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The Prediction of Currency Crises through Artificial Neural Networks*

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This study examines the causes of the Asian exchange rate crisis and compares it to the European Monetary System crisis. In 1997, emerging countries in Asia experienced financial crises. Previously in 1992, currencies in the European Monetary System had undergone the same experience. This was followed by Mexico in 1994. The objective of this paper lies in the generation of useful insights from these crises. This research presents a comparison of South Korea, United Kingdom and Mexico, and then compares three different models for prediction.

Previous studies of economic crisis focused largely on the manual construction of causal models using linear techniques. However, the weakness of such models stems from the prevalence of nonlinear factors in reality. This paper uses a structural equation model to analyze the causes, followed by a neural network model to circumvent the linear model's weaknesses. The models are examined in the context of predicting exchange rates

In this paper, data were quarterly ones, and Consumer Price Index, Gross Domestic Product, Interest Rate, Stock Index, Current Account, Foreign Reserves were independent variables for the prediction. However, time periods of each country's data are different.

Lisrel is an emerging method and as such requires a fresh approach to financial crisis prediction model design, along with the flexibility to accommodate unexpected change. This paper indicates the neural network model has the greater prediction performance in Korea, Mexico, and United Kingdom. However, in Korea, the multiple regression shows the better performance. In Mexico, the multiple regression is almost indifferent to the Lisrel. Although Lisrel doesn't show the significant performance, the refined model is expected to show the better result. The structural model in this paper should contain the psychological factor and other invisible areas in the future work. The reason of the low hit ratio is that the alternative model in this paper uses only the financial market data. Thus, we cannot consider the other important part. Korea's hit ratio is lower than that of United Kingdom. So, there must be the other construct that affects the financial market. So does Mexico. However, the United Kingdom's financial market is more influenced and explained by the financial factors than Korea and Mexico.

Key Words : Financial crises, exchange rate, datamining, structural equation model, neural network

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1. Introduction

What were the causes of Asian economic, currency and financial crises of 1997~1998? The Asian crisis has resurrected once again, and even more intensively, the debate about the origin of crises and behavior of investors at the onset of financial turmoil. Many have argued in favor of a 'fundamentals' approach. That is, crises occur when the economy is in a state of distress with a deteriorating current account, a growth slowdown or even a deep recession, the bursting of stock and real state price bubbles, and short-term foreign debt reaching dangerous levels. Many others have argued in favor of self-fulfilling crises with collapses of the peg even in countries with immaculate market fundamentals. Even for those that support the 'fundamentals' approach to the crisis based just on the behavior of fundamentals. Also, sudden shift in market expectations and confidence were the key sources of the initial financial turmoil, its propagation over time and regional contagion. While the macroeconomic performance of some countries had worsened in the mid-1990s, the extent the depth of the 1997-1998 crisis should not be attributed to a deterioration in fundamentals, but rather to panic on the part of domestic and international investors, somewhat reinforced by the faulty policy response of the International Monetary Fund and the international financial community. According to the other view the crisis reflected structural and policy distortions in the countries of the region. Fundamental imbalances triggered the currency and financial crisis in 1997, even if, once the crisis started, market overreaction and herding caused the plunge of exchange rate, asset prices and economic activity to be more severe than warranted by the initial weak economic conditions. While most of the 'fundamentalists' argue that extended credit is at the core of crises, they have to concede, that the fuel that ignites a crisis "may be some incident which snaps the confidence of the system and makes people think of the dangers of failure". That is, rumors may be the trigger to a speculative attack.

For most observers, banks have been at the heart of the Asian crisis. For instance, Krugman (1994) states, "the Asian crisis differed from previous financial crises that created a need for the IMF's assistance. It was rooted primarily in financial system vulnerabilities and other structural weaknesses". However, the reasons given for the importance of banks in this crisis differ widely across observers. For some, currency crises led to banking crises in the affected countries. With this view, banks had accumulated large currency exposures based on the belief that there was little exchange rate risk. When exchange rate collapsed, they suffered large losses on their currency exposures. For others, banks were one important contributing factor to the Asian crisis. Asian local banks are accused of too many unsound loans and moral hazard is blamed for this behavior. The International Monetary Fund and governmental bailouts have been blamed for creating banks to take on too much risk, including foreign exchange rate risk (Kho et al, 2000).

These various views of the Asian crisis raise important questions: Did foreign exchange rate play a crucial role in the crisis?

In recent years, a number of researchers have claimed success in systematically predicting which countries are more likely to suffer currency crises. Perhaps the most prominent model proposed before 1997 for predicting currency crises is the indicators approach of Kim.(1998), who monitor a large set of monthly indicators that signal a crisis whenever they cross a certain threshold.

It may seem unlikely that currency crises should be systematically predictable. Early theoretical models of currency crises suggested that crises may, be predictable even with fully rational speculators (Krugman, 1994). In 'second generation' models, a country may be in a situation in which an attack, while not inevitable, might succeed if it were to take place; the exact timing of crises would be essentially unpredictable. Even here, though, it may be possible to identify whether a country is in a zone of vulnerability, that is, whether fundamentals are sufficiently weak that a shift in expectations could causes a crisis. In this case, the relative vulnerability of different countries might predict the relative probabilities of crises in response to a shock such as a global downturn in confidence in emerging markets (Wade, 1998; The bank of Korea, 1998).

It is one thing to say that currency crises may be predictable in general, however, and another that econometric models that are estimated using historical data on a panel or cross-section of countries can foretell crises with any degree of accuracy (Berg et al, 1999; Corsetti et al, 1999). Here the question is whether crises are sufficiently similar across countries and over time to allow generalizations from past experience, and whether adequate data on the signs of crisis available. The possible endogeneity of policy to the risk of crisis may also limit the predictability of crises. For example, authorities within a country, or their creditors, might react to signals so as to avoid crises. On the other hand, a focus by market participants on particular variable could result in its precipitating a crisis where one might not otherwise have occurred.

Ultimately, the question of whether crises are predictable can only be settled in practice. The recent work claiming success in predicting crises has focused almost exclusively on in-sample prediction, that is formulating and estimating a model using data on a set of crises, then judging success by the plausibility if the estimated parameters and the size of the prediction errors for this set of crises. The key test is not, however, the ability to fit a set of observations after the fact, but the prediction of future crises. Can the model predict the crises that are not in the sample used in its estimation? Given the relatively small number of crises in the historical data, the danger is acute that specification searches through the large number of potential predictive variables may yield spurious success in 'explaining' crises within the sample. In this paper, to find out the better predictive method, we use three methods-Lisrel, neural network and regression. Lisrel is a method of structural equation that can find out the causal relation between variables. The objective of knowledge discovery and data mining lies in the generation of useful insights from the data set. The neural network has been applied to the task of prediction among nonlinear model. Previous studies of crises have largely focused on the causal models using linear techniques such as multivariate regression. Thus, this paper shows us the result of three approaches and evaluates them. This paper is composed of four chapters. First chapter is an introduction of this paper. It contains the research background and objective. Second chapter and an overview of exchange rate determination. This chapter introduce to three models of exchange rate determination. This chapter show us the direction to international financial markets. Third chapter explain the methodologies that are used in this paper-neural network, lisrel, and regression. Final chapter contains the overall plot of experimentation. The experimentation was executed by three methodologies in three countries- Korea, United Kingdom, and Mexico. The latter part of this chapter concludes this paper and shows us the future works.

