Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi 2018 6(ICEESS'18) 177-183

Journal of Social Sciences of Mus Alparslan University

anemon

Derginin ana sayfası: http://dergipark.gov.tr/anemon

Araştırma Makalesi • Research Article

Special Issue on *International Conference on Empirical Economics and Social Science (ICEESS' 18), 27-28 June, 2018, Bandirma, Turkey*

Financial Failure Estimation with Logistic Regression Model: A Study on Technology Sector Companies Treated in BIST

Lojistik Regresyon Modeli İle Finansal Başarısızlık Tahminlemesi: BİST'te İşlem Gören Teknoloji Şirketleri Üzerine Bir Çalışma

Emre Bulut [a,*], Ahmed İhsan Şimşek [b]

[a] Arş. Gör., Fırat Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü, 23119, Elazığ/Türkiye.
ORCID: 0000-0002-2884-1405

[b] Arş. Gör., Fırat Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü, 23119, Elazığ/Türkiye.
ORCID: 0000-0002-2900-3032

MAKALE BİLGİSİ

Makale Geçmişi:
Başvuru tarihi: 10 Ağustos 2018
Düzeltme tarihi: 29 Ağustos 2018
Kabul tarihi: 30 Ağustos 2018

Keywords:
Lojistik Regresyon
Finans
Finansal Oranlar
Finansal Başarısızlık
BİST

ÖZ

Bu çalışmanın amacı, BİST'de işlem gören Teknoloji Sektörü işletmelerinin finansal başarısızlıklarının 1 yıl önceden tahmin edilmesi için güvenilir bir model oluşturmaktır. Bu amaçla, öncelikle finansal başarısızlık ve bunun önceden tahmin edilmesi hakkında daha önce yapılan çalışmalar incelenmiş, sonrasında finansal başarısızlık kavramı ile nedenleri ele alınmıştır. Daha sonra finansal oranların analizi ve lojistik regresyon analizi tekniklerinin finansal başarısızlığın tahmininde birlikte kullanılması konusu teorik olarak açıklanmıştır. Son kısımda ise finansal başarısızlığın önceden tahmin edilmesinde açıklayıcı olabilecek finansal oranların belirlenmesi ve model oluşturulması amacıyla BİST'de işlem gören Teknoloji Sektöründeki işletmelerinin finansal oranları ile şirketlerin finansal başarı ve başarısızlık kategorileri lojistik regresyon yöntemi ile analiz edilerek değerlendirilmiştir. Değerlendirme sonucunda işletmelerin finansal başarı durumlarının 1 yıl önceden tahmin gücünün arttığı tespit edilmiştir.

A R T I C L E I N F O

Article history:
Received 10 August 2018
Received in revised form 28 August 2018
Accepted 30 August 2018

Keywords:
Logistic Regression
Finance
Financial Ratios
Financial Failure
BIST

A B S T R A C T

The purpose of this study is to establish a reliable model for predicting the financial failures of the Technology Sector enterprises traded in the BIST 1 year in advance. For this purpose, the previous studies on financial failure and predicting financial failure were examined first, then the concept of financial failure and its reasons were discussed. Then the theory of financial ratios and the use of logistic regression analysis techniques in predicting financial failure are explained theoretically. In the last part, the financial ratios of the companies in the Technology Sector traded in the BIST and the financial success and failure categories of the companies were analyzed and evaluated. As a result of the evaluation, it was determined that the financial success situations of the enterprises increased estimation power 1 year ago.

1. Introduction

The determination of the financial failure, the reasons for its disclosure, and the ways to avoid it have been a subject for a long time. With the impact of globalization and developing technology, commercial boundaries have erased. As a result, companies are dealing with investors, customers and

* Sorumlu yazar/*Corresponding author*.
e-posta: ebulut@firat.edu.tr

http://dx.doi.org/10.18506/anemon.452622

competitors on a global scale. This situation puts businesses into a great uncertainty. In environments where uncertainty is high, predicting financial failure is becoming increasingly complex, and risk prediction becomes more important. Early identification of financial failure and early intervention in this situation can minimize the negative effects of financial failure on both companies and investors.

