Prediction of bank failures in emerging financial markets: an ANN approach

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Abstract

Purpose – The recent financial crises in the world have brought attention to the need for a new international financial architecture which rests on crisis prevention, crisis prediction and crisis management. It is therefore both desirable and vital to explore new predictive techniques for providing early warnings to regulatory agencies. The purpose of this study is to propose a new technique to prevent future crises, with reference to the last banking crises in Turkey.

Design/methodology/approach – ANN is utilized as an inductive algorithm in discovering predictive knowledge structures in financial data and used to explain previous bank failures in the Turkish banking sector as a special case of EFMs (emerging financial markets).

Findings – The empirical results indicate that ANN is proved to differentiate patterns or trends in financial data. Most of the bank failures could be predicted long before, with the utilization of an ANN classification approach, but more importantly it could be proposed to detect early warning signals of potential failures, as in the case of the Turkish banking sector.

Practical implications – The regulatory agencies could use ANN as an alternative method to predict and prevent future systemic banking crises in order to minimize the cost to the economy.

Originality/value – This paper reveals that the ANN approach can be proposed as a promising method of evaluating financial conditions in terms of predictive accuracy, adaptability and robustness, and as an alternative early warning method that can be used along with the most common alternatives such as CAMEL, financial ratio and peer group analysis, comprehensive bank risk assessment, and econometric models.

Keywords Banks, Financial control, Turkey, Predictive process, Neural nets, Economic stability

Paper type Research paper

Introduction

The financial system all around the world has integrated as a part of the effort towards liberalization and globalization since the 1980s. The developments in information and communication technologies have created a suitable environment for new-information based financial activities and innovations in financial markets. As a result of these developments, emerging markets have gained growing attention in global financial markets. Since the investments in emerging financial markets (EFMs) are characterized as high-risk and high-return, these markets have been attractive sources and destinations for global investment portfolios. In contrast,

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internationalization of financial flows has also increased the possibilities of contagion in the global financial system. Financial instability in EFMs contributed to volatility in the global financial system, as evidenced by the outbreak of the Asian crisis in the late 1990s. The severe crisis of 1997-1999 spread from Thailand to the rest of Southeast Asia, to East Asia, Eastern Europe and South America and to the financial hearts of the developed countries.

These recent financial crises have brought attention to the need for financial architectural reform. Besides many conflicting proposals provided by developed countries and international financial institutions, Eichengreen (1999) identifies the policies of the new international financial architecture as crisis prevention, crisis prediction and crisis management. Since banks dominate the financial system in the EMFs, any instability in the banking system has a greater potential to generate contagious crises in the international financial system. In spite of heavy regulations in the last two decades, many developed and emerging countries have witnessed severe banking crises. The cost of the banking crises has had a wide impact on the economies, ranging from 3 percent to 55 percent of GDP in both developed and emerging markets[1]. Eichengreen (2002) draws special attention to threats coming from middle-income emerging markets, specifically mentioning Argentina and Turkey. He also argues that the problems of these countries have not received sufficient attention in the new financial architecture, and these emerging markets must be addressed in order to safeguard global financial stability. Among these countries we have selected Turkey as the application domain and the proposed method for crisis prediction is tested for the Turkish banking sector.

Despite the structural and regulatory developments in the Turkish banking sector since the 1980s, the regulatory and supervisory agency could not prevent the systemic banking crises due to the lack of appropriate enforcement power, credibility and autonomous structure in prudential supervision (Ozkan-Gunay and Gunay, 2007). The Turkish banking system witnessed three severe crises, the crises of 1994, November 2000 and February 2001. The last crises are the worst of its whole history, affecting 25 percent of the 81 banks. Three banks collapsed during the crisis of 1994 whereas twenty banks were taken over and seven banks merged during the last financial crises. The turbulence in the banking sector was the result of legal, regulatory and structural weaknesses, stemming from inadequate capital bases, small size and fragmented banking structures (Ozkan-Gunay, 2004); the dominance of inefficient state banks (Ozkan-Gunay, 1998; Mercan and Yolalan, 2000); low asset quality, high exposure to market risk; and the presence of full deposit insurance[2] and inadequate internal monitoring. The total cost of recent crises (bank losses, resolution of taken-over banks and recapitalizion of weak banks) was estimated to be 50 billion dollars. This chaotic financial environment during the crises bears some challenging research questions: could the failure of banks have been avoided by the supervision agency, Banking Regulation and Supervision Agency (BRSA)? Did the failed banks have financial and managerial characteristics that are different from healthy banks? Besides on-site examinations and off-site surveillance activities to monitor the banks in Turkey, could alternative methods have been used to predict and prevent future banking crisis?

