Forecasting the Performance of the Asian Currency Unit and the Causes of Contagion of the Asian Financial Crisis

Jo-Hui Chen\textsuperscript{a}, Yen-Po Fang\textsuperscript{b}

\textsuperscript{a} Department of Finance, Chung Yan Christian University, Taiwan
\textsuperscript{b} Department of International Business, National Cheng Kung University, Taiwan

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Abstract

This study analyses the prediction performance of the Asian Currency Unit (ACU) by employing variant methods including the Back-Propagation Neural Networks (BPN), Recurrent Neural Network (RNN), Time-Delay Recurrent Neural Network (TDRNN), General Autoregressive Conditional Heteroscedasticity (GARCH), and random walk models. The results show that Artificial Neural Network models outperform GARCH and random walk models. The BPN model presents prominent forecasting performance in most division conditions. The study further verifies the causes of contagion of the Asian financial crisis using the Adaptive Network-Based Fuzzy Inference System (ANFIS). The empirical results indicate that the contagion effect would most likely be influenced by tight financial linkage and conditions of macroeconomic similarity as well.

Keywords: Asian currency unit, forecasting capability, contagion causes, artificial neural network

1. Introduction

The idea of optimal regional integration was proposed by Mundell (1999). This perspective aggrandizes the concept of a single currency for establishing the European Unit (EU). The successful implementation of EU’s constitution could decrease transition cost and reduce exchange rate instability. As such, the Euro was completely put into use in 2002. In addition, the number of members for the European Union increased to a total of 25 (Letiche, 2000; Dutta, 2002).

The positive performance generated by the European Currency Unit (ECU) convinced several countries. A favorable environment for the establishment process of ECU could provide a favorable reference for the operation of ACU. In relation to this, Mundell emphasized that the possibility of constituting ACU has been feasible in recent years, and its use could bring tremendous economic benefits for the global market. The immense economic potential of Asia was viewed to be a mighty power comparable to the Euro zone and further challenge the US zone by 2020. In addition, the Asian Development Bank Institute in Tokyo proposed a concept of mutual finances center, namely, the Asian Monetary Fund (AMF), in Asia. This system implements capital support to unsteady countries so that these countries can prevent financial crisis attacks. Moreover, the Association of Southeast Asian Nations (ASEAN) has increased the interaction with China, Japan, and South Korea (ASEAN + 3 SUMMIT) since the year 2000. Meanwhile, these countries collaborated together and spearheaded the Chiang Mai Initiative in Thailand in order to accomplish economic objectives.

* Corresponding author. Email: johui@cycu.edu.tw
The East Asia Summit (EAS) were expected to further tie relationships with China, Japan, South Korea, India, Russia, New Zealand, and Australia in June 2004.

Moreover, the Asian Development Bank announced the initial formulation for constituting the central rate of Asian Currency Units (ACU) in June 2006. According to this formulation, the currencies of Taiwan and Hong Kong have also been included in the currency basket.

The reduction of exchange rate instability is one of the advantages of the establishment of a single currency such as ACU. In light of the above concern, this study further estimates the prediction of exchange rate for ACU by using several forecasting tools such as Artificial Neural Networks (ANNs) and the General Autoregressive Conditional Heteroscedasticity (GARCH) model. We consider the Asian financial crisis as an example to illustrate that several Asian countries suffered due to extreme depreciation of over 30 percent of their currencies. The depreciation extent was most serious in Indonesia, with a depreciation of more than 60 percent. The source of currency crisis could be categorized into three major causes based on the currency crisis theory. These are inconsistent economic policy, self-fulfilling investors, and the contagion effect. Notably, many researchers have discussed the contagion effect. For example, Eichengreen et al. (1996), Glick and Rose (1999), Van Rijckeghem and Weder (1999), and Leonardo and Rodrigo (2001) analysed the causes of crisis contagion. They categorized some key factors such as trade linkage, financial linkage, and macroeconomic similarity, and then analysed their relative importance. In relation to the Asian Financial Crisis that enhanced the feasibility for Asian currency integration, diminished economic difference, and increased political cooperation, we further investigated an efficient control and solution for the contagion effect. This article deals with each cause of contagion in an attempt to improve economic stability and the cooperation mechanism in Asia.

This study is mainly divided into two parts. In the first section, our purpose is to estimate the forecasting performance of the Artificial Neural Network. Particularly, we use the central rate of ACU to estimate effective prediction variables. This integration conducts central rate forecasting for ACU against 10 Asian currencies by using the Back-Propagation Network (BPN), Recurrent Neural Network (RNN), and Time-Delay Recurrent Neural Network (TDRNN). Moreover, we compared the results of the ANN models with those of time-series models in terms of forecasting performance for determining the central rate of ACU. With regard to the out-of-sample testing data, we are also concerned if the ACU volatility in the Asian financial crisis period will influence the predicting performance of ANNs and time-series models. For the Asian financial crisis, we employ the Adaptive Network-Based Fuzzy Inference System (ANFIS) model. The goal is to estimate the relevant importance in contagion sources (such as trade linkage, financial linkage, and macroeconomic similarity) for 10 Asian countries in order to provide useful information for government authorities in dealing with the contagion crisis.

