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Determination of Financial Failure Indicators by Gray Relational Analysis and Application of Data Envelopment Analysis and Logistic Regression Analysis in BIST 100 Index

Ebru Nurcan[1*], Can Deniz Köksal[2]
1. Department of Business Administration, Faculty of Economics and Administrative Sciences, Akdeniz University, Antalya, Turkey
2. Department of Business Administration, Faculty of Economics and Administrative Sciences, Akdeniz University, Antalya, Turkey

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Abstract
Financial failure prediction models have been developed by using Logistic Regression (LR) analysis from traditional statistical methods and Data Envelopment Analysis (DEA), which is a mathematically based nonparametric method over the financial reports of the companies traded in The Istanbul Stock Exchange National 100 Index (BIST 100) between the years 2014-2016. In the development of these models, the variables included in the model are as important as the method applied. For this reason, the gray relational analysis method has been considered in determining the indicators that affect the financial situation of the companies. As a result of the analysis, it was determined that the LR model, which is one of the prediction models, has a higher rate of prediction power than the data envelopment analysis in predicting the financial failure of the companies. However, DEA is also an easy and fast method for predicting financial failures, and is recommended to companies on the indicators that they need to improve in order to be successful. As a result of the study, it has been found that both methods are feasible in the prediction of financial failure, but these methods also have different advantages and disadvantages.

Keywords
Financial failure, Gray relational analysis, Data envelopment analysis, Logistic regression.

[*] **Corresponding Author, Email:** ebrunurcan@gmail.com

Introduction

Recently, companies that have attracted attention due to the sophistication and acceleration of the changes in the business environment have to compete effectively to keep up with the changes in their environment and survive. While companies that can keep up with social, economic and technological changes come to the fore, companies that cannot keep up with these changes suffer especially from economic problems (Jawabreh et al., 2017). If financial distress is not determined in time and turnaround measures are taken, then the failure/bankruptcy is likely. The costs of failure and bankruptcy are enormous and affect all stakeholders of the company (Manaseer & Oshaibat, 2018). It is inevitable for the companies to fall into failure if they do not take necessary precautions and have obstructed financial structure (Berk, 1990). Financial failure is considered as the failure to reach goals due to company policies, financial decisions, and failures of that company in other fields (Okka, 2009).

Companies that have financial failure go through various stages until bankruptcy. Bankruptcy is seen as the final stage of failure. If the problems are identified and precautions are taken in the stages before entering the bankruptcy process, the costs to bear are reduced and entering the bankruptcy process can be prevented.

The first instance of financial failure concept was suggested in the scientific study of Altman (1968). Even though there is no clear opinion on what financial failure is, how it emerges, and how its results are comprehended on interdisciplinary level, studies in this field have maintained their importance to this day (Mellahi & Wilkinson, 2004).

Even though it points to a result, it is important to determine the causes of the failure since financial failure can be foreseen, avoided, or turned into success with less costs (Özdemir, 2011). Companies that do not determine the possibility of financial failure and take precautions in early stages cause damages to not only their shareholders, creditors, executives, employees, suppliers, clients, and other shareholders, but also to the stability of the economy of the whole country. Thus, financial failure prediction models play a crucial role in avoiding the companies to drift into failure and go bankrupt (Sun & Li, 2009).

The financial ratios, obtained from financial statements that are indicators of the financial status and performance of the companies in models trying to exhibit financial failure predictions, are used as variables. However, there is not an exact model to predict financial failure in financial literature. Hence, researchers have conducted many research studies in order to obtain a better prediction regarding this issue. The model to be applied for determining financial failure is differentiated by the study nature, the variable set to be used in the model, and the features of chosen sample group.

Since there is not a clear approach to financial failure, there are some theoretical deficits that researchers face during the implementation process. These deficits consist of three groups (Aktaş, 1997).

- Uncertainty while determining the variables to be used in foreseeing financial failure,
- Uncertainty while determining the model to be applied (linear or non-linear model),
- Uncertainty regarding the focus on variables of the applied model.

There are differences in variables chosen by the researchers and the evaluation of the relations between these variables.

Early research focused on a rational analysis. It was guided by Beaver (1966), who introduced a univariate analysis for grouping companies using some financial ratios (Shetty et al., 2012). Then, Altman (1968) introduced discriminant analysis to bankruptcy prediction. Later, the logistic regression model (LR) was developed by Ohlson (1980).