2. Literature Review

2.1 Spot Exchange Rate Determination

2.1.1 Flow Models

In the flow models, foreign exchange is regarded as a medium of exchange. This means that the only reason one needs foreign exchange is for trade. The demand for Korean Won comes from non-Koreans because they want to buy Korean goods/services and pay for them in Korean Won. The demand for USD comes from Koreans because they want to buy non-Korean goods/services and pay for them in US dollars. The demand for USD is, by definition, the supply for Korean Won (Levich, 1998). As in traditional economics, the demand curve is sloping down, the supply curve is sloping up, and the exchange rate is that rate which makes the two equal (the intersection point). The units of the x-axis are won per unit time. Shifts in the demand and supply curves will affect exchange rates. As supply/demand is determined only by trade, anything which makes Korean goods/services more attractive/less attractive to foreigners or non-Korean goods/services more attractive/less attractive to Koreans will affect exchange rates.

2.1.2 Stock Models

In the stock models, foreign exchange is regarded as a store of value. The supply is controlled by the government. The demand comes because it is needed to transact and/or it is a useful asset to have in a portfolio. This is how we obtain the demand and supply curves for the Korean Won. The units of the x-axis are won at a point in time. Shifts in the demand and supply curves will affect exchange rates. As supply/demand is determined by the attractiveness of the currency as a store of value, anything which makes Korean Won more attractive/less attractive to foreigners or

USD more attractive/less attractive to Koreans will affect exchange rates.

2.1.3 Combine Both Models

One can combine both the flow and the stock approaches fruitfully. The point that is being made is the following. The flow approach – where exchange rates are being determined by trade variables – affects exchange rates in the long run. The stock approach – where exchange rates are being determined by the attractiveness of the currency as a store of value – affects exchange rates in the short run. So if the Korean Won becomes more attractive (say, because of reductions in the cost of trading in Korea), the Won will appreciate in the short run, but will fall back to its original value if the trade variables are not changed. If, however, Korean goods/services become more attractive (say, because the quality of Korean goods/services improve), the Won will not appreciate immediately, but will appreciate over the long run to a higher value. Trade variables are the long-run anchor.

2.1.4 Two Types of Stock Model

2.1.4.1 Monetary Approach

In the monetary approach, the different currencies are perfectly substitutable. This means that there is no currency risk premium. The price is defined as the ratio of money supply to money demand. The supply is controlled by the central bank. The demand is affected by income and interest rates. More the income, higher is the demand for money (Levich, 1998). More is the interest rate, less is the demand for money (because people would like to invest more in the alternative interest-bearing bonds). The same relationship holds for the other countries. Hence, if you divide the price level of one country by the price level of another country, you will get the exchange rate.

So we realize that exchange rates are determined by the money supply, income and interest rates in the two countries. To be more specific, the exchange rate increases, i.e. USD depreciates/Won appreciates if US money supply increases or Korean money supply decreases or US income decreases or Korean income increases or US interest rate increases or Korean interest rate decreases

2.1.4.2 Portfolio Approach

The portfolio balance approach assumes that one allocates one’s wealth between domestic money, domestic bonds, and foreign bonds. The attractiveness of foreign bonds is determined by the expected appreciation/depreciation of the exchange rate. This is how expectations of future exchange rates affect demand. The supply is controlled. In equilibrium, the exchange rate makes supply equal demand. Unlike the monetary approach, the different currencies are not perfectly substitutable. There is a currency risk premium. Here S increases, i.e. USD depreciates/Won appreciates if US supply of bonds increases or Korean supply of bonds decreases or US interest rate decreases or Korean interest rate increases, or

US wealth decreases.

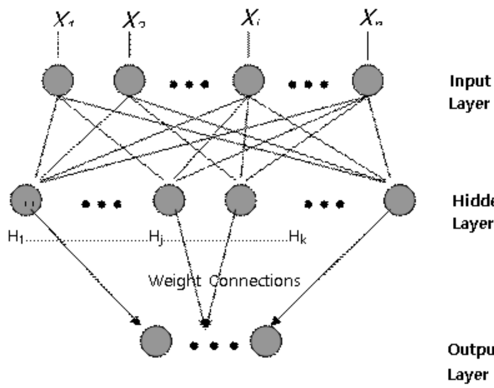
2.2 Datamining

Data mining derives its name from the similarities between searching for valuable business in a large database and mining a mountain for a vein of valuable ore. Both process require either sifting through an immense amount of material or intelligently probing it to find exactly where the value resides. Several researchers defined Knowledge discovery in database is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Back et al, 1998; Jardin et al, 2011). The process starts with identifying which data to consider in the data warehouse and then preprocessing these data to be ready for analysis.

2.2.1 Artificial Neural Network

Artificial neural networks (ANNs or NNs) are a computing technology whose fundamental purpose is to recognize patterns in data. Based on a computing model similar to the underlying structure of the brain, ANNs share the brain's ability to learn or adapt in response to external inputs. When exposed to a stream of training data, ANNs can discover previously unknown relationships and learn complex nonlinear mappings in the data (Back et al, 1998; Jardin et al, 2011).

ANNs are discriminated from the general statistical model by the typical factors called as hidden node and processing elements (PEs). ANNs are composed of many parallel and interconnected computing units, PEs, and synaptic weights used for combination. The PEs of an ANN are organized into layers with each PE in one layer having a connection to each PE in the next layer. Figure 1 represents a typical architecture of multi-layer ANN and PE in each. The hidden layer makes it possible for the networks to generate numerous mapping functions so that the desired output can be produced using a given set of inputs (Kim, 1999; Kim et al., 1999).



〈Figure 1〉 The Self-Organizing Map Structure

Each PEs combine input nodes or hidden nodes using the combination function which sums the synaptic weight times the input signal over all paths and the node bias.

$$H_j = f_j(b_j + \sum_{i=1}^{j} W_{ij} X_i)$$

Where X_i is the input signal, b_j stands for bias and W_{ij} is synaptic weight. After the combination process, H_j is activated by transformation function (activation function). This function makes the combination the form of sigmoid. Representative transformation is logistic function and hyperbolic tangent function.

Logistic Function: $f(x) = \frac{1}{1+e^{-x}}$

Hyperbolic tangent Function: $f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$

As the proper number of hidden nodes and layers is determined, the next step is to estimate the coefficient from the given data. In other words, to discover the best fitting coefficient that reflects the given data features. To reduce the error to the actual set, in general, sum of square method is used as an objective function.

$$Min\sum_{i=1}^{n}(Y_i - P_i)^2$$

where Y_i is the actual value of ith object, P_i means the predicted value of ith object. Learning occurs through the adjustment of the path weights and node bias. Several algorithms have been proposed to derive these weights and to reduce the error.

Over the last decades, and especially in the last few years, ANNs have reached into a wide range of financial and business related applications. Much of this research has focused on finance problems, with special attention to forecasting and planning in the ambit of financial markets (Refenes, 1994; Kim et al., 1999). Various ANNs applications to marketing domain have been proposed by several researchers. Almost papers have asserted the dominance of ANN approach compare to traditional data analysis approach.

2.3 LISREL

Lisrel (an acronym for linear structural relations) is general-purpose program for estimating a variety of covariance structure models, with confirmatory factor analysis being one of them (Jöreskog et al., 1998).

In exploratory factor analysis the structure of the factor model or the underlying theory is not known or specified a priori; rather, data are used the help reveal or identify the structure of the factor model. Thus, exploratory factor analysis can be viewed as a technique to aid in theory building. In confirmatory factor analysis, on the other hand, the precise structure of the factor model, which is based on some underlying theory, is hypothesized.

2.3.1 Lisrel Terminology

Consider p-indicator one factor model depicted in figure0000. The model can be represented by the following equations:

$$x_1 = \lambda_{11}\xi_1 + \delta_1$$
$$x_2 = \lambda_{21}\xi_1 + \delta_2$$
$$\vdots$$
$$x_p = \lambda_{p1}\xi_1 + \delta_p$$

These equations can be represented as:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_p \end{pmatrix} = \begin{pmatrix} \lambda_{11} \\ \vdots \\ \lambda_{p1} \end{pmatrix} \xi_1 + \begin{pmatrix} \delta_1 \\ \vdots \\ \delta_p \end{pmatrix}$$

where λij is the loading of the *i*th indicator on the *j*th factor, ξj is the *j*th construct of factor, δi is the unique factor (commonly referred to as the error term for the *i*th indicator), and *i*=1,…..,p and *j*=1,…..,m. Note that p is the number of indicators and m is the number of factors, which is one in the present case.

