Predicting Banking Sector Crisis using ANNs: Indian context

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Abstract

The purpose of this study is to develop an early warning system for the Indian banking sector. In this study, a data set covering the period of February 2001 – March 2017 of the Indian economy is used and an early warning system is constructed using two different artificial neural networks(ANNs). A banking sector fragility index is calculated to identify the period of crisis composed of variables like net bank reserves, credit, deposits, and foreign currency borrowings. This variable is converted to a dummy binary variable on the basis of the threshold, which is used as the dependent variable. The independent variables are the 15 leading indicators which are selected based on a thorough literature review. The study takes into account an Elman recurrent neural network and a Multilayered Feedforward Network(MLFN) which are trained using different transfer functions. The ANNs are evaluated based on their accuracy and calibration using Quadratic Probability Score(QPS) and Global Squared Bias(GSB) for both within the sample and out of sample. The scores depict results with Elman recurrent network outperforming the MLFN. The uniqueness of this study lies in that it uses diverse macroeconomic variables to anticipate the banking sector fragility for the Indian economy.

Key Words: Financial Crisis, Early Warning System, Banking Crisis, Global Financial Crisis, Currency Crisis, Artificial Neural Network

Classification: Financial Economics

JEL classification number: C10, C14, C45, C53, F31, F37, G00, G01

1. Introduction

In the late 20th century, a greater need to develop an early warning system for prediction of a financial crisis was felt because of its high costs implications on national and international levels. Due to increased occurrences of systemic banking crises and their all-pervasive implications, it had become important for policymakers to design policies which could help in taking preventive measures so as to at least accentuate the impact of a financial crisis. Different research studies have attempted to detect the possibility of occurrence of the financial crisis by using different tools and techniques such as signals approach and models like logit/probit models. This study attempts to develop a system that would improve upon the prediction of a banking sector fragility. It employs variants of Artificial Neural Networks (ANNs) to identify and establish its validity to predict the occurrence of a banking crisis.

The subsequent sections of the paper are organized as follows. Section 2 reviews the existing and prominent Early Warning Systems (EWS) developed. It also covers the ANNs as an alternative for conventional statistical methods for developing early warning systems. Section 3 reveals the research gaps. Section 4 covers the methodology and data used in the study. Section 5 discusses the results and findings while section 6 concludes the study and explore the scope of further research.

2. Literature Review

According to Krugman (1999, 2001) and Graciela L. Kaminsky (2003), economic theory has developed three generations of models explaining financial crises while the first and second generation models were focused on currency crises, the third generation models covered a wide range of crises to understand and explain their dynamics especially during the late 1990s.

In the late 20th century, empirical studies (G. Kaminsky, 1998; Frankel & Rose, 1996) had sought to develop models that could emit timely signals of the occurrence of a financial crisis, the so-called Early Warning Systems (EWSs). The first notable attempt to predict crises was Kaminsky, Lizondo, and Reinhart (KLR),1998. The Early Warning Systems proposed had been designed to predict the actual crises by using macroeconomic time series data. The statistical and econometric techniques and models had been used to predict the likelihood of financial crises, using a large number of indicators related to internal and external factors, as well as social and political conditions. The broad classification of the tools employed constitutes parametric and non-parametric techniques. Frankel and Rose (Frankel, J.A. & Rose, 1996) and Kaminsky (G. Kaminsky et al., 1998) are the seminal studies in terms of parametric and non-parametric respectively, applied to currency crisis prediction (Fioramanti, 2008).

2.1.1 Signals Approach

Kaminsky et al. (1998) developed the 'signals' approach to predict the 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 depreciation in the exchange rate and monthly percentage declines in gross international reserves. 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. The method proposed by KLR is essentially non-parametric since it does not involve distributional assumptions on parameters or estimation of parameter values.

2.1.2 Probit and logit models

The second approach used for the estimation and prediction of a probability of currency crisis is the Logit and Probit models. In this approach, for a given data on macro and financial 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 level. Unlike the indicators approach, this is a parametric method that involves distributional assumptions on the relevant parameters as well as estimation and tests of significance to determine which variables are critical in explaining and predicting a currency crisis.