Further, researchers used operational research techniques such as DEA, which is an alternative method to predict business failure/bankruptcy (Shetty et al., 2011). It is widely recognized that one of the major causes of financial failure is poor management, and that company operation efficiency is a good reflection of a company’s management (Xu & Wang, 2009). It is logical to assume that efficiency is associated with the probability of failure (Li et al., 2014). Cielen et al. (2004) argued that DEA can provide insights into the value of a company's efficiency for bankruptcy prediction. Premachandra et al. (2011) and Psillaki et al. (2010) also proved that

DEA could be used to classify companies as failed and non-failed (Li et al., 2017). In recent studies, a number of models based on the DEA have been developed to predict business failures (and bankruptcy) and compare these results with those achieved through other methods such as the Z-Score (Altman) or the LR (Olshon) (Monelos et al., 2011). In addition, researchers evaluated the failure prediction by including the efficiency values obtained from DEA as variables in discriminatory statistical analyses (Shiri & Salehi, 2012).

DEA analyzes the financial failure (or bankruptcy) prediction in two different ways. DEA has been used to derive a classification algorithm to separate failed companies from non-failed companies. Second, the efficiency score of companies has been calculated using DEA, and this efficiency has been used as a feature of each company in a subsequently developed classification rule (Li et al., 2014). Low DEA values show that companies tend to suffer financial difficulties and may have problems in paying their debts and fulfilling their obligations. The findings of this study could be used to take remedial measures to improve the performance of the worst performing companies (Shetty et al., 2012). In this study, the second approach is considered.

There are main advantages in using DEA to predict financial failures of companies. First, analysts can flexibly choose the factors that affect the financial status of companies, namely input and output variables. Another advantage is that DEA is a nonparametric method. Although parametric approaches are widely used in financial failure studies and offer desired features, they require previous parameters. Therefore, the score of DEA can be used as a prediction of financial failure (Paradi et al., 2014). DEA does not need a functional connection between input and output variables and the variables can have different measurements. In DEA, the decision-making units (DMU) can be compared each other. Since DEA is a non-parametric method, it does not need to provide statistical hypotheses (Monelos et al., 2011). Moreover, DEA does not need a large sample for its analyses. The need for such a large sample size is a disadvantage to investors when investment decisions are made using small samples (Premachandra et al., 2009). On the other hand, DEA has some disadvantages such as sensitivity to the selection of input and output variables. When the number of variables is close to or larger than the number of companies, efficiency scores tend to be 1, and so the discriminative power is lost (Li et al., 2014). DEA is based on comparisons between decision-making units in determining and classifying financial failure (financial success / financial failure) (Monelos et al., 2011).

In financial failure studies, determining the variables to be included in the model as well as the selection of the model (i.e., the selection of financial failure indicators) is very important in determining the financial failure. Since there has been no generally accepted method until now, researchers have created a set of variables with different methods (Li et al., 2014). Huang et al. (2015) obtained input and output variables from the set of candidate variables with the GRA method. They also proved that the GRA method is an effective method for obtaining variables for DEA. Therefore, in this study, the GRA method applied by Huang et al. (2015) is preferred to overcome the issue of variable selection. In this context, this study investigates financial ratios that have more significant correlations with the financial situations than many indicators with GRA.

In accordance with the above-mentioned points, the purpose of this study is as follows. This study aims to determine whether gray relational analysis is an effective method for determining the indicators of financial failure. As per this goal, the conformity of DEA, which is a method that can be applied quickly and easily to financial failure predictions of companies, and LR analysis, which is considered as a methodological opposition to DEA, will be examined within the scope of the advantages and disadvantages of these methods. In this context, it is expected that DEA will provide researchers, business managers, investors, and stakeholders with fast and more accurate information on predicting the financial failure of companies.

Since there is no specific set of variables, model, or measurement approach to the evaluation of financial failure in finance literature, this study is mainly aimed to contribute to the related literature by trying to present an alternative approach that facilitates the failure prediction.

In line with the study, the steps for determining financial failure indicators and applying financial failure prediction models with these indicators are as follows:

Step 1: Classifying companies as financially successful and financially failed according to the definition of financial failure.

Step 2: Determining the most effective variables from possible set of indicators that affect the financial status of companies using gray relational analysis method.

Step 3: Applying financial failure prediction models, namely data envelopment analysis and logistic regression analysis.

Step 4: Comparing the results of prediction models and explaining the advantages and disadvantages of the models.

