PREDICTING FINANCIAL DISTRESS IN PRIVATE COMPANIES:

THE CASE OF TURKISH FIRMS

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PREDICTING FINANCIAL DISTRESS IN PRIVATE COMPANIES: THE CASE OF TURKISH FIRMS

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DECLARATION OF ORIGINALITY

I, Hilmi Buğra ABBASOĞLU, certify that

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ABSTRACT

Predicting Financial Distress in Private Companies:

The Case of Turkish Firms

This thesis provides a discriminant score to predict the financial distress of privately held companies. Providing a discriminant score named PF-Score is intended to fill the gap in the literature of the private firms' financial distress prediction. In this paper, we used discriminant analysis which used in literature predominantly. Our sample consists of Turkish privately held companies involving 2.391 financially failed companies and 345.426 healthy firms' observations. Having determined coefficients of the PF-Score model, we observed that profitability ratios are more effective in distress prediction. Moreover, the coefficients of efficiency, liquidity, and leverage ratios were also found convenient estimators in the ranking of importance. After determining the threshold, we obtained that our model can distinguish distressed firms with 60% accuracy and can isolate healthy firms with a 75% accuracy rate. We also tested the accuracy of the Altman Z-Score models. Comparative ROC and AUC analyses of the prediction models are also provided in the paper. Eventually, we found that PF-Score outperformed other discriminant analysis prediction models of private firms.

ÖZET

Halka Açık Olmayan Şirketlerde Finansal Sıkıntıyı Öngörmek: Türk Firmaları Örneği

Bu tez, halka açık olmayan şirketlerin finansal sıkıntılarını tahmin eden bir diskriminant skoru geliştirmektedir. PF-Score adını verdiğimiz bu diskriminant skorunun sunulması, halka açık olmayan şirketlerin finansal sıkıntı tahminine ilişkin literatürdeki boşluğu doldurmayı amaçlamaktadır. Bu çalışmada literatürde ağırlıklı olarak kullanılan diskriminant analizi kullanılmıştır. Örneklemimiz 2.391 mali açıdan başarısız şirket ve 345.426 sağlıklı firma içermekte ve tüm gözlemler halka açık olmayan Türk şirketlerinden oluşmaktadır. PF-Score modelinin katsayılarını discriminant analizi ile belirledikten sonra finansal sıkıntı tahmininde karlılık rasyolarının daha etkili olduğunu gözlemledik. Ayrıca verimlilik, likidite ve kaldıraç rasyoları da önem sıralamasında uygun tahmin ediciler olarak bulunmuştur. Skor eşiğini belirledikten sonra modelimizin sorunlu firmaları %60 doğrulukla ayırt edebildiğini ve sağlıklı firmaları %75 doğruluk oranıyla izole edebildiği sonucunu elde ettik. Literatürdeki Altman Z-Score modellerinin tahmin gücünü de test ettik. Tahmin modellerinin karşılaştırmalı ROC ve AUC analizi de tezde verilmektedir. Son olarak PF-Score'un halka açık olmayan firmaların finansal sıkıntılarını tahmin eden diğer diskriminant analizi modellerine göre daha isabetli tahmin sonuçları ürettiğini gözlemledik.

DEDICATION

Dedicated to my father,

who raised his children with his hard work and unselfish dedication to his family.

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CHAPTER 1

INTRODUCTION

Inherently, businesses act and operate like living organisms. They have a founding day, good times, bad times, and ending days. Good days contain business success while failures happen during bad times. It may cause termination of its existence. Companies face failures somehow during their life cycle. Then, it has a serious effect on their stakeholders as well as its own. Financial failure literature consists of various fragments of business failure. Due to the lack of theoretical consensus, there is no general acceptance of the definition of "failure" and failure predictions (Oz & Yelkenci, 2017; Shi & Li, 2019). Bankruptcy and financial distress prediction models are generally aiming to distinguish failed and healthy firms.

Financial failure doesn't occur only for bankrupt firms, but also for whose have financial difficulties. We find the "financial distress" term more suitable for our research. Sun (2014) defined financial distress as a "certain degree of financial deterioration ruled by the national security management institution" (p. 43). However, we interchangeably use the terms "financial distress", "bankruptcy prediction" and "financial failure prediction" in this study.

Researchers had rummaged prediction studies of financial distress from the 1930s to 1968. In this period, studies covered univariate analysis rather than multivariate analysis. In this study, we conduct a multivariate analysis. In the literature, there are few papers focused on financial failure (or bankruptcy) prediction. Bureau of Economic Business Research's (1930) bulletin has become the initial step in the literature. BBR's study analyzed several financial ratios to distinguish bankrupt and healthy firms. Even so, BBR only implemented univariate

analysis techniques (Bellovary, Giacomino, & Akers, 2007). From 1930 to 1968, studies didn't cover any multivariate techniques. Primarily, Altman (1968) has published the first paper that proposes an accounting-based financial failure prediction model. In his study, Altman took a significant step further via using a technique called: Multiple Discriminant Analysis (MDA). MDA provides a statistical approach to classify qualitative dependent variables. In Altman's first analysis (1968), he used MDA to derive a linear combination of several financial ratios so as to discriminate bankrupt and non-bankrupt firms. We will explain the Multiple Discriminant Analysis later in this paper.

This study contributes to the literature a financial distress prediction model. We propose a prediction model for privately-held companies. The model was derived from a developing country: Turkey. Financial distress prediction studies focus on publicly-held Turkish companies in the Turkish literature. There is no study focuses on privately held companies. Studies covered publicly traded companies in Borsa Istanbul (Çolak, 2019; Özdemir, 2014; Uğurlu & Aksoy, 2006). The number of financial failures in an exchange market is insignificant to propose a prediction model. Turkey is also in the infancy stage in terms of capital markets. These reasons make it difficult to derive a model from exchange markets. The market capitalization ratio of listed domestic companies to GDP is also lower in Turkey. Turkish listed companies represent only 24% of total GDP while it is 147% in the United States (World Federation of Exchanges Database, 2018). Modeling financial distress of private firms improves risk assessment. It helps creditors, financial institutions, and stakeholders, and government agencies with their decision-making.

We tested several financial ratios to obtain a financial distress prediction model for Turkish privately-held companies. We analyzed 25 different financial

ratios to obtain the model with the highest accuracy. We picked up only four different financial ratios. The lower number ratio prevents perfect multicollinearity and difficulty in apprehensibility. We implemented Multiple Discriminant Analysis with these 4 ratios. Moreover, this paper covers two more analyses: an empirical study that queries the validity of Altman Z-score models via our dataset and calibration of the Altman Z-model with its existing financial ratio variables.

We cover a comprehensive review of financial distress prediction literature in Chapter 2. Thereafter, we explain Discriminant Analysis as our main statistical technique. We describe data in Chapter 4. We include descriptive statistics and empirical results in Chapter 5. In Chapter 6, we propose coefficient calibration of the Altman Z-Score model for private firms and PF-Score model. Lastly, this paper ends with a conclusion in the last chapter.

CHAPTER 2

LITERATURE REVIEW

Studies on financial failure prediction date back to the early 1930s. From the 1930s to Altman (1968), predicting financial failure studies covered depthless analyses. These studies only comprised financial ratio analyses rather than having multivariate analyses. Bureau of Economic Business Research examined 24 different financial ratios to observe common distinctions of financial failure (Bureau of Economic Business Research, 1930). The rest of the published studies from the 1930s to 1960s exhibited: the current ratio, working capital to total assets ratio, and debt to shareholder's equity ratio are lower in failed companies than healthy firms (Bellovary et al., 2007). Beaver (1966) has published the last elaborative univariate analysis in this period. He tested 32 different financial ratios within 6 groups: Cash-flow ratios, net-income ratios, debt to total-asset ratios, liquid-asset to total-asset ratios, liquid-asset to current debt ratios, and turnover ratios. Beaver's study revealed that non-failed firms have stable financial ratio distributions, while failed firms have weakened and fluctuated financial ratios. These fluctuations are even more as failure approaches. Especially, the last five years' financial ratios of failed firms indicate a significant differentiation from healthy firms' performance. Beaver (1966) defined failure as "inability of a firm to pay its financial obligations as they mature" (p.71).

Undoubtedly, the milestone in financial distress prediction models is Altman Z-score (Altman, 1968). In his analysis, Altman has published the first multiple discriminant model in financial failure prediction. Up to that time, MDA analysis had been used in biological and medical research since the first-time used by Fisher(1936). But it was not popular among economists until Altman's study.

As a statistical technique, Discriminant Analysis is used to examine the relationship between continuous independent variables and categorical dependent variables (a priori groups) such as healthy-unhealthy or male-female. This statistical technique allows assigning observations to the determined classifications. In other words, its suitable for descriptive or predictive studies. MDA provides a function that discriminates groups (dependent variable) with the highest accuracy. The predictors are a bundle of independent variables. It aims to maximize the variable weights between-group variance to within-group variance which distinguishes groups. MDA produces a score that arises from the weights of each independent variable. Having determined the cut-off point of the score scale, observations can be diversified in compliance with their Z-score.

2.1 Altman's Z-score Models

Even though Altman had published his first paper in 1968, he continued to develop the Z-score model in the 80s and 90s. He focused on whether the firm is privately held or publicly traded, manufacturing or non-manufacturing firm, and U.S firm or global firm.

Altman's (1968) sample comprised of 66 corporations with 33 bankrupt and 33 non-bankrupt firms. He derived financial ratios from the period of 1946-1965. He named Altman Z-score Model which has 5 different financial ratios to predict bankruptcy. He classified firms thanks to the Altman Z-score model with 94% and 97% accuracy of bankrupt and non-bankrupt firms. The predictive ability of the model was valid for one year before the financial failure of the firms. When Altman runs the model for periods that earlier than 1 year, the accuracy of the model has significantly reduced. One of the limitations of this model is that the sample only

covers publicly held US manufacturing corporations (Altman, 1968; Bellovary et al., 2007).

While selecting variables, Altman(1968) has benefited quite a lot from Beaver's (1966) financial ratio analysis. Altman's proposed Z-score model with 5 financial determinants are as below:

$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5$ (Altman, 1968)

where;

$X_1 =$ Working Capital / Total Assets

$X_2 =$ Retained Earnings / Total Assets

$X_3 =$ Earnings Before Interest and Taxes / Total Assts

$X_4 =$ Market Value Equity / Book Value of Total Debt

$X_5 =$ Sales / Total Assets

Since X_5 has an extreme level of coefficient in the model of 1968 due to the format of different variables (Altman, 2013), the discriminant function has been evolved to another form:

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$ (Altman, 2013)

where;

$X_1 =$ Working Capital / Total Assets

$X_2 =$ Retained Earnings / Total Assets

$X_3 =$ Earnings Before Interest and Taxes / Total Assts

$X_4 =$ Market Value Equity / Book Value of Total Debt

$X_5 =$ Sales / Total Assets

Altman showed that firms having a Z-Score above 2.99 can be classified as non-bankrupt or healthy firms while firms having Z-Score below 1.81 are classified as bankrupt firms. However, the area between 1.81 and 2.99 can be identified as a

“gray area”. This gray zone classification leads to mend classification error (Altman, 1968).

Altman’s first bankruptcy prediction model was only focusing on public firms rather than private firms. Because our thesis inquiries about private firms' financial distress prediction, we will work through Z’-Score and Z’’-Score models. Altman published these developed models in the following years (Altman, 1983).

Altman has revised his first Altman Z-Score Model (Altman, 1968) in 1983. In the original model, the variable X_4 is the Market Value Equity to Book Value of Total Debt Ratio. But we can’t implement this ratio for public firms due to the absence of Market Value Equity. He also stated that revising the original Altman Z-Score for private firms can help to figure out concerns of credit analysts, private placement dealers, and accountants.

To adopt his model for private firms, Altman (1983) replaced Market Value Equity with Book Value of Equity. He re-estimated all coefficients of each variable once again. Thus, he calibrated his model and determined cut-off points as well. Due to the lack of private firms' data at that time, he derived his results from private firm's financial ratios.

