Predicting the Asian Currency Crises with Artificial Neural Networks: What Role of Function Approximation?

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Abstract

A new approach to signaling currency crises is proposed and compared to two existing techniques: the indicators approach and probit and logit models. Based on the assumption of model uncertainty, an early warning system is developed with two recurrent neural network structures. The system is then implemented on a twenty-three country, 1970:01 – 1997:12 sample for within-sample and out-of-sample predictions of currency crises. The currency crises in Asia in 1997 are predicted out of sample. The results are compared with that obtained by a linear probit model. The recurrent neural network structures are found to outperform the probit model with respect to goodness of fit measures. Both systems, however, fail to predict the crises systematically.

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1. Introduction

The need for developing a warning system to systematically detect the symptoms of currency crises in advance has been avowed in both academic and policy circles. Over the last decade there have been significant developments in this area. The literature on currency market turbulence presents two important strands of research on prediction of currency crisis: the indicators approach[1] and the approach based on probit and logit models[2]. In the indicators approach a set of monthly indicators are monitored individually, and a signal to a crisis is issued whenever an indicator exceeds a certain threshold. Probit and logit models, on the other hand, are used to estimate the probability of a crisis based on the significance of coefficients of macroeconomic fundamentals. Despite their strengths, several studies however suggest that both systems may have high error rates in prediction and limited power in distinguishing between crisis and non-crisis observations. The motivation for this paper is to develop a system that would improve the performance results on these scores. It is envisaged that the issue of finding a good warning system may be entwined with the strategy of resolving the problem of *model uncertainty*[3].

Peltonen (2006) and Roy (2004) developed artificial neural network models for prediction of currency crises in transition economies. Here, I propose a modified version of these models as an alternative early warning system for currency crises. Consistent with the notion of model uncertainty the system does not rest on a pre-specified mathematical relationship between the macroeconomic fundamentals and the probability of a crisis. However, unlike the signals approach, and as in the probit and logit models, underlying the approach is the assumption of existence of a mathematical relationship as such. Under such conditions the neural network model, by virtue of its unique property, serves the purpose of approximating a non-linear function that is assumed to be unknown.

The system, based on a recurrent neural network model, is implemented for prediction of currency crises in the emerging market economies of Africa, Asia, and Latin America, and the results are compared with those of Berg and Pattillo (1999a). The recurrent neural network model performs better than the probit

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[1] See Kaminsky, Lizondo, and Reinhart (1998), and Kaminsky and Reinhart (1998, 1999)

[2] See Eichengreen, Rose and Wyplosz (2003a); Frankel and Rose (1996); Berg and Pattillo (1998, 1999a, 1999b); Kamin and Babson (1999); Reagle and Salvatore (2000); Chionis and Liargovas (2003)

[3] See Hansen and Sargent (2000, 2001), McNelis (2005) and the discussion in section 3 of this paper.

models with respect to goodness of fit measures, both within sample and out of sample. In particular, the probit models are significantly outperformed in predicting the currency crises in Asia in 1997, out of sample. While the best of the probit models can predict a significant percentage of crises in Asia with a probability of 20% and with a reasonably small percentage of false alarms, it, however, entirely fails to predict the crises with a probability of 50% or greater. In contrast, the neural network model developed in this paper performs almost equally well in predicting the crises not only with a probability of 20%, but also with probabilities 50% and 90%. This indicates that the neural network model may have greater chances of performing well out of sample in terms of distinguishing between a 'tranquil' month and a 'pre-crisis' month.[4] However, none of the systems could be considered as systematically predicting currency crises. Future research along this line is anticipated.

The rest of the paper is organized as follows. In section 2 the two most prominent early warning systems are briefly described. Section 3 provides a criticism of these systems and proposes alternatives with neural networks with the underlying assumption of model uncertainty. In section 4 the results obtained by Berg and Pattillo (1998a) with a linear probit model are reproduced and two recurrent neural network structures are implemented for the prediction of currency crises in Asia in 1997 out of sample. The models are then utilized to predict the cross-country incidence of crisis as well. Finally, the results are compared in order to suggest an alternative with a recurrent neural network structure. Section 5 concludes.

2. The early warning systems

Following the currency crises in 1970's and 1980's in Latin America, the 1990's witnessed a series of currency crises the world over. Speculative attacks on the European monetary system took place in 1992-93. But that was surpassed by the 'tequilla' crisis in Mexico in 1995. Finally, the devaluation of the Thai baht in July 1997, which brought turmoil in the currency and equity markets, was followed by currency crises in East Asia and Russia, shaking the entire global financial system.[5] Bulgaria, the Czech Republic, Romania, and Turkey suffered crises around the same time.

[4] As formally defined in section 4, a 'pre-crisis' month is defined to be in the period of twenty four months prior to a crisis. All other months are 'tranquil'.

[5] See Krugman (2000) and Roy (2004).

Starting with Krugman (1979), there has been a wealth of three generations of theoretical models to provide explanations for such crises.[6] In parallel to the theoretical developments, however, the early warning systems proposed by several authors are designed to predict the actual crises from macroeconomic time series. This section briefly describes the two most prominent such systems[7]. In the next section an alternative based on an artificial neural network is proposed.

