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PREDICTING FINANCIAL DISTRESS IN THE BIST INDUSTRIALS INDEX: EVALUATING TRADITIONAL MODELS AND CLUSTERİNG TECHNIQUES

BIST Sanayi Endeksi'nde Finansal Başarısızlık Tahmini Geleneksel Modellerin ve Kümelenme Tekniklerinin Değerlendirilmesi

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Keywords: Financial Distress, Altman Z-score, S-score Method, K-Means Clustering.

JEL Codes: G10, G17, G33

Abstract

Financial distress, which can lead to bankruptcy or liquidation, is important for companies, creditors, investors, and the economy. Recent financial crises and global economic fluctuations have brought this issue to the forefront. In an effort to foresee financial distress, methods like Altman's Z-score have been proposed while, recent developments have allowed for the incorporation of recent techniques like machine learning. The purpose of this study is to forecast the emergence of financial distress in BIST Industrials Index (XUSIN) companies by using the k-means clustering algorithm, Altman Z-score and Springate S-score models with firm level financial indicators where we investigated successful and unsuccessful companies. Our findings show that two companies met all three Altman Z-score, Z'-score, S-score and financial situation criteria in 2011, 2012, 2015, and 2017; 2 companies in 2016 and 2018; 5 companies in 2013 and 2014; 4 companies in 2019; 1 company in 2020 where no companies are grouped in the same groups in 2021, which means the methods reach different results. It has been determined that the k-means clustering algorithm, particularly due to its higher separability, provides more accurate clustering results for the concerned parties compared to other methods.

Anahtar Kelimeler: Finansal Sıkıntı, Altman Z-skor, S-skor Yöntemi, K-Ortalamalar Kümeleme.

JEL Kodları: G10, G17, G33

Öz

Firmalar, kredi verenler, yatırımcılar ve bir bütün olarak ekonomi için bir firmanın iflas veya tasfiyesi ile sonuçlanabilecek finansal sıkıntı kavramı çok önemli bir konudur. Son dönemde yaşanan finansal krizler ve küresel ekonomik dalgalanmalar bu konunun önemini artırmıştır. Önceki çalışmalar göz önünde bulundurulduğunda, finansal sıkıntıyı öngörmek amacıyla Altman Z-skoru gibi yöntemlerin geliştirildiği görülmektedir. Fakat son dönemlerde makine öğrenmesi gibi yeni tekniklerin de bu amaçla kullandığı görülmektedir. Bu çalışmanın amacı, k-ortalamalar kümeleme algoritması ile Altman Z-skoru ve Springate S-skoru modellerinden faydalanarak, BIST Sanayi Endeksi (XUSIN) firmalarında finansal sıkıntıyı tahmin etmektir. Araştırmanın bulgularına göre iki firma 2011, 2012, 2015 ve 2017 yıllarında Altman z-skoru, Z'-skoru, S-skoru ve mali durum kriterlerinin üçünü de karşılamaktayken, 2016 ve 2018 yıllarında 2 firma, 2013 ve 2014 yıllarında 5 firma, 2019 yılında 4 firma, 2020 yılındaysa 1 firma bu kriterleri karşılamaktadır. 2021 yılına bakıldığında hiçbir şirketin aynı gruplarda gruplanmadığı görülmektedir. Bu durum kullanılan yöntemlerin farklı sonuçlara ulaştığı anlamına gelmektedir. Özellikle k-means kümeleme algoritmasının, daha yüksek ayırıcı özelliği sayesinde ilgili taraflar için, diğer yöntemlere göre daha doğru kümeleme sonuçları verdiği tespit edilmiştir.

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1. Introduction

Financial distress is a situation that a company may face when it cannot fulfill its financial obligations to its creditors. If not managed properly, it can lead to companies going bankrupt or even being liquidated, a situation that could be harmful to both individuals and possibly the wider economic system. Interest in this topic has grown, and the idea of financial failure has risen to the forefront, especially in light of the growth in financial crises and the swings that countries are experiencing. Due to the recent financial crises and global economic volatility that countries are experiencing, this subject has drawn more interest in recent years (Fidan, 2021).

Since a company's financial difficulties are also related to their financial performance, via financial ratios, it is possible to determine if a company is successful or at risk of financial distress based on comparisons with past years' performance. In addition, companies employ financial ratios to understand the market status of their own sector as well as other sectors and take measures by adopting any necessary procedures. (Kalfa and Bekcioglu, 2013: 442-443). Lenders, financiers, partners, banks, and stock investors utilize financial ratios as significant decision-making criteria. Thus, these parties can determine which companies they will invest in based on financial ratios. From a management perspective, financial ratios enable the evaluation of management success, operations, and firm performance (Tekin and Temelli, 2021).

Early research on financial distress focuses on the ability of financial ratios and concerning models that could predict the potential bankruptcy of companies. One of the pioneering studies is Altman's (1968) presentation of the Z-score equation, obtained by financial ratio analysis which is the first multivariate bankruptcy prediction model (Altman et al., 2017). With this model, Altman developed one of the first systematic approaches to understanding and predicting financial failure by trying to determine the probability of bankruptcy of firms through various financial ratios. Later, this model laid the groundwork for the basis of many studies and played a significant role in the development of early prediction models and the emergence of a more refined understanding of the prediction of financial distress (Beaver, 1966; Taffler, 1984; Zmijewski, 1984). For instance, Ohlson (1980) employed a logit model in conjunction with financial ratios while Opler and Titman (1994) focused on the firm value and their industry and revealed the negative impact of financial distress on firm value and forcing these firms to alter their operational approaches to improve the efficiency.

Breakthroughs in information technology and computer science enable the retrieval of vast quantities of data in the field of finance, as well as in virtually every other discipline. Existing and previously unknown relationships raise the significance of data processing. It is argued that the solution to a problem may depend on undiscovered correlations between the given data; consequently, identifying these relationships may offer the opportunity to solve the problem (Awad and Khanna, 2015: 5). Artificial intelligence methods such as machine learning use systematic algorithms to identify and synthesize data and information correlations. Clustering analysis is an approach to machine learning that groups variables based on their shared properties and separates them into clusters. Cluster analysis groups data by similarity, with the most similar in one cluster and the least similar (those with the greatest disparities) in another (Shih et al., 2010).