$Z' = .717X_1 + .847X_2 + 3.107X_3 + .420X_4 + .998X_5$ (Altman, 1983)

where;

$X_1 =$ Working Capital / Total Assets

$X_2 =$ Retained Earnings / Total Assets

$X_3 =$ Earnings Before Interest and Taxes / Total Assts

$X_4 =$ Book Value of Equity / Total Liabilities

$X_5 =$ Sales / Total Assets (Altman, 1983)

Z’-Score model has also a considerable level of accuracy with 91% and 94%. As a result of decreasing the mean of non-bankrupt firms', the gray zone has become wider. The new classification cut-off points have turned into 1.23 and 2.90(Altman, 1983).

Table 1. Altman Z'Score Classification Intervals

> 2.90	Non-bankrupt
1.23-2.90	Grey zone
<1.23	Bankrupt

Financial ratios of Altman Z-Score Models are as below;

$X_1 =$ Working Capital / Total Assets

Working Capital to Total Assets ratio is one of the Turnover Ratios that Beaver found purposeful to predict bankruptcy (Beaver, 1966; Ohlson, 1980). Working capital is the difference between current assets and short-term liabilities which indicates how much a firm is closer to insolvency in a short term. In other words, the working capital/total assets ratio is the evaluation of net liquid assets to a firm’s total wealth.

$X_2 =$ Retained Earnings / Total Assets

In another saying, this ratio is earned surplus to total capitalization ratio since it measures reinvested earnings and losses of a company along its operating lifetime. It should be noted that this ratio is open to manipulation intentionally through dividend declarations. Additionally, this ratio is also depending on the age of the firm (Altman, 2000). That is why we didn’t include this ratio in our analysis.

X_3 = Earnings Before Interest and Taxes / Total Assets

EBIT to Total Assets Ratio indicates the profitability that firm generates from its total assets without consideration of tax and non-operating income/losses.

X_4 = Book Value of Equity/ Total Liabilities

Book Value to Total Liabilities ratio is one of the most used ratios in the literature. Equity financing shows a lower risk of financial distress compared to debt financing (Frank & Goyal, 2009). The higher level of B.V. of Equity to Total Liabilities ratio means lower insolvency risk. Otherwise, the company will struggle to pay its interest payments as well as debt liabilities (Njeru & Waititu, 2018).

X_5 = Sales / Total Assets (Altman, 1983)

The "Sales to total assets" ratio shows the company's ability to generate sales from its capitalization. However, the sales to total assets ratio changes majorly depending on industries or countries (Altman & Hotchkiss, 2005). That is why Altman has adopted a new model including only 4 variables without considering the Sales to Total Asset ratio.

Altman also showed that his Z-Score predictions have a correlation with S&P Bond Ratings within the period of 1996-2001 (Altman & Hotchkiss, 2005). Due to the lack of private firm data availability, Altman couldn't test his proposed models with private firms with a secondary sample until 2017. Altman et al. (2017) has tested Z-Score for private firms with ORBIS data. ORBIS is the database that provides financial information of companies across the world, mostly from European countries. This database also contains private companies' financial information over 98 million global corporations. He showed that his accounting-based analysis still keeps its validity and is worth studying (Altman et al., 2017; Altman & Saunders, 1997).

2.2 Financial distress prediction of private firms

Most of the studies on bankruptcy and financial distress prediction examine publicly traded firms as their model sample. This disallows achieving the characteristics of bankruptcy in distressed firms. (Charalambakis, 2014). Private firms have different debt patterns. They have higher financing costs and higher returns from investments. A portfolio of a private equity investor's ROE is 2.5 times bigger than a publicly traded equity investor's (Faccio, Marchica, McConnell, & Mura, 2012). Moody's proposed a default model for private firms which is called RiskCalc. The sample of RiskCalc contains 28.104 companies and 1.604 defaults (Falkenstein, Boral, & Carty, 2000). Mselmi et al. (2017) examined small and medium-sized French firms' financial distress prediction. Altman also examined creditworthiness and default risk for SME firms (Altman, Esentato, & Sabato, 2020; Altman, Giannozzi, Roggi, & Sabato, 2013; Altman & Sabato, 2007). Koyuncugil & Ozgulbas (2012) developed an early warning system for SMEs. They implemented a data mining application for Turkish SMEs. Charalambakis (2014) showed that GDP and a firm's trade openness have a significant effect on its default risk. His analysis also contains 1.772 bankrupt firms and 29.162 healthy firms.

Most of the studies on financial distress forecasting models of privately-held companies have been derived from developed countries. This caused that the implementation of these models in emerging markets can be inadequate due to the dissimilar costs of borrowing in developing countries compared to advanced countries (Charalambakis & Garrett, 2019; Matenda, Sibanda, Chikodza, & Gumbo, 2021). In his literature review of bankruptcy prediction for private firms in developing countries, Matenda et al. (2021) found that there are 11 peer-reviewed journal articles from 2000 to 2021 which are mostly after the 2008 global financial

crisis. The number of models using data from more than 1000 companies is only 4 while some papers examined less than 50 firms (Altman et al., 2017; Charalambakis, 2014; Charalambakis & Garrett, 2019; Jacoby, Li, & Liu, 2019).

2.2.1 Prevalence and importance of privately held companies in Turkey

As of May 2021, the Turkish stock exchange market, Borsa İstanbul, has only 496 listed companies (KAP, 2021). The market capitalization of listed domestic companies in Turkey was 184 billion USD. It represents 24.2% of total GDP in 2019 (World Bank, 2019). The average of the world is 119.2%. It can be said that the Turkish exchange market is in its infancy compared to developed countries (Ekin, Altaş, Ceylan, Deniz, & Onur, 2021). Turkish SMEs represent 72.4% of overall employment and 50.4% of total financial turnover. This given leads us to emphasize the importance of private companies. Remember that most of the non-SME companies are still privately held companies(TÜİK, 2019).

2.3 Financial distress and bankruptcy in Turkey

Having said that we don't include sole proprietorship in our analysis. We use the terms "firm" and "company" interchangeably for equity companies (both for limited liability corporations and joint-stock companies).

Literature defined the term financial distress variously. Gordon (1971) defined financial distress as the state of decline in a firm's revenue-generating ability. It causes an important probability of difficulties in discharging obligations. These obligations are usually interest and debt. Financial distress is confused with insolvency at times. Despite this fact, insolvency is a more arduous situation that companies may struggle with. Purnanandam(2008) defined financial distress as a

circumstance of having inadequate cash flow and a decrease in revenue without experiencing insolvency. Anyway, financial distress is a substantial indicator of bankruptcy, insolvency, and liquidation of companies.

According to the Turkish Commercial Code, corporations acquire legal status by obtaining trade registration (Article 12; Article 355; Article 588). All corporations and limited liability companies are required to be enrolled in to trade registry and they are supposed to keep requisite commercial books by the act of Commercial Law (Art. 18). That is why the only appropriate and accessible indicator of a private firm's financial failure is the termination of the trade registry for Turkish private companies. Data selection and variables organization will be explained later in Chapter 5.

The Union of Chambers and Commodity Exchanges of Turkey publishes the number of closed firms every month. Unfortunately, the data of closed firms do not contain the reason for termination. This causes difficulty to distinguish whether the company is financially failed or closed for another reason. Thanks to UCCET's data, we extracted the number of closed Turkish firms by year in Figure 1 (The Union of Chambers and Commodity Exchanges of Turkey, 2021).

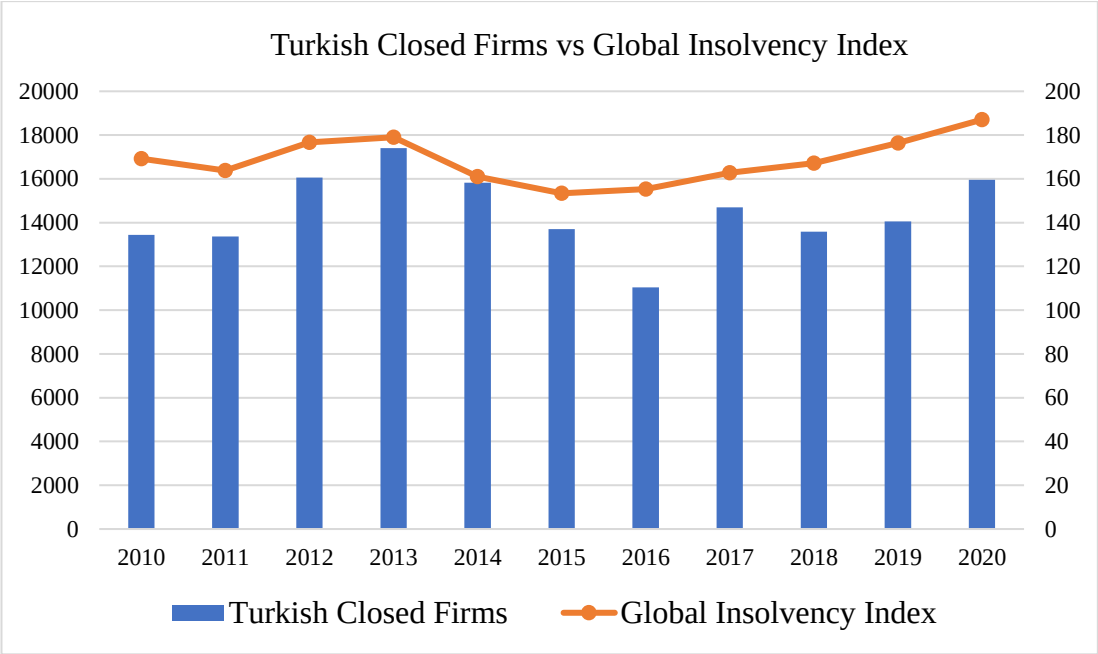

Figure 1. The comparison of the number of closed firms in Turkey and the Global Insolvency Index

Figure 1 shows that the bankruptcy trend in Turkey happened in the same direction as the global insolvency index (Allianz, 2020). This may imply that domestic economic problems haven't affected the statistics of closed firms in Turkey (see Figure 1). Turkish firm closing routine usually takes one year period before its legal termination. Moreover, global business insolvencies are expected to increase more than 30% in 2021 due to the Covid-19 global pandemic (Euler Hermes, 2020).

Euler Hermes' insolvency heat map indicates that Turkey is one of the troubled countries in terms of insolvency (see Figure 2). UCCET is also sharing the NACE classification of the closed firms. Having analyzed this classification, we obtained that more than 60% of the closed firms are wholesale and retail trade firms, construction, and manufacturing. Since construction firms are usually highly leveraged and sensitive to foreign exchange shocks (Alp, 2013), the number of closed construction firms are fluctuating year by year. Apart from construction firms, the number of closed firms is thereabout stable (see Figure 3).

