A Systematic Approach to Bankruptcy Prediction in Banks: A Case Study from Turkey

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Abstract

This study proposes a systematic approach to bankruptcy prediction in banks that integrates multivariate statistical methods, multi-factor productivity analysis and multi criteria decision making (MCDM). In its first stage, the approach respectively employs factor analysis and discriminant analysis to explore the main financial factors that affect the financial performance of the banks, and to assess the banks as healthy or non-healthy. In the second stage, the classification results are compared with that of ELECTRE TRI. To explore the viability of the proposed approach, computational experiments are performed on a real-world problem from Turkish banking sector.

Keywords: Financial Risk Management, Banking Sector, Factor Analysis, Discriminant Analysis, ELECTRE TRI

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Bankaların İflas Riskinin Tahminlenmesine Yönelik Sistematik bir Yaklaşım: Türkiye Örneği

Özet

Bu çalışmada bankacılık sektöründe başarısızlık ve iflas tahminlemesine yönelik olarak sistematik bir yaklaşım geliştirilecektir. Bu kapsamda, istatistiksel yöntemler, çok kriterli karar verme ve çok faktörlü verimlilik analizi kullanılacaktır. Metodolojinin ilk aşamasında faktör analizi ve diskriminant analizi kullanılarak finansal performansı etkileyen temel rasyolar belirlenecek, bankalar bu rasyolar kullanılarak başarılı-başarısız olarak sınıflandırılacaktır. İkinci aşamada ise elde edilen sınıflandırma sonuçları ELECTRE TRI ile elde edilen sonuçlarla karşılaştırılacaktır. Geliştirilen metodolojinin uygulanabilirliği Türk bankacılık sektörü üzerinde bir uygulama ile test edilecektir.

Anahtar Kelimeler: finansal risk yönetimi, bankacılık sektörü, faktör analizi, diskriminant analizi, ELECTRE TRI

1. Introduction

Today, performance evaluation of banks attracts considerable attention of bank customers, investors and regulators as well as the bank management since highly competitive business environment forces the banks to use their economic sources effectively. Canbaş and Erol (1985) categorized the reasons of bank failures in two groups, external and internal reasons. According to the authors, external reasons arise from the economic policy followed in the country and internal reasons are related to the qualifications of the top management and employees of the bank. Financial ratios, which provide meaningful quantitative information about the changes of internal conditions of the banks, are widely utilized by a variety of statistical methods, operational research and artificial intelligence techniques for evaluating the performance and efficiency of the banks.

Lin et al. (2011) explored financial ratios that could be potentially useful. They selected six new financial ratios from Taiwan Economic Journal feature set together with four ratios from current literature to be treated as potential candidates for the establishment of models for effective identification of financial distressed firms. Tinoco and Wilson (2013) tested the business financial failure classification accuracy and predictive power of three types of variables namely, financial statement ratios, macroeconomic indicators and market variables by using logistic regression analysis. Öğüt et al. (2012) used multiple discriminant analysis and ordered logistic regression, Support Vector Machines and Artificial Neural Network to estimate the financial strength of Turkish banks using 26 financial ratios. Ravisankar and Ravi (2010) used three neural network architectures for bankruptcy prediction in banks namely, Group Method of data Handling, Counter Propagation Neural Network and fuzzy Adaptive Resonance Theory Map. They apply these techniques to four different data sets belonging to Spanish, Turkish, UK and US banks. Celik and Karatepe (2007) examined the performance of neural networks in evaluating and forecasting banking crises. They formed two artificial neural network models for evaluating and forecasting banking crises and used Taguchi Approach in the optimization of the network topologies. Canbas et al. (2005) proposed a methodological framework based on multivariate statistical analysis to predict commercial bank failure and applied the methodology on Turkish commercial banks. They used principal component analysis to explore the most important financial factors. Cox and Wang (2014) used linear and quadratic discriminant analyses to predict US bank failures during the financial crisis of 2008-2010. They tested four models for their ability to classify the survived and failed banks correctly. This study proposes an approach for bankruptcy prediction in banking sector. Different from the previous research, it integrates multivariate statistical methods, multi-factor productivity analysis and MCDM, and use a wide range of financial ratios under nine categories.