When investors and lenders make decisions about a company, they analyze the financial statements of the companies with various analysis techniques. In the same way, company owners and managers also have information about the company's current situation by examining their own financial statements and shape their strategic decisions in line with this information in the decision-making process. Financial analysis techniques are generally used in evaluating the financial structures of the companies. For this, financial ratios are calculated. Financial ratios are derived from numerical values in financial statements such as balance sheet, income statement, cash flow statement. These rates provide information about the current state of the business. Financial ratios warn the company against various threats such as bankruptcy, financial failure, comparison of the current situation with the past periods, and other companies.

It is important to recognize the signals beforehand about the possibility of financial failure for many people and institutions such as companies, investors, lenders, insurance companies. Models are supported with certain financial ratios for predicting financial failure have an important place in predicting financial failure. These models provide important and critical information for the companies to take precautions in the financial domain.

The first serious work on the use of financial ratios in measuring financial failure was made by Beaver in 1966. Financial ratios are analyzed using various methods of analysis and the risk of financial failure is determined together with many relevant information about the company. Depending on the developments in technology and statistical techniques, financial failure measurement models are also evolving and diversifying day by day.

The purpose of this study is to establish a reliable model for predicting the financial failures of the Technology Sector enterprises traded in the BIST 1 year in advance. For this purpose, the previous studies on financial failure and predicting financial failure were examined first, then the concept of financial failure and its reasons were discussed. Then the theory of financial ratios and the use of logistic regression analysis techniques in predicting financial failure are explained theoretically. In the last part, the financial ratios of the companies in the Technology Sector traded in the BIST and the financial success and failure categories of the companies were analyzed and evaluated with the IBM SPSS Statistics 22 program.

2. Literature Review

As a result of the massive bankruptcy of the companies in the Great Depression of 1929, some financial tables and the ratios obtained with them helped to predict the financial failure and the first studies in this area were seen in this period. The first study on the prediction of financial failure was a discriminant analysis developed by R. A. Fischer in the 1930s just after the Great Depression (Altman, 1968).

The first studies after that were made about 30 years later. Beaver (1966) identified 30 different financial ratios and applied individual discriminant analysis for each ratio. As a result of the examination of the ratios formed by the 5-year data of the companies, it has been found that the liquidity ratios, the ratios representing the debt solvency, and the profitability ratios can be used in anticipation of the financial failure. However, Beaver's work has been criticized by other researchers for being univariate and for examining only certain rate groups.

Tamari (1966) set up a risk-index model against the likelihood that Beaver's rates would be inadequate to account for failure, and tried to anticipate financial failure by rating businesses according to this index.

Altman (1968) examined the financial statements of 66 different companies between 1946-1965 and identified the five financial ratios to anticipate financial failure. These ratios are determined by working capital / total assets, undistributed profits / total assets, interest and pre-tax profits / total assets, the market value / total liabilities of the business, sales / total assets. With these ratios the Z-Score model has been established and the financial failure has been successful in predicting 95% of the last year and 72% of the last two years.

Meyer and Pifer (1970) established a model of financial failure prediction in their research. According to this model, the dependent variable has been subjected to linear regression analysis to be assigned to one of the financially successful and unsuccessful variables.

In 1972 Daikin compared Altman's Z-Score model with Baevar's single discriminant model and found that Baever's model achieved a higher predictor result in single rate calculations and made some changes on discriminant analysis.

Edmister (1972) examined 594 small-scale companies operating in the United States between 1954 and 1969. Through this model, he made multiple regression estimates with 19 different financial ratios and predicted the success or failure of the companies with an accuracy of over 90%.

In 1977 Moyer found that the model developed by Altman had a weak estimation power, and found that a stepwise discriminant analysis could generate a model with a higher predictive power.

The first study on the financial failure in Turkey was made by Ertuna (1978). In the study, the financial ratios of 195 companies between 1973 and 1975 were examined and it was determined that the variables are not normally distributed in the failure prediction model.