2.1. Signals approach

Kaminsky, Lizondo, and Reinhart (1998) (henceforth KLR) develop the 'signals' approach to prediction of currency crisis. It involves monitoring the evolution of a set of economic variables that are likely to exhibit anomalous behavior within the period of twenty four months prior to a crisis. A currency crisis is identified by the movements of an index of exchange market pressure, which is a weighted average of monthly percentage depreciations in the exchange rate and monthly percentage declines in gross international reserves. A crisis is defined as a period in which the index exceeds its mean by more than three standard deviations. Extracting from the theoretical models, KLR consider 15 indicators for a 20-country, 1970-95 sample. A signal is issued if an indicator exceeds an optimum threshold. If a signal is issued within the period of twenty four months prior to a crisis then it is taken as a good signal; otherwise a signal is bad or false. The optimal thresholds, calculated as percentiles with respect to each variable and country, are determined by minimizing the 'noise-to-signal' ratio (ratio of 'good' signals to 'bad' signals) across countries. Edison (2003) analyzes and extends this approach to apply to an individual country.

The method proposed by KLR is essentially non-parametric, since it does not involve distributional assumptions on parameters, or estimation of parameter values. As discussed by Berg and Pattillo (1999a), the method is also bivariate, since the optimal threshold for each indicator is calculated separately.

[6] Starting with Krugman (1979), the early theoretical models of currency crisis (see Agenor, Bhandari and Flood, 1992, and the references therein) focus on macroeconomic policy inconsistencies, particularly in the form of expansionary monetary policy to finance a fiscal deficit, which triggers current account deficit, shrinkage of foreign exchange reserves, and eventual collapse of the fixed exchange rate system. The development of the 'second generation' models was in the context of turmoil in the European exchange rate mechanism and currency and banking crises in Mexico and Asia. The literature casts a shift of emphasis from policy inconsistencies to contagion, herd behavior and self-fulfilling expectations. An excellent review of these models can be found in Eichengreen, Rose and Wyplosz (2003a, 2003b). In the third generation models (Aghion, Bacchetta and Banerjee, 2000, 2001) currency crisis is explained in terms of nominal price rigidities and credit constraints on firms.

[7] See Kaminsky, Lizondo, and Reinhart (1998) for other approaches

Kaminsky (1998) also proposes a composite indicator, which is computed as a weighted sum of the indicators, where weights are taken to be inverses of the noise-to-signal ratios. The composite indicator is utilized to calculate a probability of crisis corresponding to a given value of the indictor. A probability of crisis related to a particular value of the indicator is taken as the ratio of the frequency at which the value corresponds to a crisis within twenty four months to the total frequency of that value in a sample.

2.2. Probit and logit models

Several other authors use probit and logit models for the estimation and prediction of a probability of currency crisis.[8] In this approach, given data on several variables, a probability of crisis related to an observation is estimated. An alarm for crisis is generated when the estimated or predicted probability crosses a threshold. Unlike the indicators approach, this is a parametric method in that it involves distributional assumptions on the relevant parameters as well as estimation and tests of significance to determine which variables are most important in explaining and predicting a currency crisis.

3. Model uncertainty and quest for an alternative

3.1. Limitations of existing early warning systems

Despite their popularity and success, both 'indicators' approach and probit and logit models have their own limitations. The indicators approach relies heavily on *data mining*: except for initial selection of indicators, the entire methodology does not rest on economically meaningful assumptions or statistical tests. In addition, when tested empirically, the procedure does not perform well in out of sample

[8]Eichengreen, Rose, and Wyplosz (2003a) take this approach to estimate the increase in probability of crisis resulting from contagion effects. Frankel and Rose (1996) use panel data for more than hundred developing countries from 1971 through 1992 to find out the key variables leading to currency collapse. Berg and Pattillo (1999a) develop probit models to analyze and predict the crises in Africa, Latin America and Asia. They find that a linear probit model does better than a piece-wise linear model in predicting the crises. They also compare the probit models to the 'signals' approach, and conclude that the former performs better in predicting the currency crises in Asia in 1997, out of sample. Similarly, Kamin and Babson (1999) estimate several probit models of balance of payments crises for six Latin American countries; they conclude that the crises in those countries were caused principally by domestic economic factors rather than external shocks. Reagle and Salvatore (2000) devise a composite indicator of crisis potential and use a probit model to predict the crises in Asia in 1997. Chionis and Liargovas (2003) consider a logit model in analyzing the currency crises in Bulgaria, Romania, Russia, and Ukraine and find that the deteriorating fundamentals could explain the crises.

predictions. It performs rather poorly in anticipating the currency crises in Asia in 1997 (see Berg and Pattillo, 1999a) as well as the recent crisis in Argentina (see Alvarez-Plata and Schrooten, 2004).

Methodologically probit and logit models may be more appealing to economists. These are based on a mathematical relationship with certain distributional assumptions on the parameters. Hence, these provide a description of the underlying decision making and data generating process, and utilize suitable statistical tests to confirm or reject significance of variables explaining a crisis.