2. Literature review

2.1 The researches for Asian Currency Unit (ACU)

With regard to monetary concern among Asian currencies, Raj and Mbodja (1996) evaluated and proposed that the Japanese yen has greater extent of influence compared with other Asian currencies. This demonstrates that Japan has promoted its international position gradually in a manner that has awakened the integrated consciousness of the Asian economy’s development.

Tzeng (1999) assessed the principal members that constituted the Asian currency unit. The results show that Taiwan, Indonesia, South Korea, Malaysia, the Philippines, and Thailand should be included in the Asian Union mainly due to their similar economic scale, which exhibits best integration performance for a single currency.
Bayoumi and Mauro (2001) compared regional currency agreement among the ASEAN, Mercosur, and the NAFTA. They found that the integrating process of the Asian currency unit could emulate the successful currency integration experience of the EU. In addition, to analyze the extent of stability adjustment in the central exchange rate of ACU, Chen et al. (2001) indicated that inflation rate, current balance, government debt, and short-term interest rate exhibit significant correlation with the fluctuation of ACU. Meantime, Chen (2001) estimated the stability of Asian Currency Unit constitution. The results showed that Japan’s short-term interest rate and export volume could considerably influence the volatility of ACU.

Chen and Hsieh (2004) by examining the threshold of currency crises via the Ordered Probit and Ordered Logit models indicated that trade variables such as term of trade, volume of trade, and trade balance could influence ACUs. Chen and Hisao (2006) definitely proved that CPI could reduce the probability of currency crisis eruption after constituting the central rate of ACU. Chen and Chen (2006) further analyzed the optimal target zone for each member’s exchange rate to ACU. They categorized the target zone into five different levels. For instance, for countries with a superior economic system such as Japan, Singapore, Hong Kong, and China, an interval of 0 to 2.25 percent could be estimated.

2.2 Discussion on regional currency crisis

The contagion effect of a currency crisis spreads to neighboring countries through closer trade relationship. The great deal of capital outflows, just like the domino effect, takes place in the same region that influenced the financial system subsequently. In relation to this, Eichengreen et al. (1996) utilized the binary probit model to estimate the factors contributing to currency crises based on trade linkage and similar macroeconomic variables. They pointed out that the trade linkage exhibited superior contagion effect as compared to another spreading channel and similar macroeconomic condition.

In regional currency crises, Glick and Rose (1999) found that currency crises cause a dramatic damage to a country’s currency and its banking system. The empirical results of their study demonstrate that the crisis is influenced by trade and other macroeconomic variables such as the annual growth rate of domestic credit, the government’s budget as a percentage of GDP, and the current account as a percentage of GDP.

Tatsuyoshi (2000) used the probit model to verify the causes of currency crisis as proposed by the IMF. In an analysis of macroeconomic factors, he implemented a comparative research on the studies of Frankel and Rose (1996), Eichengreen et al. (1996), and Glick and Rose (1999). The empirical results showed that bilateral aggregate could better explain the general currency crisis.

In order to further confirm the ideas of Eichengreen et al. (1996) and Glick and Rose (1999), Kenneth et al. (2002) estimated the trade affinity among five East Asian countries. As a result, South Korea emerged with a higher elasticity of export substitution than Thailand and Malaysia, but it was also confronted with a serious impact during the currency collapse of the Thai Baht.

Following the idea of Van Ricjkeghem and Weder (1999) who defined the concept of absolute and relative financial competition, Leonardo and Rodrigo (2001) found the relative importance of three main channels, such as trade linkage, neighbourhood effect, and financial linkage, to the contagion effect. The effects of financial competition appeared relatively important to trade linkage and nationhood effects due to their ability to explain a contagion issue. To further consider the source of contagion incidence, they state that the three main origins were common bank loan, trade linkage, and macroeconomic features of the country. More specifically, the contagion effect through common bank lenders was more important than others in spreading the Mexican, Thai, and Russian currency crises. To improve performance, they recommend that BIS data be employed to represent the indicator of financial linkage.
Except for the idea of the occurrence of contagion of currency crises by regional trade linkage and financial linkage, Sander and Kleimeier (2003) expanded the issue from the regional to the global level. They focused on the 11 sovereign bonds market which denominated via daily spreads of the US dollar, including the five ASEAN countries. The empirical result showed that the Asian financial crisis resulted from the original causality relation and generated a new change pattern. Marais and Bates (2006) focused on the type of currency crisis in the sovereign debt market. The result showed the contagion effect link between countries revealed closer causal relations among the five Asian countries compared with the tranquil period. In addition, they found that South Korea was the most damaged by the cross-country contagion.