Literature Review

Failure models are usually projected using financial ratios. The use of ratios is as much due to their predictive power as to their availability and standardizations. Financial ratios generally provide a good classification between failed and non-failed companies (Jardin, 2016). There are several models for financial failure prediction in the literature. While the oldest studies in financial failure prediction (Ramser & Foster, 1931; Fitzpatrick, 1932; Winakor and Smith, 1935; Merwin, 1942) focused on comparing the financial ratios of successful or failed companies without using statistical methods, later studies put emphasis on prediction models (Shepherd, 2003). The very first studies in this matter are those of Beaver (1966) and Altman (1968).

The application of financial statement analysis on failure prediction started first with single variable models based on calculated value of single financial ratio. After a little while, studies regarding the early warnings for financial problems were developed using multivariate models such as multi discriminant analysis, regression analysis, and linear discriminant analysis. After that, non-linear statistical techniques such as LR were observed to present better results in early studies of financial problems than multi discriminant analysis. Later studies focused on developing and implementing artificial intelligence and machine learning techniques (Sun & Li, 2009).

Multivariate statistical analyses aim to classify the units by reducing the cases to a simpler level, and to reduce the size by investigating multi-connections between variables. In short, these analyses aim to explain the subject case using significant parameters by reducing the number of variables (Küçükönder et al., 2004). Before applying multivariate statistical analysis methods, the structure of the model, the variables in the model, and their coefficients must be determined (Yıldırım, 2006).

The first study that utilized linear multi discriminant analysis in financial failure prediction belongs to Edward I. Altman. In his study, Altman (1968) developed "Z-Score Model" that has five factors in order to predict the failure of manufacturing companies. In his model, the financial statements of a sample group of 66 companies were split into two groups (successful and failed). He started his study with 22 financial ratios. He claimed 5 of these 22 ratios would provide sufficient information regarding the sales of this company, using the multivariate statistical method. The ratios that Altman determined for analysis and the discriminant function he established according to these ratios are as follows:

$$Z_{\text{score}} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

$X_1 = \text{Working capital/total assets}$
$X_2 = \text{Retained profits/total assets}$
$X_3 = \text{Trading profits/total assets}$
$X_4 = \text{Market capitalisation/total liabilities}$
$X_5 = \text{Sales/total assets}$

Logistic Regression Analysis: This is considered as a developed version of Discriminant analysis. It has been widely used to predict the financial failure of companies since the end of 1960s. Logistic regression model is interpreted as determining the prediction parameters of the model, measuring competency, and explaining the importance of predicted parameters. Some restrictive principles, such as linearity, normality, and correlation between standard variables, restrict the implementation of these models (Chen, 2011). Logistic regression model is a multivariate statistical analysis used where dependent variable is categorical and independent variables are quantitative or qualitative, and where the multivariate normality assumption is not fulfilled (Wijekoon & Azeez, 2015).

The study by Ohlson in 1980 is a leading study used LR analysis for predicting financial failure. In the study, a sample group of 105 failed companies and 2058 successful ones between 1970 and 1976were analyzed. As a result, it was observed that the LR model that determines financial failure had a high rate of accuracy (Ohlson, 1980). Zavgren (1985) examined a sample group consisting of industrial companies in order to predict the failure 1-5 years prior. The model was established with seven independent variables, and dependent variables were obtained by factor analysis for the LR model. As a result, it was observed that the LR model gave similar results as Ohlson's (1980) study regarding the ability to predict the failure one year prior. However, it has been found out that the prediction ability of the model decreases in the long term.

Data Envelopment Analysis (DEA): This is a non-parametric technique based on linear programming designed to measure relative activities of relevant units during the process of obtaining one or more variable values using one or more input variables (Ramanathan, 2003). DEA scales the relative efficiency prediction between 0 and 1 where 1 represents an efficient operation relative to others in the sample, and a decision-making unit with a score less than 1 is defined as inefficient (Avkıran, 2011). DEA was used in many studies to predict financial failure due to the information it provides about the activities of companies (Shetty et al., 2012).

For instance, Cielen et al. (2004) have examined classification performance of a linear programming model by comparing the DEA model and the decision trees (C05.0) model. In the study, the companies that go bankrupt or declare concordatum were considered as failed. The study considered 11 financial ratios as variables for each year. As a result, DEA model was observed to produce better results in terms of accuracy, cost, and comprehensibility than decision trees model (C5.0).

Premachandra et al. (2009) have tried to determine how sufficient the DEA in bankruptcy prediction by comparing it to the LR method using the sample they established that consists of failed corporate companies in USA. They established the input and output variables, which would be included in the model, from the financial ratios, which might cause financial issues, within the context of bankruptcy evaluation. As a result of their study, they observed that DEA model performed better in terms of defining bankrupt companies than LR model.

