TÜRKİYE CUMHURİYET MERKEZ BANKASI

A New Index Score for the Assessment of Firm Financial Risks

Mehmet Selman ÇOLAK

February 2019

Working Paper No: 19/04

Address:
Central Bank of the Republic of Turkey
Head Office
Structural Economic Research Department
İstiklal Caddesi No: 10
Ulus, 06050 Ankara, Turkey

Phone:
+90 312 507 80 04

Facsimile:
+90 312 507 78 96

A New Index Score for the Assessment of Firm Financial Risks

by

Mehmet Selman Çolak
Assistant Economist
Central Bank of Republic of Turkey

Abstract

There are several indicators and univariate ratios that measure the soundness of firms' balance sheets (Leverage, profitability, liquidity ratio, etc.). However, each indicator alone cannot measure the overall financial risk or the financial distress level of firms. In this study, we measure the financial strength of the real sector firms quoted in Borsa Istanbul (BIST) by producing a composite index score which is a combination of several different corporate finance ratios. In the first part, we will apply multiple discriminant analysis to the variables used in Altman Z-score (1968), which is the most prevalent composite index score measuring the firms' financial risks in the literature. In the second part, a new index, named as MFA-score (Multivariate Firm Assessment Score) will be introduced by using the ratios that best explain the characteristics of the BIST companies. Both the tailored version of Altman Z-score and our new index score have a predictive power around 90 percent. Furthermore, MFA-score is capable of detecting the impact of macro-economic developments on firm balance sheets, which enables us to use MFA-score as an early warning indicator of financial distress for Turkish firms. Our analyses with MFA-score suggest that non-exporter firms and firms with FX open position have relatively weaker balance sheets.

Jel Codes: G30, G33, C18, C43

Key Words: Balance Sheets, Financial Risk, Altman Z-Score, Multiple Discriminant Analysis, Financial Distress, Solvency, MFA-Score

Non-Technical Summary

For financial risk analysis of real sector firms, several indicators and univariate ratios can be derived from the financial statements of firms. Each univariate ratio measures the firm's position such as liquidity, profitability or indebtedness, however; they are incapable of testing the firm's overall financial strength or financial distress level. For this reason, some composite index measures have been produced in literature to rate the financial risk level of firms comprehensively.

This study contributes to the literature by producing two novel composite index measures that test the financial health of non-financial firms in Borsa İstanbul (BIST). In the first part, we will apply multiple discriminant analysis to the variables used in Altman Z-score (1968), which is the most prevalent composite index score measuring the firms' financial risks in the literature. In the second part, a new index, named as MFA-score (Multivariate Firm Assessment Score) will be introduced by using the ratios that best explain the characteristics of the BIST companies. Our dataset consists of 361 listed firms operating in BIST in the period of 2001-2017.

Our results suggest that MFA-score correctly predicts firm bankruptcy with more than 90 percent success. MFA-score model is capable of detecting the impact of macro-economic developments on balance sheets, which was clearly observed through the significant correlation of MFA-Score with GDP growth rate, exchange rate movements and industrial production index. This enables us to use MFA-Score as an early warning indicator of financial distress for Turkish firms and also to quantify the impacts of macro shocks or policies on firm balance sheets. MFA-scores are smaller in firms with FX open position and exporter firms have larger scores compared to non-exporters. Also, as the amount of FX open position of the firms increases, MFA scores decline.

We can also categorize firms into risk classes by their MFA-scores; distress, grey and safe zones. We found that more than 20 percent of BIST firms are in distress zone, but their asset share constitutes less than 10 percent of the total. Among firms with FX open position, more than 30 percent of total firms are in distress zone but these firms' asset and open position amount shares are less than 20 percent, which clearly signifies that FX open position posits higher risks for relatively smaller firms and large-sized firms are more capable of FX risk management. Additionally, the early warning characteristic of MFA-score allows us to form a more comprehensive measure of "debt-at-risk" than the definition of IMF. By this measure, we found that the debt share of firms in distress zone is around 10 percent and this share rises during turbulent periods.

1. Introduction

The financial soundness or distress of a firm is of vital importance not only for the sector in which the firm operates but for the financial system and the entire economy. A firm that cannot meet its liabilities, comes to a point of economic inactivity, has a negative equity account or is on the verge of bankruptcy is defined as a financially distressed firm. A firm experiencing financial distress can damage the financial structure of its lenders, shareholders and their lenders, and cause losses in the economy as a whole depending on the size of the firm's operations. For this reason, prediction of firm failure before its occurrence and taking sufficient measures in order to prevent it have been among the main concerns of the analysts. This has led to the evolution of a huge literature on firm financial risk analysis through indicators from balance sheets.

For financial risk analysis, several indicators and univariate ratios can be derived from the financial statements of firms. Each ratio measures the firm's position such as liquidity, profitability or indebtedness, however; they are incapable of testing the firm's overall financial strength or financial distress level. For this reason, some composite index measures have been produced to rate the financial risk level of firms comprehensively (Altman Z-score, 1968, Deakin, 1972, Ohlson O-score, 1980, Zmijewski, 1984). In these rating methods; various univariate ratios are weighted using statistical techniques and converted into a single score. Multivariate Discriminant Analysis (MDA) used initially by Altman (1968) has been the most prevalent statistical tool used in the aggregation of univariate ratios to a composite indicator in the firm bankruptcy literature.

Even though Altman Z-score is widely used in the literature for the firms in different countries, the ratios and their coefficients in the score were derived from the listed U.S. firms. Since firms in different countries especially emerging markets behave differently from the US firms, using the original Altman (1968) Z-score ratios and coefficients may not be sufficient to capture the distinctive firm characteristics in these economies. Hence, in order to measure the financial risk of firm balance sheets in a country, it would be more convenient to calculate new coefficients using new ratios which could best represent the characteristics of the firms in that country.

Our paper aims to construct two new composite index scores using MDA methodology for non-financial firms quoted in Borsa Istanbul (BIST). The first one is the tailored version of Altman Model which uses the same ratios in Altman Z-score for the estimation of ratio coefficients for BIST firms. And secondly, we introduce a new index score, named as Multivariate Firm Assessment Score (MFA-score), produced by applying MDA to the distinctive balance sheet ratios of non-financial companies quoted in Borsa Istanbul. These composite measures will allow us to effectively analyze the overall financial risk of Turkish firms and develop an early warning indicator of financial distress.

Initially in the paper, detailed literature survey on firm failure studies will be presented. Secondly, data set and MDA methodology used in the paper will be explained. Later on, tailored Altman score and MFA score models will be constructed using a novel approach in the model selection process. Following section will be devoted to the application of MFA-score to the whole data set and its implications for Turkish firms. Finally, we will conclude the paper by summarizing all the findings.

2. Literature Review

The prediction of firm failure has long been the focus of interests among academicians and practitioners. The literature on firm failure could be divided into two main approaches. The first one is the accounting based approach which regards the ratios obtained from firm financial statements to measure the soundness of firms. The second one is the market based approach which relies on the stock prices and market value of firms.

As of the accounting based approach, initially in the early 20th century, univariate measures were used to discriminate between distressed and solvent firms (Fitzpatrick, 1932; Mervin, 1942, Chudson; 1945 and Beaver, 1966). Starting with the seminal work of Altman (1968) multivariate measure of financial distress became the mainstream methodology. He introduced multiple discriminant analysis (MDA) as a tool to combine several financial ratios obtained from the financial statements into a single composite indicator. He applied MDA to discriminate 33 bankrupted firms from 33 solvent firms quoted in NYSE (New York Stock Exchange) during the period 1946-1965. After Altman, several pioneering papers adapted MDA in their own firm failure studies for various countries. For the US firms, Deakin (1972) developed a multivariate measure of financial distress using 32 failed and 32 solvent firms in 1962-66, Moyer (1977) for total of 54 firms in 1965-75, Blum (1974) for 115 firms in 1954-68, Dambolena and Khoury (1980) for 68 firms in 1969-75, and Edmister (1972) for 84 small and medium sized firms in 1958-65. There are also several other studies for other countries carrying out MDA (Taffler, 1982; Goudie,1987; Boritz, Kennedy and Sun, 2007).

In addition to MDA, logistic regression methodology (logit and probit) became popular in the accounting based firm failure prediction models with the leading study by Ohlson (1980). In this method, the probability of a firm default is estimated using the accounting data of the firms and several other controls (Lennox, 1999; Zmijewski, 1984; Shumway, 2001; Koh, 1992; Ooghe and Verbaere,1985; Charitou & Trigeorgis, 2002; Lizal, 2002; Becchetti & Sierra, 2003; Fitzpatrick and Ogden, 2011).

In the market based approach, stock prices of firms are used to estimate the firm's probability of default (Scott, 1980; Merton, 1974, Black and Scholes, 1973). In this approach, when the market value of a firm decreases below a certain book value of liabilities, the firm is assumed to be bankrupted. The papers using this approach tried to estimate the probability of this event in different firms in various countries (Bharath and Shumway, 2004; Hillegeist et al., 2004; Reisz and Perlich, 2004; Vassalou and Xing, 2004; Campbell et al., 2006).

Both approaches have their pros and cons and there is still debate whether accounting or market based approach is more efficient in predicting bankruptcy (Agarwal and Tafler, 2007; Mossman et. al. 1998 and Wu, Gaunt and Gray, 2010). The answer changes depending on the data set and variables used in the analyses. Nevertheless, since market based approach requires the calculation of market value of firm assets, it is purely market based and only applicable for listed firms. Hence, accounting based methods were utilized predominantly. Among accounting methods, MDA has been the most prevalent technique in the literature (Aziz and Dar, 2006).[1]

[1] Aziz and Dar (2006) have found in their detailed literature survey that 30% of the bankruptcy studies are carried out via MDA and logit estimation stands as the second commonly used method with 21% share.