Researchers like Babecký et al. (2014), had explored different methodologies like Binary Classification Tree technique, Bayesian Model Averaging (BMA) for the construction of an early warning system as the Global Financial Crisis has revived interest among academicians to predict the crisis. In the study by Babecký et al. (2014), Bayesian Model Averaging technique had been used for the selection of early warning indicators. After the selection of indicators, they had used signaling analysis to evaluate the performance of early warning indicators of banking crises in developed countries. Christofides et al. (2016) also employed the BMA methodology to address the omitted variable bias and model uncertainty existent in previous approaches. The main policy implication that emerged from the study highlighted that the nature of the impending crisis needs to be specified before Early Warning Signals are examined since they are crisis-specific. Caggiano et al. (2014) had proposed a Multinomial Logit approach, compared to Binomial Logit model, which had improved the predictive power of their EWS in low-income countries in Sub-Saharan Africa. There had been attempts to integrate the two approaches through the use of the Binary Classification Tree technique. An alternative stock-market-based credit risk model had been developed to estimate banking fragility by Eichler et al. (2011), and (Eichler & Sobanski, 2012). Candelon et al. (2014) proposed a new generation of EWSs which reconcile the binary-choice property of the crisis variable with the persistence dimension of the crisis process. The specifications considered include both macroeconomic variables, i.e., the source of exogenous crisis persistence, and the source of endogenous persistence. In conclusion, they had proposed a dynamic EWS model.

2.2 Artificial Neural Networks as an alternative

During the last two decades, Artificial Neural Networks (ANNs) have been recognized by many researchers as a popular technique in financial prediction studies due to its high prediction accuracy rate (Akkoc, 2012). Fethi & Pasiouras (2010) discussed the applications of various Artificial Intelligence (AI) techniques, such as ANN, Decision Tree, and Support Vector Machines, in bank failure prediction, assessment of bank creditworthiness, and underperformance (Sevim, Oztekin, Bali, Gumus, & Guresen, 2014). Nan, Zhou, Kou, & Li (2012) compared neural networks on generating early warning signals of bankruptcy in a given company and reported that ARTMAP (a self-organizing neural network architecture based on Adaptive Resonance Theory) outperforms the other models. Sevim et al. (2014) developed an early warning system with Artificial Neural Networks (ANNs), Decision Trees, and Logistic regression models to predict currency crises and tested the three models in the Turkish economy. This study presented its uniqueness in the decision support model developed. It used basic macroeconomic indicators to predict crises up to a year before they actually happened with an accuracy rate of approximately 95%. Similarly, Sekmen, Fuat & Kurkcu (2014) employed the multilayer perceptron methodology (multilayer ANN) to forecast the economic crisis for Turkey. (Martinez, 2016) used Machine Learning techniques to assess the significance of 26 indicators in forecasting crises for 20 high-income countries.

3. Research Gap

The literature review suggests that there are limited studies on the prediction of a banking crisis in the Indian context. The traditional methods like Logit/ Probit models had not succeeded in anticipating the crisis. Therefore, new sophisticated techniques are required to be explored. Further, studies deploying ANN are scant in the area of crises prediction. Thus, there is a need to explore the Machine Learning techniques as tools for exploring the dynamics of a crisis. The objective of the study is to develop an EWS for the Indian banking sector using ANNs.

4. Methodology and Data

The present study is exploratory in nature. It attempts to study the relationships among the macroeconomic, financial and crisis variables and also tests the performance of neural networks in predicting the crisis in the Indian context. The dependent variable is a binary dummy variable identifying the crisis periods based on Banking Fragility index. The independent variables constitute a comprehensive set of variables like Oil prices, Stock prices, International Reserves, interest rates, Inflation, Industrial Production, Current Account Balance relative to GDP, Foreign Direct Investment relative to GDP, Gross Fiscal Deficit relative to GDP, Broad Money Supply relative to Foreign Exchange Reserves. The study tries to compare the performance of neural networks in an empirical manner as it uses Quadratic Probability Score and Global Squared Bias for evaluation of the performance. The methodologies adopted had been discussed in a detailed manner in the following sections.