Huang et al. (2015) have provided two-staged DEA as a quick and applicable tool for financial failure prediction of companies. They provided an integrated approach by combining super efficiency data envelopment analysis (SE-DEA) and gray relational analysis (GRA) in order to determine financial indicators that show a more significant correlation with the financial status of the companies. In their study, they put emphasis on the superiority of the two-staged DEA over the SE-DEA/GRA and CCR-DEA/BCC-DEA models.

Data and Methodology

As the universe of this study, the BIST 100 index, which is used as the main index in the Istanbul Stock Market, was determined. This index consists of 100 large companies. Banks, real estate investment trusts, and holdings were excluded from the scope of the study from among the companies that were continuously traded in the BIST 100 index between the years 2014-2016, because their financial evaluations and structures of financial statements were different from the included companies. In addition, the analysis was based on the three-year moving average of financial ratios to nullify any one-year abnormalities (Shetty et al., 2012). Then, the sample of the study came to be consisted of 60 companies after the exclusion of 40 companies that were not suitable for the reasons stated above. The financially successful and failed companies were determined by considering companies' financial statements of different years as though they were of the same year. However, considering financial statements of different years as though they were of the same year would bring up the effect of different inflation levels throughout years. The study tried to overcome this issue by using the financial ratios obtained from financial statements in the analysis section of the study (Aktaş, 1997).

In this study, in order to determine the financial status of companies, Altman Z Score model (1968), which is one of the most frequently used models in the literature, and the profit/loss criteria of the relevant year were taken as basis. In Altman Z score model, once the Z-scores are calculated for each sample and as a result of this calculation, if Z score is found to be below 1.81, it is classified as failed. However, if it is found to be between 1.81 and 2.99, it is classified as gray, and if it is above 2.99, it is classified as non-failed (Altman, 1968).

Within this context of above mentioned criteria, while determining which company was successful and which one was failed, the companies that acquired a Z score of lower than 1.81 and/or declared loss for the relevant year were considered as failed. Then the rest of the companies were considered as financially successful. For this study, the financial statement data from the years 2014 to 2016 (3 year) were gathered. Sixty companies out of 100 ones that were actively traded in BIST100 index were selected to be used in analyses according to the company selection criteria mentioned in the above section.

The data set of the study included 180 (60 sample for each year) sample, and 34 of these were considered as financially failed according to specified failure criteria that were mentioned in the previous section.

Analyses and Findings

1. Selection of Financial Failure Indicators Based on Gray Relational Analysis

When it comes to financial failure, the choice of financial failure indicators is as important as the choice of models. The goal in determining financial failure indicators is to reduce the dimensionality of the property space, reduce the cost of calculation, and increase the accuracy of the prediction. If the sample group is large enough and normally distributed, statistical or econometric methods such as factor analysis, cluster analysis, and discriminant analysis can be used in order to determine representative indicators. However, if the sample size is not sufficient and the sample distribution is not fully determined, the gray relational analysis method may be preferred to select representative indicators (Feng & Wang, 2000).

Due to the many indicators in the financial statements, it is necessary to determine the variables that have the most impact on the financial situation before the implementation of financial failure prediction models. Gray relational analysis is a method of analysis that measures the relationship between factors according to the degree of similarity between factors or their developmental tendencies (Feng & Wang, 2000). In other words, gray relational analysis is a method that can determine qualitative and quantitative relations between factors even if there is incomplete information during the comparison of the reference factor and other factors. In this method, the relationship between indexes is calculated numerically, and the values, named the gray relation degree and range between 0 and 1, are obtained. If the change between factors occurs together and continuously, the degree of relationship is high, otherwise the degree of gray relationship is low if no change is observed (Altan & Candoğan, 2014).

The purpose of GRA in this study is to calculate the Gray Relational Degree (GRD) of financial indicators and to determine the indicators that effect the financial situation the most, i.e. the ones with high GRD. The steps of the GRA application to calculate GRD are as follows.