Strongly Deteriorating (+5% and more)	Hong-Kong(+9%) Canada (+5%) The Netherlands (+5%)		Denmark (+6%) GLOBAL (+6%)	Chile(+21%) Slovakia (+12%) China (+10%) Singapore (+10%) Bulgaria (+8%) Colombia (+5%) Ireland (+5%) Morocco (+5%) Spain (+5%) Turkey (+5%)
Deteriorating(+1% to less than +5%)	South Africa (+4%) US (+4%) Germany(+3%) Romania(+3%) Estonaia (+2%) Japan(+2%) Russia (+2%) South Korea (+2%) Taiwan (+2%) Latvia (+1%)	UK (+3%) Austria (+2%)	Italy (+4%) Czech Rep (+2%) Finland (+2%) Sweeden (+2%) Switzerland (+1%)	Australia (+2%) Belgium (+2%) Portugal (+2%)
Stable or Slightly Improving (less than -5% to 0%)	Greece (-2%) Hungary (-3%)	New Zealand (0%) Poland (0%) Brazil (-3%)	France(0%)	Luxembourg (0%) Norway (0%) Lithunia (-2%)
Strongly Improving (strictly more than -5%)				
	Very Low Level (more than 20% below the 2003-2007 level)	Low Level (between 0% and 20% below the 2003-2007 level)	High Level(bet ween 1% and 20% above the 2003-2007 level	Very High Level (more than 20% above the 2003-2007 level)

Figure 2. Euler Hermes Insolvency heat map(Allianz, 2020)

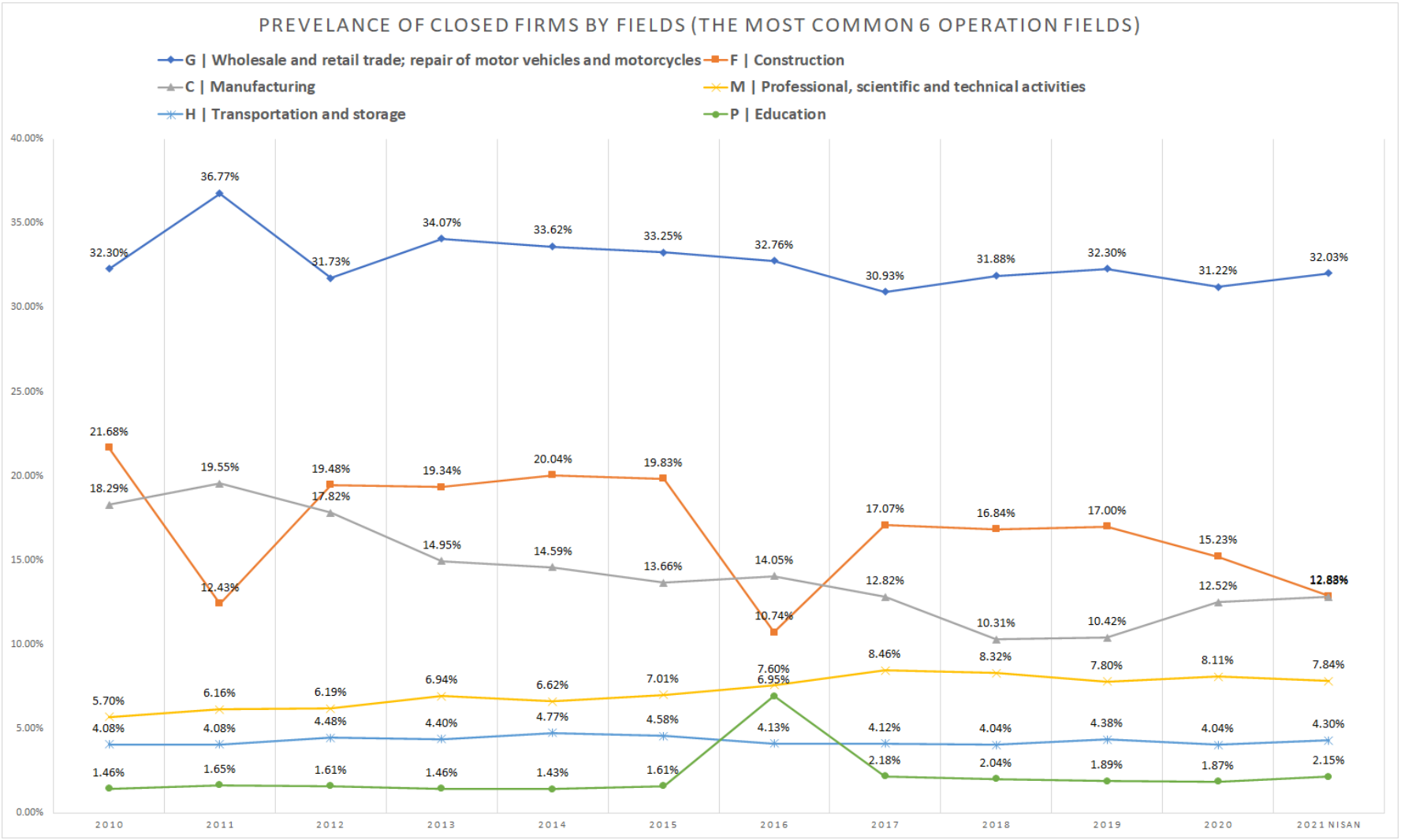

Figure 3. Number of closed companies by operations Field 2010-2020

CHAPTER 3

EMPIRICAL METHODOLOGY & MODELS

After Beaver's (1966) and Altman's (1968) studies, financial distress and bankruptcy prediction models have become popular. Shi & Li (2019) indicated that more than 1.259 papers have been published related to financial distress and bankruptcy prediction. Even though studying bankruptcy prediction models have commenced in the 1960s, it gained momentum after the 2000s. The motive of this momentum was the Global Economic Crisis of 2008.

Accounting-based bankruptcy prediction models can be classified into two main groups: Classical statistical models and machine learning-artificial intelligence models. The most common machine learning methods are the neural network, support vector machine, decision tree, genetic algorithm, fuzzy, rough set, and data mining models (Shi & Li, 2019).

Classical statistical methods in bankruptcy prediction are classified as:

- Probit models and logit regression models
- Discriminant Analysis and Z-Score models

3.1 Logit models

Having become popular in the 1980s, logit models provided a different method of distress prediction. Ohlson's (1980) bankruptcy prediction model is the first conditional logit analysis in the literature. One of the reasons for choosing logit analysis is that Multivariate Discriminant Analysis has some assumptions which are usually violated. On the other side, despite the logit models, MDA also has a score with an ordinal ranking that sometimes causes difficulty in the interpretation (Ul

Hassan, Zainuddin, & Nordin, 2017). Ohlson's study contains 105 bankrupt and 2058 healthy (non-bankrupt) firms from 1970 to 1976 (Ohlson, 1980). He found that the size of companies is a substantial element to predict bankruptcy. In some papers, logit-probit models were compared with Discriminant Analysis. They found that logit-probit models are more useful and reliable at times (Lennox, 1999). Logit model contains a cumulative logistic function with a dichotomous dependent variable which lies from 0 to 1 (Mihalovič, 2016). Zmijewski (1984) made his criticism on the oversampling bias of the distressed firms that other financial distress estimation models usually did.

3.2 Discriminant analysis

The discriminant analysis provides an index score that can classify into two or more categorical dependent variables (Garson, 2012). More precisely, discriminant analysis inquires whether predictors can come together to estimate group classification. Multivariate analysis of variance aims to find out whether there are statistically significant mean differences among combined dependent variables. Discriminant analysis is mathematically the other way around of multivariate analysis of variance (Tabachnick & Fidell, 2019). The core intuition of discriminant analysis is to understand the underlying reason for the differentiation of each group.

The function of discriminant analysis (also known as "discriminant function" or "canonical root") is a linear combination of discriminating variables:

$DF = ß_1X_1 + ß_2X_2 + ß_3X_3 + \cdots + ß_nX_n + c$ (Garson, 2012)

where;

$ß_n = Discriminant\ coeffients$

$X_n = Discriminant\ variables$

$C = constant$ (Garson, 2012)

Following Garson (2012), the discriminant function targets to maximize the distance between the centroids (multivariate version of the term "mean") of discriminators.

Discriminant analysis has several assumptions which are very similar to MANOVA's assumptions and limitations (Tabachnick & Fidell, 2007) :

- The number of dependent variables should be less than n-2, where n is the sample size. Nevertheless, a reliable analysis's sample size should be at least 4-5 times bigger than the number of predictors (independent variables). Unequal group sizes are also acceptable for discriminant analysis.
- Predictors should be independent of each other and should have similar covariance/correlation. Multicollinearity of the independents is also unwished-for MDA analysis.
- Residuals are randomly distributed.
- The independent variables should be normally distributed
- Since Discriminant Analysis is strictly sensitive to the presence of outliers, homoscedasticity is also required for MDA analysis.
- Categorical variables are mutually exclusive
- MDA analysis assumes that predictors are linearly related within each group.

CHAPTER 4

DATA & DESCRIPTIVE STATISTICS

4.1 Data preparation

To examine financial distress with the multivariate discriminant model for Turkish private firms, we obtained private firms financial data called Enterprise Information System from the Ministry of Industry and Technology. This data is an integrated database of the Ministry of Industry and Technology, consisting of data provided by the Turkish Revenue Administration, Ministry of Commerce, Social Security Institution, The Scientific and Technological Research Council of Turkey, Turkish Patent and Trademark Office, Small and Medium Industry Development Organization and Turkish Statistical Institute. This comprehensive data allowed us to observe the financial data of private firms. Our sample incorporates firms published balance sheets between 2010-2017.

In Turkey, there are 5 types of tax obligation for firms:

1- Corporate taxpayer
2- Income taxpayer - balance sheet basis (Natural person)
3- Income taxpayer – operation account method
4- Self-employment income tax
5- Small business taxation – bookkeeping by a single entry

Our comprehensive data consists of all the firms above. Firms outside of corporations don’t submit balance sheet declarations in compliance with international accounting standards. That is why this study focuses on only corporations.

As of 2017, there are 789.458 corporate taxpayers. This represents 24% of all taxpayers. Even though the number of corporations is not dominant, corporate

taxpayers employ 78.3% of entire formal workers (10.8 million of 13.8 million in Turkey). That emphasizes the importance of corporate firms in Turkey's economy. Within this dataset, 99.14% of total firms are SMEs (602.000 micro, 149.000 small-size, 31.000 medium-size, and 6.000 macro companies).

There are 1.2 million corporate firms' financial data regardless of size, field, or type. Closed firms per year in our data are as below:

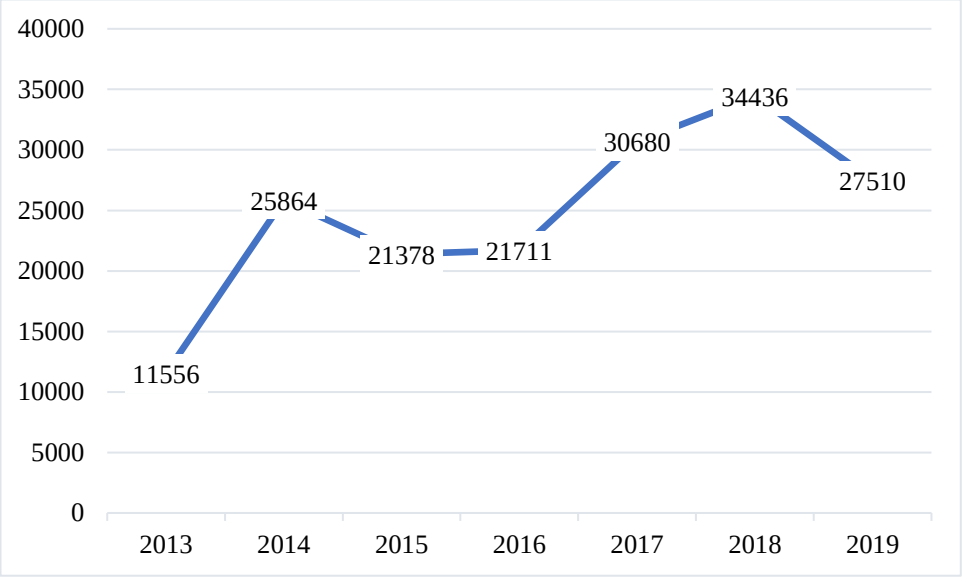

Figure 4. Number of closed firms in our financial data

In our sample, we focused on the reliability of the firms' balance sheets as a matter of priority. Remember that these firms are privately-held companies and they may tend to manipulate financial statements on behalf of their corporate policies. Since they are not publicly traded, they are not required to share their financial reports. However, since they are taxpayers, they are supposed to share their financial data with government institutions. Therefore, believing that firms that are more likely to be subject to government scrutiny will have more reliable balance sheets, we have turned to some restrictions.