Altman (1968) developed Z-score as a linear combination of ratios from financial statements. The Altman Z-score model and the ratios used in the linear function are as follows:

Altman Z-score= $1.2\ X_1 + 1.4\ X_2 + 3.3\ X_3 + 0.6\ X_4 + 1.0\ X_5$

X_1: Working Capital / Total Assets

X_2: Retained Earnings / Total Assets

X_3: EBIDTA / Total Assets

X_4: Market Value of Equities / Book Value of Total Liabilities

X_5: Net Sales / Total Assets

If the Z-score value of a firm is below 1.8, the firm is classified as distressed and is likely to experience bankruptcy in the upcoming period. Z-score has 91 percent accuracy in predicting bankruptcy among 66 NYSE firms in 1946-65. There are some other papers which apply the Altman Z-score model for the firms in different countries (Gerantonis et. al., 2009; Lifschutz & Jacobi, 2010; Dandago & Baba, 2014; Celli, 2015; Kulalı, 2016). Nevertheless, the prediction accuracy measured for different economies, especially the ones for developing countries, is not as high as what Altman has found for NYSE firms. The main reason is that the variables and their loadings in Altman model reflect more the firm behaviors in developed countries. For instance, the ratio of market value of equities to book value of liabilities is purely dependent on the stock price of the firms and the fact that most developing countries do not have a financially deep stock market, share prices do not usually reflect the firm financial health, rather the speculative position of the investors. Hence, X_4 is not a good measure of balance sheet structure for developing economies. Furthermore, as Altman (1968) noted, the ratio of retained earnings to total assets represent the accumulated profit/loss of a firm over years and give information about the age of a firm. Since firms in developing economies are short-lived in general and the accumulated earnings are more volatile, this ratio does not give sufficient information about the firms' balance sheet strength in developing countries. Finally, the standardized coefficients of the variables in Altman model reveal that X_3 and X_5 have the highest contribution to distress level of a firm, which contradicts with the facts of developing country firms. Although EIDTA is an important factor in discriminating solvent and distressed firms in developing countries, we do not expect a large contribution of net sales/asset ratio in these countries. Developing country firms are dependent on imported machines and equipments in their production process and hence imported materials constitute a large part of their costs of goods sold. Due to this dependence, even though a firm has a significant amount of net sales, its costs might be high and volatile, which makes the operating or net profit of the firm also volatile and vulnerable to shocks. Hence, net sales/asset ratio should not have such a power in explaining financial distress in developing countries.

For all these concerns, dozens of country-specific papers revised the Altman model either by using the same variables but re-calculating the coefficients or by using different variables and corresponding coefficients for their countries. Examples are Leksrisakul, Evans (2005) for Thailand, Rashid and Abbas (2011) for Pakistan, Lifschutz and Jacobi (2010) for Israel, Pascale (1988) for Uruguay, Grammatikos and Globus (1984) for Greece, Rıfqı and Kanazaki (2016) for Indonesia, Wang and Campbell (2010) for China, Thai et. al. (2014) for Malaysia, Micha (1984) for France, Izan (1984) for Australia, Pervan, Pervan and Vukoja (2014) for Crotia.

For Turkish economy, there are some studies which adapt the same coefficients and variables of Altman to Turkish firms and limited numbers of papers which tailored Altman coefficients using Turkish firms' data (Muzır and Çağlar; 2009; Yılmaz and Yıldıran, 2015). Even though these models contain worthwhile information, creating a more comprehensive model which utilizes the ratios that best describe the specific characteristics of Turkish firms other than the Altman ratios would be invaluable. Nevertheless, so far there is no study designing a firm failure model with novel variables for Turkish firms.

In this study, initially we attempt to replicate Altman with its original ratios for Borsa İstanbul Firms. Later, in order to fill the gap in the literature, we will create a new score with 7 different ratios using MDA, which we call as MFA-Score (Multivariate Firm Assessment).

3. Methodology

3.1 Multiple Discriminant Analysis

The Multiple Discriminant Analysis is a way of deriving an index score which can best distinguish two or more groups with similar number of members from each other. This index score is obtained through weighted sum of several indicators that characterize the members of each group and the difference between mean index scores of the groups is maximized (Johnson and Wichern, 1982; Anderson T.V, 2003 and Naranyan; 2003). The coefficients of the model are determined in a way that between-group variance is maximized and within-group variance is minimized (Gnanadesikan, 1988 and Kocisova & Misankova, 2014).[2]

In case of corporate bankruptcy models, there are usually two groups; one is formed by financial distressed firms and the other group consists of firms that remained solvent. MDA is carried out using a priori groupings of the firms as a qualitative dependent variable, and multiple ratios from the earlier financial statements as quantitative independent variables. As a result, we obtain the coefficients of each independent variable, predicted grouping of each firm and cut-off value discriminating predicted groups.[3] Usually if the index score is above the cut-off, the firm is grouped as solvent and if below, grouped as distressed.[4] Furthermore, the cut-off point is subject to prior probabilities of belonging to the failing or non-failing group and the costs of a type I and a type II errors (Zavgren, 1983; Steele, 1995). Nevertheless, in our study we assume prior probabilities are same and the costs of Type 1 and Type 2 errors are equal.

The performance of the model is simply measured as the number of correctly predicted firms divided by total number of firms. If total number of firms in distressed group is denoted by T_d, in solvent group by T_s; and number of correctly predicted firms in distressed group is denoted by C_d, in solvent group by C_s, the performance, Type 1 and Type 2 errors of the model are formulated as follows:

$$Performance = \frac{C_d}{T_d} + \frac{C_s}{T_s} \qquad Type\ 1\ Error = 1 - \frac{C_d}{T_d} \qquad Type\ 2\ Error = 1 - \frac{C_s}{T_s}$$

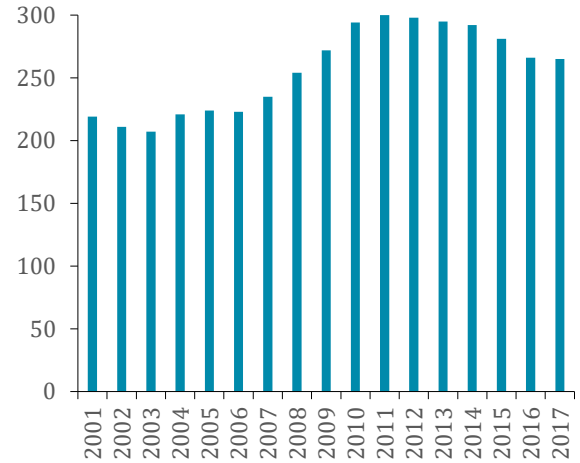
[2] Between group variance is the variation between the mean score values in two groups. Within-group variance demonstrates the variance of the score value in each group.

[3] The reason for naming the groups as "predicted" is that we actually predict the correct grouping of the firm by looking at its financials in one or more earlier periods.

3.2 Data Set

In our paper, we use the data from financial statements of non-financial firms quoted in Borsa İstanbul between 2001 and 2017. There are 361 different firms in total and 250 firms on average each year (Figure 1). Since the firms' shares are traded in the stock exchange, all balance sheets are prepared by independent auditors and checked by authorities of both BIST and Capital Markets Board. Furthermore, due to the firms' responsibility to their shareholders, they should have avoided balance sheet make-up and misinformation. For this reason, the BIST data is the most reliable source of firm level balance sheets in Turkey.

Figure 1: Number of Firm Observations in Each Year



Source: FINNET

Table 1: Representativeness of the Sample for the whole Turkish Economy

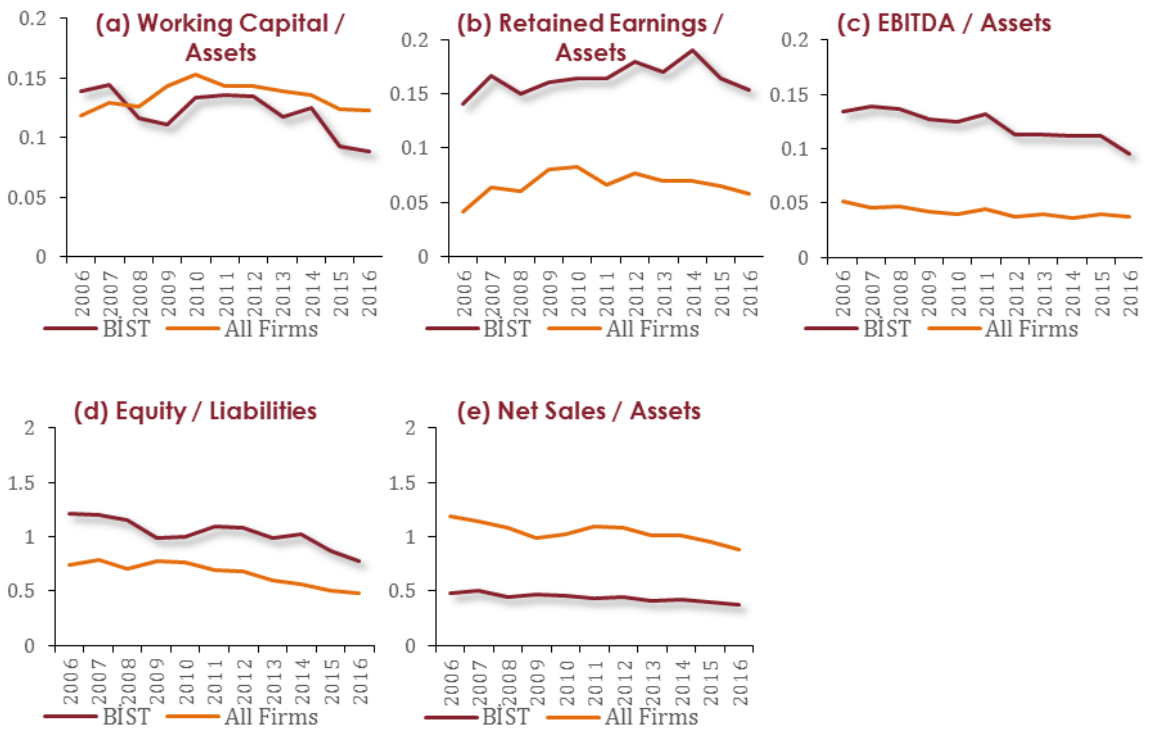
Sales/ GDP	14.80%
Export Share	23.60%
FX Net Position Share	12.50%
FX Debt Share	16.70%

Source: FINNET and CBRT

The sample representativeness of Turkish economy is provided in Table 1. Even though the sample is relatively small in order to generalize the results obtained in this paper to the whole economy, the firm behaviors of BIST firms resemble firm population in Turkey. It could be observed by comparing the balance sheet ratios of our data set with the largest firm level dataset (MoSIT) which includes almost the whole firm population in Turkey. [5] If we compare the trends in the financial ratios used in Altman Z-score between our dataset and MoSIT, both the trend and movements are similar. Working capital / assets and equity / liabilities ratios do not differ from each other and fluctuations in these indicators over time are very similar (Figure 2). BIST firms have in general larger earnings ratios compared to the population, however, the trends and short-term movements are similar in both data sets.

[5] The largest dataset containing firm balance sheets in Turkey is stored by Ministry of Science, Industry and Technology for corporate tax purposes. This dataset including more than one million firms represents almost whole population in Turkey. The data is strictly confidential and only the annual aggregated data is published. The figures in this paper are drawn using the aggregated data.