4.1 Artificial Neural Networks

A neural network can be seen as a device for acquiring knowledge and making intelligent decisions. Usually, the neural network has a high tolerance for noisy data and good predictive power. In general, the 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 can be predicted or the output values get as close as possible to the target values (Roy, 2009).

The two networks employed are Multilayered Feedforward Backpropagation network (MLFN) and Elman recurrent neural network. The two neural networks differ in their structures as Elman considers lags of the inputs, where the output of hidden layers is fed back as an input in comparison to MLFN which has the inputs feeding in the forward direction only. The superiority of ANNs lies in the fact that it devises the relationship among the variables based on experience instead of hypothesizing a linear relation among the variables, like logit or probit models, which may not be the case.

4.1.1 Multi-Layered Feedforward 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). 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 feedforward since the weighted outputs are always fed into the layer ahead.

For a mathematical description, let us consider a network with one hidden layer. Let there be I input units, J hidden units, and one output unit. Let (x_1, x_2,......,x_G) be an input vector. The activation of the i^{th} input unit is given by an activation/transfer function: $T_1(x_i)$. The input to the j^{th} hidden unit is given by:

$$y_j = w_{i0} + \sum_{i=1}^{I} w_{ij}\, T_1(x_i) \qquad (3)$$

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:

$$z = w_0 + \sum_{j=1}^{J} w_j\, T_2(y_j) \qquad (4)$$

Where w_0 is the bias term and w_j is the weight connecting the j^{th} hidden unit and the output unit. Finally, the output unit is activated by the transfer function: $T_3(z)$. The weights are chosen such that the transfer function $T_3(z)$ is brought as close as possible to the pre-specified target values.

4.1.2 Elman recurrent neural network

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 the past. A recurrent network serves this purpose. An Elman recurrent network (1990) has similarities with an MA process in econometrics. 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 feedbacks to the current units. This property of the network is useful in explaining time-varying patterns. Mathematically, let there be one output unit, one hidden layer, I input units and J hidden units. Let (x_{1t}, x_{2t}, x_{3t},… x_{Nt}) be an input vector of period t . The activation of the i^{th} input unit is given by a transfer function: $T_1(x_{it})$. The input to the j^{th} unit of the hidden layer is given by:

$$y_{jt} = w_{i0} + \sum_{k=1}^{J} w_{kj} y_{j(t-1)} + \sum_{i=1}^{I} w_{ij}\, T_1(x_{it}) \quad \text{……………………………………..(5)}$$

Where w_{i0} is the bias term, w_{ij} is the weight connecting the i^{th} input unit and the j^{th} hidden unit and w_{kj} is the weight connecting the k^{th} lagged hidden unit and the jth hidden unit while T_1 is the transfer function at the input layer.

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

$$z_t = w_0 + \sum_{j=1}^{J} w_j\, T_2(y_{jt}) \quad \text{…………………………………………………………(6)}$$

Where w_0 is the bias term and w_j is the weight connecting the j^{th} hidden unit and the output unit and T_2 is the transfer function at the hidden layer. Finally, the output unit is activated by the transfer function: $T_3(z)$.

4.2 Crisis Variable

The study has adopted the index method of identification of banking crises. The index is based on Banking Sector Fragility (BSF) index developed by Kibritçioğlu to identify the exact months during which the Indian banking sector experienced crises (Kibritçioğlu, 2002). The sample data is monthly and spans from January 2001 to March 2017. The BSF index is a composite index constituting aggregate time deposits, foreign currency borrowing, net bank reserves and domestic credit as proxies for credit risk, liquidity risk, and interest rate risk. Data has been sourced from Monthly RBI bulletin. Two variants of the BSF index has been constructed. BSF4 is defined as an average of standardized values of real deposits, real foreign currency borrowing, real credit, and real bank reserves. BSF7 is defined as an average of real deposits, real foreign currency borrowing, real credit, real bank reserves, real investment, and real foreign currency assets. Following is the mathematical representation for the construction of indices.

