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A New Bankruptcy Forecast Modelling for Energy Companies

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ABSTRACT

Due to the Covid-19 epidemic, there was a significant increase in company bankruptcies in 2020. In this period, especially the energy sector has been one area where bankruptcies are the most seen. In this context, this study aims to build a model that can predict financially unsuccessful companies that have declared bankruptcy and successful companies operating in the energy sector in the U.S.A. For the study sample, 30 financial ratios of 23 energy companies that declared bankruptcy in the U.S.A. in 2020 and 30 financial ratios of 23 energy companies that were financially successful in the same period were selected. The multiple discriminant analysis (M.D.A.) was chosen to differentiate between the groups. According to the research results, the accuracy rate of the created function was found to be 87.0%. According to the sensitivity and specificity (R.O.C.) results, testing the process's performance to differ between unsuccessful and successful companies was found to be strong.

Keywords: Financial Failure, Bankruptcies, Financial Failure Prediction Models, Multiple Discriminant Analysis, Energy Sector

1. INTRODUCTION

Bankruptcy is defined as the inability of a company to continue its current operations due to high debt obligations (Pongsatat et al., 2004). Generally, bankruptcy is the inability of the company to meet its obligations with the cash flow it derives from its activities. In other words, the firm's net worth is negative. On the one hand, Beaver (1966) pointed out that the company could not pay its debt interests while describing bankruptcy. On the other hand, Altman (1968), Deakin (1972), Ohlson (1980), Zmijevski (1984) used the criterion that bankruptcy is when the company filed for bankruptcy. According to Taffler (1983), bankruptcy is when the creditors apply to the court. In addition, Wu et al. (2010) used the firm's criterion to the court for bankruptcy (Ertan, 2018, p. 184). Bankruptcy is a situation that occurs when the value of the firm's assets is less than the value of its debts (Knox et al., 2009). Because of the lack of a standard definition, Beaver (1966) and Tavlin et al. (1989) defined bankruptcy according to the reason and scope of the research study.

The definition and scope of bankruptcy vary from country to country, depending on applicable laws. For example, when a company in the United States declares bankruptcy, there are two choices under the United States Bankruptcy Code, "Liquidation" found in Chapter 7 and "Reorganization" (or Rehabilitation bankruptcy) clause found in Chapter 11.[1] According to Chapter 7, the life of companies that go into bankruptcy end under the control of an audit firm. Company assets or personal assets of partners are sold so that as much debt as possible can be repaid.[2] According to Chapter 11, the bankrupt company can manage and control its operations. During this period, the company partners can prepare a restructuring plan. Companies whose debt payments are postponed by restructuring can reorganize with a sigh of relief and can pay at least a specific part of their debts (Summers, 1989). If companies cannot reorganize themselves successfully, the "Liquidation" process begins in Chapter 7 (Gu, 2002).

"Recently, the concept of bankruptcy has become one of the critical issues. The economic crisis experienced in 2020 due to the Covid-19 epidemic affected all world economies and disrupted the financial balances of companies. With the epidemic, there has been a tremendous increase in company bankruptcies. The restrictions

[1] Chapter 11, US Code
[2] Responsibilities of the partners of the company against the debts of the company vary according to the share ratio they have in the company and the type of company.

imposed because of the epidemic and the contraction in demand for consumption brought many companies whose incomes and cash flows deteriorated to bankruptcy. The debt repayment capacity of companies has decreased (Mirza et al., 2020). Supports such as tax deferrals, debt moratoriums, cash transfers, government loans, and grants implemented by countries since 2020 have delayed company bankruptcies. However, with the end of state support, companies with a high risk of bankruptcy will be inevitable in the upcoming period. A significant increase is expected in 2022, especially from the number of “zombie companies” whose financial situation deteriorates and debt sustainability problems increase (Hermes, 2021, p. 3).

According to the Global Bankruptcy Index report prepared by one of the world's leading financial service providers, a 15% increase in bankruptcies is expected in 2022 (Hermes, 2021; 3). In addition, according to this report, the U.S.A. (28.6%), China (19.1), and Japan (6.9%) take the largest share in global bankruptcies for 2021. Especially the energy sector in these countries has been one of the areas where the most considerable losses were experienced. In this period, energy companies had to contend with limited energy demand and low prices (Fu & Shen, 2020). The world's largest energy producer companies in the U.S.A. declared their bankruptcy one by one during this period (Reuters, 2020). As is known, the U.S.A. economy is one of the largest economies in the world. In the globalizing world, every move in the US economy affects the rest of the world. Therefore, the U.S.A. economy should be watched carefully for the stability of the world economy.

Financial distress is one of the most critical threats companies face, regardless of their size and activities (Charitou et al., 2004). Van Horne (1998) stated that financial ratio analysis is a popular technique to predict this threat. The author stated that, in most cases, the bankruptcy of a firm could be expected with the help of financial statements or financial ratio analysis. However, the question arises as to which ratios are most important in determining the potential for bankruptcy, what weights should be attached to these selected financial ratios, and how the consequences will be designed objectively (Altman, 1968). To make this analysis, many models in the literature can predict the bankruptcy of companies. Fitzpatrick (1932) and Beaver (1966) were the first researchers in this field to study the bankruptcy prediction model of firms using univariate analysis. Fitzpatrick (1932) found that the financial indicators of companies that went bankrupt before the occurrence of financial distress varied for a long time (Kliestik et al., 2018). Then, Beaver (1966) found that the value of financial ratios is higher in successful firms than in unsuccessful firms. (Berk, 1998, p.470). In the following years, Altman (1968), Springate (1978), Fulmer (1984), Legault et al. (1987), and Zmijewski (1984) are some of the models that are still widely used to measure the financial failure probability of companies. However, the accuracy of the estimation of models using the multiple discriminant analysis (M.D.A.) method decreases significantly when the model is used in another industry, at another date, or in a commercial setting different from the data used to derive the model (Wu et al.., 2010; Grice et al., 2001; Pitrova, 2011; Wieprow et al., 2021).

In this context, this study aims to build a model that can predict successful companies operating in the energy sector and unsuccessful companies in the U.S.A. Another goal of the study is to create a forecasting model against bankruptcies that may occur in the energy sector after the epidemic period and start a guide for researchers by explaining the steps to create this model one by one. The importance of this study lies in the application of the forecast model created to prevent the bankruptcy of companies when the energy sector is struggling with high bankruptcies. The universe of the study includes all companies in the energy sector. The study sample is 23 energy companies that declared bankruptcy in the U.S.A. in 2020 and 23 financially successful in the same period.

As a result of the research, it is expected that the model obtained will correctly classify over 80% of financially unsuccessful and successful companies.