3. Empirical methodology

Concerning the components of ACU in previous studies, three major macro-factors such as export volume, net reverse, and GDP per capita constitute the central weights of ACU. This study particularly focuses on the issues related to forecasting for ACU and the cause of the contagion effect. We used a popular forecasting technique, the Artificial Neural Network, GARCH, and random walk models.

The Artificial Neural Network possesses parallel computation capability in line with the neural structure of a human being. The most unique characteristic of ANN models is that they are equipped with a non-linear structure and non-assumption limitation for implementation. In addition, because ANN models exhibit greater learning capability through regulative learning algorithm and recursive interaction with environmental information, they are widely utilized for forecasting and classification (Joseph et al., 1998; Hu and Christos, 1999; Chang et al., 2003). Since conditional heteroscedasticity is equipped with the properties of previous disturbance square and lagged conditional variance, the conditional variance models could be more flexible. In this article, we also apply the GARCH (1, 1) because of its simplicity and stability (West and Cho, 1995). Furthermore, we use a benchmark model called random walk model as another comparative analysis tool. These models are presented in the Appendix.

3.1 The calculation of ACU

This study utilized the mechanism of the current basket in Euro to constitute the ACU as shown in Table 1. The central exchange rate was formulated using the currency exchange rate of 10 Asian countries, which included Taiwan, Japan, South Korea, Hong Kong, Malaysia, Singapore, Thailand, the Philippines, Indonesia, and China against the U.S. dollar. With regard to selecting macroeconomic variables, the central exchange rate of ACU consisted of weights of export volume, net reverse, and GDP per capita. The period for realigning the exchange rate of ACU was three year-period, mainly because of the highly intricate political and economic relations among Asian countries. The research spell started from beginning of 1992 when the Singapore declaration was signed. This declaration drives the development for the ASEAN Free Trade Area (AFTA) and enhances the economic cooperation for ASEAN countries. It opened the road of economic integration for Asian countries. In addition, this study has referred to the constitution process of European Unit (EU) to conduct the ACU simulation. Therefore, this period is from March 2, 1992, when the treaty of Maastricht was passed, to June 30, 2005, and in total, 724 simulating observations were made. Although the research spell includes the impact period of the Asian financial crisis, one of the advantages for constituting ACU is the decrease in extraordinary fluctuation resulting from abnormal events (Chen et al., 2001). Therefore, the impact of data volatility has been controlled.
Table 1. The computation approach of Asian Currency Unit

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Gathering the data of export volume, net reserve, and GDP per capita on five base periods in March 1992, 1995, 1998, 2001, and 2004. The research sample is retrieved from ten currencies against USD.</td>
</tr>
<tr>
<td>Step 2</td>
<td>Computing average weight ratio of the above three variables in five base periods.</td>
</tr>
<tr>
<td>Step 3</td>
<td>Calculating SDR ratio when weight was calculated against USD.</td>
</tr>
<tr>
<td>Step 4</td>
<td>Computing each country’s weight on respective variables in five base times.</td>
</tr>
<tr>
<td>Step 5</td>
<td>Figuring out each country’s unit in current basket; each country’s value of export volume, net reserve and GDP per capita multiplied by each variable’s weight. Consequently, the percent of summation weight is multiplied by exchange rate against USD and then multiplied by SDR. On the basis of the unit in current basket, we can further calculate the weight of each base period.</td>
</tr>
<tr>
<td>Step 6</td>
<td>Using each country’s unit in current basket to multiply each country’s cross exchange rate could yield individual value in ACU.</td>
</tr>
<tr>
<td>Step 7</td>
<td>Converting each currency’s value in ACU to USD so as to generate central rate of ACU.</td>
</tr>
</tbody>
</table>

Note: SDR is a Special Drawing Right measured by International Monetary Fund, IMF.

The input variable was determined via one or more lagged central rates of ACU. In each neural network model, we have to estimate the forecasting accuracy for a one-day to five-day lag and select the three highest significant lag values as the inputs (Cornell and Dietrich, 1978). After evaluating the above pre-test, these neural forecasting models have been manipulated in one-day, two-day, and five-day lag assortments as input variables, which is in line with the findings of Walczak (2001).

The tendency chart in terms of ACU against the U.S. dollar for the past 13 years is shown in Figure E (See Appendix). Moreover, we manipulated the forecasting chart for three ANN models in six different division cases which compared the estimated value of ACU. This way, we were able to check each value of the desired outputs for BPN, TDRNN, and RNN as it was close to the actual value of the weekly ACU exchange rate. For instance, the BPN has the most proximate outcomes with the actual value of ACU (See Appendix for Figures F-K). We extracted the data from the AERMOS database, the Taiwan Economic Journal (TEJ), and the Asian Development Bank (Key Indicators, 2005).