There is the flip side of the coin, however. A model as such – like most other econometric models – pre-specifies the underlying data generating process and the corresponding mathematical relationship between macroeconomic fundamentals and the probability of a crisis which, otherwise, are unknown. The approach, in other words, hardly accounts for 'model uncertainty' that has been felt consistently in theoretical and empirical modeling.[9] This may be taken as a method of convenience rather than perfection. Of course admitting that models are approximations for economic agents, analysts, and policy-makers raises serious questions (Hansen and Sargent, 2000): how to evaluate and test models? How the economic agents should be modeled? How the policy makers should use misspecified models? While Hansen and Sargent (2000) address the last two questions explicitly, the growing literature on model averaging and model approximation handles the first issue in different ways[10].

Perhaps the poor prediction accuracies of probit and logit models are sheer reflections of this limitation. To the best of my knowledge, the most comprehensive study of currency crises with probit models are done by Berg and Pattillo (1999a). They consider twenty three emerging market economies of Africa, Asia, and Latin America, having monthly observations from January 1970 through December 1997. They estimate several probit equations based on the data through April 1995, and predict the currency crises in Asia in 1997 out of sample. Although the models do reasonably well at 25% threshold probability, all of them essentially fail to explain and predict the crises at 50% threshold probability, both

[9] As discussed by Hansen and Sargent (2000, 2001) and McNelis (2005, pp 55-56), this seems to be resulting from the conditions imposed by rational expectations hypothesis: the economic analyst, the policy maker, and the agents in the model share the same model, where the economic environment is known completely.

[10] For linear models a common practice is to use Bayesian model averaging, other methods are available though; see Bates and Granger (1969), Chua, Griffiths, and O'Donnell (2001), Hendry and Clements (2002), Fernandez, Ley, and Steel (2001), Jacobson and Karlsson (2004), Min and Zellner (1993), Raftery, Madigan, and Hoeting (1998), Stock and Watson (2004) for a representative bundle. For nonlinear models artificial neural networks have been proposed as *universal function approximators* (Hornik, Stinchcombe, and White, 1989, 1990). For surveys of application of artificial neural networks in finance and forecasting problems see Deboyeck (1994), Kaastra and Boyd (1996), McNelis (2005), Wong and Selvi (1998), and Zhang et. al. (1998, 2001).

within sample and out of sample. A similar study by Fontaine (2005) examines the implications of a number of theoretical models in predicting crises with logistic regressions in developed countries and emerging market economies taken separately. While the estimated parameters demonstrate some success in predicting the crises within sample, they however fail completely in out of sample predictions at a threshold probability of 50%. Other studies along this line do not report greater rates of accuracy.

It may be unlikely that currency crises would be predicted systematically. Nonetheless, the discussion so far suggests that there is a need for searching an alternative warning system that would account for model uncertainty and reduce the error rates in prediction.

3.2. Artificial neural network: an alternative

It is assumed that the economic agents face model uncertainty and learn from the environment. In other words, they will have to use approximations to learn how the key variables interact. In the same vein, the analyst and the forecaster would face uncertainty of the exact model or the functional relationship among the variables explaining an economic outcome. Under these conditions and when the functional relationship is assumed to be non-linear, neural networks have been proposed as *universal function approximators* (Hornik, Stinchcombe, and White, 1989) that can map any non-linear function. Moreover, neural networks mimic the way human brain processes information and constantly learn from the environment. From these considerations Roy (2004) proposes an alternative early warning system for currency crisis based on artificial neural network. In this paper the system is adopted with certain modifications.

Naturally, unlike probit and logit models and most other models in econometrics, a neural network model involves no hypothesis on the coefficients to be estimated or of the functional form describing the data. Although a functional relationship is estimated, there is no limit to the number of parameters in the model; neither do they have straightforward interpretation (McNelis, 2005). In this sense, from a statistical perspective, artificial neural network models are *semi-parametric*. The unique properties of neural networks have inspired many applications in finance (see Deboyeck, 1994, Kaastra and Boyd, 1996, McNelis, 2005, Wong and Selvi, 1998, and Zhang, 1998, 2001 for surveys).

Good descriptions of different types of neural networks can be found in Bishop (1995) and Faussette (1994). A neural network can be seen as a device for acquiring knowledge and making intelligent decisions. Usually neural network has high tolerance to noisy data and good predictive power. In general, neural network can be described as a set of connected input and output units where each connection has an associated weight. The output values are determined by the weights and the input values. The 'learning' of a neural network is conducted by adjusting the weights so that the correct class labels [11] can be predicted or the output values get as close as possible to the target values.

The following paragraphs present two early warning systems with two different types of neural network models: multi-layered feed-forward neural network (adopted and utilized by Roy, 2004), and Elman recurrent neural network, which is adopted and utilized in the present paper.

3.2.1. Multi-layered feed-forward neural network

A multi-layered, feed-forward neural network contains an input layer (where the input values are fed), an output layer (where the final output values are determined), and hidden layers (having other units).[12] The inputs are fed into the input layer, the weighted outputs of the input layer are fed as input to a hidden layer, the weighted outputs of the hidden layer are fed as input to another hidden layer, and so on, depending on the number of hidden layers. Finally, the weighted outputs of the last hidden layer are fed to the output layer, and this yields the network's prediction for the given input. The network is called feed-forward since the weighted outputs are always fed into the layer ahead. A multilayered neural network with one hidden layer and one output unit is shown in Fig. 1.

