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Borsa İstanbul Review

Borsa İstanbul Review 21-3 (2021) 239−255
http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450

Full Length Article

# A new multivariate approach for assessing corporate financial risk using balance sheets

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Received 30 December 2019; revised 18 October 2020; accepted 19 October 2020
Available online 23 October 2020

**Abstract**

Several indicators and univariate ratios can be used to measure the soundness of firms as reflected in their balance sheets (leverage, profitability, liquidity ratio, etc.). However, each indicator alone cannot measure a firm's overall financial risk or financial distress level. In this study, we measure the financial strength of the real sector firms listed on the Borsa Istanbul (BIST) by producing a composite index score that combines several different corporate finance ratios. In the first section, we conduct a multiple discriminant analysis of the variables used in Altman's z-score (1968), which is the most prevalent composite index used to measure firms' financial risk in the literature. In the second section, we introduce a new index, called the multivariate firm assessment (MFA) score, which uses the ratios that best explain the characteristics of companies listed on the BIST. The Tailored version of the Altman z-score and our new index have predictive power of around 90 percent. Furthermore, the MFA score reflects the impact of macroeconomic developments on firms' balance sheets and thus serves as an early warning of financial distress for Turkish firms. Our analyses using the MFA score suggest that non-exporting firms and firms with an open foreign exchange position have weaker balance sheets.


*JEL classification:* C18; C43; G30; G33

*Keywords:* Altman Z-score; Balance sheets; Financial distress; Financial risk; Multiple discriminant analysis; MFA score; Solvency

## 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. Depending on the scale of a firm's operations, the firm's financial distress can damage the financial structure of its lenders, its shareholders, and its shareholders' lenders and cause losses in the economy as a whole. For this reason, predicting a firm's failure and taking sufficient measures to prevent it are among the main concerns of analysts. This has led to the development of a large body of literature on using indicators from balance sheets and market valuations to analyze corporate financial risk.

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 in terms of liquidity, profitability, or indebtedness, for example, but these ratios cannot test the firm's overall financial strength, financial distress level, or potential for bankruptcy or survival. For this reason, some composite indices have been produced to comprehensively rate firms' financial risk levels and the probability of default (Altman, 1968; Deakin, 1972; Ohlson, 1980; Zmijewski, 1984). In these rating methods, various univariate ratios are weighted using statistical techniques and converted into a single score that indicates how close a firm is

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Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

https://doi.org/10.1016/j.bir.2020.10.007

to default. Multivariate discriminant analysis (MDA), used initially by Altman (1968), is the most prevalent statistical tool used in the corporate bankruptcy literature to aggregate univariate ratios to form a composite indicator.

The work of Altman (1968), the technical details of which are in the next section, provides the basis for almost all other firm rating methodologies developed since then. Nevertheless, even though the Altman Z-score is widely used in the literature for firms in different countries, the z-score ratios and their coefficients were derived from US manufacturing firms listed on the New York Stock Exchange (NYSE) between 1946 and 1965. This raises the question of whether those same ratios can be used effectively in default analyses for firms in other countries or industries (Grice & Ingram, 2001; Wang & Campbell, 2010). Because firms in different countries—especially emerging markets—behave differently from US firms, the original Altman (1968) z-score ratios and coefficients may not adequately capture the distinctive characteristics of firms in these economies. To measure the financial risk reflecting on the balance sheets of emerging market firms, it would therefore be more convenient to calculate new coefficients using new ratios that better represent the characteristics of the firms in the country in question.

Turkey is a typical example of an emerging market that opened its economy to global markets in the late 1980s and went through a structural financial deepening process in the early 2000s. These efforts at global integration and financialization have brought invaluable gains to the Turkish economy in terms of rising export earnings and greater availability of financing for real sector firms. In the past three decades, Turkey's share in the global trade volume has substantially increased, banking sector loans to the real sector have soared, and international capital flows have risen (Uygur, 2010). However, the integration and financial deepening process has also led to numerous vulnerabilities. Persistent current account deficits increased the economy's dependence on external funds, rising banking sector credit facilities caused excessive indebtedness of real sector firms, and the dependence on the imports of intermediate goods in manufacturing led to inflation volatility. All these factors made the Turkish economy more fragile, that is, vulnerable to external shocks, friction in the financial sector, and currency devaluation. As a result, the business cycle has been very volatile in recent decades, and Turkey experienced severe financial turbulence in 1994, 2001, and 2008. This was inarguably an era of numerous firm defaults in Turkey, which pro-cyclically exacerbated the extent of negative growth shocks. Firm defaults not only amplify economic problems but also lead to more social problems, including increased unemployment and greater poverty. Firm default is therefore a critical issue for the Turkish economy (as it is for any emerging market) and should be handled seriously by policy makers and academics. They must appropriately assess the financial risk of real sector firms, develop early warning tools to predict default, and take measures to prevent bankruptcy.

All these characteristics of the Turkish economy make Turkey an excellent case study for predicting firm default and developing an early warning indicator of financial distress in emerging market firms. Furthermore, its large population and relatively strong position in the global economy as a member of the G20 increase the importance of firm-level research on the Turkish economy in the literature. Although some studies have been done on the financial distress of Turkish real sector firms (Kulalı, 2016; Yılmaz & Yıldıran, 2015), most of these studies (detailed in the literature review section) measure this financial distress and/or predicted default using existing models, such as the Altman z-score or Ohlson o-score, which were calculated mainly for developed countries to. As explained above, the lack of Turkey-specific balance-sheet ratios in those models raises several issues. Although some studies have attempted to develop a new measure of financial distress for Turkey, they analyzed only a limited number of firms or a specific sector within a relatively short period.

Our paper aims to use MDA methodology to construct two new composite indices to measure the financial distress and solvency of nonfinancial firms listed on the Borsa Istanbul (BIST) between 2001 and 2017. First we develop a tailored version of the Altman model that uses the same ratios as the Altman z-score does, but the coefficients of the ratios are reestimated to capture the dynamics of a large sample of BIST real sector firms. This paper makes a contribution to the existing literature that uses the Altman ratios with a limited sample of BIST firms. Second, we introduce a novel index, called the multivariate firm assessment (MFA) score, produced by applying MDA to the seven selected balance-sheet ratios of nonfinancial companies listed on the BIST. This composite measure allows us to effectively analyze the overall financial risk of Turkish firms and develop an early warning indicator of financial distress based on Turkey-specific balance-sheet ratios. The MFA score model enables us to see how predictive performance increases when Turkey-specific ratios are used instead of the Altman and Tailored Altman models. We also contribute to the literature by analyzing the relationship between macroeconomic developments and firms' balance-sheet risk as measured by the MFA score.

The rest of this paper is organized as follows. In Section 2, we give a detailed review of the literature on firm failure. The dataset and the MDA methodology used in the paper are then explained in Section 3. Next, we construct the Tailored Altman and MFA-score models using a novel approach to model selection in Section 4. Section 5 is devoted to the application of the MFA score to the whole dataset, and to the relationship between the MFA score and macroeconomic factors. We conclude the paper by summarizing the findings.

## 2. Literature review

Academics and practitioners have long been interested in predicting firm failure. The literature on firm failure can be divided into two main approaches: the market-based approach, which relies on the market valuation of firms by investors, and the accounting-based approach, which assesses a firm's soundness using the ratios obtained from the financial statements.

In the market-based approach, a firm's stock price is used to estimate the probability of default (Black & Scholes, 1973; Merton, 1974; Scott, 1987). When a firm's market value decreases below a certain book value of liabilities, the firm is assumed to be bankrupt. The papers that used this approach tried to estimate the probability of default for different firms in various countries (Bharath & Shumway, 2008; Campbell et al., 2008; Hillegeist et al., 2004; Reisz & Perlich, 2007; Vassalou & Xing, 2004).