$$BSF4 = \left[\frac{(Dep_t - \mu_{Dep})}{\sigma_{Dep}} + \frac{(Cred_t - \mu_{Cred})}{\sigma_{Cred}} + \frac{(FCB_t - \mu_{FCB})}{\sigma_{FCB}} + \frac{(NBR_t - \mu_{NBR})}{\sigma_{NBR}}\right]/4 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$BSF7 = \left[\frac{Dep_t - \mu_{Dep}}{\sigma_{Dep}} + \frac{Cred_t - \mu_{Cred}}{\sigma_{Cred}} + \frac{FCB_t - \mu_{FCB}}{\sigma_{FCB}} + \frac{NBR_t - \mu_{NBR}}{\sigma_{NBR}} + \frac{FCA_t - \mu_{FCA}}{\sigma_{FCA}} + \frac{Inv_t - \mu_{Inv}}{\sigma_{Inv}}\right]/7 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where $Dep_t = \frac{D_t - D_{t-12}}{D_{t-12}}$; $Cred_t = \frac{C_t - C_{t-12}}{C_{t-12}}$; $FCB_t = \frac{CB_t - CB_{t-12}}{CB_{t-12}}$; $NBR_t = \frac{BR_t - BR_{t-12}}{BR_{t-12}}$; $Inv_t = \frac{I_t - I_{t-12}}{I_{t-12}}$; $FCA_t = \frac{CA_t - CA_{t-12}}{CA_{t-12}}$

The time series have been deflated using the Wholesale Price Index (WPI, Base: 1993-94=100). The data has been deflated to make the variables comparable as converting to the same base year helps taking care of any regime shifts in an economy. D_t, C_t, CB_t, BR_t, I_t and CA_t represent the Schedule Commercial Banks' real deposits, real credit, real foreign currency borrowings, real net bank reserves, and real foreign currency assets respectively, in time t. Dep_t, $Cred_t$, FCB_t, NBR_t, Inv_t, and FCA_t represent the annualized changes in real deposits, real credit, real foreign currency borrowings, real net bank reserves, real investment, and real foreign currency assets respectively, in time t. The annual percentage change in the data has been used instead of the month- to- month variation to take care of seasonality and stationarity in the data. This transformation also considers that any difficulties in the banking sector are signaled by long term fluctuations instead of short term fluctuations. The mean and standard deviation of the variables have been represented by μ and σ respectively. Data on all the time series have been standardized so that no individual component may dominate the index.

When the value of BSF is greater than 0, it is a no-crisis zone. However, a value below 0 represents a condition of banking sector fragility. Based on the set threshold, the standard deviation of the index, the fragility has been distinguished between medium and high.

Medium: $-\theta < BSF < 0$

High: $BSF < -\theta$

This study considers the systemic banking crisis as a phenomenon of continuous alternating phases of medium and high fragility. A banking system is considered to be fully recovered when the value of BSF ≥0. Based on this continuum, a dummy binary variable has been deduced where a value of 0 represents a state of no crisis and a value of 1 represents a state of crisis.

4.3 Potential Early Warning Indicators

The banking sector crisis occurs as a result of different variables emanating from macro indicators- both domestic and international and financial market variables. Therefore, total 15 indicators have been chosen to reflect the channels affecting the banking sector based on a comprehensive literature review (Abumustafa, 2006; Ari, 2008; Ciarlone & Trebeschi, 2005; Cumperayot & Kouwenberg, 2013; Davis & Karim, 2008; Fioramanti, 2008; Frankel & Saravelos, 2012; Fuertes & Kalotychou, 2007; Holopainen & Sarlin, 2016; Lin, Khan, Chang, & Wang, 2008; Sarlin, 2012)

Stock Prices: Historically, banking crises have often been preceded by asset price booms. Banking crises associated with house price booms and busts, could, for example, not only be observed during the Global Financial Crisis of 2008, but also in a number of industrial countries in the late 1970s to early 1990s, such as in Spain, Sweden, Norway, Finland, and Japan (Reinhart & Rogoff, 2008). A decline in asset prices results in loss of investor confidence which further leads to increased defaults on loans. Nifty 50 index prices had been used as an indicator for stock prices for India.