Figure 2 (a,b,c,d,e) : Representativeness of the Sample for the whole Turkish Economy



Source: FİNNET, MoSIT

3.3 Selection of Financially Distressed Firms

In order to apply MDA, we need a priori groupings of the firms and hence we need a list of financially distressed and solvent firms. To find out which firms experienced financial distress in 2001 -17 period, we utilize the following criteria: If a firm had a negative equity account in its balance sheet, declared bankruptcy, applied for suspension of bankruptcy or got bankruptcy petition by creditors; these are sufficient conditions for financial distress. Furthermore, if the firm began to be traded under Watch List market in the BIST and the firm exits the BIST, we suspect insolvency. In order to ensure that these firms are under financial distress, we made a detailed check by contacting to the experts in the BIST. Finally, we end up with 56 firms that satisfy sufficient criteria for financial distress in 2001-17.[6]

The firms are mostly manufacturing firms, as expected (Table 2). Textile and Food subsectors have the largest share among the distressed manufacturers, which might lead some to question that the analyses in the paper will not represent all sectors. Nevertheless, the sub-sectoral distribution among manufacturers is similar to the distribution in the firm population in Turkey. Credit Registry dataset of Turkey suggests that the number of firms in Textile and Food sectors have 49.6 share among total number of manufacturers. Among the distressed

[6] Even though the sample includes the crises years of 2001 and 2009 in Turkish economy, the number of firms found to be distressed in our sample in these years are similar to other years. Hence there is no bias towards the crises years in our sample in making our analyses.

manufacturers, which could be proxied by having a non-performing loan in credit registry dataset, food and textile sectors have the largest number of firms with 40.2 percent share.[7] However, the results in this paper will represent mostly manufacturers in BIST firms since manufacturers constitute more than 90 percent of BIST real sector firms and distressed BIST firms.

Having determined the list of distressed firms, we need a second group containing solvent firms. The firms in the second group are attained as a match of each firm in the first group (Platt & Platt,1990 and Zavgren, 1985). By matching, we consider each pair operates in the same sub-sector, have similar asset sizes and the peer in the second group is solvent at the same period when other peer fell into distress.[8] According to these criteria, we have found 54 matches and couldn't find any solvent matches for 2 distressed firms. Finally we have now a main sample of 108 firms consisting of 54 distressed firms in the first group and 54 solvent firms in the second group for conducting MDA.

Table 2: Sub-Sectors of Financially Distressed Firms

Sector	Firm Numbers
Food	11
Service	2
Paper-Wood	1
Chemistry	6
Basic Metal	2
Metal Product	4
Furniture	1
Hotel & Retaurant	2
Wholesale & Retail	5
Stone & Earth	1
Textile	18
Transport	2
Construction	1

Source: FINNET

3.4 Selection of the Best Model

In both Tailored Altman model and MFA-score estimation, we have selected the model which have the highest predictive power among numerous models we have run with different samples. The normal procedure in the literature is to divide the main sample into two, running MDA to one sample and carrying out performance test in another (Ooghe and Verbaere, 1985; Keasey and Watson, 1991; Dirickx and Van Landeghem, 1994). The rationale is to check the performance in a different group where the model parameters are not obtained from, otherwise we could have biased performance measure.

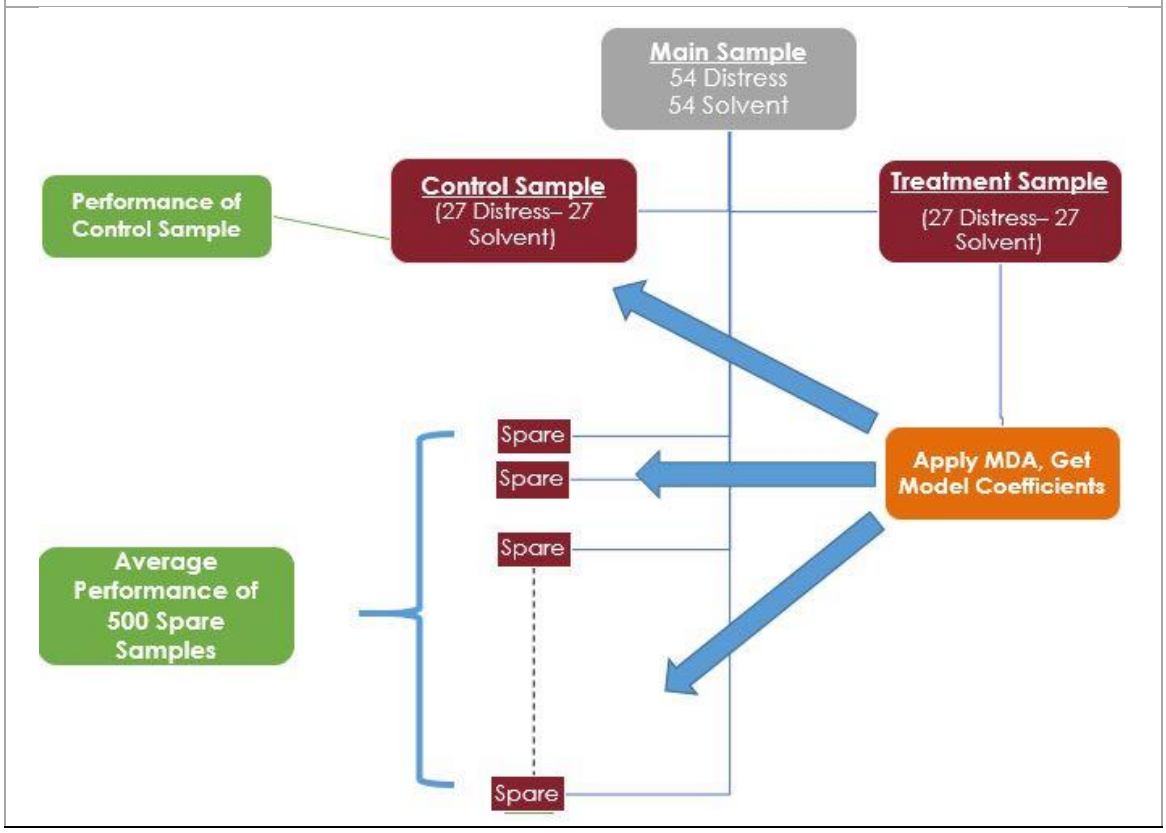
In our paper, we applied a different procedure from the literature. Out of 108 firms in the main sample, we randomly select 54 firms (27 distressed and 27 solvent) as treatment sample. The remaining 54 firms (27 distressed and 27 solvent) are put aside as control sample. We conduct MDA to treatment sample and the coefficients obtained from treatment sample are used for performance test in control sample. Afterwards, 500 random samples (spare samples) of 54 firms (27 distressed and 27 solvent) were selected from the main sample of 108 firms. The performance tests are also applied to these spare samples using the coefficients obtained from the treatment sample. The control sample performance and the average performance of 500 spare samples are noted as the performance of the coefficients obtained from the randomly selected treatment sample (Figure 3). [9]

[7] Credit registry data set includes all the firms having a loan relationship with a bank in Turkey. The firm numbers are calculated using the data of December 2017.

[8] The asset size of one peer should not exceed by threefold the other's asset size.

[9] Millions of different 54-firm samples could be drawn from the main sample of 108 firms, but it would take weeks to run the model on all possible combination of samples. Also, the average performance does not change much as the number of spare

Figure 3: Design of the Performance Tests



Afterwards, the above steps are repeated for 1000 times with 1000 randomly selected treatment samples and each time, the performance of each model on the control and 500 spare samples are noted. As a result, we end up with a matrix of 1000 different coefficient sets, control sample performance and average of spare samples performances for each coefficient set. From these 1000 different coefficient sets, those with control sample performance over 85% are picked. Among those picked, the model with the highest average performance in 500 spare samples is chosen in both Altman replication and MFA score analysis.

4. Tailored Altman Model

Initially we conducted MDA with Altman Z-score variables for our main sample using the methodology detailed in previous section. The variables' pre-estimation statistics are provided in Tables 3 and 4. In all 5 variables, solvent firms have higher mean values than distressed firms, which is in line with the expectations. According to t-test, mean differences are statistically significant, noting that the least significance is observed in Net Sales / Asset ratio.[10] Furthermore, pairwise correlations suggest that multicollinearity is not a serious concern.

samples increase. For example, there is only slight difference in the average performance results among 100, 500 and 1000 spare samples. Hence, we cut the spare sample generating process at 500.

[10] Altman (1968) have also manifested that X_5 does not significatly differ between groups.

Table 3: Group Means of Altman Z-score Variables and T-test for Mean Differences

	Mean		
	Distress	Solvent	t-stat
Working Capital / Asset	-0.08	0.19	-6.18***
Retained Earnings / Asset	-0.86	0.06	-5.54***
EBITDA / Asset	-0.03	0.11	-5.73***
M.V. of Equity / B.V. of Debt	0.72	2.58	-3.63***
Net Sales / Asset	0.85	1.10	-1.76*

Note: * indicates significance level of 10%, ** is of 5% and *** is of 1%
Source: FİNNET

Table 4: Pairwise Correlations of Altman Z-score Variables in BIST database

	Working Capital / Asset	Retained Earnings / Asset	EBITDA / Asset	M.V. of Equity / B.V. of Debt	Net Sales / Asset
Working Capital / Asset	1.00				
Retained Earnings / Asset	0.38	1.00			
EBITDA / Asset	0.20	0.39	1.00		
M.V. of Equity / B.V. of Debt	0.27	0.07	0.04	1.00	
Net Sales / Asset	-0.02	0.04	0.12	-0.09	1.00

Source: FİNNET, MOSIT

As explained in model selection part, MDA was applied to 1000 different randomly-selected treatment samples in order to reach the best model. Among these, the model with the highest performance is as follows:

$$\underset{(Standardized\ Coefficients)}{Tailored\ Z-Score =} \quad \underset{(0{,}64)}{1{,}06X_1} + \underset{(0{,}21)}{1{,}17X_2} + \underset{(0{,}42)}{2{,}59X_3} + \underset{(0{,}51)}{0{,}23X_4} + \underset{(0{,}11)}{0{,}13X_5}$$

The model coefficients are all positive, which is consistent with the expectations. The standardized canonical discriminant function coefficients allow us to compare the impact of each ratio to final score. Among five variables, working capital to asset ratio and market value of equity to book value of debt ratio seem to be main determinants of the financial distress or solvency level of the firm. Since all coefficients are positive and mean values are greater in the solvent group; rising tailored z-score means sounder balance sheets.

The previous literature on the adjustment of Altman Z-score for Turkish economy finds different coefficients and performance rates. For instance, in their studies on 35 failed and 35 non-failed BIST firms, Muzır and Çağlar (2009) found negative coefficients for X_3 and X_5, and the correct classification rate of their model is 73.3%. Yılmaz and Yıldıran (2015) have also revised Altman Z-score model by using 18 failed and 18 non-failed BIST firms and the coefficient of X_1 has been found negative and the prediction accuracy of their model is 79%. Our revised model differs from these studies in a way that it spans longer time frame, which enables us to study on a larger sample of failed and non-failed firms.

There are some post-estimation diagnostics in order to evaluate the discriminating power of the model. For a good model, one should also obtain significant results on these diagnostic tests (Table 5). Canonical correlation is the measure of association between classification variable and discriminant function (Rencher and Christenseni, 2012 and Huberty, 1994). A high and significant value of canonical correlation (0.72) is an indication of high discriminating power of the model. The F-value which tests the null hypothesis that canonical correlation is equal to zero demonstrates the rejection of the null. Eigenvalue is the ratio of explained variance to unexplained variance in the model and should be greater than one for a good model (Landau and Everitt, 2004). Wilk's lambda is one minus explained variance of the model and represents the discriminating power of the model similar to eigenvalue. When the Wilk's lambda is smaller, the function is more discriminative.

