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PERFORMANCE EVALUATION AND DISTRESS PREDICTION FOR EFFECTIVE RISK MANAGEMENT IN FINANCE SECTOR: AN INTEGRATED DECISION MAKING PROCEDURE

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ABSTRACT

Considering its important role in the socio-economic status of the developing countries, finance sector, which is one of the core components of the service sector, is the focus of this study. The main drivers of this study are, to explore the most significant factors influencing the performance of the financial institutions in a risky environment, to evaluate the economic and financial performances using the selected factors and predict the future distress/bankruptcy possibility of the institutions by a comparative analysis employing a quantitative three-step decision making procedure. To explore the viability of the proposed approach, an up-to-date and comprehensive application on commercial banks operating in Turkish Banking sector is presented by using a wide range of financial ratios. To this aim, 44 commercial banks operating in Turkish financial sector are assessed as healthy and non-healthy by using 57 selected fundamental financial ratios to provide a comprehensive insight to the bank managers, investors, government units and rating agencies to predict the financial performances of banks and make related decisions when a risky socio-economic environment is a matter of a country.

Keywords: *Financial Risk Management; Distress Prediction; Commercial Banks; Multivariate Statistics; DEA.*

JEL Codes: *G31, G21, C44, C38*

FİNANS SEKTÖRÜNDE ETKİLİ RİSK YÖNETİMİ İÇİN PERFORMANS DEĞERLENDİRME VE BAŞARISIZLIK TAHMİNİ: BÜTÜNLEŞİK BİR KARAR VERME PROSEDÜRÜ

ÖZ

Gelişmekte olan ülkelerin sosyo-ekonomik statüsünde önemli bir yere sahip olan ve hizmet sektörünün temel bileşenlerinden biri olan finans sektörü bu çalışmanın temel konusunu oluşturmaktadır. Bu çalışmanın temel amaçları; riskli ortamlarda finansal kurumların performansını etkileyecek en önemli faktörlerin belirlenmesi, bu faktörler kullanılarak ekonomik ve finansal performansın değerlendirilmesi ve kurumların gelecekteki başarı/başarısızlık durumlarının üç aşamalı analitik ve karşılaştırmalı bir karar verme yaklaşımı kullanılarak tahmin edilmesidir. Sunulan yaklaşımın uygulanabilirliği Türk bankacılık sektöründe faaliyet gösteren ticari bankaların konu alındığı kapsamlı bir uygulama üzerinde çok sayıda finansal rasyo kullanılarak gösterilecektir. Bu amaçla, Türk finans sektöründe faaliyet gösteren 44 ticari banka 57 temel finansal rasyo kullanılarak sınıflandırılacaktır. Sunulan yaklaşımın banka yöneticilerine, yatırımcılara, hükümet birimlerine ve

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derecelendirme kuruluşlarına bankaların finansal performanslarının tahminlenmesi ve riskli sosyo-ekonomik ortamlarda karar verilmesi için kapsamlı bir bakış açısı sunması hedeflenmektedir.

Anahtar Kelimeler: *Finansal Risk Yönetimi; Başarısızlık Tahmini; Ticari Bankalar; Çok Değişkenli Istatistik; VZA.*

JEL Kodları: *G31, G21, C44, C38*

1. INTRODUCTION

Globalization of the world economy induces increased competition in the service sector, which plays a central role in economic and social development of countries. To gain a competitive advantage, it is important to analyze and evaluate the operational and financial risks and perceive the current financial situation of the service institutions. As financial performance of companies/institutions has a significant impact on the economic stability in especially developing countries (emerging markets), it is crucial to be able to foresee the financial risks, evaluate the performance of the components of the service sector and assess them as healthy and non-healthy to prevent or lessen the adverse consequences on the economic system.

Financial institutions which bridge the needs of lenders (savers) and those of borrowers, provide the flow of resources from one party to the other. Among financial institutions, commercial banks are at the very core of a financial system, having the largest share of intermediation (Mercan et al., 2003). Evaluation of financial performances of banks plays an important role in making managerial and organizational decisions related to strategic planning process in banking sector which represents a major part of the financial sector in Turkey. The performance of the banking sector has improved especially in the last years in terms of main performance criteria such as growth, capital adequacy, asset quality, liquidity, and profitability. According to the Banks Association of Turkey, June 2014 Report, over the last five years, total assets has risen by 62 percent in fixed prices, and the ratio of total assets to gross domestic product has risen by 31 points to 105 percent. The number of banks operating in Turkey was 49, including four participation banks in 2013. The number of deposit banks, development, and investment banks was 45. Table 1 reports the number of banks operated in Turkish banking sector from 2007 to 2013.

In consequence of a stand-by arrangement between Turkey and the International Monetary Fund at the year 2000, Turkey implemented an exchange-rate based stabilization program to combat its high inflation. However, two financial crises followed: one in November, 2000 and the other in February, 2001. As the result some banks became problematic and vulnerable, which necessitated restructuring of the banking sector to increase its financial efficiency (Mercan et al., 2003).

Table 1: Number of Banks Operated in Turkish Banking Sector From 2007 to 2013

Types of the banks	2007	2008	2009	2010	2011	2012	2013
Commercial banks	15	14	14	14	14	14	15
State-owned	3	3	3	3	3	3	3
Private	12	11	11	11	11	11	12
Foreign banks	17	18	17	17	16	16	16
Founded in Turkey	10	11	11	11	10	10	10
Opened branches in Turkey	7	7	6	6	6	6	6
Development and investment banks	13	13	13	13	13	13	13
State-owned	3	3	3	3	3	3	3
Private	6	6	6	6	6	6	6
Foreign	4	4	4	4	4	4	4
Banks that are transferred to The Savings Deposit Insurance Fund (SDIF)	1	1	1	1	1	1	1
Total	46	46	45	45	44	44	45
Total number of branches	7388	8304	9093	9340	9617	9922	10,470

The Euro fund's European Restructuring Monitoring reports the number of bankruptcies peaked in many countries in 2008 and 2009 as the global recession spread. For example, in Denmark, commercial firms filed 85% more bankruptcies in 2008 and in Belgium 239% more firms filed for bankruptcy in 2009 (Evans and Borders, 2014). Capital inflow to developing countries slowed down, capital outflow was observed in some countries, cost of borrowing from international markets increased, and global capital became more sensitive towards macroeconomic imbalances. In several developing countries, national currencies depreciated, interest rates increased, and asset prices dropped rapidly. Most of the developing countries implemented rebalancing policies to minimize the negative effects of global risks at the expense of slowing down the growth rate. 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. Hence, it is vital to evaluate the performances of banks in an economic system in order to avoid severe socio-economic consequences.