First, the performance of all alternatives is transformed into a comparable series to obtain a decision matrix. The decision matrix has m amount of factor series (Equation 1) and shows the options of x_i. In contrast, the decision matrix is formed as in Equation (2) by showing its values as $x_i(j)$ (Chan & Tong, 2007).

$$x_i = (x_i(j), \dots x_i(n)), \quad i = 1,2,\dots,m \text{ and } j = 1,2,\dots,n \tag{1}$$

$$X=\begin{bmatrix} x_1(1) & x_1(2)\dots & x_1(n) \\ x_2(1) & x_2(2)\dots & x_2(n) \\ \vdots & \ddots & \vdots \\ x_m(1) & x_m(2) & x_m(n) \end{bmatrix} \tag{2}$$

According to these series, the reference series (ideal target series) is defined. Equation (3) shows obtaining the reference series (Chan & Tong, 2007). Then, the gray relational coefficient between all comparable series and the reference series is calculated.

$$x_{i0} = \left(x_{0i}(j)\right), \quad \text{ve } j = 1,2,\dots,n \tag{3}$$

Since the values in the decision matrix are in different units, they are standardized by the normalization process in order to compare these units within them. In the normalization step, it is standardized in different ways by looking at maximization and minimization trends according to the aspects of the targets, and in other words, the benefit-cost or optimum situations of the series (Kuo et al., 2008). Equation (4) is used if the series maximization is directional, and Equation (5) is used if the minimization is directional. If the value is examined for optimum status, the calculation is done with Equation (6) (Özbek, 2017).

$$x_i^* = \frac{x_i(j) - \min j x_i(j)}{\max j\, x_i(j) - \min j\, x_i(j)} \quad (4)$$

$$x_i^* = \frac{\max j\, x_i(j) - x_i(j)}{\max j\, x_i(j) - \min j\, x_i(j)} \quad (5)$$

$$x_i^* = \frac{I\, x_i(j) - x_{0b}(j) I}{\max j\, x_i(j) - \min j\, x_i(j)} \quad (6)$$

After the normalization process, the absolute values of the obtained values are calculated, and the absolute value matrix is obtained. Then Equation (7) is used to construct the gray relation coefficient matrix. However, first the greatest and least values taken by the absolute value matrix must be determined. The distinguishing coefficient (ζ) in the Equation is a value between 0 and 1. However, it was observed that this parameter is usually taken at 0.5 (Deng, 2002) in the literature analysis (Chan & Tong, 2007).

$$\gamma_{0i}(j) = (\Delta \min + \zeta \Delta \max) / (\Delta_{0i}(j) + \zeta \Delta \max),$$
$$\Delta \max = \max_i \max_j \Delta_{0i}(j) \text{ and } \Delta \min = \min_i \min_j \Delta_{0i}(j) \quad (7)$$

If, after obtaining the gray relation coefficients, the significance of the criteria is equal, the mean of these coefficients is used as the gray relation degree. The gray relation degree (τ) is calculated as shown in Equation (8) (Sallehuddin et al., 2008).

$$\tau_{0i} = \sum_{j=1}^{n} \gamma_{0i}(j), \qquad i=1,\ldots,m \quad (8)$$

Then, the gray relation degrees are sorted from the greatest to the smallest, allowing an accurate assessment of the best alternative compared to the worst (Kuo et al. 2008).

The failure status of the companies that are seen as financially failed is reflected in their financial statements and their financial ratios. The study identified 18 ratios under five categories that provide information on the financial structure of companies. However, since the use of these ratios in the DEA method may adversely affect the correct classification of the model, the number of variables was tried to be reduced (size reduced) in the first step. The gray relational analysis method was applied to determine the indicators that effected the financial situation the most. These ratios are given in Table 1.

Table 1. Growth Ratios and Financial Ratios Used in the Study

Growth Ratios and Financial Ratios	
Growth ratios	Asset growth , net sales growth, equity capital growth
Valuation ratios	Market value/book value
Activity ratios	Assets turnover ratio, activity duration, asset turnover ratio, times interest earned ratio, inventory holding period, receivable collection period, cash cycle period
Profitability ratios	Operating profit margin, return on assets , gross operating profit margin, net profit margin, equity capital profitability
Financial structure ratios	Tangible assets/fixed assets , short-term debt/equity capital

The objective was to determine the most related financial ratios by ranking them from the highest related financial ratios to the lowest related financial ratios using the gray relational analysis method. In order for this to represent all financial ratios, relevant ones at 50% and above were selected. Financial ratios with a relationship level of 50% and above were determined as 8 variables with the most impact on the measurement of financial failure, representing the 18 ratios. The selected variables were correctly sorted from the most effective to the least effective as follows: short-term debts/equity capital, equity capital profitability, receivable collection period, inventory holding period, cash cycle period, equity capital growth, net sales growth, and net profit margin ratios. When the benefit-cost structures of the 8 financial ratios determined by the analysis were examined, it was observed that four of them were in the maximization (profit) direction and the other four were in the minimization (cost) direction.