We've found that 1.045 million firms were existing in Turkey from 2010 to 2018. We've determined such limitations to acquire more remarkable observations in our sample. We've included firms which are:

- Having 100.000₺ total assets on average during the lifespan
- Having employed 20 workers at least once and 10 workers on average
- Having submitted financial statements consecutively for at least 3 years before going bankrupt

In Turkey, trade registration terminates also in case of transfer of the company. Even though the trade register number changes during handovers, the employer registration number remains the same. It helped us to determine which firms are both officially and essentially ended. Therefore, we obtained a sample that contains 347.817 observations.

Having extracted the observations accordingly to our limitations, we have excluded predecessor and acquiree firms as well. We've included these firms in the sample since closed firms are not divided by authorities in terms of their termination reasons. This helps us to prevent selection bias.

MDA analysis in financial distress prediction modeling consists of a dichotomous dependent variable which is bankrupt/non-bankrupt and independent variables which are financial ratios. Our data is consisting of 345.426 healthy firms' observations and 2.391 bankrupt firms' observations from 2010 to 2017.

Table 2. Descriptive Statistics of Healthy and Failed Firms in the Sample

Bankrupt of financially failed	Healthy firms	Total
2.391	345.426	347.817

The sample consists of companies of different sizes. Financial balance sheet sizes range from 100,000 Turkish Liras to 1 billion Turkish Liras. We know that the

Turkish lira depreciated from 2010 to 2018 due to various exchange rate shocks. Therefore, according to the inflation data shared by the Central Bank of the Republic of Turkey (TCMB, n.d.), we have reduced the balance sheet sizes to 2018. Thus, we arrived at the net present value data. This is how we did our classification.

Table 3. Descriptive Statistics of Firm Size Groups

	Number of firms
100.000 ₺-2.000.000 ₺	6.002
2.000.000 ₺ - 4.000.000 ₺	8.779
4.000.000 ₺ - 10.000.000 ₺	15.470
10.000.000 ₺ - 20.000.000 ₺	9.360
20.000.000 ₺ - 40.000.000 ₺	5.883
40.000.000 ₺ - 80.000.000 ₺	3.310
80.000.000 ₺ - 200.000.000 ₺	1.872
200.000.000 ₺ - 500.000.000 ₺	782
500.000.000 ₺ - 1.000.000.000 ₺	218
> 1.000.000.000 ₺	183
Total Number of Firms:	51.859

According to “Regulation on Definition, Characteristics, and Classification of Small and Medium Enterprises” (Turkish Government Cabinet Decree, 2018);

1. Micro Firms are:

- Enterprises employing less than 10 employees per year and whose annual net sales revenue or financial balance sheet does not exceed 3.000.000 Turkish Liras (Article5a).

2. Small firms are:

- Employing less than 50 employees and annual net sales revenue or businesses whose financial balance sheet does not exceed 25 million Turkish Liras (Article 5b).

3. Medium-size firms are:

- Businesses that employ less than 250 people and whose annual net sales revenue or financial balance sheet does not exceed 125 million Turkish Liras Article 5c).

4. Non-SME firms are:

- Firms out of Micro-Size, Small-Size, and Medium-Size firms.

In our sample, Micro companies are predominant among other types of firms. Since small firms have more tendency to be financially failed than major firms, the number of failed companies is accumulated within micro and small businesses.

Table 4. Frequencies of Firm Types in our Sample

	Failed	Non-failed	Failed/Non-Failed (%)
Micro	690	5.875	10,5%
Small	1.120	30.229	3,6%
Medium	502	10.875	4,4%
Non-SME	79	2.489	3,1%
Total	2.391	49.468	51.859

4.2 Variables selection

We've chosen Multivariate Discriminant Analysis for predicting financial distress. We've explained our chosen dependent variable as bankrupt or non-bankrupt. The predictors are obtained from the financial ratios of the companies. Having reviewed the literature, we've decided to benefit from Çolak's (2019) study for determining financial ratios that we should take into consideration. Moreover, we also analyzed Altman's and Ohlson's prediction model's financial ratios (Altman, 1968; Ohlson, 1980). Outliers are winsorized. Financial firms are also excluded from the sample. Our dependent variables are not paired in size.

To predict financial distress, we divided companies into two classes accordingly whether they are closed or not. If the company is closed, bankrupt, default, failed, or financially distressed (we used these terms interchangeably), we take the penultimate year's financial data of the closed company into consideration as a predictor year of the company's financial failure. We don't include last year's financial data of distressed firms. During the liquidation, balance sheets are generally meaningless.

4.2.1 Descriptive statistics of financial ratios as predictors

First, we examined Altman Z-Score's independent variables which all of them are expected to be positively correlated with being healthy as theoretically. Nevertheless, retained earnings to total assets ratio don't indicate the power of being healthy.

Apart from retained earnings to total assets ratio, we observe that liquidity, profitability, leverage, and efficiency ratios are significantly lower in closed firms as expected. Distressed firms are more levered. They have less ability to generate profit

from their assets than healthy firms. They have limited resources for short-term investments. The mean of short-term liabilities to current assets ratio is 0.85 for healthy firms while it is 1.11 for distressed firms. It shows that distressed firms are the ones that have cash shortage issues. This is what we expected. Moreover, financially healthy firms haven't only better profit performances, but also better sales performances from their assets.

Table 5. Descriptive Statistics of Financial Ratios by Financial Status

	Healthy Firms			Closed Firms (1-year before the termination)		
	N	Mean	SD	N	Mean	SD
Financial Ratios						
Altman Z-score Variables						
Working Capital / Total Assets	345.426	0.16	0.26	2.391	0.02	0.42
Retained Earnings / Total Assets	345.426	0.10	0.13	2.391	0.11	0.16
EBIT / Total Assets	345.426	0.07	0.09	2.391	0.00	0.14
Book Value of Eq/ Total Liab.	345.426	0.66	0.73	2.391	0.47	0.83
Sales / Total Assets	345.426	1.41	1.05	2.391	0.93	0.98
Profitability Ratios						
Net Income / Net Sales	345.426	0.02	0.07	2.391	-0.04	0.13
Net Income / Total Assets	345.426	0.03	0.06	2.391	-0.01	0.08
EBIT / Net Sales	345.426	0.05	0.08	2.391	0.00	0.13
EBIT / Total Assets	345.426	0.06	0.07	2.391	0.02	0.08
Net Income /Shareholder's Eq.	345.426	0.10	0.21	2.391	0.05	0.35
Leverage Ratios						
Total Liabilities / Total Assets	345.426	0.68	0.19	2.391	0.76	0.21
Total Liab. / Shareholder's Eq.	345.426	4.07	4.69	2.391	5.48	6.90
Retained Earnings/ T. Assets	345.426	0.09	0.11	2.391	0.10	0.13
Long Term. Liab./ Fixed Asset	345.426	0.61	1.17	2.391	0.75	1.47
Long Term Liabilities / Equity	345.426	0.67	1.23	2.391	0.59	1.30
Shareholder's Eq. / Total Liab.	345.426	0.65	0.66	2.391	0.49	0.69
EBIT / Total Liabilities	345.426	0.12	0.17	2.391	0.04	0.16

	Healthy Firms			Closed Firms (1-year before the termination)		
	N	Mean	SD	N	Mean	SD
Liquidity Ratios						
Short T. Liab. / Current Assets	345.426	0.86	0.49	2.391	1.12	0.70
Acid-Test Ratio	345.426	0.97	0.79	2.391	0.85	0.78
Inventory / Short Term Liab.	345.426	0.38	0.29	2.391	0.33	0.31
Working Capital / Total Assets	345.426	0.16	0.25	2.391	0.06	0.30
Current Assets / Total Assets	345.426	0.71	0.23	2.391	0.74	0.27
Cash and C. Eq./ Total Liab.	345.426	0.16	0.24	2.391	0.12	0.22
Quick Assets / Current Liab.	345.426	0.97	0.79	2.391	0.85	0.78
Efficiency Ratios						
Sales / Total Assets	345.426	1.39	0.97	2.391	0.92	0.90
Sales / Current Assets	345.426	2.22	1.83	2.391	1.74	2.07
Sales / Fixed Assets	345.426	13.67	23.55	2.391	16.26	30.91
Sales / Quick Assets	345.426	4.93	6.43	2.391	4.17	7.19

4.2.2 Firm size effect on bankruptcy

Having discounted the total asset accounts of each firm to 2018, we observed that small-size firms are more likely to be failed in our sample. 9% of private firms with less than 2 million₺ in asset size were failed while firms with more than 40 million₺ in asset size face financial failure with less than 3% probability (see Table 6).

Figure 5. Financial failure probability by firm size groups

Table 6. Asset Size Groups by Financial Status

Asset Size	Closed Firms	Healthy Firms	Total	% of failed firms
100.000 ₺-2.000.000 ₺	545	5457	6002	9.08%
2.000.000 ₺ - 4.000.000 ₺	438	8341	8779	4.99%
4.000.000 ₺ - 10.000.000 ₺	644	14826	15470	4.16%
10.000.000 ₺ - 20.000.000 ₺	381	8979	9360	4.07%
20.000.000 ₺ - 40.000.000 ₺	220	5663	5883	3.74%
40.000.000 ₺ - 80.000.000 ₺	97	3213	3310	2.93%
80.000.000 ₺ - 200.000.000 ₺	52	1820	1872	2.78%
200.000.000 ₺ - 500.000.000 ₺	11	771	782	1.41%
500.000.000 ₺ - 1.000.000.000 ₺	3	215	218	1.38%
> 1.000.000.000 ₺	0	183	183	0.00%

In the literature, the terms “financial failure”, financial distress”, “insolvent firms” or “default firms” are used interchangeably in prediction analysis (Altman & Hotchkiss, 2005; Habib, Costa, Huang, Bhuiyan, & Sun, 2020; Korol, 2019). In this paper, we aim to estimate which company is financially distressed or not. We don’t use paired samples. In other words, the number of the failed and non-failed firm are not equal. Then, we considered prediction from a different angle. We used the firm’s closing dummy variable as one of the most common results of financial distress. Obviously, many firms face financial distress but most of these distress situations are not concluded with bankruptcy. That is why our proposed model should be evaluated as a score of a firm’s bankruptcy degree. Naturally, a higher score may be considered as a lower probability of financial distress while a lower score should be considered

as a higher risk of having financial distress. To provide an interpretable result, we also determined a threshold for the prediction models. These thresholds emphasize a kind of landmark to separate firms as healthy or distressed. Closed firms according to Turkish Commercial Law are considered as a financial failure in this thesis.

CHAPTER 5

TESTING AND CALIBRATING EXISTING PREDICTION MODELS

5.1 Application of Altman Z'-Score for private firms with existing coefficients

First, we examined the empirical results of the existing Altman Z'Score model which was proposed in 1983: $Z' = .717X_1 + .847\,X_2 + 3.107\,X_3 + .420\,X_4 + .998\,X_5$ (Altman, 1983). The classification results of the Altman Z-Score model present us that (see Table 7) the predictive power of the model is not as strong as the derived sample. Moreover, since the determined cut-off points are relatively far from each other, it causes that grey zone represents more than half of the total sample. It causes a misaccumulation within an uncertain group. Nevertheless, this model still keeps its prediction ability (see Table 7). To improve this ability, we propose a calibrated version of the Altman Z'Score model with new coefficients. We adopted these coefficients via our sample.