Macroeconomic problems experienced by economies all around the world were also observed in Turkey for the period of 1997–2003. As researches in this field reveal, negative economic conditions in a country increase the probability of bank failure. However, the healthy banks were continuing to survive while the other non-healthy group failed under the same negative macroeconomic environment. It is vital to predict the bankruptcy of banks in an economic system avoid severe consequences. This study aims to propose a systematic approach to bankruptcy prediction in banks. To this aim, multivariate statistical methods, multi-factor productivity analysis and MCDM are employed in a combined manner. More specifically, factor analysis, discriminant analysis and ELECTRE TRI are used by the approach. A case study from Turkish banking sector is presented to confirm the practicability of the proposed approach.

2. The Methodology

To confirm the viability of the proposed approach, a case study from Turkish banking sector is presented. In the application, performances of 72 commercial banks are assessed by using 39 financial ratios for the period of 1997 to 2003. The sample set consists of 51 non-bankrupt and 21 bankrupt banks that are transferred to The Savings Deposit Insurance Fund (SDIF). SDIF is an association that insures savings, deposits and participation funds in order to protect the rights of depositors and to contribute confidence and stability of the banking system and it resolves the banks and assets transferred to it in the most proper way in Turkey. The financial ratios considered in this study are grouped into nine categories: capital ratios, assets quality, liquidity, profitability, income-expenditure structure, activity ratios, share in sector, share in group and branch ratios.

2.1. Factor analysis

Factor analysis is a statistical data reduction method that is used to remove redundancy or duplication from a set of correlated variables and examine whether a number of variables of interest are linearly related to a smaller number of unobservable factors.

In this study, we use Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity to specify the sampling adequacy. KMO is an index used to examine the appropriateness of factor analysis, and it takes the values between 0 and 1. The values between 0.5 and 1 imply factor analysis is appropriate. Bartlett's Test of Sphericity is a statistic used to examine the hypothesis that the variables are uncorrelated in the population. The results of the tests are presented in Table 1. The results reveal that the sample is adequate for factor analysis.

Table 1. Results of KMO and Bartlett's Test of Sphericity

Bartlett's Test of Sphericity		KMO
Chi-square	4330.646	0.624

Degree of Freedom	741
Significance	0.000

In this study, we use PCA to extract the factors. Linear combinations of the observed variables are formed in this method. In this step, it is important to determine the number of factors needed to represent the data. We use Kaiser's criteria that determines the number of factors by considering only factors with eigenvalues greater than 1. In Table 2, the eigenvalues of the ratios are presented with percentages that indicate explanation of the total and cumulative variances. The estimated ten-factor model explains 83.27% of the total variation of financial conditions of the banks under concern.

Tablo 2. Eigenvalues of the financial ratios

Factor	Eigenvalue	Total Variance (%)	Cumulative Variance (%)
1	11,566	29,656	29,656
2	5,142	13,186	42,842
3	3,124	8,01	50,852
4	2,842	7,286	58,138
5	2,343	6,007	64,144
6	1,963	5,03	69,175
7	1,633	4,186	73,361
8	1,455	3,73	77,091
9	1,284	3,291	80,382
10	1,126	2,888	83,27

After reduction of the factors, they are rotated to make them more meaningful and easier to interpret. The purpose of rotation is to reduce the number factors on which the variables under investigation have high loadings. Different rotation methods are used in the literature. The most commonly used rotation method is Varimax that use orthogonal rotations yielding uncorrelated factors/components and attempts to minimize the number of variables that have high loadings on a factor. In this study, Varimax rotation method is used to enhance the interpretability of the financial factors. The factor loadings and rotated factor loadings are presented in Table 3.

Table 3. Rotated factor loadings

	Rotated factor loadings						
Variables	**1**	**3**	**4**	**5**	**6**	**8**	**10**
1	0,947						
2			0,525				
3	0,94						
4	0,727						
5					-0,522		0,502
9		-0,763					
10				0,814			
11		0,853					
12		0,72					
13		0,719					0,894
14	0,904						
15						0,532	
16	0,773						
17	0,897						
18	-0,736						
19	-0,933						

20	0,916						

An increase in the variables (ratios) that have positive loadings leads to increase in the score of the related factor. Conversely, an increase in the variables that have negative loadings leads to decrease in the score of the related factor. Selected factors represent the feature groups of the variables that have loadings for the same factors. For example, the tenth factor is explained by the sixth and the thirteenth variables, which are in the feature groups of “assets quality” and “profitability”, hence the factor represents “assets quality and profitability”. Table 4 presents the feature groups represented by ten factors that are obtained in the same manner.