In the United States Ohlson (1980) used logistic regression analysis for the first time. With the model Ohlsson has developed, it has successfully estimated about 96% of the cases before 3 years of bankruptcy.

Göktan (1981) developed a model that predicts financial failure by 93% with 19 financial ratios calculated by examining the financial statements of 39 companies operating between 1976 and 1980.

Hill and Perry (1996) examined companies traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). Accordingly, they found that the liquidity ratios of financially unsuccessful companies were lower than those of financially successful companies. In addition, they found that interest and unemployment rates had an impact on financial failure.

Altaş and Giray (2005) found that the rates that have the greatest impact on the financial failures of publicly traded companies operating in the textile sector in 2001 are the current rate, the acid test ratio, and the cash rate.

İçerli and Akkaya (2006) examined the financial success-failure situation with 10 financial ratios of 80 publicly traded companies traded between 1990 and 2003. They found that financial failure was the result of management errors

Lin (2009) compared the logit, probit, multi-discriminant and artificial neural network analyzes for power estimation using 20 different financial ratios. As a result the logit method has found better estimation.

Çelik (2010) applied artificial neural networks and discriminant analysis methods to estimate the financial failures of 36 private banks. As a result of the research, artificial neural network analysis gave successful results 1 year before the financial failure, whereas discriminant analysis gave successful results 2 year before the financial failure.

Ekşi (2011) used regression trees (CART) and classification models to determine the risk of financial failure with the help of 4 year financial tables of BIST companies. The correct classification rate of the generated CART model is calculated as 88%.

Terzi (2011) reviewed 22 different companies operating in the food sector using 19 financial ratios. As a result of the study, it has been determined that asset profitability ratio and debt-equity ratio are effective when financial success is determined.

Altunöz (2013) used artificial neural network analysis method to estimate the financial failures of 36 private capital banks. As a result of the study, the financial failure rate can be estimated with 88% accuracy 1 year before and 77% accuracy 2 years before.

Ural, Gürarda and Önemli (2015) used logistic regression analysis to determine whether it was possible to predict financial failure 3 years before using publicly traded food, beverage, and tobacco companies' data between 2005-2012. As a result of the study, it was found that financial failure can be estimated as 91% before 1 year, 91% before 2 years, and 74.5% before 3 years.

Selimoğlu and Orhan (2015) used 23 financial ratios to help measure the financial failures of textile, apparel and leather businesses traded in BIST. As a result of the multivariate analysis, it was found that 7 financial ratios showed significant differences among the groups. As a result of discriminant analysis made by using these 7 ratios, it was determined that the model used has a prediction accuracy of 92%.

Yazıcı (2018) compares discriminant analysis, logistic regression and artificial neural network methods to reveal an alternative method for predicting financial failure in SMEs. It has been observed that the separation of good and bad credit has been done more successfully with artificial neural network method.

3. Reasons for Financial Failure

Today, when competition between businesses has reached a high level, companies fail to comply with difficult competition conditions due to internal problems or developing external factors. Companies are aiming to minimize these internal and external factors, although they can not completely prevent it.

According to Weitzel and Jonsson (1989), failure is defined as failure to adapt to the environment of the employer, stagnation, organizational mortality, bankruptcy, collapse, downsizing, termination of business activities, closure, and so on.

It has been stated that there must be at least one of the four possible cases in order to say that an entity has failed financially (Özdemir et al., 2012: 23):

(i) Termination of the company's activities or bankruptcy,
(ii) Exposure of the firm to a statutory practice such as execution or custody,
(iii) The company's spontaneous termination of its activities,
(iv) Negotiation of the debt of the firm with the debt restructuring.

When examined in the literature, it is seen that the criteria used in determining the companies are sometimes considered as financial failure and sometimes as bankruptcy. However, it is also important for the years when the companies to be examined will be selected as well as the companies to be selected. Different selection preferences can give different results under the same conditions (Balcaen and Ooghe, 2006).