Table 7. Results of Altman Z'Score

		Predicted			
		Bankrupt	Grey Zone	Healthy	
Original	Failed	1.405	726	260	**2.391**
	Healthy	96.095	174.528	74.803	**345.426**
	Total	**97.500**	**175.254**	**75.063**	

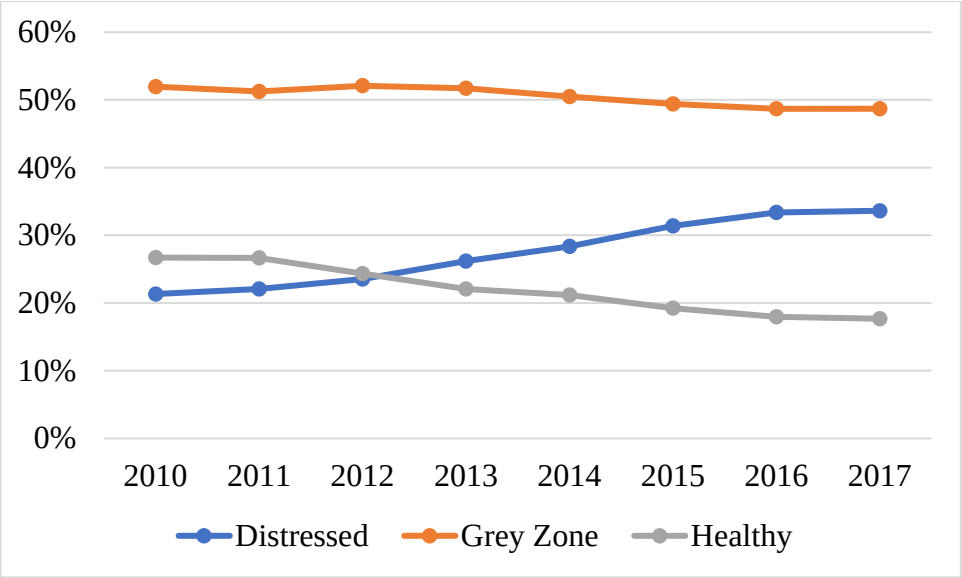

Figure 6. Distribution of Altman Z'Score by year

5.2 Calibration of Altman Z'Score model (Z_2' *and* Z_3' *Model*)

Altman's prediction model for private firms was derived from the publicly held firms' financial data. We thought that Altman's original score should be calibrated using privately held companies' financial data. Private firms are different from public firms in terms of their financial performances. Their revenue ratio and financing costs are higher than public firms (Faccio et al., 2012). We call this model "Z_2' - Model".

5.2.1 Criticism of the Retained Earnings to Total Assets Ratio

Having analyzed Altman's financial ratios, we realized that Retained Earnings to Total Assets ratio is very sensitive to firm age. Contrary to the expectations, we found that RE to TA ratio has a feebly negative effect on financial failure prediction although this ratio is known as an indicator of a firm's strong performance. We observe that firm age affects retained earnings to total asset ratio. The firm age variable should be omitted from the analysis. We believe that this bias causes misleading financial failure prediction. Inherently, if the company operates longer, it

enhances the ability of retained earnings accumulation. It allows having time for growing in sales and generating profit over years (Nustini & Amiruddin, 2019).

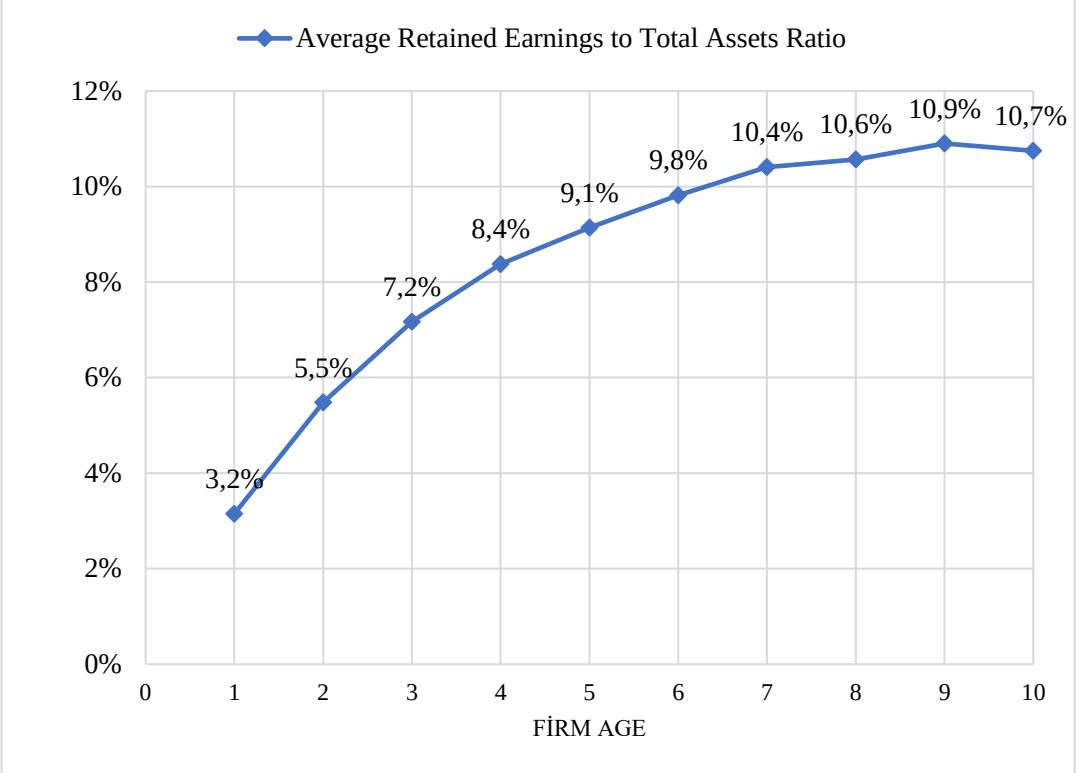

Figure 7. Mean of Retained Earnings to Total Assets Ratio by firm age

For these reasons, we excluded Retained Earnings to Total Assets Ratio for calibration of Altman Z'Score.

Table 8. Descriptive Statistics of Altman Z' Score Independent Variables (Financial Ratios as Bankruptcy Predictors)

	Healthy Firms					
Variables	N	Mean	SD	min	max	Kurtosis
Working Capital / Total Assets	345426	0.16	0.26	-1.72	0.91	3.57
Retained Earnings / Total Assets	345426	0.10	0.13	0.00	0.90	9.80
EBIT / Total Assets	345426	0.06	0.09	-0.60	0.63	12.46
Book Value of Eq. / Total Liab.	345337	0.66	0.73	-0.62	5.00	9.94
Sales / Total Assets	345426	1.41	1.05	0.00	7.00	6.36

	Failed Firms					
Variables	N	Mean	SD	min	max	Kurtosis
Working Capital / Total Assets	2391	0.02	0.42	-1.80	0.91	6.21
Retained Earnings / Total Assets	2391	0.11	0.16	0.00	0.90	10.21
EBIT / Total Assets	2391	0.00	0.14	-0.57	0.63	7.44
Book Value of Eq. / Total Liab.	2382	0.47	0.83	-0.62	4.97	10.11
Sales / Total Assets	2391	0.93	0.98	0.00	6.79	9.77

Table 9. Significant Levels of Altman Z' Score Financial Ratios by Financial Situations

	Mean		t-stat
	Healthy Firms	Failed Firms	
X1	0.160	0.017	-26.62***
X2	0.097	0.114	-6.39***
X3	0.065	-0.001	-35.9***
X4	0.664	0.470	-12.92***
X5	1.406	0.932	-22.11***

* p<0.05 ** p <0.01 ***p<0.001

Table 9 shows us that means of all variables are significantly different between the two groups (see Table 9).

Table 10. Correlation Matrix of Altman Z'Score Variables

	X1	X2	X3	X4	X5
X1	1				
X2	0.18	1			
X3	0.22	0.16	1		
X4	0.41	0.39	0.29	1	
X5	0.09	0.12	0.29	0.12	1

Pairwise correlation of Altman Z'Score variables shows us that there is no multicollinearity problem (see Table 10).

Having implemented Multivariate Discriminant Analysis to Altman Z' Score ratios (excluding with Retained Earnings to Total Assets ratio), we found the model as follows:

$Z_2' = .5181X_1 + .677\,X_3 + -.141\,X_4 + .2919\,X_5$

where;

$X_1 =$ Working Capital / Total Assets

$X_3 =$ Earnings Before Interest and Taxes / Total Assets

$X_4 =$ Book Value Equity / Book Value of Total Debt

$X_5 =$ Sales / Total Assets

Unexpectedly, the coefficient of X_4 has a negative value which is not consistent with Altman's model. However, it has a relatively low effect on Z_2'Score calibration. Having obtained this inappropriate model, we have decided to exclude Variable X_4 as well.

After excluding the Book Value Equity to Book Value of Total Debt Ratios, we obtained the model above;

$Z_3' = .458X_1 + .662\,X_3 + .293\,X_5$

where;

$X_1 =$ Working Capital / Total Assets

$X_3 =$ Earnings Before Interest and Taxes / Total Assets

$X_5 =$ Sales / Total Assets

Z_3' model shows us that EBIT to Total Assets ratio is the most powerful predictor of financial failure. EBIT to Total Assets ratio indicates the profitability of the firm. The working capital to total assets ratio has the second-highest coefficient. The higher WC to TA ratio shows the lower probability of short-term insolvency. The third and the last ratio which is the Sales to Total Assets ratio indicates that how efficiently the firms generate revenue from their assets. It is the weakest predictor in our calibrated Altman Z_3' model. Mean of Z_3' is also significantly different between the two groups.

Table 11. t-stat for Z'3 Model by Financial Status

	Mean of Z_3'		t-stat
	Healthy Firms	Failed Firms	
$\boldsymbol{Z_3'}$	0.528	0.28	-26.62***

* p<0.05 ** p <0.01 ***p<0.001

Table 12. Descriptive Statistics for Z'3 Model - Healthy and Failed Firms

	Healthy Firms					
	N	mean	SD	1%	99%	kurtosis
Z'_3	345426	0.525	0.36	-0.09	1.71	5.15
	Failed Firms					
	N	mean	SD	1%	99%	kurtosis
Z'_3	2391	0.28	0.39	-0.65	1.49	6.01

Table 13. Results for Canonical Discriminant Functions Results of Z'3 Model

	Canonical Correlation	Eigen-Value	F	Prob>F	Likelihood Ratio
Z'_3	0.0718	0.01	600.06	0.000e	0.9949

5.2.2 Determining cutoff scores for Z'_3Score model and accuracy

To determine cutoff scores for Z'_3Score model, we pursued the ROC analysis technique. We obtained accuracy rates. While determining the threshold, we considered achieving lower Type-2 Error. Having optimized accuracy rates for bankruptcy firms, we determined that “0.29” would be a good fit for the financial distress prediction model.

Table 14. Results of Z'3 Model Classification

		Predicted		
		Distressed	Healthy	Total
True Condition	Distressed	1.379	1.012	2.391
		58%	**42%**	100%
	Healthy	88.742	256.684	345.426
		26%	74%	100%
	Total	90.121	257.696	

CHAPTER 6

EMPIRICAL ANALYSIS: PF-SCORE MODEL

As we discussed in the literature review section, there is a lack of research in the financial distress prediction for private firms. Studies frequently focus on private companies in developed countries. This gap in the literature leads us to propose a model for Turkish privately-held companies. In our study, we used Multivariate Discriminant Analysis as statistical analysis.

6.1 Determining financial distress predictors

As it can be seen in Table 5, we classified financial ratios into 4 different main categories:

- Profitability Ratios
- Leverage Ratios
- Liquidity Ratios
- Efficiency Ratios (Çolak, 2019)

We think that each predictor that we've chosen from each category of financial ratios may help us to evaluate the financial performances of the private firms. The mixture of these 4 financial performance ratios reveals adequate information to predict financial distress and financial failure.

Having tested all the variables that we picked up from Table 5 (we tested approximately 200 different models), we found that 4 financial ratios have the highest prediction ability. We also did a correlation test between these 4 variables. There is no multicollinearity problem between the variables. These four variables are:

- Profitability Ratio: **Net Income / Net Sales**
- Leverage Ratios: **Total Liabilities / Total Assets**
- Liquidity Ratios: **Short Term Liabilities / Current Assets**
- Efficiency Ratios: **Sales / Total Assets**

Table 15. Correlation Matrix for PF-Score Model Variables

	Net Income / Net Sales	Total Liabilities / Total Assets	Short Term Liabilities / Current Assets	Sales / Total Assets
Net Income / Net Sales	1			
Total Liabilities / Total Assets	-0.23	1		
Short Term Liabilities / Current Assets	-0.15	0.33	1	
Sales / Total Assets	0.04	-0.16	-0.08	1

6.2 Descriptive statistics of the independent variables

When we made the statistical analysis for the selected independent variables, we observe that the mean of variables is as expected. Moreover, the mean difference of each variable is statistically significant within each group. We've implemented a t-test that can be seen in Table 16. Moreover, we put the distribution of PF-Score in Figure 8. It shows that assumption of normal distribution requirement is not suffered. The kurtosis of PF-Score is 3.76 (see Table 17).