According to Demirguc-Kunt and Detragiache (1998) vulnerability to crises in the banking sector appears to be associated with the following factors:

1. A weak macroeconomic environment characterized by slow gross domestic product growth and high inflation,

2. Vulnerability to sudden capital outflows,

3. Low liquidity in the banking sector,

4. High share of credit to the private sector,

5. Past credit growth,

6. Existence of explicit deposit insurance,

7. Weak institutions.

For effective risk management in financial sector, the financial performance of a bank should be measured and evaluated based on the foregoing factors, which can be quantitatively estimated depending on different financial ratios. The review of the literature reveals that there is a need to propose and use an integrated approach to systematically select the most important financial indicators, assess the performances of the institutions in the finance sector according to these indicators, and evaluate and compare the institutions in terms of their financial success and distress/bankruptcy possibility. Considering this gap in the literature, this study proposes a three-step approach to predict and evaluate the financial performances of commercial banks by integrating statistical and operations research techniques. More specifically, a multivariate statistical method, a clustering approach and multi-factor productivity analysis approach are employed in a combined manner for financial performance evaluation. The proposed approach respectively employs factor analysis, k-means clustering and data envelopment analysis (DEA) for the following specific purposes;

- Exploring the main financial performance indicators that have a significant effect on the financial performances of the institutions in the banking sector and that can be reliably utilized to evaluate the success of the institutions in risky environments,
- Evaluating the financial performances and future distress/bankruptcy possibility of the financial institutions based on the factors explored,
- Comparing the financial situations of the banks and specifying the most reliable, safe and secure ones for the investors assessing them as healthy and non-healthy ones to enhance

decision making in risky conditions.

A computational experiment from Turkish banking sector is presented in this study to confirm the practicability of the proposed approach. In this regard, performances of 44 commercial banks operating in Turkish banking sector are assessed by using 57 selected fundamental financial ratios using 2011 data. Using the data of the year 2011 enables to observe the effects of global economic recession realized in 2008 and 2009 on the Turkish banking sector. To the best of our knowledge, this study is the first attempt to assess the commercial banks according to their financial performances using the above mentioned techniques.

The rest of the paper is organized as follows. Section 2 presents an overview of the literature on financial performance evaluation and distress prediction in the banking sector classifying the studies in four categories; the review studies, studies using artificial intelligence or multivariate statistical methods, studies using multi-factor productivity analysis and studies on Turkish banking sector. Section 3 covers the proposed three-step decision making procedure with its application to a real world problem in Turkey finance sector. Finally, Section 4 presents the concluding remarks.

2. RELATED LITERATURE

This section presents an overview of the literature on financial performance evaluation in corporations, especially in banks. The related studies are classified into four categories in this paper namely; the review studies, studies using artificial intelligence or multivariate statistical methods, studies using multi-factor productivity analysis and studies on Turkish banking sector.

2.1. The Review Studies

Amongst the related studies, Fethi & Pasiouras (2010) presented a literature survey of 196 studies published between 1996 and 2009 that apply operational research and artificial intelligence techniques to assess bank efficiency and performance. They handled the use of DEA in predicting bank efficiency in detail and then mentioned briefly the studies using other operational research and artificial intelligence techniques such as neural networks and MCDM methods. Kumar & Ravi (2007) presented a comprehensive review of the studies published between 1968 and 2005 that solve the bankruptcy prediction problem with statistical and intelligent techniques. Sun et al. (2014) made a full summary, analysis and evaluation on the literature of financial distress prediction (FDP). The literature is reviewed from four aspects namely; definition of financial distress in the new century, FDP modeling, sampling approaches for FDP and featuring approaches for FDP. The authors classified FDP modeling into the following groups: modeling with pure single classifier, modeling with hybrid single classifier, modeling by ensemble techniques, dynamic FDP modeling, and modeling with group decision-making techniques. Lin et al. (2011) explored the 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 the financial distressed firms. The authors applied support vector machines based on the selected ratios and determined five ratios that yields the best estimation performance, two from Taiwan Economic Journal feature set and three from the literature feature set. Paradi & Zhu (2013) surveyed 80 published DEA applications in 24 countries/areas that focus on bank branches. Key issues related to the design of DEA models are presented in the paper and a discussion on how to design future experiments and studies in this domain is included.

2.2. Studies Using Artificial Intelligence or Multivariate Statistical Methods

2.2.1. Artificial Intelligence Based Studies

Alam et al. (2000) used fuzzy clustering and two self-organizing neural networks as classification tools for identifying potentially failing banks and presented experimental results. They compared the results of the closest hard partitioning of fuzzy clustering and of two self-organizing neural networks. Tam (1991) presented a neural network approach to bank failure prediction and compared its performance with current models. Ravisankar & 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. Iturriaga & Sanz (2015) developed a neural network model to study the bankruptcy of U.S. banks. The model detects failures and assesses bank risk in the short, medium and long term using bankruptcies that occurred from May 2012 to December 2013 in U.S. banks. Ravi et al. (2008) presented a soft computing based bank performance prediction system, which is an ensemble whose components are a multi-layered feed forward neural network trained with backpropagation, a probabilistic neural network, a radial basis function neural network, support vector machine, classification and regression trees and a fuzzy rule based classifier.

2.2.2. Discriminant Analysis and Logit Model Based Studies

Cox & 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. Kolari et al. (2002) assessed the failure risk among US commercial banks by using computer-based early warning systems. They used parametric and nonparametric approaches namely, logit analysis and trait recognition to construct prediction models based on 28 financial ratios. Lanine & Vennet (2006) employed a logit model and a trait recognition approach to predict failures among Russian commercial banks. Karaca and Çiğdem (2013) evaluated the effects of economic crises occurred in Turkey in 1994 and 2001 and encountered globally in 2008 on Turkish Manufacture Industry by Factor and Discrimination Analysis using financial ratios. Looney et al. (1989) focused on misclassifications: the individual banks that were predicted by a model to fail and yet have not, and those predicted to survive and yet have failed. They employed linear and quadratic multiple discriminant analysis models and Cox proportional hazards models. The performances of these models are tested by the authors in terms of misclassification. Grice and Ingram (2001) evaluated the generalizability of Altman's (1968) Z-score model using a proportionate sample of distressed and non-distressed companies from time periods, industries, and financial conditions other than those used by Altman to developed his model.

2.3. Studies Using Multi-Factor Productivity Analysis

Baidya & Mitra (2012) evaluated the technical efficiency of 26 Indian public sector banks for the years 2009-2010 and provided the efficiency ranking of these banks using two popular DEA models: CCR and Andersen and Petersen's super-efficiency model. Xu & Wang (2009) proposed a failure prediction approach that use business operation efficiency as predictor of the financial failure of the corporations. In their approach, efficiency of the corporations are obtained through DEA and used as predictors in prediction methods such as multiple discriminant analysis, logistic regression and support vector machines along with some selected financial ratios. Abu-Alkheil et al. (2013) employed DEA to examine the relative efficiency of Islamic and conventional banks in the UK and Switzerland during 2008-2009, accounting ratio analysis to measure the financial performance of the European Islamic Investment Bank (EIIB) during 2005-2008, and a matched-pairs t-test to determine the differences in the EIIB performance in the pre-versus post financial crisis periods, respectively. Chen (2005) employed both deterministic and chance-constrained DEA approaches to measure the technical efficiency in Taiwan's banks during the period of the Asian financial crisis. A regression model was also used in the study to highlight the rationales for the causes of bank efficiency. Huang et al. (2015) proposed a two-level DEA model as a quick and feasible tool for corporate financial failure prediction, which is able to handle quite a large number of inputs and outputs by utilizing hierarchical structures of financial indicators. Betz et al. (2014) developed an early-warning model for predicting vulnerabilities leading to distress in European banks using both bank and country-level data. Rebai et al. (2012) presented their view of "sustainable bank" and developed a framework based on multi-attribute utility approach aiming to assess the performance of a bank from different stakeholders points of views in order to appraise the degree of sustainability of the bank. The framework was applied to five French banks. Liu and Tone (2008) proposed a threestage methodology to measure DEA efficiency while controlling for the impacts of both statistical noise and environmental factors. They used panel data on Japanese banking over the period 1997–2001 to demonstrate that the proposed approach greatly mitigates these weaknesses of DEA models.