The preceding equations can be written in matrix form as

$$X = \Lambda_x \xi + \delta$$

Where x is a p x 1 vector of indicators, Λx is a p x m matrix of factor loadings, ξ is an m x 1 vector of latent constructs (factors), and δ is a p x 1 vector of errors (i.e., unique factors) for the p indicators. The covariance matrix for the indicators is given by

$$\Sigma = \Lambda_x \Phi \Lambda_x' + \Theta_\delta$$

Where Λx is a p x m parameter matrix of factor loadings, Φ is an m x m parameter matrix containing the variances and covariances of the latent constructs, and Θ_δ is a p x p matrix of variances and covariances of the error terms.

The objectives of Lisrel are:

- Given the sample covariance matrix, to estimate the parameters of the hypothesized factor model.
- To determine the fit of the hypothesized factor model. That is, how close is the estimated covariance matrix, Σ, to the sample covariance matrix, S?

The parameters of confirmatory factor models can be estimated using the maximum likelihood estimation technique (Jöreskog et al., 1998).

2.4 Regression

The term regression was introduced by Francis Galton (Galton, 1886). In a famous paper, Galton found that, although there was a tendency for tall parents to have tall children and for short parents to have short children, the average height of children born of parents of a given height tended to move or “regress” toward the average height in the population as a whole. In other words, the height of the children of unusually tall or unusually short parents tends to move toward the average height of the population. Galton’s law of universal regression was confirmed by his friend Karl Pearson, who collected more than a thousand records of heights of members of family groups. He found that the average height of sons of group of tall fathers was less than their fathers’ height and the average height of sons of a group of tall fathers was less than their fathers’ height and the average height of sons of a group of short fathers was greater than their father's height, thus "regressing" tall and short sons alike toward the average height of all men. In the words of Galton, this was "regression to mediocrity" (Hair et al, 2014).

The modern interpretation of regression is, however, quite different. Broadly speaking, we may say

Regression analysis is concerned with the study of the dependence of one variable, the dependent variable, on one or more other variables, the explanatory variables, with a view to estimating and/or predicting the (population) mean or average value of the former in terms of the known or fixed (in repeated sampling) values of the latter.

Although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. In the words of Kendall and Stuart, "A statistical relationship, however strong and however suggestive, can never establish causal connection: our ideas of causation must come from outside statistics, ultimately from some theory or other."

In the crop yield example, there is no statistical reason to assume that rainfall (among other things) is due to nonstatistical considerations: Common sense suggests that the relationship cannot be reversed, for we cannot control rainfall by varying crop yield.

A statistical relationship per se cannot logically imply causation. To ascribe causality, one must appeal to a priori of theoretical considerations.

Closely related to but conceptually very much different from regression analysis is correlation analysis, where the primary objective is to measure the strength or degree of linear association between two variables.

Regression and correlation have some fundamental differences that are worth mentioning. In regression analysis there is an asymmetry in the way the dependent and explanatory variables are treated. The dependent variable is assumed to be statistical, random, or stochastic, that is, to have a probability distribution. The explanatory variables, on the other hand, are assumed to have fixed values. In correlation, on the other hand, we treat any (two) variables symmetrically; there is no distinction between the dependent and explanatory variables. Most of the correlation theory is based on the assumption of randomness of variables, which whereas most of the regression theory is conditional upon the assumption that the dependent variable is stochastic but explanatory variables are fixed or nonstochastic(Hair et al, 2014).

3. Overall Methodology

3.1 Selection of Variables and Model Construct

The case study involves the prediction of currency crises for foreign exchange rate. The variables of data for this study are listed in Table1.

〈Table 1〉 Data for Variables

Korea	Mexico	England	Definition
KO_EX	MX_EX	UK_EX	Exchange Rate
KO_CPI	MX_CPI	UK_CPI	Consumer Price Index
KO_GDP	MX_GDP	UK_GDP	Gross Domestic Product
KO_91CD	MX_3M	UK_3M	Interest Rate
KO_ST	MX_ST	UK_ST	Stock Index
KO_CUR	MX_CUR	UK_CUR	Current Account
KO_RES	MX_RES	UK_RES	Foreign Reserve

This input data were quarterly figures.

Korea: From 1991 to 1999

Mexico: From 1988 to 1998

United Kingdom: From 1986 to 1995

Data Sources: DataStream, Bank of Korea

Total number of Observation (Korea): 32

Total number of Training (Korea): 26Total

Total number of data using in the Prediction (Korea): 6

Total number of Observation (Mexico): 43

Total number of Training (Mexico): 27

Total number of data using in the Prediction (Mexico): 16

Total number of Observation (United Kingdom): 44

Total number of Training (United Kingdom): 27

Total number of data using in the Prediction (United Kingdom): 17

The entire data set consisted of different observations. The training data were also different observations and the test set was the different set.

This paper estimates the currency crisis as predicting the foreign exchange rate. Because the rapid change of foreign exchange rate let us perceive the economy's turmoil. The radical change is a result of the economic collapse.

The first approach is a multiple regression, second approach is a LISREL, and third approach is neural network. All the approaches use time series data. The methodology in this paper constructs the models just before the currency crises' data and test the model using data of which is from currency crises period. In multiple regressions, using version 4.5 STATISTICA, construct the prediction model and test the hold out sample. And then use a period k=t data as input variables to predict k=t+1 exchange rate. Second approach is a LISREL. In this method, using version 8.30 LISREL student, construct the prediction model and test the hold out sample. And then use a period k=t data as input variable to predict k=t+1 exchange rate again. Third method is a neural network. A standard three-layer back propagation neural network is the method of this book. The number of input layer is 6, and the hidden layer has two nodes and the output layer is one. So, the 6*2*1 structure is used. The iteration times are 10,000times. In this method and Lisrel method, the variables are normalized as

$$NX_i = \frac{X_i - \min X}{MaxX - \min X}$$

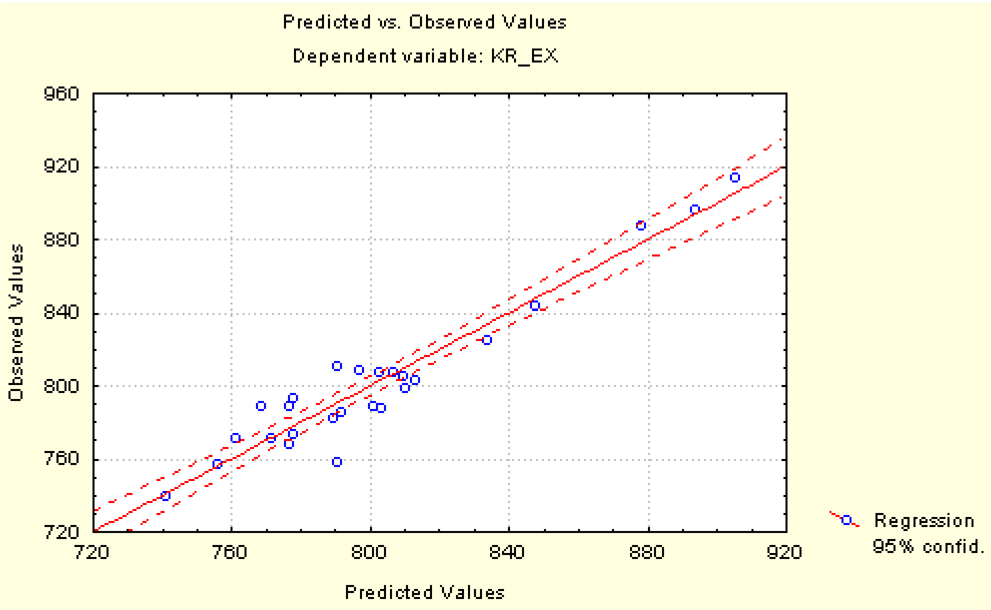
The most prediction algorithms such as artificial neural networks, CBR, and SVM require two groups of dataset for the validation of each model: training and hold-out dataset. Thus, we split the collected data into training set and hold-out set, and the portion of each set is set at 80% and 20% each. However, in order to apply artificial neural networks, we should split the dataset into three groups: training, test, and hold-out dataset. So, we also split the data into these three groups, and we set the portion of each one at 60% for training, 20% for test and hold-out datasets each.