As for the accounting-based approach, initially, in the early twentieth century, univariate measures were used to distinguish between distressed and solvent firms (Beaver, 1966; Chudson, 1945; Fitzpatrick, 1932; Merwin, 1942). Starting with the seminal work of Altman (1968), multivariate measures of financial distress became the mainstream methodology. Altman introduced MDA as a tool to combine several financial ratios obtained from the financial statements into a single, composite indicator. He applied MDA to distinguish 33 bankrupt firms from 33 solvent firms listed on the NYSE during the period 1946–1965. MDA methodology has since been extensively used in other studies. For US firms, a multivariate measure of financial distress was developed by Deakin (1972) using 32 failed and 32 solvent firms listed on the NYSE between 1962 and 1966, by Moyer (1977) for a total of 54 firms listed between 1965 and 1975, by Blum (1974) for 115 firms listed between 1954 and 1968, by Dambolena and Khoury (1980) for 68 firms listed between 1969 and 1975, and by Edmister (1972) for 84 small and medium-size firms listed between 1958 and 1965. Several other studies use the MDA methodology to predict bankruptcies in other developed countries (Boritz et al., 2007; Goudie, 1987; Izan, 1984; Micha, 1984; Taffler, 1982).

In addition to MDA, logistic regression methodology (logit and probit) became popular in the accounting-based firm failure prediction models, with the leading study being Ohlson's (1980). In this method, the probability of firm default is estimated using the firm's accounting data and several other controls (Becchetti & Sierra, 2003; Fitzpatrick & Ogden, 2011; Koh, 1992; Lennox, 1999; Lízal, 2002; Ooghe & Verbaere, 1985; Shumway, 2001; Zmijewski, 1984). The most recent firm default literature using logistic regressions has evolved into global or cross-country bankruptcy models, where the probability of default is calculated not only for one country's firms but for the firms of several countries or regions collectively. Alaminos, Castillo, and Fernandez (2016) develop a global bankruptcy applicable to firms all over the world, as well as separate models for firms in Asia, Europe, and the Americas. They found that the global model is superior to the regional model in terms of bankruptcy prediction accuracy because bankruptcy indicators have converged globally because of the rising globalization of the financial characteristics of firms. However, Platt and Platt (2008) question whether a single, global model for bankruptcy prediction is superior to the regional models developed separately for firms in the US, Asia, and Europe. Unlike Alaminos et al. (2016), they document that individual region-specific models perform better than a single, global model because of regional differences in accounting rules, lending practices, management skill levels, and legal requirements. In addition to the global models, Fernández-Gámez et al. (2020) investigated the roles of country-specific factors in explaining firm defaults in the European Union. Their results suggest that country-specific macroeconomic and regulatory factors, such as inflation, risk premiums, and government size, significantly increase the accuracy of financial distress predictions. Finally, in a study analyzing the regional differentiation in the performance of European small and medium-size enterprises (SMEs), Filipe et al. (2016) demonstrate that, whereas systemic variables increase the prediction accuracy, region-specific models outperform the generic model designed for all European firms.

The market- and accounting-based approaches each have pros and cons, and debate continues as to which approach is more efficient at predicting bankruptcy (Agarwal & Taffler, 2008; Mossman et al., 1998; Wu et al., 2010). The answer changes, depending on the dataset and variables used in the analyses. Nevertheless, because the market-based approach requires calculation of the market value of a firm's assets, it is purely market based and applies only to listed firms. Therefore, accounting-based methods have been used predominantly and MDA is the most prevalent accounting-based technique in the literature (Aziz & Dar, 2006).[1]

In his pioneering study adapting MDA, Altman (1968) developed the z-score as a linear combination of ratios from the financial statements of nonfinancial firms. The Altman z-score model and the ratios used in the linear function are as follows:

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

$X_1$: Working capital/total assets;
$X_2$: Retained earnings/total assets;
$X_3$: EBITDA/total assets;
$X_4$: Market value of equities/book value of total liabilities;
$X_5$: Net sales/total assets.

If a firm's z-score is below 1.8, the firm is classified as distressed and is likely to experience bankruptcy in the upcoming period. The z-score predicted bankruptcy among 66 firms listed on the NYSE between 1946 and 1965 with 91 percent accuracy. Other papers use the original Altman z-score model to measure the financial distress of firms in different countries (Celli, 2015; Dandago & Baba, 2014; Gerantonis et al., 2009; Lifschutz & Jacobi, 2010), but the discriminant power of the ratios in Altman z-scores for different economies, especially emerging economies, is often not as strong as Altman found for NYSE-listed firms. The main reason is that the Altman model's variables and their loadings tend to reflect the behavior of firms in developed countries. For instance, the ratio of the market value of equities to the book value of liabilities ($X_4$) depends entirely on the firm's stock price. Because most developing countries do not have a financially deep stock market, share prices do not usually reflect a firm's financial

[1] Aziz and Dar (2006) found in their detailed literature survey that 30% of the bankruptcy studies were carried out via MDA, and logit estimation is the second most commonly used method (21% of the studies).

health. Instead, they reflect the speculative positions of 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 represents a firm's cumulative profits/losses over a period of years and provides information about the firm's age. Because firms in developing economies are short-lived in general and their cumulative earnings are more volatile, this ratio does not give sufficient information about balance-sheet strength in developing countries. Moreover, the standardized coefficients of the variables in the Altman model reveal that $X_3$ and $X_5$ contribute the most to a firm's distress level, but this is not true for firms in developing countries. Although EBITDA (Earnings Before Interest, Tax, Depreciation and Amortization) is an important factor in distinguishing solvent from distressed firms in developing countries, we do not expect a large contribution from the net sales/asset ratio in these countries. Because firms in developing countries depend on imported machines and equipment in their production processes, imported materials constitute a large part of their cost of goods sold. Because of this dependence, even though a firm has significant net sales, its costs might be high and volatile, such that its operating or net profit are also volatile and vulnerable to shocks. The net sales/asset ratio therefore should be given less power when it comes to explaining financial distress in developing countries.

Because of these concerns, dozens of papers have adapted the Altman model to study developing countries using the same variables but recalculating the coefficients or using new representative variables and related coefficients. Leksrisakul and Evans (2005) used Altman’s (1968) ratios but reestimated the coefficients for firms listed on the Stock Exchange of Thailand for the period between 1997 and 2002. Their prediction accuracy rate for firm distress was 59.6 percent, which was much lower than the rate achieved for NYSE firms with the original Altman model. Rashid and Abbas (2011) developed a new distress model using MDA with three new balance-sheet ratios selected from 24 ratios for nonfinancial firms in Pakistan. Their model achieved 76.9 percent accuracy in forecasting financial distress or solvency for 52 firms between 1996 and 2006. For manufacturing firms in Uruguay, Pascale (1988) adapted MDA with different balance-sheet ratios and was nearly 90 percent successful in predicting bankruptcy with his model. Grammatikos and Gloubos (1984) introduced two new models to predict bankruptcy in Greek nonfinancial firms using MDA and the linear probability model (LPM). They concluded that MDA, with a nearly 80 percent success rate, is superior to LPM for distress prediction. For Indonesian firms, Rifqi and Kanazaki (2016) applied both MDA and logit analyses to selected balance-sheet ratios (out of 24 candidate ratios) and concluded that the MDA method has higher error rates than logit does. For Chinese real sector firms, Wang and Campbell (2010) tested the prediction accuracies of Altman's original model, a reestimated model with Altman's ratios, and a revised model with new ratios. They found that the revised model, which was nearly 90 percent successful, is significantly more accurate than the other models are. Thai et al. (2014) reestimated the Altman model with new coefficients for thirty firms on the Malaysia Stock Exchange and achieved an accuracy rate of 76.7 percent. Finally, for Croatian firms, Pervan et al. (2011) applied MDA to three balance-sheet ratios and achieved 79.5 percent prediction accuracy for 78 bankrupt firms with their model.