Beaver (1966) and Altman (1968), who made the first important studies on financial failure and bankruptcy, used financial statement data and ratio analyzes in their work (Atan and Güneş, 2004). They found that the five ratios set out in these studies were more explicative than the other ratios while detecting failure: the ratio of cash flow to total debt, the ratio of net profit to equity, the ratio of current assets to short-term debt, the ratio of total credits to equity, and the ratio of working capital to equity.

The causes of financial failure in the literature are mainly based on two factors: internal factors and the economic, social, and financial conditions of the country's economy besides the company. Steel (2010) stated that in a survey to determine the reasons for failure in companies, the reasons for failure were determined as follows:

Table 1. Causes of Failure

Causes of Failure	Weights in Failure
Unprecedented Developments in the Economy	%20
Administrative Inefficiencies	%60
Natural disasters	%10
Other	%10

Reference: Steel (2010)

According to the results of this research, it is seen that the main cause of company failures is the inability to manage efficiently due to the managerial inadequacies of the company. After that, it is seen that the economical developments, natural disasters, and other reasons that have been unpredictable in the aftermath.

4. Statistical Methods

Logistic regression, also called logit regression, is a multivariate statistical analysis method that helps predict the dependent variable between two possible options.

Logistic regression requires fewer presuppositions than other methods of analysis. The logistic regression method provides important advantages to the researcher in this respect. The main facilities provided by the assumptions of the logistic regression are given below (Ege and Bayrakdaroğlu, 2009; Özdinç, 1999; İşyar, 1999; Aktaş, 1993)

The underlying assumptions are more realistic than the assumptions of the other models. In this case it gives more realistic results.

Defined for the use of regression analysis and discriminant analysis, the disadvantages of the assumption that the distributions of the main masses are appropriate for the multivariate normal distribution are solved by the logistic regression method. In other words, it does not require the assumption of a multivariate normal distribution, which is an advantage of the logistic regression method.

In the case of assumptions defined for the discriminant model, logistic regression analysis makes more successful estimates. The logistic regression model is an appropriate method to reflect the difference between analysis based on individual observations and analysis based on group data.

In regression analysis, there is a normal distribution of independent variables and a continuous condition of dependent variables. These conditions are not required in the logistic regression. Logistic regression assumes that there are no multiple-link problems between independent variables. In the logistic regression analysis, the equality condition of the variance-covariance matrices is not required.

The logistic regression function assumes that the linear probability function has a cumulative probability distribution of the error term "e". It also assumes that the linear regression model p is in linear relation to the X independent variable. The logit model assumes that the odds ratio (ratio to the likelihood of not having probability of being) is linearly related to X independent variable.

On the other hand, the most important disadvantage of the logistic regression model is the sensitivity to the number of observations. Sometimes the inadequate sample size can cause problems in hypothesis tests related to logistic models (Aktaş, 1993).

The method of logistic regression is based on the concepts of odds and probabilities. Probability is the ratio of the number of results of a given type to the total number of occurrences. In the logistic regression, the probability ratio is defined as the ratio of the likelihood of occurrence of an event being unlikely (Mertler and Vannatta, 2005).

If the probability of occurrence of an event is p, then the probability that this event will not occur is 1-p. Accordingly, the odds ratio is: $p/(1-p)$. This is called odds ratio. For the logistic transformation of the odds ratio, the natural logarithm is taken and expressed as:

$$\mathrm{Ln(Odds)} = \mathrm{Ln}\,(p/(1-p))$$

If the possible x's are assumed to represent independent variables, when the above equation is considered as a correlation function in the generalized linear model frame, the following logit model is obtained:

$$L = \mathrm{Ln}\,(\ ) = \beta 1 + \beta 2X + e$$

In the above form, L is called Logit. Logit or logistic regression model name comes from here (Gujarati, 2001:555).