3.2 Regression

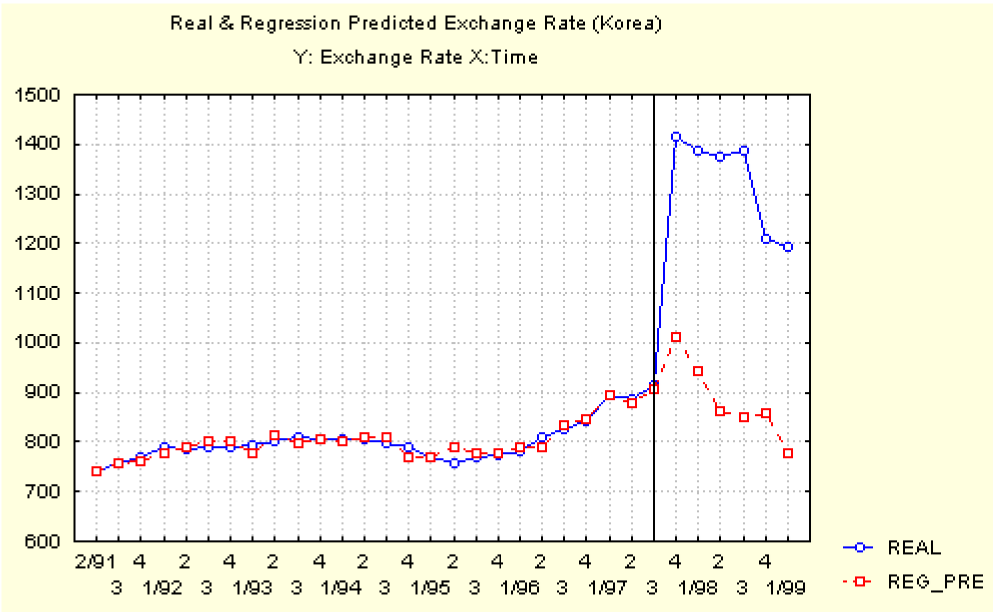
This table shows us the result of regression analysis for Korea. To produce a forecast of k=1 period ahead, the "current" time t also has to be shifted forward by k=1 period.

〈Table 2〉 Regression Table for Korean Exchange Rate

R^2=0.9178, Adjusted R^2=0.8919
KO_Ex_{t+1}=363.5324 + 7.3214KO_CPI_t + 0.001KO_GDP_t - 4.2125KO_91CD_t − 1.0589KO_ST_t - 0.0003KO_CUR_t - 0.0078KO_RES_t



〈Figure 2〉 Predicted vs. Observed Values (Korea)



〈Figure 3〉 Real & Regression Predicted Exchange Rate (Korea)

〈Table 3〉 Hit ratio & Durbin-Watson for Korea

Hit Ratio	0.67
Durbin-Watson	1.900495

From the Durbin-Watson' coefficient, there is no autocorrelation.

The left side of a vertical line in the above figure is the area of training and the right side of the vertical line is the area of test. In following figures, which explanation is applied.

This table shows us the result of regression analysis for United Kingdom. To produce a forecast of k=1 period ahead, the "current" time t also has to be shifted forward by k=1 period.

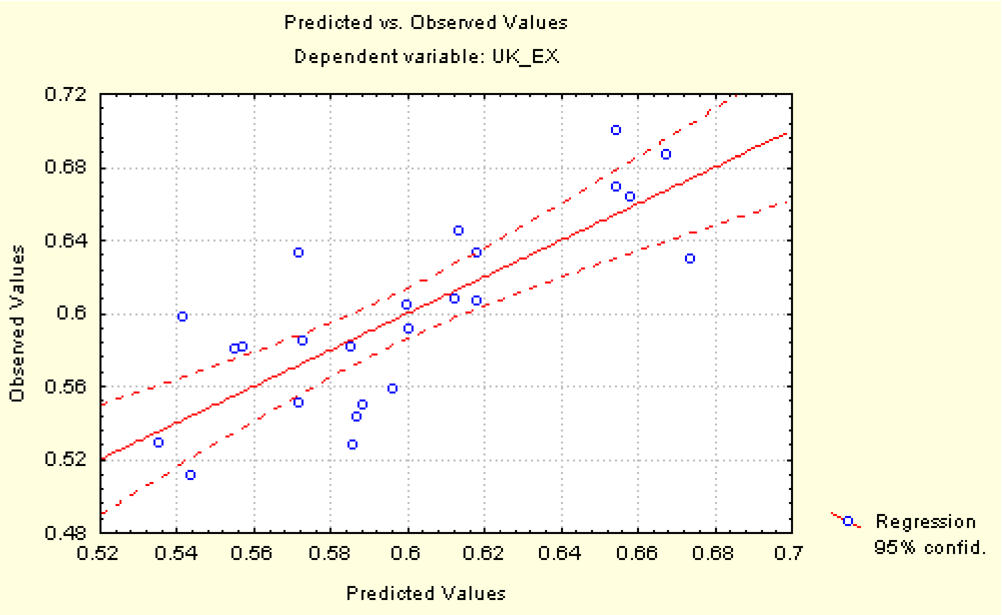
〈Table 4〉 Regression Table for United Kingdom Exchange Rate

R^2=0.6511, Adjusted R^2=0.5465
UK_Ex_{t+1}=0.463033-0.00911UK_CPI_t + 0.007054UK_GDP_t - 0.002671UK_3M_t − 0.000058UK_ST_t - 0.000011UK_CUR_t - 0.000001UK_RES_t

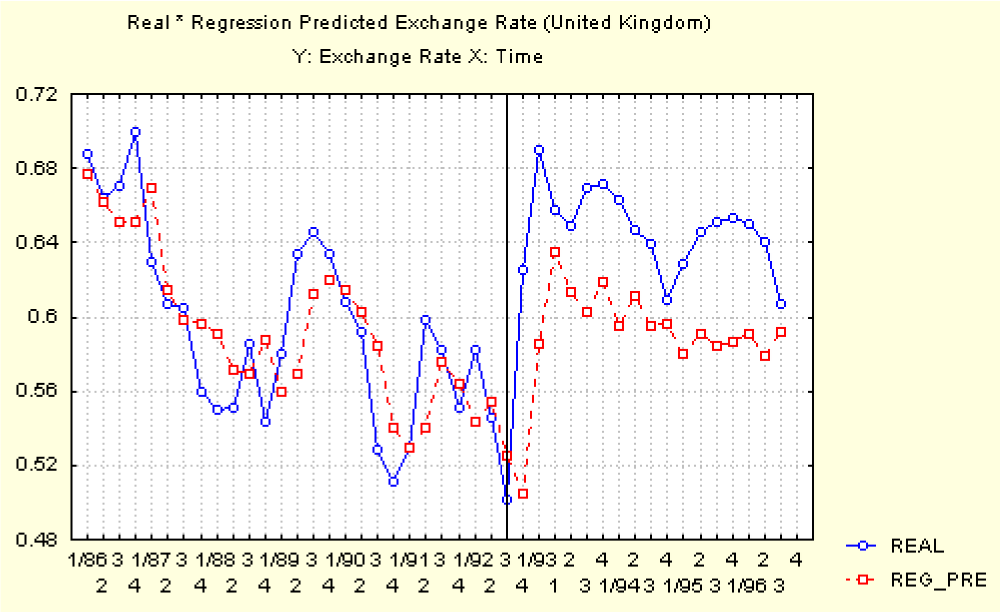
〈Table 5〉 Hit ratio & Durbin Watson for United Kingdom

Hit Ratio	0.56
Durbin-Watson	1.575037

From the Durbin-Watson's coefficient, we can't say that there is an auto correlation.