The most common early warning systems are financial ratio and peer group analysis, comprehensive bank risk assessment systems, and statistical and econometric models (Van Greuning and Bratanovic, 2003). Until 2001, the supervisory agency in Turkey monitored the financial soundness of banks by traditional methods, on-site bank examinations and off-site surveillance activities, as well as statistically evaluated reports. The Banking Regulation and Supervision Agency (BRSA) took full control of bank supervision and regulation as an independent agency since 2000 and introduced a new approach, "Risk Focused Monitoring (RFM)" in risk management. This approach has changed the inspection techniques and focuses on the determination of risk profile of the bank and competency of the bank in managing risks instead of avoiding the risk taking behavior of the banks.

Even with a proper regulatory framework, bank regulators and supervisors cannot prevent bank failures because risk taking is a natural part of banking transactions. It is not a one-time monitoring, but an ongoing process: financial risks must be continuously monitored and controlled using all of the early warning systems in the phase of crisis prevention. Therefore, forecasting and monitoring financially troubled banks is of prime importance in minimizing the cost of banking crises and preventing contagious crisis.

In this study, we have utilized a non-linear Artificial Neural Network (ANN) approach in discovering predictive knowledge structures in financial data as a new tool to predict bank failures. The proposed method is tested for the Turkish banking sector. In the business finance and economics literature, several prediction models are based on statistical techniques or hyroustic rules which rely on strong underlying assumptions. The proposed ANN, on the other hand, does not assume certain probabilistic behavior while it can produce decision rules for non-linear systems. To test the proposed method we use the financial ratios of 59 Turkish banks for 1989 to 2000 out of which 36 are successful and 23 are failed banks. The neural networks can be illustrated to differentiate patterns or trends in financial data and utilize them as early warning signals of potential failures. ANN can predict the banks correctly 90 percent of the time while this predictive rate declines to 70 percent for the failed banks. We found that ANN can be successfully applied as an alternative early warning method for assisting both the banking supervisor and bank managers in emerging economies.

Tam and Kiang (1992) mention the need for more empirical studies before the full potential of neural nets can be asserted. Therefore, the main contribution of this study is to illustrate the possibility of predicting bank failures with a robust forecasting tool. ANN for an emerging market can be used as an alternative tool by the banking supervision agencies and bank managers for crisis prevention in order to minimize the devastating effects of crises in both emerging and global financial markets. However, Thompson (1991) draws attention to the sensitivity of the banking system to regional economic conditions. The economic condition where a bank operates also affects the probability of bank failures. A trained system should not be expected to perform equally successfully in another region or country unless it is refined specifically for the new region. Hence, a prediction tool is better tuned and tested for a specific market. In our case the Turkish banking system with its unique characteristics is the application domain.

The next section provides a brief review of previous studies in the prediction of bank failures. The methodology, data and financial ratios; the empirical findings of ANN; and concluding comments are presented in consecutive sections.

Prior studies

The applied studies in the business finance and economics literature has developed a wide variety of statistical techniques to test the effectiveness of financial ratios used in explaining a firm's financial health. These studies have employed discriminant and multivariate discriminant analyses (MDA), statistical techniques which include regression analysis and multivariate probit or logit analysis to determine the ratios that most closely correlate with some signal of financial instability, usually bankruptcy. The later phase of these studies are prediction models that predict future financial distress based on the "best" correlations detected in historical samples of bankrupt institutions.

The ANN model is suggested as a more effective technique than MDA and parametric models for the early detection of financially distress firms. Basic distinguishing features of ANN are:

- multi-modal distribution;
- adaptive model adjustment; and
- robustness.

ANN allows adaptive adjustment to the predictive model as the underlying statistical behavior changes, therefore offering better approximation of the sample distribution by transforming the data into a linearly separable feature space. It has an ability to adaptively adjust the model by modifying the synaptic weights of a neural net. As a result, the model responds swiftly to changes in the real world. In addition, ANN does not need to assume any probability distribution for the model.

The early studies use financial ratios such as profitability, liquidity and solvency as significant indicators for the detection of financial difficulties. The difficulty with these ratios is that the order of their importance is not clear and several studies suggest different ratios as an effective indication of potential problems. Altman (1968) proposes the discriminant analysis approach as an alternative to traditional ratio analysis for corporate bankruptcy prediction. He employs a sample of sixty-six corporations with thirty-three firms in each of the two groups with different asset sizes and reports Z-scores. He concludes that the model is accurate in predicting bankruptcy correctly 94 percent of the time. He also claims that bankruptcy can be accurately predicted up to two years prior to actual failure with the accuracy diminishing rapidly after the second year. Altman and Eisenbeis (1978) repeat the 1968 study of Altman with refinements in the utilization of discriminant analysis for the data 1969-75. The accuracy rate for bankruptcy classification was reported as 93 percent. However, they do not apply the predictive performance of their recent ZETA model on the 1974 sample as Ohlson (1980) criticizes. Sinkey (1975) also uses MDA to identify and describe the characteristics of problem banks with a sample of 110 banks for the years 1969-1972. The findings indicate that the measures of banking factors such as asset composition, loan characteristics, capital adequacy, sources and uses of revenue, efficiency and profitability are good discriminators between groups.