Credit developments: High private sector indebtedness poses risks to the financial system when asset price booms are debt-financed, asset prices decrease and borrowers are unable to repay (Kindleberger, Aliber, & Wiley, 2005; Jordà, Schularick, & Taylor, 2015). This may result in deleveraging by banks particularly when the banks, relying on short term funding, face a liquidity mismatch. Deleveraging may induce a credit crunch which can potentially result in a recession. Fire sales can amplify the effects of the asset price losses and it may spill over to other assets as these are sold to meet the regulatory requirements such as capital and liquidity ratios. Moreover, bank runs may occur due to the decreased net worth of banks and loss of investor confidence (Allen & Gale, 2007). Thus, to capture the risks related to credit, *Credit - Deposit ratio* had been used as an indicator.

Macroeconomic environment: Macroeconomic developments are closely related to stock prices and credit developments. A rapid economic growth boosts risk appetite, credit growth and asset prices (Drehmann, Borio, & Tsatsaronis, 2011; Kindleberger et al., 2005; Minsky, 1982) while an economic downturn may lead to difficulties in repayment of debt. To capture the economic environment, variables like *Inflation*, *Industrial production* have been considered. Further, *yield to maturity on 91 days T-bills*, *spread between bank rate and yield to maturity* and *weighted average call money rates* have been included as investors and banks may take on excessive risk when interest rates are low and low-risk assets are less attractive (Maddaloni & Peydró, 2011; Allen & Gale, 2007; Rajan, 2005).

External and global imbalances: The external sector played an important role in the first seminal contributions to the early warning literature (Frankel & Rose, 1996; G L Kaminsky & Reinhart, 1999). These studies were focused on the Balance of Payment crises but a balance of payment crisis and a banking crisis can occur jointly and often reinforce each other and hence known as "twin crisis" (G L Kaminsky & Reinhart, 1999). The external sector can add to the vulnerabilities in the banking sector when there is a sudden stop or decline in the large capital inflows from abroad. Therefore, we include variables like *current account balance relative* to *GDP*, *real exchange rate overvaluation*, *reserves*, *broad money relative to foreign exchange reserves, foreign direct investment relative to GDP and short term debt*. The *oil prices* had also been included as global oil shocks can affect domestic banking sector through contagion and various financial and trade linkages.

All the variables are monthly in frequency however, the variables with annual or quarterly frequency have been converted to monthly frequency using Cubic Spline Interpolation method. All the variables except interest rates and overvaluation of Real Effective Exchange Rate have been transformed into their yearly percentages. Overvaluation from real exchange rate has been calculated by differencing the real effective exchange rate and its Hodrick- Prescott (HP) filtered values. All the data, except Stock prices, Oil prices and the Real Exchange Rate, has been collected from Database on Indian Economy from Reserve Bank of India[1]. Stock prices have been sourced

[1] *Handbook of Statistics on the Indian Economy, Time-Series Publications, Database of Indian Economy, RBI. The URL has been given: https://dbie.rbi.org.in/DBIE/dbie.rbi?site=publications*

from the official site of NSE Nifty 50, Oil prices have been collected from Federal Reserve Bank of St. Louis and Real Effective Exchange Rates have been collected from IMF. The indicators and their transformations have been depicted in Table 1.

Table1: Potential Early Warning Indicators and their data transformations

Variable Indicator/Symbol/Frequency/Transformation
*Yield to Maturity-91 Days T-bill/ **YTM**/Monthly/ none*
*Spread between Bank Rate and Yield to Maturity/ **SPREAD**/Monthly/none*
*Weighted Average Call Money Rate/ **CMR**/Monthly/none*
*Current Account Balance relative to GDP/**GCAB_GDP**/Monthly/y_o_y*
*Foreign Direct Investment relative to GDP/ **GFDI_GDP**/Monthly/y_o_y*
*Gross Fiscal Deficit relative to GDP/**GGFD_GDP**/Monthly/y_o_y*
*Index of Industrial Production(base 1993-94=100)/**GIIP**/Monthly/y_o_y*
*Wholesale Price Index(base 1993-94=100)/**GWPI**/Monthly/y_o_y*
*Reserve Money/**GRM**/Monthly/y_o_y*
*Broad Money relative to Foreign Exchange Reserves/**M3_FEX**/Monthly/y_o_y*
*Oil Prices/ **GOILP**/Monthly/y_o_y*
*Stock Prices(Nifty 50)/ **GSP**/ Monthly/y_o_y*
*Short Term Debt/ **GSTD**/ Monthly/y_o_y*
*Credit to Deposit Ratio/**GCDR**/Monthly/y_o_y*
*Overvaluation of Real Exchange Rate/**REER_DEV**/Monthly/y_o_y*