2. LITERATURE REVIEW

Beaver (1966) separately examined the predictive power of 30 financial ratios to predict financial failure up to 5 years before the bankruptcy. According to his research, the author found that the variables that best predict financial failures are Cash Flow / Total Debt, Net Incomes / Total Assets, Total Debt / Total Assets, Working Capital / Total Assets, and Current Ratio. The results of research at single variable models can be useful in predicting the financial failures of companies five years in advance. Beaver's (1966) pioneering work was extended with multivariate modelling by Altman (1968). Altman (1968) developed a multivariate bankruptcy model using the financial ratios of companies one year before the bankruptcy and tested it empirically. In his study, he developed a bankruptcy prediction model by choosing five out of twenty-two financial ratios, using the multiple discriminant analysis (M.D.A.) method for 1945-1965. These five financial ratios included in the model are Working Capital / Total Assets, Retained Profit / Total Assets, Earnings Before Interest and Taxes / Total Assets, Market Value of Equity / Total Liabilities and Sales / Total Assets. With this model, Altman classified companies as successful and unsuccessful with 95% accuracy up to one year before their bankruptcy and 72% until two years ago. These prior empirical results allowed us to assume the following research hypotheses:

H1: *Company bankruptcies can be predicted with financial forecasting models using financial ratios.*

Based on the model developed by Beaver (1966) and Altman (1968), Deakin (1972) tried to combine the high predictive power of the Beaver model with the multivariate approach of the Altman model. In his study, the author tested 32 randomly selected financially successful firms and 32 financially unsuccessful firms between 1964 and 1970. The researcher used Beaver's (1966) grouping tests of financial ratios according to their characteristics and Altman's (1968) multiple discriminant analysis (M.D.A.) method. According to the results of the author's study, the classification performance of companies as successful and unsuccessful for the 3 years before the bankruptcy was quite high (Deakin, 1972: 167-179). Edmister (1972) analyzed 42 small-scale, financially successful, and 42 financially unsuccessful companies in the U.S.A. between 1954-1969. Using the 19 financial ratios of these companies, the author attributed the companies as successful and unsuccessful according to their debt and profitability status. Shirita (1998) examined the financial failure probabilities of Japanese companies using 61 financial variables. The correct classification success of the model developed by the author, who used data mining as a method, was 86%. Atiya (2001) created a financial failure prediction model using 120 financial ratios. The correct estimation rate of the models created by the author for the 3 years, using the artificial neural network method, was between 81% and 86%. Gu (2002) used the multiple discriminant analysis (M.D.A.) model to identify bankrupt restaurants and financially successful restaurants in the U.S.A. As a result of his research, the author found that restaurants with low EBIT and high total debt liabilities are more likely to go bankrupt. The acquisition of the author's model in distinguishing between bankrupt and non-bankrupt companies was 92%. Wong and Ng (2010) built a model with financial ratios and macroeconomic variables to determine companies' probability of financial failure. Using multiple discriminant analysis (M.D.A.) as a method, the authors found that 4 variables were important in determining the risk of financial failure. Yap et al. (2010) tried to develop a model using 16 financial ratios to see the probability of financial failure of companies in Malaysia. The study generated a prediction model with 7 variables, using multiple discriminant analysis (M.D.A.). The correct classification success of the model was between 88% and 94% in the 5-year prediction period. Terzi (2011) tested 22 companies operating in the food industry with the discriminant analysis method to predict financial failure. The author determined 6 financial ratios as important. According to the research results, the success of the correct classification of companies in the model was at the level of 90.9%. Moreover, the author pointed out that ROA and Debt/Equity ratios are important in determining financial failure. Selimoglu et al. (2015) used 23 financial ratios to determine the financial failure probabilities of Borsa Istanbul Companies operating in the textile, clothing and leather industries. The researchers stressed that 7 financial ratios are important in determining financial failures in the study using the discriminant analysis method. The correct classification success of the model built because of the study was 92%. Klieštik et al. (2018) developed a model to reveal the probability of financial failure of firms in Visegrad group countries3 with multiple discriminant analysis methods. According to the research results, researchers conducted that Current Assets / Current Liabilities, Net Income / Total Liabilities / Total Assets, Cash and Cash Equivalents / Total Assets and Return on Equity ratios are important predictors for predicting company bankruptcies. The model developed by the authors has achieved over 80% classification success. Islam (2020) has developed a model to distinguish between financially successful and unsuccessful companies in the U.S.A. The author took some bankrupt and non-bankrupt companies as a data set and also used a second data set to control the model he formed. Wieprow et al. (2021) implied the multiple discriminant analysis (M.D.A.) method and logit models to assess the bankruptcy risks of tourism companies in Poland during the Covid-19 pandemic period. As a result of their research, the authors contributed to measuring enterprises' bankruptcy risk in Poland's tourism sector and evaluated this market's collapse risk with the models they developed. Sfakianakis (2021) tried to define the ratios that play an important role in the financial failures of manufacturing companies traded on the Greek Stock Exchange using the multiple discriminant analysis (M.D.A.) method. In his research, the author investigated 28 companies that went bankrupt and 28 financially successful companies between 2008 and 2015. According to the research results, the author reported that the quick ratio, cash flow interest coverage, and economic value added (E.V.A.) divided by total assets is significant. In addition, the author's model correctly classified successful and unsuccessful companies up to 1 year before bankruptcy at the level of 96.4%. These prior empirical results allowed us to assume the following research hypotheses:

H2: *The accuracy rate of financial forecasting models is over 80%.*

[3] The Visegrad Group is a regional partnership between the countries of the Czech Republic , Slovakia , Poland and Hungary .

3. RESEARCH METHODOLOGY

3.1. Data

The firms operating in the energy sector in the U.S.A. were classified into three sub-sectors: oil & gas producers, energy service & equipment providers, and renewable energy producers. All companies in these three sectors were included in the sample of the study. According to Bloomberg data, 698 companies were active in the energy sector between 01.01.2020 and 31.12.2020 in the U.S.A. According to Chapter 7 and Chapter 11 of the U.S. Federal Bankruptcy Code, 56 energy companies declared bankruptcy in the same period. All the financial data of 23 of these 56 companies that declared bankruptcy under the Chapter 11 could be accessed. 46 American energy companies were selected for the research sample, 23 of which declared bankruptcy (group 1) and 23 financially successful companies (group 2). The number of companies in group (1) and group (2) is arranged to be equal (Altman, 1968, p.593). Group (2) (control group) has been randomly selected among companies actively involved in the energy sector in the U.S.A. in 2019 and have no financial problems. In this study, the financial statements and ratios announced by the companies 1 year before the bankruptcy[4] were used to estimate the classification model as in the studies of Altman (1968), Cho (1994), and Gu et al. (2000).

Table 1. List of Companies Included in the Sample of the Study, Which Filed Bankruptcy in the Energy Sector in the U.S.A. in 2020 (Group 1) and Financially Successful Companies in the Same Period (Group 2)