While the standard discriminant analysis (DA) has been the most popular technique for bankruptcy studies using vectors of predictors, later it suffered from methodological or statistical problems that have limited the practical usefulness of their erroneous results. The standard discriminant analysis procedures assume that the variables used to characterize the members of the groups being investigated are multivariate normally distributed. However, in real life deviations from the normality assumptions are more likely and this violation may result in biased results. Eisenbeis (1977) draws attention to some difficulties of the DA:

- the distributions of the variables;
- the group dispersions;
- the interpretation of the significance of individual variables;
- the reduction of dimensionality;
- the definitions of the groups;
- the choice of the appropriate a priori probabilities and/or costs of misclassification; and
- the estimation of classification error rates.

Ohlson (1980) also mentions simply the problems associated with MDA. Violations of the normality assumptions may bias the tests of significance and estimated error rates. In the applied literature, the problem of testing for the appropriateness of the distributional assumption has been largely ignored. This is due to the fact that most available normality tests are for univariate normality. Altman and Eisenbeis (1978) also draw attention to the applicability of discriminant analysis to time series type problems. This method is only useful for prediction purposes if the basic underlying relationships and parameters are stable over time. Otherwise, the model and estimated error rates will only be valid for the specific periods investigated. Coats and Fant (1993) point out that invalidity of MDA is based on two limitations: firstly, MDA requires that the decision set used must be linearly separable, and secondly, ratios in MDA are treated as completely independent.

The theoretical and statistical work dealing with the problems of discriminant analysis are of three types:

(1) applying parametric models such as logistic regressions;
(2) developing expert systems with limitless potential due to their capacity to mimic the ability of human analysts and perform other logic processes; and
(3) using a neural network approach with their non-linear classification abilities by learning from examples.

A non-linear logistic function is preferred over MDA and Harrel and Lee (1985) claim that even when all the assumptions of MDA hold, a logit model is virtually as efficient as a linear classifier. Ohlson (1980) analyzes the corporate failures in the context of an econometric methodology, conditional logit model, for the data between 1970 and 1976. A Probabilistic Model is chosen to eliminate the problems associated with MDA. He reduces the fundamental estimation problem to the following statement: "given that a firm belongs to some prespecified population, what is the probability that the firm fails within some prespecified time period?" He also makes no assumptions regarding prior probabilities of bankruptcy and the distribution of predictors. The statistical significance of the different predictors is obtained from asymptotic (large sample) theory. He also points out the importance of accurate data collection of bankrupt firms. Ohlson concludes that the predictive powers of the linear transforms of a vector of ratios seem to be robust across large sample estimation procedures. Zmijewski (1984) argues that potential biases caused by sample selection/data collection results in asymptotically biased parameter and probability estimates. The results demonstrate the existence of a bias for choice-based samples when unadjusted probit is used but the bias decreases as the sample composition approaches the population composition.

Thompson (1991) estimates FDIC-insured bank failures for the period 1984-1989 by logit model. He prefers logit rather than probit because logit is not sensitive to the uneven sampling frequency problem. The results indicate that the probability of failure can be detected as much as four years before a bank fails. The model can classify correctly more than 94 percent of failed banks between 6 and 12 months before the call date. Among the CAMEL-based variables, solvency and liquidity are the most important predictors of failure. However, as the time to failure increases, asset quality, earnings and management gain importance as predictors of failure. He also draws attention to the importance of regional economic risk where banks operate. Similarly, Persons (1999) uses the logistic model to differentiate 26 failed finance companies from 15 surviving ones from 1993-1996. The results indicate that failed companies could have been predicted by employing the proposed method where auditors' reports from the 1996 financial statements did not differentiate the failed ones. Rahman *et al.* (2004) also use the logistic technique to identify problem banks for Indonesia, South Korea and Thailand as separate cases with time periods ranging from 1995 to 1997. Financial ratios such as capital adequacy, loan management and operating efficiency are found to be common performance indicators in identifying problem banks in Asia.