Insert Fig. 1 here

For a mathematical description let us consider a network with one hidden layer.[13] Let there be I input units, J hidden units and one output unit[14]. Let $(x_1, x_2, ..., x_G)$ be an input vector. The activation of the i^{th}

[11] In the present context 'tranquil' or 'pre-crisis'

[12] See Han and Kamber (2002)

[13] See Bishop (1999)

input unit is given by an activation/transfer function: $T_1(x_i)$[15]. The input to the j^{th} hidden unit is given by:

$$y_j = w_{i0} + \sum_{i=1}^{I} w_{ij} T_1(x_i), \tag{1}$$

where w_{ij} is the weight connecting the i^{th} input unit and the j^{th} hidden unit, and w_{i0} is the bias term which is similar to a constant term in statistical regressions. The j^{th} hidden unit is activated by the transfer function: $T_2(y_j)$.

The input to the output unit is given by:

$$z = w_0 + \sum_{j=1}^{J} w_j T_2(y_j), \tag{2}$$

where w_j is the weight connecting the j^{th} hidden unit and the output unit, and w_0 is the bias term. Finally, the output unit is activated by the transfer function: $T_3(z)$. The essential idea here is that, during the training phase, those values of all weights are chosen that bring $T_3(z)$ as close as possible to some pre-specified target value.

In the present context of prediction of crises this means, the inputs are observation vectors on different indicators, the value of one indicator in each such vector being fed at one input unit. The target values would be ‘zero’ or ‘one’ depending on whether the observation corresponds to a ‘tranquil’ or ‘pre-crisis’[16] month. In such a case, during the training phase, the weights have to be chosen in such a way that $T_3(z)$ gets close to zero for a ‘tranquil’ observation, and it gets close to ‘one’ for a ‘pre-crisis’ observation. In the prediction phase, based on the transfer functions and the estimated weights, an observation is predicted as ‘tranquil’ or ‘pre-crisis’ depending on whether $T_3(z)$ exceeds a certain threshold or not.

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[14] There could of course be more than one

[15] Different transfer functions are available, and the one used will depend on the particular problem. The most commonly used are sigmoid, log-sigmoid and tan-sigmoid.

[16] Any month within the period of twenty four months prior to a crisis is a ‘pre-crisis’ month. This is defined explicitly in a later section.

For example, an observation may be predicted as ‘tranquil’ if $T_3(z) < 0.50$ and as ‘pre-crisis’ if $T_3(z) > 0.50$.[17]

3.2.2. *Elman recurrent neural network (1990)*

A feed-forward neural network does not allow lagged values, either at the input nodes or at the hidden nodes, to explain or predict an output value. From a time-series perspective, however, it may be important to capture the impacts of indicators from past. A recurrent network serves this purpose.

An Elman recurrent network (1990) has similarities with an MA process in econometrics.[18] In an Elman recurrent network, in addition to all the connections involved in a feed-forward neural network, lagged units at the first hidden layer have *feed-backs* to the current units. This property of the network is useful in explaining time-varying patterns.

Mathematically, let there be one hidden layer, *I* input units, *J* hidden units, and one output unit. Let t denote the time subscript. Let $(x_{1t}, x_{2t}, \ldots\ldots, x_{Gt})$ be an input vector of period *t*. The activation of the i^{th} input unit is given by an activation/transfer function: $T_1(x_{it})$. The input to the j^{th} hidden unit is given by:

$$y_{jt} = w_{i0} + \sum_{k=1}^{J} w_{kj} y_{j(t-1)} + \sum_{i=1}^{I} w_{ij} T_1(x_{it}) \tag{3}$$

where, w_{ij} is the weight connecting the i^{th} input unit and the j^{th} hidden unit, w_{i0} is the bias term, w_{kj} is the weight connecting the k^{th} lagged hidden unit and the j^{th} hidden unit and T_1 is the activation function at the input layer. Note that while the expression above has sum of weighted, activated outputs of the input layer, it also has sum of weighted lagged hidden units which are *not activated.*

Finally, the input to the output unit is given by:

$$z_t = w_0 + \sum_{j=1}^{J} w_j T_2(y_{jt}) \tag{4}$$

[17] Note here the similarity with probit and logit regressions.

[18] Faussette (1994) and McNelis (2005) are followed for a description.

where, w_j is the weight connecting the j^{th} hidden unit and the output unit, w_0 is the bias term, and T_2 is the transfer function at the hidden layer. As before, the output unit z_t is activated by the transfer function T_3. The network is trained and output values are produced in the same way as in a feed-forward neural network by adjusting the weights repeatedly.

Several algorithms are available for training a neural network to find out appropriate values of the weights. The most popular and commonly used is *back-propagation* (Werbos, 1974, and Parker, 1985). In this procedure the network is trained by processing a set of training observations iteratively. The prediction of the network is compared with the actual value of the output, and the weights are adjusted with a certain factor of the error to minimize a performance function. The error, in other words, is *propagated backwards* to adjust the weights in view of minimizing a performance function. The standard practice is to take the mean squared error between the prediction of the network and the actual value of the output as the performance function.

The Elman neural network with the back-propagation training algorithm is proposed as an alternative to the probit and logit models for the prediction of currency crises. In the next section this warning system is implemented on the same data used by Berg and Pattillo (1999a) for the prediction of currency crises in Asia in 1997, out of sample. The results are then compared with those obtained by Berg and Pattillo (1999a).