Net Income to Net Sales ratio, also known as the Net profit margin ratio, has less mean in healthy firms as expected.

Secondly, the total liabilities to total assets ratio, also known as debt/assets ratio, indicates that financially failed firms are more levered than healthy firms as expected. Debt financing increases financial distress and firms with debt financing are more likely to face insolvency situations.

Thirdly, the short-term liabilities to current assets ratio is used as a predictor to test the liquidity performance of the firm. Just as we thought, distressed firms have more liabilities than their assets on average. To compare healthy firms, they also have a significantly greater level of short-term liabilities to current assets ratio.

Lastly, we obtained that the sales to total asset ratio are significantly lower in distressed firms. It shows that distressed firms have lower efficiency in generating revenue from their assets.

Table 16. Descriptive Statistics for PF-Score Variables by Financial Status

	Healthy Firms			Closed Firms			t-stat
Financial Ratios	N	Mean	SD	N	Mean	SD	
Net Income / Net Sales	345.426	0.02	0.07	2.391	-0.04	0.13	-43.97***
Total Liab. / Total Assets	345.426	0.68	0.19	2.391	0.76	0.21	21.83***
Short Term Liab./C.Assets	345.426	0.86	0.49	2.391	1.12	0.70	25.6***
Sales / Total Assets	345.426	1.39	0.97	2.391	0.92	0.90	-23.39***

* p<0.05 ** p <0.01 ***p<0.001

6.3 Discriminant analysis results for PF-Score Model

We aimed to obtain a better performance model of financial distress prediction. Thus, we applied a new prediction model via using multivariate discriminant analysis. As we discussed in the previous sections, we considered the situation of firm closing as the dependent variable. This dependent variable is a dichotomous variable where; 1 if the firm is healthy or 0 if the firm is financially failed. For independent variables, we have decided to choose the financial ratios that we include in Table 16. Outliers are winsorized and missing values were removed from the sample. Our MDA analysis function is:

$$PF\ Score = .760\mathrm{M}_1 + -077.\ \mathrm{M}_2 + -.320\ \mathrm{M}_3 + .378\ \mathrm{M}_4$$

where;

$\mathrm{M}_1 =$ Net Income / Net Sales

$\mathrm{M}_2 =$ Total Liabilities / Total Assets

$\mathrm{M}_3 =$ Short Term Liabilities / Current Assets

$\mathrm{M}_4 =$ Sales / Total Assets

PF-Score model coefficients say that net income to net sales ratio and sales to total assets ratio has a positive effect on firms' financial performances while total liabilities to total assets ratio and short-term liabilities to current assets ratio harms firm's financial health. We obtained that the net income to net sales ratio has the strongest weight in the function. This function indicates that profitability is the most important predictor of whether the firm will be failed or not. Efficiency and liquidity ratios have similar magnitude coefficients. Unexpectedly, the leverage ratio is not so effective in predict financial distress. Even though weakened firms suffer from a lack of internal financing, growing firms also prefer debt financing due to the tax shield of interest payments. This might be a reason for this lower coefficient of M_2 variable.

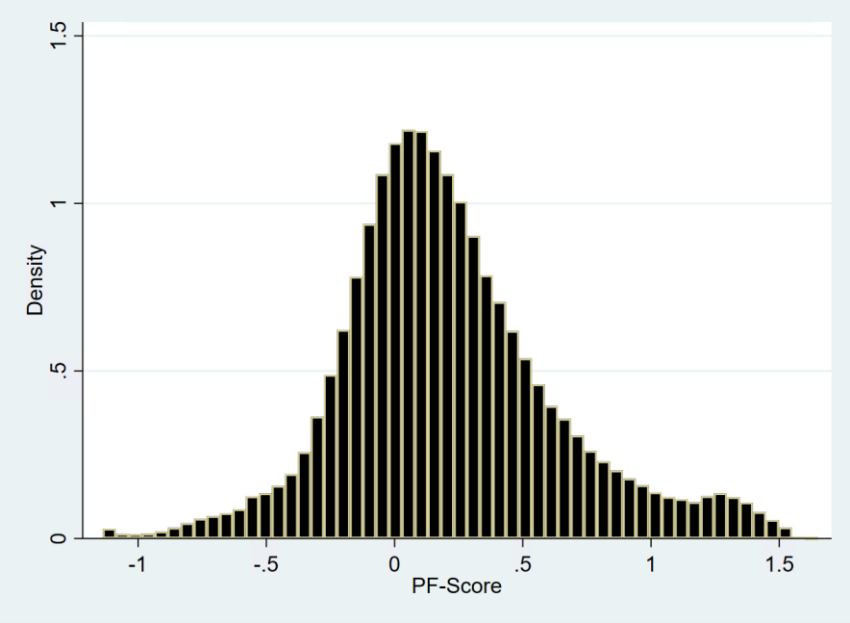

Figure 8. Distribution of PF-Score

Table 17. Descriptive Statistics for PF-Score of Financially Healthy Firms

	Healthy Firms					
	N	mean	SD	1%	99%	kurtosis
PF Score	345.426	0.213	0.42	-0.75	1.38	3.76

Table 18. Descriptive Statics for PF-Score of Financially Failed Firms

	Failed Firms					
	N	mean	SD	1%	99%	kurtosis
PF Score	2.391	-0.09	0.46	-1.11	1.29	3.9

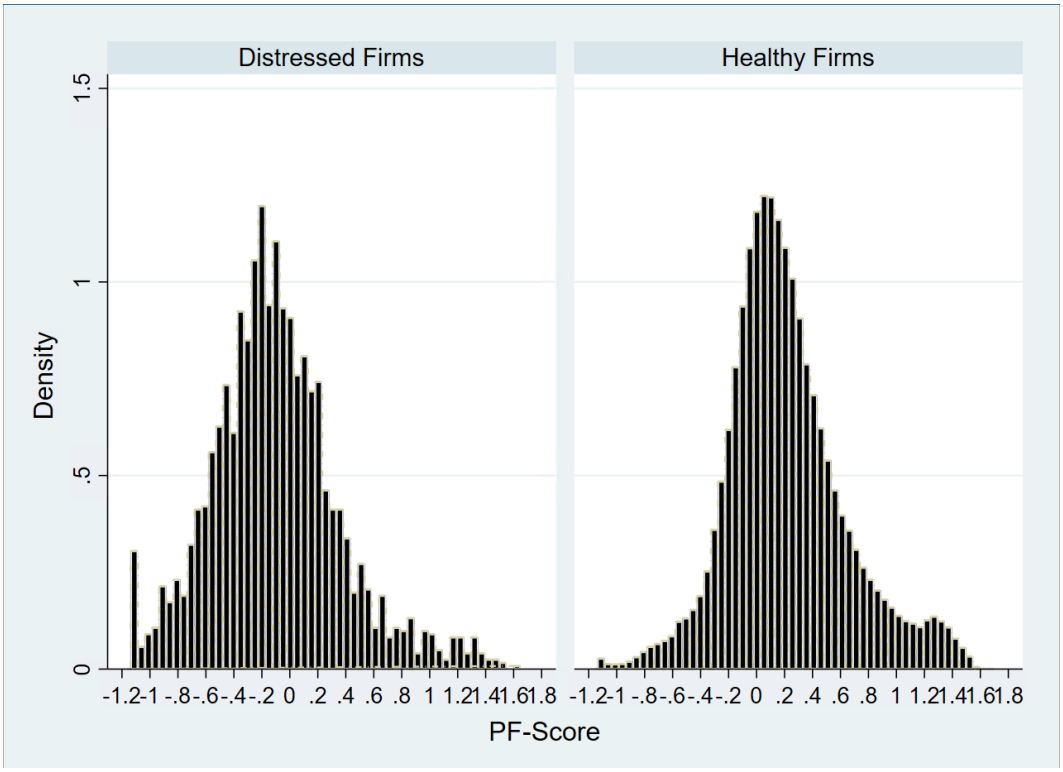

Figure 9. Distribution of PF-Score by financial status

The mean PF-Score for healthy firms is 0.213 while failed firms' PF Score has a -0.09 mean. This is consistent with our expectations (see Table 20). Each group has a normal distribution (Figure 9).

Table 19. Descriptive Statistics for PF-Score Model by Financial Status

	Healthy Firms	Failed Firms	t-stat	S.E. for healthy firms	S.E. for closed firms
PF-Score	0.213	-0.09	-36.1***	0.0007	0.0094

* p<0.05 ** p <0.01 ***p<0.001

Table 20. Discriminant Analysis Results of PF-Score Model

	Canonical Correlation	Eigenvalue	F	Prob>F	Likelihood Ratio(Wilk's Lambda)
PF-Score	0.0882	0.01	681.8	0.0000e	0.9922

In MDA models, the higher canonical correlation and lower Wilk's Lambda rate show the predictive ability of discriminant analysis. In our analysis, the predictive ability seems pretty lower. However, the F-value shows that our model is significantly valid (see Table 20). Moreover, the purpose of our study is to predict financial distress. Inherently, there is a great number of financially distressed firms that are not closed or bankrupt. Thus, our unpaired sample's discriminant analysis shows lower predictability in statistics.

6.4 Determining Cut-off Score and accuracy of PF-Score model

Having implemented the accuracy rate method, we found that **"-0.048"** is the best fit threshold for PF-Score. PF-Score has isolated distressed firms with a 59% accuracy and healthy firms with a 75% accuracy rate. Type 1 error is 41% while Type 2 error is only 25%. These error rates indicate that our model performs above agreeable levels.

One of the methods to test the predictability robustness of MDA analysis is ROC (Receiver operating characteristic) and AUC (Area Under Curve) analysis (Charalambakis & Garrett, 2019). The more area under the curve shows the better results for prediction.

The empirical results (see Table 21) and ROC analysis show that PF-Model prevailed over other Altman Z', Z'2, and Z'3 models. We could segregate 1.400 firms out of 2.391 firm samples through the PF-Score model.

Table 21. Results of PF-Score Model in Distressed Firms Prediction

		Predicted		
		Distressed	Healthy	Total
True Condition	Distressed	1.400	991	2.391
		59%	**41%**	100%
	Healthy	87.446	257.980	345.426
		25%	75%	100%
	Total	88.846	258.971	

Since all of the Area Under Curve results are above 0.70, it can be said that both the PF-Score model and Altman prediction models are moderately performed well.

Table 22. AUC Results for the Financial Distress Prediction

Altman Score Model:	0.7028
Calibrated Altman Z-Score for private firms:	0.706
PF-Score:	0.7099

6.5 Analyzing PF-Score results

Table 23 indicates that PF-Score has similar accuracy every year. The model performs with the highest accuracy in 2015 and 2016.