4. Empirical results

4.1 Forecasting the performance of the ACU

In the first part, we compared forecasting capability in terms of the central rate of ACU between artificial neural networks and time-series models (i.e. GARCH (1, 1) and Random Walk). Three ANN models, BPN, RNN, and TDRNN, were employed to make a prediction. Selection of the training and testing sets is a very important step. It should be noted that selection of different periods may result in a poor forecasting performance, mainly because some unexpected variance may occur in the time series. In order that no available information is missed for the forecasting of the performance of ACU using the ANN model, this article manipulated six types of training data and testing data via randomly selected proportion (Andreou et al., 2002).
When the parameter setting for our forecasting models is considered, we follow the initial mode of NeuroSolutions to set up the learning rate at 0.7. At the next step, each neural network model is tested for four kinds of design neurons (i.e. 5, 10, 15, and 20) (Wu and Yang, 2007). The fittest hidden neurons have been selected via the test results obtained from Mean-Square Error (MSE), Normalized Mean-Square Error (NMSE), and Mean Absolute Percent Error (MAPE). For implementing different iteration examinations (i.e. 1000, 10000, 100000) for each ANN model, the best epoch number is 100,000.

For analyzing each forecasting performance, the MSE, NMSE, and MAPE are the main criteria for evaluating the results. The detailed parameter setting and estimated outcomes for the ANNs are shown in Table 2.

Table 2. ANN’s testing results for six types of training and testing data

<table>
<thead>
<tr>
<th>Types</th>
<th>Parameters setting</th>
<th>Back-propagation neural network (BPN)</th>
<th>Recurrent neural network (RNN)</th>
<th>Time-lag recurrent neural network (TDRNN)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hidden nodes</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Transfer function</td>
<td>Sigmoid</td>
<td>Sigmoid</td>
<td>Sigmoid</td>
</tr>
<tr>
<td></td>
<td>Learning rate</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>Maximum epochs</td>
<td>100,000</td>
<td>100,000</td>
<td>100,000</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>144</td>
<td>144</td>
<td>144</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**8.53E-05</td>
<td>0.0001855</td>
<td>0.0002981</td>
</tr>
<tr>
<td>I</td>
<td>NMSE</td>
<td>**6.86E-03</td>
<td>0.0189313</td>
<td>0.0210514</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.2857763</td>
<td>0.2322710</td>
<td>0.3738279</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>181</td>
<td>181</td>
<td>181</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**8.41E-05</td>
<td>0.0003327</td>
<td>0.0002468</td>
</tr>
<tr>
<td>II</td>
<td>NMSE</td>
<td>**6.48E-03</td>
<td>0.0256348</td>
<td>0.0140322</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.2813149</td>
<td>0.3768648</td>
<td>0.3768201</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>217</td>
<td>217</td>
<td>217</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**7.83E-05</td>
<td>0.0002076</td>
<td>0.0002104</td>
</tr>
<tr>
<td>III</td>
<td>NMSE</td>
<td>**4.27E-03</td>
<td>0.0118017</td>
<td>0.0162085</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.1903855</td>
<td>0.3480001</td>
<td>0.4581389</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>289</td>
<td>289</td>
<td>289</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**5.29E-05</td>
<td>0.0001819</td>
<td>0.0001025</td>
</tr>
<tr>
<td>IV</td>
<td>NMSE</td>
<td>**2.90E-03</td>
<td>0.0099798</td>
<td>0.0056242</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.1820859</td>
<td>0.4004241</td>
<td>0.3181315</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>325</td>
<td>325</td>
<td>325</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**8.29E-05</td>
<td>0.0002145</td>
<td>0.0001057</td>
</tr>
<tr>
<td>V</td>
<td>NMSE</td>
<td>**4.36E-03</td>
<td>0.0105127</td>
<td>0.0051488</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.2080173</td>
<td>0.4343572</td>
<td>0.3280998</td>
</tr>
<tr>
<td></td>
<td>Testing data</td>
<td>362</td>
<td>362</td>
<td>362</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>**8.54E-05</td>
<td>0.0001914</td>
<td>0.0001149</td>
</tr>
<tr>
<td></td>
<td>MAPE</td>
<td>**0.1908531</td>
<td>0.4263369</td>
<td>0.3467340</td>
</tr>
</tbody>
</table>

Note: **indicates better performance consequence based on the testing criteria of MSE.

According to the empirical results using three ANN models, the BPN model exhibits better performance ability for testing the exchange rate of ACU at all combinations. The values of MSE above six segment periods are lower than those of the RNN and TDRNN models. This finding illustrated that the BPN model outperforms other neural network models in the testing due to its outstanding forecasting accuracy.

Most interestingly, this study found that the forecasting error criteria showed a slight increase when the testing data were close to the Asian financial crisis spell in the specifications of V and VI. Technically, the impact of the Asian financial crisis on the central rate of ACU will reduce the forecasting performance of the BPN models. However, the RNN and TDRNN models did not present significant differences in all specifications. In addition, three neural
network models revealed coherent outcome, which points out that the best forecasting measure was in specification IV with 40% testing data. Again, the forecasting spell which did not include the Asian financial crisis period presented better forecasting accuracy. The findings of our study support the use of the BPN model to conduct a longer spell prediction for the central rate of ACU based on the outstanding forecasting performance for 289 weekly ACU data, which was equal to the length of the predicting period of 5.5 years.