4.4 Evaluation of Warning Systems

The assessment of the models is based on two attributes namely accuracy and calibration. The closeness of average of predicted probabilities and observed realizations indicates the accuracy of an indicator. Mathematically, QPS is defined as:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2 \quad \ldots\ldots(7)$$

Where $0 \leq QPS \leq 2$. P_t is the predicted probability of the event at time t, T is the total number of observations in the sample and R_t is the realization of the event at time t. The highest possible value of QPS is 2 and the lowest is 0 which implies perfect accuracy. QPS test determines the discrepancy between the realization of an event R_t and its estimated probability P_t (Diebold & Rudebusch, 1989). The second attribute considered is Global Squared Bias(GSB) which measures the calibration. Mathematically, GSB is defined as:

$$GSB = 2(\bar{P} - \bar{R})^2 \quad \text{.......(8)}$$

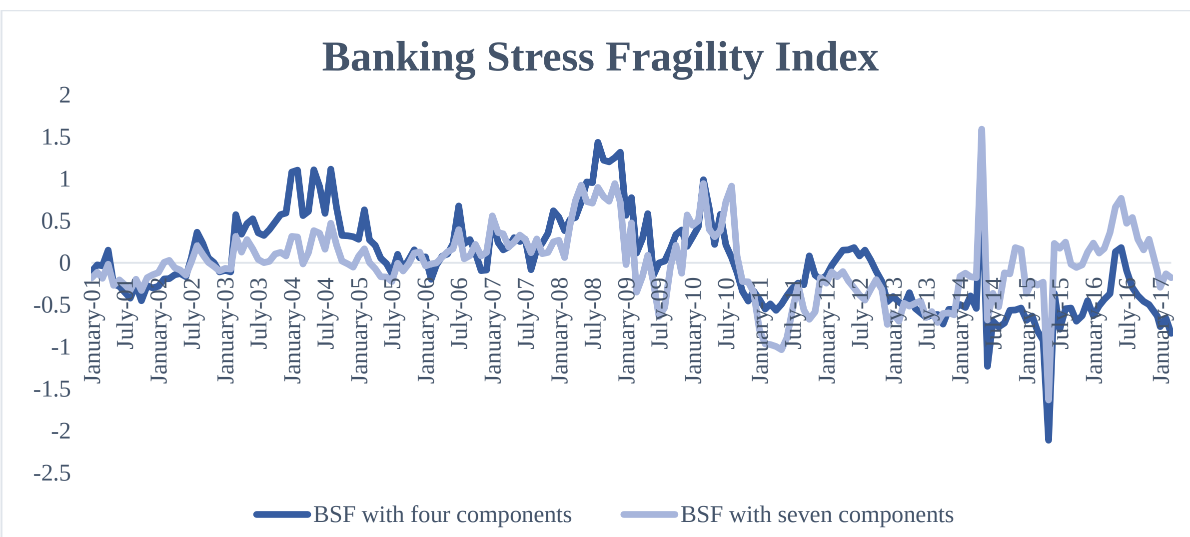
Where $\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_t$ and $\bar{P} = \frac{1}{T}\sum_{t=1}^{T} P_t$ and $0 \leq \text{GSB} \leq 2$. The value of 0 corresponds to perfect calibration which occurs when average probability forecasts equal average realizations.

Both the measures were calculated for in sample and out of sample performance. For out of sample prediction, the training set was taken from 2001 to 2014 and forecasting was done for 2015 to 2017.