In the financial failure prediction application of the research, the financial ratios obtained from GRA were included as input-output variables in the DEA, and as independent variables in the LR analysis.

2. Data Envelopment Analysis in Financial Failure Prediction

Eight relevant financial ratios were determined as a result of the GRA. Of these ratios, maximization-oriented ones were included as output variables, while minimization-oriented ones were included as input variables in DEA. The variable set of DEA is shown in Table 2.

Table 2. Input and Output Variables Determined for Data Envelopment Analysis

Input Variables	Output Variables
Short-term debts / equity capital	Equity capital profitability
Receivable collection period	Equity capital growth
Inventory holding period	Net sales growth
Cash cycle period	Net profit margin

In order to assess the financial failure of 60 companies selected from the BIST 100 Index, activity was measured via DEA and as a result, inactive companies were considered as financially failed. In order to evaluate companies and determine their effectiveness within the markets, DEA provides easier and more accessible information about the success and failure of companies. This Linear Programming-based analysis provides an overview of companies and stakeholders who want to learn about the business with a single value. In order to take advantage of these benefits of the DEA model, CCR-DEA and BBC-DEA models were implemented using the DEAP 2.1 package program. LR uses the cut-off point of 0.5 for the classification (potential failure probability, cut-off point to rate the cases). In terms of probability, this means that the companies that are over the cut-off point are successful and the others that are under and equal the cut-off value are failed (Monelos et al., 2011).

Therefore, in the DEA analysis section of this study, 0.5 technical efficiency values were taken as cut-off points to classify the financial success status of companies according to their efficiency levels. In DEA run time section, there were two groups: those with technical efficiency value over 0.5 were stated as financially successful, and those with 0.5 and under this threshold were stated as financially failed companies. As a result of this classification, the correct classification ratio of DEA was achieved when financially failed companies determined by financial failure criteria were considered as control variables. In other words, the companies determined as failed and non-failed according to the results of DEA analyses were compared to companies determined by financially failure criteria (Altman Z score and in related financial year loss / profit declaration criteria), and from this comparison the values of Table 3 were obtained. The average, maximum, and minimum values in Table 3 were determined according to the technical efficiency values that the companies received as a result of DEA analysis. In other words, while the average of CCR-DEA technical efficiency values of financially non-failed companies between the years 2014-2016 was 0.723, the average value of financially failed companies was 0.505. Table 3 provides descriptive statistical indicators and correct classification ratios for DEA.

Table 3. Evaluation of Financial Failure Prediction of DEA Models

Model	**DEA-CCR (Technical efficiency)**		**DEA- BCC Technical efficiency)**	
Companies	Financially failed company	Financially Non-failed company	Financially failed company	Financially Non-failed company
Average	0.505	0.723	0.610	0.779
Maximum	1.000	1.000	1.000	1.000
Minimum	0.090	0.200	0.277	0.225
Variance	0.072	0.060	0.054	0.057
P (FC*/FC)	79.41 %		67.64 %	
P (NFC*/NFC)	78.76 %		84.93 %	
P (NFC*/FC)	21.24 %		15.07 %	
P (FC*/NFC)	20.59 %		32.36 %	
Correct classification	79.09 %		76.29 %	
Incorrect classification	20.91 %		23.71 %	

(a) P (FC/FC): Percentage of financially failed companies predicted as financial financially failed. P (NFC/NFC): Percentage of financially non-failed companies predicted as financial non-failed. **(b)** P (NFC/FC): Percentage of financially non- failed companies misclassified as financially failed companies. P (FC/NFC): Percentage of financially failed companies misclassified as financially non-failed companies. **(c)** The correct classification is the percentage of companies predicted correctly in all companies. The incorrect classification is (1- the correct classification). **(e)** * The sign indicates the financial status (Financially failed / financially non-failed) of the companies determined as a result of DEA.

When Table 3 was examined, the average activity values of financially failed companies were 0.505 (CCR model) and 0.610 (BCC model), while those of financially non-failed companies were 0.723 (CCR model) and 0.779 (BCC model). The variances of financially failed companies were calculated as 0.072 (CCR model) and 0.054 (BCC model), while those of financially non-failed companies were 0.060 (CCR model) and 0.057 (BCC model). Compared to these results, the DEA models are expected to be better able to identify and classify financially failed companies because the variance of efficiency values is lower. However, since the BCC model's efficiency limit is variable on scale, more companies fall to the efficiency limit, and the efficiency values are slightly higher than the CCR model. This is also seen in the higher calculation of the efficiency averages of financially failed companies in the BCC model. More companies in the BCC model rise above this value when the breaking point of financial success is 0.5. This also affects the correct classification percentages of models.