The Altman z-score methodology has also given rise to several papers dealing with the prediction of financial distress for the firms operating in Turkish economy. These papers mainly apply the Altman z-score to selected Turkish firms to measure the default prediction accuracy and determine which balance-sheet ratios truly increase predictive power. Kulalı (2016) applied the Altman z-score model to 19 BIST-listed firms that defaulted between 2000 and 2013 and found that the model accurately predicted the defaults of 17 of those firms two years before bankruptcy. Yılmaz and Yıldıran (2015) conducted a similar analysis of 18 solvent and 18 insolvent firms listed on the BIST between 2007 and 2012, using the averages of their balance-sheet ratios for the 2001–2006 period. Their findings suggest that the Altman z-score can predict solvency with 89 percent accuracy and insolvency with 71 percent accuracy. However, in their study comparing the performance of five different globally known models used to predict the distress of 45 BIST firms between 2000 and 2012, Oz and Yelkenci (2015) obtained results contrary to those mentioned above. Their analyses reveal that Altman z-score model performs the least when classifying firms as distressed or solvent, with an accuracy level of less than 40 percent. Özdemir (2014) uses the Altman z-score model to analyze a sample of 80 listed and 62 unlisted manufacturing firms and reports a Type 1 error rate of 40 percent. His overall conclusion is that the z-score can successfully detect the financial distress of listed firms two years before such distress and of unlisted firms one year before financial distress. In addition to all these studies on the balance sheet performance of private firms, Kablan (2020) attempts to measure the performance of 30 metropolitan municipalities with Altman's emerging-market z-score model. Based on data from 2012 to 2017, his findings suggest that only two cities appeared to be the in distress zone, while ten municipalities had medium-level performance.

This paper makes several contributions to the existing literature on predicting financial distress at Turkish firms. First, we do not concentrate on a single sector or a limited number of sample firms but, rather, cover all nonfinancial companies on the BIST and a large sample of solvent and insolvent firms. Our sample, therefore, provides sufficiently large coverage of BIST firms in terms of both timespan and the number of firms. Second, we produce a novel model that contains the most representative balance-sheet ratios for BIST firms and clearly distinguishes between distressed and solvent firms based on several quantitative measures. Third, as detailed in the methodology section, the predictive performance of our model is tested not with merely one sample of failed and solvent firms but with nearly a thousand different samples, including a mixture of failed and solvent firms. This enables us to obtain a selective model that has robust predictive performance and to apply our model to a large range of firms in various sectors. Finally, in addition to proposing a new model, this paper is the first to verify the relationship between the balance-sheet scores and macroeconomic factors in the Turkish economy. That relationship is analyzed thoroughly in the following sections.

## 3. Methodology and data

### 3.1. Multiple discriminant analysis

Multiple discriminant analysis is a way of deriving a score that distinguishes two or more groups that have a similar number of members. This score is the weighted sum of several indicators that characterize the members of each group; and the distance between the mean index scores of the groups is maximized (Anderson, 2003; Johnson & Wıchern, 1982; Naranyan, 2003). The coefficients (weights) of the model are determined such that intergroup variance is maximized and intragroup variance is minimized (Gnanadesikan, 1988; Kočišová & Mišanková, 2014).[2]

In corporate bankruptcy models, usually two firm groups are used; financially distressed firms and solvent firms. MDA is carried out using these firm groups as a qualitative dependent variable and several ratios from earlier financial statements as quantitative independent variables. As a result, we obtain the coefficients of each independent variable, the predicted grouping of each firm, and the cut-off value separating the predicted groups.[3] A firm is placed in the solvent group if its score is above the cut-off and in the distressed group if it is below the cut-off.[4]

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

$$Performance = \frac{C_d}{T_d} + \frac{C_s}{T_s}$$

$$Type\ 1\ Error = 1 - \frac{C_d}{T_d} \quad Type\ 2\ Error = 1 - \frac{C_s}{T_s}$$

### 3.2. Dataset

In our paper we use the data from the financial statements of nonfinancial firms listed on the BIST between 2001 and 2017. There are 361 different firms in total and 250 firms on average each year. Because the firms' shares are traded on the stock exchange, all balance sheets are prepared by independent auditors and checked by the authorities of the BIST and the Capital Markets Board. Furthermore, because firms are liable to their shareholders, they have probably not doctored their balance sheets or intentionally provided incorrect information. For this reason, the BIST data is the most reliable source of corporate balance sheets in Turkey.

As of the 2016 fourth-quarter data, the sample firms' total net sales represent 14.8 percent of Turkish gross domestic product (GDP), and their exports constitute 23.6 percent of total export volume. The sample firms hold 16.7 percent of all corporate foreign exchange (FX) debt, and their net FX position is the same as that of 12.5 percent of Turkish firms. Although the sample is relatively small for generalizing the results obtained in this paper to the entire economy, the BIST firms behave similarly to other Turkish firms. This can be seen by comparing our data set's balance-sheet ratios with those in the largest firm-level dataset (MoSIT), which includes almost all the firms in Turkey.[5] If we compare the trends in the financial ratios used in the Altman z-score, the trends and the movements in our dataset and MoSIT are similar. The working capital, assets and equity, and liability ratios are similar, and the fluctuations in these indicators over time are also similar (see Supplementary Figure S1, available online). BIST firms generally have larger earnings ratios than non-BIST firms do, but the trends and short-term cyclical movements are similar in both datasets.

### 3.3. Selection of financially distressed firms

To apply MDA, we use the firm groups mentioned earlier, and hence we need a list of financially distressed and solvent firms. To determine which firms experienced financial distress between 2001 and 2017, we checked to see whether they had a negative equity account on the balance sheet, had declared bankruptcy, had applied for a suspension of bankruptcy, or had been the subject of a bankruptcy petition by creditors. If any of these conditions were met, the firm was deemed financially distressed. We also suspected insolvency if a firm began to be traded on the BIST's Watch List market and then exited the BIST. To ensure that these firms are financially distressed, we conducted a detailed check by contacting experts at the BIST. In the end, 56 firms that satisfied our criteria for financial distress between 2001 and 2017.[6]

[2] Intergroup variance is the variation between the mean scores of two groups. Intragroup variance demonstrates the variance of the scores within each group.

[3] We call the groups "predicted" because we actually predict the correct grouping of the firm by looking at its financials in one or more earlier periods.

[4] The cut-off value is subject to prior probabilities of belonging to the failing or solvent group and the costs of Type 1 and Type 2 errors (Steele, 1995; Zavgren, 1983). Nevertheless, in our study we assume the prior probabilities are the same and the costs of Type 1 and Type 2 errors are equal.

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

[6] Even though the sample includes 2001 and 2009—crisis years for the Turkish economy—the number of sample firms found to be distressed in those years is similar to other years. Hence there is no sample bias toward the crisis years in our analyses.

The firms are mostly in manufacturing, as expected (see Supplementary Table S1, available online). The textile and food subsectors have the largest share of distressed manufacturers, which might lead some to question whether the analyses in the paper are representative of all sectors. The subsectoral distribution among manufacturers is similar to the distribution among all firms in Turkey. The dataset on Turkey's credit registry suggests that 49.6 percent of the manufacturers are in the textile and food sectors and that the food and textile sectors have the largest share (40.2%) of distressed manufacturers (a proxy for distress is the fact of having a nonperforming loan in the credit registry dataset).[7] However, this paper's results represent mostly BIST-listed manufacturers because 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 for solvent firms. The firms in the second group are matched with firms in the first group (Platt & Platt, 1990; Zavgren, 1985) such that we have pairs of firms that operate in the same subsector and have similar amounts of assets and the only significant difference being that the firm in the second group remains solvent while its first-group peer falls into distress.[8] According to these criteria, we found 54 matches but could not find any matches among the solvent firms for two of the distressed firms. As a result, our main sample for conducting MDA has 108 firms: 54 distressed firms in the first group and 54 solvent firms in the second group.

### 3.4. Selection of the best model

For both the Tailored Altman model and MFA-score estimation, we selected the model that has the highest predictive power from among the numerous models we ran on various samples. The normal procedure in the literature is to divide the main sample in two, running MDA on one sample and carrying out performance tests on the other (Dirickx & Van Landeghem, 1994; Keasey & Watson, 1991; Ooghe & Verbaere, 1985). The rationale is to test performance on a group other than the group from which the model parameters are obtained; otherwise, we could have a biased performance measure.