Table 3 shows the test result of the best ANN model in each different forecasting periods, which is compared with GARCH (1, 1) and the Random Walk models. Incontrovertibly, the ANN models have better forecasting capability than the GARCH (1, 1) and the Random Walk models when compared with the BPN model. For instance, in the case of a 20 percent testing set, the value of MSE for BPN is 8.53E-05, which is extremely lower than that of GARCH (1, 1) at a value of 1.3903 and that of the Random Walk model at a value of 0.009749. Besides, the Random Walk model reveals better forecasting performance for all combinations when it is weighed against GARCH (1, 1). With regard to the forecasting accuracy of the exchange rate in the time-series model, the Random Walk model shows modest results (Kilian and Taylor, 2003).

<table>
<thead>
<tr>
<th>Testing Data</th>
<th>Back-propagation neural network (BPN)</th>
<th>GARCH (1, 1)</th>
<th>Random Walk</th>
</tr>
</thead>
<tbody>
<tr>
<td>20% (144)</td>
<td><strong>MSE (8.53E-05)</strong></td>
<td>MSE (1.9329)</td>
<td>MSE (0.009749)</td>
</tr>
<tr>
<td>25% (181)</td>
<td><strong>MSE (8.41E-05)</strong></td>
<td>MSE (1.8799)</td>
<td>MSE (0.010203)</td>
</tr>
<tr>
<td>30% (217)</td>
<td><strong>MSE (7.83E-05)</strong></td>
<td>MSE (1.8279)</td>
<td>MSE (0.009704)</td>
</tr>
<tr>
<td>40% (289)</td>
<td><strong>MSE (5.29E-05)</strong></td>
<td>MSE (1.8282)</td>
<td>MSE (0.010408)</td>
</tr>
<tr>
<td>45% (325)</td>
<td><strong>MSE (8.29E-05)</strong></td>
<td>MSE (1.8621)</td>
<td>MSE (0.010196)</td>
</tr>
<tr>
<td>50% (362)</td>
<td><strong>MSE (8.54E-05)</strong></td>
<td>MSE (1.8728)</td>
<td>MSE (0.010315)</td>
</tr>
</tbody>
</table>

Note: 1. ** indicates better performance consequence based on the testing criteria of MSE.
2. The numbers of forecasting performance are illustrated in the parentheses.

We then compare the multi-step ahead forecast with the one-step ahead forecast. The ANNs models were designed to conduct a two-step ahead forecast. Again, the output value is the central rate of ACU, but this time, we make a prediction for ACU from $y(t+1)$ to $y(t+2)$, which means that the $(t+1)$ input is used to forecast the $(t+2)$ output value (Fierascu and Badea, 2004). Chang et al. (2004) proposed that the two-step ahead forecast outperforms the one-step ahead forecast. However, our finding shows a diverse result, suggesting that the performance of the one-step ahead forecast is superior to the two-step ahead forecast according to MSE as shown in Table 4.
<table>
<thead>
<tr>
<th>Central rate of ACU</th>
<th>Back-propagation neural network (BPN)</th>
<th>Recurrent neural network (RNN)</th>
<th>Time-lag recurrent neural network (TDRNN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-step (20% testing)</td>
<td><strong>MSE (8.53E-05)</strong></td>
<td><strong>MSE (1.85E-04)</strong></td>
<td><strong>MSE (2.98E-04)</strong></td>
</tr>
<tr>
<td>Two-step (20% testing)</td>
<td>MSE (7.35E-04)</td>
<td>MSE (8.92E-04)</td>
<td>MSE (1.13E-03)</td>
</tr>
<tr>
<td>One-step (50% testing)</td>
<td><strong>MSE (8.54E-05)</strong></td>
<td><strong>MSE (1.90E-04)</strong></td>
<td><strong>MSE (1.14E-04)</strong></td>
</tr>
<tr>
<td>Two-step (50% testing)</td>
<td>MSE (4.38E-04)</td>
<td>MSE (3.97E-04)</td>
<td>MSE (5.59E-04)</td>
</tr>
</tbody>
</table>

Note: **indicates better performance consequence based on the testing criteria of MSE.

4.2 The empirical results for contagion cause

On the basis of the previous discussion, there is a great likelihood that the contagion broke out because of the change in similar macroeconomic similarity fundamentals and trade and financial linkages. The flow path is briefly illustrated in Figure 1.