Also in Table 3, there are type 1 and type 2 error rates of DEA models. The type 2 error rate in the CCR model (20.59%) is less than that in the BCC model (32.36%). This also affects the correct classification of models as well. This is why the CCR model (79.09%) is higher than the BCC model (76.29%) when the correct classification percentages are examined. In other words, this means that CCR-DEA is more effective and has a better evaluation capability. For these reasons, the CCR model of the DEA models can be said to have done better in predicting financial failure than the BCC-DEA model.

3. Logistic Regression Analysis in Financial Failure Prediction

In this part of the study, LR analysis method was used to predict the financial failures of companies. This method of analysis is chosen primarily because the eight variables, obtained from GRA results as independent variables, do not show normal distribution, and the financial success status of the companies, selected as dependent variables, is of the categorical variable type. In LR model used in the analysis, the financial success situation, determined as a dependent variable, consists of two categories. In this model, the dependent variable, which is the categorical variable, is symbolized by Y. In LR model, which gives the probability of financial success or failure, the categories of dependent variable are given the codes “0” for financially failed companies and “1” for financially non-failed companies. In this study, 180 samples for three fiscal (2014-2016) years of 60 companies were used for LR analysis. The financial failure classification of companies, taken as categorical variables in the initial model (Step 0), is given in Table 4.

Table 4. Logistic Regression Analysis Classification Table (Step 0)

Observed		Predicted			
		Financially failed	Financial Non-failed	Total	Percentage correct (%)
Step 0	Financially failed	0	34	34	.00
	financially Non-failed	0	146	146	100.00
	Total	0	180	180	79.90

The Cut Off value is 0.5

The results of the test, known as conformity level, is given in Table 5, as a result of the LR analysis that applied "Enter Method". The difference between the 2-Log likelihood value of the model, containing only the constant term, and the 2-Log likelihood value of the model, in which the independent variables are added, was 111.126. The hypothesis, in which there is no significant difference between the model containing independent variables at 5% significance level of the generated model and the model containing only the constant term, was rejected. In other words, the H_1 hypothesis was accepted and the model was observed to be better. Then, it was observed that at least one of the independent variables was significantly related to the dependent variable.

Table 5. Omnibus Test for Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	111,126	8	0.000
	Block	111,126	8	0.000
	Model	111,126	8	0.000

Then, by using the Hosmer and Lemeshow test, it was tested whether there was a significant difference between the predicted values and the observed values. According to Table 6, the results of this test, which is a chi-square test, were examined, the H_0hypothesis was accepted because the Chi-Square value was 8.802, and the significance value was 0.359 (p>0.05). It was concluded that the model was appropriate, meaning that there was no difference between the predicted values of model and the actual values.

Table 6. Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8,802	8	0.359

The results, that show the extant to which the independent variables explain the dependent variable, are given in the model summary table. As Table 7 shows, the Cox & Snell R^2 value of the model, in which the independent variables are included, is calculated as 0.462, while the Nagelkerke R^2 value is 0.730.

Table 7. Model Summary

Step	-2Log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	68.571[a]	0.462	0.730

a) Significance level is 0.05.

It is seen in Table 8 that the LR model, obtained from the analysis, shows that the power to accurately predict the financially successful and failed companies is 96.50% and 80.60%, respectively. As a result, the percentage of the correct classification is increased from 79.90% to 93.30%, when LR model is compared to the initial model obtained without adding the independent variables.

Table 8. Logistic Regression Analysis Classification Table (Step 1)

Observed		Predicted			
		Financial failure	Non-financial failure	Total	Percentage correct (%)
Step 1	Financial failure	27	7	34	80.60
	Non-financial failure	6	140	146	100.00
	Total	33	147	180	93.30

a) The Cut Off value is 0.5.

In the LR analysis applied in the study, a higher proportion of prediction accuracy (93.30%) was obtained than in the DEA models (79.09% in the CCR model and 76.29% in the BCC model). On the other hand, the LR model accurately identified financially successful companies in the sample at 96.50%, while performing well relative to the DEA models (78.76% in the CCR model and 84.93% in the BCC model). According to these results, LR analysis makes predictions with higher accuracy when working with a sample and a variable set with a good representative group. However, when this condition is not present, DEA analysis has been observed to be preferable over LR.