Table 5: Post-Estimation Diagnostics of Tailored Altman Model

Canonical Correlation	Eigen-value	F	Prob>F	Wilk's Lambda
0.7213***	1.0843	10.409	0.0000	0.479

The performances of the model in treatment and control samples are depicted in tables 6 and 7. The model classifies 22 firms correctly out of 27 distressed firms in treatment sample one year prior to falling into financial distress. Additionally, 26 of the 27 solvent firms in the treatment sample are correctly classified as solvent by Tailored Z-score according to one year earlier financial statements. The performance of the model in the treatment sample is 88.8 percent. For the control sample, the correct classification rate for distressed firms is 92.59% and for solvent firms 88.8% as well. Hence overall performance in control sample is 90.74 percent. The model has an average of 87.4 percent success rate for 500 spare samples, which is the highest performance among all alternative tailored models.

Table 6: Model Performance in Treatment Sample (Tailored Altman Model)

		Predicted		
		Distress	Solvent	
Actual	Distress	22 81.48%	5 18.52%	27 100%
	Solvent	1 3,70%	26 96,29%	27 100%
	Total	23	31	54
	Overall Performance			**88.8%**

Source: Author's calculation

Table 7: Model Performance in Control Sample (Tailored Altman Model)

		Predicted		
		Distress	Solvent	
Actual	Distress	24 88.88%	3 11.11%	27 100%
	Solvent	2 7.41%	25 92.59%	27 100%
	Toplam	26	28	54
	Overall Performance			**90.74%**

Source: Author's calculation

To test the predictive ability of the model, Reciever Operating Characteristics (ROC) approach could also be utilized using the Type I and Type II error rates. ROC approach gives us a cut-off score that best discriminates the solvent and distress groups and predictive power of the model with this optimal cut-off point (Agarwall and Taffler, 2008). Optimal cut-off point is calculated via minimizing the sum of Type 1 and Type II error rates, while treating the costs

of both error rates as equal (Engelmann et al., 2003). When we apply the ROC approach to Tailored Altman scores of the whole main sample (108 firms with 54 distressed and 54 solvent), the optimal cut-off value is found to be 0.3, above which the firm is classified as solvent and below as distressed. Area under the ROC curve, which takes a value between 0 – 1, is a performance measure for testing the predictive power of the model given the cut-off point (Sobehart and Keenan, 2001). For the tailored Altman model scores of the main sample, area under the ROC curve is calculated as 0.93, which points out a solid predictive power.

When the original Altman model coefficients are applied to the same treatment and control samples, we end up with performance rates of 79 and 82 percent (Tables 8 and 9). Hence estimation of Tailored Z-score, whose coefficients are specific to BIST firms, increased the performance of the model by nearly 10 percent. ROC analyses with the original Altman Z-score model using the main sample suggest that optimal cut-off point is 1.63 and the area under the ROC curve associated with this cut-off value is 0.87. It is evident that predictive power increases if one uses tailored Altman model besides the original Altman z-score.

Table 8: Model Performance in Treatment Sample (Original Altman Model)

		Predicted		
		Distress	Solvent	
Actual	Distress	22 81.48%	5 18.52%	27 100%
	Solvent	6 22.22%	21 77.78%	27 100%
	Total	28	26	54
	Overall Performance			**79.63%**

Source: Author's calculation

Table 9: Model Performance in Control Sample (Original Altman Model)

		Predicted		
		Distress	Solvent	
Actual	Distress	22 81.48%	5 18.52%	27 100%
	Solvent	5 18.52%	22 81.48%	27 100%
	Total	27	27	54
	Overall Performance			**81.48%**

Source: Author's calculation

Table 10: Set of Financial Ratios subject to Selection Process

Profitability	Leverage	Liquidity	Efficiency
Net Profit (Loss) / Net Sales	Total Liabilities / Total Assets	Short-Term Liabilities / Current Assets	Sales / Total Assets
Net Profit (Loss) / Total Assets	Total Liabilities / Equity	Acid-Test Ratio	Sales / Current Assets
EBITDA / Net Sales	Retained Earnings / Total Assets	Inventory / Short Term Liabilities	Sales / Fixed Assets
EBITDA / Total Assets	Long-term Liabilities / Fixed Assets	Working Capital / Total Assets	Sales / Quick Assets
Earning before Tax / Net Sales	Long-term Liabilities /Equity	Current Assets / Total Assets	Financial Expenses / Sales
Earning before Tax / Total Assets	M.V. Of Equity / B.V. Of Liabilities	Cash / Current Liabilities	Inventory / Sales
Net Profit (Loss) / Equity	EBITDA / Total Liabilities	Quick Assets / Current Liabilities	Working Capital / Sales

5. MFA-Score Model

Even though we obtained better predictive ability through the tailored Z-score than the original Altman score, using different ratios which best capture the characteristics of BIST firms would provide more robust estimation results. In this sense, we produced an index measure with new variables, named as MFA Score.

5.1 Variable Selection

Among 30 ratios procured from financial statements and widely used in literature, we eliminated many of them according to both statistical and intuitional criteria (Table 10). These criteria are;

(i) At least one ratio from liquidity, profitability, leverage and efficiency indicators should be contained for strong comprehensiveness.

(ii) The chosen variable should be able to discriminate distressed and solvent firms correctly. This criterion is tested by statistical significance of the mean difference between both groups via t-test. If the means of the ratio in both groups do not significantly differ from each other, we eliminate the ratio.

(iii) Two ratios should not be collinear to each other. If any pairwise correlation is greater than 0.6, one of the peers is eliminated.[11] The procedure is to eliminate the one having higher correlation with other variables on average.

(iv) Having completed the first three steps, 12 ratios remained for the next stage. Initially, we carried out MDA via 4 variables, one from each liquidity, profitability, leverage and efficiency categories. Every 4 variable combination is tested and the one with the lowest Wilk's Lambda is chosen. Later on, in addition to 4 variables, the remaining ratios added to the model with every possible combination. After testing all model combinations, we pick the variable set whose MDA result provides the lowest Wilk's Lambda. Finally, ratios to be used in final MFA score calculation are presented in Table 11.

The descriptive statistics are depicted in tables 12 and 13. The means of the variables in both groups differ from each other. Solvent firms on average have higher acid test, EBITDA / Asset, Net Profit / Net Sales and Retained Earnings / Asset ratios than the distressed firms. And the ratios of ST Debt/Current Assets, Total Debt / Equity and Financial Exp. / Net Sales are higher in distressed firms as expected. For multicollinearity check, all pairwise correlations are smaller than 0.6 and the highest correlation is observed between net profit and financial expenses variables. One might have expected a higher correlation between EBITDA and Net profit variables than the actual value of 0.27. EBITDA is the net earning obtained from the firm's main business operations and after the deduction of financial expenses and tax payments, we end up with net profit/loss. Since firms in Turkey are highly leveraged and indebted in

[11] Literature suggests that multicollinearity is a serious concern that should be treated before applying MDA (Yoo et. al., 2014). It produces biased and unstable coefficients because the effect of an independent variable is captured by others (Hair,Tatham and Anderson, 1988 and Blum, 1974). Hence, analysts tried to remove variables whose pairwise correlations are greater than a certain cut-off value. Pervan et. al. (2011) uses 0.8 as the threshold for multicollinearity, Leksrisakul and Evans (2005) uses 0.9 and Vinh (2005) uses 0.5. For our study, we followed a relatively conservative approach and determine 0.6 as the cut-off correlation value for variable deletion because we want to remove biasedness completely.

foreign currency, they have a large financial expenses account. Specifically, in times of TL depreciation, financial expenses increase significantly. Even though firms earn sound operating income, financial expenses or tax payments can reduce this income to very low levels in net profit account. Hence, for the case of Turkish firms, net profit is less correlated with EBITDA compared to financial expenses.

Table 11: Financial Ratios used in MFA Score Estimation

$X_1 = (Cash\ Equivalents\ + Securities + Short\ Term\ Trade\ Recievables)\ /\ (Short\ Term\ Liabilities)$:

This indicator, also known as the acid-test ratio, shows how much the short-term debt of the firm can be met with cash and cash equivalents.

$X_2 = Short\ Term\ Liabilites/Current\ Assets$:

It measures the firm's ability to pay its short-term liabilities with short-term assets.

$X_3 = Total\ Liabilities\ /\ Equities$:

It shows how much sufficient the firm's equities to pay its debt

$X_4 = EBITDA\ /\ Total\ Assets$:

It is the profitability of the firm from its main activities by asset size.

$X_5 = Financial\ Expenses\ /Net\ Sales$:

Indicates the capacity of the company to pay the FX and interest expenses arising from its debts

$X_6 = Net\ Profit(Loss)/\ Net\ Sales$:

It is the net earnings (or loss) of the firm per sale at the end of the period.

$X_7 = Retained\ Earnings/Total\ Assets$:

It is the measure of cumulative profit or loss from the past periods. It also contains information about the age of the company.

Table 12: Group Means of MFA-Score Variables and T-test for Mean Differences

	Mean		
	Distress	Solvent	t-stat
Acid Test Ratio	0.59	1.54	-3.47***
ST Debt / Current Asset	1.57	0.66	5.07***
Total Debt / Equity	13.83	1.41	2.82***
EBITDA/ Asset	-0.01	0.12	-5.98***
Financial Exp. / Net Sales	0.17	0.02	1.49*
Net Profit/ Net Sales	-0.83	0.03	-3.4***
Retianed Earnings / Asset	-0.86	0.06	-5.54***

Note: * indicates significance level of 10%, ** is of 5% and *** is of 1%

Table 13: Pairwise Correlations of MFA Score Variables in Main Sample

	Acid Test Ratio	ST Debt / Current Asset	Liability / Equity	EBITDA/ Asset	Financial Exp. / Net Sales	Net Profit/ Net Sales	Retianed Earnings / Asset
Acid Test Ratio	1.00						
ST Debt / Current Asset	-0.37	1.00					
Total Debt / Equity	-0.12	0.06	1.00				
EBITDA/ Asset	0.06	-0.21	0.08	1.00			
Financial Exp. / Net Sales	-0.10	0.52	-0.01	-0.05	1.00		
Net Profit/ Net Sales	0.07	-0.55	0.01	0.27	-0.57	1	
Retianed Earnings / Asset	0.16	-0.28	-0.05	0.38	-0.04	0.09	1

5.2. MFA-Score Coefficients and Performances

Using the chosen 7 variables, we followed the steps detailed in the methodology part for the selection of the best model. This analysis resulted in the following model and coefficients:

$$\begin{array}{lllllllll} MFA\ score = & 0.24X_1 & -\ 0.14X_2 & -\ 0.03X_3 & +\ 3.76X_4 & -\ 0.72X_5 & +\ 0.20X_6 & +\ 1.14X_7 \\ (Standardized\ coeff.) & (0.44) & (-0.12) & (-0.47) & (0.45) & (-0.13) & (0.29) & (0.49) \end{array}$$

The signs of the coefficients are consistent with the expectations and in line with economic intuitions. When the standardized coefficients are examined, main determinants of a firm's financial distress or overall financial strength are found to be the firm's liquidity position (acid-test ratio), total leverage, EBITDA and retained earnings. Financial expenses and short-term debt to current assets ratios seem to have less relevance with the financial distress or soundness of firms compared to others. Post-estimation diagnostics reveal higher discriminating power of MFA-score than the Tailored Altman model (Table 14). Correlation between the grouping variable and the discriminant function is larger. Higher eigenvalue and lower Wilk's lambda values also demonstrate that the discriminating power significantly increased with MFA-score.