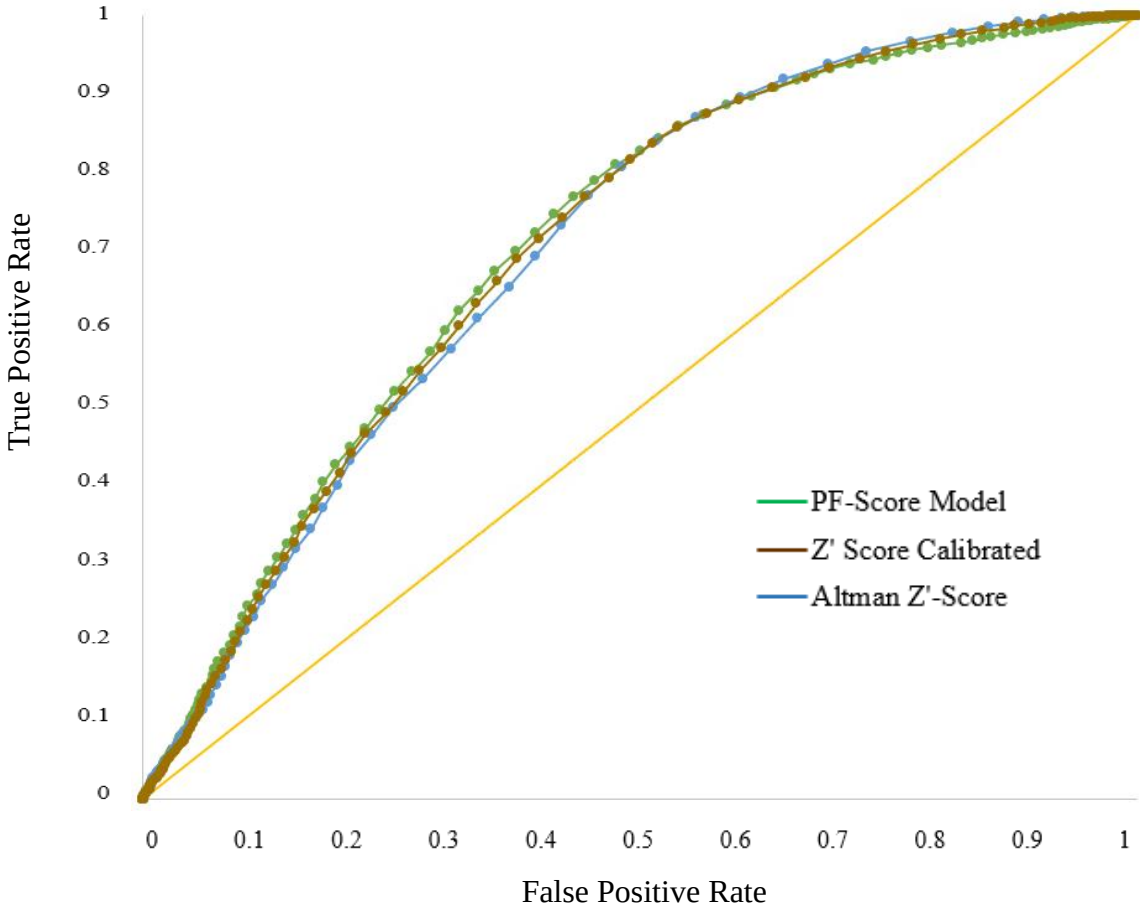

Figure 10. ROC Curve for PF-Score model, calibrated Z' score model and Altman Z' score model

Table 23. Distribution of Closed Firms within PF-Score Classification

	Failed		Total	% of Dis	Non-failed		Total	% of Dis
	Failed	Healthy			Failed	Healthy		
2013	148	133	281	52,7%	9.609	32.295	41.904	77,1%
2014	206	163	369	55,8%	11.209	33.225	44.434	74,8%
2015	457	259	716	63,8%	13.154	34.055	47.209	72,1%
2016	270	146	416	64,9%	15.166	34.239	49.405	69,3%
2017	307	264	571	53,8%	14.568	34.824	49.392	70,5%

As it can be seen in Figure 11, from 2012 to 2016, there is a significant decrease in closed firms' average PF-Score. Despite this result, from 2015 to 2017, on-going firms' average PF-Score has increased. In my opinion, it shows that financially

distressed firms have been suffered from fluctuations in the global economy as well as Turkish domestic issues such as the foreign exchange-rate crisis and failed coup attempts. These issues make the companies weaker than before, and they are more likely to be bankrupt due to higher financing costs and lower real income in their domestic sales.

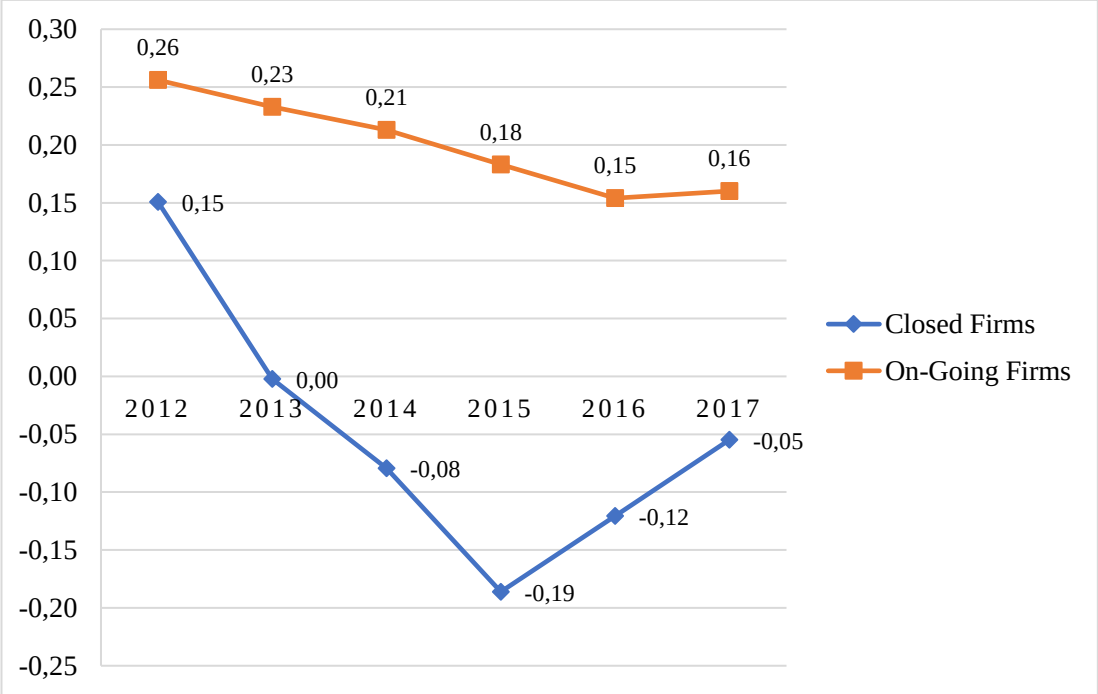

Figure 11. Mean of PF-Score by the financial status of firms

Having tested the impact of trade openness on the probability of bankruptcy, we've found that exporting companies are less likely to be failed. As can be seen in Table 24, 82% of financially failed firms are not exporting companies. We analyzed logistic regression to test this correlation. We observed that the odds ratio of the binary export variable (1 if exporting - 0 if not-exporting) is 2.285. The resulting odds ratio of 2.285 means that non-exporting companies were about 2.2 times tend to be failed compared to exporting companies (see Table 26).

Table 24. Exporting vs. Non-Exporting Firms by Financial Status

	Export		
	Not Exporting	Exporting	Total
Financially Failed	1.958	433	2.391
	82%	18%	100%
Healthy	229.485	115.941	345.426
	66%	34%	100%
Total	231.443	116.374	

Table 25. Descriptive Statics of PF-Score by Export Dummy Variable

	Non-Export Firms	Exporting Firms	t-stat	S.E. for Non-Exporting Firms	S.E. for Exporting Firms
PF-Score	0,201	0,233	-21,1***	0,0009	0,0011

* p<0.05 ** p <0.01 ***p<0.001

Table 26. Logistic Regression Results for Trade Openness in Failed Firms

Variables	(1) Logit coeff	(2) Odds Ratio
FailedFirms		
Export	0.826***	2.285***
	(0.0532)	(0.122)
Constant	4.764***	117.2***
	(0.0227)	(2.660)
Observations	347.817	347.817

* p<0.05 ** p <0.01 ***p<0.001
Standard errors in parentheses

6.6 Testing the PF-Score Model

For testing the accuracy of the PF-Score model, we also obtained 2 different samples that derived from the out of tested data as control groups. The first control sample consists of 5 failed companies and 995 healthy firms, so there are 1.000 companies in total. The second control sample incorporates 33 financially failed and 4.967 healthy firms.

The results showed us that Type 1 errors are 40% and 42% and Type 2 errors are 24% and 25%. These results are consistent with the source data of the PF-Score model (Type 1 Error 41% and Type 2 Error 25%).

Table 27. PF-Score Sample-1 Testing Results

		PF-Score Prediction		
		Distressed	Healthy	Total
True Condition	Distressed	3	2	5
		60%	**40%**	100%
	Healthy	235	760	995
		24%	76%	100%
	Total	238	762	

Table 28. PF-Score Sample-2 Testing Results

		PF-Score Prediction		
		Distressed	Healthy	Total
True Condition	Distressed	19	14	33
		58%	**42%**	100%
	Healthy	1.259	3.708	4.967
		25%	75%	100%
	Total	1.278	3.722	

6.7 Limitations of PF-Score Model

Remember that we aimed to propose a continuous score. We don't purpose to classify categorized or discrete variables. Determining financially distressed firms with only financial ratios is not enough. It needs more examination and financial information. One of the limitations of our analysis is that we don't operate a paired sample (345.436 healthy firms – 2391 closed firms). Secondly, since our data is provided without information of the firm's closing reason in detail, there might be some noises in the data. Moreover, the significance of MDA analysis for both models is not as strong as the existing financial distress prediction models of public firms. MDA assumptions compose of strict assumptions which are usually violated. Financial companies and most of the micro companies were also excluded due to a lack of reliability on their financial data. We used financial data of failed firms' financial statements one year before bankruptcy.

CONCLUSION

In this thesis, we aimed to propose an estimator model that measures financial distress. One of the difficulties that we faced was terminological ambiguity. As we explained in Chapter 4, our goal was modeling financial distress prediction rather than constructing a model to predict bankruptcy. Even though we used the terms: "distress, bankruptcy, failure, and default" interchangeably, we concluded that financial distress is a more comprehensive term. As discussed in the methodology chapter, we preferred to implement multivariate discriminant analysis in this paper. MDA provides us a continuous score. This score is appropriate to interpret intuitively. We proposed a model named the PF-Score model. The lower PF-Score tells a higher probability of bankruptcy and vice versa.

In the literature, the prediction of financial failure has been widely investigated since 1968. Altman (1968) has pioneered the bankruptcy prediction models. We elaborately reviewed the literature then we provide valuable findings in Chapter 2. Nevertheless, a clear majority of these studies were derived from public firm financial data. That is why we focused on providing a financial distress prediction model for private firms. It is difficult to interpret private firm financial data since they are not precisely audited by authorized institutions. Thus, we intended to provide a model by using a large-scale sample. This provided PF-Score may be an initial step for the evaluation of the financial performance of Turkish privately held firms. This might be a concern of governmental institutions and money lenders. A great majority of employment, turnover, and credits are possessed by private firms(Biery, 2013). This emphasizes the importance of measuring the financial distress level of private firms. Moreover, the number of publicly traded

firms decrease in the world year by year since 2014 while private companies' growth rate is positive (World Bank, 2019a).

Having a chance to drive Turkish private firms' financial data leads us to focus on reviewing previous bankruptcy and financial distress prediction models of private firms. After examination of existing literature, we've decided to implement Discriminant Analysis. One of the reasons for choosing discriminant analysis is that MDA gives us a metric scale consisting of a discriminant score. Indeed, determining the threshold also eases interpreting results. We also explained logit and discriminant analysis in Chapter 3 with their pros and cons. Addedly, we described our sample in Chapter 4.

Afterward, we tested the existing Altman Z-Score for private firm models with rectified independent variables and calibrated coefficients in the Chapter 5. This analysis showed us that Altman models still keep their validity while it's not as strong as it gives result in the original paper (Altman, 1983).

Finally, Chapter 6 has proposed a new prediction model. This model composes of relatively more convenient independent variables from several financial ratios that we covered in Chapter 4. We calculated coefficients of the PF-Model via discriminant analysis. We also tested the accuracy rate and classification ability results of the PF-Model. We obtained that profitability is the most important predictor meanwhile efficiency and liquidity ratios are equally effective in our model. We didn't find leverage so important to distinguish between failed and healthy firms. Having determined the threshold, we obtained that our model could distinguish distressed firms with 60% accuracy and can isolate healthy firms with a 75% accuracy rate.