5. Estimation and Analysis of Results

The crisis variable has been defined as a binary dummy variable based on an index constructed using different components.

Fig. 1: Banking Stress Fragility Index



It can be observed from Fig. 1, depicting the two indices, (BSF4 with four components and BSF7 with seven components), that both do not differ much in their time paths. However, BSF4 captures the turbulence in the banking sector post-2010 period more efficiently than BSF7. This implies that investments in other approved securities and in non-SLR securities have not played a major role in causing banking distress in India. Therefore, the crisis period has been determined based on BSF4 index.

The standard deviation for BSF4 is 0.54. As mentioned in Section 4, the standard deviation of the constructed index has been used as the threshold to distinguish between the moderate and high fragility zones. Therefore, a medium fragility zone exists when -0.54<BSF4<0 and a high fragility zone is identified when BSF4<-0.54.

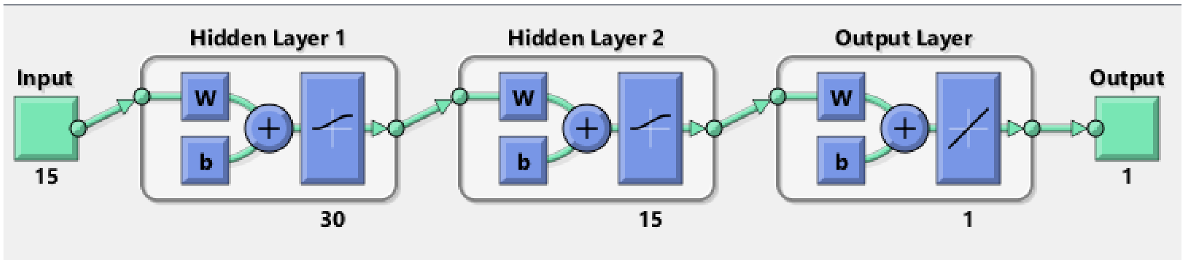
5.1 Prediction with Elman recurrent neural network and Multilayered Feedforward Back Propagation neural network

Elman recurrent neural network has been employed to test the prediction of a crisis. For experimental purpose, different structures with a different number of neurons and combinations of hidden layers and transfer functions have been tested. Two network structures RNN1 corresponding to MLFN and RNN2 corresponding to Elman Neural Network are reported below. The construction of both ANNs has been depicted in Fig. 2 and Fig. 3.

RNN1:

1) Input layer: 15 input units/neuron (for fifteen indicators).
2) Two Hidden layers: 30 neurons in the first layer and 15 neurons in the second layer.
3) One Output layer with a targeted value equal to 1 for crisis periods and 0 for tranquil periods.
4) Training function: Gradient descent with momentum and adaptive learning rate backpropagation.
5) The ‘Pure-linear’ function is applied to the network output while ‘Log-Sigmoid’ is applied to both the hidden layers.
6) Mean Square Error is taken to be the performance function.

Fig. 2: Feedforward BackPropagation Neural Network

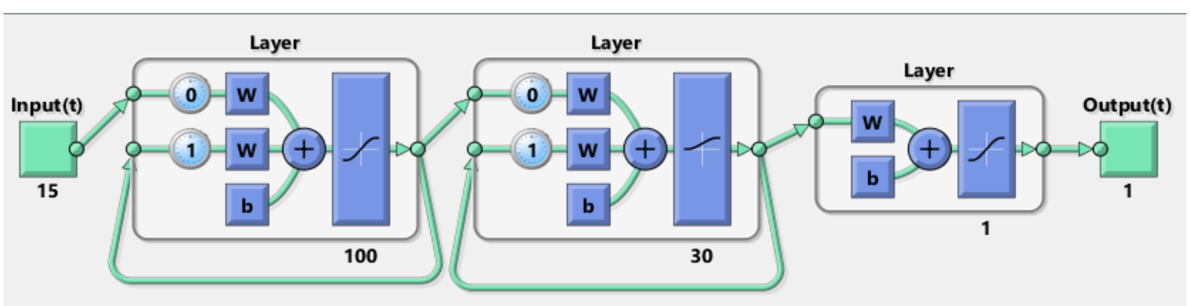


Author's construction: MATLAB

RNN2:

1) Input layer: 15 input units/neuron (for fifteen indicators)
2) Two Hidden layers: 100 neurons in the first layer and 30 neurons in the second layer.
3) One Output layer with a targeted value equal to 1 for crisis periods and 0 for tranquil periods.
4) Training function: Conjugate gradient backpropagation with Fletcher-Reeves updates.
5) The 'Pure-Linear' function is applied to the network output while 'Tan-Sigmoid' is applied to the first hidden layer and 'Log-Sigmoid' is applied to the second hidden layer.
6) The transfer function at all layers is such that it simply reproduces the value of its own argument.
7) Mean Square Error is taken to be the performance function.

Fig. 3: Elman Recurrent Neural Network



Author's construction: MATLAB

Table 2: Calibration Scores – within the sample and out of sample for Neural Networks

Neural Network	In sample		Out of Sample	
	QPS	GSB	QPS	GSB
Feedforward BP	0.135	$4.3*10^{-5}$	0.156	0.035
Elman BP	0.068	0.0002	0.148	0.011

The calibration scores from within the sample and out of sample are reported in Table 2. As can be observed from Table 2, the Quadratic Probability Score(QPS) for Elman recurrent network is lesser than the QPS for MLFN for in sample data. However, the Global Squared Bias(GSB) for MLFN is lesser than the GSB for Elman recurrent neural network. As mentioned earlier, a QPS value lies between 0 and 2. A score of zero implies perfect accuracy while a value nearer to 2 implies that the indicator is not accurate at prediction. The results reported show that Elman recurrent neural network is more accurate than MLFN as the QPS_E is less than QPS_M. The calibration score measured by GSB shows that the overall forecast calibration for MLFN is better than that of Elman recurrent neural network. Similar to QPS, the GSB also lies between zero and two. The value equal to zero corresponds to perfect global calibration. These results correspond to within-sample prediction. The results can be compared with the study by Roy (2009). The study reports QPS of 0.926 and 0.846 and GSB of 0.20 and 0.117 for the constructed Elman neural networks for in-sample data. It can be observed that the values of QPS and GSB in the present study are much less than the ones reported by Roy (2009).

The QPS and GSB scores for out of sample data were also calculated. The neural networks were trained on data spanning from 2001 to 2014 and using the trained networks the probabilities were simulated for two years spanning from 2015 to 2017. The results show that the out of sample QPS scores were greater than in sample QPS scores respectively which is intuitive. The QPS for Elman network rose from 0.068 to 0.148 while for MLFN, it rose from 0.135 to 0.156. The GSB scores also increased for both the networks, however, the performance for the Elman network was found to be superior to MLFN. This was in contrast to in sample results where MLFN performed better than Elman in calibration. In comparison with Roy (2009), which reports QPS scores of 0.560 and 0.599 and GSB scores of 0.124 and 0.137, the present analysis again estimates smaller values of corresponding scores indicating better performance.

6. Conclusions

In this study, an EWS for the Indian banking sector has been constructed using Artificial Neural Networks. The BSF index constructed with four components in comparison to the one with seven components performs better in identifying the episodes of vulnerabilities in Indian banking sector. The study also reveals that the Elman network performs better than the MLFN in terms of accuracy, depicted by QPS score for both in the sample and out of sample. However, in terms of calibration, Elman is better only for out of sample relative to MLFN. It can be concluded that the recurrent network performance is better as it considers the lags of the input variables. As expected, the indicators start showing the signs of a vulnerability prior to financial turmoil. Thus, including lags of variables makes sense and helps to improve the prediction of a financial turmoil. Finally, it is evident from the study that ANNs can act as tools for the prediction of a crisis.

The outcome of this study suggests the work can further be extended by incorporation of a number of alternative variables can be analyzed like political variables, contagion effects and degree of openness of capital account. Other countries can also be studied by clustering them on the basis of their economic situation. Further work can be extended to study other non-linear modeling techniques that could provide insights into the relationships among the leading indicators and the signal.

7. Bibliography

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