BANKRUPT FIRMS (Group 1)				NON-BANKRUPT FIRMS (Group 2)	
No	**Company Symbol**	**Company Name**	**Bankruptcy Filing Date[5]**	**Company Symbol**	**Company Name**
1	MDRIQ	Mcdermott Intl Inc.	01/21/2020	X.O.M.	Exxon Mobil Corp.
2	CHKAQ	Chesapeake Energy Corp.	06/28/2020	CVX	Chevron Corp.
3	CRCQQ	California Resources Corp.	07/15/2020	M.P.C.	Marathon Petroleum Corp.
4	OASPQ	Oasis Petroleum Inc.	09/30/2020	V.L.O.	Valero Energy Corp.
5	VALPQ	Valaris Plc	08/19/2020	P.S.X.	Phillips 66
6	9998865D	Whiting Petroleum Corp.	04/01/2020	INT	World Fuel Services Corp.
7	SPNX	Sesi Holdings Inc.	12/07/2020	RUBBISH	ConocoPhillips
8	DNRCQ	Denbury Inc-Pre Bankruptcy	07/30/2020	S.L.B.	Schlumberger Ltd.
9	NEBLQ	Noble Holding Corp. Plc.	07/31/2020	STATUS	Halliburton Co.
10	XOGAQ	Extraction Oil & Gas Inc.	06/14/2020	HFC	Hollyfrontier Corp.
11	R.D.C.	Rowan Companies Plc-A	08/19/2020	E.O.G.	Eog Resources Inc.
12	DOFSQ	Diamond Offshore Drilling	04/26/2020	S.U.N.	Sunoco Lp
13	UPLCQ	Ultra Petroleum Corp.	05/14/2020	G.L.P.	Global Partners Lp
14	UNTCQ	Unit Corp.	05/22/2020	MOSES	Murphy U.S.A. Inc.
15	HCRSQ	Hi-Crush Inc.	07/12/2020	DK	Delek Us Holdings Inc.
16	ROSUQ	Rosehill Resources Inc.	07/26/2020	P.X.D.	Pioneer Natural Resources Co.
17	HOSSQ	Hornbeck Offshore Services	05/19/2020	CVI	Cvr Energy Inc.
18	PESXQ	Pioneer Energy Services Corp.	03/01/2020	T.A.	Travel Centers of America Inc.
19	LONEQ	Lonestar Resources Us I-Cl A	09/30/2020	C.L.R.	Continental Resources Inc/Ok
20	LLEXQ	Lilis Energy Inc.	06/28/2020	M.R.C.	Mrc Global Inc.
21	YUMAQ	Yuma Energy Inc.	04/15/2020	SRLP	Sprague Resources Lp
22	RGSEQ	Real Goods Solar Inc-Class A	03/05/2020	CLMT	Calumet Specialty Products
23	ESESQ	Eco-Stim Energy Solutions In	04/16/2020	ENS	Enersys

Source: own study.

(Altman, 1968; Blum, 1974; Taffler & Tisshaw, 1977; Zmijewski, 1984; Aziz et al., 1988; Rujoub et al., 1995, and Gu, 2002) used the paired sample format shown in Table 1 to construct their bankruptcy prediction models.

After the companies assigned to the sample are determined, the essential issue is the selection of the financial ratios to be used in the analysis. Financial ratios should be the values that best reflect energy companies' economic conditions and performance. Table 2 and Table 3 show that financial ratios are grouped under five main headings in this study. While the first four groups comprise business-specific financial ratios and variables related to corporate governance, the fifth group is assigned from among the financial ratios frequently used in the literature. Beaver (1966) also selected independent variables to predict financial failure based on their popularity in the literature and their predictive success in previous research (Garcia Gallego et al., 2021).

Bellovary (2007) examined 165 bankruptcy prediction models from 1965 to 2006. The author stated that ten financial ratios are crucial among the 752 factors used in these studies. These financial ratios; Net incomes / Total Assets, Current Ratio, Working Capital / Total Assets, Retained Profits / Total Assets, EBITDA / Total Assets,

[4] 2019 financial statements and ratios
[5] Companies that declare bankruptcy according to Chapter 11

Sales / Total Assets, Acid Test Ratio, Total Liabilities / Total Assets, Current Assets / Total Assets, Net Incomes / Net Worth6 (Monica-Violeta et al., 2012, p. 133).

The financial ratio groups frequently used in literature research and the names of the researchers who use these ratios in their studies are given below (Monica-Violeta et al., 2012, p.133).

- ✓ Liquidity Ratios: Lennox 1999; Zavgren et Dugan, 1989; Low et al., 2001; Zulkarnain, 200; Ivoniciu, 1998; Bailesteanu, 1998; Anghel, 2002.
- ✓ Financial Structure Ratios: Beaver, 1966; Deakin, 1972; Ohlson, 1980; Zmijewski, 1984; Zavgren et al., 1989; Mohamed, 2001; Anghel, 2002; Lykke et al., 2004; Abdullah; 2008.
- ✓ Activity Turnover Rates: Ohlson, 1980; Lennox, 1999; Shumway, 2001; Lykke et al., 2004.
- ✓ Profitability Ratios: Beaver, 1966; Deakin, 1972; Libby, 1975; Ohlson, 1980; Lennox, 1999; Abdullah, 2008; Zulkarnain, 2001; Lykke et al., 2004; Siminica, 2005.
- ✓ Ratios Frequently Used in Bankruptcy Models in the Literature: Altman, 1968; Springate, 1978; Ohlson, 1980; Grover, 2001; Fulmer, 1984; Zmijewski, 1984; Ohlson, 1980.

Table 2. Financial Ratios Selected for the Sample of Study I

Code[7]	**Financial Ratios**	**Formula**	**Sources**
	Liquidity Ratios		
X1	Current Ratio	Current Assets / Current Liabilities	Bloomberg
X2	Quick Ratio	(Current Assets - Inventories) / Current Liabilities	Bloomberg
X3	Cash Ratio	Cash and Equivalents / Current Liabilities	Bloomberg
	Financial Structure Ratios		
X4	Debt to Equity Ratio	Total Liabilities / Total Shareholders' Equity	Bloomberg
X5	The Current to Total Liabilities Ratio	Current Liabilities / Total Liabilities	Bloomberg
X6	Equity to Fixed Assets Ratio	Equity / Fixed Assets	Bloomberg
X7	EBIT to Interest Expense Ratio	EBIT / Interest Expenses	Bloomberg
	Operating Turnover Rates		
X8	Accounts Receivables Turnover Ratio	Net Annual Credit Sales / Average Accounts Receivables	Bloomberg
X9	Average Collection Period[8]	360/(Net Annual Credit Sales / Average Accounts Receivables)	Bloomberg
X10	Inventory Turnover Rate	Cost of Goods Sold/ Average Inventory	Bloomberg
X11	Days Sales of Inventory (DSI)	360/(Cost of Goods Sold/ Average Inventory)	Bloomberg
X12	Account Payable Turnover Ratio	Total purchases[9] / Average accounts payable	Bloomberg
X13	Asset Turnover Rate	Net Sales / Average Total Assets	Bloomberg
X14	Equity Turnover Rate	Net Sales / Average Shareholders' Equity	Bloomberg
X15	Fixed Asset Turnover Ratio	Net Sales / (Gross fixed assets - Accumulated depreciation)	Bloomberg
X16	Current Asset Turnover	Net Sales / *Average Current Assets*	Bloomberg
X17	Average Duration of Activity	(360/Accounts Receivables Turnover Ratio) + (360/(Inventory Turnover Rate)	Bloomberg
	Profitability Ratios		
X18	Gross Margin	Gross Profit / Net Sales	Bloomberg
X19	Operating Profit Margin	Operating Profit / Net Sales	Bloomberg
X20	Net Profit Margin	Net Profit / Net Sales	Bloomberg
X21	Return On Equity (ROE)	Net Profit / Equity	Bloomberg
X22	Return of Assets (ROA)	Net Profit / Total Assets	Bloomberg
X23	EBIT/Total Assets	EBIT/ Total Assets	Bloomberg

Source: (Selimoğlu et al., 2015, p. 29-30).