2.4. Studies on Turkish Banking Sector

Boyacioglu et al. (2009) applied various neural network techniques, support vector machines and multivariate statistical analysis to predict the bank financial failures in Turkish banking sector and presented a computational comparison of the methods. They used 20 financial ratios with six feature groups in their analyses. Öğüt et al. (2012) used two multivariate statistical techniques, multiple discriminant analysis and ordered logistic regression, and two data mining techniques, Support Vector Machines and Artificial Neural Network, to estimate the financial strength of Turkish banks using 26 financial ratios. They compared the estimation performance of these methods in their study. Celik & 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. They presented an application on Turkish banking sector. Alper and Anbar (2011) examined the bank-specific and macroeconomic determinants of the banks' profitability in Turkey over the time period from 2002 to 2010. The bank profitability is measured by return on assets and return on equity as a function of bank-specific and macroeconomic determinants. 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 that can significantly explain the changes in financial conditions in banks. Then, they used discriminant, logit and probit models to provide information about the future prospects of the banks. Bayyurt (2013) compared the performance of foreign and Turkish banks by using multi criteria decision making methodologies, namely TOPSIS, ELECTRE III and DEA. Yayar and Baykara (2012) used TOPSIS method to measure the efficiency and productivity of fast growing and developing participation banks' activities in Turkey between the years of 2005-2011.

The literature review reveals that, there is a need to propose a combined framework to simultaneously select the crucial financial factors, assess the performances of the companies/institutions in the finance sector, and evaluate/compare the institutions in terms of their financial success and distress/bankruptcy possibility. This study contributes to the related body of literature proposing a three-step approach to predict and evaluate the financial performances of commercial banks by integrating a multivariate statistical method, a clustering approach and multi-factor productivity analysis first time in the literature. It differs from the previous studies in that it integrates factor analysis, k-means clustering and DEA. In addition, this study is one of the studies in the literature that use such a wide range of financial ratios in performance evaluation of the banks. Furthermore it presents an up-to-date and comprehensive application on performance evaluation of commercial banks operating in Turkish Banking sector using the above mentioned methods for the first time in the literature. The following section presents the proposed approach with a real world application.

3. THE RESEARCH METHODOLOGY

This section covers, the proposed three-step quantitative decision making methodology with its application in Turkish banking sector. In the application, performances of 44 commercial banks are assessed by using 57 financial ratios using the data of the year 2011. The financial ratios considered in this study are grouped into nine categories namely, capital ratios, assets quality, liquidity, profitability, income-expenditure structure, activity ratios, share in sector, share in group and branch ratios. Table in Appendix 1 presents the financial ratios with corresponding means and standard deviations for the banks handled in the application. The methods employed by the proposed three-step decision making approach and their application to the case problem are presented in the following subsections.

3.1 Factor Analysis

Factor analysis, which is a statistical data reduction method, is the first step of the proposed approach. It is used to remove redundancy or duplication from the set of correlated variables and examine whether a number of variables of interest are linearly related to a smaller number of unobservable factors. Factor scores corresponding to each bank that are obtained by factor analysis will be used in further steps of the proposed approach. Reliability is the fact that a scale should consistently reflect the construct it is measuring. A reliability test is applied to 57 financial ratios before performing factor analysis. In this regard, "Cronbach's alpha coefficient", which is a measure of internal consistency or reliability, is used. Cronbach's alpha measures how closely related a set of items are as a group. It is commonly used as an estimate of the reliability of a test for a sample of data. Table 2 reports the commonly accepted rule for describing internal consistency using Cronbach's alpha.

Table 2: The Rule for Describing Internal Consistency Using Cronbach's Alpha

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent (High-Stakes testing)
$0.7 \leq \alpha < 0.9$	Good (Low-Stakes testing)
$0.6 \leq \alpha < 0.7$	Acceptable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

The reliability analysis, which is conducted for the data set consisting of 57 financial ratios, expose that Cronbach's alpha takes the value of 0.614. "Item-total correlation test" is performed to check if any item in the set is inconsistent with the averaged behavior of the others, and thus can be discarded. The analysis is performed to purify the measure by eliminating 'garbage' items prior to determining the factors that represent the construct; that is, the meaning of the averaged measure. Results of the item-total test are presented in Appendix 2. Variables with the "Corrected Item-Total Correlation" values bigger than or equal to 0.4 to pass the reliability test. Variables which are depicted in bold in Appendix 2 are the ones that pass the reliability test. Results of the reliability analysis performed for the data set consisting of the selected 15 financial ratios reveal that the Cronbach's alpha takes the value of 0.798. The results of "Corrected Item-Total Correlation" which is performed with 15 variables are presented in Table 3.

Table 3 reports that "Corrected Item-Total Correlation" values corresponding to all variables are bigger than 0.4. As a result, among 57 variables, 15 variables are selected to be considered in the factor analysis. Table 4 presents the selected financial ratios with corresponding means and standard deviations for the banks handled in our application.

Table 3. Results of The Corrected Item-Total Correlation Test With 15 Variables

Variable	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
1	962.45	268266.15	0.71	0.98	0.79
2	970.00	274395.97	0.69	0.99	0.79
3	972.69	273637.24	0.73	0.99	0.79
4	962.82	263996.02	0.62	1.00	0.78
16	946.42	265040.42	0.79	0.99	0.78
17	905.61	234316.11	0.54	0.99	0.77
19	932.43	248080.57	0.86	1.00	0.77
31	735.88	174987.10	0.58	0.94	0.79
33	848.09	266134.35	0.48	0.98	0.79
44	836.20	178200.78	0.59	0.99	0.79
45	907.78	243689.33	0.53	0.98	0.77
47	947.86	245525.65	0.60	0.97	0.77
50	983.09	280084.22	0.50	0.99	0.80
52	895.31	236786.27	0.71	0.99	0.76
56	979.22	280768.18	0.54	0.95	0.80

Table 4. Selected Financial Ratios with Corresponding Means and Standard Deviations

Variable No	Group	Variable	Mean	Standard Deviation
1	Capital Ratios	Shareholders' Equity / (Capital to be employed to credit + market + operational risk)	33.6	29.1
2		Shareholders' Equity / Total Assets	25.0	23.8
3		(Shareholders' Equity - Permanent Assets) / Total Assets	21.0	22.9
4		Shareholders' Equity / (Deposits +Non-deposit Funds)	540.4	2758.8
16	Liquidity	Liquid Assets / Total Assets	43.4	27.0
17		Liquid Assets / Short-term Liabilities	217.1	554.1
19		Liquidity Assets / (Deposits + Non-deposit Funds)	546.8	2677.5
31	Income-Expenditure Structure	Interest Income / Interest Expenses	54093.2	288481.5
33		Total Income / Total Expenses	154.9	57.3
44	Branch	Total Assets / No. of Branches	613.2	1002.7
45		Total Deposits / No. of Branches	160.6	318.7
47		FX Deposits / No. of Branches	117.4	316.3
50		Net Profit / No. of Branches	10.2	21.0
52	Activity	(Salary and Employee Benefit + Reserve for Retirement) / No. of Personnel (Billion TL)	115.9	91.4
56		Total Operating Expenses / Total Assets	6.1	4.0