Discussion and Conclusions

Since there is no clear definition of financial failure in the finance literature, researchers have tried to find out the best predictions by using different research models and variables. In such studies, determining the variables to be used in models is as important as model selection. In the process of determining these variables, it is also important that the variables be in optimum numbers and importance. The determination of the model or models to be used in the study by reference to the relevant literature also ensures that the results of the study are comparable to those of other studies.

Researchers prefer to use either the variables of similar studies previously conducted or the variables obtained by different methods (e.g., factor analysis, gray relational analysis, etc.) to determine the variables to be used in their studies. In this study, we preferred GRA method to reduce the number of variables by eliminating them with the highest interactivity power from the set of variables for predicting financial failure. The GRA method is preferred because it is a newer technique compared to factor analysis. As a result of this analysis, 8 out of 18 variables that affect the financial success status of the companies the most were identified, and then were included in the model as a set of variables in DEA and LR analysis.

In this study, using 8 variables obtained via GRA, companies having financial failure were tried to be determined by DEA and LR models. In addition, the discriminatory powers of DEA and LR were also compared. The feasibility of DEA as an alternative to statistical methods in predicting financial failure was examined as a method that provides easy and fast information. In the related studies carried out in this field, it was seen that DEA can also be used as an alternative method to statistical models in predicting financial failure and bankruptcy (Li et al., 2014; Min & Lee, 2008; Monelos et al, 2012; Premachandra et al., 2009; Premachandra et al., 2011; Psillaki et al., 2010; Xu & Wang, 2009).

According to Shiri and Salehi (2012), DEA is one of the techniques that calculate efficiency by concentration on input and output variables for the prediction of financial failure. Premachandra et al. (2009) compared DEA and LR results for bankruptcy prediction, and found that DEA is a practically appealing method.

When the results of DEA models in the study were examined, it was seen that the correct classification percentages of CCR-DEA and BCC-DEA models were found similar to the study of Huang et al. (2015). Although DEA gives satisfying results, they have mentioned some criticisms besides its advantages. DEA can guide managers and researchers for the evaluation of companies by taking into account their past year data. Since DEA is a mathematically based model, it cannot form a forward-looking prediction model. In addition, DEA analysis should be repeated when a new company or a variable is added to or removed from model.

LR, which is one of the traditional statistical methods, was also preferred for establishing financial failure prediction models in literature. Therefore, in this study, the LR model was also applied to the same data and variables.

DEA and LR methods have strengths and weaknesses. It is important to pay attention to the sample size, especially in LR model, although both methods are non-parametric. The LR model is required to undergo some statistical tests in order to create a meaningful model. In the LR model, selection-based sampling is used, which causes bias in parameter and probability estimates. In contrast, since the DEA model is a non-parametric and normal-distribution-free approach, preference-based sampling has no effect on the results compared to the LR model. The LR model also requires a time-cross-section condition, whereas DEA does not need this.

As the results of the study, the correct classification ratios were 79.09% and 76.29% in predicting financial failure of CCR-DEA and BCC-DEA models, respectively. It was determined that the LR model had a high prediction power with 93.30% of the correct classification ratio. On the other hand, it appeared that a significant proportion of companies, which were generally considered to be failed, were correctly classified in both LR and DEA models at high rates. In addition to this, it was found out that the correct classification ratios for the failed companies were 80.60% in the LR model and 79.41% in DEA-CCR model. Therefore, it was seen that the DEA model has a very close prediction ratio as that of LR model.

As for conclusions, this study had two major outcomes. Firstly, it was determined that the GRA method was effective in the selection of financial failure indicators. This way, it was seen that DEA and LR models make a good classification using these indicators selected by GRA. Secondly, it was determined that even though the LR statistical model was mostly used to predict the financial failure of companies, DEA model was also found out to predict the same goals at a satisfactory level. In other words, DEA method can be applied as an alternative model to LR with its prominent benefits that were mentioned in the Introduction section. With the results of DEA analysis, a researcher can obtain not only the efficiency values of companies, but also information about the variables (financial ratios) that companies need to improve in order to achieve financial success.

Finally, in this study, a sampling research was presented on how to choose explanatory financial ratios for the business owners, managers, lenders, companies, and other stakeholders to conduct financial reviews and to predict financial failures of companies. Additionally, it was explained that how the selected ratios will be classified, and how the financial failure prediction models will be evaluated after the financial ratios included as variables in the related researches.

For further studies, it is suggested that sample selection should be done on a sectoral basis in order to determine the financial ratios with high explanation power, and DEA can be used for comparison with different methods by taking into account its ease of use.

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