The model to be constructed using the above formula gives the logistic regression model. The variables for each observation are also replaced by the logistic regression function generated and the logistic regression score for each observation is calculated. For example, when the logistic regression method is used to determine successful and unsuccessful enterprises, the logistic regression score is calculated separately for each business. The calculated logistic regression score is positioned according to the pre-calculated limit value. If the calculated logistic regression score is below the limit value, the company is not successful and if the calculated logistic regression score is above the limit value, the company is classified as successful.

5. Purpose and Scope of the Study

The aim of this study is to investigate whether financial success or failure of companies in Technology Sector traded in Borsa İstanbul A.Ş. (BIST) can be predicted 1 year in advance with financial ratios in the related period by using logistic regression analysis.

The reason for selecting companies listed on the BIST is that they are more transparent and robust than other companies because they are subject to both the Turkish Commercial Code and the Capital Markets Law and under strict supervision by the relevant institutions. For this reason, in the case of a possible success or failure, it will be more quantitatively accountable than if it is attributed to chance. The fact that selected companies are subject to certain legislation will also contribute to the homogeneity of the datas.

The scope of the study constitutes the enterprises that operate in the technology sector in the BIST. Analyzes made within the scope of the research were made with 15 companies operating in the technology sector. The financial ratios of the companies and the indicators of the failure criteria were taken from the official websites of the BIST and Public Disclosure Platform (KAP).

In the analysis of the data, Logistic Regression Analysis technique was used and Microsoft Excel and SPSS 22 package programs were used.

6. Datas and Variables Used in Research

The universe of the study is the technology sector companies operating in the BIST. In this context, the pre-determined financial ratios were calculated by using the balance sheet and income statement data of 15 of the technology sector companies operating in the BIST. At the same time, the financial success of the mentioned companies for 2017 has also been determined. The companies subject to the work and the codes they have processed in BIST are listed below:

Table 2. Firms Subject to Analysis

Row Number	Name of the Company	Company Code in BIST
1	ALCATEL LUCENT TELETAŞ	ALCTL
2	ANEL TELEKOM.	ANELT
3	ARENA BİLGİSAYAR	ARENA
4	ARMADA BİLGİSAYAR	ARMDA
5	ASELSAN	ASELS
6	DATAGATE BİLGİSAYAR	DGATE
7	DESPEC BİLGİSAYAR	DESPC
8	ESCORT TEKNOLOJİ	ESCOM
9	İNDEKS BİLGİSAYAR	INDES
10	KAREL ELEKTRONİK	KAREL
11	KRON TELEKOMÜNİKASYON	KRONT
12	LİNK BİLGİSAYAR	LINK
13	LOGO YAZILIM	LOGO
14	NETAŞ TELEKOM	NETAS
15	PLASTİKKART	PKART

The 29 financial ratios calculated by using the balance sheets and income statements datas of the companies mentioned in Table 2 are listed below:

Table 3. Financial Ratios

X1	Current Ratio
X2	Quick Ratio
X3	Number of Interest Earned (EBIT /Financing Expenditure)
X4	Cash Ratio
X5	Receivable Collection Time (Day)
X6	Stock Retention Time (Day)
X7	Trade Debt Payment Time (Day)
X8	Total Debt / Total Assets
X9	Short Term Financial Debt / Net Sales
X10	(Short Term Financial Debt + Long Term Financial Debt) / Net Sales
X11	Profitability of Equity (Earnings Before Taxes / Equity)
X12	Assets Profitability (EBIT/ Total Assets)
X13	Profitability Leverage (Profitability of Equity / Assets Profitability)
X14	Gross Profit Margin
X15	EBIT Margin
X16	Earnings Before Taxes Margin
X17	Net Profit Margin
X18	Sales Growth
X19	Equity / Total Assets
X20	Short Term Financial Debt /Total Debt
X21	Long Term Financial Debt /Total Debt
X22	Fixed Assets / Equity
X23	Total Debt / Equity
X24	Net Profit / Total Assets
X25	Operating Profit Margin
X26	Stock Turnover Rate
X27	Receivable Turnover Rate
X28	Current Asset Turnover Rate
X29	Fixed Asset Turnover Rate

Other financially unsuccessful criteria have also been included in the analysis, since it is thought that only by looking at bankruptcy as a financial failure criterion would restrict the work. The following criterias were used to classify a company as unsuccessful: If the company discloses the bankruptcy or enters the bankruptcy process, net loss notification at the end of the year, due to financial difficulties, the company is sent to the detention market in BIST, the total debt-to-asset ratio of the company is more than 75%, and the company has fallen into the difficulty of paying its debts.