In order to comprehensively analyze the impact on contagion causes for Asian countries in terms of the Asian financial crisis spell, we designed the testing model with seven cause combinations, including Trade linkage (TRA), Financial linkage (FIN), Macroeconomic similarity (M.S.), TRA & FIN, TRA & M.S., FIN & M.S., and the full-input model which contains three contagion cause variables. We employ the method of Glick and Rose (1999) to determine binary output value, which indicates as to which Asian countries have suffered due to the Asian Financial crisis. The tool used for the analysis of contagion causes was the ANFIS model. We considered that the ANFIS model was equipped with fuzzy inference logic and self-learning capability. This vantage could enhance the inductive effect for contagion causes described in this section. Besides, this model shows a shorter convergence epoch than other ANN models. The Member Functions (MFs) per input value determines the number of membership functions assigned to each network input. After setting two to four rules for each input in order to implement previous simulation which also compares the testing performance and epoch time, this article considered that a value of two for MFs is the most suitable for the sample size. Table 5 illustrates the test results for contagion analysis.
<table>
<thead>
<tr>
<th>Parameters setting</th>
<th>Trade linkage</th>
<th>Financial linkage</th>
<th>Macroeconomic similarity</th>
<th>Trade and financial</th>
<th>Trade and macroeconomic similarity</th>
<th>Financial and macroeconomic similarity</th>
<th>Full-input model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input values</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>6</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
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<td>Bell Function</td>
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<td>0.1</td>
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<tr>
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<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
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<td>MSE</td>
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<td>0.2018</td>
<td>0.0066</td>
<td>0.1860</td>
<td>0.0597</td>
<td>**0.0040</td>
<td>0.0778</td>
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<tr>
<td>NMSE</td>
<td>1.2812</td>
<td>1.3284</td>
<td>0.0337</td>
<td>1.2938</td>
<td>0.3228</td>
<td>**0.0217</td>
<td>0.4322</td>
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</tbody>
</table>

Note: 1. ** represents better performance consequence based on the testing criteria of MSE and NMSE.
2. Trade Linkage has only one input value and Financial Linkage has one input value also. There are five Macroeconomic variables to represent Macroeconomic Similarity.
3. TSK fuzzy model was known as Sugeno fuzzy model.
4. The research period covers three-year data including one year before and after the financial crisis in 1997.
The findings of our study reveal that the contagion effect could be fully expressed via financial linkage combined with macroeconomic similarity inputs. Van Rijckeghem and Weder (1999) found that financial linkage is the most critical factor in terms of contagion occurrence via probit regression. During destabilization of financial system, creditor nations such as Japan are unable to receive their loans from debtor nations such as Thailand. Consequently, this may cause spillover effects to nearby Asian countries. On the other hand, the profile of macroeconomic structure can provide relevant explanation in this study. It demonstrates that five macroeconomic variables (such as the ratio of M2 to international reserves, the current account balance as a percentage of GDP, the ratio of government budget deficit (surplus) to GDP, the ratio of short-term debt to reserve, and the discount rate for each country) could illustrate the contagion process effectively. According to the results of the contagion cause analysis, firm financial lending system for international finance and solid macroeconomic strength are further proven in terms of their ability to detect the occurrence of the contagion effect. Specifically, the above two factors could increase the manipulation power of foreign exchange authorities as their tool for adjusting the demand of foreign currency. Moreover, macroeconomic similarity has a higher influence than trade linkage. This result shows a perspective of relative sequence that is opposite to that found in the works of Glick and Rose (1999), Van Rijckeghem and Weder (1999), and Leonardo and Rodrigo (2001).
5. Conclusion

The main contribution of this research could be summarized into two aspects. First, we prove that ANN models outperform GARCH (1, 1) and the Random Walk models in forecasting the performance of ACU. Second, the BPN model reveals the best forecasting accuracy when weighed against the RNN and TDRNN models based on three different input lag values for ACU. To estimate the forecasting performance of multi-step ahead forecasting, the one-step ahead forecasting is a good choice for the prediction of ACU’s central rate as compared to two-step ahead forecasting. Moreover, by discussing the contagion causes for the Asian financial crisis, this paper utilizes the ANFIS model to analyze the topic and finds different empirical results when these are compared with those in the works of Eichengreen et al. (1996), Glick and Rose (1999), Van Rijckeghem and Weder (1999), and Leonardo and Rodrigo (2001). Both financial linkage and macroeconomic similarity could significantly explain the contagion source for the Asian financial crisis. This finding could provide a solution for authorities as they strive to diminish the probability of the contagion by controlling the financial correspondence in inter-bank flows and fundamental macroeconomic similarity. In this research, we recommend that authorities and investors should take notice of the ratio of M2, short-term debt to reserves, and government budget deficit. This is because these macroeconomic factors reflect the ability of a country to deal with enormous crash to their currency exchange.

References


Chen, S.J. (2001) The evaluation analysis of Asian Currency Unit (ACU) mechanism-The study of integration for Asian countries economic variables. Graduate School of Business Administration, Chung Yuan Christian University, Taiwan.