[6] Net Worth = Assets-Liabilities
[7] In the next stages of the study, the financial ratios will be expressed with the short codes shown in Table 2 so that the reader can easily follow them.
[8] Receivable turnover in days
[9] Total Purchases = Cost of sales + Ending inventory – Starting inventory

Table 3. Financial Ratios Selected for the Sample of Study II

	Reference Model	In The Model Coeff.	Formula	Sources
	Ratios Commonly Used in Bankruptcy Models in the Literature			
X24	Altman Model (1968) Springate Model (1978) Fulmer Model (1984) Ohlson Model (1980) Grover Model (2001)	*Z1* *S1* *F8* *O3* *G1*	Working Capital / Total Assets	Bloomberg
X25	Springate Model (1978)	*S3*	EBT / Current Liabilities	
X26	Fulmer Model (1984)	*F3*	EBT / Equity	Bloomberg
X27	Altman Model (1968)	*Z4*	Market Value of Equity / Total Liabilities	Bloomberg
X28	Ohlson Model (1980)	*O6*	Cash flows from operation / Total Liabilities	Bloomberg
X29	Altman Model (1968) Fulmer Model (1984)	*Z2* *F1*	Retained Earnings/ Total Assets	Bloomberg
X30	Fulmer Model (1984)	*F5*	Total Liabilities / Total Assets	Bloomberg

Source: own study.

In this study, the financial ratios in Table 3 were selected from among the ratios commonly used in the literature. The coefficient column shows the coefficient number of the variable in the reference model.

3.2. Empirical Approach

The multiple discriminant analysis (M.D.A.) estimates group memberships in the sample based on a group of variables (Tabachnick & Fidell, 2001). M.D.A. is a statistical method that reveals a significant difference between two or more groups. Back et al. (1996) defined discriminant analysis as the linear combination of two or more independent variables that can best separate two or more predetermined groups. Discriminant analysis is a successful technique that can classify and predict the dependent variable as male-female, sick-non-sick, or using a specific product versus never using it. Discriminant analysis is a method frequently used by researchers in classifying financially successful and unsuccessful companies (Beaver, 1966; Altman, 1968; Gentry et al., 1987; Aly et al., 1992; Sori et al., 2009; Wong et al., 2010).

The discriminant analysis is achieved by maximizing the variance between the groups, with the variance of each group included in the analysis. This relationship is given by the Fisher criterion function and is expressed as in equation (1) (Mihalovič, 2016, p. 105).

$$J(w) = \frac{w^T(\sum_i (x_i - \mu)^T (x_i - \mu))w}{w^T \sum_c \sum_{i\varepsilon c} (x_i - \mu)^T (x_i - \mu_c))w'} \quad (1)$$

(w) the value represents the projection matrix that maximizes the ratio of the values that determine the group variance to the values that determine the within-group variances. x_i, indicates the values of the data included in the sample. μ, indicates the average of the data included in the model. w^T=transpose indicates the value of the projection matrix. μ_c, shows the group average for class c (Mihalovič, 2016, p.105).

$$Z_i = a_1 + a_1 x_{i1} + a_2 x_{i2} + a_3 x_{i3} + \cdots + a_n x_{in} \quad (2)$$

Z_i in equation (2) shows the discriminant value for i. the company. $a_n$values indicate coefficients (load values) of the discriminant analysis equation. $x_{i1}, x_{i2} \ldots . x_{in}$values i. is the company's n number of independent variables.

After data is collected, the discriminant analysis attempts to construct a linear combination equal that best discriminates between groups. If the financial ratios included in the sample have a measurable level of significance for all companies examined, a coefficient is assigned to this variable in the discriminant analysis formula. These coefficients take different values (loads) according to the importance of the independent variables (financial ratios) in determining which group the company is in.

It should be noted that the M.D.A. model has some assumptions in its application (Altman and Narayanan, 1997).

1. The data should have a normal distribution. (Dietrich et al., 1984; Ballard et al., 1988).
2. There shouldn't be a multicollinearity problem between the variables (Mihalovič, 2016, p. 105).
3. The covariance matrices should be equal (Wieprow et al., 2021; Ohloson, 1980: 112).

Dimitras et al. (1996) stated that if the variables classified in the discriminant analysis do not fit the normal distribution, which can create contradictions or poor model predictions. The discriminant analysis assumes that the financial ratios are generally distributed. The variance-covariance structures of successful and bankrupt firms are equivalent. But both of these assumptions are rarely seen (Ezzamel et al., 1987). However, performing logarithmic transformations of the data is a widely used method in the literature to improve the normality of the variables.

Altman et al. (1977), Karels and Prakash (1987) applied the logarithmic transformation method to get multivariate normality while developing M.D.A. bankruptcy prediction models. However, zero or negative values of financial ratios make logarithmic calculations impossible. However, this problem can be solved if a constant value larger than the absolute value of the smallest value among the values included in the sample is added to the values in the entire data set (Zhang, 2011).

$$x'_{ij} = x_{ij} + A \qquad (3)$$

x_{ij} represents the original data and x'_{ij} represents the standard value after conversion. “A” value represents the constant term. The equation must be like x'_{ij}>0 and A >Ι (min (x_{ij})Ι. The closer the value referred to for the A value is to the Ι (min (x_{ij})Ιvalue, the more statistically significant results can be obtained (Zhang, 2011, p. 3). The smallest value obtained from financial ratios is minxij= (-38.89) in this study. Therefore, by adding the constant value A = (+39) to all the values in the study. Thus, appropriate transformation is provided for logarithmic calculations.

4. RESULTS AND DISCUSSION

4.1. Normality Test Results

Kurtosis and Skewness values were used to test the normality of the distribution of the independent variables (financial ratios).

Table 4. Skewness and Kurtosis Values

Fin. Ratios	N	Minimum	Maximum	Mean	Skewness	Kurtosis
X1	46	1.59	1.62	1.6045	.638	-.298
X2	46	1.59	1.62	1.6014	1.292	1.589
X5	46	1.59	1.60	1.5950	1.179	.232
X9	46	1.60	2.16	1.8925	-.183	-.543
X10	46	1.63	3.22	1.9667	1.624	1.316
X11	46	1.59	2.11	1.7752	.584	-.325
X17	46	1.64	2.28	2.0002	-.241	-.313
X27	46	1.59	1.64	1.6076	1.275	1.689
X30	46	1.60	1.61	1.5984	1.027	1.180

**P<0.05*

Source: own study.

If the skewness and kurtosis values are in the range of ±2, the distribution can be interpreted as a normal distribution (Demir et al., 2016). In this context, the variables X1, X2, X5, X9, X10, X11, X17, X27, and X30 have been chosen because they are typically distributed. The remaining variables were excluded from the sample because they did not fit the normal distribution.

4.2. T-Test Significance Results

With the independent sample t-test, the differences in the mean of the groups in the sample are tested. This test measures whether variable changes between different groups. Whether the financial ratios in this study change in bankrupt or non-bankrupt companies was also measured with the help of this test.

Table 5. Descriptive Data

Independent Variables		N	Average	Standard Deflection	Standard Error
X1	Bankrupt Firms	23	1.60	.0099	.0021
	Non-Bankrupt Firms	23	1.61	.0060	.0012
X2	Bankrupt Firms	23	1.60	.0088	.0018
	Non-Bankrupt Firms	23	1.60	.0047	.0010
X5	Bankrupt Firms	23	1.60	.0037	.0008
	Non-Bankrupt Firms	23	1.59	.0017	.0003
X9	Bankrupt Firms	23	1.94	.1608	.0335
	Non-Bankrupt Firms	23	1.84	.1225	.0256
X10	Bankrupt Firms	23	2.19	.5301	.1105
	Non-Bankrupt Firms	23	1.75	.1001	.0209
X11	Bankrupt Firms	23	1.71	.1253	.0261
	Non-Bankrupt Firms	23	1.84	.1327	.0277
X17	Bankrupt Firms	23	2.01	.1604	.0334
	Non-Bankrupt Firms	23	1.99	.1624	.0339
X27	Bankrupt Firms	23	1.60	.0037	.0008
	Non-Bankrupt Firms	23	1.61	.0096	.0020

X30 Bankrupt Firms	23	1.60	.0031	.0007
Non-Bankrupt Firms	23	1.60	.0020	.0004

Source: own study.