Tam and Kiang (1992) present a new approach to bank bankruptcy prediction using ANN and compare it with linear classifier and logistic regressions. A neural network represents a nonlinear discriminant function as a pattern of connections between its processing units. They also argue that a neural net-based system offers on-line capabilities while rule-based expert systems are satisfactory for off-line processing. In ANN the rules are hidden in the weights of the neural connections and can be changed on-line as long as a set of training data can be presented to the system. They tested a sample of 118 Texas banks based on 19 financial ratios for the period 1985-1987 by employing DA, logit, and ANN techniques. Their empirical results showed that neural nets offered better predictive accuracy than DA, logit and other distribution free techniques. Coats and Fant (1993) also propose ANN as an alternative method of the same ratios used by MDA. They estimate the future financial health for the data of 282 firms, 94 of which were in financial difficulty, and then compare the results of ANN and MDA. Their findings indicate that the ANN technique outperforms the traditional approach MDA, having predicted distress for 80 percent of firms that received bad audit reports. MDA can be considered equivalent to a special case of ANN when the input variables are linearly separable. Alam *et al.* (2000) present experimental results of fuzzy clustering and two self-organizing neural networks used as classification tools for identifying potentially failing banks.

Since the ANN model is free of linear separability and the requirement of independence of the predictive variables, it allows superior results. Olmeda and Fernandez (1997) compare the accuracy of parametric and nonparametric classifiers on the problem of predicting bankruptcy and conclude that ANN provides the best results among classical statistical classifiers.

ANN compared to some other techniques does not assume specific probability distribution functions while it can handle non-linearities in the data structure.

Consequently, the ANN approach with black box architecture makes statistical modeling much easier and outcomes more accurate due to its flexibility. Therefore, the ANN approach is proposed as a promising method of evaluating financial conditions in terms of predictive accuracy, adaptability and robustness in the Turkish banking sector in this study.

Methodology and database

ANN is a mathematical and algorithmic model imitating the way the biological brain works. It works through artificial neurons which combine input data, on a number of processing elements called neurons and the weighted sums of the neurons are processed with a nonlinear decision function to compute the output of the active neuron. The output can be the final product, or it can be an input to another neuron. Neurons can be organized in layers as input, hidden, and output. Neurons can be interconnected as an input layer, a hidden layer and an output layer. An input layer consists of neurons that receive information from the external environment. An output layer contains neurons that produce output. A hidden layer, or intermediate layer, includes neurons that receive information from other neurons and send signals to other neurons. It is the hidden layer that provides the non-linear modeling ability to a neural network. With this ability, ANN does not require pre-specification of any relationship and can approximate whatever functional form best characterizes the data. It uses training cases to find patterns and mappings linking input and output variables through the concept of self-learning. An ANN without a hidden layer can only solve linear functions (Fu, 1998).

In this study, a multi-layer Backpropagation ANN is utilized to tackle the non-linearity of the problem by employing the generalized delta learning rule (GDLR) and nonlinear hyperbolic tangent decision functions for the nodes, as it is shown in Figure 1.

The output of a neuron "j" in Figure 1 is:

$$o_j = \varphi(net_j),$$

where φ is the nonlinear, differentiable, and monotonically increasing activation function such as a hyperbolic tangent function:

$$\varphi(net_j) = \tanh(net_j) = \frac{e^{net_j} - e^{-net_j}}{e^{net_j} + e^{-net_j}}.$$

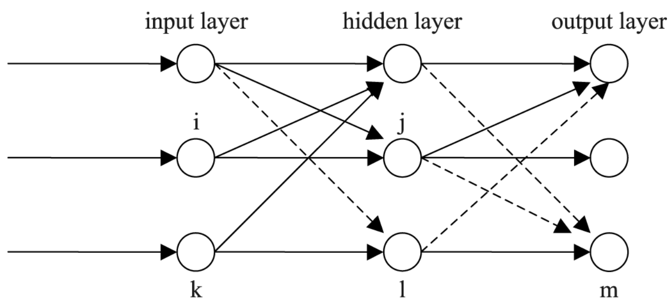

Figure 1.
A multi-layer Backpropagation Artificial Neural Network

Hyperbolic tangent has a continuous output in the range $(-1:1)$ yielding a balanced output compared to other activation functions.

The weighted sum of the k neuron outputs, o_i feeding the jth neuron is:

$$net_j = \sum_{i}^{k} w_{ji} o_i.$$

where k is the number of nodes in the preceding layer, o_i is the output of a neuron i.

Each processing element receives the outputs of the incoming neurons through the links represented as connecting lines between the neurons. Each link has an associated weight "w_{ji}" connecting the node i to node j. In our study, as in many typical applications, the output layer presents the forecasted values in a prediction scheme. There may be several hidden layers with finite number of neurons. The number of neurons in a hidden layer and the number of hidden layers are experimentally determined.