〈Figure 4〉 Predicted vs. Observed Values (United Kingdom)



〈Figure 5〉 Real & Regression Predicted Exchange Rate (United Kingdom)

This table shows us the result of regression analysis for Mexico. To produce a forecast of k=1 period ahead, the “current” time t has to be shifted forward by k=1 period.

〈Table 6〉 Regression Table for Mexico Exchange Rate

R^2=0.9605, Adjusted R^2=0.9487
$MK\_Ex_{t+1}=1.6692 + 0.25744MK\_CPI_t - 0.00000018MK\_GDP_t - 0.000461MK\_3M_t + 0.00107MK\_ST_t + 0.00068MK\_CUR_t - 0.000000008MK\_RES_t$

〈Table 7〉 Hit ratio & Durbin Watson for Mexico

Hit Ratio	0.57
Durbin-Watson	1.12746

From the Durbin-Watson’coefficient, we can’t say there is autocorrelation.

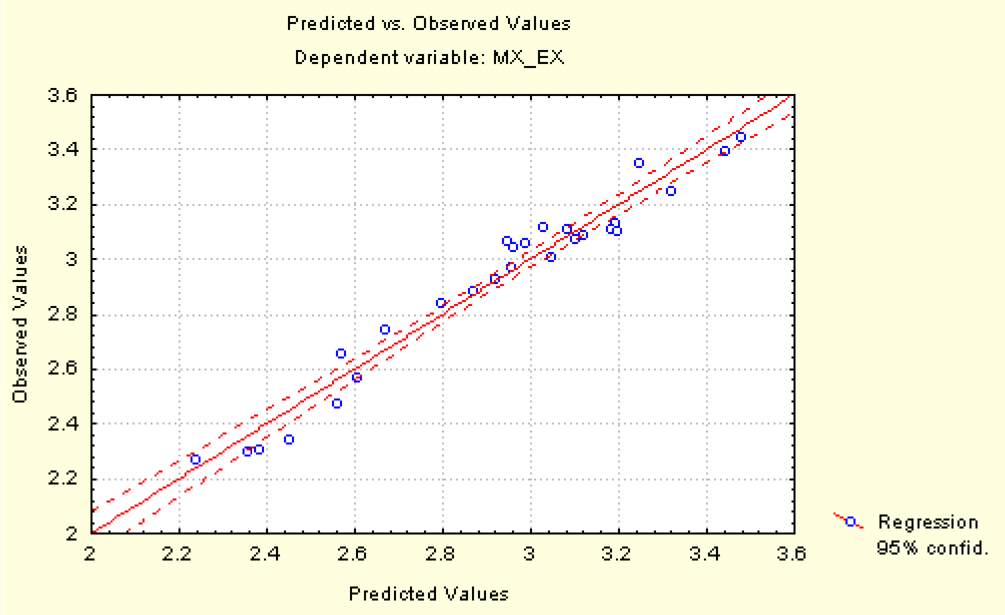
3.3 Lisrel Analysis

From the correlation matrix of Korean variables, we can establish the Linear structural relation and we can estimate the construct by maximum likelihood estimation. Through this process, the model architecture for Korea is established.

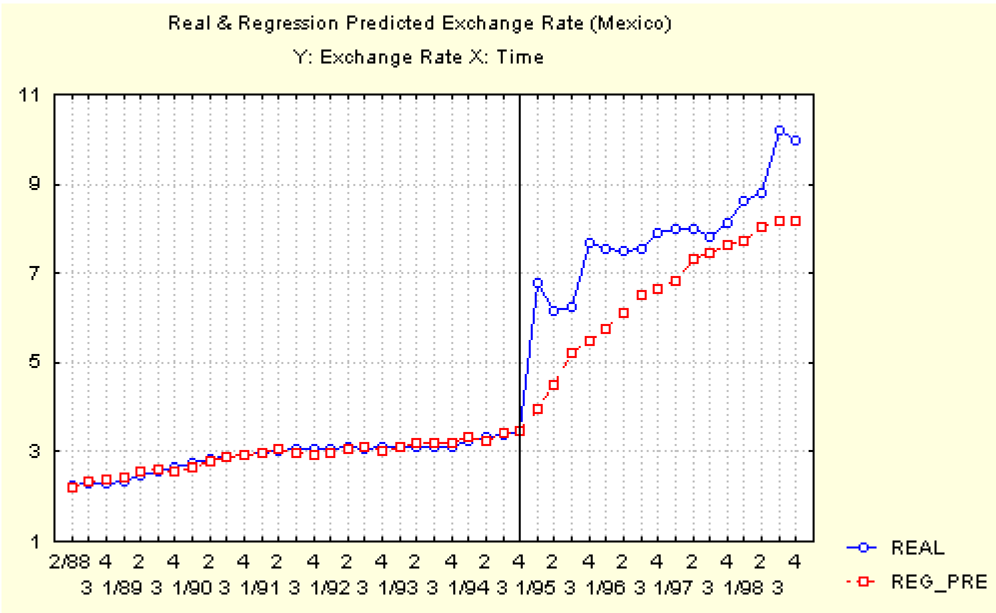
$$\eta * \lambda + \delta = Ko\_Ex$$

$$\xi * \beta = \eta$$

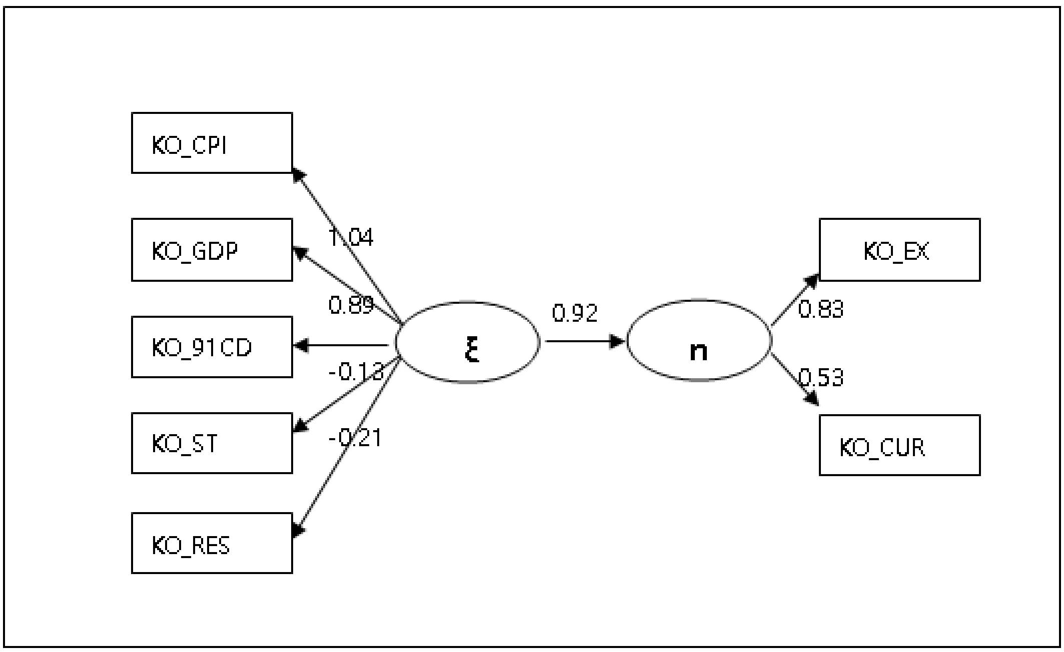
$$(\xi * 0.92) * 0.83 + \delta = Ko\_Ex$$



〈Figure 6〉 Predicted vs. Observed Values (Mexico)



〈Figure 7〉 Real & Regression Predicted Exchange Rate (Mexico)



〈Figure 8〉 Architecture for Linear Structural Relation (Korea)

〈Table 8〉 Hit Ratio & Reliability of ξ for Korea

Hit Ratio	0.58
Reliability of ξ	0.814

From the above structural equations, we can estimate the Korean exchange rate.