Factor analysis is categorized in two main classes: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). In EFA, the researcher has no expectations of the number or nature of the variables while CFA is employed to test a proposed theory or model. In contrast to EFA, CFA has assumptions and expectations based on priori theory regarding the number of factors, and which factor theories or models best fit. We use EFA in this study with the following steps;

Step 1. Generation of the correlation matrix: Correlation matrix displaying the relationships between individual variables should be used in the EFA process. This matrix is generated for all variables. Various tests are used to assess the suitability of the respondent data for factor analysis. 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 presented in Table 5 reveal that the sample is adequate for factor analysis.

Table 5: KMO Measure and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.551
	Chi-Square	275.7
Bartlett's Test of Sphericity	Degree of Freedom	105
	Significance	0

Step 2. Factor extraction: The aim of this stage is to determine the factors. There exists numerous ways to extract factors such as principal components analysis (PCA), principal axis factoring, image factoring, maximum likelihood, alpha factoring, unweighted least squares and generalized least squares. 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. Various methods can be used in this regard such as Kaiser's criterion (eigenvalue > 1 rule), the Scree test, the cumulative percent of variance extracted and parallel analysis. In this study, we use Kaiser's criterion that determines the number of factors by considering only factors with eigenvalues greater than 1. In Table 6, eigenvalues of the financial ratios are presented with percentages indicating the explanation level of the total and cumulative variances.

Table 6 demonstrates that the first factor (Shareholders' Equity / Capital to be employed to credit + market + operational risk) explaining 23.6% of the total variance is the most important dimension in explaining the changes in financial conditions of the banks under concern. The second and third factors both explain 15.9% of the total variance while the explanation levels by the factors other than the first five ones are less than 1%.

Considering the Kaiser's criterion, we determine the number of factors as five in this study. The estimated five-factor model explains 78.6% of the total variation of financial conditions of the banks under concern.

Table 6: Eigenvalues of the Financial Ratios

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Variable	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.74	31.6	31.6	4.74	31.6	31.6	3.544	23.6	23.6
2	2.56	17.0	48.7	2.56	17.0	48.7	2.395	15.9	39.5
3	1.92	12.8	61.5	1.92	12.8	61.5	2.395	15.9	55.5
4	1.59	10.6	72.1	1.59	10.6	72.1	2.292	15.2	70.8
5	0.978	6.52	78.6	0.978	6.52	78.6	1.179	7.8	78.6
6	0.869	5.79	84.4						
7	0.795	5.29	89.7						
8	0.477	3.18	92.9						
9	0.383	2.55	95.5						
10	0.299	1.99	97.5						
11	0.165	1.09	98.6						
12	0.087	0.579	99.1						
13	0.056	0.376	99.5						
14	0.038	0.253	99.8						
15	0.027	0.182	100						

Step 3. Factor rotation: After factor extraction, the factors are rotated to make them more meaningful and easier to interpret. To rotate the factors, the factor loading matrix should be formed. Factor loadings are the coefficients of correlations that show the relationship between each variable and each factor. It is desired that each variable is associated with a minimal number of factors. 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. One of the other common rotational methods is Oblique rotations which yield correlated factors. In this study, Varimax rotation method is used to enhance the interpretability of the financial factors. The factor loadings and rotated factor loadings are partly presented in Tables 7 and 8, respectively.

Table 7: Factor Loadings

Variable	Factor				
	1	2	3	4	5
3	0.847			0.306	
2	0.841	-0.315			
1	0.821				
17	0.744			-0.365	
4	0.737	-0.510			
19	0.657		0.414		
45		0.600			
44	0.357	0.594			
52		0.564	0.418	0.472	

Table 8: Rotated Factor Loadings

Variable	Component				
	1	2	3	4	5
19	0.868				
1	0.864				
4	0.796	0.374			
17	0.767				0.345
56		0.886			
3	0.463	0.828			
2	0.551	0.776			

52		0.880
16	0.468	0.709
44		0.685

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 first factor is explained by the first, fourth, seventeenth and the nineteenth variables, which are in the feature groups of "liquidity" and "capital ratios", hence the factor represents "liquidity and capital ratios". Table 9 presents the feature groups represented by the five factors.

Table 9: The Feature Groups Represented by Five Factors

Factor	Feature Group
1	Liquidity, Capital Ratios
2	Capital Ratios
3	Activity, Liquidity
4	Income-Expenditure Structure, Branch
5	Branch

Step 4. Calculation of the factor scores: In this step, score of each factor is calculated for each observation. Factor scores of each bank are presented in Appendix 3. By using factor analysis, 57 financial ratios are reduced to five factors that can be used for evaluating the financial performances of the banks under concern. In the following section, these factors are used to classify the banks as healthy or unhealthy.

3.2. K-means Clustering

Clustering is the process of partitioning a group of data points into a small number of clusters. The K-means clustering procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early grouping is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop, we may notice that the k centroids change their location step by step until no more changes are done. In other words, centroids do not move any more.

Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function is presented in the following.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{1}$$

where $\left\| x_i^{(j)} - c_j \right\|$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, J is an indicator of the distance of the n data points from their respective cluster centers.

The algorithm is composed of the following steps:

1. Place k points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the k centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

In our application, the banks to be classified according to their financial performances are clustered using k-means algorithm using the financial ratios obtained in the factor analysis. The number of clusters is selected as four in the application. Tables 10-14 present the results obtained by the k-means clustering algorithm. Table 10 reports the initial cluster centroid locations.

Table 10: Initial Cluster Centroid Locations

	Cluster			
	1	2	3	4
Factor score 1	0.44546	0.36520	-0.94900	5.16479

Factor score 2	-0.74110	-0.48613	4.60223	0.41621
Factor score 3	0.08788	-0.80277	1.28514	-0.69377
Factor score 4	-0.15771	4.60433	-0.69399	-1.09354
Factor score 5	5.75943	-0.48721	0.32342	-0.48221

The locations given in Table 10 are optimized by an iteration process. The changes in cluster centers with the iterations and the optimized cluster centroid locations obtained by the process are presented in Tables 11 and 12, respectively.

Table 11: Iteration of Centroid Locations

Iteration	Change in Cluster Centers			
	1	2	3	4
1	2.351	4.514	3.971	2.868
2	0	0.160	0.419	1.120
3	0	0.082	0.217	0
4	0	0	0	0

Table 12: Optimum Cluster Centroid Locations

	Cluster			
	1	2	3	4
Factor score 1	-0.06498	-0.28575	0.13577	3.46161
Factor score 2	-0.63471	-0.37475	1.10312	0.00139
Factor score 3	0.83977	-0.33237	0.82473	-0.55649
Factor score 4	0.22343	-0.00806	0.22229	-1.32908
Factor score 5	3.62705	-0.19472	-0.10302	-0.23704

To assign each object to the cluster that has the closest centroid, distances between clusters should be determined. Table 13 reports the distances between cluster centroids. Table 14 presents the assignments of each bank to the clusters by k-means algorithm.