The ANN is trained by presenting a set of input patterns with known output behavior. For our purposes an input pattern comprises 20 financial ratios, $(k = 20)$. The neural network output layer has a single neuron $(m = 1)$. The output for the known inputs is set as either -1 (failure) or $+1$ (success). Training is an iterative process. In each iteration, the values of the connecting links weights are tuned according to the GDLR, which is nothing more than the error minimization for the data contained in the training set with the known output values (failure or success).

For the hyperbolic tangent function, this error minimization is expressed as:

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n) + m \Delta w_{ji}(n-1). \tag{1}$$

Here $\Delta w_{ji}(n)$ is the change of a weight after the nth training iteration; η is the learning rate $(\eta < 1)$; m is called the momentum rate (<1). $\delta_j(n)$ is computed from the output error for the output nodes as:

$$\delta_j(n) = e_j(n) \varphi_j'\big(net_j(n)\big) \tag{2}$$

$e_j(n)$ is the difference between the known output and the actual output of the NNET at nth iteration, defined as:

$$e_j(n) = d_j(n) - o_j(n).$$

For an output node Equation 2 is reduced to:

$$\delta_j(n) = \big[e_j(n)\big]\big[1 - \varphi_j(n)\big]\big[1 + o_j(n)\big]$$

For a node in the hidden layer:

$$\delta_j(n) = \big[1 - \varphi_j(n)\big]\big[1 + o_j(n)\big] \sum \delta_k(n) w_{kj}(n).$$

The proof of the GDR algorithm can be found in Hagkin (1999).

There are 20 financial ratios (representing the financial health of the banks) used for the classification of failed and non-failed banks. Therefore, there are 20 input values $(k = 20)$ for our neural network presented in Figure 1. The weights of the neural network are adjusted to produce the targeted output for each of the inputs during the training process for a set of known input-output relations. The weights are adjusted to minimize the output error according to the GDLR as described in Equation 1. This well-defined iterative algorithm modifies the weights of the neural network in the negative Mean Squared Error (MSE) gradient direction. Several iterations are required until a consistent set of weights that work for all the training data is achieved. In our application, the single output node, $m = 1$, is targeted to be either $+1$ (success) or -1 (fail) during the training process. Regarding hidden nodes, 40 ($l = 40$) are decided upon using several experimental observations. The number 40 for the hidden nodes was achieved by gradually increasing the number of nodes, until no significant change in the MSE convergence is detected. With 40 hidden nodes, the training continued until the MSE could no longer be decreased significantly with the selected training set. This corresponded to 3,500 epochs with a MSE converging to a MSE of 10^{-4}, an acceptable level for our purposes. An epoch is one cycle of training achieved by presenting all the training patterns in the training set. In our case, the training set contains a total of 30 samples of successful and failed cases randomly selected as described below.

Data

Of the ratios in the input vector, 20 are grouped into four of five of the CAMEL rating system. The generally accepted criteria to generate financial soundness are referred to as the CAMEL rating system, which is composed of five components: C, for capital adequacy; A, for asset quality; M, for management competence; E, for earnings; and L, for liquidity. It is difficult to measure the quality of the management with the available data; therefore no explicit ratio is used for management criteria. It is assumed that the ratios will eventually reflect different strategies of decision makers. Besides the four components of the CAMEL rating system, two additional criteria are also included as income-expense structure and branch performance, as described in Table I. These

Capital adequacy	R2 = Shareholders' equity + total income/deposit + non-deposit funds
	R3 = Net working capital/total assets
	R4 = FX position/shareholders' equity
Asset quality	R5 = Non-performing loans/total loans
	R6 = Permanent assets/total assets
	R7 = FX assets/FX liabilities
Earnings	R8 = Net income/average total assets
	R9 = Net income/average shareholders' equity
Liquidity	R10 = Liquid assets/total assets
	R11 = Liquid assets/deposit + non-deposit funds
	R12 = FX liquid assets/FX liabilities
Income-expense structure	R13 = Interest income/interest expenses
	R14 = Non-interest income/non-interest expenses
	R15 = Interest income/average earning assets
	R16 = Interest income/average
	R17 = Non-interest income/total income
	R18 = Interest expenses/total expenditure
Branch performance	R19 = Total asset per branch
	R20 = Total deposit per branch
	R21 = Total loan per branch

Table I.
Ratios used in ANN bankruptcy prediction

features are selected after eliminating some redundancies, and based on the availability of the parameters for all the banks under study.

The data depend on the financial statements published by the Banks Association of Turkey (BAT) and covers the period from 1990 to 2000. The descriptive statistics of the entire sample as well as two groups of banks (Failed and Success) is presented in Table II.