Table 5 shows data descriptions, such as the number of participants, mean, standard deviation, and standard error of the research data.

Table 6. Independent Sample Test Results

Variables	**T statistic**	***P-Value***
X1	-2.280	.027*
X2	-.608	.547
X5	.620	.540
X9	2.376	.022*
X10	3.917	.001*
X11	-3.352	.002*
X17	.240	.811
X27	-4.976	.000*
X30	1.358	.181

Notes: * *P<0.05*
Source: own study.

T-test statistics and corresponding P-values are presented in Table 6. P values show the significance levels of the two-tailed t-tests. The t-test shows that the independent variables X1, X9, X10, X11 and X27 differ significantly at least at the 0.05 level in bankrupt and non-bankrupt companies. The variables X2, X5, X17 and X30 that did not meet this condition were excluded from the sample.

4.3. Multiple Linear Connection Problem Tests

Table 7. Correlation Matrix of Variables

	Y	**X1**	**X9**	**X10**	**X11**	**X27**
Y	1	.325	-.337	-.508	.451	.600
X1	.325	1	.120	-.258	.465**	.151
X9	-.337	.120	1	.180	.113	.012
X10	-.508	-.258	.180	1	-.739**	-.327
X11	.451	.465**	.113	-.739	1	.364*
X27	.600	.151	.012	-.327*	.364*	1

Notes: * *P<.01, **P<.05 (two-tailed test).*
Source: own study.

In Table 7, statistically positive and negative correlations were found between the variables at p=.000, p<.05, and p<.01 levels.

The correlation between the variables is not higher than .80 is a sign that the independent variables may be suitable for discriminant analysis (Büyüköztürk, 2006). However, if the Variance Inflation Factor (V.I.F.) is less than 10, it is a sign that there is no multicollinearity problem for the variables (Büyüköztürk, 2017).

Table 8. Tolerance and V.I.F. Values of the Independent Variables

Variables	Multiple Linear Correlation Statistics	
	Tolerance	**VIF**
X1	.767	1.305
X9	.833	1.200
X10	.374	2.672
X11	.322	3.107
X27	.860	1.163

Source: own study.

Looking at the V.I.F. values in Table 8, it is seen that the highest V.I.F. value is 2.672. This shows that there is no multicollinearity problem in the equation.

4.4. Results of Covariance Tests

F distribution is used in the “Box M” test, which tests the equal covariance assumption.

Table 9. Box's Test of Equality of Covariance Matrices

	Box's M	3.059
F	Approximately	2.992
	df1	1
	df2	5808.00
	Sig.	.084

Source: own study.

The Box M test is performed to test the assumption that the covariance matrix must be equal[10]. The X17 value was excluded from the sample because it distorted the covariance matrix. According to the test results, covariance matrices can be interpreted as equal since p = 0.319 and p > 0.05.

4.5. Multiple Discrimination Analysis (M.D.A.) Results

After the assumptions of the discriminant analysis were met, the testing phase was started. For this, tests were made to see the eigenvalue, Wilks' Lambda value, canonical correlation and coefficients. Many discriminant analyzes were applied with the financial ratios X1, X9, X10, X11, X27, and the most successful classification ratio was tried to be achieved.

Table 10. Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.259	100.0	100.0	.747

Source:own study.

The eigenvalue shows the explanatory power of functions in all variables in Table 10. The square of the canonical correlation shows the variance explained. In this study, the explained variance was measured as 0.558 ((0.747) 2 =55.8%). The variance (%) value shows how much of the total explained variance is explained by the first function. The discriminant function in this study alone explains 100% of the total variance. It is stated in the literature that the eigenvalue should be higher than 0.40. In this study, the eigenvalue was high (1.259).

Table 11. Wilks' Lambda

Wilks' Lambda	Chi-Square	Sig.
.443	**34.637**	**.000**

Source: own study.

Wilks' Lambda value, shown in Table 11, shows the unexplained variance. This value comprises numbers between "0" and "1". If the value is close to "0" shows that the group means differ, while the value is close to "1" shows that the group means are the same. A low Wilks Lamda value, significance level and a large Chi-Square value show that the discrimination analysis model has an effective discriminating power (Yap et al., 2010: 170). As seen in Table 11, our function distinguishes the groups from each other significantly (p=.000; p<.05).

The standardized canonical discriminant function coefficients table is used to determine which variable has a greater effect on the formation of the function.

Table 12. Standardized Canonical Discriminant Function Coefficients

Financial Ratios	Function
	1
X1	.545
X9	-.717
X27	.904

Source: own study.

The load value of each variable in the function presented in Table 12 is shown. Accordingly, variable X27 has a load value of .904, variable X9 has a load value of -.717 and variable X1 has a load value of .545.

Table 13. Structure Matrix

Financial Ratios	Function
	1
X27	.669
X9	-.319
X1	.306

Source: own study.

Table 13 shows the correlation with the discrimination function of the independent variables.

[10] In this study, Box's Test results were significant (p<.05). In other words, since the variance-covariance matrices between the groups were not equal to each other, the covariance matrices were made according to the separate group option, and the data got from these results are presented in the table.

Table 14. Prior Probabilities for Groups

Dependent Variables	Prior	Cases Used in Analysis		
		Unweighted	Weighted	= 1.25 *(Before *Unweighted)
1	.50	23	23	14.38
2	.50	23	23	14.38
Total	1.00	46	46	

Source: own study.

Table 14 gives the minimum number of variables that need to be grouped correctly to show that the function generated as a result of the discriminant analysis was not designed by chance. This number is determined by multiplying the prior value with the unweighted value and adding the 25% margin of error in the light of the studies in the literature. If, by chance, companies were placed in the first or second group in this study, up to 15 companies could be placed at random. Therefore, the developed function should place at least 15 companies in the correct group so that a guess is not made by chance. As seen in Table 15, this study was able to classify at least 19 companies as successful, even at the lowest rate. Therefore, it can be said that the results obtained with the developed function are not coincidental.

Table 15. Classification Results

			Predicted Group Membership		Total
			Bankrupt	Non-Bankrupt	
Original	**Amount**	**Bankrupt**	21	2	23
		Non-bankrupt	4	19	23
	Per cent (%)	**Bankrupt**	91.3	8.7	100.0
		Non-Bankrupt	17.4	82.6	100.0

Notes: * 87.0% of original grouped cases were correctly classified.
Source: own study.

As seen in Table 15, the function developed because of the discriminant analysis has classified 21 of 23 bankrupt companies correctly (as bankrupted), while 2 of them are classified incorrectly (as non-bankrupted). The acquisition rate of the function in this group was 91.3%. The other function classified 19 of 23 successful companies as correct (non-bankrupt) while 4 of them were classified as wrong (bankrupt). The acquisition rate of the function in this group was 82.6%. The average overall acquisition rate of the function for both groups was calculated as 87.0%. The results supported the first and the second hypothesis that "company bankruptcies can be predicted with financial forecasting models using financial ratios" and "the accuracy rate of financial forecasting models is over 80%". Moreover, bankruptcy models show successful results in predicting the bankruptcy of firms and can classify firms with reasonable accuracy ranging from 70% to 88% (Islam, 2020). In this sense, the 87.0% accuracy rate of the function developed because of this analysis is a reasonable figure.

$$\boldsymbol{Z_i} = .306 * \boldsymbol{X_1} - .319 * \boldsymbol{X_9} + .669 * \boldsymbol{X_{27}} \qquad (4)$$

(Standardized coefficient) (.545) (−.717) (.904)

In Equation (4), the final form of the function created as a result of the discriminant analysis is given. The signs of the coefficients are in line with expectations and line with economic logic (Çolak; 2020). When the standardized coefficients are examined, the main determinants of a firm's financial distress or overall financial strength are found to be the firm's current ratio, average collection period ratio and market value of equity / total liabilities.