In the finance literature, cluster analysis has been used to look at how companies are put into groups based on their differing characteristics and, these groups are formed based on known variables such as companies' sector and size. However, sectorial classification is an expected clustering criterion. In this study, cluster analysis was used to group companies in the same sector according to their financial ratios. Thus, organizations can be categorized based on financial criteria that are not sector-specific, even if they are in the same industry and have financial ratios that are dispersed around the sector average. When these groupings are analyzed in detail, it is possible to rank the companies financially. Hence, cluster analysis is employed to detect financial distress and to rank companies so they differ in terms of financial distress. Therefore, cluster analysis can be used to detect financial distress, and companies can be categorized according to their risk of financial distress. Financial distress is a critical issue that concerns companies, investors, creditors, and the wider economy. Studies conducted over the last few decades in identifying this situation have enriched the literature and provided insights into companies' effective management practices and formulated sound strategic decisions.

With the recent studies, the methods and models applied in this field are evolving and contributed by the latest trends such as machine learning and its applications. This study stands out by employing the k-means clustering algorithm by using financial ratios, an unsupervised learning data mining technique, to identify the financial distress of the firms listed on XUSIN. Previous studies have used clustering techniques for financial performance analysis in various contexts. For example, Horobet et al. (2008) identified similarities between clusters of forest product companies and other sectors. Akyuz et al. (2012) used the alignment of clusters via financial ratios of manufacturing firms with their respective sectors. Ozkan and Boran (2014) examined clusters of firms in the manufacturing sector, while Ari et al. (2016) and Gazel and Akel (2018) analyzed the financial performance and sector classification compatibility of firms listed on BIST (Borsa Istanbul).

However, no prior study has been found that predicts financial distress by clustering firms based on their financial ratios. Another distinctive aspect of this study is its approach to predicting financial distress. Typically, methods including artificial neural networks require official identification of firms experiencing financial distress for prediction. The k-means clustering method, in contrast, does not require an official diagnosis of financial distress. It predicts financial distress by forming clusters based on similarities in financial ratios and identifying distinct characteristics within these clusters. Additionally, the specific financial ratios used in this study add another layer of perspective compared to other research.

This study consists of 4 sections. Following the introduction, a thorough review of the relevant literature is presented. And, in the third section, the data, methodology and approaches are explained where the findings are displayed. The results were then analyzed in the discussion and conclusion which is the fourth section.

2. Literature Review

The concept of financial distress describes various situations in which companies face financial difficulties. In general, terms such as “bankruptcy,” “failure,” “inability to pay debts,” and “default” have been used to explain these situations. Altman (1993) initially provided a comprehensive definition of financial distress. According to this definition, the term “bankruptcy” was considered the closest legal definition of financial distress. Zmijewski (1984) defined financial distress as the act of filing for bankruptcy. However, Theodossiou et al. (1996)

stated that when financially troubled firms were evaluated, many of them did not file for bankruptcy due to mergers or privatizations, whereas financially sound firms often filed for bankruptcy to avoid taxes or lawsuits. Additionally, “failure” was defined as the firm’s inability to make payments to its creditors, preferred shareholders, or suppliers, or the firm’s state of bankruptcy. These situations resulted in disruptions to the firm’s operations (Dimitras et al., 1996). Altman (1993) defined failure as a significant and persistent decrease in the realized return on invested capital, risk assessment allowance, and rates of return compared to similar investments. Zopounidis and Dimitras (1998) defined “inability to pay debts” as negative performance due to liquidity problems. Companies commonly go bankrupt by accumulating excessive debt. “Default” was defined as a situation where the firm violates the agreement condition with its creditor, leading to a legal action. The Ministry of Corporate Affairs in India has previously published a list of companies that defaulted on their obligations (Zopounidis and Doumpos, 1999).

Financial distress refers to a financial decline experienced by a company before its bankruptcy or liquidation occurs. Indicators of a company experiencing financial distress include the inability to meet its obligations due to insufficient funds and difficulties in conducting operational activities (Plaat and Platt, 2002). Financial distress occurs when a company has insufficient cash flow to fulfill matured obligations such as trade debts or interest expenses (Mohammed, 2017). Agustini and Wiriwati (2019) defined financial distress as the inability of a firm to manage and sustain its financial performance, leading to losses within the current fiscal year. If financial distress is accurately identified in a firm, preventive measures can be taken to address situations such as liquidation or bankruptcy by evaluating the company.

Edward I. Altman developed the Z-score factor in 1968 to predict corporate bankruptcy risk. This score has helped analyze the financial distress of manufacturing firms using publicly available financial data. Altman (1968) emphasized that solvency, liquidity, and profitability ratios are the most critical determining financial indicators for bankruptcy prediction. Furthermore, it was found that the Z-score model accurately predicted the likelihood of default for 94% of the sampled firms across different periods. Additionally, it was concluded that the Z-score could effectively predict firms’ credit risk up to two years in advance (Altman, 1968). Altman et al. (1977) later developed a new default prediction model by modifying the independent variable data. Altman (2005) also developed an emerging markets model applicable to developing countries which employed by numerous later research (Saif and Al Zaabi, 2011; Ozdemir, 2014; Pradhan, 2014; Ariesta et al., 2015; Joshi, 2020). The Altman Z-score model has been tailored for specific applications by modifying the variables used from 1968 to 2005. The Altman Z-score model is being widely used today. For example, Cleary and Hebb (2016) increased the variables of the Altman Z-score by including credit dependency, credit quality, capital adequacy ratio, and off-balance sheet items when using discriminant analysis to predict bank distress. Almamy et al. (2016) created a new J-UK model with a prediction power of 82.9% by adding cash flow variables to the Z-score model.

Previous research has predicted the financial condition of companies using the Altman Z-score model. Kulali (2016) used the Altman Z-score to predict the financial failure risk by using data from bankrupt firms listed on Borsa Istanbul between 2000 and 2013 and, obtained results indicating the high predictive power of the Altman score model in forecasting financial failure. Gunawan et al. (2017) found that the variables included in the Altman Z-score model explained 65% of the financial distress, while the remaining portion was influenced by other variables in the study. Mohammed (2017) and Panigrahi (2019) used the Z-score model to predict the financial distress of companies operating in the cement and pharmaceutical sectors. The findings indicated that bankruptcy was not a concern for companies in these sectors, and investors should have confidence in their investments. Utilizing the Altman Z-score, Springate S-score and Zmijewski J-score financial distress prediction methods, Kiraci (2021) indicates that in times of crisis, airline companies' bankruptcy scores are affected by firm level indicators such as leverage, asset structure, size, profitability, and liquidity. Guizani and Abdalkrim (2022) employed Altman Z-score model as a proxy for financial distress and employed two regression models to indicate the impact of board gender diversity on financial distress. The study by Ullah et al. (2023) investigates the impact of corporate social responsibility on the financial distress of non-financial firms in Pakistan. The research found a negative relationship between corporate social responsibility and financial distress where, Islam et al. (2023) examined the relationship between the comparability of financial statements and financial distress. Their study discovered that as accounting comparability increases, the likelihood of financial distress decreases. The Altman Z-score model used in the studies has been criticized for unrealistic assumptions such as multivariate normality and independent predictive variables. Dimitras et al. (1996) extensively examined statistical methods used for financial distress prediction. Logistic regression was commonly employed to predict the probability of financial distress. However, with the development of AI-based methods, they are widely used in research for predicting financial distress.