Table 14: Post-Estimation Diagnostics of Tailored Altman Model

Canonical Correlation	Eigen-value	F	Prob>F	Wilk's Lambda
0.7558***	1.333	8.756	0.0000	0.428

MFA-Score correctly predicted 24 firms out of 27 firms which experienced financial distress in treatment sample one year prior to distress period. Furthermore, 26 firms out of 27 are correctly predicted as being solvent according to MFA score derived from one year earlier financial statements (Table 15). In the treatment sample, Type 1 error is 0.11 (3 / 27) and Type 2 error is 0,037(1/27). In short, MFA Score has a performance of 92.6 percent in predicting the financial distress or soundness among 54 firms in treatment sample.

Table 15: Model Performance in Treatment Sample (MFA-Score Model)

Actual	Predicted: Distress	Predicted: Solvent	
Distress	24 88.89%	3 11.11%	27 100%
Solvent	1 3.70%	26 96.30%	27 100%
Total	25	29	54 92.59%

Source: Author's calculation

Table 16: Model Performance in Control Sample (MFA-Score Model)

Actual	Predicted: Distress	Predicted: Solvent	
Distress	23 85.19%	4 14.81%	27 100%
Solvent	0 0.00%	27 100.00%	27 100%
Total	23	31	54 92.59%

Source: Author's calculation

Since model coefficients are obtained from treatment sample through MDA, relying on performance result of treatment sample may lead to biased outcomes. In order to apply MFA score for different firms later on, MFA score is expected to have a high predictive power for different samples. In this respect, the performance of control sample gives us a better measure of predictive power of the model. Type 1 error of the control sample is 14,8 percent (4 / 27) and Type 2 error is 0 percent (0/27) and hence total performance on control sample is 92,6 (50/54) percent (Table 16). The average performance of MFA score on 500 spare samples is found to be 91.4 percent. In sum, MFA score measures the financial soundness of a firm with a correct prediction rate above 90 percent from one year earlier. And performance rates increased considerably compared to both original and tailored Altman models. An application of ROC analysis to the MFA scores of the main sample gives us -0.02 as the cut-off value which discriminates the solvent and distressed firms. Area under ROC curve is calculated as 0.94, which indicates the predictive power further increased with MFA score.

After completing MFA score modeling and ensuring the performance, the next step is how to interpret the value of any firm's MFA-score. For this, two different threshold values are determined according to the score values. The first threshold is the cut-off value of -0.02 and is set to separate firms that are likely to experience financial distress within a year and are financially solvent. Then, among the financially sound 54 firms in the main sample, the median MFA-score of 0.556 is selected as the second threshold value.[12] Therefore, if a firm's MFA-score is less than -0.02 (distress zone), the firm will likely experience financial distress in one year; if between -0.02 – 0.56 (gray zone) it is interpreted as having a low probability of experiencing financial distress and if greater than 0.56, the firm is financially stable (safe zone).

5.3 Robustness Checks

In order to be sure that our results are robust to different scenarios we applied several robustness checks. Initially, different variable selection criteria are conducted. Instead of using 0.6 as the cut-off value for the pairwise correlations, we also tested 0.5, 0.7 and 0.8. When we use 0.5, there remain 15 ratios for MDA and among them, a combination of 9 ratios yielded the lowest Wilk's Lambda (0.463). However, this value is greater than our original model's value and other model diagnostics have also worsened compared to original model. When we use cut-off correlation values of 0.7 and 0.8 as a robustness check, number of ratios included in the best performing model declined to 4 and 2, respectively. This considerably decreased the comprehensiveness of our model. In case of 0.7, even though model diagnostics seem to have improved slightly, 3 of 4 ratios come from leverage category.

For robustness, we also tested different models using different criteria for model selection and the same ratios of MFA score. In addition to original MFA-score, we obtained two more model coefficients. One is obtained by taking the average of the coefficients of the models with control sample performances above 85 percent. The other one is attained by averaging the coefficients of the models with total performances (treatment + control) above 85 percent. In these two new models, coefficients have expected signs and there is no significant difference from our original MFA-score model. Furthermore, the standardized coefficients in

[12] There might be more than 2 threshold values and several risk groups as in rating scales of the rating companies. Since our sample is not that large to categorize more groups and the aim of the paper is to assess overall risk of the corporate sector, 3 risk categories used as in Altman (1968).

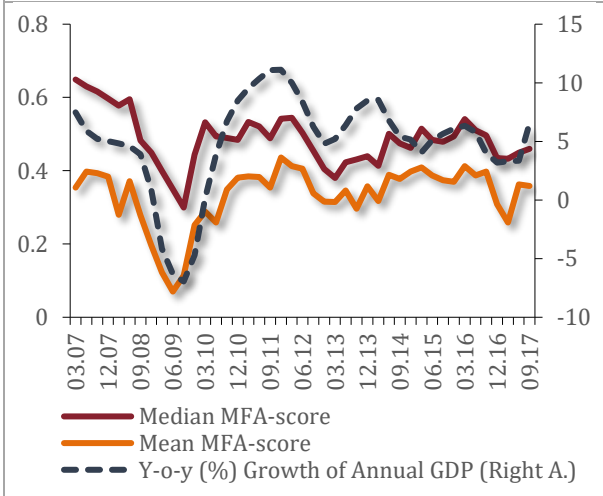
these models suggest that main determinants of a firm's financial distress are liquidity position, total debt leverage and EBITDA, which is a similar finding of MFA-score model.

5.4 Application of MFA-Score

MFA score formula are applied to quarterly published financial statements of firms that were quoted in the BIST between 2007 and 2017.[13] The median and mean MFA-scores of the data set, which includes 361 firms in total and 230 balance sheet observations on average per year, are presented in Figures 4 and 5.[14] Median values are greater than the mean, which imply MFA-score distribution is skewed to left and scores above median dispersed over larger values. MFA-scores move in line with GDP growth and inversely with foreign exchange rate. The correlation of the MFA-Score with annual GDP growth rate is 0.48 and with annual change in FX basket rate is (-0.41). This significantly high correlation with these two important macro variables indicates that the model is successful in detecting the effects of macro-economic developments on the firms' balance sheets.

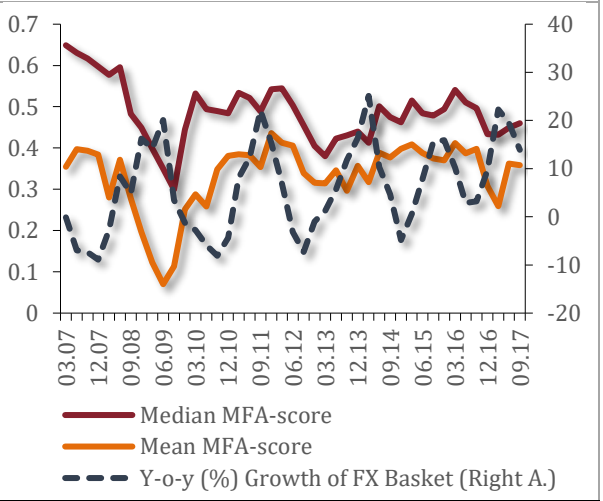
At any time, including the global crisis, the score did not fall below the distress threshold value of -0.02 and moved within the gray zone boundaries. The MFA-score fell sharply during the global crisis and remained low throughout 2013 due to the slowdown in growth at the end of 2012 and volatility in the wake of the Fed tapering in 2013. MFA-score, which rose in the following period, declined sharply in the last quarter of 2016 due to the increasing volatility in exchange rates and recovered afterwards owing to the high economic growth.

Figure 4: MFA-Score and GDP Growth (Score, Percent Growth)



Note: Growth rate is the y-o-y percent change of annual GDP
Source: TURKSTAT, FINNET, Author Calculations

Figure 5: MFA-Score and FX Basket Rate (Score, Percent Growth)



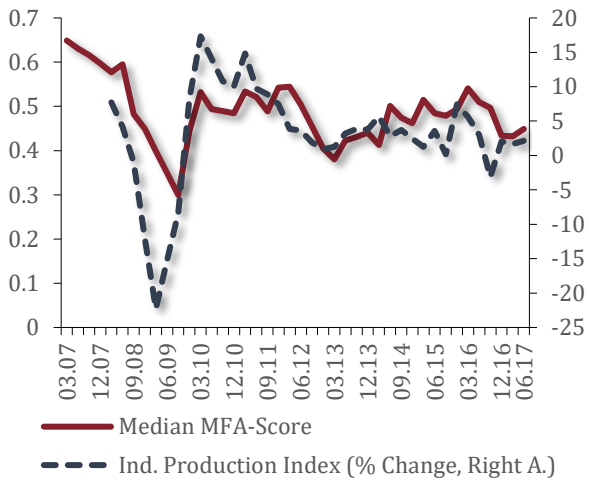
Not: FX basket rate is obtained using weights 0.7 for TL / USD rate and 0.3 for TL / Euro. Growth rate is y-o-y percent change of quarterly average of FX Basket rate.
Source: TURKSTAT, FINNET, Author Calculations

Besides macro variables, MFA-Score has significant correlation with industry level indicators. The score mirrors, to a large extent, the movement in industrial production index with a correlation of 0.54 (Figure 6). Also it is expected that the balance sheet soundness of firms should have association with the number of newly established or exited firms. As balance sheets deteriorate in an economy, the rate of firms exiting the market should be higher than

[13] In each quarter, income statement variables are annualized.
[14] In mean and median calculation, the observations in the highest and lowest 1 percentile are excluded.

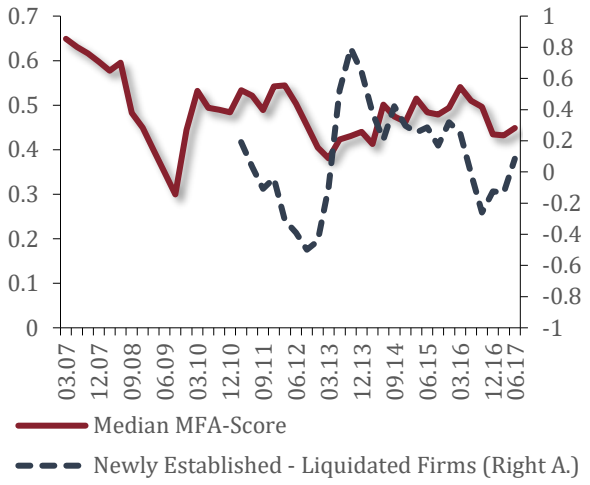
firms entering into the market. MFA-score successfully captures the firm entry-exit statistics. According to Figure 7, as MFA-score increases, the difference between the number of newly established firms and number of liquidated or exited firms narrowed; and as MFA-score declines, the difference widened.