4. Prediction of currency crises

Based on the definition of currency crisis (provided by KLR and outlined in section 2.1), following KLR and Berg and Pattillo (1999a, henceforth BP), a 'pre-crisis' month is defined to be in the period of twenty four months prior to a crisis. All other months are 'tranquil'. In a prediction exercise the relevant question is whether a pre-crisis month can be identified with a probability exceeding a threshold.

4.1. Reproducing BP

First the results obtained by BP with a linear probit model[19] which performs the best in out of sample forecasting are reproduced. Monthly data on eleven indicators from January, 1970 through December, 1997 in twenty-three emerging market economies[20] that experienced currency crisis at least once over this period are considered. The indicators are: real exchange rate misalignment[21] (*RDEV*), growth rate of international reserves (*RESG*), ratio of *M2* to reserves (*MRES*), growth rate of ratio of *M2* to reserves (*MREG*), growth rate of exports (*EXPG*), growth rate of imports (*IMPG*), excess M1 balances (*M1EX*)[22], growth rate of domestic credit by GDP (*DCRG*), growth rate of money multiplier (*MM2G*), current account by GDP (*CA*), and growth rate of real bank deposits (*DEPG*). The dependent variable, *C24*, is equal to 'one' if the corresponding month is 'tranquil', and equal to 'zero' if it is a 'pre-crisis' month.

Following BP first the values of the crisis index (as defined by KLR) for all countries are computed, and the corresponding crisis months are identified. Then, using panel data, the model over the period from January 1970 through April 1995 is estimated and re-estimated based on significance of coefficients at 10% level, within sample forecasting exercises are performed, and finally the crises in Asia in 1997 are predicted with out-of-sample forecasts over the period from May, 1995 through December, 1997. All indicators are considered in percentiles of the country-specific distribution. The results are found to be nearly the same as that obtained by BP, with a few minor discrepancies. We assume the discrepancies arise largely due to differences in the way the data are cleaned and processed. [23] Tables 1 through 3 present the estimation results, calibration of scores[24], and goodness of fit measures within sample and out of sample respectively obtained by BP and under the replication.

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[19] They also estimate a piece-wise linear probit model and an indicator probit model which perform worse than the linear model in out of sample forecasting.

[20] Argentina, Bolivia, Brazil, Chile, Columbia, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, Phillippines, Sri Lanka, South Africa, Taiwan Province of China, Thailand, Turkey, Uruguay, Venezuela, and Zimbabwe

[21] Percentage deviation from a deterministic trend

[22] Residual from regression of real M1 on real GDP, inflation, and a deterministic trend

[23] BP, while attempting to reproduce the results by KLR, find major discrepancies.

[24] Following BP quadratic probability score (QPS), log probability score (LPS), and global squared bias (GSB) are considered. Let R_t be the actual value (0 or 1) and P_t be the predicted value of of *C24* in period *t*. Let *T* be the number of forecasts. Then,

Insert Tables 1, 2, and 3 here

In particular, values of the crisis index and the crisis months identified by BP and me are found to be exactly the same for all countries. All coefficients that are significant in BP are also found significant under the replication; in addition a constant term and M1EX are found to be significant. In general the calibration scores under the replication are slightly better than what obtained by BP, both within sample and out of sample. The values of goodness of fit measures obtained by BP within sample are almost same as what got here at both 25% and 50% thresholds. The values of goodness of fit measures out of sample are exactly the same at 50% threshold. However, these values obtained by BP out of sample at 25% threshold could nearly be reproduced at 20% threshold.

4.2. Prediction with Elman recurrent neural network

Now the Elman recurrent neural network is implemented in a similar fashion. The indicators are considered either as percentage growth rates over twelve months, or are converted into values over a scale ranging from zero to hundred. For selection of indicators *stepwise discriminant analysis* [25] is employed, and the *Wilks statistics* are computed to determine the most relevant combination of indicators. Except M1EX and RESG, all indicators are found to be significant. For experimental purposes different structures for the network with different combinations of number of hidden layers and neurons, transfer functions,

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$$\text{QPS} = 1/T\sum_{t=1}^{T} 2(P_t - R_t)^2;$$

$$\text{LPS} = 1/T\sum_{t=1}^{T} [(1-R_t)\ln(1-P_t) + R_t\ln(P_t)];$$

$$\text{GSB} = 2(P_m - R_m)^2, \text{ where } P_m = 1/T\sum_{t=1}^{T} P_t, \; R_m = 1/T\sum_{t=1}^{T} R_t$$

[25]See Rencher (1995) for a description of this procedure. In brief, the indicators are considered one by one and are tested for their explanatory powers in distinguishing between ‘tranquil’ and ‘pre-crisis’ months.

and different types of back-propagation training algorithms are considered. Two network structures (henceforth RNN1 and RNN2) are found to be the best for forecasting exercises.[26] These are given below.

RNN1:

i) Input layer: nine input units/neurons[27] (for nine indicators) and a bias term.

ii) Two hidden layers: 27 units/neurons at the first layer, and 9 units/layers at the second layer.

iii) One output unit, which has targeted value equal to zero (if the corresponding month is 'tranquil'), or one (if the corresponding month is 'pre-crisis').

iv) The transfer function at all layers is such that it simply reproduces the value of its own argument.

v) Training function: conjugate gradient backpropagation with Fletcher-Reeves updates[28]

vi) Finally, the 'satlin' function is applied to define the output of the network to be between zero and one.

vii) Mean squared error is taken to be the performance function.