In the literature, the usual procedure is to apply a performance test to only one control sample, composed of distressed and solvent firms. However, it would be more robust to check the performance of the model with several more control samples. This would give us the opportunity to see whether our model performs well in various groups of firms. In our study, we design our model selection procedure based on the performance results obtained from many control samples.

Of the 108 firms in the main sample, we randomly select 54 firms (27 distressed and 27 solvent) as a treatment sample. The remaining 54 firms (27 distressed and 27 solvent) are put aside as a control sample. We conduct MDA on the treatment sample and use the coefficients we obtain to run a performance test on the control sample. Next, 500 samples (spare samples) of 54 firms (27 distressed and 27 solvent) are randomly selected from the main sample of 108 firms. The performance tests are run on these spare samples using the coefficients obtained from the treatment sample. The control sample's performance score and the average performance score for the 500 spare samples are noted as the performance score for the coefficients obtained from the randomly selected treatment sample (Fig. 1).[9]

These steps are then repeated 1000 times with 1000 randomly selected treatment samples and each time, the performance of each model on the control sample and the 500 spare samples are noted. As a result, we have a matrix of 1000 different coefficient sets with the control sample performance score and the average of the spare samples' performance scores for each coefficient set. From these 1000 different coefficient sets, we select the sets in which control sample performance is over 85 percent. From those sets, we then select the model with the highest average performance in 500 spare samples for Altman replication and MFA-score analysis.

## 4. Results

### 4.1. Tailored Altman model

Initially we conducted MDA with Altman z-score variables for our main sample using the method detailed in the previous section. The variables' pre-estimation statistics are in Supplementary Tables S2 and S3 (available online). In all five variables, solvent firms have higher mean values than distressed firms, which is in line with the expectations. According to the *t*-test, mean differences are statistically significant, with the least significance observed in the net sales/asset ratio.[10] Furthermore, pairwise correlations suggest that multicollinearity is not a serious concern.

As explained in the model selection discussion, MDA was applied to 1000 different randomly selected treatment samples to obtain the best model. The model with the highest performance is as follows:

[7] The credit registry dataset includes all firms that have obtained a loan from a bank in Turkey. The firm numbers are calculated using the data from December 2017.

[8] The assets of one peer should not be more than two times greater than the other's assets.

[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 combinations of samples. In addition, the average performance score does not change much as the number of spare samples increases. For example, there is only a slight difference in the average performance results obtained from 100, 500, and 1000 spare samples. We therefore ended the spare sample generating process at 500.

[10] Altman (1968) has also shown that $X_5$ does not significantly differ between groups.

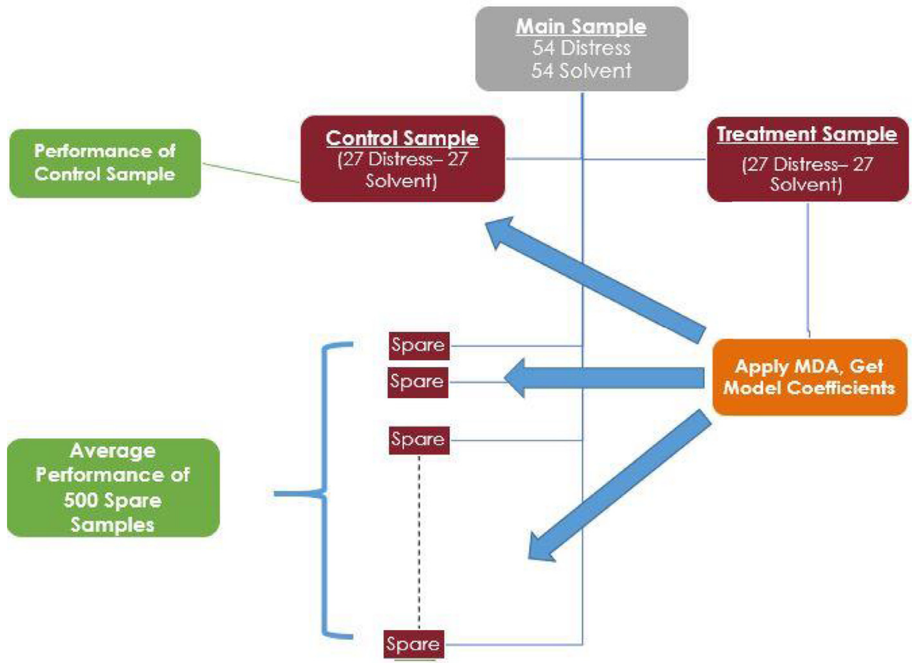


Fig. 1. Design of the performance tests.

$$\begin{array}{llllll} \textit{Tailored Z} - \textit{Score} = & 1.06X_1 & + 1.17X_2 & + 2.59X_3 & + 0.23X_4 & + 0.13X_5 \\ (\textit{Standardized Coefficients}) & (0.64) & (0.21) & (0.42) & (0.51) & (0.11) \end{array}$$

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 the final score. Of the five variables, the working capital-to-asset ratio and the market value of equity-to-book value of debt ratio seem to be the main determinants of a firm's level of financial distress or solvency. Because all coefficients are positive and mean values are greater in the solvent group, the rising Tailored z-score means sounder balance sheets.

The previous literature on the adjustment of the Altman z-score for the Turkish economy finds different coefficients and performance rates. For instance, in their study of 35 failed and 35 solvent 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 percent. Yılmaz and Yıldıran (2015) also revised the Altman z-score model, using 18 failed and 18 solvent BIST firms. The coefficient of $X_1$ was found to be negative and the prediction accuracy of their model is 79 percent. Our revised model differs from these studies in that it spans a longer time frame. This enables us to study a larger sample of failed and solvent firms.

Some post-estimation diagnostics can be used to evaluate the discriminant power of the model. A good model requires significant results on these diagnostic tests (see Supplementary Table S4, available online). Canonical correlation measures the association between a classification variable and a discriminant function (Huberty, 1994; Rencher & Christensen, 2012). A high and significant value of canonical correlation (0.72) indicates that the model has high discriminant power. The F-statistic, which tests the null hypothesis that canonical correlation equals zero, demonstrates rejection of the null. The eigenvalue is the ratio of explained variance to unexplained variance in the model and should be greater than one for a good model (Landau & Everitt, 2004). Wilks's lambda is one minus the explained variance of the model and, like the eigenvalue, represents the discriminant power of the model. When Wilks's lambda is smaller, the function is more discriminatory.

The model's performance on the treatment and control samples is depicted in Tables 1 and 2. In treatment sample, the model classifies 22 of the 27 distressed firms correctly one year before their falling into financial distress. In addition, 26 of the 27 solvent firms in the treatment sample are correctly

Table 1
Model performance in treatment sample (Tailored Altman Z-score model).

| | Predicted | | |
|---|---|---|---|
| | Distress | Solvent | |
| **Actual** | | | |
| Distress | 22 | 5 | 27 |
| | 81.48% | 18.52% | 100% |
| Solvent | 1 | 26 | 27 |
| | 3.70% | 96.29% | 100% |
| Total | 23 | 31 | 54 |
| **Overall Performance** | | | **88.8%** |

Table 2
Model performance in control sample (Tailored Altman Z-score model).

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

classified as solvent by the Tailored z-score based on the financial statements for the previous year. The model's performance with respect to the treatment sample is 88.8 percent. For the control sample, the correct classification rate for distressed firms is 92.59 percent and 88.8 percent for solvent firms. The overall performance in the control sample is therefore 90.74 percent. For the 500 spare samples, the model has an average success rate of 87.4 percent, which is the highest performance rate of all the alternative Tailored models.

To test the model's predictive ability, a receiver operating characteristics (ROC) approach could also be employed using the Type 1 and Type 2 error rates. The ROC approach gives us the best cut-off score for distinguishing the solvent and distressed groups from each other and the true prediction rate of the model with this optimal cut-off point (Agarwal & Taffler, 2008). The optimal cut-off point is calculated by minimizing the sum of the Type 1 and Type 2 error rates while treating the costs of both error rates as equal (Engelmann et al., 2003). When we apply the ROC approach to the Tailored Altman scores of the full main sample (108 firms, 54 distressed and 54 solvent), the optimal cut-off value is found to be 0.3, above which firms are classified as solvent and below which they are classified as distressed. The area under the ROC curve, which takes a value between 0 and 1, is a performance measure for testing the predictive power of the model given the cut-off point (Sobehart & Keenan, 2001). For the Tailored Altman model scores of the main sample, the area under the ROC curve is calculated as 0.93, which points to 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 percent and 82 percent (see Supplementary Tables S5 and S6, available online). Hence estimation of the 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 the 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 a Tailored Altman model is used instead of the original Altman z-score.