From the correlation matrix of United Kingdom variables, we can establish the Linear structural relation and we can estimate the construct by maximum likelihood estimation. Through this process, the model architecture for United Kingdom is established.

$$\eta * \lambda + \delta = UK\_Ex$$

$$\xi * \beta = \eta$$

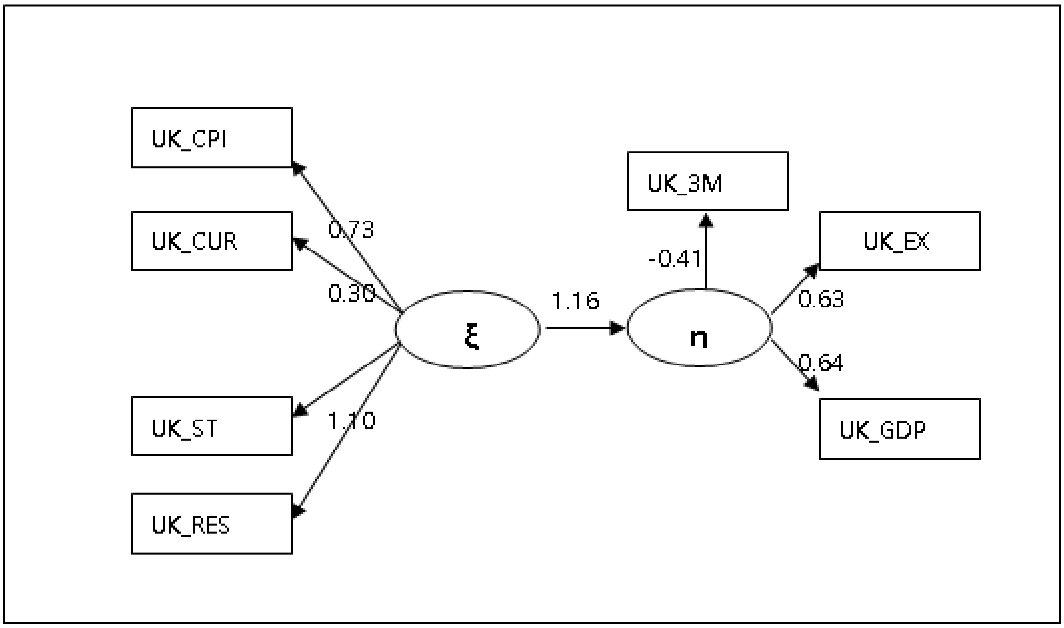
$$(\xi * 1.16) * 0.63 + \delta = UK\_Ex$$

〈Table 9〉 Hit Ratio & Reliability of ξ for United Kingdom

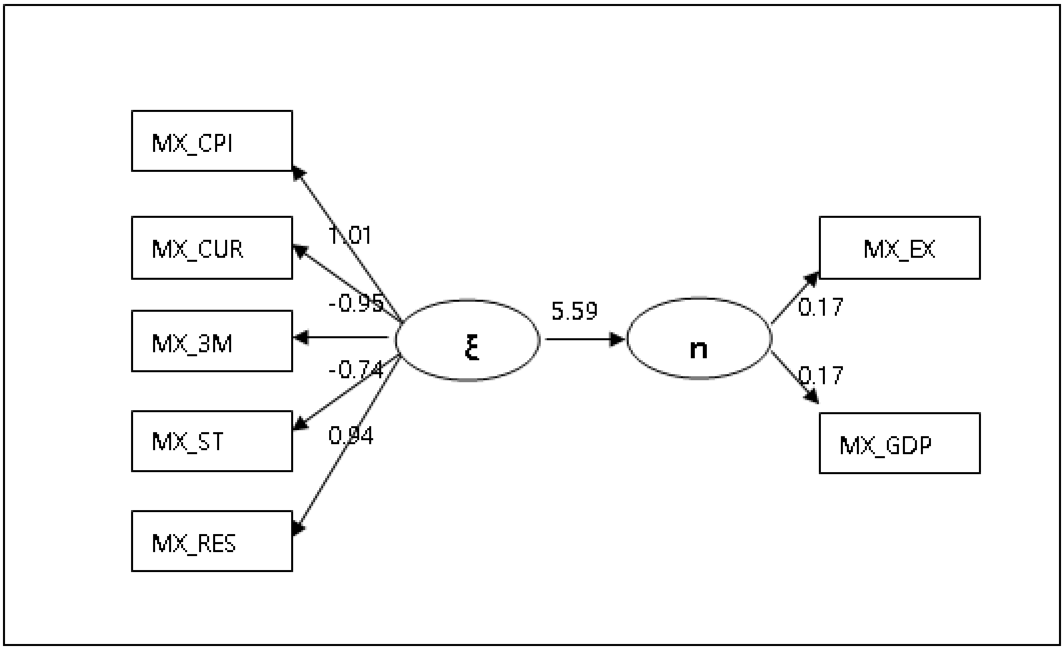
Hit Ratio	0.645
Reliability of ξ	0.817

From the same process, we can also estimate the United Kingdom's exchange rate. Hit ratio of United Kingdom' exchange rate model is better than that of the Korea.

From the correlation matrix of Mexico variables, we can establish the Linear structural relation and we can estimate the construct by maximum likelihood estimation. Through this process, the model architecture for Mexico is established.



〈Figure 9〉 Architecture for Linear Structural Relation (United Kingdom)



〈Figure 10〉 Architecture for Linear Structural Relation (Mexico)

$$\eta * \lambda + \delta = MK\_Ex$$

$$\xi * \beta = \eta$$
$$(\xi * 5.59) * 0.17 + \delta = MX\_Ex$$

〈Table 10〉 Hit Ratio & Reliability of ξ for Mexico

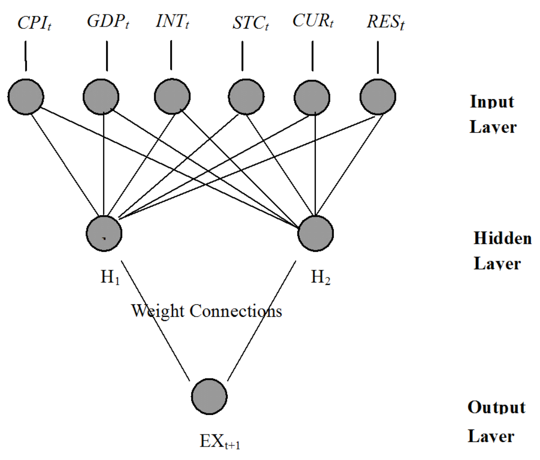
Hit Ratio	0.588
Reliability of ξ	0.7955

From the same process, we can also estimate the Mexico's exchange rate. Hit ratio of Mexico' exchange rate model is better than that of the Korea.