The difference in the mean for two bank groups (successful and failed) is compared for CAMEL parameters as well as income-expense structure and branch performance. Mean values for capital adequacy parameters (R2 and R3) show that successful banks perform better than the failed banks. Asset quality variables, R5 and R6, present a better performance with lower values of the share of non-performing loans to total loans and share of permanent assets to total assets for the successful banks. Higher value for R4 and a negative value for R7 indicate that failed banks carry relatively larger short positions, carrying higher currency risk. Earnings (R8 and R9) for the successful banks are much higher than the failed banks where the share of net income in average total assets (R8) is negative for the failed banks. Successful banks preferred to stay more liquid in both local and foreign currency. Liquidity levels (R10, R11 and R12) for the successful banks are below the average and the mean of failed banks. On the other hand, this could also be interpreted as a sign of inefficient use of funds. Similarly, successful banks carry out better performance in terms of income-expenditure structure (R13, R14, R15, R16, R17 and R18). Higher value for R13 shows that successful banks generate more income from interest based transactions. A negative value of R14 demonstrates that failed banks had difficulty in matching up non-interest expenses with less risky income such as non-interest income. The performance of branches is compared with assets, deposits and loans per branch. The average asset (R19) and average loan (R20) level per branch is higher for the successful banks where the average deposit level per branch (R21) is lower. This may also indicate that successful banks can create other meanings of funding and do not only depend on the deposits.

Of 59 banks, 23 failed, were closed, or merged between late 1999 and 2001, leading to the ‘Twin Crises” in Turkey. The decision to close or merge these banks was a result of a Government policy and therefore we do not expect to have a time dependent description for the closures or mergers. Instead, the proposed study claims the indications of failure were present long before the closures and the failures were predictable simply based on the analysis of financial ratios. From the 36 successful banks 18 are selected randomly for the training set and the remaining 18 are used for testing. Similarly 12 of the 23 failed banks are used for training while the remaining 11 constitute the testing set for the failed banks. Since there are 18 banks representing Success and 12 banks representing Failure in the training set, some of the failed bank data are repeated in the training set so as not to cause bias. Again to avoid bias the order of Fail and Success banks are presented in mixed order during the training.

Since the data for some banks were not available for all the years, each yearly performance was treated independently from the other years. Treating financial ratios as static parameters for a single year is possible with the backprobagation ANN model. This enables to analyze bank performances on a yearly basis. In the end, the training set contains 391 training samples (vectors) with all the 20 financial ratios. Two testing sets, one for Fail and one for Success were presented to the trained ANN for the

Table II. Summary statistics

Variables	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21
Entire sample																				
Mean	30.4	4.6	125.6	29.1	8	86.7	1.9	76.3	47.5	88.6	52.3	273.8	−0.8	43.5	25.6	7.7	42.4	9,162	4,129	2,073
Median	14.6	5.8	59.3	1.9	5	87.4	3.9	53.8	45.7	59.4	47.7	180.7	21.3	39.7	22.4	5.7	49.3	1,028	496	304
Standard deviation	117.2	23.2	312.3	314	9	85.8	2.1	0.9	51.3	51.1	33.2	443.5	120.1	26.8	17.8	95.6	97.8	29,432	15,871	8,013
No. of obser.	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639	639
Sample of successful banks																				
Mean	33.8	8.7	115.9	6.2	7.7	91.3	5.5	99.0	49.4	101.2	56.8	311.5	11.3	41.4	25.1	4.9	62.0	10,369	3,416	2,130
Median	16.7	6.7	45.3	1.9	4.9	90.4	5.1	59.4	47.7	66.4	52.5	200.6	33.7	38.1	21.2	7.7	64.9	952	408	267
Standard deviation	55.9	12.1	272.6	19.7	8.5	32.7	5.9	426.7	17.7	161.2	35.5	541.1	120.4	21.2	18.9	24.3	18.4	30,757	10,260	6,423
No. of obser.	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388	388
Sample of failed banks																				
Mean	25.2	−1.7	140.7	64.7	8.4	79.8	−3.4	41.2	44.6	69.4	45.3	215.6	−19.7	46.7	26.4	12.0	12.0	7,296	5,231	1,985
Median	12.3	4.7	100.3	2.0	5.2	81	2.3	46.9	41.6	52.4	41.3	155.6	0.5	42.0	24.4	1.1	1.1	1104	699	340
Standard deviation	173.6	32.9	365.3	499	10	27.7	26.5	341.6	18.2	171	27.9	207.5	117.4	33.4	15.8	149	149	27,211	21,859	9,999
No. of obser.	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251

classification of unseen data. The Fail set with its 11 banks had 123 test vectors including the years with available data for each bank. Similarly the Success set had 192 test vectors belonging to 18 banks.

Prediction results

The comparison is based on a training set with an equal proportion of failed and non-failed banks. The test sample consists of both healthy banks and failed one, altogether 29 banks. It is important to note again the training and testing sets are mutually exclusive. When the neural network classifier's outputs are compared for the healthy banks and failed banks, it is seen that most of the failed banks signaled trouble long before their failure during the pre-crisis period, as can be seen in Table III.