Figure 6: MFA-Score and Y-o-y Change in Industrial Production Index (Score, Percent Growth)



Note: Growth rate is the y-o-y percent change of 3-month moving average industrial production index.
Source: TURKSTAT, FINNET, Author Calculations

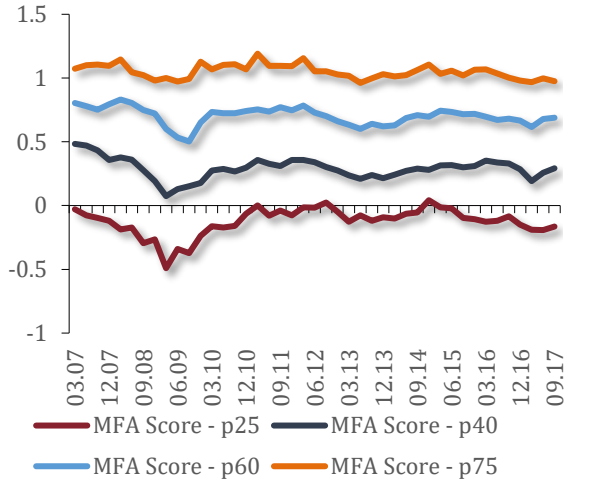
Figure 7: MFA-Score and the Difference between Number of Newly Established and Liquidated Firms (Score, Number)



Note: Dashed line depicts the y-o-y growth of the difference between the number of newly established firms in 3-month period and of liquidated or exited firms in the 3-month period. This data is available since 2010.
Source: TURKSTAT, FINNET, Author Calculations

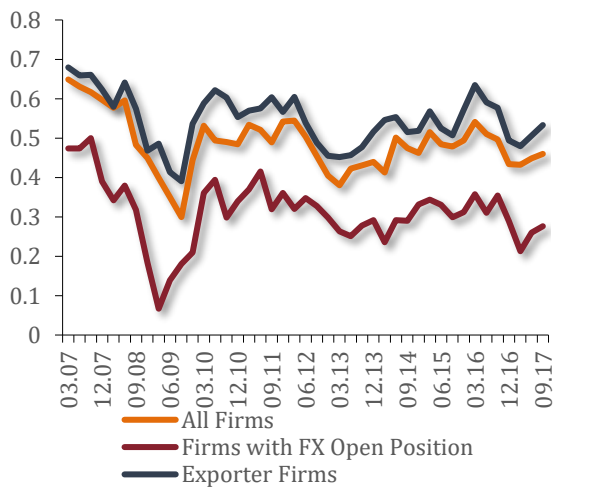
Firms with lower MFA-Score seem to be more vulnerable to macroeconomic fluctuations. While firms positioning above 50th percentile by MFA score follow a stable course over time, MFA scores are more volatile in lower percentiles (Figure 8). This enables us to infer that sound balance sheets make firms robust against shocks.

Figure 8: MFA-Score by Percentiles (Score)



Source: FINNET, Author Calculations

Figure 9: Median MFA Score of Exporter Firms and Firms with FX Open Position

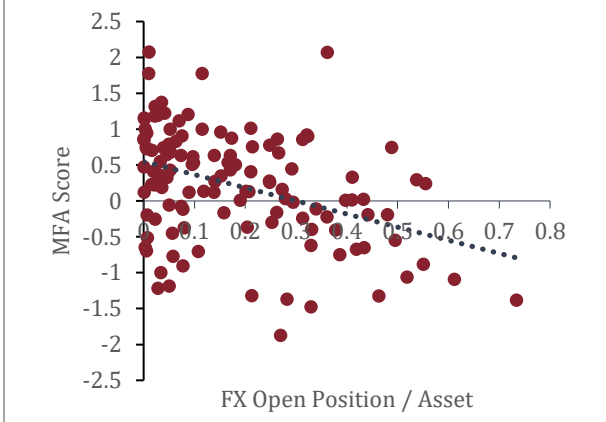


Source: FINNET, Author Calculations

Exporter firms generally have higher MFA-scores and firms with open foreign exchange positions have lower scores (Figure 9). Exporters in Turkey are in general large-sized

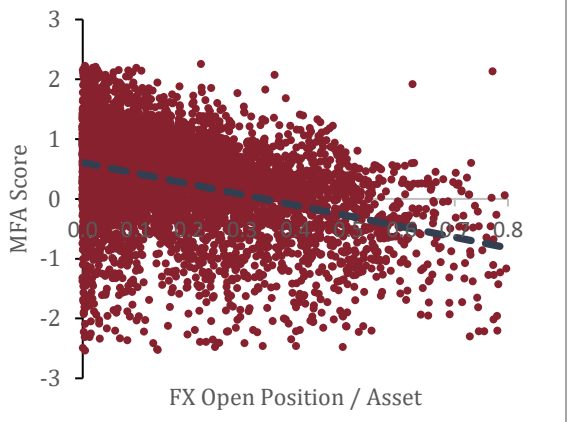
institutional firms who are capable of effective risk management and this figure is explicitly observed through their larger scores. FX open position is one of the significant determinants of firms' financial strength in Turkey since Turkish economy has a large current account deficit over a long time. Another critical finding is that FX open positions make firms' balance sheets weaker, which is observed in their lower MFA scores in the whole period. In addition, the reactions of firms in open positions against macro shocks are more evident. Particularly during the turbulences in the global crisis and the end of 2016, the decline in the scores of the firms with open position is sharper. Among firms with FX open position, as the amount of open position rises, the MFA scores are declining (Figure 10 and 11).

Figure 10: Firm Level MFA Score and FX Open Position, as of 4th quarter 2016



Source: FINNET, Author Calculations

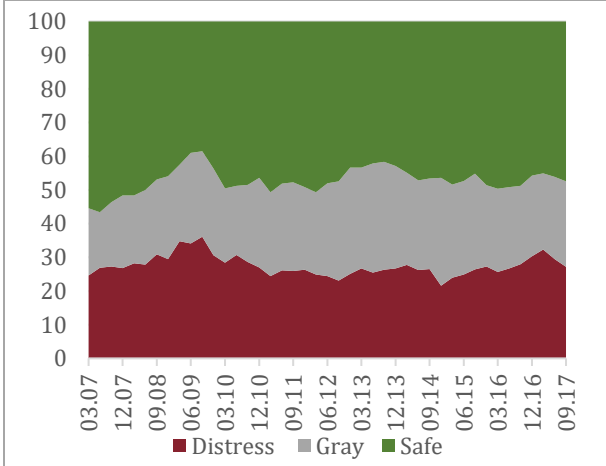
Figure 11: Firm Level MFA Score and FX Open Position, all quarters in 2001-17



Source: FINNET, Author Calculations

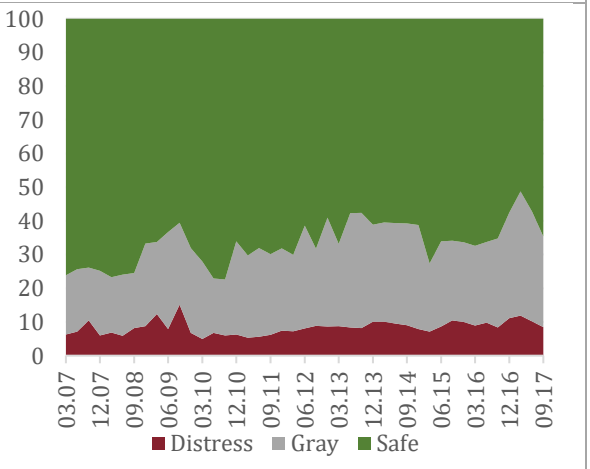
When the distribution of all firms in the MFA risk zones is examined, it is observed that the majority of the firms are in the safe zone (Figure 12) and gray and distress zones have similar numbers of firms. During the global crisis, the share of safe zone significantly declined and distress zone increased. In 2013, there was a transition from the safe zone to the gray zone and in the last period of 2016, number of firms in the distress zone increased.

Figure 12: Number of Firms in MFA-Score Zones (Percent Share)



Source: Author Calculations

Figure 13: Total Asset Size in MFA-Score Zones (Percent Share)

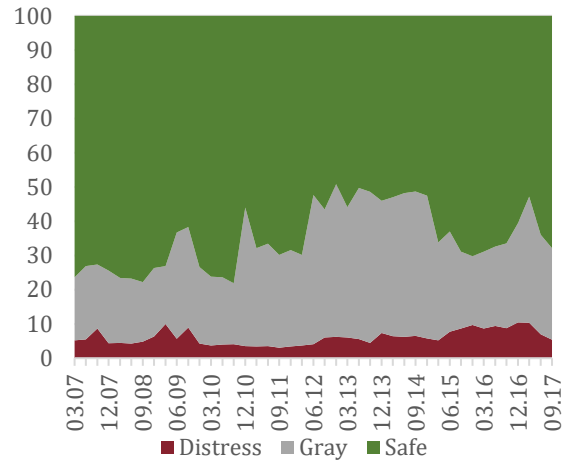


Source: Author Calculations

Asset size distribution of the firms in the MFA-score zones indicates that firms in the safe zone have the highest share in the total assets and nearly 10% of total asset size belongs to

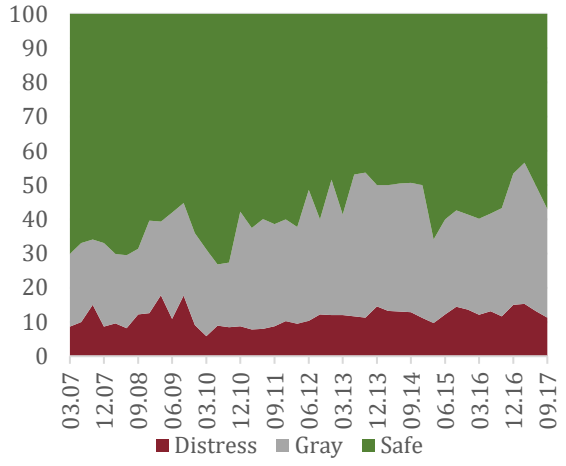
firms in distressed zone (Figure 13). This suggests that firms with a high probability of financial distress are relatively small-scale firms and that large-scale firms have greater MFA scores. In the global crisis, some large-sized firms moved towards distress zone and in 2016 turbulence, gray zone's asset share significantly increased. Lastly, the distribution of net sales amount in risk zones is very similar to asset size distribution (Figure 14).