### 4.2. MFA-score model

Even though we obtained better predictive ability with the Tailored z-score than with the original Altman score, using different ratios that better capture the characteristics of BIST firms would provide more robust estimation results. In this sense, we produce an index measure with new variables, called the MFA score.

#### 4.2.1. Variable selection

We started with 30 ratios procured from financial statements and widely used in the literature, then eliminated many of them according to both statistical and intuitive criteria (see Supplementary Table S7, available online). These criteria are:

- At least one ratio from the liquidity, profitability, leverage, and efficiency indicators should be included for strong comprehensiveness.
- The variable chosen should be able to correctly distinguish distressed from solvent firms. This criterion is tested by looking at the statistical significance of the difference between the means of the ratio in both groups using the *t*-test. If the means of the ratio in both groups do not significantly differ from each other, we eliminate the ratio.
- Two ratios should not be collinear. If any pairwise correlation is greater than 0.6, one of the pairs is eliminated.[11] The procedure is to eliminate the one with a higher correlation with the other variables, on average.

After we eliminated ratios according to the criteria above, 12 ratios remained. First, we carried out MDA using four variables, one each from the liquidity, profitability, leverage, and efficiency categories. Every four-variable combination was tested, and the one with the lowest Wilks' lambda was chosen. Later, in addition to the four variables, the remaining ratios were added to the model with every possible combination. After testing all model combinations, we picked the variable set for which the MDA result provides the lowest Wilks' lambda.

The ratios to be used in the final MFA-score calculation are thus as follows:

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

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.

$$X_2 = Short\ TermLiabilites/CurrentAssets$$

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

[11] The 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 (Blum, 1974; Hair et al., 1988). Hence, analysts have 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) use 0.9, and Vinh, 2015 uses 0.5. For our study, we followed a relatively conservative approach and determined 0.6 to be the cut-off correlation value for variable deletion because we want to remove bias completely.

$X_3 = Total\ Liabilities / Equities$

shows whether the firm's equities are adequate for repaying debt.

$X_4 = EBITDA / Total\ Assets$

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

$X_5 = Financial\ Expenses / Net\ Sales$

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

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

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

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

$X_7 = Retained\ Earnings / Total\ Assets$

cumulative profit or loss from the past periods, with information about the age of the company.

The descriptive statistics are listed in Tables 3 and 4. The means of the variables in both groups vary. Solvent firms on average have higher acid test, EBITDA/asset, net profit/net sale and retained earnings/asset ratios than the distressed firms. And the ratios of short-term debt/current assets, total debt/equity, and financial exp./net sales are higher at distressed firms as expected. For a multicollinearity check, all pairwise correlations are smaller than 0.6, and the highest correlation is observed between net profit and financial expenses. 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. Because firms in Turkey are highly leveraged and indebted in foreign currency, they have a large financial expenses account. Specifically, in times of depreciation of the Turkish lira, 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, at Turkish firms, net profit is less correlated with EBITDA than financial expenses.

Table 3
Group means of MFA-Score variables and T-test for mean differences.

| | Mean | | t-stat |
|---|---|---|---|
| | Distress | Solvent | |
| Acid-test ratio | 0.59 | 1.54 | −3.47*** |
| ST debt/current assets | 1.57 | 0.66 | 5.07*** |
| Total debt/equity | 13.83 | 1.41 | 2.82*** |
| EBITDA/assets | −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*** |
| Retained earnings/assets | −0.86 | 0.06 | −5.54*** |

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

*4.2.2. MFA-score coefficients and performances*

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

The signs of the coefficients are consistent with the expectations and in line with economic intuitions. When the standardized coefficients are examined, the main determinants of a firm's financial distress or overall financial strength are found to be the firm's liquidity position (acid-test ratio), total leverage, EBITDA, and retained earnings. The ratios of financial expenses and short-term debt to current assets seem to have less relevance to the financial distress or soundness of firms than others. Post-estimation diagnostics reveal higher discriminant power of the MFA score than the Tailored Altman model (see Supplementary Table S8, available online). Correlation between the grouping variable and the discriminant function is larger. Higher eigenvalue and lower Wilks's lambda values also demonstrate that the discriminant power significantly increased with MFA score.

The MFA score correctly predicted 24 of the 27 firms that experienced financial distress in treatment sample one year before the distress period. Furthermore, 26 of the 27 firms are correctly predicted as solvent according to the MFA score derived from financial statements one year earlier (Table 5). In the treatment sample, Type 1 error is 0.11 (3/27), and Type 2 error is 0.037 (1/27). In short, the MFA score has a performance of 92.6 percent in predicting the financial distress or soundness among 54 firms in treatment sample.

Because model coefficients are obtained from the treatment sample through MDA, relying on the performance result of the treatment sample may lead to biased outcomes. In order to apply the MFA score to different firms later, the MFA score is expected to have high predictive power for different samples. In this respect, the performance of the 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 (0/27), and hence total performance for the control sample is 92.6 percent (50/54) (Table 6). The average performance of the MFA score on 500 spare samples is 91.4

Table 4
Pairwise correlations of MFA-Score variables in main sample.

| | Acid-Test Ratio | ST Debt/ Current Asset | Liability/Equity | EBITDA/Assets | Financial Exp./Net Sales | Net Profit/Net Sales | Retained Earnings/ Assets |
|---|---|---|---|---|---|---|---|
| Acid-test ratio | 1.00 | | | | | | |
| ST debt/current assets | −0.37 | 1.00 | | | | | |
| Total debt/equity | −0.12 | 0.06 | 1.00 | | | | |
| EBITDA/assets | 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 | 1.00 | |
| Retained earnings/assets | 0.16 | −0.28 | −0.05 | 0.38 | −0.04 | 0.09 | 1.00 |

Table 5
Model performance in treatment sample (MFA-Score model).

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

Table 6
Model performance in control sample (MFA-Score model).

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

percent. In sum, the 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 the 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. The area under the ROC curve is calculated as 0.94, which indicates that the predictive power further increased with the MFA score.

After completing MFA score modeling and ensuring performance, the next step is interpreting the value of any firm's MFA score. Two different threshold values are determined for this, 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 it is between −0.02 and − 0.56 (gray zone), it is interpreted as having a low probability of experiencing financial distress and if it is greater than 0.56, the firm is financially stable (safe zone).

#### 4.2.3. Robustness checks

To ensure that our results are robust to different scenarios, we conducted several robustness checks. Initially, different variable selection criteria are used. 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 nine ratios yielded the lowest Wilks's lambda (0.463). However, this value is greater than the value from our original model, and other model diagnostics have also worsened compared to the original model. When we use cut-off correlation values of 0.7 and 0.8 as a robustness check, the number of ratios included in the best-performing model declined to 4 and 2, respectively. This considerably decreased the comprehensiveness of our model. When it is 0.7, even though model diagnostics seem to have improved slightly, 3 of 4 ratios come from the leverage category.