The empirical results show that neural networks can differentiate patterns or trends in financial data and use them as early warning signals of potential failures. When a confidence level of 90 percent is selected, 76 percent of the failed banks are correctly indicated, and the non-failed banks are classified 90 percent of the time correctly. Percent of correct predictions on a yearly basis is also presented in Table III.

The developments in the Turkish banking sector support the empirical results of the study. Banks that were identified as troubled banks during the 1990-2000 period based on the ANN results were either transferred to the SDIF or merged with the other holding banks (sister banks). Bank 1 and Bank 2 seemed to have deteriorating financial status during the 1990s. Both banks merged with their sister banks in 2001. Bank 5, Bank 10 and Bank 11 were taken over by the SDIF at the end of 1999 while Bank 4, Bank 6, Bank 8 and Bank 9 were transferred to SDIF in 2001. Bank 3 was taken over by the SDIF in 2002.

On the other hand, the misclassifications among the troubled banks can be attributed to the change of ownership, and the years the banks were established, particularly for the failed group. For example, Bank 4 and Bank 9, previously foreign-owned banks, were sold to two local groups in 1995 and exhibited a different pattern until 1998. Bank 4 started signaling trouble after 1998 whereas Bank 9 started to improve its financial status. Bank 8 was established in 1992 with high ratios of capital adequacy and asset quality, presenting a healthy status. Bank 10 was taken over by the SDIF at the end of 1999 and measures to strengthen the institutional capacity of the SDIF banks might have resulted in an improvement. Therefore, the model can signal any type of change (ownership, merge etc.) that indicates a kind of trouble in the bank.

ANN results predict the non-failed banks 90 percent of the time correctly in the data set which also supports the real life status of these banks. As of April 2005, all of the non-failed banks continue to operate successfully after 2000 with one exception. The exception bank, Bank 12, was taken over by the SDIF in July 2003. The investigations of both domestic and international auditors proved that Bank 12 indeed was a special case because all the financials given to the authorities by Bank 12 were incorrect and were not showing the real financial status of the bank. Two different computer systems were created in the bank, one for the authorities and the other for the top management in order to run illegal operations.

ANN is proved to differentiate patterns or trends in financial data and could be proposed as a new approach to detect early warning signals of potential failures. Empirical findings in the Turkish banking sector substantiate the fact that ANN can

Bank	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	Real status
1	−0.95	−0.98	−0.98	−0.99	−0.98	−0.91	−0.11	0.97	0.00	−0.45	0.30	Fail
2	−0.96	−0.95	−0.93	−0.98	−0.93	−0.95	−0.97	−0.98	−0.98	−0.63	−0.62	Fail
3	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.95	Fail
4		−0.99	−0.99	−0.97	−0.87	−0.59	0.75	−0.75	−0.99	−0.99	−0.99	Fail
5	−0.97	−0.99	−0.99	0.97	0.12	−0.89	−0.99	−0.99	−0.99	−0.99	−0.99	Fail
6	−0.98	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	Fail
7	−0.93	−0.97	−0.99	−0.99	−0.99	−0.99	−0.99	−0.61	−0.60	−0.99	−0.98	Fail
8			0.77	−0.89	−0.99	−0.99	−0.98	−0.97	−0.96	−0.97	−0.95	Fail
9	−0.31	−0.52	0.48	−0.66	0.79	−0.95	−0.99	−0.96	−0.62	0.90	−0.77	Fail
10	−0.93	−0.99	−0.99	−0.99	−0.98	−0.99	−0.99	−0.99	−0.99	−0.90	0.32	Fail
11				−0.89	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	−0.99	Fail
12	1.00	1.00	1.00	0.97	0.98	0.99	0.98	0.96	0.93	0.95	0.96	Success
13									0.99	0.98	0.92	Success
14	0.99	0.99	0.99	0.99	0.99	0.98	0.96	0.98	0.98	0.98	0.91	Success
15	0.99	1.00	0.99	0.97	0.98	0.98	0.98	0.98	0.98	0.97	0.98	Success
16	1.00	1.00	0.99	0.93	0.97	0.77	0.16	0.95	0.71	0.28	0.88	Success
17	0.97	−0.83	0.67	−0.54	0.33	0.61	−0.03	0.77	0.84	0.86	0.92	Success
18			0.98	1.00	0.87	−0.41	−0.37	0.96	0.97	0.97	0.83	Success
19		0.99	0.99	0.99	0.91	0.56	0.96	0.98	0.98	0.98	0.98	Success
20									0.42	1.00	1.00	Success
21	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.96	0.98	0.98	Success
22	1.00	0.99	0.97	0.97	0.99	0.98	0.99	1.00	0.99	0.97	0.99	Success
23	0.98	0.99	0.99	0.98	0.99	0.98	0.98	0.98	0.98	0.99	0.98	Success
24	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98	Success
25	0.93	0.93	1.00	1.00	1.00	0.99	0.99	0.99	0.99	1.00	1.00	Success
26	1.00	0.99	1.00	0.99	0.99	0.99	0.98	0.98	0.97	0.98	0.47	Success
27	1.00	0.99	0.99	0.99	0.23	0.99	0.98	0.98	0.98	0.99	0.59	Success
28	1.00	0.99	0.99	0.99	0.99	0.95	0.96	0.96	0.96	0.98	0.96	Success
29	1.00	1.00	1.00	1.00	0.99	0.99	0.97	0.97	0.98	0.98	0.98	Success
Correct predictions (%)												
Failed group	100	100	80	91	82	100	91	91	91	91	91	
Success group	100	93	100	94	100	94	88	100	100	100	100	