It is accepted that the company that complies with any of the above criterias is financially unsuccessful.

7. Research Findings

In BIST, logistic regression analysis was applied to predict the financial failures of companies traded in the Technology Sector. Due to the failure criteria listed earlier in the study, the companies were divided into two groups as financially successful and unsuccessful.

$$Y = \begin{cases} 1, \text{ financially successful} \\ 0, \text{ financially unsuccessful} \end{cases}$$

Because of the dependent variable has two categorical values, binary categorical logistic regression analyzes were used in the study.

In the logistic regression analysis used in the study, the confidence interval was taken as 90% and the cut-off point at the assignment to the groups was determined as 0,5. While these values are determined, widespread use in the literature is taken into consideration. (Erdoğan, 2002; Hosmer and Lemeshow, 2000; Albayra, 2006).

In the logistic regression analysis used in the study, forward stepwise variable selection method (Forward Stepwise-LR) was applied. First, the model in which constant value takes place is created. Then, a new variable model was added at each subsequent step to start variable with the largest contribution, and it was looked at whether the model contributed significantly. If it makes a meaningful contribution to the model, it is added; if it does not make a meaningful contribution to the model, it is not added.

While applying the model in the first step, only the constant value added model is considered so that units belonging to a group can be classified correctly, and this group has the highest number of members. Accordingly, in the first step approximately 73.3% of total variables are correctly classified. In this step, only the constant value is added to the model and the search for a new iteration was terminated because the -2logLikelihood statistic showed a decrease below 0.001 in the fourth iteration of this phase. Accordingly, the coefficient of the constant term at the end of the fourth iteration of the first step is 1,012 and -2logLikelihood statistic is 17,397. The relevant values are shown in Table 4:

Table 4. 1st Stage Iteration History

Iteration	-2logLikelihood Statistics	Constant Coefficients
1	17,416	0,933
2	17,397	1,010
3	17,397	1,012
4	17,397	1,012

Only the fixed value is included and the model to be considered as a reference has been created in the improvement of the next model. After this, other independent variables will be included in order to determine which financial ratios are indicative of financial failure one year in advance. Models will be included in the models that make a meaningful contribution, and those that do not make a meaningful contribution to the model will not be included in the model. In the second model, which is formed using forward stepwise variable selection method, it is seen that the independent variable that best explains the financial failure of the companies is Total Debt / Equity represented as x23.

The regression equation containing the constant value and the independent variable of the model obtained as a result of two categories of logistic regression analysis was constructed as:

Yi = 3,218 – 1,305 x23 + e

According to the obtained model, it is seen that the most important financial ration which can be used in predicting financial success is Total Debt / Equity.

While the estimation power of the initial model, which has only constant value, is 77.3%, the classification success of the model estimate based on the year ahead of the current year was realized as 93.3%. In other words, the financial success or failure status of 14 of the 15 technology companies traded in the BIST has been correctly estimated by using the model one year before. While 11 of the 11 successful firms in the financial direction were also correctly estimated, 3 of the 4 firms that were financially unsuccessful were correctly estimated by the model.

Table 5. Correct Forecast Rates

Group	Number of members	Estimated Financially Successful	Estimated Financially Failure	Accurate Forecast Ratio
Financially Successful	11	11	0	%100
Financially Failure	4	1	3	%75
Total	15			%93,3

In addition Cox&Snell R^2 and Nagelkerke R^2 statistics, which show the relationship between dependent variable and independent variables, were also calculated in the study. Accordingly, the Cox&Snell R^2 and Nagelkerke R^2 statistical values for the latest model are 0,326 and 0,475 respectively. In other words, the independent variable included in the model according to the Nagelkerke R^2 statistic value can account for 47,5% of the dependent variable changes.