Table 4. The feature groups represented by ten factors

Factor	Feature Group
1	Capital Ratios, Profitability, Income-Expenditure Structure, Activity
2	Share in Sector
3	Liquidity, Profitability, Share in Group, Share in Branch
4	Capital Ratios, Income-Expenditure Structure, Share in Sector, Activity
5	Liquidity, Income-Expenditure Structure
6	Capital Ratios, Share in Branch, Activity
7	Income-Expenditure Structure
8	Profitability, Share in Sector
9	Share in Branch
10	Assets Quality, Profitability

Score of each factor is calculated for each observation. Factor scores are interpreted as reduced variables that are values representing the original variables. Factor scores of each bank are presented in Table 5.

Table 5. Factor scores for each bank

BANKS	F 1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Türkiye Cumhuriyeti Ziraat Bankası	0,00	0,60	0,01	0,00	0,00	- 0,01	0,02	0,01	0,01	0,00
Türkiye Emlak Bankası A.Ş.	-0,02	0,07	-0,01	-0,01	0,01	-0,01	0,00	-0,01	0,00	0,05
Türkiye Halk Bankası A.Ş.	0,02	0,32	0,00	-0,02	0,00	-0,01	0,04	0,01	0,01	-0,01
Türkiye Vakıflar Bankası T.A.O.	0,01	0,17	0,00	0,00	0,01	0,00	-0,01	0,00	0,00	0,00
Adabank A.Ş.	0,04	-0,09	0,03	-0,02	0,03	-0,02	0,00	0,00	-0,01	0,00
Akbank T.A.Ş.	0,05	0,22	0,00	0,01	-0,01	-0,01	-0,01	0,00	0,00	0,00
Alternatif Bank A.Ş.	0,06	-0,01	0,00	0,01	-0,03	0,00	-0,01	0,00	0,00	0,01
Anadolubank A.Ş.	0,05	-0,04	0,00	0,00	-0,02	-0,01	-0,01	0,01	0,00	0,01
Bayındırbank A.Ş.	0,03	-0,06	0,01	-0,01	0,01	-0,01	-0,01	0,00	0,00	0,00
Birleşik Türk Körfez Bankası A.Ş.	0,04	-0,02	0,01	0,00	-0,01	0,01	-0,01	0,01	0,03	0,01
Denizbank A.Ş.	0,05	-0,05	-0,01	0,01	-0,01	-0,01	-0,01	0,00	0,00	0,00

By using factor analysis, 39 financial ratios are reduced to ten factors so as to include all of the variables, which affect the financial performances of the banks. In the following section, these factors are used to classify the banks under consideration as healthy or failed banks.

2.2. Discriminant analysis

Discriminant analysis derives a linear combination of the characteristics which best discriminates the qualitative dependent variable which is bankrupt or non-bankrupt banks in our case. In this classification, the success indicator is related to the transferring of the banks to SDIF. That is, if a bank is transferred to SDIF, it is financially failed or bankrupt.

The assumption of homogeneity of variance is particularly important in the classification stage of discriminant analysis. Homogeneity of variance is tested with Box's M test, which tests the null hypothesis that the group variance-covariance matrices are equal. Results of the Box's M test are presented in Table 6. The results reveal that the variances are heterogeneous. Therefore, we apply quadratic discriminant analysis in this study.

Table 6. Results of the Box's M test

Box's M		449,73
F	Value	6,508
	Degree of Freedom (1)	55
	Degree of Freedom (2)	5108,844
	Significance (P)	0,000

Discriminant function is constructed to transform individual variable values to a single discriminant score which is then used to classify the object. In our application, the discriminant function is obtained as follows.

$$Y_a = 0.908F_{a1} + 0.213F_{a2} + 0.184F_{a3} + 0.441F_{a4} + 0.197F_{a5} + 0.487F_{a6} + 0.149F_{a7} + 0.648F_{a8} + 0.077F_{a9} + 0.650F_{a10} \quad (1)$$

where a denotes the respective bank, the subscripts 1, 2,..., p denote the p variables (factors), Y_a is the discriminant score of bank a, V_{aj} is the weight of factor j of bank a on the discriminant score and F_{aj} is the observed value of factor j of bank a.

To evaluate the significance of the discriminant function, eigenvalue, canonical correlation and *Wilks' Lambda* statistics are used, which takes the value of 1.275, 0.749 and 0.440 in our analyses. It can be concluded here that the discriminating ability of the analysis is high.