Table 13: Distances Between Cluster centroids

Cluster	1	2	3	4

1	-	4.019	4.120	5.669
2	4.019	-	1.940	3.998
3	4.120	1.940	-	4.075
4	5.669	3.998	4.075	-

Table 14: Assignments of Each Bank to the Clusters by K-Means Algorithm

Banks	Distance	Banks	Distance
Cluster 1		Cluster 2 (cont.)	
Arap Türk Bankası A.Ş.	2.351	Turkland Bank A.Ş.	0.649
Bank Mellat	2.351	JPMorgan Chase Bank N.A.	2.231
Cluster 2		Société Générale (SA)	0.833
Türkiye Cumhuriyeti Ziraat Bankası A.Ş.	0.471	Türk Eximbank	4.692
Türkiye Halk Bankası A.Ş.	0.509	Türkiye Kalkınma Bankası A.Ş.	0.779
Türkiye Vakıflar Bankası T.A.O.	0.437	Aktif Yatırım Bankası A.Ş.	0.977
Akbank T.A.Ş.	0.361	İMKB Takas ve Saklama Bankası A.Ş.	2.161
Alternatif Bank A.Ş.	0.571	Türkiye Sınai Kalkınma Bankası A.Ş.	2.142
Anadolubank A.Ş.	0.625	BankPozitif Kredi ve Kalkınma Bankası A.Ş.	0.857
Şekerbank T.A.Ş.	0.668	Cluster 3	
Tekstil Bankası A.Ş.	0.598	Birleşik Fon Bankası A.Ş.	2.025
Turkish Bank A.Ş.	0.902	Deutsche Bank A.Ş.	2.009
Türk Ekonomi Bankası A.Ş.	0.615	Habib Bank Limited	1.776
Türkiye Garanti Bankası A.Ş.	0.411	The Royal Bank of Scotland N.V.	1.739
Türkiye İş Bankası A.Ş.	0.422	WestLB AG	2.542
Yapı ve Kredi Bankası A.Ş.	0.487	İller Bankası A.Ş.	1.542
Citibank A.Ş.	0.952	Diler Yatırım Bankası A.Ş.	2.361
Denizbank A.Ş.	0.526	GSD Yatırım Bankası A.Ş.	1.455
Eurobank Tekfen A.Ş.	0.689	Nurol Yatırım Bankası A.Ş.	1.589
Fibabanka A.Ş.	0.558	Credit Agricole Yatırım Bankası Türk A.Ş.	3.828
Finans Bank A.Ş.	0.52	Merrill Lynch Yatırım Bank A.Ş.	3.671

HSBC Bank A.Ş.	0.509	Cluster 4	
ING Bank A.Ş.	0.656	Taib Yatırım Bank A.Ş.	1.791
		Adabank A.Ş.	1.791

The banks in cluster 1 are foreign banks that have branches in Turkey which generally aim to facilitate the foreign exchange. Cluster 2 includes the commercial and development banks. The banks in this cluster are financial corporations that provide financing for institutional and nationwide economic development. The banks in cluster 3 are investment banks, which assists individuals, corporations, and governments in raising financial capital by underwriting or acting as the client's agent in the issuance of securities. An investment bank may also assist companies involved in mergers and acquisitions and provide ancillary services such as market making, trading of derivatives and equity securities. Cluster 4 involves the unsuccessful banks that made loss in the year 2011. The data obtained from The Banks Association of Turkey verify the results of k-means clustering algorithm. Therefore, it can be concluded that the banks are featly assessed by the algorithm. The results also demonstrate that the five factors used in the analysis successfully represent 57 financial ratios considered in the factor analysis.

3.3 Data Envelopment Analysis

In this section, we present an application of DEA to evaluate the financial performances of the banks in our case study. In this regard, we use the previously determined factor scores presented in Appendix 3. DEA is a nonparametric method in operations research and economics. The method is used to empirically measure the efficiency of decision making units (DMU). DEA compares DMUs by considering the resources used, and identifies the most efficient ones. Some of the advantages of DEA can be stated as in the following.

- It is proven to be useful in uncovering relationships.
- It is capable of handling multiple inputs and outputs.
- It can be used with any input-output measurement.
- Inputs and outputs can have different units.

There exist various DEA models that largely fall into the categories of being either input-oriented or output-oriented. CCR (Charnes et al., [27]) and BCC (Banker et al., [28]) models are the two basic DEA models which have input-oriented and output-oriented versions, respectively. With input-oriented DEA, a linear programming model is configured so as to determine how much input should be used in order to achieve a predetermined output level in the most efficient way. In contrast, with output-oriented DEA, a linear program is configured to obtain potential output with the given inputs. In this study, we used input-oriented model. Mathematical formulation of the model is presented in the following.

$$\begin{aligned}
&Max\ h_k = \sum_{r=1}^{s} u_r y_{rk} \\
&subject\ to \\
&\sum_{i=1}^{m} v_i x_{ik} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \ \ (j = 1,\dots,n) \\
&u_r \geq \varepsilon \ \ (r = 1,\dots,s), \quad v_i \geq \varepsilon \ \ (i = 1,\dots,m)
\end{aligned} \tag{2}$$

where, xij is the observed magnitude of i - type input for entity j (xij > 0, i = 1, 2, ..., m, j = 1, 2, ...,n), yrj is the observed magnitude of r-type output for entity j (yrj > 0, r = 1, 2, ..., s, j = 1, 2, ...,n), vi is the weight to be determined for input i, m is the number of inputs, ur is the weight to be determined for output r, s is the number of outputs, hk is the relative efficiency of DMUk, yrk is the observed magnitude of r-type output for DMUk, n is the number of entities and ε is a non-Archimedean element smaller than any positive real number. The model is linear, and in practice it is often solved by using the dual form represented as in the following.

$$\begin{aligned}
&Min\ Z_k - \varepsilon\left(\sum_{r=1}^{s} s_r^{+} + \sum_{i=1}^{m} s_i^{-} \right) \\
&subject\ to \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{+} = y_{rk}, (r = 1,2,\dots,s) \\
&Z_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^{-} = 0, (i = 1,2,\dots,m) \\
&\lambda_j, s_r^{+}, s_i^{-} \geq 0;\ Z_k \text{ - sign unbound}
\end{aligned} \tag{3}$$

where, Si- is the slack value of ith input of the kth DMU, Sr+ is the slack value of rth output of the kth DMU and λj is the dual variable of jth DMU.

We used the following ratios as outputs in our application.

- Shareholders' Equity / Total Assets
- Liquid Assets / Total Assets

- Net Income (Loss) / Shareholders' Equity
- Total Income / Total Expenses

We used Efficiency Measurement System (EMS) software as the solver in our analysis. The results of the DEA are presented in Table 15.