Regarding the use of artificial intelligence-based machine learning methods, Ravi Kumar and Ravi (2007) stated that researchers employed various techniques, along with neural networks being the most commonly used. Recently Zhang et al. (2022) proposed a new XAI (explainable artificial intelligence) model to predict financial distress for Chinese listed firms where they employ a filter and wrapper technique. Ben Jabeur et al. (2023) employ an improved version of XGBoost algorithm where they reach more accurate predictions compared to the traditional feature selection models and provide an alternative for financial failure prediction. Other techniques included decision trees (Frydman et al., 1985), case-based reasoning (Li and Sun, 2009), genetic algorithms (Shin and Lee, 2002), simulation analysis (Cohen et al., 2012), and support vector analysis (Gestel et al., 2006). Altinirmak and Karamasa (2016) utilized support vector machines and artificial neural networks, which are machine learning techniques, to early detect the financial distress of banks operating in Turkey. The results of the prediction indicated that those methods were superior as early warning systems for assessing financial distress. Research by Kristianto and Rikumahu (2019) in Indonesia asserted that financial predictions using artificial neural networks outperformed conventional methods. Similarly, Alamsyah et al. (2021) successfully predicted the financial distress of 33 companies listed on IDX using artificial neural networks and achieved an accuracy rate of 95.6%. Zhu et al. (2022) predicted the financial distress of 3424 companies listed on the Chinese stock exchange using neural networks, support vector machines, decision trees, and logistic models. The analysis yielded better results compared to traditional methods. Wu et al. (2022) combined a multilayer perceptron artificial neural network (MLP-ANN) with the conventional Altman Z-score to create a financial distress prediction model using data obtained from Chinese companies. The results indicated that the new model achieved an average accuracy rate of 99.40%, compared to 86.54% for the Altman Z-score and 98.26% for artificial neural networks alone. This indicates that the new model provides earlier warning signals compared to the others. Kristanti et al.

(2023) predicted financial distress using artificial neural networks on data from 17 construction firms listed on the Indonesian Stock Exchange. The analysis revealed financial distress in 6 firms and stability in 11 firms. In their research, Dube et al. (2023) utilized artificial neural networks to predict the financial distress of companies in the financial services and manufacturing sectors listed on Johannesburg Stock Exchange (JSE). The analysis reveals that artificial neural networks accurately predicted financial distress 96.6% of the time. Similarly, Aker and Karavardar (2023) employed Logistic Regression, Decision Tree, Random Forest, Support Vector Machines, K-Nearest Neighbor, and Naive Bayes models in their study to predict financial distress in small and medium-sized enterprises in Turkey. Their results showed a 97% improvement in classification accuracy.

As seen by previous research, financial ratios have been used as basic data input in cluster analysis, as well as in numerous other analyses and methods. For example, Kalbuana et al. (2022) benefitted from financial ratios such as profitability ratio besides other firm level variables as diversity and board size where they proved profitability ratio has a negative impact on financial distress. In their paper, Tekin and Temelli (2021) analyze financial success and evaluate the companies' financial situation using cluster analysis and financial ratios, where they include 72 companies listed on BIST for 2011-2019 period, obtaining 14 clusters. In the two-step cluster analysis used as another method, companies are grouped in 5 clusters. As a result of the analysis, it was seen that the banking, non-bank finance and real estate investment trusts sectors differ significantly from the others. Since the financial ratios of companies from different sectors are used in the study, these ratios are naturally expected to vary. This can lead to sector-based differentiation, which is a factor that facilitates grouping in cluster analysis. This may make the distinctiveness of the clusters formed dependent on the sector. Using cluster analysis with financial ratios, Alexandra et al. (2008) clustered 115 companies operating in four different countries. As a result, the companies were grouped in 8 clusters and both of the financial ratios used in this grouping had significant effect. Horobet et al. (2008) examined the profitability of companies operating in different sectors in four different countries using hierarchical clustering and K-means clustering analysis. It has been determined that cluster structures have changed during the time period considered and the companies' financial performances are predicted. Bassetto and Kalatzis (2011) used a hybrid clustering method to analyze the presence of financial constraints on investment decisions in 367 Brazilian firms. Results indicate that clustering techniques give robust results on financial constraint determination. Using financial ratios and clustering and separation analysis, Akyuz et al. (2012) focused on the manufacturing industry sector. They found that the cluster of industries producing forest products shared characteristics with other industrial sectors. Prediction accuracy was one of the comparison criteria which 21 models conducted on five related datasets. Ozkan and Boran (2014) examined manufacturing industry companies with k-means cluster analysis using financial ratios detecting the companies in the clusters were compatible with their sectors. Arı et al. (2016) evaluated the financial performance of companies listed on BIST using financial ratios. The two-stage clustering analysis produced two clusters with a medium quality. Gazel and Akel (2018) attempted to determine the BIST sector classification through cluster analysis in their study. It was discovered that some stocks were clustered according to their sector classification in the analyses carried out using hierarchical agglomerative clustering analysis.

3. Data and Method

The study included companies that were listed on the BIST Manufacturing Industry Index between 2011 and 2021 and whose data was available. Data were obtained from Thomson Reuters Datastream database and Public Disclosure Platform (KAP). K-means cluster analysis was used in the analyses, and it was performed for each year, offering researcher the chance to look at how the companies in the clusters have changed over time. Since the data used in the analyzes were financial ratios, no adjustments were needed due to scale differences. The aim of the study is to sort 24 companies whose data are useable into clusters, considering that companies with similar characteristics will have similar financial ratios, it is envisaged that companies with and without financial distress risk can be divided into clusters.

3.1. Traditional Methods

Altman's Z-score model (1968) is a discrimination and prediction model designed to predict corporate bankruptcy by estimating the distance between the financial values and default values of manufacturing companies (Al Zaabi, 2011). Altman Z-score approach combines the 5 variables (shown in Table 1) with different weights in a single Z-score value. The calculation function of Altman's approach is shown in equation 1.