8. Conclusion

It is very important to anticipate the financial situation of the companies to invest for investors who are reluctant and uncertain. Models used for this purpose help investors and funders to anticipate firm failure and minimize costs associated with company performance by helping businesses to anticipate future situations.

In this study, it was aimed to predict the financial failure of the firm with the logistic regression model by using the annual balance sheet and income tables based on the companies traded in the BIST Technology Sector. With the help of the 29 financial ratios included in the analysis, it was tried to explain what rates or rates could help the financial failure one year in advance.

According to the model aiming to forecast the financial failure 1 year ago, it was seen that the independent variable that best explained the financial failure of the companies was Total Debt / Equity. The correct classification power of the model obtained as a result of logistic regression was determined as 93,3%.

Taking into account the correct classification performance of the model we obtained, it can be said that the estimates of the logistic regression model are a good tool for predicting the financial success or failure of the enterprises. I believe that the model used in this study will be useful for business managers and investors in the decision-making process and for the evaluations they will make.

References

Aktaş, R. (1993). *Endüstri İşletmeleri İçin Mali Başarısızlık Tahmini*. Ankara: Türkiye İş Bankası Kültür Yayınları.

Albayrak, A. S. (2006). *Uygulamalı Çok Değişkenli İstatistik Teknikleri*. Ankara: Asil Yayınları.

Altaş, D., & Giray, S. (2005). Mali Başarısızlığın Çok Değişkenli İstatistiksel Yöntemlerle Belirlenmesi: Tekstil Sektörü Örneği. *Sosyal Bilimler Dergisi*, 5(2), 13-27.

Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 23(4), 589-609.

Altunöz, U. (2013). Bankaların Finansal Başarısızlıklarının Yapay Sinir Ağları Modeli Çerçevesinde Tahmin Edilebilirliği. *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 28(2), 189-217.

Atan, M., & Güneş, B. (2004). İMKB'ye Kote Şirketlerde Bilançoya Dayalı Risk Analizi ve Erken Uyarı Göstergelerinin Araştırılması. In: Dokuz Eylül Üniversitesi 4. İstatistik Günleri Sempozyumu, İzmir-Kuşadası, 19 - 22 May.

Balcaen, S., & Ooghe, H. (2006). 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and Their Related Problems. *The British Accounting Review*, 38, 63-93.

Beaver, W. H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 4, 71-111.

Çelik, M. K. (2010). Bankaların Finansal Başarısızlıklarının Geleneksel ve Yeni Yöntemlerle Öngörüsü. *Celal Bayar Üniversitesi Yönetim ve Ekonomi Dergisi*, 17(2), 129-143.

Deakin, E. B. (1972). A Diskriminant Analysis of Predictors of Business Failure. *Journal of Accounting Ressearch*, 10, 167-179.

Edmister, R. O. (1972). An Empirical Test of Ratio Analysis for Small Business Failure Prediction. *Cambridge University Press*, 7(2), 1477-1493.

Ege, İ., & Bayrakdaroğlu, A. (2009). İMKB Şirketlerinin Hisse Senedi Getiri Başarılarının Lojistik Regresyon Tekniği ile Analizi. *ZKÜ Sosyal Bilimler Dergisi*, 5(10), 139-158.

Ekşi, İ. H. (2011). Classification of Firm Failure with Classification and Regression Trees. *International Research Journal of Finance and Economics*, 76, 113-120.

Erdoğan, B. E. (2002). *Bankaların Mali Performanslarının Lojistik Regresyon ile Analizi ve İleriye Yönelik Tahmin ile Bir Uygulama*. Doktora Tezi. İstanbul: Marmara Üniversitesi.

Ertuna, Ö. İ. (1978). *İmalat Sektörü Özel Kesiminde Mali ve Ekonomik Göstergeler (1973-1975) Bilrapor Sistemi*. İstanbul: Boğaziçi Üniversitesi Yayınları.