Notes: Negative numbers suggest failure; positive numbers indicates success; as the output approaches to -1 or 1 certainty of the decision increases

Table III.
Prediction of 29 bank status before crises

be used as an effective tool to detect early warning signal about the banks' deteriorating financial health.

Concluding remarks

As a result of financial liberalization and globalization, national economies have integrated more closely, leading to rapid and significant knock-on effects amongst themselves. Since the elimination of financial crises is not possible due to the natural characteristic of risk taking behavior in financial transactions, it might be possible to reduce their frequency, severity and contagion in the global financial system by strengthening supervision and regulation. If financial crises can be detected early, the cost to the economy could be minimized and a systemic banking crisis could be prevented by the regulatory agencies. Bank managers as well as the monetary authorities can also benefit from the early prediction of financially weak banks and take proper measures.

The objective of this study is to introduce a new approach to bank bankruptcy prediction by using neural networks as an inductive algorithm in the Turkish banking sector. The empirical results show that ANN can differentiate patterns or trends in financial data and use them as early warning signals of potential failures. Since the ANN method is non-parametric, it is not vulnerable to the criticisms attributed to parametric approaches. In our sample, the accuracy rate seems superior. Though we are not claiming that ANN always outperforms the other techniques. We suggest that ANN can be utilized as an alternative early warning method for assisting both the banking supervisor and bank managers especially in emerging economies. The regional operational and regulatory environment shape up the ability of banks to function efficiently and financially stable. Therefore, policy makers and regulators should monitor the banks closely by employing alternative early warning techniques and revise regulatory and supervisory policies by taking into account changing global and local conditions.

There may be several possibilities for the extension of this study. This study covers the pre-crisis period, immediately preceding the November 2000 and February 2001 crises. Firstly, if the BRSA provides the consistent data set, this study can also be replicated by monthly data which may increase the predictive performance of the ANN model. Secondly, it can be replicated for "the post-crisis period (2005- ....)" in order to compare the predictive performance of an ANN approach in financially stable and distress environments[3]. Another possible extension of the study could be employing an ANN approach to determine the financial soundness of the banks between two emerging countries, or the comparison of one emerging and one developed economy to gain an insight into country specific factors. Lastly, the ANN approach could be employed along with other approaches such as TOBIT, "value at risk," or "distance to default" to determine the efficiency of the banks and compare the results of the parametric and non-parametric approaches.

Notes

1. Argentina 55 percent, 1980-1982; Chile 41 percent, 1981-1983; Venezuela 1994-1995, 18 percent; Mexico 12-15 percent, 1995; Brazil 5-10 percent, 1994-1995; Finland 8 percent, 1991-1993; Uruguay 7 percent, 1981-1984; Sweden 6 percent, 1991; Colombia 5 percent,

1982-1987; Norway 4 percent, 1987-1989; USA 3 percent, 1984-1991 (Mishkin and Eakins, 2000); Turkey 20-25 percent, 2000-2003.

2. Full deposit insurance was introduced during the 1994 crisis until the May of 2000 to all types of savings deposits to prevent the public panic. However, this guarantee led to unfair competition and moral hazard problems.
3. From 2001 on and thereafter, the evaluation of the end-year financial statements of the banking system was changed in compliance with the inflation accounting principle. The BRSA also asked banks to adjust the financial statements of subsequent years in accordance with inflation accounting as of December 31, 2001 which had never been realized. As of April 21, 2005, the implementation of the inflation accounting principles was abolished with the announcement of the BRSA due to declining trend in inflation.

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Further reading

Bank Association of Turkey (1980-2003), issues from 1980 to 2003, available at: www.tbb.org.tr

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