Table 1. Variable Definitions

Variable	Ratio	
X1	WC/TA	Working Capital to Total Assets (CA=CA-CL)
X2	P/TA	Profit to Total Assets
X3	EBIT/TA	Earnings Before Interest and Taxes to Total Assets
X4	MVE/TL	Market Value of Equity to Total Liabilities
X5	STA	Sales to Total Assets

Note: WC: Working Capital, TA: Total Assets, CA: Current Assets, CL: Current Liabilities, P: Profit, EBIT: Earnings before interests and Taxes, MVE: Market Value of Equity, TL: Total Liabilities, S: Sales

$$Z= 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.99X5 \tag{1}$$

The threshold value of z=2,675 is found best for separation by Altman. The classification of Z-score values is shown below, equation 2.

$$f(z) = \begin{cases} z > 2.675, & Financially\ healty, no\ risk \\ 1.8 \leq z \leq 2{,}675, & Grey\ area, risky\ zone \\ z < 1.8, & Danger\ zone \end{cases} \tag{2}$$

Altman Z'-score Approach

$$Z'= 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4' + 0.998X5 \tag{3}$$

The criterion in equation 4 is used to evaluate the calculated z'-score value.

$$f(z') = \begin{cases} z' > 2.90, & Financially\ healty, no\ risk \\ 1.23 \leq z' \leq 2{,}90, & Grey\ area, risky\ zone \\ z' < 1.23, & Danger\ zone \end{cases} \tag{4}$$

The Springate S-score approach, which is an enhanced iteration of the Altman Z-score model (1968), has proven to be effective for organizations in the manufacturing sector. The variables have been removed from this method; they are defined as follows: X1 working capital to total assets; X2 earnings before interest and taxes to total assets. For the calculation of S-score, see below.

$$S= 1.03X1 + 3.07X2 +0.66X3 + 0.4X4 \quad (5)$$

Evaluating the calculated S-score value requires the scale in Equation 6.

$$f(S) = \begin{cases} S > 0.862, & Financially\ healty, no\ risk \\ S < 0.862, & Danger\ (risky) zone \end{cases} \quad (6)$$

This study also predicted financial distress via firm level financial criteria. (Ural et al., 2015; Salur, 2021; Susler, 2022). These criteria are as follows; (i) Having made a loss for at least 2 years in a row, (ii) 10% decrease in assets, (iii) The equity value is negative.

In order to assess the efficacy of this method, it is necessary to have knowledge of the examined companies' financial distress. Thus, the method's efficacy can be determined by comparing the Altman Z-score result to the actual situation. The model Wu et al. (2022) used showed a very high performance with a successful prediction of 86.4%. However, there is no outcome data to determine the efficacy of such methods in markets such as Turkey, where financial distress is not formally defined, and companies avoid filing for bankruptcy. However, there is no outcome data to determine the efficacy of such methods in markets such as Turkey, where financial distress is not formally defined, and companies avoid filing for bankruptcy. As a matter of fact, when the Altman Z-score method is employed, During the 12-year period of 35 companies, only 3 were determined to be financially healthy in 11 time periods, while 1 was determined to be risky in only 1 time period and financial distress was calculated for all other companies and time periods (Appendix 1). Based on this analysis, 1 indicates unsuccessful, 2 indicates risky, and 3 indicates unsuccessful companies.

According to the analysis results given in Annex 1 and Table 2, it was seen that the Altman Z-score method classified the companies as mostly unsuccessful for all years, evaluated at most 1 company as successful and 3-4 companies as risky. This shows that the Altman Z-score method is not discriminative enough for manufacturing sector in Turkey. While corporate financial indicators may suggest financial distress, the rarity of official bankruptcy may also contribute to the occurrence of this circumstance.

The Altman z'-score method identifies a bigger portion of companies as financially successful and financially risky in comparison to the Z-score method. Although there were a comparatively greater number of successful companies from 2013 to 2019, the number of successful companies in the pandemic periods of 2020 and 2021 was determined as 2 and 3, respectively.

When the results of the Springate S-score method are examined (Appendix 1), considering that the method evaluates two situations as financial success and failure without a financial risk criterion, it is seen that the number of companies evaluated as financially successful is more than half.

Table 2. Circumstances in which Methods Produce Identical or Dissimilar Outcomes

		Aksa Akrilik Kimya	Alkim Alkali Kimya	Anadolu Efes	Anadolu Isuzu	Arcelik	Bagfas Gubre	Bursa Cimento	Cimsa Cimento	Coca Cola Icecek	EGE Endustri	Eregli Demir Celik	Ford Otomotiv	Gubre Fabrikalari	Konya Cimento	Otokar Otomotiv	Oyak Cimento	Petkim	Sasa Polyester	Selcuk Ecza Deposu	Tofas Turk Otomobil	Tupras	Turk Traktor	Ulker Biskuvi Sanayi	Vestel Beyaz Esya
2010	Z and Z' score results same	-	-	-	+	-	+	-	-	-	+	-	-	+	-	+	-	-	+	+	+	-	-	-	-
	Z, Z' and S-score results same	-	-	-	+	-	-	-	-	-	+	-	-	+	-	+	-	-	+	+	+	-	-	-	-
	All traditional methods result same	Not Available																							
	K-means clustering results	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
2011	Z and Z' score results same	-	-	-	+	+	+	-	-	-	-	-	-	+	-	+	-	-	+	+	+	-	+	-	+
	Z, Z' and S-score results same	-	-	-	+	+	-	-	-	-	-	-	-	+	-	+	-	-	+	-	+	-	-	-	+
	All traditional methods results same	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-	-	-	-
	K-means clustering results	2	2	2	1	2	2	2	2	2	2	2	2	1	2	1	2	1	1	2	2	1	2	2	2
2012	Z and Z' score results same	-	-	-	+	+	-	-	-	-	+	-	-	-	-	+	-	+	+	+	+	-	+	+	+
	Z, Z' and S-score results same	-	-	-	+	+	-	-	-	-	-	-	-	-	-	+	-	+	+	+	-	-	-	+	+
	All traditional methods results same	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	+
	K-means clustering results	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1
2013	Z and Z' score results same	-	-	-	+	+	+	-	-	-	+	-	+	+	-	+	-	+	+	+	+	-	-	+	+
	Z, Z' and S-score results same	-	-	-	-	-	-	-	-	-	+	-	-	+	-	+	-	+	+	-	-	-	-	+	+
	All traditional methods results same	-	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	+	+	-	-	-	-	+	+
	K-means clustering results	2	2	2	2	2	2	2	2	2	2	2	2	1	2	1	2	1	+	2	2	1	2	1	2
2014	Z and Z' score results same	-	-	+	-	+	+	-	-	-	+	-	+	+	-	+	-	+	+	+	+	-	-	-	-
	Z, Z' and S-score results same	-	-	+	-	-	-	-	-	-	+	-	-	+	-	+	-	+	+	-	-	-	-	-	-
	All traditional methods results same	-	-	+	-	-	-	-	-	-	+	-	-	-	-	+	-	+	+	-	-	-	-	-	-
	K-means clustering results	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	2	1	2	2	2
2015	Z and Z' score results same	-	+	+	+	+	-	-	-	+	+	-	-	+	-	+	-	-	-	+	+	-	-	-	-
	Z, Z' and S-score results same	-	-	+	-	-	-	-	-	-	+	-	-	+	-	+	-	-	-	-	-	-	-	-	-
	All traditional methods results same	-	-	+	-	-	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	1	1	2	1	1	2	1	1	2	1	1	2	2	1	2	1	2	2	1	2	2	2	1	1