Figure 14: Total Net Sales in MFA-Score Zones (Percent Share)



Source: Author Calculations

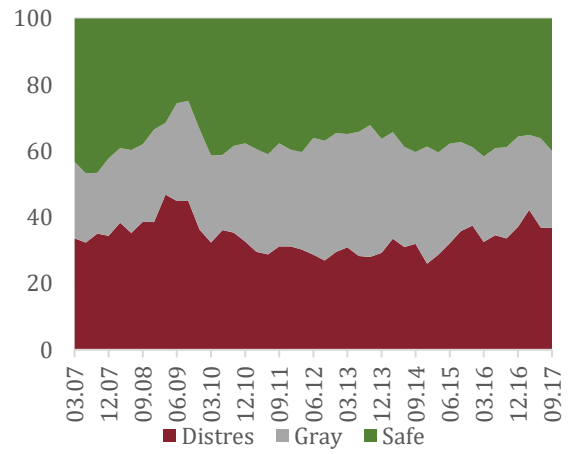
Figure 15: Total Debt in MFA-Score Zones (Percent Share)



Source: Author Calculations

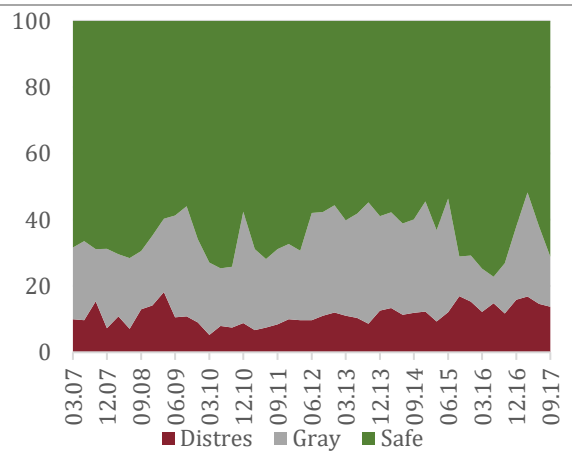
How much of the firms' total debt is concentrated in firms that are more likely to experience financial distress is a critical question for the financial risk of the real sector. In the IMF (2015, 2016 and 2017) global financial stability reports, the share of risky firm debt within total firm debt is used as the criterion of real sector financial risk (debt-at-risk). With the MFA-score, it is possible to define a broader and more comprehensive risk indicator by calculating the debt ratio of firms' in the distress zone to the total debt of whole firms. By this measure, it is observed that the share of risky firm debt (debt-at-risk) is around 10 percent, and that the most of the debt is concentrated in financially strong firms (Figure 15). Debt-at-risk rose moderately in 2016 and considerably in the global crisis.

Figure 16: Number of Firms with FX Open Position in MFA-Score Zones (Percent Share)



Source: Author Calculations

Figure 17: Total Asset Size of Firms with FX Open Position in MFA-Score Zones (Percent Share)

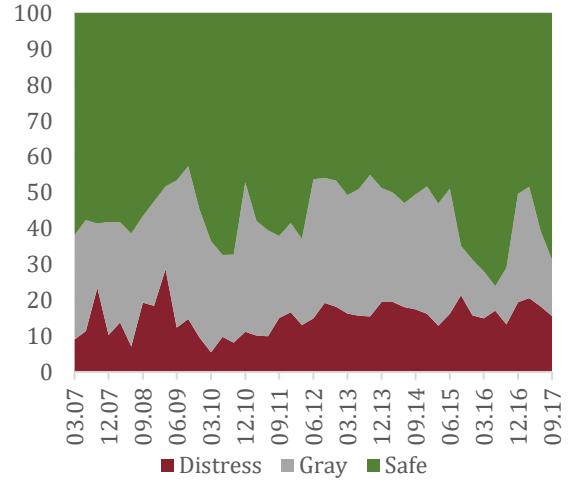


Source: Author Calculations

Among firms with FX open position, in general, distress zone has the largest number of firms compared to other two zones (Figure 16). The firm numbers in distress zone increased in the global crisis and in the second half of 2016. Although share of firm numbers is high, their asset size has a very limited share, which implies risky firms holding FX open position is relatively small-sized firms (Figure 17). This result is consistent with the expectation that large-sized firms are more capable of FX risk management and open position does not harm their balance sheets as much as others.

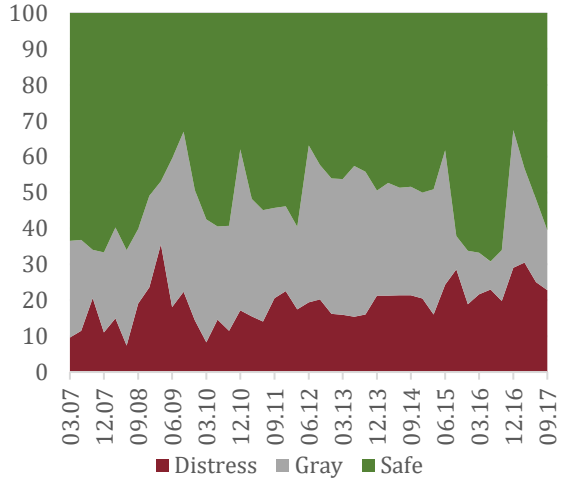
The amount of FX open position concentrates mainly in firms with solid balance sheet structure and the open position of firms in the distress zone constitutes 20-25% of the total (Figure 18 and 19). Furthermore, the transitions among zones very much mimic the exchange rate movement. As exchange rates volatility increases the share of safe zone drops and as stability obtained in exchange rate, the share rises concurrently. For instance, due to exchange rate fluctuations, there was an increase in the gray zone in the end of 2016 and the first quarter of 2017, however; the open position share of the safe zone increased again in the second quarter of 2017 due to stabilizing exchange rates.

Figure 18: Total FX Debt of Firms with FX Open Position in MFA-Score Zones (Percent Share)



Source: Author Calculations

Figure 19: Total FX Open Position Amount in MFA-Score Zones (Percent Share)

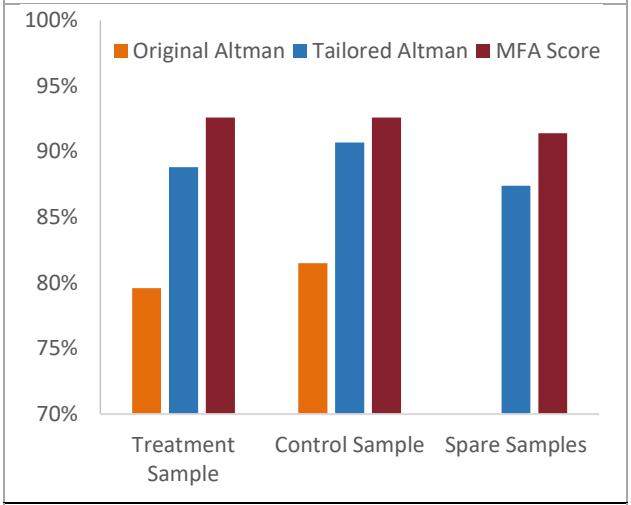


Source: Author Calculations

6. Conclusion

In summary, this study contributed to literature by producing two novel composite index measures that test the financial health of non-financial firms in Borsa İstanbul. First one is the tailored version of Altman model designed for Turkish firms and the second one is the MFA-score model whose ratios are specific to Turkish firms. Both scores have significantly increased the predictive performance of bankruptcy or solvency compared to original Altman Z-score model. Tailored Altman model have a performance rate of 89 percent and MFA-score has 92 percent on average (Figure 20). Furthermore, MFA score has a better discriminating ability compared to both original and tailored Altman models, which are evident from model diagnostics results.

Figure 20: Performance Results of Different Models



Source: Author Calculation

MFA-score model is capable of detecting the impact of macro-economic developments on balance sheets, which was clearly observed through the significant correlation of MFA-Score with GDP growth rate, exchange rate movements and industrial production index. This enables us to use MFA-Score as an early warning indicator of financial distress for Turkish firms and also to quantify the impacts of macro shocks or policies on firm balance sheets. Using this capability of MFA score, it is convenient to make some inferences about BIST firms.

MFA-scores are smaller in firms with FX open position and exporter firms have larger scores compared to non-exporters. Also, as the amount of FX open position of the firms increases, MFA scores decline. In other words, FX open position makes the balance sheets of Turkish firms vulnerable to shocks, which should be treated cautiously by policymakers.

More than 20 percent of BIST firms are in distress zone, but their asset share constitutes less than 10 percent of the total. This implies firms in distress zone are relatively small-sized, while firms in safe zone are relatively large-sized. Among firms with FX open position, more than 30 percent of total firms are in distress zone but these firms' asset and open position amount shares are less than 20 percent. This clearly signifies that FX open position posits higher risks for relatively smaller firms and large-sized firms are more capable of FX risk management. Additionally, the early warning characteristic of MFA-score allows us to form a more comprehensive measure of "debt-at-risk" than the definition of IMF. By this measure, we found that the debt share of firms in distress zone is around 10 percent and this share rises during turbulent periods.

Finally, the use of MFA-score may pioneer further studies such as rating the credit risk of firms, calculating probability of default of a firm, analyzing the impacts of policies on non-financial sector or response of firm financials on global volatilities. MFA score might effectively be used in corporate sector stress testing methods in which several different shocks under various scenarios are applied to macro variables and how firm financials are influenced by these shocks are measured quantitatively.

7. Refrences

Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance*, *32*(8), 1541-1551.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589-609.

Anderson, T. W. (2003). *An Introduction to Multivariate Statistical Analysis*. New York: Wiley

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71-111.

Becchetti, L., & Sierra, J. (2003). Bankruptcy risk and productive efficiency in manufacturing firms. *Journal of Banking & Finance*, *27*(11), 2099-2120.

Bharath, S., Shumway, T. (2004). Forecasting default with the KMV Merton model. Working paper, University of Michigan.

Blum, M. (1974) Failing company discriminant analysis. *Journal of Accounting Research*, Vol. 12, nr.1, p. 1-25.

Boritz, J. E., Kennedy, D. B., & Sun, J. Y. (2007). Predicting business failures in Canada. *Accounting Perspectives*, *6*(2), 141-165.

Campbell, J.Y., Hilscher, J., Szilagyi, J. (2006). In search of distress risk. Working paper, Harvard University.

Celli, M. (2015). Can Z-Score Model Predict Listed Companies' Failures in Italy? An Empirical Test. *International Journal of Business and Management*, *10*(3), 57.

Chudson, W. A. (1945). The pattern of corporate financial structure: a cross-section view of manufacturing, mining, trade, and construction, 1937. *NBER Books*.

Dambolena, I. G., & Khoury, S. J. (1980). Ratio stability and corporate failure. *The Journal of Finance*, 35(4), 1017-1026.

Dandago, K. I., & Baba, B. U. (2014). The Use of Multi-discriminant Analysis for the Prediction of Corporate Bankruptcy in Malaysian Textile Industry. *Journal of Business and Economics*, 5(6), 813-822.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of accounting research*, 167-179.