For robustness, we also tested different models using different criteria for model selection and the same ratios of the MFA score. In addition to the original MFA score, we obtained two more model coefficients. The first is obtained by taking the average of the coefficients of the models with control sample performances above 85 percent. The second is attained by averaging the coefficients of the models with total performance (treatment + control) above 85 percent. In these two new models, coefficients have the expected signs, with no significant difference from our original MFA-score model. Furthermore, the standardized coefficients in these models suggest that the main determinants of a firm's financial distress are liquidity position, total debt leverage, and

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

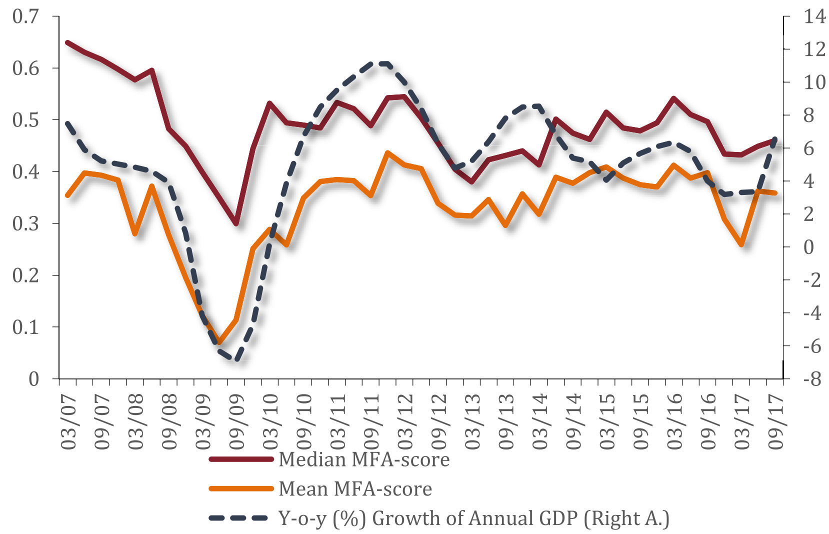


Fig. 2. MFA score and GDP growth (score, percent growth).
Note: Growth rate is the y-o-y percent change of annual GDP. Source: TURKSTAT, FINNET, author calculations.

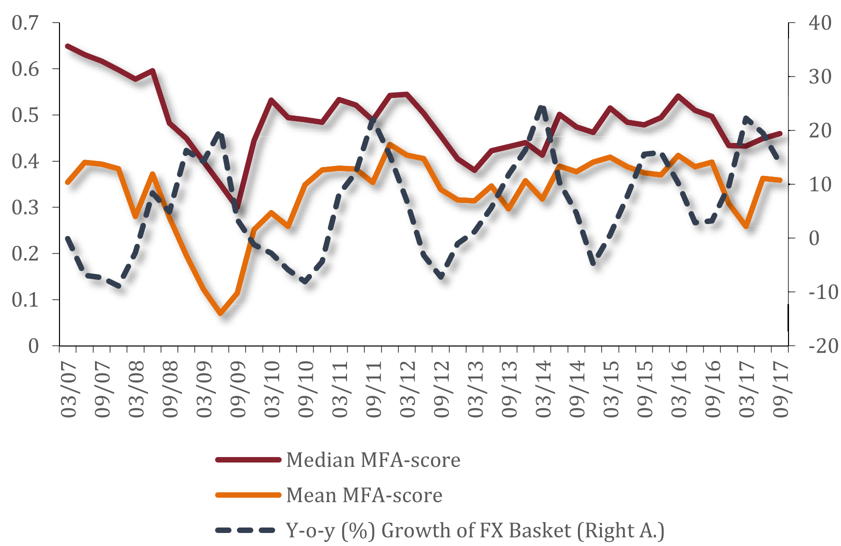


Fig. 3. MFA Score and FX Basket Rate (Score, Percent Growth). Note: The FX basket rate is obtained using weights 0.7 for TL/USD rate and 0.3 for TL/Euro. The growth rate is y-o-y percent change of the quarterly average FX basket rate. Source: TURKSTAT, FINNET, author calculations.

EBITDA, which is similar to the finding of the MFA-score model.

#### *4.2.4. MFA score and macroeconomic factors*

The MFA-score formula is applied to quarterly published financial statements of firms listed on the BIST between 2007 and 2017.[13] The median and mean MFA scores of the dataset, which includes 361 firms in total and 230 balance-sheet observations on average per year, are in Figs. 2 and 3.[14] Median values are greater than the mean, which implies that the MFA-score distribution is skewed to the left. MFA scores move in line with GDP growth and inversely with the foreign exchange rate. The correlation of the MFA score to the annual GDP growth rate is 0.48, and the correlation with the annual change in the 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 macroeconomic developments on the firms' balance sheets.

The MFA score has never—even during the global crisis—fallen below the distress threshold value of −0.02 but has always stayed within the gray zone. However, it did fall sharply during the global crisis and remained low throughout 2013 due to the slowdown in growth at the end of 2012, the

[13] In each quarter, income statement variables are annualized.

[14] In mean and median calculation, the observations in the highest and lowest one percentile are excluded.

global volatility in the wake of the US Federal Reserve's tapering, and domestic social and political unrest in 2013. It then rose in the following period, declined sharply in the last quarter of 2016 due to the increasing exchange rate volatility, then recovered owing to the high economic growth.

In addition to its significant correlation with macro variables, the MFA score has significant correlation with industry-level indicators. To a large extent, the score mirrors the movement in the industrial production index, with a correlation of 0.54 (see Supplementary Figure S2, available online). It is also expected that the balance-sheet soundness of firms will be associated with the number of firms that have newly entered or exited the market. As balance sheets deteriorate in an economy, the rate of firms exiting the market is higher than the rate of firms entering the market. The MFA score successfully captures the firm entry and exit statistics. As shown in Supplementary Figure S3, as the MFA score increases, the difference between the number of newly established firms and liquidated or exited firms narrows, and as the MFA score declines, the difference widens.

Firms with lower MFA scores seem to be more vulnerable to macroeconomic fluctuations. While firms positioned above the 50th percentile per the MFA score follow a stable course over time, MFA scores are more volatile in lower percentiles (Supplementary Figure S4, available online). This shows that as the balance sheets get sounder, it is less likely to observe fluctuations in financial health of the firms over time.

Exporting firms generally have higher MFA scores and firms with open foreign exchange positions have lower scores (Supplementary Figure S5, available online). Exporters in Turkey are generally large institutional firms capable of effective risk management, which is clearly observed in their larger scores. An open FX position is a significant determinant of firms' financial strength in Turkey because the Turkish economy has had a large current account deficit for a long time. Another critical finding is that open FX positions make firms' balance sheets weaker, as shown by their lower MFA scores over the full period. In addition, the reactions to macro shocks of firms with open positions are more evident. In particular, the scores of the firms with open positions declined more sharply during the periods of turbulence caused by the global financial crisis and the rising domestic political tensions in the second half of 2016. As shown in Supplementary Figure S6 (available online), as the amount of a firm's open position rises, its MFA score declines.

Consequently, because of the significant correlation between the main macroeconomic variables and the MFA score, we claim in this section that the MFA-score model can detect the effects of macroeconomic variables on the balance-sheet health of nonfinancial firms. Because the representation of correlation simply demonstrates the co-movements between the macroeconomic indicators and the MFA score, to capture a more causal relationship and quantify the impact of macroeconomic factors, a regression framework is needed. As a way of supporting our arguments further and checking the robustness of our findings, we conducted an experiment in which we tested the macroeconomic variables' explanatory power separately and collectively in a panel regression. To do this, we used the fixed-effects technique, where quarterly firm-level MFA scores are regressed on several macroeconomic variables at a quarterly frequency. Firm-fixed effects are included to control for time-invariant firm-level heterogeneity. Our empirical model is as follows:

$$MFA_{i,t} = \beta_1 Macro_{t-1} + \gamma_i + \varepsilon_{i,t} \tag{1}$$

The dependent variable is the MFA score of firm $i$ at time $t$. $Macro_{t-1}$ stands for five macroeconomic variables, which are the year-on-year (y-o-y) percentage growth rate of real GDP, y-o-y percentage growth rate in the weighted average of the USD/TL and EUR/TL rates, the y-o-y change in the spread between commercial loan rates and deposit interest rates, the y-o-y change in the LIBOR (London Interbank Offered Rate) rate, and the annual consumer price index (CPI) inflation rate.[15] Macro variables also include a global crisis dummy variable to control for the impact of the financial crisis on firm balance sheets. This dummy takes a value of 1 during the four quarters between 2008Q4 and 2009Q3, when the Turkish economy experienced negative GDP growth.