Appendix

A. Back-propagation multilayer perception (BPN)

With regard to the forecasting of the performance of ACU, we compared three types of the ANN model (such as the Back-Propagation Neural Network, Recurrent Neural Network, and Time-Delay Recurrent Neural Network) with GARCH (1, 1) and Random Walk models. Three estimated criteria were utilized to evaluate the forecasting performance, namely, Mean-Square Error (MSE), Normalized Mean-Square Error (NMSE), and Mean Absolute Percent Error (MAPE). Before implementing the ACU forecast, the first step was to determine the algorithm for Multilayer Perception (MLP) as shown in Figure A. This integration employs traditional error back propagation algorithm to collocate with BPN. The formulation of error function likewise appears in Equation (1). The speculative output values from BPN model were labeled as $D_j$; consequently, these were compared with authentic output value $A_j$. The difference between these values will generate a feedback mechanism to revise the connection weight for MLP model (Chang et al., 2003):

$$E = \frac{1}{2} \sum_j (A_j - D_j)^2,$$

(A1)

where $E$ represents error function, $A_j$ represents actual output value from output layer, and $D_j$ represents desired output value from output layer.

![Figure A. The architecture of MLP](source: Theory and practice of artificial neural network. (Chang et al., 2003)
Note: A general structure for multilayer perception with a single hidden layer and single output layer; each line exist individual weight.)

Figure B illustrates the development of linkage weight. The activation function was determined by the symbol $\phi$ (Joseph et al., 1998; Chang et al., 2003). In this study, we selected the sigmoid function to represent the activation function, and the formulation of the sigmoid function is shown in Equation (2). To briefly explain the calculation process of BPN, the input values were calculated in a hidden layer, and the revised connection weights which are transmitted to the output layer were noted. Eventually, the output values were figured out by summing up of all the values, which were calculated using the activation function.
\[ f(x) = \frac{1}{1 + \exp(-\alpha x)}. \]

(A2)

Source: Theory and Practice of Artificial Neural Network. (Chang et al., 2003)

**Figure B. Graphical demonstration weights link process of neuron**

**B. Recurrent neural network (RNN)**

This study used the recurrent and time-delay recurrent neural network models to conduct forecasting for ACU. The test results of the Recurrent Neural Network (RNN) and Time Delay Recurrent Neural Network (TDRNN) were compared with those of the GARCH (1, 1) and the Random Walk models. The RNN also contained feedback and feed-forward connections equipped with long-term forecasting performance, provided there is greater dynamic adaptation capability for the data’s temporal memory (Barak et al., 1995; Chang et al., 2003).

RNN belonged to a multilayer perception. When information \( Y(t) \) was generated from the processing layer, except for transference into the output layer, \( Y(t) \) will transmit back the concatenated input–output layer with time delay and then will connect with the input value \( X(t+1) \). Besides, the concatenated input-output layer and processing layer require full connection. The structure is shown in Figure C:

Source: Theory and Practice of Artificial Neural Network. (Chang et al., 2003)

**Figure C. The Architecture for the RNNs model**
C. Time-delay recurrent neural network (TDRNN)

The TDRNN is an extensive neural model that is different from the traditional recurrent neural network. The TDRNN is equipped with the advantages of adaptive time delays and recurrences. This neural network manipulates the temporal information of input sequences by employing adaptive time delays and recurrent connections. The internal state units act as the additional inputs at time t and copies from the activations of the hidden units at time t-1. The network has modifiable synaptic weights and modifiable time lags via interconnections between the input and hidden units while both time delays and weights are adjusted. The delay box constitutes interconnections from the input layer to the first hidden layer and also from the internal state layer to the first hidden layer. We selected the sigmoid function to be the activation function for this part (Kim, 1998).

D. Adaptive network-based fuzzy inference system (ANFIS)

We utilized the ANFIS model to analyze the source of the contagion effect in 10 Asian currencies. The advantages of the ANFIS model are its shorter convergence time and superior training effect than the ANN model (Nayak et al., 2004). Following the trade competition computation of Glick and Rose (1999) to generate the trade linkage indicator, the equation can be shown as follows:

\[
\text{Trade}_i = \sum \left\{ \left[ \frac{I(x_{0k} + x_{ik})}{I(x_0 + x_i)} \right] \left[ 1 - \left( \frac{x_{ik} - x_{0k}}{x_{ik} + x_{0k}} \right) \right] \right\}, \tag{A3}
\]

where 0 means the “first victim” country, \(x_{ik}\) indicates the aggregate bilateral exports from country \(i\) to country \(k\), and \(x_i\) represents the aggregate bilateral exports from country \(i\). In light of the finance competition for bank funds, we utilized a similar indicator of financial competition from Van Rijckeghem and Weder (1999). They denoted the estimation variable for the financial linkage as follows:

\[
\text{Financial}_i = \frac{b_{0c} + b_{ic}}{b_0 + b_i} \left[ 1 - \left( \frac{b_{0c}}{b_0} - \frac{b_{ic}}{b_i} \right) \left( \frac{b_{0c}}{b_0} + \frac{b_{ic}}{b_i} \right) \right], \tag{A4}
\]

where 0 means the “first victim” country, \(c\) represents the common lender, and \(b_{ic}\) stands for the bank loan from country \(c\) to country \(i\). Finally, the macroeconomic fundamental extracted from a relevant study could explain the incidence of currency crises. The relevant variables used in this study were as follows: (a) the ratio of M2 to international reserves, (b) the current account balance as a percent of GDP, (c) the ratio of government budget deficit (surplus) to GDP, (d) the discount rate, and (e) the ratio of short-term debt to reserves (Van Rijckeghem and Weder, 1999).