RNN2: Everything is same as in RNN1, except that there are 50 units at the first hidden layer, and 25 units at the second hidden layer.

The calibration scores and goodness of fit measures from within sample and out of sample forecasts with RNN1 and RNN2 are reported in Tables 4 and 5 respectively. For the purpose of comparison the tables also present results obtained from applying the linear probit model (earlier reported in Tables 2 and 3).[29]

Insert Tables 4 and 5 here

[26] Even a given structure of a network would produce different estimations of weights, calibration scores, and goodness of fit measures under different runs with different sets of starting values of the weights. For each structure that set of weights is considered which is found to be the best in terms of goodness of fit.

[27] In the literature of neural network 'units' and 'neurons' are used interchangeably.

[28] See Scales (1985) for a detailed discussion.

[29] BP also report percent of 'tranquil' months and percent of all observations correctly called. However, these percentage figures are redundant when the percent of correctly called 'pre-crisis' months and the percent of correctly generated signals are known.

The linear probit model is clearly outperformed in terms of goodness of fit measures on both within sample and out of sample forecasts. The linear probit model, RNN1, and RNN2 are found to be performing almost equally well with respect to percent of ‘pre-crisis’ months correctly called and percent of false alarms at a threshold of 25% or 20%. But the linear probit model fails entirely if the threshold is considered to be 50%, let alone 90%. On the other hand, both RNN1 and RNN2 can predict almost equal percentage of ‘pre-crisis’ months at 25%, 50% and 90% threshold values without having any significant variation in the percent of false alarms. While the performance of RNN1 in this respect is slightly better than RNN2 within sample, the latter however is found to be more stable across thresholds and performing better on out of sample predictions.

Thus, considering the goodness of fit measures, a recurrent neural network may have greater chances of distinguishing between a ‘pre-crisis’ month and a ‘tranquil’ month than a probit model. It is therefore recommended as an alternative early warning system.

Note that the probability of a crisis within twenty four months following an alarm (i.e. true alarms as percent of total alarms) is rather small on within sample forecasting: around 17% under RNN1 and RNN2 at all threshold values, and 33% under linear probit at 25% threshold. All models have a value equal to around 40% for this probability on out of sample forecasting. However, these are still equal to or greater than the respective unconditional probabilities. The period 1970:01 – 1995:04 has 17% ‘pre-crisis’ observations, and the period 1995:05 – 1997:12 has 22% ‘pre-crisis’ observations. Nevertheless, the moderate value of this probability out of sample has special significance. In 60% of cases an alarm would actually not predict a crisis. This implies that currency crises may not be predicted systematically.

Finally, the calibration scores for the linear model are better than for either RNN1 or RNN2, irrespective of type of forecasts. While this may appear to be a point in favor of the linear probit model, the reason for this may be the percentage composition of ‘tranquil’ and ‘pre-crisis’ observations in the sample, and the poor predictive power of the probit model itself. When more than 75% of the observations in the sample are ‘tranquil’, and if a model almost never predicts a crisis with more than 25% probability, the difference between the actual value of C24 and the predicted probability is expected to be small most of the time.

4.3. *Predicting cross-country incidence of crisis in 1997*

The performance of the probit model and the two neural network models in predicting cross-country incidence of crisis in 1997 is also evaluated. First the values of the crisis index (as defined by KLR) for all countries[30] are computed in the standardized form by subtracting the mean and dividing by the standard deviation. The countries are ranked accordingly. Then country ranks are found for the average predicted probabilities of the linear probit model and the neural network models over 1996:01-12. The results are reported in Table 6. In all cases significant correlations are found between the actual values of the crises index and the predicted probabilities. The correlation coefficient is noticeably higher for RNN2 than for RNN1 and the linear probit. However, the linear probit is found to be performing better than the neural network models with respect to rank correlation. The goodness of fit measures of a regression of the fitted probabilities on the actual values of the crisis index also indicate a strong association as such. But such an association is stronger with the neural network models, and noticeably stronger with RNN2. We therefore conclude in favor of recurrent neural network even in identifying and predicting the intensity of a crisis.

Insert Table 6 here

5. Conclusion

Despite some authors claiming success in predicting currency crises, the remarkable differences among the incidences of such crisis the world over suggest that these are hardly predictable in a systematic manner. Predicting currency crisis is therefore ‘likely to remain as an elusive goal’ (KLR). This paper, aimed at providing an alternative to the prevailing warning systems, confirms this fact. The two most popular models for prediction of currency crisis have been examined. The indicators approach proposed by KLR and the probit and logit models adopted by several authors have their own strengths and limitations. None of the models, however, explicitly takes into consideration ‘model uncertainty’ that has been felt consistently in theoretical and empirical modeling. This paper suggests this limitation to be at least partly responsible for poor rates of prediction accuracy of these systems. From this standpoint an artificial recurrent neural network has been suggested and explored as an alternative.

[30] Indonesia and Zimbabwe had to be dropped due to missing observations over the period, 1995:04 – 1997:12.