3.4 Neural Network

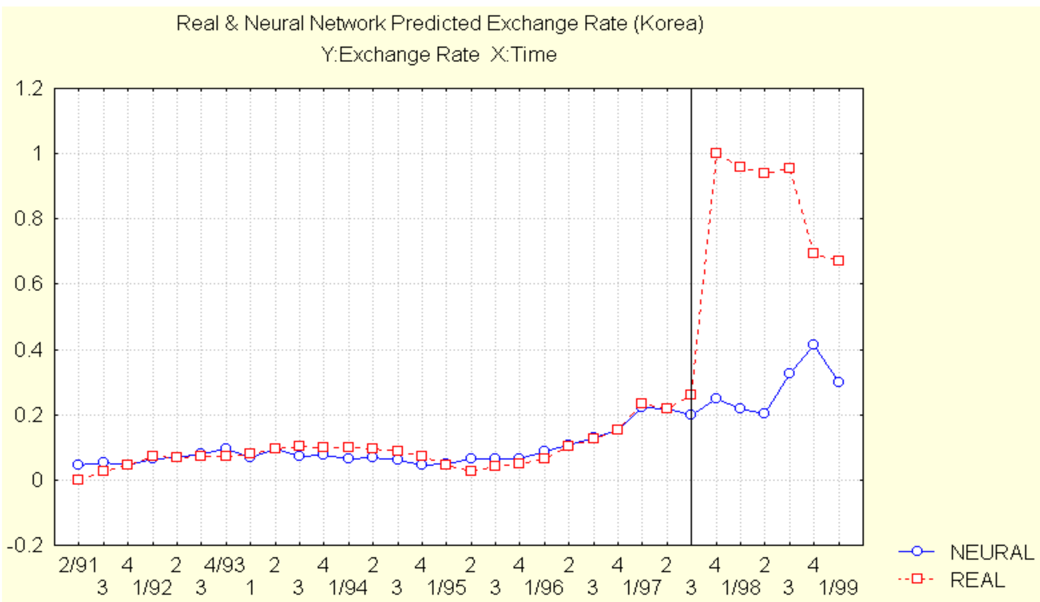
<Figure 11> Strategy for multivariate prediction. The neural network architecture uses vectors as both inputs and outputs. Each iteration involves a forecast for k= 1 period ahead.

Above figure shows us the architecture for exchange rate forecasting. Neural Network Architecture is useful when the non-linearity exists. <Figure 11> illustrates the neural network using vectors as the inputs. The hit ratio of Korea exchange rate is 0.75 and the hit ratio of United Kingdom exchange rate is 0.714 and the hit ratio of Mexico exchange rate is 0.647.



〈Figure 11〉 Architecture for Neural Network

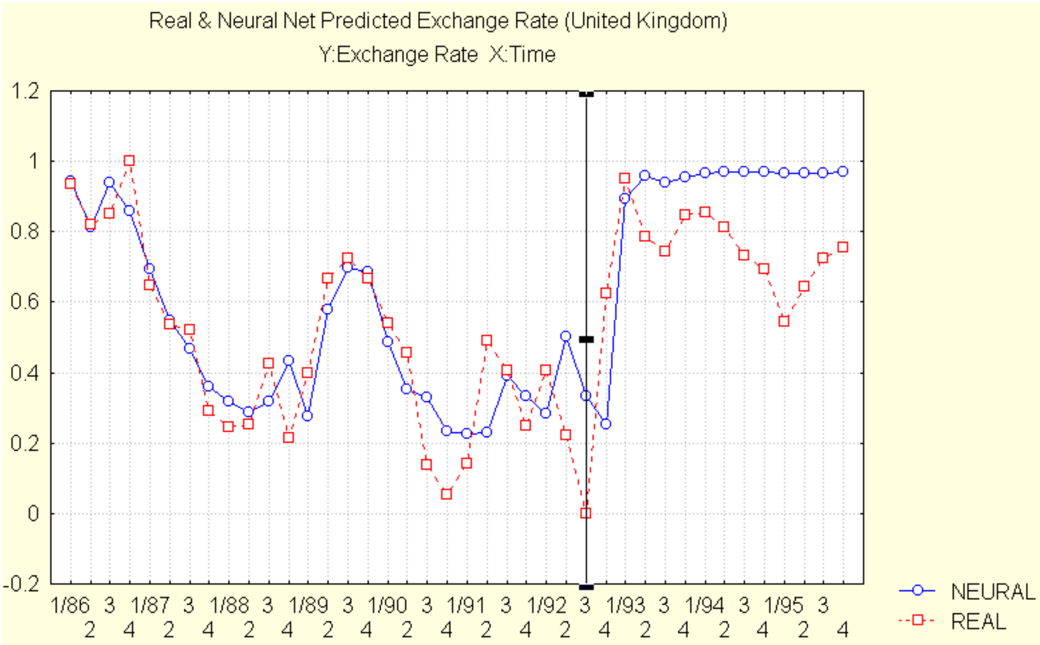
The CPI and Current Account are the most effective causes to Korean exchange rate before crisis. Including the post currency crisis period, besides the previous causes, the Interest Rate and Foreign Reserves are effective causes to Korean exchange rate. The neural network model is 6*2*1 model and the iteration is 10,000 times.



〈Figure 12〉 Real & Neural Network Predicted Exchange Rate (Korea)

〈Table 11〉 Influence Table of Korea Exchange Rate

	CPI	GDP	91CD	ST	CUR	RES
Before Crisis	32.4	3.36	1	3.84	14.84	8.494
Entire	39.67	1.49	21.92	29.63	1	11.44

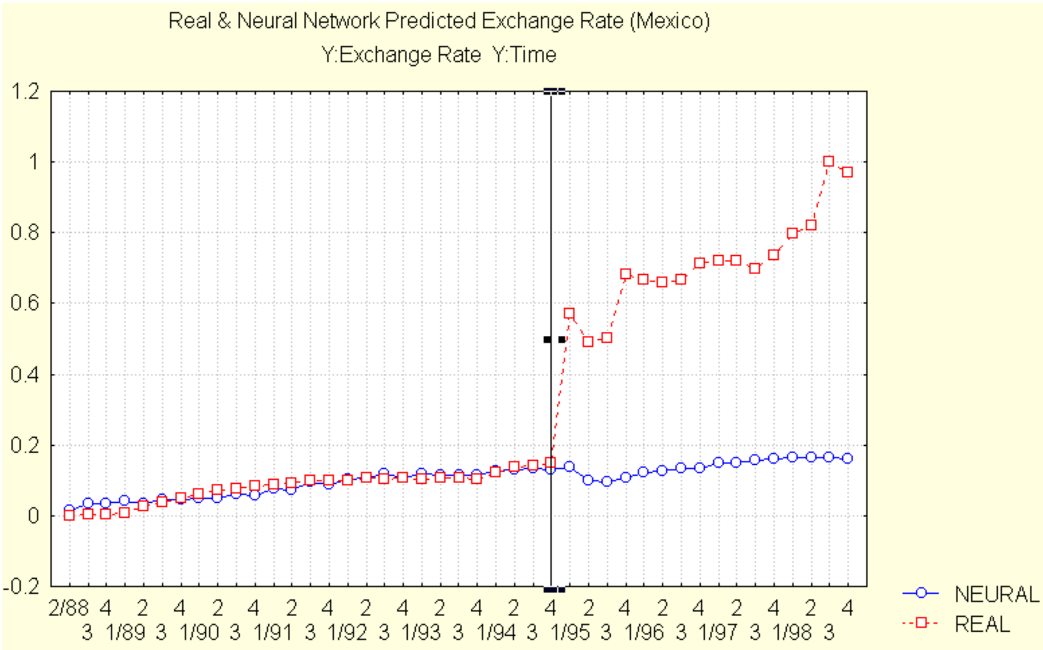


〈Figure 13〉 Real & Neural Network Predicted Exchange Rate (United Kingdom)

〈Table 12〉 Influence Table of United Kingdom Exchange Rate

	CPI	GDP	3M	ST	CUR	RES
Before Crisis	3.05	34.389	2.28	3.71	1	10.22
Entire	4.25	11.998	12.64	3.64	1	20.43

The GDP and Foreign Reserves are the most effective causes to United Kingdom's exchange rate before crisis. Including the post currency crisis period, besides the previous causes, the Interest Rate is also the effective cause to the exchange rate. The neural network model is 6*2*1 model and the iteration is 10,000 times.