Table 15: Results of the DEA

Bank	Efficiency (%)	Bank	Efficiency (%)
Türkiye Cumhuriyeti Ziraat Bankası A.Ş.	89	HSBC Bank A.Ş.	100
Türkiye Halk Bankası A.Ş.	100	ING Bank A.Ş.	64
Türkiye Vakıflar Bankası T.A.O.	79	Turkland Bank A.Ş.	92
Adabank A.Ş.	100	Bank Mellat	100
Akbank T.A.Ş.	100	Habib Bank Limited	100
Alternatif Bank A.Ş.	58	JP Morgan Chase Bank N.A.	100
Anadolubank A.Ş.	100	Société Générale (SA)	100
Şekerbank T.A.Ş.	75	The Royal Bank of Scotland N.V.	100
Tekstil Bankası A.Ş.	76	West LB AG	100
Turkish Bank A.Ş.	100	İller Bankası A.Ş.	100
Türk Ekonomi Bankası A.Ş.	62	Türk Eximbank	100
Türkiye Garanti Bankası A.Ş.	100	Türkiye Kalkınma Bankası A.Ş.	100
Türkiye İş Bankası A.Ş.	85	Aktif Yatırım Bankası A.Ş.	100
Yapı ve Kredi Bankası A.Ş.	86	Diler Yatırım Bankası A.Ş.	100
Birleşik Fon Bankası A.Ş.	100	GSD Yatırım Bankası A.Ş.	100
Arap Türk Bankası A.Ş.	75	İMKB Takas ve Saklama Bankası A.Ş.	96
Citibank A.Ş.	100	Nurol Yatırım Bankası A.Ş.	94
Denizbank A.Ş.	100	Türkiye Sınai Kalkınma Bankası A.Ş.	100
Deutsche Bank A.Ş.	100	Bank Pozitif Kredi ve Kalkınma Bankası A.Ş.	100
Eurobank Tekfen A.Ş.	91	Credit Agricole Yatırım Bankası Türk A.Ş.	100

Fibabanka A.Ş.	51	Merrill Lynch Yatırım Bank A.Ş.	100
Finans Bank A.Ş.	100	Taib Yatırım Bank A.Ş.	100
Average Efficiency = 92.6%			

The banks with efficiency value of 100% are relatively more efficient than the other banks. Table 16 is the "summary of peers" table, which is obtained as a result of DEA and compares each bank with the reference banks. It also presents the rate of decrease in inputs for each bank needed to achieve the financial performances of the reference banks.

Table 16: Summary of Peers Table

Banks	Efficiency (%)	Summary Peers – Reference Banks					Decrease rate of inputs to achieve the financial performances of the reference banks				
1	89	18	5	40			0.254	0.699	0.042		
2	100	2					1				
3	79	29	22	35	12		0.013	0.027	0.106	0.794	
4	100	4					1				
5	100	5					1				
6	58	5	22	29	12		0.375	0.234	0.096	0.185	
7	100	7					1				
8	75	33	23	22	5	29	0.016	0.418	0.335	0.126	0.016
9	76	22	41	12	44	32	0.184	0.253	0.434	0.015	0.007
10	100	10					1				
11	62	41	33	5	29	22	0.071	0.024	0.404	0.092	0.190
12	100	12					1				
13	85	12					0.968				
14	86	35	22	12	2	29	0.284	0.240	0.359	0.061	0.015
15	100	15					1				
16	75	22	33	29	23		0.533	0.051	0.844	0.033	
17	100	17					1				
18	100	18					1				
19	100	19					1				

20	91	10	17	34	5	30			0.144	0.149	0.148	0.320	0.081		
21	51	12	5	22	33	29			0.215	0.418	0.093	0.006	0.048		
22	100	22							1						
23	100	23							1						
24	64	33	5	41	29	22			0.012	0.100	0.077	0.131	0.515		
25	92	33	41	22	17	12	44	31	0.030	0.168	0.437	0.137	0.020	0.031	0.036
26	100	26							1						
27	100	27							1						
28	100	28							1						
29	100	29							1						
30	100	30							1						
31	100	31							1						
32	100	32							1						
33	100	33							1						
34	100	34							1						
35	100	35							1						
36	100	36							1						
37	100	37							1						
38	96	29	12	35	5				0.212	1.124	0.626	0.510			
39	94	35	29	37	36	42	32		0.468	0.063	0.118	0.097	0.050	0.141	
40	100	40							1						
41	100	41							1						
42	100	42							1						
43	100	43							1						
44	100	44							1						

For example, bank 38 should decrease its inputs by the rate of 22.2%, while keeping its outputs constant, to achieve the financial performance of the bank 29. Table 17 presents the numbers of being references for each bank which are utilized to obtain the banks with the best financial performances.

Table 17. The Number of Being Referenced for Each Bank

Türkiye Cumhuriyeti Ziraat Bankası A.Ş.	0	HSBC Bank A.Ş.	2
Türkiye Halk Bankası A.Ş.	1	ING Bank A.Ş.	0
Türkiye Vakıflar Bankası T.A.O.	0	Turkland Bank A.Ş.	0
Adabank A.Ş.	0	Bank Mellat	0
Akbank T.A.Ş.	8	Habib Bank Limited	0
Alternatif Bank A.Ş.	0	JP Morgan Chase Bank N.A.	0
Anadolubank A.Ş.	0	Société Générale (SA)	10
Şekerbank T.A.Ş.	0	The Royal Bank of Scotland N.V.	1
Tekstil Bankası A.Ş.	0	West LB AG	1
Turkish Bank A.Ş.	1	İller Bankası A.Ş.	2
Türk Ekonomi Bankası A.Ş.	0	Türk Eximbank	6
Türkiye Garanti Bankası A.Ş.	8	Türkiye Kalkınma Bankası A.Ş.	1
Türkiye İş Bankası A.Ş.	0	Aktif Yatırım Bankası A.Ş.	4
Yapı ve Kredi Bankası A.Ş.	0	Diler Yatırım Bankası A.Ş.	1
Birleşik Fon Bankası A.Ş.	0	GSD Yatırım Bankası A.Ş.	1
Arap Türk Bankası A.Ş.	0	İMKB Takas ve Saklama Bankası A.Ş.	0
Citibank A.Ş.	2	Nurol Yatırım Bankası A.Ş.	0
Denizbank A.Ş.	1	Türkiye Sınai Kalkınma Bankası A.Ş.	1
Deutsche Bank A.Ş.	0	Bank Pozitif Kredi ve Kalkınma Bankası A.Ş.	4
Eurobank Tekfen A.Ş.	0	Credit Agricole Yatırım Bankası Türk A.Ş.	1
Fibabanka A.Ş.	0	Merrill Lynch Yatırım Bank A.Ş.	0
Finans Bank A.Ş.	10	Taib Yatırım Bank A.Ş.	2

4. CONCLUSIONS

Assessing financial performances and predicting financial distress/bankruptcy possibility have a vital importance for the companies/institutions in service industry to subsist in the financial markets and to avoid unfavorable consequences in risky conditions. Considering this fact, this study proposes an integrated methodology to evaluate the performances of financial institutions with a focus on commercial banks. The proposed approach combines a multivariate statistical method, a clustering approach and multi-factor productivity analysis. More specifically, the proposed approach respectively employs factor analysis, k-means clustering and DEA to explore the financial factors that have a significant influence on the financial performance of commercial banks, and to evaluate and compare the financial performances and distress/bankruptcy possibility of the banks.