Table 2. Continued

2016	Z and Z' score results same	+	+	+	+	-	+	-	-	+	+	-	-	+	-	+	-	-	-	+	+	-	-	+	-
	Z, Z' and S-score results same	-	-	+	+	-	-	-	-	+	+	-	-	+	-	+	-	-	-	-	-	-	-	+	-
	All traditional methods results same	-	-	-	+	-	-	-	-	-	+	-	-	+	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	2	1	2	2	1	1	2	1	2
2017	Z and Z' score results same	+	-	+	+	+	+	-	+	+	+	-	+	+	-	+	-	-	+	+	+	-	-	+	+
	Z, Z' and S-score results same	-	-	+	+	-	-	-	-	+	+	-	-	+	-	+	-	-	+	-	-	-	-	+	-
	All traditional methods result same	-	-	-	-	-	-	-	-	-	+	-	-	+	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	1	2	1	1	1	1	2	1	1	2	1	1	1	2	1	2	1	1	1	1	1	1	1	1
2018	Z and Z' score results same	+	-	+	+	+	+	-	+	+	+	-	+	+	-	+	-	-	+	+	-	-	-	-	+
	Z, Z' and S-score results same	-	-	+	+	+	+	-	-	+	+	-	-	+	-	+	-	-	+	-	-	-	-	-	-
	All traditional methods result same	-	-	-	-	-	+	-	-	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	2	1	2	2	2	2	1	2	2	1	2	2	2	1	2	1	2	2	2	2	2	2	2	2
2019	Z and Z' score results same	+	+	+	+	+	+	-	+	-	-	-	+	+	-	-	-	+	+	+	-	-	+	+	+
	Z, Z' and S-score results same	-	+	+	+	+	-	-	-	-	-	-	-	+	-	-	-	+	+	-	-	-	+	+	-
	All traditional methods results same	-	+	-	+	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-	-	+	-	-
	K-means clustering results	1	2	1	1	1	1	2	1	1	2	1	1	1	2	1	2	1	1	1	1	1	1	1	1
2020	Z and Z' score results same	+	-	+	+	+	+	+	+	-	+	-	-	+	+	-	-	-	+	+	+	-	-	-	-
	Z, Z' and S-score results same	-	-	+	+	+	+	-	-	-	-	-	-	+	-	-	-	-	+	-	-	-	-	-	-
	All traditional methods results same	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	2	1	2	2	2	2	1	2	2	1	1	1	2	1	2	2	1	2	1	2	2	1	1	2
2021	Z and Z' score results same	+	+	+	+	+	+	-	-	-	+	-	-	+	-	-	-	+	+	+	-	-	-	+	+
	Z, Z' and S-score results same	+	-	+	+	+	+	-	-	-	+	-	-	+	-	-	-	-	+	-	-	-	-	+	+
	All traditional methods results same	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	K-means clustering results	2	1	2	2	2	2	1	1	2	1	1	1	2	1	1	1	1	2	1	1	2	1	2	2

Note: The "+" sign denotes whether the compared methods evaluated the same group of companies while, the "-" sign indicates if they are not included in the same group. 1 and 2 represents the groups assigned by the k-means clustering algorithm (exclusively applicable to the k-means clustering algorithm).

In previous studies, the Altman Z-score, Z'-score, and S-score are employed commonly to predict financial distress. Table 2 provides a comprehensive analysis of the compatibility and similarity of the outcomes generated by these methods which demonstrates whether the methods yield identical results annually or whether the same group is assigned to the same company (successful, risky, unsuccessful). A "+" symbol indicates if a company was assessed by the compared methods for the same group. They are denoted with a "-" sign if they are not included in the same group. For instance, in 2010, eight companies were categorized in the same class by both the Altman Z-score and Z'-score methods, and seven companies were categorized in the same class by the combination of the Altman Z-score, Z' -score, and Springate S-score methods. It is evident that even very similar methods yield very different classification results.

Studies by Salur (2021), Susler (2022), and Ural et al. (2015) demonstrate that analyses that consider financial circumstances produce results that are comparable to those of the S-score approach. Table 2 compares successful and unsuccessful companies via Altman Z-score, Z'-score and S-score methods, using the financial situation as a criterion. Since one of the financial criteria is "Having made a loss for at least 2 years in a row" and our data is available from 2011 to 2021, there are no results available for 2010. Two companies met all three Altman Z-score, Z'-score, S-score and financial situation criteria in 2011, 2012, 2015, and 2017; 2 companies for 2016 and 2018; 5 companies for 2013 and 2014; 4 companies for 2019; 1 company for 2020 where no companies are grouped in the same groups for 2021, meaning the methods' ability to produce same result is low.

3.2. K-means Clustering Approach

Cluster analysis is a multivariate technique that allows multiple factors to be evaluated and grouped together. The groups obtained by cluster analysis are similar to each other in terms of various variables, and different groups differ from each other in terms of various variables (Karaatlı and Yıldız, 2021). In the study, the companies in the XUSIN Index were clustered in terms of their financial ratios, and companies that were similar and different from each other were grouped.