X1: Current Ratio (Current Assets / Current Liabilities):

The current ratio shows the ability of all current assets to meet current liabilities. This ratio is used to measure the company's power to pay its current liabilities and determine whether the networking capital is sufficient (Sümer et al., 2013). In the studies in the literature, it is accepted that the current ratio should be "2" and should not be below "1" (Akgüç, 2010). In this study, the ability to exist assets to meet current liabilities is expected to be positive and high in successful companies.

X9: Avr. Collection Period Ratio (360 / (Net Annual Credit Sales / Average Acc. Receivables)):

The average collection period ratio shows how many days a firm collects its account receivables on average. The increase in credit sales and the problems in collecting their receivables arising from credit sales may cause companies to encounter financial difficulties. If businesses that cannot collect their receivables do not have sufficient cash assets, they may not pay their debts on time (Dayı, 2019: 468).

Extending the amount and maturity of receivables may also cause companies to have cash problems in the future (Demireli, 2004: 1). The prolongation of the average collection period may be one reason that can cause companies to experience financial failure.

X27: (Market Value of Equity / Total Liabilities):

This ratio shows how much the market value of the capital stock can drop before the firm's assets exceed total liabilities and the firm goes bankrupt. According to Altman (1968), this ratio is interpreted as a more effective predictor of bankruptcy than other commonly used financial ratios (Altman, 1968: 595).

4.6. Sensitivity, Specificity Test and Cut-off Value (R.O.C. Curve Analysis)

The function's classification accuracy performance from the discriminant analysis was tested with sensitivity and specificity tests (R.O.C.). A sensitivity test evaluates the probability of a test predicting a financially unsuccessful company (which is about to go bankrupt) as unsuccessful. The specificity test measures the likelihood of distinguishing an unsuccessful company from a successful one.

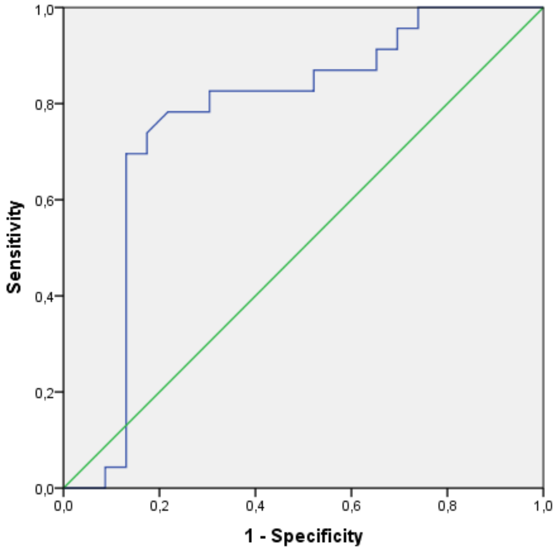

Figure 1. R.O.C. Curve
Source: own study.

The evaluation results made using the R.O.C. curve analysis are given in Figure 1. The green and the solid line indicate the reference line. A higher sensitivity value for a given specificity value indicates the higher performance of the function. The area under the R.O.C. curve (A.U.C.) is a widely used measure to evaluate the performance of the classifier (function) (Li et al., 2017, p. 792).

Table 16. Area Under the Curve (A.U.C.)

Area	Standard Error [a]	Asymptotic Sig. [b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.768	.077	.002	.618	.919

a Under the nonparametric assumption
b Null hypothesis: true area= .5
Source: own study.

According to the analysis results, the A.U.C. (Area Under the Curve) value was .768. In addition, the test results state that our developed function is usable because the p-value is $p<.05$. This figure out that the function's probability of detecting bankrupt and non-bankrupt companies is vital.

The coordinate curve in Table 17 is used to define the cut-off point of the function.

Table 17. Coordinates of the Curve

Positive If Less than or Equal to [a]	Sensitivity	(1-Specificity)	Likelihood Ratio (L.R.)
.92850	.826	.478	1.73
.93550	.826	.435	1.90
.94800	.826	.348	2.38
.95550	.826	.304	2.71
.95800	.783	.304	2.57
.95950	.783	.261	3.00
.97100	.783	.217	3.60
.98250	.739	.174	4.25
.98900	.696	.174	4.00
.99650	**.696**	**.130**	**5.33**
.99900	.652	.130	5.00
1.00250	.565	.130	4.33
1.00850	.522	.130	4.00
1.01250	.478	.130	3.67

Source: own study.

According to the data in Table 17, the highest likelihood ratio (L.R.) was calculated as 5.33. An L.R. (Likelyhood Ratio) of 5 indicates a moderate test, and a 10 or higher indicates an excellent test. This means that the function developed as a result of the research can be used alone to detect financial success and failure. In addition, the cut-off point of the function is (.9965), with a sensitivity of 69.6% and a specificity of 87%.

5. CONCLUSION

The economic crisis experienced in 2020 because of the Covid-19 epidemic affected all economies in the world and disrupted companies' financial balance. In this period, there was a great increase in company bankruptcies. The concept of bankruptcy has once again become one of the popular topic for both investors and researchers.

This study aims to create a model that can predict financially bankrupt and non-bankrupt firms operating in the energy sector. In addition, the study aims to develop a forecasting model against bankruptcies that may occur in the energy sector after the epidemic period and provide a guide for researchers by explaining the steps to develop this model one by one. The study sample comprises 23 energy companies that declared bankruptcy between 01.01.2020 and 31.12.2020 in the energy sector in the U.S.A., and 23 energy companies (control group) that were financially successful on the same dates and in the same sector. In this study, multiple discriminant analysis (M.D.A.) was used as a method to distinguish between bankrupt and non-bankrupt companies. As the result of the analysis, the following function has been developed to predict the bankruptcy of companies in the energy sector.

$$\mathbf{Z_i} = .306 * \mathbf{X_1} - .319 * \mathbf{X_9} + .669 * \mathbf{X_{27}}$$

(Standardized coefficient) (.545) (−.717) (.904) (4)

X1: Current Assets / Current Liabilities

X9: 360 / (Net Annual Credit Sales / Average Accounts Receivables)

X27: Market Value of Equity / Total Liabilities

The accuracy rates of the financial failure of similar studies in the literature are following; Altman (1968) 98%, Springate (1978) 92.5%, Ohlson (1980) 87.6%, Fulmer (1984) 91%, Zmijewski (1984) 99%. The accuracy rate of the function developed in this study was calculated as 87.0%. In this sense, the accuracy rate achieved is at an acceptable level. Likewise, the results of the sensitivity and specificity test (R.O.C.) applied to assess the performance of the function also found the performance of the function to be strong in identifying unsuccessful and successful companies. According to the other results of the R.O.C. analysis, the cut-off point of the function was found to be (.9965). Suppose the scores of energy companies, calculated according to the result of the function (equation 3) developed because of the research, are below the value (.9965). In that case, it can be said that the probability of financial failure is high. *The Market Value of Equity / Total Liabilities, 360 / (Net Annual Credit Sales / Average Accounts Receivables*) and *Current Assets / Current Liabilities* are seen as critical financial ratios to predict the bankruptcy of companies in the energy sector in the U.S.A. These financial ratios provide useful information about the financial status of companies operating in the energy sector.