The system is found to be outperforming a linear probit model that best predicted the currency crises in Asia in 1997 out of sample in a comprehensive study by BP. Tow different structures of Elman recurrent neural network were considered and the calibration scores and goodness of fit measures were compared to those obtained with the linear probit model. It is found that the recurrent neural network models clearly perform better in predicting the crises, within sample as well as out of sample. While the linear probit model predicts certain percentages of currency crises with reasonably small percentages of false alarms at a threshold probability of 20% or 25%, the recurrent networks perform equally well or better even at threshold probabilities 50% and 90%. The linear probit model fails entirely at 50% and 90% threshold probabilities. The early warning system proposed in this paper therefore remains superior in distinguishing a 'crisis' month and a 'tranquil' month. However, true alarms as percent of total alarms is found to be only around 40% under all systems, indicating near impossibility of systematic prediction of currency crises.

Finally, the proposed early warning system is also found to be performing better than the linear probit model in predicting the cross-country incidence of crisis, out of sample. The system is therefore recommended not only for identification of timing of a crisis, but also for predicting the intensity of a crisis as such. Further investigations and experiments are warranted.

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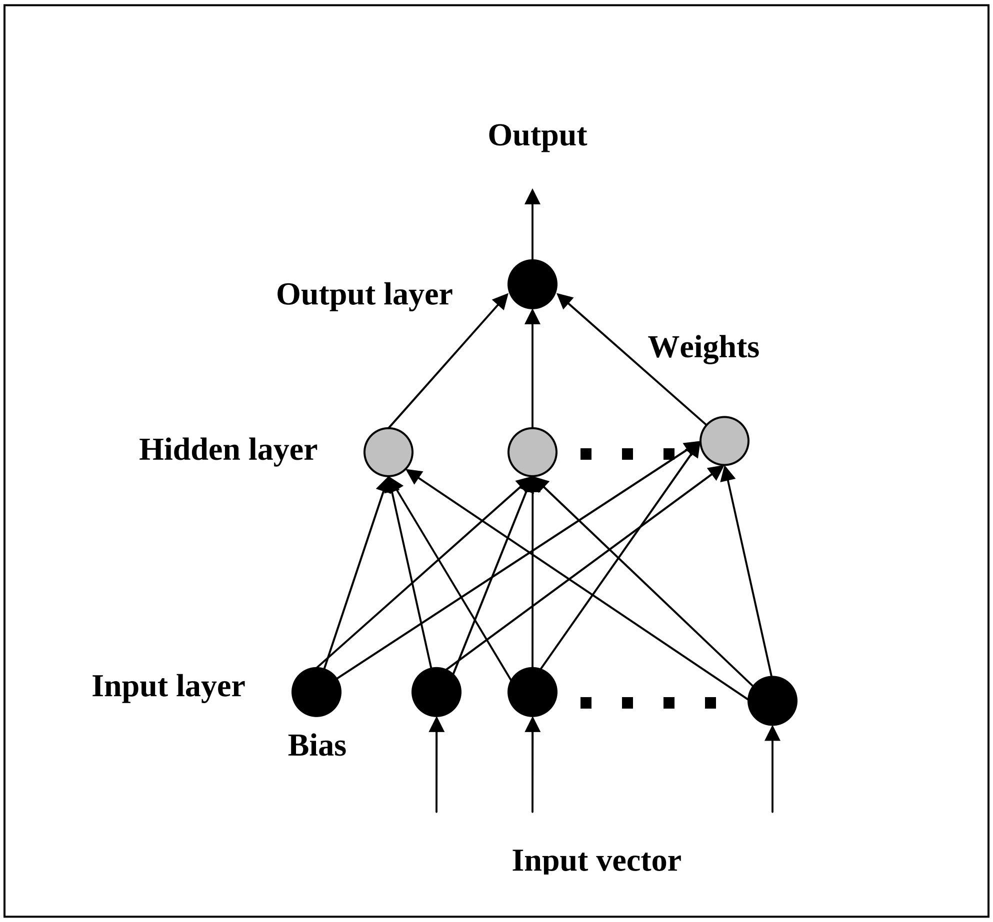

Figure 1: Multi-layered feed-forward neural network

Table 1
Multivariate linear probit model – coefficient estimates: BP and the replication

	BP		Replication	
Variable	Coefficient	*T*-statistic	Coefficient	*T*-statistic
Constant			-0.185167	-9.54
Real exchange rate misalignment	0.00232	13.50	0.002353	13.27
Current account	0.00178	9.50	0.001157	6.22
Reserve growth	0.00128	6.20	0.001470	7.26
Export growth	0.00064	3.65	0.000776	4.43
M2/reserves	0.00053	2.80	0.000822	4.26
Excess M1 balance			0.000435	2.50
Sample size	5025		5056	
Log-likelihood	-1970		-1944	
Pseudo-R^2	0.098		0.088	

Table 2
Performance results of the linear probit model — within sample: BP and the replication[a]

	BP	Replication
Calibration scores		
Quadratic probability score	0.236	0.251
Log probability score	0.386	0.10
Global Squared bias	0.00040	0.00001
Goodness-of-fit (threshold probability = 50%)		
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	7	0
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	89	no alarm issued
Goodness-of-fit (threshold probability = 25%)		
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	48	51
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	37	33

[a] An alarm is issued whenever the estimated probability exceeds the threshold probability

Table 3
Performance results of the linear probit model — out-of-sample: BP and the replication[a]