The results in Table 7 mostly confirm our previous findings. The simple baseline models (1)–(5) indicate that, although the GDP growth rate positively affects firms' MFA scores, the other macro factors have adverse effects. Model (6) provides more accurate results because, in this setting, we also control for the interrelationship among macroeconomic variables. According to model (6), a one-percentage-point rise in the GDP growth rate translates into a 0.021-percentage-point increase in the MFA score of an average firm. If the Turkish lira depreciates one percentage point more against basket currencies, this leads to a 0.01 fall in MFA scores. In addition, both domestic and global interest rates have a negative influence on firm balance-sheet strength. A one-percentage-point rise in the domestic interest rate spread or the LIBOR rate causes MFA scores to drop by 0.011 or 0.063 percentage points. Finally, a one percentage point rise in the inflation rate worsens the MFA score of an average firm by 0.02 points.

Model (7) uses the standardized values (z-statistics) of each variable to reduce all variables to the same scale and make coefficients comparable. In this regard, a one-standard-deviation increase in the GDP growth rate leads to a rise in the MFA score of 0.073 standard deviation. After comparing all the coefficients, we conclude that the greatest influence on firm balance sheets comes from the FX basket and GDP growth rates, while the lowest impact comes from the annual CPI rate. All these econometric findings support our previous argument that the MFA score can capture the effects of macroeconomic developments on firm balance-sheet strength. Of the various macroeconomic factors, balance sheets are most sensitive to changes in the FX rate and the GDP growth rate.

[15] Full definitions of the macro variables are in the notes to Table 7.

Table 7
The impact of macroeconomic variables on MFA score.

| | Dependent Variable: Firm-Level MFA Score | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | Standardized |
| Real GDP Y-o-y Growth | 0.018*** | | | | | 0.021* | 0.073*** |
| | (0.0049) | | | | | (0.0095) | (0.022) |
| FX Basket Y-o-y Growth | | −0.005*** | | | | −0.010*** | −0.101*** |
| | | (0.0016) | | | | (0.0024) | (0.023) |
| Interest Rate Spread | | | −0.017*** | | | −0.011* | −0.011** |
| | | | (0.0092) | | | (0.0072) | (0.008) |
| LIBOR Rate (y-o-y change) | | | | −0.010*** | | −0.063** | −0.065*** |
| | | | | (0.0159) | | (0.0328) | (0.0223) |
| Annual Inflation | | | | | −0.022*** | −0.020** | −0.035** |
| | | | | | (0.0068) | (0.0970) | (0.0150) |
| Observations | 10,521 | 10,549 | 10,549 | 10,801 | 10,549 | 10,240 | 10,240 |

Notes: The dependent variable in all specifications is firm-level MFA scores. Real GDP Y-o-y Growth: Annual growth rate of quarterly real GDP. FX basket y-o-y Growth: Annual growth rate of quarterly average of FX basket rate and FX basket rate is weighted average of USD/TL and EUR/TL FX rates, with weights of 0.7 and 0.3, respectively. Interest rate spread: Annual change in the difference between average commercial loan interest rates and average deposit interest rates in the Turkish banking sector. LIBOR rate y-o-y change: The annual change in the quarterly average of the London Interbank Offered Rate. Annual inflation: Quarterly average of the annual growth rate of the consumer price index. All explanatory variables are lagged one period to remove possible endogeneity issues. We use the fixed effects panel regression method in all specifications. The standardized model depicts the regression with z-values of each variable (the difference from the mean is divided by the standard deviation). Heteroscedasticity robust standard errors are in parentheses. *** Significant at 1%, ** significant at 5%, and * significant at 10%.

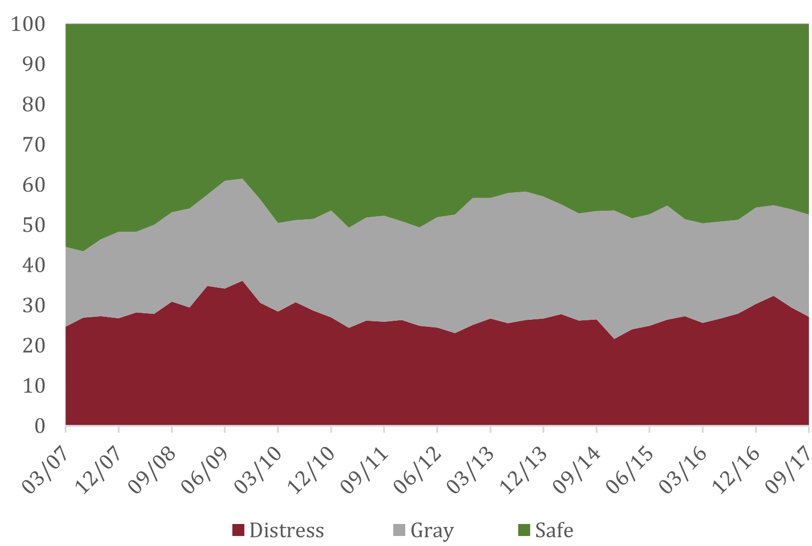


Fig. 4. Number of firms in MFA-Score zones (percent share).

### 4.2.5. Firm distribution in MFA-Score zones

The distribution of all firms in the MFA risk zones show that the majority of the firms are in the safe zone (Fig. 4), while the gray zone has similar number of firms to distress zone. During the global crisis, the number of firms significantly declined in the safe zone and increased in the distress zone. In 2013, there was a transition from the safe zone to the gray zone, and in the last period of 2016, the number of firms in the distress zone increased.

The distribution of the firms in the MFA-score zones based on assets indicates that firms in the safe zone have the highest share of the total assets of all firms combined, and that the firms in the distress zone are in the lowest 10% of firms, ranked by asset value (Fig. 5). This suggests that firms with a high probability of financial distress are relatively small firms and that large firms have higher MFA scores. During the global crisis, some large firms moved toward the distress zone, and during the domestic turbulence in 2016, the number of firms, and therefore the value of potentially at-risk assets, in the gray zone increased. Lastly, the distribution of net sales amount in risk zones is very similar to the asset value distribution (see Supplementary Figure S7, available online).

How much of the total debt is concentrated in firms that are more likely to experience financial distress is a critical

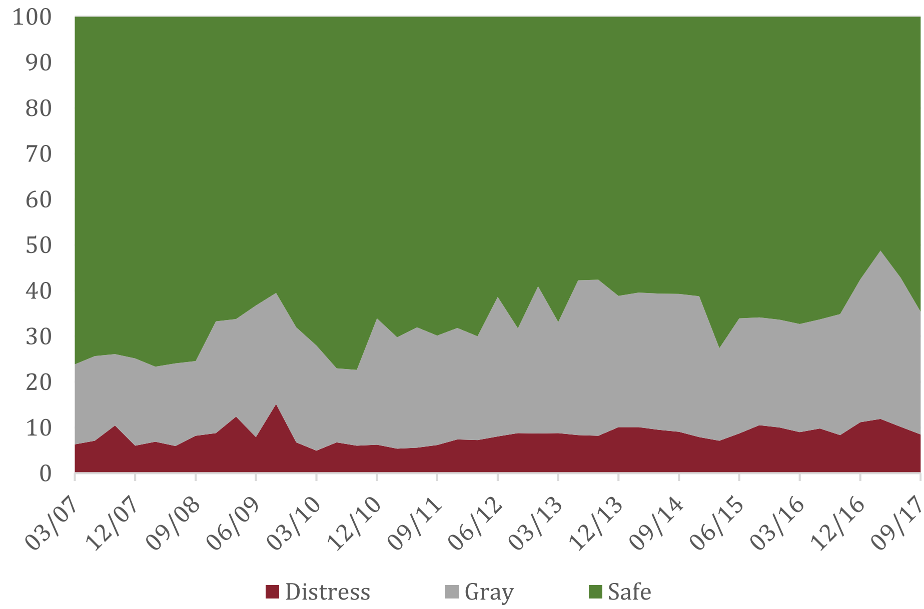


Fig. 5. Total asset size in MFA-Score zones (percent share).