Göktan, E. (1981). *Muhasebe Oranları Yardımıyla ve Diskriminant Analiz Tekniği Kullanarak Endüstri İşletmelerinin Mali Başarısızlığının Tahmini Üzerine Amprik Bir Araştırma*. Doçentlik Tezi.

Gujarati, D. N. (2001). *Temel Ekonometri*. İstanbul: Literatür Yayınları.

Hill, N. T., & Perry, S. E. (1996). Evaluating Firms in Financial Distress: An Event History Analysis. *Journal of Applied Business Research*, 12(3), 60-71.

Hosmer, D. W., & Stanley L. (2005). *Applied Logistic Regression*. USA: John &Wiley Sons.

İçerli, M. Y., & Akkaya, G. C. (2006). Finansal Açıdan Başarılı Olan İşletmelerle Başarısız Olan İşletmeler Arasında Finansal Oranlar Yardımıyla Farklılıkların Tespiti. *Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 20(1), 413-421.

İşyar, Y. (1999). *Ekonometrik Modeller*. Bursa: Vigas A.Ş.

Lin, T. H. (2009). A Cross Model Study of Corporate Financial Distress Prediction in Taiwan: Multiple Discriminant Analysis, Logit, Probit and Neural Networks Models. *Neurocomputing*, 72(16), 3507-3516.

Mertler, C. A., & Vannatta, R.l A. (2005). *Advanced and Multivariate Statistical Methods: Practical Application and Interpretation*. Glendale, CA: Pyrczak Publishing.

Meyer, P. A., & Pifer, H. W. (1970). Prediction of Bank Failures. *The Journal of Finance*, 25, 853-868.

Moyer, C. R., McGuigan, J. R., & Kretlow, W. (1992). *Contemporary Financial Management*. New York: West Publishing Company.

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109-131.

Özdemir, F. S., Choi, F. D. S., & Bayazıtlı, E. (2012). Finansal Başarısızlık Tahminleri Yönüyle UFRS ve Bilginin İhtiyaca Uygunluğu. *Mali Çözüm Dergisi*, 112, 17-52.

Özdinç, Ö. (1999). *Derecelendirme Sürecinde Ekonometrik Bir Değerlendirme*. No: 130. Ankara: SPK Yayınları.

Sayılgan, G. (2008). *İşletme Finansmanı*. Ankara: Turhan Kitabevi.

Selimoğlu, S., & Orhan, A. (2015). Finansal Başarısızlığın Oran Analizi ve Diskriminant Analizi Kullanılarak Ölçümlenmesi: BİST'de İşlem Gören Dokuma, Giyim Eşyası ve Deri İşletmeleri Üzerine Bir Araştırma. *Muhasebe ve Finansman Dergisi*, 66, 21-40.

Tamari, M. (1966). Financial Ratios as a Means of Forecasting Bankruptcy. *Management International Review*, 6(4), 15-21.

Terzi, S. (2011). Finansal Rasyolar Yardımıyla Finansal Başarısızlık Tahmini: Gıda Sektöründe Ampirik Bir Araştırma. *Çukurova Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 15(1), 1-18.

Ural, K., Gürarda, Ş., & Önemli, M.B. (2015). Lojistik Regresyon Modeli İle Finansal Başarısızlık Tahminlemesi: Borsa İstanbul'da Faaliyet Gösteren Gıda, İçki Ve Tütün Şirketlerinde Uygulama. *Muhasebe ve Finansman Dergisi*, 67, 85-100.

Weitzel, W., & Jonsson, E. (1989), Dicline in Organizations: A Literature Integration and Extension. *Administarative Science Quarterly*, 34(1), 91-109.

Yazıcı, M. (2018). Kredi Risk Analizlerinde Diskriminant Analizi, Lojistik Regresyon ve Yapay Sinir Ağlarının Karşılaştırılması. *Maliye ve Finans Yazıları*, 109, 91-106.