For further research, we recommend for researchers to model by not only considering domestic firms but also financial data from other countries. We couldn’t test this model's accuracy except for the sample of Turkish companies due to the lack of data. Moreover, prediction modeling for specific industries also may be useful owing to the different debt and asset patterns of some particular sectors.

REFERENCES

Allianz, E. H. E. R. (2020). *Global Insolvency Outlook 2020 - A Softer But Broader Based Rise in Corporate Insolvencies*.

Alp, B. (2013). *Türkiye'deki Reel Sektör Firmalarında Borç Dolarizasyonu ve Reel Kur Değişimlerinin Bilanço Etkisi*. Türkiye Cumhuriyet Merkez Bankası İstatistik Genel Müdürlüğü.

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. In *Source: The Journal of Finance* (Vol. 23).

Altman, E. I. (1983). Corporate financial distress - a complete guide to predicting, avoiding, and dealing with bankruptcy. In *Wiley professional banking and finance series*. A Wiley-Interscience publication. Retrieved from https://openlibrary.org/books/OL3496073M/Corporate_financial_distress

Altman, E. I. (2000). Predicting Financial Distress of Companies: Revisiting The Z-Score And Zeta® Models. *Journal of Banking and Finance*, *1*(July), 1–302. https://doi.org/10.4324/9781315064277

Altman, E. I. (2013). Predicting financial distress of companies: revisiting the Z-Score and ZETA® models. In *Handbook of Research Methods and Applications in Empirical Finance*. Cheltenham, UK: Edward Elgar Publishing.

Altman, E. I., Esentato, M., & Sabato, G. (2020). Assessing the credit worthiness of Italian SMEs and mini-bond issuers. *Global Finance Journal*, *43*(April 2018), 100450. https://doi.org/10.1016/j.gfj.2018.09.003

Altman, E. I., Giannozzi, A., Roggi, O., & Sabato, G. (2013). Building Sme rating: is it necessary for lenders to monitor financial statements of the borrowers? *Bancaria*, *10*(October), 54–71.

Altman, E. I., & Hotchkiss, E. (2005). Corporate Financial Distress and Bankruptcy. In *Corporate Financial Distress and Bankruptcy*. https://doi.org/10.1002/9781118267806

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. *Journal of International Financial Management and Accounting*, *28*(2), 131–171. https://doi.org/10.1111/jifm.12053

Altman, E. I., & Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the U.S. market. *Abacus*, *43*(3), 332–357. https://doi.org/10.1111/j.1467-6281.2007.00234.x

Altman, E. I., & Saunders, A. (1997). Credit risk measurement: Developments over the last 20 years. *Journal of Banking and Finance*, *21*(11–12), 1721–1742. https://doi.org/10.1016/S0378-4266(97)00036-8

Beaver, W. H. (1966). Financial Ratios As Predictors of Failure Authors (s): William H . Beaver Source : Journal of Accounting Research , Vol . 4 , Empirical Research in Accounting : Selected Published by : Wiley on behalf of Accounting Research Center , Booth School of Busi. *Journal of Accounting Research*, *4*(1966), 71–111. Retrieved from www.jstor.org/stable/2490171

Bellovary, J., Giacomino, D., & Akers, M. (2007). A Review of Bankruptcy Prediction Studies : 1930 to Present A Review of Bankruptcy Prediction Studies : 1930 to Present. *Review Literature And Arts Of The Americas*, *33*(May 2021), 1–42.

Biery, M. E. (2013). 4 Things You Don't Know About Private Companies. *Forbes*, 1–4. Retrieved from https://www.forbes.com/sites/sageworks/2013/05/26/4-things-you-dont-know-about-private-companies/?sh=2c67f0c4291a

Bureau of Economic Business Research. (1930). A Test Analysis of Unsuccessful Industrial Companies. In *Bureau of Economic and Business Research. Bulletins* (Vol. 31). University of Illinois.

Charalambakis, E. C. (2014). *On corporate financial distress prediction: What can we learn from private firms in a small open economy?*

Charalambakis, E. C., & Garrett, I. (2019). On corporate financial distress prediction: What can we learn from private firms in a developing economy? Evidence from Greece. *Review of Quantitative Finance and Accounting*, *52*(2), 467–491. https://doi.org/10.1007/s11156-018-0716-7

Çolak, S. (2019). *A New Index Score for the Assessment of Firm Financial Risks* (No. 19/04).

Ekin, F., Altaş, G., Ceylan, A., Deniz, K., & Onur, S. (2021). *Türkiye Sermaye Piyasası 2020 Raporu*. Retrieved from www.tspb.org.tr

Euler Hermes. (2020). *Calm Before The Storm: Covid-19 and the Business Insolvency Time Bomb*.

Faccio, M., Marchica, M.-T., McConnell, J. J., & Mura, R. (2012). Returns and Risks to Private Equity. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1781070

Falkenstein, E. G., Boral, A., & Carty, L. V. (2000). RiskCalc for Private Companies: Moody's Default Model. *SSRN Electronic Journal*, (May). https://doi.org/10.2139/ssrn.236011

Frank, M. Z., & Goyal, V. K. (2009). Capital structure decisions: Which factors are reliably important? *Financial Management*, *38*(1), 1–37. https://doi.org/10.1111/j.1755-053X.2009.01026.x

Garson, G. D. (2012). *Discriminant Function Analysis*. Statistical Associates Publishers.

Gordon, A. M. J. (1971). *Towards a Theory of Financial Distress Source : The Journal of Finance , May , 1971 , Vol . 26 , No . 2 , Papers and Proceedings of the Twenty-Ninth Annual Meeting of the American Finance Association Detroit , Published by : Wiley for the American Finance*. *26*(2), 347–356.

Habib, A., Costa, M. D., Huang, H. J., Bhuiyan, M. B. U., & Sun, L. (2020). Determinants and consequences of financial distress: review of the empirical literature. *Accounting and Finance*, *60*(S1), 1023–1075. https://doi.org/10.1111/acfi.12400

Jacoby, G., Li, J., & Liu, M. (2019). Financial distress, political affiliation and earnings management: the case of politically affiliated private firms. *European*

Journal of Finance, *25*(6), 508–523. https://doi.org/10.1080/1351847X.2016.1233126

KAP. (2021). KAP. Retrieved May 29, 2021, from https://www.kap.org.tr/en/bist-sirketler

Korol, T. (2019). Dynamic Bankruptcy Prediction Models for European Enterprises. *Journal of Risk and Financial Management*, *12*(4), 185. https://doi.org/10.3390/jrfm12040185

Koyuncugil, A. S., & Ozgulbas, N. (2012). Financial early warning system model and data mining application for risk detection. *Expert Systems with Applications*, *39*(6), 6238–6253. https://doi.org/10.1016/j.eswa.2011.12.021

Lennox, C. (1999). Identifying failing companies: A reevaluation of the logit, probit and DA approaches. *Journal of Economics and Business*, *51*(4), 347–364. https://doi.org/10.1016/s0148-6195(99)00009-0

Matenda, F. R., Sibanda, M., Chikodza, E., & Gumbo, V. (2021). Bankruptcy prediction for private firms in developing economies: a scoping review and guidance for future research. In *Management Review Quarterly*. Springer International Publishing. https://doi.org/10.1007/s11301-021-00216-x

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

Mselmi, N., Lahiani, A., & Hamza, T. (2017). Financial distress prediction: The case of French small and medium-sized firms. *International Review of Financial Analysis*, *50*, 67–80. https://doi.org/10.1016/j.irfa.2017.02.004

Njeru, M. M., & Waititu, A. (2018). Using Altman's Z score (Book Value of Equity/Total Liabilities) Ratio Model in Assessing Likelihood of Bankruptcy for Sugar Companies in Kenya. *International Journal of Academic Research in Business and Social Sciences*, *8*(6), 578–601. https://doi.org/10.6007/IJARBSS/v8-i6/4259

Nustini, Y., & Amiruddin, A. R. (2019). Altman model for measuring financial distress: Comparative analysis between sharia and conventional insurance companies. *Journal of Contemporary Accounting*, *1*(3), 161–172. https://doi.org/10.20885/jca.vol1.iss3.art4

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

Oz, I. O., & Yelkenci, T. (2017). A theoretical approach to financial distress prediction modeling. *Managerial Finance*, *43*(2), 212–230. https://doi.org/10.1108/MF-03-2016-0084

Özdemir, F. S. (2014). Turkish Uniform Accounting System and Applicability of Altman Z Score Models in the Context of Public and Private Companies. *Ege Akademik Bakış Dergisi*, *14*(1), 147–162.

Purnanandam, A. (2008). Financial distress and corporate risk management: Theory and evidence. *Journal of Financial Economics*, *87*(3), 706–739. https://doi.org/10.1016/j.jfineco.2007.04.003

R. A. Fisher. (1936). The Use of Multiple Measurements In Taxonomic Problems. *Annuals of Eugenics*, *7*, 465–475.

Shi, Y., & Li, X. (2019). An overview of bankruptcy prediction models for corporate firms: A systematic literature review. *Intangible Capital*, *15*(2), 114–127. https://doi.org/10.3926/ic.1354

Sun, J., Li, H., Huang, Q. H., & He, K. Y. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems*, *57*, 41–56. https://doi.org/10.1016/j.knosys.2013.12.006

Tabachnick, B. G., & Fidell, L. S. (2007). Using multivariate statistics, 5th ed. In *Using multivariate statistics, 5th ed.* Boston, MA: Allyn & Bacon/Pearson Education.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using Multivariate Statistics Title: Using multivariate statistics*. Retrieved from https://lccn.loc.gov/2017040173

TCMB. (n.d.). Enflasyon Hesaplayıcısı. Retrieved June 4, 2021, from http://www3.tcmb.gov.tr/enflasyoncalc/enflasyon_hesaplayici.html

The Union of Chambers and Commodity Exchanges of Turkey. (2021). *Company Establishment and Liquidation Statistics*. Retrieved from https://www.tobb.org.tr/BilgiErisimMudurlugu/Sayfalar/Eng/KurulanKapananSirketistatistikleri.php

TÜİK. (2019). *KOBİ İstatistikleri Raporu*. Retrieved from https://www.tuik.gov.tr/indir/duyuru/kobi-istatistikleri-raporu.pdf

Turkish Government Cabinet Decree. (2018). *Regulation on Definition, Characteristics and Classification of Small and Medium Enterprises*.

Uğurlu, M., & Aksoy, H. (2006). Prediction of corporate financial distress in an emerging market: The case of Turkey. *Cross Cultural Management: An International Journal*, *13*(4), 277–295. https://doi.org/10.1108/13527600610713396

Ul Hassan, E., Zainuddin, Z., & Nordin, S. (2017). A Review of Financial Distress Prediction Models: Logistic Regression and Multivariate Discriminant Analysis. *Journal of Accounting and Finance (IPJAF)*, *1*(3), 13–23. Retrieved from www.ipjaf.omjpalpha.com

World Bank. (2019a). Listed domestic companies, total | Data. Retrieved June 15, 2021, from https://data.worldbank.org/indicator/CM.MKT.LDOM.NO

World Bank. (2019b). Market capitalization of listed domestic companies (% of GDP) - Turkey. Retrieved May 29, 2021, from World Federation of Exchanges database website: https://data.worldbank.org/indicator/CM.MKT.LDOM.NO?locations=TR

World Federation of Exchanges database. (2018). Market capitalization of listed domestic companies (% of GDP). Retrieved May 20, 2021, from The World Data Bank website: https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS?end=2019&locations=US-TR&start=1980&view=chart

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models Published by : Wiley on behalf of Accounting Research Center , Booth School of Business , University of Chicago Stable URL : http://www.jstor.com/stable/2490859 Method. *Journal of Accounting Research*, *22*, 59–82. Retrieved from https://www.jstor.org/stable/2490859