〈Figure 14〉 Real & Neural Network Predicted Exchange Rate (Mexico)

〈Table 13〉 Influence table of Mexico exchange rate

	CPI	GDP	3M	ST	CUR	RES
Before Crisis	7.24	1	2.53	2.02	2.89	5.33
Entire	3.97	8.54	2.25	4.68	1.67	1

The CPI and Foreign Reserves are the most effective causes to Mexico's exchange rate. Including the post crisis period, while the GDP and the stock increase their influence on the exchange rate, the previous causes decreases their effects. The neural network model is also 6*2*1 model and the iteration is 10,000 times.

The overall effect of a feature on the output node is defined as overall weight (OW) that is a following equation;

$$OW(x_i) = \frac{\sum_{j=1}^{h}\sum_{k=1}^{0}|w_{ji}||w_{kj}|}{\sum_{j=1}^{h}\sum_{k=1}^{0}|w_{kj}|}$$

Where X_i denotes the *i*th feature of the input vector, W_{ji} the connection weight from the *i*th input node to the *j*th hidden node, and W_{kj} the connection weight from the *j*th hidden node to the *k*th output node (Kim et al, 1999)

4. Conclusion and Future Woks

From the results of the experiment, we show that artificial neural networks may improve the prediction accuracy of traditional prediction methods such as Lisrel, and Multiple regression. In particular, our experimental results reveal that artificial neural networks may be more effective than other forecasting methodologies.

Lisrel is an emerging method and as such requires a fresh approach to financial crisis prediction model design, along with the flexibility to accommodate unexpected change. Many trials or point solutions in the financial variable prediction fail to take an integrated view of the entire economy lifecycle and focus only on data structures to support their own specific components of that lifecycle. As structural model matures as an operational reality, it is imperative that organizations have an integrated view of invisible pattern and data.

<Table 14> indicates the neural network model has the greater prediction performance in Korea, Mexico, and United Kingdom. However, in Korea, the multiple regression shows the better performance. In Mexico, the multiple regression is almost indifferent to the Lisrel. Although Lisrel doesn't show the significant performance, the refined model is expected to show the better result. The structural model in this paper should contain the psychological factor and other invisible areas in the future work. The reason of the low hit ratio is that the alternative model in this paper uses only the financial market data. Thus, we cannot consider the other important part. Korea's hit ratio is lower than that of United Kingdom. So, there must be the other construct that affects the financial market. So does Mexico. However, the United Kingdom's financial market is more influenced and explained by the financial factors than Korea and Mexico. Generally speaking, Mexico and Korea's exchange rate is difficult to predict by only economic variables. In these countries, there are lots of side effects such as political or environmental circumstances. In future work, we have to develop the delicate model that can estimate the other causes and compare the univariate time lagged model. The comparison of univariate model to multivariate is supposed to give the crucial implication.

〈Table 14〉 Hit Ratio of Three Methodologies

	Hit Ratio		
	Korea	United Kingdom	Mexico
Multiple Regression	0.66	0.56	0.57
Lisrel	0.58	0.645	0.588
Neural Network	0.75	0.71	0.64

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국문요약

인공신경망을 이용한 경제 위기 예측

이형용* · 박정민**

이 연구에서 Asia 금융 위기의 원인을 고찰하여 보고, European Monetary Systems의 금융 위기와 비교하여 본다. Asian 신흥 국가들은 1997년도에 금융 위기를 경험하였고, European Monetary Systems의 국가들도 1992년도에 동일한 경험을 하였다. 또한, 중남미의 신흥 경제국가인 Mexico 역시 1994년에 금융위기를 겪었다. 이 연구의 목적은 이들 금융위기의 내면을 고찰하고 그 결과로부터 일반화된 법칙을 추출하는 것이다. 이 연구에서는 금융위기를 경험한 한국과 영국과 멕시코를 각각 세가지 다른 모형으로 연구하고 비교하였다. 이 접근 방법은 체계적인 조사를 통하여 세 국가의 차이점을 보여주고 또한 공통적인 내재 요인을 관찰한다.

이전의 많은 연구 방법들은 대부분 선형 회귀식을 통한 causal model에 초점을 맞추고 있지만, 이러한 선형 회귀 모형의 약점을 보완하여서 현실에 산재하며 존재하는 비 선형의 문제를 해결하기 위하여 또 다른 방법을 제안하여 본다. 이 연구에서 사용한 구조 방정식(Structural Equation Model) 모형은 현실로부터 원인을 추출하고 분석하는 연구에 적합하며, 신경망(Artificial Neural Network) 모형은 선형 모형의 단점을 보완하여서 비 선형 요인을 설명해 준다. 구조방정식 모형에 적용하기 위하여서 LISREL(LInear Structural RELationship)을 사용하였다. LISREL은 확인적 요인분석과 계량경제학에서 개발된 연립방정식모델에 토대를 둔 다중회귀분석 및 경로분석 등이 결합된 성격을 갖는 방법론으로 다양한 연구에 적용된다. 또한 인공지능(Artificial Intelligence) 기법 중의 하나인 신경망 모형은 선형 회귀 분석과 다른 형태의 결과를 도출한다. 세가지 방법론의 우수성을 비교하기 위하여 Hit ratio를 각 국가/ 각 방법론 별로 구분하여서 비교한 결과 다른 방법론 보다 신경망이 더 좋은 성과를 나타내고 있는 것을 확인할 수 있었다. 세가지 방법론에 각각 일반적인 환율 예측에 사용되는 변수를 사용하였다. 소비자 물가지수(Consumer Price Index), 국내총생산(Gross Domestic Product), 이자율(Interest rate), 주가지수(Stock Index), 경상수지(Current Account), 외환보유고(Foreign Reserves)의 6가지 변수를 이용하여서 환율을 예측하여서 급격한 환율 변화로 초래되는 경제위기를 예측하려고 하였다. 각각의 국가

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의 데이터는 대한민국은 1991년부터 1999년까지, 영국은 1986년부터 1995년까지, 멕시코는 1988년부터 1998년까지의 기간을 정하여서 시계열자료를 분기별로 사용하였다. 각각의 데이터는 Data Stream과 한국은행(Bank of Korea)의 데이터를 이용하여서 분석하였다. 선형회귀방정식을 이용한 분석과 구조방정식인 LISREL을 이용한 분석은 각각 Hit ratio가 국가별로 순위가 변동되기도 하였으나, 인공지능 방법론인 인공신경망의 경우는 모든 국가에서 가장 좋은 예측 결과를 나타내고 있었다.

이 논문은 환율의 변동에 대한 다양한 예측 모형을 비교하고 평가하여서 연구에서 제시하는 개념을 검토하였다는 점에서 의의를 갖는다.

주제어 : 금융위기, 환율, 데이타마이닝, 구조방정식, 인공신경망

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저 자 소 개

이 형 용

현재 한성대학교 경영학부에 부교수로 재직 중이며, 성균관대학교 경제학부를 졸업하고, KAIST 경영대학에서 석사와 박사학위를 취득하였다. SKT, (주)SK, 전국신용연합재단 등 다수의 프로젝트를 수행하고, Expert Systems with applications, International Journal of Mobile Communications, Technological Forecasting & Social Change 등에 논문을 발표하였고, 주요 연구 관심 분야는 Virtual community, Trust, Financial Fraud Detection, Accounting Auditing 등이 있다.

박 정 민

서강대학교 화학과를 졸업하고, KAIST에서 경영공학 석사 및 박사학위를 취득하였다. 하나은행 리스크관리부에서 신용리스크 관리업무를 담당하였다. 주요 관심분야는 재무회계, K-IFRS, 신용평가, 인공지능 등이다.