To confirm the practicability of the proposed approach, a case study from Turkish banking sector is presented. In this regard, performances of 44 commercial banks operating in Turkish banking sector in the year 2011 are assessed by using 57 financial ratios. By using factor analysis, 57 financial ratios are reduced to five factors that can be used practically for evaluating the financial performances of the banks under concern. Factor scores that are obtained in the factor analysis are utilized in k-means clustering and DEA, respectively, to cluster banks and obtain financial efficiencies of them. Table 17 reports that, Akbank T.A.Ş., Türkiye Garanti Bankası A.Ş., Finans Bank A.Ş. and Societe Generate (SA) are the most referenced banks, which means they realize the best financial performances among the banks. The facts that Europe, Middle East and Africa (EMEA) Finance Journal named Akbank T.A.Ş. as the "Best Bank in Turkey", and that the prestigious business and finance magazine Global Finance named Türkiye Garanti Bankası A.Ş. the "Best Bank in Turkey" in the Best Emerging Market Banks in Central and Eastern Europe category verify the reliability and applicability of the proposed performance evaluation approach in this study.

This study differs from the previous studies in that it integrates factor analysis, k-means clustering and DEA in performance evaluation in banking sector. In addition, this study uses a wide range of financial ratios in bank performance evaluation. It also presents an up-to-date and comprehensive application on performance evaluation of commercial banks operating in Turkish Banking sector. The results of the application reveal the practicability of the proposed approach. Financial performance of commercial banks in a developing country has a significant impact on the economic stability of that country and on the durability of the banking sector in risky conditions such as economic/financial crises. Also, foreseeing the failure of a financial institution is vital for the management of assets and investment decision making to protect the investors from unfavorable consequences. Considering this fact, the proposed approach can be employed by the managers and customers of the banks as well as the government units, rating agencies and investors to predict the future financial performances and distress possibility of the financial institutions. As stated before, using the data of the year 2011 enables to observe the effects of global economic recession realized in 2008 and 2009 on the Turkish banking sector. However, the proposed approach can be utilized in different cases by using different data set to evaluate and compare the financial performances of the banks in different time periods. Also, future research may include using different MCDM techniques, such as ELECTRE and TOPSIS, to evaluate and compare the financial performances of banks and the results can be compared with the results obtained by the methodology used in this study.

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Appendix 1: Financial Ratios with Corresponding Means and Standard Deviations

Ratio		Mean	Standard Deviation
Capital Ratios			
1	Shareholders' Equity / (Capital to be employed to credit, market and operational risk)	33.600	29.123
2	Shareholders' Equity / Total Assets	24.986	23.806
3	(Shareholders' Equity - Permanent Assets) / Total Assets	21.049	22.909
4	Shareholders' Equity / (Deposits + Non-deposit Funds)	540.387	2758.786
5	Fx Position/Shareholders' Equity	83.901	161.001
6	Net On Balance Sheet Position / Total Shareholders' Equity	-53.418	168.687
7	Net On and Off Balance Sheet Position / Total Shareholders' Equity	0.787	7.843
Assets Quality			
8	Financial Assets (net) / Total Assets	20.888	18.317
9	Total Loans and Receivables / Total Assets	47.919	27.696
10	Total Loans and Receivables / Total Deposits	98.948	89.225
11	Loans Under Follow-up (gross) / Total Loans and Receivables	261.038	1313.962
12	Loans Under Follow-up (net) / Total Loans and Receivables	2.114	8.170
13	Specific Provisions / Loans Under Follow-up	78.196	21.788
14	Permanent Assets / Total Assets	3.937	8.783
15	Consumer Loans / Total Loans and Receivables	22.679	27.042
Liquidity			
16	Liquid Assets / Total Assets	43.422	27.010
17	Liquid Assets / Short-term Liabilities	217.073	554.067
18	TC Liquid Assets / Total Assets	32.169	26.110
19	Liquidity Assets / (Deposits + Non-deposit Funds)	546.792	2677.494
20	Fx Liquid Assets / Fx Liabilities	42.260	65.781
Profitability			
21	Net Income(Loss) / Total Assets	1.169	3.880
22	Net Income(Loss) / Shareholders' Equity	8.579	9.651

23	Profit(Loss) Before Taxes / Total Assets	1.568	4.139
24	Net Income(Loss) / Paid in capital	28.017	35.794
Income-Expenditure Structure			
25	Net Interest Income After Specific Provisions / Total Assets	3.657	1.850
26	Net Interest Income After Specific Provisions / Total Operating Income (Expenses)	63.344	26.208
27	Non-interest Income (net) / Total Assets	2.196	3.587
28	Non-interest Income (net) / Other Operating Expenses	67.734	62.968
29	Other Operating Expenses / Total Operating Income (Expenses)	84.385	189.189
30	Capital to be Employed to credit + market + operational risk / Total Assets	0.640	0.479
31	Interest Income / Interest Expenses	54093.16	288481.54
32	Non-Interest Expenses/Other Operating Expenses	67.734	62.968
33	Total Income / Total Expenses	154.872	57.298
34	Interest Income / Total Assets	6.791	2.284
35	Interest Expenses / Total Assets	2.870	1.746
36	Interest Income / Total Income	78.370	20.382
37	Interest Expenses / Total Expenses	44.230	22.831
Share in Sector			
38	Total Assets	2.273	4.009
39	Total Loans	2.273	3.884
40	Total Deposits	3.226	4.748
Share in Group		4.538	6.818
41	Total Assets	4.543	7.310
42	Total Loans	3.212	4.757
43	Total Deposits	613.192	1002.711
Branch		160.594	318.713
44	Total Assets / No. of Branches	43.153	36.550
45	Total Deposits / No. of Branches	117.441	316.308

46	TL Deposits / No. of Branches	277.017	698.079
47	Fx Deposits / No. of Branches	61.255	112.776
48	Total Loans / No. of Branches	10.165	21.044
49	No. of Personnel / No. of Branches	1.926	1.889
50	Net Profit / No. of Branches	115.934	91.428
Activity		4.261	9.537
51	(Salaries and Employee Benefits + Reserve for Retirement) /Total Assets	49.080	10.404
52	(Salaries and Employee Benefits + Reserve for Retirement / No. of Personnel (Billion TL)	3.909	3.786
53	Reserve for Seniority Pay / No. of Personnel (Billion TL)	6.117	4.011
54	Salaries and Employee Benefits / Other Operating Expenses	1.568	4.139
55	Other Operating Expenses / Total Assets	2.273	4.009
56	Total Operating Expenses / Total Assets	2.273	3.884
57	Net Operating Profit (Loss) / Total Assets	3.226	4.748

Appendix 2: Results of the Item-Total Test

Variable	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
1	**1953.99**	**260185.21**	**0.64**	**0.60**
2	**1959.18**	**261191.48**	**0.63**	**0.60**
3	**1961.98**	**260562.64**	**0.67**	**0.60**
4	**1952.05**	**250523.29**	**0.61**	**0.59**
5	1894.91	291523.30	-0.30	0.70
6	2010.96	291286.42	-0.29	0.71
7	1972.96	266604.66	0.20	0.61
8	1954.86	268825.53	-0.13	0.62
9	1918.04	278259.50	-0.67	0.63
10	1859.41	265745.20	-0.07	0.64
11	1968.92	265790.00	0.50	0.61
12	1972.42	267828.19	-0.13	0.61