Dirickx Y., Van Landeghem G. (1994). Statistical failure prevision problems. *Tijdschrift voor Economie en Management*, 39 (4) p. 429-462.

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative analysis*, *7*(2), 1477-1493.

Engelmann, B., Hayden, E. and Tasche, D. (2003). Testing rating accuracy. *Risk*, 16(1), 82–86.

FitzPatrick, P. (1932) A comparison of ratios of successful industrial enterprises with those of failed companies. *The Certified Public Accountant*

Fitzpatrick, J., & Ogden, J. P. (2011). The detection and dynamics of financial distress. *International Review of Finance*, *11*(1), 87-121.

Gerantonis, N., Vergos, K., & Christopoulos, A. (2009). Can Altman Z-Score Model Predıct Busıness Faılures In Greece?. In Proceedings of the 2nd International Conference: Quantitative and Qualitative Methodologies in the Economic and Administrative Sciences

Grammatikos, T. and Gloubos (1984). Predicting bankruptcy of industrial firms in Greece. SPOUDAI-Journal of Economics and Business, 34(3-4), 421-443.

Gnanadesikan, R. (1988). *Discriminant analysis and clustering*. National Academies.

Goudie, A. W. (1987). Forecasting corporate failure: the use of discriminant analysis within a disaggregated model of the corporate sector. *Journal of the Royal Statistical Society. Series A (General)*, 69-81.

Hair, JF., Tatham, RL., Anderson, RE. (1998). *Multivariate Data Analysis*. 5. Prentice Hall;.

Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, 9, 5–34.

Huberty, C., J. (1994). *Applied Discriminant Analysis.* Wiley, Michigan

Izan, H. Y. (1984). Corporate distress in Australia. *Journal of Banking & Finance*, 8(2), 303-320.

Johnson, R. A. and Wıchern, D.W. (1982). *Applied Multivariate Statistical Analysis*. Edition, New Jersey: Prentice-Hall, Inc.

Keasey K., Watson R. (1991). Financial distress models: a review of their usefulness. *British Journal of Management*, 2 (2), p. 89-102.

Kočišová, K., & Mišanková, M. (2014). Discriminant analysis as a tool for forecasting company's financial health. *Procedia-Social and Behavioral Sciences*, *110*, 1148-1157

Koh H.C. (1992). The sensitivity of optimal cutoff points to misclassification costs of Type I and Type II errors in the going-concern prediction context. *Journal of Business Finance & Accounting*, 19(2), 187-197.

Kulalı, İ. (2016). Altman Z-Score Modelinin BIST Şirketlerinin Finansal Başarısızlık Riskinin Tahmin Edilmesinde Uygulanması. *Uluslararası Yönetim İktisat ve İşletme Dergisi*, *12*(27), 283-292.

Landau, S and Everitt, B., S. (2004). *A Handbook of Statistical Analyses Using SPSS.* Taylor & Francis

Lennox, C. (1999). Identifying failing companies: a re-evaluation of the logit, probit and DA approaches. *Journal of Economics and Business, 51(4),* 347-364.

Leksrisakul, P., & Evans, M. (2005). A model of corporate bankruptcy in Thailand using multiple discriminant analysis. *Journal of Economic and Social Policy, 10*(1), 5.

Lifschutz, S. and Jacobi, A. (2010). Predicting bankruptcy: evidence from Israel. International Journal of Business and Management, 5(4), 133.

Lízal L. (2002). Determinants of financial distress: what drives bankruptcy in a transition economy? The Czeck Republic case. *William Davidson Working Paper* nr. 451

Micha, B. (1984). Analysis of business failures in France. *Journal of Banking & Finance, 8*(2), 281-291.

Mossman Ch.E., Bell G.G., Swartz L.M., and Turtle H. (1998). An empirical comparison of bankruptcy models. *The Financial Review*. 33 (2), 35-54.

Moyer, R.C. (1977). Forecasting financial failure: A re-examination. *Financial Management*, Vol. 6, nr.1, p. 11-17.

Muzır, E., & Çağlar, N. (2009). The Accuracy of Financial Distress Prediction Models In Turkey: A Comparative Investigation with Simple Model Proposals. *Anadolu University Journal of Social Sciences*. 9(2), 15-48

Naranyan, C.G. (2003). *Multivariate Statistical Analysis: Revised And Expanded.* Taylor & Francis

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109-131.

Ooghe, H., & Verbaere, E. (1985). Predicting business failure on the basis of accounting data: The Belgian experience. *The International Journal of Accounting, 9*(2), 19-44.

Pascale, R. (1988). A multivariate model to predict firm financial problems: the case of Uruguay. *Studies in Banking and Finance, 7*, p. 171-182.

Pervan, I., Pervan, M., & Vukoja, B. (2011). Prediction of company bankruptcy using statistical techniques–Case of Croatia. *Croatian Operational Research Review, 2*(1), 158-1

Platt H.D., Platt M.B. (1990) Development of a class of stable predictive variables: the case of bankruptcy prediction. *Journal of Business Finance & Accounting*, 17(1), p. 31-51.

Rashid, A., & Abbas, Q. (2011). Predicting Bankruptcy in Pakistan. Theoretical & Applied Economics, 18(9).

Reisz, A., Perlich, C. (2004). A market-based framework for bankruptcy prediction. Working paper, Baruch College, City University of New York.

Rencher, A. C. and Christensen, W. F. (2012). *Multivariate Regression, in Methods of Multivariate Analysis, Third Edition*, John Wiley & Sons, Inc., Hoboken, NJ, USA.

Rifqi, M., & Kanazaki, Y. (2016). Predicting Financial Distress in Indonesian Manufacturing Industry (No. 62). Graduate School of Economics and Management, Tohoku University.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, *74*(1), 101-124.

Sobehart, J., & Keenan, S. (2001). Measuring default accurately. Risk, 14(3), 31-33.

Steele A., (1995). Going concern qualifications and bankruptcy prediction. Paper presented at the European Accounting Association

Taffler, R. J. (1982). Forecasting company failure in the UK using discriminant analysis and financial ratio data. *Journal of the Royal Statistical Society. Series A (General)*, 342-358.

Thai, S. B., Goh, H. H., HengTeh, B., Wong, J., & San Ong, T. (2014). A Revisited of Altman Z-Score Model for Companies Listed in Bursa Malaysia. *International Journal of Business and Social Science*, *5*(12).

Vassalou, M., Xing, Y. (2004). Default risk in equity returns. *Journal of Finance*, 59 (2), 831–868.

Wang, Y., & Campbell, M. (2010). Business failure prediction for publicly listed companies in China. Journal of Business and Management, 16(1), 75.

Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics*, *6*(1), 34-45.

Xuân Vinh, V. (2015). Using Accounting Ratios in Predicting Financial Distress: An Empirical Investigation in the Vietnam Stock Market. *Journal of Economics and Development*, *17*(1), 41.

Yılmaz, H., & Yıldıran, M. (2015). Borsada İşlem Gören İşletmelerde Mali Başarısızlık Tahmini: Altman Modeli'nin Bıst Uygulaması. Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 7(3), 43-49.

Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q. P., & Lillard Jr, J. W. (2014). A study of effects of multicollinearity in the multivariable analysis. *International Journal of Applied Science and Technology*, 4(5), 9.

Zavgren C. (1983). The prediction of corporate failure: the state of the art. *Journal of Accounting Literature*, 2, 1-37.

Zavgren C.V. (1985). Assessing the vulnerability to failure of American industrial firms: A logistic analysis. *Journal of Business Finance and Accounting*, 12(1) p. 19-45.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting research*, 59-82.

Central Bank of the Republic of Turkey

Recent Working Papers

The complete list of Working Paper series can be found at Bank's website

(**http://www.tcmb.gov.tr**)

Estimation of FX Option Implied Density Functions: Nonparametric-Malz Approach
(Halil İbrahim Korkmaz, Doruk Küçüksaraç, Yiğit Onay, Ahmet Şenol Working Paper No. 19/03, February 2019)

An Analysis on the Domestic Sales and Exports: A Dynamic Model for the Turkish Manufacturing Firms
(Selçuk Gül Working Paper No. 19/02, February 2019)

Tax Elasticity Estimates for Capital Stocks
(Fatih Yılmaz, Jean-François Wen Working Paper No. 19/01, January 2019)

Explaining Exchange Rate Movements Using Yield Curves in Emerging Countries
(Murat Duran Working Paper No. 18/20, November 2018)

Real Exchange Rate Misalignment and Economic Growth: An Update
(Bülent Ulaşan Working Paper No. 18/19, November 2018)

An Anatomy of a Sudden Stop and the Credit Supply Channel
(Salih Fendoğlu, Steven Ongena Working Paper No. 18/18, November 2018)

Dependence of "Fragile Five" and "Troubled Ten" Emerging Markets' Financial System to US Monetary Policy and Monetary Policy Uncertainty
(Meltem Gülenay Chadwick Working Paper No. 18/17, October 2018)

Measuring Financial Systemic Stress for Turkey: A Search for the Best Composite Indicator
(Meltem Gülenay Chadwick, Hüseyin Öztürk Working Paper No. 18/16, October 2018)

VAT Treatment of the Financial Services: Implications for the Real Economy
(Fatih Yılmaz, İsmail Baydur Working Paper No. 18/15, October 2018)

Net External Position, Financial Development, and Banking Crisis
(Aytül Ganioğlu Working Paper No. 18/14, October 2018)

Transportation Mode Choice and International Fragmentation of Production: Evidence from a Developing Country
(Hülya Saygılı, Kemal Türkcan Working Paper No. 18/13, October 2018)

Türkiye'de Reel Kur Hareketlerinin İhracat Üzerindeki Asimetrik Etkileri
(Selçuk Gül Working Paper No. 18/12, Ekim 2018)

The Impact of Monetary Policy Stance, Financial Conditions, and the GFC on Investment-Cash Flow Sensitivity
(Selçuk Gül, Hüseyin Taştan Working Paper No. 18/11, July 2018)

Inflation Dynamics in Turkey from a Bayesian Perspective
(Fethi Öğünç, Mustafa Utku Özmen, Çağrı Sarıkaya Working Paper No. 18/10, July 2018)

The Effect of Fed's Future Policy Expectations on Country Shares in Emerging Market Portfolio Flows
(Zelal Aktaş, Yasemin Erduman, Neslihan Kaya Ekşi Working Paper No. 18/09, March 2018)

Evolution of the University Wage Premium in Turkey: 2004-2015
(Okan Eren Working Paper No. 18/08, March 2018)

Multivariate Filter for Estimating Potential Output and Output Gap in Turkey
(Selen Andıç Working Paper No. 18/07, February 2018)

Quantifying Uncertainty and Identifying its Impacts on the Turkish Economy
(Evren Erdoğan Coşar, Saygın Şahinöz Working Paper No. 18/06, February 2018)

Forecasting Industrial Production and Inflation in Turkey with Factor Models
(Mahmut Günay Working Paper No. 18/05, February 2018)