Although there are various algorithms used for clustering variables, the K-means algorithm is an effective clustering algorithm that minimizes the sum of distance squares. The K-means algorithm is a simple clustering algorithm that divides data points into a specified number of discrete subsets (Lloyd, 1957). Since the sum of squares is the square of the Euclidean distance, the intuitive meaning of "nearest" (equation 3) can be expressed as the sum of the squares of the distance of each value of the variable to the average value of the variable (Awad and Khanna, 2015: 10). The K-means clustering algorithm has two basic steps; i) data points are assigned to the cluster to which the cluster center closest to it belongs, ii) recalculation of each cluster center to be the center of all assigned data points. The steps of the algorithm are repeated until a stopping criterion is met, such as no change in the clusters to which data points are assigned. In each iteration, comparisons are made equal to the number of data points x the number of clusters and require a significant processing load.

$$J = \sum_{j=1}^{K} \sum_{n \epsilon S_j} \left| X_n - \mu_j \right|^2 \tag{7}$$

X_n represents the n^{th} data point and μ_j represents the geometric centroid of the data points in Sj, "K" represents a data point in the dataset, while "Sj" denotes the relevant cluster. Equation 7 facilitates cluster formation by measuring the distance of each data point from the geometric mean of the data points in a cluster. This measurement aids in deciding which cluster to assign a specific data point to.

Table 3. K-Means Clustering With 2 Clusters

Companies	2 Group Clustering											
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Aksa Akrilik Kimya Sanayi	1	2	1	2	2	1	1	1	2	1	2	2
Alkim Alkali Kimya	1	2	1	2	2	1	2	2	1	2	1	1
Anadolu Efes Biracilik Limited	1	2	1	2	2	2	1	1	2	1	2	2
Anadolu Isuzu Otomotiv Limited	1	1	1	2	2	1	2	1	2	1	2	2
Arcelik	1	2	1	2	2	1	2	1	2	1	2	2
Bagfas Bandirma Gubre	1	2	1	2	2	2	1	1	2	1	2	2
Bursa Cimento Fabrikasi	1	2	1	2	2	1	2	2	1	2	1	1
Cimsa Cimento Sanayi ve Ticaret	1	2	1	2	2	1	1	1	2	1	2	1
Coca Cola Icecek	1	2	1	2	2	2	1	1	2	1	2	2
EGE Endustri ve Ticaret	1	2	1	2	2	1	2	2	1	2	1	1
Eregli Demir Celik	1	2	1	2	2	1	2	1	2	1	1	1
Ford Otomotiv Sanayi	1	2	1	2	2	2	1	1	2	1	1	1
Gubre Fabrikalari	1	1	1	1	2	2	1	1	2	1	2	2
Konya Cimento Sanayi	1	2	1	2	2	1	2	2	1	2	1	1
Otokar Otomotiv ve Savunma	1	1	1	1	2	2	1	1	2	1	2	1
Oyak Cimento Fabrikalari A S	1	2	1	2	2	1	2	2	1	2	2	1
Petkim Petrokimya Holding	1	1	1	1	2	2	1	1	2	1	1	1
Sasa Polyester A	1	1	2	1	1	2	2	1	2	1	2	2
Selcuk Ecza Deposu	1	2	1	2	2	1	2	1	2	1	1	1
Tofas Turk Otomobil Fabrikasi	1	2	1	2	2	2	1	1	2	1	2	1
Tupras Turkiye Petrol Rafineleri	2	1	1	1	1	2	1	1	2	1	2	2
Turk Traktor ve Ziraat Makineleri	1	2	1	2	2	2	2	1	2	1	1	1
Ulker Biskuvi Sanayi	1	2	1	1	2	1	1	1	2	1	1	2
Vestel Beyaz Esya Sanayi ve Ticaret	1	2	2	2	2	1	2	1	2	1	2	2

With the K-means clustering algorithm, the financial ratios of the companies included in the analysis were grouped according to their similar characteristics. Two situations were examined in the application of cluster analysis. In the first case, the companies were divided into two groups, so that the companies were divided into two groups as financially successful and less successful. In the two-group analysis results shown in Table 3, it was seen that the algorithm had the power to distinguish companies. By examining the financial information of any two companies selected from the clusters formed by the k-means algorithm, it can be determined which group (risky and risk-free) the companies belong to. For instance, by evaluating the financial indicators of companies assigned to the clusters, the cluster with more successful financial indicators can be identified as the one containing financially healthy companies. Thus cluster 1 denotes risky companies whereas cluster 2 denotes risk-free companies.

Table 4. K-Means Clustering With 3 Clusters

Companies	3 Group Clustering											
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Aksa Akrilik Kimya Sanayi	1	1	2	2	1	1	3	1	1	1	2	1
Alkim Alkali Kimya	1	1	2	2	1	2	1	3	3	2	1	2
Anadolu Efes Biracilik Limited	3	1	2	1	3	3	3	2	1	1	2	1
Anadolu Isuzu Otomotiv Limited	1	1	2	2	1	3	2	2	1	1	2	1
Arcelik	1	1	2	1	1	3	2	2	2	3	2	3
Bagfas Bandirma Gubre	1	3	2	1	3	1	3	1	1	1	2	1
Bursa Cimento Fabrikasi	1	3	2	2	1	1	1	3	3	2	1	2
Cimsa Cimento Sanayi ve Ticaret	3	1	2	2	1	1	3	1	1	1	2	2
Coca Cola Icecek	3	1	2	1	3	3	3	2	1	3	2	1
EGE Endustri ve Ticaret	1	3	2	2	1	2	1	3	3	2	3	2
Eregli Demir Celik	1	1	2	1	1	3	2	2	2	3	2	2
Ford Otomotiv Sanayi	1	3	2	1	3	1	3	1	1	1	2	2
Gubre Fabrikalari	3	1	2	1	3	3	3	1	1	1	2	1
Konya Cimento Sanayi	1	3	2	2	1	2	1	3	3	2	3	2
Otokar Otomotiv ve Savunma	1	1	2	1	3	3	3	2	2	3	2	2
Oyak Cimento Fabrikalari A S	1	3	2	2	1	1	1	3	2	2	2	2
Petkim Petrokimya Holding	1	1	2	1	3	3	3	2	2	3	2	2
Sasa Polyester A	2	2	1	2	3	3	2	2	1	1	2	1
Selcuk Ecza Deposu	1	3	2	2	1	3	2	2	2	3	2	2
Tofas Turk Otomobil Fabrikasi	1	1	2	1	3	3	3	1	1	1	2	2
Tupras Turkiye Petrol Rafineleri	3	2	2	1	3	3	3	2	1	1	2	1
Turk Traktor ve Ziraat Makineleri	1	3	3	2	1	3	2	2	2	3	1	2
Ulker Biskuvi Sanayi	1	1	2	1	1	3	3	2	2	3	1	3
Vestel Beyaz Esya Sanayi ve Ticaret	1	1	1	1	1	3	2	2	1	1	2	1

In the second case, companies were evaluated in 3 groups. Companies with similar characteristics were categorized via this approach while it does not differentiate between successful and unsuccessful companies. The analysis results, in which companies are grouped as risky, less risky and risk-free, are shown. Based on the three groups formed in Table 4 above, it can be determined to which group (risky, less risky and risk-free) the companies belong, as categorized by the clusters created by the k-means algorithm, where the cluster 1 denotes risky companies, cluster 2, less risky companies and cluster 3 represents risk-free companies, respectively.