In this study, we employ Fisher's classification function as the classification method. The classification functions for financially failed (0) and successful (1) bank groups are presented in the following.

$$S_0 = -2.198 - 1.574F_1 - 0.369F_2 - 0.319F_3 - 0.765F_4 - 0.341F_5 - 0.845F_6 - 0.259F_7 - 1.124F_8 - 0.133F_9 - 1.127F_{10} \quad (2)$$

$$S_1 = -0.948 + 0.648F_1 + 0.152F_2 + 0.131F_3 + 0.315F_4 + 0.14F_5 + 0.348F_6 + 0.106F_7 + 0.463F_8 + 0.055F_9 + 0.464F_{10} \quad (3)$$

The classification score is compared with discriminant score for each bank to estimate the group memberships of the banks. Table 7 partly presents the actual and estimated group memberships, discriminant scores and the probabilities of being failed and successful for each bank. In addition, the classification results are summarized in Table 8.

Table 7. The real and estimated group memberships, discriminant scores and probabilities of being failed and successful for each bank

BANKS	Real Group	Estimated Group	Discriminant Function	Probability of Being Failed	Probability of Being Successful
Türkiye Cumhuriyeti Ziraat Bankası	1	1	0,86857	0,03302	0,96698
Türkiye Emlak Bankası A.Ş.	1	1	1,22615	0,01402	0,98598
Türkiye Halk Bankası A.Ş.	1	1	0,26119	0,1313	0,8687
Türkiye Vakıflar Bankası T.A.O.	1	1	0,36395	0,10515	0,89485
Adabank A.Ş.	1	1	-0,35148	0,40398	0,59602
Akbank T.A.Ş.	1	1	0,84648	0,03479	0,96521
Alternatif Bank A.Ş.	1	1	0,64534	0,0557	0,9443
Anadolubank A.Ş.	1	1	0,33847	0,11117	0,88883

Table 8. Summary of the classification results

		Estimated Membership		
	Group	**0,00**	**1.00**	**Total**
Actual Membership	**0,00**	14	7	21
	1.00	1	50	51
%	**0,00**	66.7	33.3	100.0
	1,00	2.0	98.0	100.0

Table 8 reports that, 64 of the 72 banks under concern are accurately classified with discriminant analysis, which means an 89% success rate in classification. According to the results, seven failed banks are classified as successful while only one successful bank is classified as failed.

2.3. ELECTRE TRI

ELECTRE TRI is a multiple criteria sorting method, i.e., a method that assigns alternatives to predefined categories. In this section, we apply ELECTRE TRI to the bankruptcy prediction problem. We classify the banks under consideration by using the success indicator of them as in our discriminant analysis. The application of the procedure to our problem is explained stepwise in the following.

Step 1. Choose and normalize the data: Since the input values must be in a common scale in ELECTRE TRI, we normalized the factor scores obtained by the factor analysis.

Step 2. Determine the parameters of ELECTRE TRI.: ELECTRE TRI model includes the following parameters.

- Upper limit for each ratio

$$g_j(b_h) = \frac{1}{2}\left(\frac{\sum g_j(a_i)}{\eta_h} + \frac{\sum g_j(a_i)}{\eta_{h+1}} \right) \quad (4)$$

where $g_j(a_i)$ denotes the value of criterion g_j that belongs to alternative a_i. The number of alternatives that are determined or estimated to be in the first category is η_h and the number of alternatives that are not in the first category is η_{h+1}.

- The indifference threshold, $q_j(b_h)$

$$q_j(b_h) = 0.05\, g_j(b_h) \quad (5)$$

where $q_j(b_h)$ specifies the largest difference between $g_j(a)$ and $g_j(b_h)$ that preserves indifference between a and b_h on criterion g_j.

- The preference threshold, $p_j(b_h)$

$$p_j(b_h) = 0.10\, g_j(b_h) \quad (6)$$

where $p_j(b_h)$ represents the smallest difference between $g_j(a)$ and $g_j(b_h)$ compatible with a preference in favor of a on criterion g_j.