13	1900.91	257847.38	0.50	0.60
14	1970.75	268354.23	-0.47	0.62
15	1947.49	272333.66	-0.22	0.62
16	**1937.45**	**256134.52**	**0.66**	**0.60**
17	**1896.56**	**223193.44**	**0.51**	**0.56**
18	1950.26	261945.10	0.38	0.61
19	**1924.26**	**240597.70**	**0.76**	**0.57**
20	1940.17	259390.36	0.46	0.60
21	1972.26	267069.84	0.67	0.61
22	1963.67	266651.86	0.15	0.61
23	1971.98	266931.59	0.67	0.61
24	1938.45	267366.56	-0.03	0.62
25	1969.98	267400.78	0.20	0.61
26	1908.02	271431.96	-0.22	0.62
27	1972.02	267037.26	0.43	0.61
28	1919.01	252197.91	0.34	0.60
29	1915.06	275062.79	-0.43	0.63
30	1972.81	267746.61	-0.12	0.61
31	**1721.59**	**147292.99**	**0.73**	**0.47**
32	1919.01	252197.91	0.34	0.60
33	**1835.37**	**244650.59**	**0.77**	**0.58**
34	1965.85	268623.33	-0.48	0.62
35	1969.77	268918.45	-0.86	0.62
36	1890.22	275606.05	-0.52	0.63
37	1919.95	279735.45	-0.75	0.63
38	1969.72	268135.47	-0.09	0.62
39	1969.71	268201.44	-0.11	0.62
40	1969.57	268170.16	-0.09	0.62
41	1969.58	268139.52	-0.09	0.62

42	1969.56	268217.86	-0.11	0.62
43	1969.56	268151.75	-0.09	0.62
44	**1848.38**	**194629.20**	**0.68**	**0.52**
45	**1898.62**	**229496.88**	**0.55**	**0.57**
46	1933.46	262910.42	0.18	0.61
47	**1938.82**	**233482.50**	**0.58**	**0.57**
48	1912.26	254017.03	0.45	0.60
49	1952.26	262529.36	0.48	0.61
50	**1971.66**	**265275.88**	**0.86**	**0.61**
51	1972.01	267686.05	0.03	0.61
52	**1893.46**	**240938.93**	**0.70**	**0.58**
53	1971.96	266820.91	0.47	0.61
54	1924.91	267887.80	-0.03	0.62
55	1970.37	267486.01	0.17	0.61
56	**1968.06**	**266725.38**	**0.58**	**0.61**
57	1971.98	266931.59	0.67	0.61

Appendix 3: Factor Scores for Each Bank

	F1	F2	F3	F4	F5
Türkiye Cumhuriyeti Ziraat Bankası A.Ş.	-0.42	-0.52	-0.48	-0.40	-0.14
Türkiye Halk Bankası A.Ş.	-0.68	-0.22	-0.58	-0.10	-0.08
Türkiye Vakıflar Bankası T.A.O.	-0.59	-0.28	-0.43	-0.27	-0.08
Adabank A.Ş.	5.16	0.42	-0.69	-1.09	-0.48
Akbank T.A.Ş.	-0.35	-0.34	-0.34	-0.27	0.04
Alternatif Bank A.Ş.	-0.60	-0.40	-0.59	-0.40	-0.29
Anadolubank A.Ş.	-0.52	-0.11	-0.71	-0.32	-0.34
Şekerbank T.A.Ş.	-0.46	-0.24	-0.63	-0.56	-0.27
Tekstil Bankası A.Ş.	-0.45	-0.30	-0.68	-0.46	-0.19
Turkish Bank A.Ş.	0.22	-0.62	-0.38	-0.71	-0.28

Türk Ekonomi Bankası A.Ş.	-0.42	-0.37	-0.61	-0.53	-0.30
Türkiye Garanti Bankası A.Ş.	-0.47	-0.25	-0.26	-0.24	0.04
Türkiye İş Bankası A.Ş.	-0.55	-0.31	-0.42	-0.29	-0.05
Yapı ve Kredi Bankası A.Ş.	-0.63	-0.23	-0.54	-0.24	-0.14
Birleşik Fon Bankası A.Ş.	0.96	1.68	0.28	1.43	1.05
Arap Türk Bankası A.Ş.	-0.58	-0.53	1.59	0.60	1.49
Citibank A.Ş.	-0.28	-0.34	0.36	-0.60	0.09
Denizbank A.Ş.	-0.47	-0.18	-0.63	-0.32	-0.34
Deutsche Bank A.Ş.	-0.30	-0.50	1.76	0.38	0.50
Eurobank Tekfen A.Ş.	-0.22	-0.44	-0.49	-0.67	-0.18
Fibabanka A.Ş.	-0.59	-0.44	-0.50	-0.44	-0.19
Finans Bank A.Ş.	-0.48	-0.12	-0.55	-0.35	-0.22
HSBC Bank A.Ş.	-0.32	-0.19	-0.43	-0.47	-0.24
ING Bank A.Ş.	-0.49	-0.27	-0.64	-0.49	-0.43
Turkland Bank A.Ş.	-0.39	-0.21	-0.48	-0.61	-0.20
Bank Mellat	0.45	-0.74	0.09	-0.16	5.76
Habib Bank Limited	1.14	0.73	-0.25	0.97	-0.63
JPMorgan Chase Bank N.A.	0.46	-0.98	1.12	1.35	-0.50
Société Générale (SA)	-0.17	-0.35	-0.04	0.02	-0.97
The Royal Bank of Scotland N.V.	0.01	0.58	2.22	0.68	-0.86
WestLB AG	0.70	-0.31	2.39	-1.08	-0.10
İller Bankası A.Ş.	0.90	1.31	-0.34	0.79	0.19
Türk Eximbank	0.37	-0.49	-0.80	4.60	-0.49
Türkiye Kalkınma Bankası A.Ş.	0.12	-0.59	-0.32	0.62	-0.17
Aktif Yatırım Bankası A.Ş.	-0.73	0.20	0.23	-0.10	0.13
Diler Yatırım Bankası A.Ş.	0.30	2.27	-1.21	0.41	-0.11
GSD Yatırım Bankası A.Ş.	-0.56	1.26	-0.39	0.29	-0.44
İMKB Takas ve Saklama Bankası A.Ş.	1.25	-1.40	0.65	0.50	-0.37
Nurol Yatırım Bankası A.Ş.	-0.66	1.18	-0.41	-0.28	0.24
Türkiye Sınai Kalkınma Bankası A.Ş.	-0.38	-0.54	-0.36	2.10	0.16

BankPozitif Kredi ve Kalkınma Bankası A.Ş.	-0.04	-0.33	-0.12	-0.59	0.34
Credit Agricole Yatırım Bankası Türk A.Ş.	-0.95	4.60	1.29	-0.69	0.32
Merrill Lynch Yatırım Bank A.Ş.	-0.05	-0.65	3.74	-0.46	-1.29
Taib Yatırım Bank A.Ş.	1.76	-0.41	-0.42	-1.56	0.01