The architecture of the ANFIS contains a total of five layers. Each layer’s function and structure are shown in Figure D (Jang, 1993; Jang and Sun, 1995; Jang et al., 1997; and Wu and Goo, 2005).

Layer 1: Input nodes

In the first layer, the main function is to map the input nodes into fuzzy sets in order to enhance the treatment capability of this model. In light of the precise illustration and outstanding performance for the bell-shaped functions, we selected the bell-shaped function as the MFs in this study (Wu and Goo, 2005).

\[
O_{i, j} = \mu_j(\chi_i) = \frac{1}{1 + \left( \frac{\chi_i - c_{j \mu}}{a_{j \mu}} \right)^2}, \quad \text{for} \quad i = 1,2,...,N; j = 1,2,...,M_j. \tag{A5}
\]
where parameters \( \{a_i, b_i, c_i\} \) represent a set of MFs in the fuzzy if-then rules; \( c_i \) indicates the middle value of MF; \( a_i \) refers to the half width; and \( b_i \) is a parameter for controlling the slope at crossover points. \( \mu_j(x_i) \) represents input nodes, and \( i \) is the set of membership function \( j \).

Layer 2: Rule nodes
The next step is to coordinate each fuzzy set of input node with the rules of fuzzy logic computation. \( A_i \) and \( B_j \) indicate the linguistic symbols characterized by the bell shape of the membership function. In this article, we utilized the T-norm computing method to implement the fuzzy calculation (Jang, 1993 and Jang et al., 1997).

\[
O_{2,k} = W_k = uA_i(\chi) \times UB_j(y), \quad k = 1, \ldots, k.
\]  
(A6)

where \( O_{2,k} \) represents the outcomes from layer 1.

Layer 3: Normalization nodes
\( k \) means the normalization output from the previous layer. More precisely, we used \( i_{th} \) rule node’s output, which can be divided by all rules node’s output. As a result, the output values are shown in the range of 0 to 1. It should be noted that \( w_k \) means the outcome of normalization.

\[
O_{3,k} = \overline{w_k} = \frac{w_k}{\sum_{k=1}^{k} w_k}.
\]  
(A7)

Layer 4: Consequent nodes
In this layer, the research employs the node’s output from the previous layer for multiplication with the first-order Sugeno fuzzy mode (Jang, 1993 and Jang et al., 1997).

\[
O_{4,k} = \overline{w_k} f_k = \overline{w_k} (p_i x + q_i y + r_i),
\]  
(A8)

where \( \{p_i, q_i, r_i\} \) is used to determine the relative coefficients based on the consequence of the first-order Sugeno fuzzy model.

Layer 5: Output nodes
This study manipulates one output node in this model and utilizes the technique of defuzzification inference to convert the fuzzy outcome into a crisp value. To sum up all previous layer nodes’ output, Equation (9) is used as follows (Jang, 1993 and Jang et al., 1997):

\[
O_{5,1} = \sum_{k=1}^{k} w_k f_k = \frac{\sum_{k=1}^{k} w_k f_k}{\sum_{k=1}^{k} w_k},
\]

where \(\sum_{k=1}^{k} w_k f_k\) represents overall output after using \(w_k\) output value to multiply the first-order Sugeno fuzzy model.

**E. General autoregressive conditional heteroscedasticity model (GARCH)**

Reviewing some papers related to forecasting of exchange rate by using GRACH (1, 1) model, Caporale and Doroodian (1994) and Yuko (2005) estimated the influence of cross-rate volatility process via the GRACH family model. Bollerslev (1986) modified the ARCH model by adding a lagged conditional heteroscedasticity \(h_{t-j}\) to overcome overly complex parameters manipulation. The architecture of the equation is as follows.

\[
Y_i = X_i b + \varepsilon_i, \quad Y_i | \psi_{t-1} \sim N(X_i b, h_t), \quad \varepsilon_i | \psi_{t-1} \sim N(0, h_t), \quad \varepsilon_i = Y_i - X_i b,
\]

\[
h_t = \alpha_0 + \sum_{i=1}^{i} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{j} \beta_j h_{t-j},
\]

where \(\varepsilon_{t-i}^2\) means residual influence of \(t-1\) residual. \(\alpha\) and \(\beta\) represent the parameters.
Figure E. The thirteen years tendency of ACU
Figure F
Training  Testing
80%  20%

Figure G
Training  Testing
75%  25%

Figure H
Training  Testing
70%  30%

Figure I
Training  Testing
60%  40%

Figure J
Training  Testing
55%  45%

Figure K
Training  Testing
50%  50%

Figure F-K ANN’s forecasting charts