Step 3. Compute the partial concordance indices: The concordance index can be computed with the following formula.

$$C_j(a,b_h) = \begin{cases} 0 & \text{if } g_j(a_i) \leq g_j(b_h) - p_j(b_h) \\ 1 & \text{if } g_j(a_i) > g_j(b_h) - q_j(b_h) \\ \text{otherwise}, & \left(g_j(a_i) - g_j(b_h) + p_j(b_h) \right) / \left(p_j(b_h) - q_j(b_h) \right) \end{cases} \quad (7)$$

Step 4. Compute the discordance indices: The discordance indices can be computed with the following formula.

$$d_j(a,b_h) = \begin{cases} 0 & \text{if } g_j(a_i) \leq g_j(b_h) + p_j(b_h) \\ 1 & \text{if } g_j(a_i) < g_j(b_h) + q_j(b_h) \\ \text{otherwise}, & \left(g_j(b_h) - g_j(a_i) + p_j(b_h) \right) / \left(p_j(b_h) - q_j(b_h) \right) \end{cases} \quad (8)$$

Step 5. Compute the weighted scores: The weighted concordance and discordance scores for each bank are calculated as in the following.

$$\text{The weighted concordance score} = \sum_{j=1}^{m} w_j c_j(a_i, b_h) \quad (9)$$

$$\text{The weighted discordance score} = \sum_{j=1}^{m} w_j d_j(a_i, b_h) \quad (10)$$

where w_j is the weight of factor j that is determined by decision maker. In this study, the weights are taken as equal ($w_j = 1/10=0.1$).

The first formulation gives the success scores of the banks while the second one gives the failure scores of the banks considering the ten factors. Table 9 partly presents the weighted concordance and discordance scores for each bank.

Step 6. Classification: The banks are classified as failed or non-failing using a cut off level λ. The value of λ is taken as 0.5 as the common approach in the literature. If $\sum_{j=1}^{m} w_j c_j(a_i, b_h) \geq \lambda$ and $\sum_{j=1}^{m} w_j d_j(a_i, b_h) \leq \lambda$ then the bank is classified as non-failing. The classification results are also partly presented in Table 9.

Table 9. The weighted concordance and discordance scores for each bank

BANKS	Weigted Concordance	Weighted Discordance	Real Group	Estimated Group
Türkiye Cumhuriyeti Ziraat Bankası	0,5	0,5	1	0
Türkiye Emlak Bankası A.Ş.	0,4	0,6	1	0
Türkiye Halk Bankası A.Ş.	0,5	0,5	1	0
Türkiye Vakıflar Bankası T.A.O.	0,6	0,4	1	1
Adabank A.Ş.	0,4	0,6	1	0
Akbank T.A.Ş.	0,7	0,3	1	1
Alternatif Bank A.Ş.	0,5	0,5	1	0
Anadolubank A.Ş.	0,4	0,6	1	0

The results reveal that 44 of the 72 banks under consideration are accurately classified with ELECTRE TRI, which means a 61.11% success rate in classification of the banks. In addition, 20 of the 21 bankrupt banks under consideration are accurately classified by this method, which implies a 95.2% success rate in classification of the failed banks. Furthermore, the method accurately classified the non-failing banks with a percentage of

47.06%. As conclusion, ELECTRE TRI is much more successful in classifying the failed banks in our application.

3. Conclusions

This study proposes a systematic approach to bankruptcy prediction in banks. To confirm the practicability of the proposed approach, a case study from Turkish banking sector is presented. In the application, performances of 72 commercial banks are assessed by using 39 financial ratios for the period of 1997 to 2003. The sample set consists of 51 non-bankrupt and 21 bankrupt banks. The approach proposed in this study uses a wide range of financial ratios under nine categories and provides a decision tool that integrates multivariate statistical methods, and MCDM for better-quality prediction of bankruptcy in banking sector. The results of the case study reveal the practicability of the proposed approach. Table 10 presents summary of classification results obtained by the methods employed.

Table 10. Summary of the classification results obtained by the methods

Method	Total Percentage	Percentage of classifying failed banks	Percentage of misclassifying failed banks (Type I error)	Percentage of classifying non-failed banks	Percentage of misclassifying non-failed banks (Type II error)
Discriminant Analysis	89%	67%	33%	98%	2%
ELECTRE TRI	61.11%	95.24%	4.76%	47.06%	52.94%

Table 10 reports that, discriminant analysis classified the non-failed banks more accurately than ELECTRE TRI while it has the worst performance in classifying the failed banks. The results also reveal that discriminant analysis performs better than ELECTRE TRI in terms of total classification. Table 10 also depicts type I and type II errors which means respectively an actually failed bank is classified as non-failed and an actually non-failed bank is classified as failed. In bank failure prediction problems, type I error is more critical than type II error as accurate prediction of failed banks can reduce the prospective cost of bank failures, protect savings, deposits and participation funds of depositors, and contribute confidence and stability of the banking system. The results reveal that type I error is relatively higher in discriminant analysis.

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