For future studies, using the financial ratios used in this study, methods with strong accuracy classification capacity, such as artificial neural networks (ANN), can also be tried to determine companies' financial failures. The accuracy rate of discriminant analysis and artificial neural networks can be compared.

REFERENCES

1. Akgüç, Ö. (2010). *Mali Tablolar Analizi*. Istanbul: Avcıol Publishing.
2. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609. https://doi.org/10.2307/2978933.
3. Altman, E.I., & Narayanan, P. (1997). An International Survey of Business Failure Classification Models. *Financial Markets, Institutions & Instruments*, 6(2), 1-57.
4. Altman, E.I., Haldeman, R.G., & Narayanan, P. (1977). Zetatm analysis A new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance*, 1(1), 29-54. https://doi.org/10.1016/0378-4266(77)90017-6.
5. Aly, I.M., Barlow, H.A., & Jones, R.W. (1992). The Usefulness of SFAS No. 82 (Current Cost) Information in Discriminating Business Failure: An Empirical Study. *Journal of Accounting, Auditing & Finance*, 7(2), 217–229. https://doi.org/10.1177/0148558X9200700209
6. Atiya, A.F., (2001). Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results, IEEE Transactions on Neural Networks, 12 (4): 929-935. (Accessed: 16.09.2014).
7. Aziz, A., Emanuel, D.C. and Lawson, G.H. (1988). Bankruptcy prediction – an investigation of cash flow-based models. *Journal of Management Studies*, 25(5), 419-37. https://doi.org/10.1111/j.1467-6486.1988.tb00708.x
8. Back, B., Laitinen T., Sere K. (1996). Neural networks and genetic algorithms for bankruptcy predictions. *Expert Systems with Applications*, 11(4), 407-413. https://doi.org/10.1016/S0957-4174(96)00055-3
9. Ballard, D.J., Strogatz, D.S., Wagner, E.H., Siscovick, D.S., James, S.A., Kleinbaum, D.G. & Ibrahim, M.A. (1988). Hypertension control in a rural southern community: medical care process and dropping out. *American Journal of Preventive Medicine*, 4 (3), 133-139.
10. Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71-111. https://doi.org/10.2307/2490171
11. Bellovary, J., Giacomino, D. & Akers, M. (2006). A review of bankruptcy prediction studies: 1930 to present. *Accounting Faculty Research and Publications*, 33.
12. Berk, N. (1998). *Finansal Yönetim*. İstanbul: Türkmen Kitabevi.
13. Blum, M. (1974). Failing Company Discriminant Analysis. *Journal of Accounting Research*, 12(1), 1-25. https://doi.org/10.2307/2490525
14. *Büyüköztürk, Ş. (2006). Sosyal bilimler için veri analizi elkitabı*. Ankara: PegemA Yay.
15. Büyüköztürk, Ş. (2017). *Sosyal bilimler için veri analizi el kitabı: istatistik, araştırma deseni, SPSS uygulamaları ve yorum.* Ankara: Pegem Akademi
16. Charitou, A., Neophytou, E. & Charalambous, C. (2004). Predicting Corporate Failure: Empirical Evidence for the U.K., *European Accounting Review*, 13(3), 465-497. https://doi.org/10.1080/0963818042000216811
17. Cho, M. (1994). Predicting business failure in the hospitality industry: An application of logit model (PhD Thesis), Polytechnic Institute and State University, Virginia.
18. Çolak, M. S. (2020). A new multivariate approach for assessing corporate financial risk using balance sheets, Borsa Istanbul Review, 21(3), 239-255. https://doi.org/10.1016/j.bir.2020.10.007.
19. Dayı, F. (2019). Vadesi Geçen Ticari Alacakların Net Kâra Etkisinin İncelenmesi: Borsa İstanbul'da Bir Uygulama. *Nevşehir Hacı Bektaş Veli Üniversitesi SBE Dergisi*, 9(2), 467-486.
20. Deakin, E. (1972) A discriminant analysis of predictors of business failure. Journal of Accounting Research, 10, 167-179. https://doi.org/10.2307/2490225.
21. Demir, E., Saatcioğlu, Ö. & İmrol, F. (2016). Uluslararası dergilerde yayımlanan eğitim araştırmalarının normallik varsayımları açısından incelenmesi, *Current Research in Education*, 2(3), 130 148.
22. Demireli, E. (2004). Alacak yönetiminde finans tekniği olarak faktöring yöntemi ve uygulaması, Yayımlanmamış Yüksek Lisans Tezi, Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü, İzmir.

23. Dietrich, Jk, & Sorensen, E. (1984). An application of logit analysis to prediction of merger targets. *Journal of Business Research*, 12 (3), 393-402. https://doi.org/10.1016/0148-2963(84)90020-

24. Dimitras, Ai, Zanakis, Sh, & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Researc*h, 90 (3), 487-513. https://doi.org/10.1016/0377-2217(95)00070-4

25. Dugan, M.T., Christine V. Zavgren. (1989, May). How a bankruptcy model could be incorporated as an analytical procedure. *The C.P.A. Journal*, 59(5), 64-65.

26. Edmister, R. (1972). An empirical test of financial ratio analysis for small business failure prediction, *Journal of Financial and Quantitative Analysis*. https://doi.org/10.2307/2329929.

27. Ertan, A. S. & Ersan, Ö. (2019). Finansal başarısızlığı belirleyen etkenler: Türkiye imalat sektörü örneği. *Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 40(2), 181-207.

28. Ezzamel, M., Cecilio Mm, & Alistair B., (1987). On the distributional properties of financial ratios. *Journal of Business Finance and Accounting*, 14, 463–81. https://doi.org/10.1111/j.1468-5957.1987.tb00107.x

29. Fitzpatrick, P.J. (1932). A comparison of ratios of successful industrial enterprises with those of failed firm. *Certified Public Accountant*, 6, 727-731.

30. Fu, M., & Shen, H. (2020). Covid-19 and corporate performance in the energy industry. *Energy Research Letters,* 1 (1). https://doi.org/10.46557/001c.12967.

31. Fulmer, J.G., Moon, J.E., Gavin, T.A.& Erwin, M.J. (1984). A bankruptcy classification model for small firms, Journal of Commercial Bank Lending, 66(11), 25-37.

32. Garcia-Gallego, A. & Mures-Quintana, M.J. (2012). Business failure prediction models: Finding the connection between their results and the sampling method. *Economic Computation and Economic Cybernetics Studies and Research*, 3, 157-168.

33. Gentry, J. & Newbold, P. & Whitford, D. (1987). Funds flow components, financial ratios, and bankruptcy. *Journal of Business Finance & Accounting*, 14(4), 595-606. https://doi.org/10.1111/j.1468-5957.1987.tb00114.x.

34. Grice, J.S., & Michael T.D. (2001). The limitations of bankruptcy prediction models: some cautions for researchers. *Review of Quantitative Finance and Accounting*, 17, 151–66. https://doi.org/10.1023/A:1017973604789.