4. Discussion and Conclusion

Increase in uncertainty have forced companies to utilize their resources even more cautiously with recent adverse global events. Thus, it would be beneficial for companies to use appropriate models and technological innovations to forecast financial distress or bankruptcy.

The focus of this study is to predict financial distress in XUSIN companies using the Altman Z-score and Springate S-score models, financial ratios, and the k-means clustering method for 2010-2021 period. One of the machine learning approaches, the k-means clustering algorithm of cluster analysis, and traditional techniques used to predict financial distress. It has been determined that the Altman Z-score model, which has been utilized in numerous previous studies, is incapable of distinguishing between companies in the XUSIN index based on their financial ratios in terms of financial distress. The k-means clustering algorithm, as a data mining tool able to determine the undiscovered relationships in data, has been utilized to the prediction of financial distress which allows items to be grouped based on their similarities and differences in terms of numerous variables.

In this study, the Altman (1968) model indicates that the Altman Z-score method classifies companies as mostly unsuccessful for all years, evaluates at most 1 company as successful and 4 companies as risky. The Altman Z-score method identifies a relatively small number of financially successful companies, indicating that the method's distinctiveness is insufficient for Turkish manufacturing sector. The second model utilizes the criteria for financial distress established by Ural et al. (2015), Salur (2021), and Susler (2022). Unlike the z'-score method, the Altman Z-score method identifies over fifty percent of the companies as financially successful. Evaluating the number of companies determined to be financially successful via Altman Z-score approach year by year, it is shown that relatively more companies were deemed financially successful between 2013 and 2019 while, only two companies were deemed successful in the first of the last two years of pandemic and, only three companies in the second. The Springate S model is a method to forecast the financial distress of manufacturing companies. Since our sample consists of manufacturing companies, s-score was used for the forecast. Similar to the z'-score method, the S-score method groups successful companies more evenly and reveals more financially successful companies. By considering solely two potential outcomes—successful and unsuccessful—the s-score method yields results that are comparable to those produced by the Z-score method. Apart from the financial distress prediction models, machine learning based forecasts are also being utilized more often recently.

In this study, the k-means clustering method was used to create groups. Considering companies with similar financial characteristics will be clustered in the same group, it is possible to rank the companies as financially healthy and less healthy as a result of clustering and examining these clusters. As a result of the application of the 2-group k-means clustering algorithm, it has been seen that the algorithm has the ability to separate companies according to their characteristics and companies can be classified as financially healthy and less healthy. The K-means clustering algorithm only groups firms based on how similar their financial ratios are. Once these groups have been established, the financial ratios can be used to determine which group relates to which. The important thing is the separation of data based on undiscovered features and relations. For example, in 2012 which was considered a financial crisis period in the world, only 2 firms SASA and Vestel clustered in the same group that can be considered as financially healthy due to the export capability of these firms. This situation changed where it can be considered a relatively financially stable period after 2014. Financial indicators such as sales, profits, and liabilities have more effect on determining the clusters resulting in more mixed groups with more firms.

In previous research, financial distress prediction models, cannot perform well in every country due to the economic conditions of the country, financial rules and strategies of firms, etc. While Altman and Springate S-score models performed better for Chinese firms, they didn't have enough separability for Turkish firms. On the other hand, clustering techniques provide robust results in determining financial constraints in Brazilian firms (Bassetto and Kalatzis, 2011). Tsai (2014) combines cluster analysis with classifier methods to predict financial distress. The clustering techniques and classifier ensembles were combined to predict the failure. These studies show the effective usability of clustering techniques which supports the main idea of this research.

Investors, creditors, or managers who are concerned with the financial distress and bankruptcy of companies will benefit more from using the K-means clustering algorithm, as it provides more accurate results in clustering due to its higher ability to separability, compared to other traditional methods. Since only manufacturing sector enterprises were included within the limitations of the study, comparisons can be made with different sectors. However, in methods such as machine learning and artificial neural networks, more financial ratios can be utilized since there are no assumption restrictions among the independent variables. In studies proceeding in this direction, an appropriate set of financial ratios can be created by trying different combinations using the financial ratios of companies in different sectors.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