	BP	Replication
Calibration scores		
Quadratic probability score	0.281	0.299
Log probability score	0.433	0.169
Global Squared bias	0.00581	0.00264
Goodness-of-fit (threshold probability = 50%)		
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	0	0
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	no alarm issued	no alarm issued
Goodness-of-fit (threshold probability = 25% for BP and 20% for replication)		
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	80	80
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	51	39

[a] An alarm is issued whenever the estimated probability exceeds the threshold probability

Table 4
Performance results — within sample: the linear probit model and Elman recurrent neural networks[a]

	Linear probit	RNN1	RNN2
Calibration scores [b]			
Quadratic probability score	0.251	0.926	0.846
Global Squared bias	0.00001	0.20	0.117
Goodness-of-fit (threshold probability = 90%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	0	44	41
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	no alarm issued	17	18
Goodness-of-fit (threshold probability = 50%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	0	50	43
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	no alarm issued	17	17
Goodness-of-fit (threshold probability = 25%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	51	54	44
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	33	17	17

[a] An alarm is issued whenever the estimated probability exceeds the threshold probability

[b] The log probability score is not considered to avoid logarithm of zero that arose frequently under both RNN1 and RNN2 due to perfect prediction of a crisis or tranquil month

Table 5
Performance results — out of sample: the linear probit model and Elman recurrent neural networks[a]

	Linear probit	RNN1	RNN2
Calibration scores[b]			
Quadratic probability score	0.299	0.560	0.599
Global Squared bias	0.00264	0.124	0.137
Goodness-of-fit (threshold probability = 90%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	0	71	87
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	no alarm issued	42	42
Goodness-of-fit (threshold probability = 50%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	0	84	88
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	no alarm issued	40	40
Goodness-of-fit (threshold probability = 20%)			
Probability of an alarm conditional on a crisis within 24 months (percent of pre-crisis periods correctly called)	80	93	89
Probability of a crisis within 24 months following an alarm (true alarms as percent of total alarms)	39	37	39

[a] An alarm is issued whenever the estimated probability exceeds the threshold probability

[b] The log probability score is not considered to avoid logarithm of zero that arose frequently under both RNN1 and RNN2 due to perfect prediction of a crisis or tranquil month

Table 6
Crisis intensity: correlation of actual and predicted rankings of countries

	Actual		Predicted[c]					
	Crisis index		Linear probit		RNN1		RNN2	
Country[a]	Value[b]	Rank	Probability	Rank	Probability	Rank	Probability	Rank
Thailand	**10.19**	1	0.23	8	0.94	8	1.00	3.5
Korea	**9.52**	2	0.22	10	0.96	7	0.92	7
Malaysia	**4.42**	3	0.30	1	0.72	11	1.00	3.5
Taiwan	**3.37**	4	0.28	3	1.00	2.5	1.00	3.5
Colombia	**3.01**	5	0.26	4	1.00	2.5	1.00	3.5
Philippines	2.68	6	0.22	9	0.97	6	0.00	17.5
Brazil	0.82	7	0.23	7	1.00	2.5	1.00	3.5
Turkey	0.65	8	0.11	18	0.12	18	0.00	17.5
Venezuela	0.62	9	0.14	16	0.80	10	0.00	17.5
Pakistan	0.57	10	0.19	12	0.62	12	0.14	13
South Africa	0.52	11	0.21	11	0.54	14	0.57	9
Jordan	0.45	12	0.16	14	0.23	16	0.00	17.5
India	0.39	13	0.10	19	0.00	20.5	0.00	17.5
Sri Lanka	0.36	14	0.23	6	0.57	13	0.00	17.5
Chile	0.24	15	0.26	5	0.40	15	0.39	11
Bolivia	0.18	16	0.08	20	0.10	19	0.79	8
Argentina	0.15	17	0.17	13	0.13	17	0.00	17.5

continued..

Table 6
Continued

	Actual		Predicted[c]					
	Crisis index		Linear probit		RNN1		RNN2	
Country[a]	Value[b]	Rank	Probability	Rank	Probability	Rank	Probability	Rank
Mexico	0.15	18	0.08	21	0.91	9	0.27	12
Peru	0.12	19	0.14	17	0.00	20.5	0.00	17.5
Uruguay	-0.02	20	0.15	15	0.98	5	0.54	10
Israel	-0.11	21	0.29	2	1.00	2.5	1.00	3.5
Correlation[d]				0.389		0.429		0.518
Rank Correlation[e]				0.405		0.338		0.35
P-value[f]				0.081		0.051		0.016
R^2				0.151		0.184		0.268

[a] Due to missing observations in the period, 1995:05-1997:12, the average predicted probabilities could not be computed for Indonesia and Zimbabwe

[b] Values of the crisis index are computed according to the definition by KLR. These are reported here in the standardized form by subtracting the mean and dividing by the standard deviation. A value above three - defined as a crisis – is shown in bold

[c] All predicted probabilities are average of probabilities predicted over 1996:1-12

[d] Correlation coefficient of the actual values of crisis index and predicted average probabilities

[e] Spearman's rank correlation coefficient of the actual values of crisis index and predicted average probabilities

[f] *p*-values of the *F*-statistic and the R^2 are from regressions of predicted probabilities on actual values of the crisis index