35. Gu, Z. & Gao, L. (2000). A multivariate model for predicting business failures of hospitality firms. *Tourism and* Hospitality Research, 2(1), 37–49. https://doi.org/ 10.1177/146735840000200108

36. Gu, Z. (2002). Analyzing bankruptcy in the restaurant industry: a multiple discriminant model. International *Journal of Hospitality Management*, 21. 25-42. https://doi.org/10.1016/S0278-4319(01)00013-5.

37. Hermes, E. (2021). İflaslar geri geliyor. Retrieved from https://www.eulerhermes.com/tr_TR/ekonomik-arastirmalar/ekonomik-gorunum-raporlari/iflaslar-geri-geliyor.html Accessed November 20, 2021.

38. Islam, Md. S. (2020). Predictive capability of financial ratios for forecasting of corporate bankruptcy. *IOSR Journal of Business and Management* (IOSR-JBM), 22(6), 13-57. https://doi.org/10.2139/ssrn.3637184.

39. Karels, G.V., & Prakash, A.J. (1987). Multivariate normality and forecasting of business bankruptcy. Journal of *Business Finance & Accounting*, 14 (4), 573-593. https://doi.org/10.1111/j.1468-5957.1987.tb00113.x.

40. Kliestik, T. & Vrbka, J. & Rowland, Z. (2018). Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis. *Equilibrium*, 13, 569-593. https://doi.org/10.24136/eq.2018.028.

41. Knox, K., Blankmeyer, E., Trinidad, J., & Stutzman, J. (2009). Predicting bankruptcy in the Texas nursing facility industry. *The Quarterly Review of Economics and Finance*, 49(3), 1047-1064. https://doi.org/10.1016/j.qref.2008.08.004.

42. Legault, J.C.A. & Score, A. (1987). CA-score, a warning system for small business failures, *Bilanas*, 29-31.

43. Li, A., Wu, J., Liu, Z. (2017). Market manipulation detection based on classification methods. *Procedia Computer Science*, (122), 788-795. https://doi.org/10.1016/j.procs.2017.11.438.

44. Mirza, N., Rahat, B., Naqvi, B. & Rizvi, Ska (2020). Impact of Covid-19 on corporate solvency and possible policy responses in the E.U. *The Quarterly Review of Economics and Finance*. https://doi.org/10.1016/j.qref.2020.09.002.

45. Mihalovič, M. (2016), Performance Comparison of multiple discriminant analysis and logit models in bankruptcy prediction. *Economics and Sociology*, 9(4), 101-118. https://doi.org/10.14254/2071-789X.2016/9-4/6.

46. Monica-Violeta, A., Codruta, M. & Sorin, B. (2012). A statistical model of financial risk bankruptcy applied for Romanian manufacturing industry. *Procedia Economics and Finance*, 3, 132–137. https://doi.org/10.1016/S2212-5671(12)001131-1.

47. Ohlson, J.A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109. https://doi.org/10.2307/2490395.

48. Pitrova, K. (2011). Possibilities of the Altman Zeta model application to Czech Firms. *E&M Economics and Management*, 3.

49. Pongsatat, S., Ramage, J. & Lawrence, H. (2004). Bankruptcy prediction for large and small firms in Asia: a comparison of Ohlson and Altman. *Journal of Accounting and Corporate Governance*, 1(2), 1-13.

50. Rujoub, M. A., Cook, D. M., & Hay, L. E. (1995). Using cash flow ratios to predict business failures. *Journal of Managerial Issues*, 7(1), 75-90.

51. Qi, L. (2019). Analysis on zero inventory management of new energy enterprises. *I.O.P. Conference Series: Materials Science and Engineering*. 677, 032110. https://doi.org/10.1088/1757-899X/677/3/032110.

52. Reuters. (2020). US energy bankruptcy surge continues on credit, oil-price squeeze. Retrieved from https://www.reuters.com/article/us-north-america-oil/us-energy-bankruptcy -surge-continues-on-credit-oil-price-squeeze-idUSKCN25727W Accessed October 29, 2021.

53. Selimoğlu, S. & Orhan, A. (2015). Finansal başarısızlığın oran analizi ve diskriminant analizi kullanılarak ölçümlenmesi: bist'de işlem gören dokuma, giyim eşyası ve deri işletmeleri üzerine bir araştırma. *Muhasebe ve Finansman Dergisi*, (66), 21-40. https://doi.org/10.25095/mufad.396529

54. Sfakianakis, E. (2021). Bankruptcy prediction model for listed companies in Greece. *Investment Management and Financial Innovations*, 18(2), 166-180.

55. Shirata, C.Y. (1998). Financial Ratios as predictors of bankruptcy in Japan: an empirical research, proceedings of the second Asian pacific interdisciplinary research in accounting conference.

56. Shumway, T. (2001). Forecasting bankruptcy more accurately: a simple hazard model. *The Journal of Business*, 74(1), 101–124. https://doi.org/10.1086/209665.

57. Sori, Z.M. & Jalil, H.A. (2009). Financial Ratios, discriminant analysis and the prediction of corporate distress, journal of money, *Investment and Banking*, 11, 5-15.

58. Springate, G.L.V. (1978). Predicting the possibility of failure in a Canadian firm: a discriminant analysis, (Master Thesis), Simon Fraser University, Canada.

59. Summers, M.S., (1989). Bankruptcy explained: a guide for business. John Wiley & Sons, Inc., NY.

60. *Sümer, H. & Peker, A. (2013). Bilançolarda cari oranın önemi ve hesaplanması. Journal of Accounting and Taxation Studies*, 6(1), 47-62.

61. Tabachnick, B.G. & Fidell, L.S. (2001). Using multivariate statistics, Fourth Edition. Needham Heights, MA: Allyn & Bacon. ISBN 0-321-05677-9. hardcover.

62. Taffler, R. & Tisshaw, H. (1977). Going Going Gone-four factors which predict. *Accountancy*, 88(1003), 50-54.

63. Taffler, R.J. (1983). The assessment of company solvent and performance using a statistical model. *Accounting and Business Research*, 13(52), 295–308. https://doi.org/10.1080/00014788.1983.9729767.

64. Tavlin, E., Moncarz, E., & Dumont, D. (1989). Financial failure in the hospitality industry. *F.I.U. Review*, 7(1), 55–75.

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

66. Van Horne, J.C. (1998), *Financial management and policy*, Prentice Hall, Michigan University.
67. Wieprow, J., Agnieszka G. (2021). The use of discriminant analysis to assess the risk of bankruptcy of enterprises in crisis conditions using the example of the tourism sector in Poland. *Risks*, 9(78). http://dx.doi.org/10.3390/ risks9040078.
68. Wong, J.M.W., Thomas, N.G. S. (2010, April), *Company failure in the construction industry: a critical review and a future research agenda*, *XXIV Fig. International Congress*, Sydney, Australia.
69. Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, 6(1), 34–45. https://doi.org/10.1016/j.jcae.2010.04.002.
70. Yap, B.C.-F., Yong, D.G.-F. & Poon, W.-C. (2010), How well do financial ratios and multiple discriminant analysis predict company failures in Malaysia. *International Research Journal of Finance and Economics*, 54, 166-175.
71. Zhang, H., Gu, Cl, Gu, Lw, Zhang, Y. (2011). The evaluation of tourism destination competitiveness by Topsis & Information entropy–a case in the yangtze river delta of China. *Tourism Management*, 32(2), 443-451. https://doi.org/10.1016/j.tourman.2010.02.007.