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APPENDIX-1

Annex 1. Traditional Methods Results for 2010 – 2021

	2010				2011				2012				2013			
Full Name	**Z-score**	**Z'-score**	**S-score**	**Fin. Sit. Cri.**	**Z-score**	**Z'-score**	**S-score**	**Fin. Sit. Cri.**	**Z-score**	**Z'-score**	**S-score**	**Fin. Sit. Cri.**	**Z-score**	**Z'-score**	**S-score**	**Fin. Sit. Cri.**
Aksa Akrilik Kimya Sanayi	0	1	2		0	1	2	2	0	1	2	0	0	1	2	2
Alkim Alkali Kimya	0	1	2		0	1	2	2	0	1	2	0	0	1	2	0
Anadolu Efes Biracilik Limited	0	1	2		0	1	2	0	0	1	2	2	0	1	2	2
Anadolu Isuzu Otomotiv Limited	0	0	0		0	0	0	0	0	0	0	2	1	1	2	2
Arcelik	0	1	2		0	0	0	2	0	0	0	2	0	0	2	2
Bagfas Bandirma Gubre	1	1	2		1	1	2	2	0	1	2	0	0	0	2	2
Bursa Cimento Fabrikasi	0	1	2		0	1	2	2	0	1	2	0	0	1	2	0
Cimsa Cimento San. and Tic.	0	1	2		0	1	2	2	0	1	2	2	1	2	2	0
Coca Cola Icecek	0	1	2		0	1	2	2	0	1	2	2	0	1	2	2
EGE Endustri and Ticaret	0	0	0		0	1	2	2	1	1	2	0	2	2	2	2
Eregli Demir Celik	0	1	2		0	1	2	0	0	1	0	0	0	1	2	0
Ford Otomotiv Sanayi	0	1	2		0	1	2	2	0	1	2	0	0	0	2	2
Gubre Fabrikalari	0	0	0		0	0	0	2	0	1	2	0	0	0	0	2
Konya Cimento Sanayi	1	2	2		1	2	2	2	1	2	2	0	1	2	2	0
Otokar Otomotiv and Savunma	0	0	0		0	0	0	2	0	0	0	2	0	0	0	2
Oyak Cimento Fabr.A.S.	1	2	2		1	2	2	0	0	1	2	0	1	2	2	0
Petkim Petrokimya Holding	0	1	0		0	1	0	0	0	0	0	0	0	0	0	0
Sasa Polyester A	0	0	0		0	0	0	2	0	0	0	2	0	0	0	0
Selcuk Ecza Deposu	0	0	0		0	0	2	0	0	0	0	2	0	0	2	0
Tofas Turk Otomobil Fabrikasi	0	0	0		0	0	0	0	0	0	2	0	0	0	2	0
Tupras Turkiye Pet. Raf.	0	2	0		0	2	0	0	0	2	0	2	0	2	0	2
Turk Traktor ve Ziraat Mak.	0	1	2		1	1	2	2	1	1	2	0	0	1	2	2
Ulker Biskuvi Sanayi	0	1	0		0	1	2	0	0	0	0	2	0	0	0	0
Vestel Beyaz Esya San. Tic.	0	1	0		0	0	0	2	0	0	0	0	0	0	0	0
	2014				**2015**				**2016**				**2017**			
Aksa Akrilik Kimya Sanayi	0	1	2	2	0	1	2	2	0	0	2	2	0	0	2	2
Alkim Alkali Kimya	0	1	2	0	1	1	2	2	1	1	2	2	1	2	2	0
Anadolu Efes Biracilik Ltd.	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2
Anadolu Isuzu Otomotiv Ltd.	0	1	2	0	0	0	2	2	0	0	0	0	0	0	0	2
Arcelik	0	0	2	0	0	0	2	0	0	1	2	2	0	0	2	2
Bagfas Bandirma Gubre	0	0	2	2	0	1	2	2	0	0	2	0	0	0	2	0
Bursa Cimento Fabrikasi	0	1	2	0	0	1	2	2	0	1	2	2	0	1	2	2
Cimsa Cimento San.ve Tic.	0	1	2	0	0	1	2	2	0	1	2	2	0	0	2	2
Coca Cola Icecek	0	1	2	0	0	0	2	2	0	0	0	2	0	0	0	2
EGE Endustri ve Ticaret	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Eregli Demir Celik	0	1	2	2	0	1	2	2	0	1	2	2	0	1	2	2
Ford Otomotiv Sanayi	0	0	2	2	0	1	2	2	0	1	2	2	0	0	2	2
Gubre Fabrikalari	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0
Konya Cimento Sanayi	1	2	2	2	1	2	2	0	1	2	2	0	1	2	2	0
Otokar Otomotiv ve Sav.	0	0	0	0	0	0	0	2	0	0	0	2	0	0	0	2

Table 5. Continued

Oyak Cimento Fabr. A S	1	2	2	0	0	2	2	0	0	2	2	0	0	2	2	2
Petkim Petrokimya Holding	0	0	0	0	0	1	0	0	0	1	2	2	0	1	2	2
Sasa Polyester A	0	0	0	0	0	1	0	0	0	1	2	2	0	0	0	2
Selcuk Ecza Deposu	0	0	2	0	0	0	2	2	0	0	2	2	0	0	2	2
Tofas Turk Otomobil Fabr.	0	0	2	0	0	0	2	0	0	0	2	0	0	0	2	0
Tupras Turkiye Petrol Raf.	0	2	0	0	0	2	0	2	0	2	0	2	0	2	0	2
Turk Traktor ve Ziraat Mak.	0	1	2	2	0	1	0	0	0	1	2	2	0	1	0	2
Ulker Biskuvi Sanayi	0	1	2	0	0	1	2	2	0	0	0	2	0	0	0	2
Vestel Beyaz Esya San. Tic.	0	1	2	0	0	1	2	0	0	1	2	2	0	0	2	2
	2018				**2019**				**2020**				**2021**			
Aksa Akrilik Kimya Sanayi	0	0	2	2	0	0	2	0	0	0	2	2	0	0	0	2
Alkim Alkali Kimya	1	2	2	2	2	2	2	2	1	2	2	2	1	1	2	1
Anadolu Efes Biracilik Ltd.	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	1
Anadolu Isuzu Oto. Ltd.	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0	1
Arcelik	0	0	0	2	0	0	0	2	0	0	0	2	0	0	0	1
Bagfas Bandirma Gubre	0	0	0	0	0	0	2	2	0	0	0	2	0	0	0	1
Bursa Cimento Fabrikasi	1	2	2	0	0	1	2	0	1	1	2	2	1	2	2	1
Cimsa Cimento San.ve Tic.	0	0	2	0	0	0	2	0	0	0	2	2	0	1	2	0
Coca Cola Icecek	0	0	0	0	0	1	2	2	0	1	2	2	0	1	2	1
EGE Endustri ve Ticaret	2	2	2	2	1	2	2	2	1	1	2	0	2	2	2	1
Eregli Demir Celik	0	1	2	2	0	1	2	2	0	1	2	2	0	1	2	1
Ford Otomotiv Sanayi	0	0	2	2	0	0	2	2	0	1	2	2	0	1	2	1
Gubre Fabrikalari	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0	1
Konya Cimento Sanayi	1	2	2	0	1	2	2	0	1	1	2	2	0	1	2	1
Otokar Otomotiv ve Sav.	0	0	0	2	0	1	2	2	0	1	2	2	0	1	2	1
Oyak Cimento Fabr. A.Ş.	0	1	2	0	1	2	2	0	0	1	2	2	0	1	2	1
Petkim Petrokimya Holding	0	1	2	2	0	0	0	2	0	1	2	2	1	1	2	1
Sasa Polyester A	0	0	0	2	0	0	0	2	0	0	0	2	0	0	0	1
Selcuk Ecza Deposu	0	0	2	2	0	0	2	2	0	0	2	2	0	0	2	1
Tofas Turk Otomobil Fabr.	0	1	2	0	0	1	2	0	0	0	2	2	0	1	2	1
Tupras Turkiye Petrol Raf.	0	2	0	0	0	2	0	2	0	2	0	0	0	2	0	1
Turk Traktor ve Ziraat Mak.	0	1	0	2	0	0	0	0	0	1	2	2	0	1	2	1
Ulker Biskuvi Sanayi	0	1	2	2	0	0	0	2	0	1	2	2	0	0	0	1
Vestel Beyaz Esya San. Tic.	0	0	2	2	0	0	2	0	0	1	2	2	0	0	0	1