**	1.00	69.23**	1.00
5	61.54	0.94	74.73**	1.00	74.73**	1.00
6	59.34	0.86	68.13**	1.00	70.33**	1.00
7	60.44	0.71	68.13**	1.00	73.63**	1.00
8	67.03**	1.00	69.23**	1.00	73.63**	1.00
9	58.24	0.85	69.23**	1.00	69.23**	1.00
10	61.54*	0.96	71.43**	1.00	76.92**	1.00

* denotes significance at the 5 percent level
** denotes significance at the 1 percent level

Table 2. Performance for the Canadian dollar

	1 month		**6 month**		**12 month**	
Hidden node	DA (%)	PT	DA (%)	PT	DA (%)	PT
1	49.45	0.66	63.74	0.83	72.53**	1.00
2	51.65	0.79	60.44**	0.99	79.12**	1.00
3	56.04	0.94	62.64**	1.00	80.22**	1.00
4	56.04	0.87	61.54**	1.00	82.42**	1.00
5	61.54**	0.99	67.03**	1.00	75.82**	1.00
6	56.04	0.85	60.44**	0.99	78.02**	1.00
7	56.04	0.90	58.24*	0.97	76.92**	1.00
8	63.74	1.00	57.14*	0.96	79.12**	1.00
9	61.54**	0.99	58.24*	0.98	72.53**	1.00
10	53.85	0.89	62.64**	1.00	75.82**	1.00

* denotes significance at the 5 percent level
** denotes significance at the 1 percent level

Table 3. Performance for the Deutsche mark

	1 month		**6 month**		**12 month**	
Hidden node	DA (%)	PT	DA (%)	PT	DA (%)	PT
1	61.54**	0.99	58.24*	0.98	60.43**	1.00
2	59.34*	0.96	64.84**	1.00	69.23**	1.00
3	57.14	0.90	63.74**	1.00	61.54**	1.00
4	58.24*	0.96	63.74**	1.00	63.74**	1.00
5	56.04	0.93	65.93**	1.00	74.73**	1.00
6	60.44*	0.98	62.64**	1.00	62.64**	1.00
7	56.04	0.89	67.03**	0.99	73.63**	1.00
8	60.44*	0.98	68.13**	1.00	67.03**	1.00
9	61.54*	0.98	67.03**	1.00	62.64**	1.00
10	59.34*	0.98	69.23**	1.00	68.13**	1.00

* denotes significance at the 5 percent level
** denotes significance at the 1 percent level

Table 4. Performance for the Japanese yen

	1 month		6 month		12 month	
Hidden node	DA (%)	PT	DA (%)	PT	DA (%)	PT
1	58.24**	0.99	68.13**	1.00	80.22**	1.00
2	57.14	0.93	70.33**	1.00	87.91**	1.00
3	58.24*	0.98	71.46**	1.00	85.71**	1.00
4	58.24*	0.95	69.23**	1.00	89.01**	1.00
5	62.64**	1.00	71.43**	1.00	86.81**	1.00
6	58.24	0.94	68.13**	1.00	87.91**	1.00
7	62.64**	1.00	73.63**	1.00	86.81**	1.00
8	54.95	0.88	71.43**	1.00	87.91**	1.00
9	57.14*	0.97	68.13**	1.00	86.81**	1.00
10	61.54**	0.99	71.43**	1.00	86.81**	1.00

* denotes significance at the 5 percent level
** denotes significance at the 1 percent level

6. Conclusions

This paper introduces the method using NN model with two relative countries' leading indicators to forecast the exchange rate direction. We want to prove that many potential macroeconomic fundamentals other than ordinary monetary ones could influence aggregate demand and supply of money between different countries. Our results show that the leading indicators could probably be used to represent macroeconomic conditions, and the direction of exchange rate depends deeply on relative variation of corresponding macroeconomic conditions. These results lead to three conclusions: (1) At the 1-month horizon, we find that most results of direction accuracy (DA) are above 56% and some of them are better than pure chance at the 5% and 1% significant levels. For 6- and 12-month horizons, all four countries' outcomes show that most DAs are above 62%, and these results are significant at the 5% or 1% levels. (2) To forecast exchange rate direction via NN model, leading indicators as inputs are more appropriate than standard monetary fundamentals. (3) The input layer design of our NN model is suitable for our empirical research.

Some issues are still not discussed in this paper. All the leading indicators provided by corresponding countries are used in our paper. Among them, there might be some noisy ones that can be drop for improving the performance. Furthermore, a periodical phenomenon may exist in the direction of exchange rate. If we can find the period, we can use this information to design our training and testing horizons.

7. References

[1] M.R. El Shazly, H.E. El Shazly, "Forecasting currency prices using a genetically evolved neural network architecture." *International Review of Financial Analysis*, Vol. 8, pp. 67-82, 1999.

[2] C. Engel, "Can the Markov switching model forecast exchange rates?" *Journal of International Economics*, Vol. 36, pp. 151-165, 1994.

[3] J. Faust, J.H. Rogers, J.H. Wright, "Exchange rate forecasting: the errors we've really made." *Journal of International Economics*, Vol. 60, pp. 35-59, 2003.

[4] G.P. Hopper, "What determines the exchange rate: economic factors or market sentiment?" *Business Review-Federal Reserve Bank of Philadelphia*, Sep/Oct. pp. 17-29, 1997.

[5] T. Jasic, D. Wood, "Neural network protocols and model performance." *Neurocomputing*, Vol. 55, pp. 747-753, 2003.

[6] L. Kilian, M.P. Taylor, "Why is it so difficult to beat the random walk forecast of exchange rates?" *Journal of International Economics*, Vol. 60, pp. 85-107, 2003.

[7] G. Leitch, J.E. Tanner, "Professional economic forecasts: are they worth their costs?" *Journal of Forecasting*, Vol. 14, pp. 143-157, 1995.

[8] M.T. Leung, A.S. Chen, H. Daouk, "Forecasting exchange rates using general regression neural networks." *Computers & Operations Research*, Vol. 27, pp. 1093-1110, 2000.

[9] N. Mark, "Exchange rate and fundamentals: evidence on long-horizon predictability." *American Economic Review*, Vol. 85, Issue 1, pp. 201-218, 1995.

[10] R.A. Meese, K. Rogoff, "Empirical exchange rate models of the seventies: do they fit out of sample?" *Journal of International Economics*, Vol. 14, pp. 3-24, 1983.

[11] M.H. Pesaran, A. Timmermann, "A simple nonparametric test of predictive performance." *Journal of Business and Economic Statistics*, Vol. 10, pp. 461-465, 1992.

[12] M. Qi, Y. Wu, "Nonlinear prediction of exchange rates with monetary fundamentals." *Journal of Empirical Finance*, Vol. 10, pp. 623-640, 2003.

[13] PAFIC, http://fx.sauder.ubc.ca/

[14] http://www.globalindicators.org/

[15] Canadian Socio-economic Statistics, http://www.statcan.ca/english/ads/cansimII/index.htm

[16] http://www.esri.cao.go.jp/en/stat/menu.html