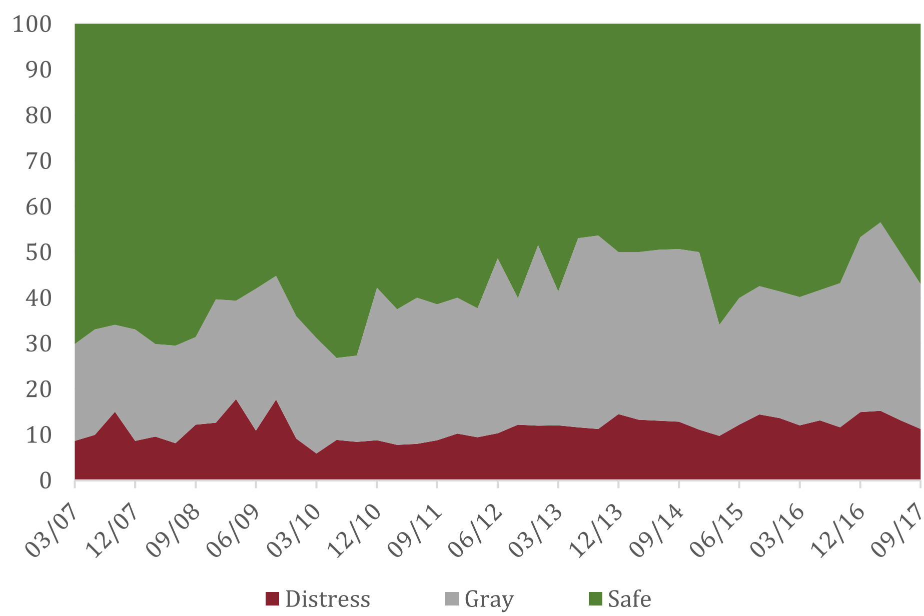


Fig. 6. Total debt in MFA-Score zones (percentage share).

question for the financial risk of the real sector. In the International Monetary Fund's (IMF's) (2015, 2016, 2017) global financial stability reports, the share of risky firm debt in total firm debt is used as the criterion of real sector financial risk (debt-at-risk). The IMF defines a risky firm as one that has an interest coverage ratio below 1.5. With the MFA score, it is possible to define a broader and more comprehensive risk indicator by calculating the ratio of the debt of firms' in the distress zone to the total debt of all firms. This ratio indicates that the share of risky firm debt (debt-at-risk) is around 10 percent and that most of the debt is concentrated at financially strong firms (Fig. 6). Debt-at-risk rose moderately in 2016 and considerably in the global crisis.

In general, more firms with an open FX position are in the distress zone than in the other two zones (see Supplementary Figure S8, available online). The number of firms in the distress zone increased during the global crisis and in the second half of 2016. However, these firms have limited assets, which implies that risky firms with an open FX position are relatively small (see Supplementary Figure S9, available online). This result is consistent with the expectation that large firms are more capable of FX risk management and an open position does not harm their balance sheets as much as it does that of others.

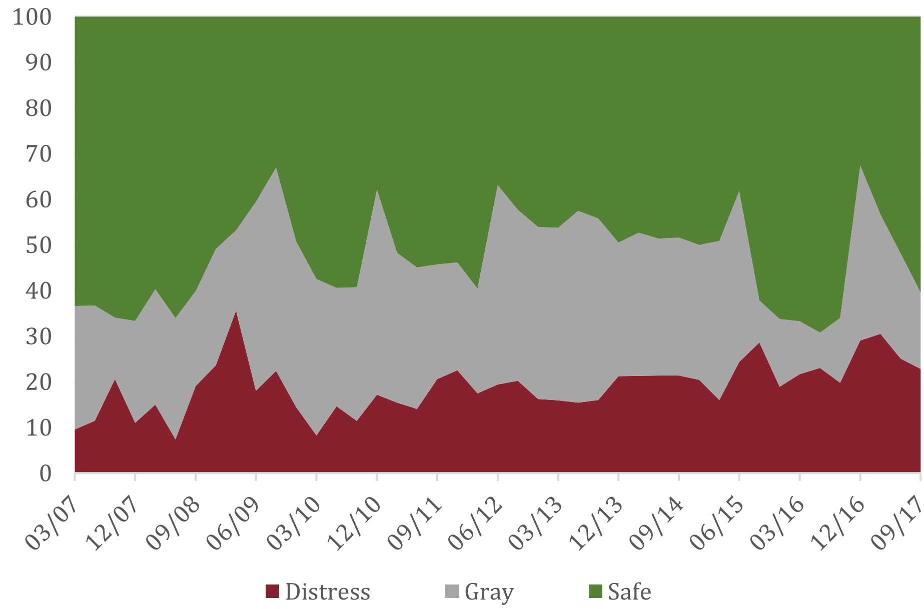


Fig. 7. Total FX open position amount in MFA-Score zones (percent share).

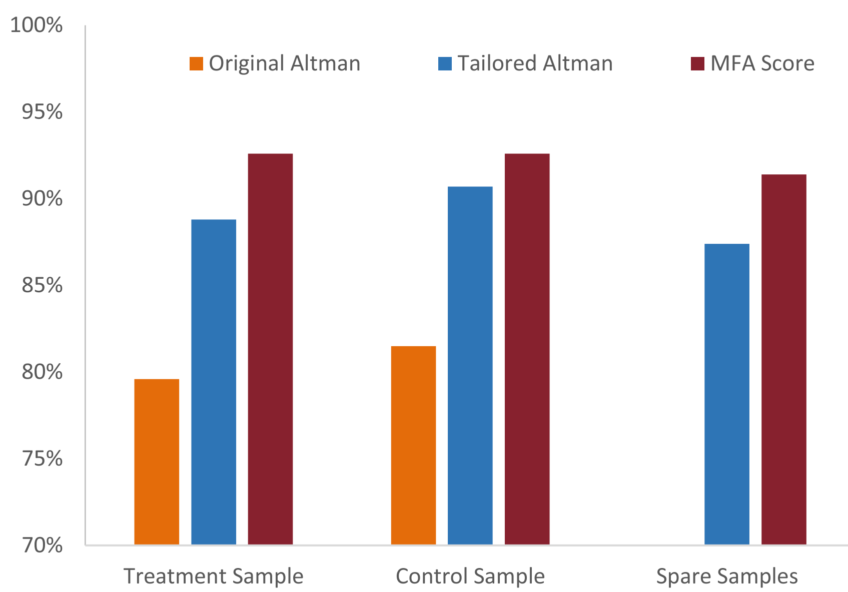


Fig. 8. Performance results of different models.

The open FX positions are concentrated mainly at firms with solid balance sheets. The open position of firms in the distress zone constitutes 20 percent to 25 percent of the total (Fig. 7). Furthermore, the transitions through zones reflect exchange rate movement. As exchange rate volatility increases, the share of firms in the safe zone drops, and as the exchange rate stabilizes, the share rises concurrently. For instance, due to exchange rate fluctuations, there was an increase in the gray zone in late 2016 and the first quarter of 2017, but the share of firms with open positions in the safe zone increased again in the second quarter of 2017 due to stabilizing exchange rates.

## 5. Conclusion

In summary, this study contributes to the literature by producing two novel composite indices that test the financial health of nonfinancial firms listed on the BIST. The first is a version of the Tailored Altman's model for Turkish firms, and the second is the MFA-score model with ratios specific to Turkish firms. Both indices have significantly increased predictive performance with respect to bankruptcy and solvency over the original Altman z-score model. The Tailored Altman model has a performance rate of 89 percent, and the MFA score has an average performance rate of 92 percent (Fig. 8).

The MFA score has a greater ability to discriminate than the original and Tailored Altman models do, as evidenced by the model diagnostics results.

The MFA-score model can detect the impact of macroeconomic developments on balance sheets, as is clearly shown by the significant correlation between the MFA score and the GDP growth rate, exchange rate movements, and the industrial production index, as well as by the statistically significant effects of the main macroeconomic variables on firms' MFA scores. This enables us to use the MFA score as an early warning indicator of financial distress for Turkish firms and to quantify the impacts of macro shocks or policies on firm balance sheets. It also allows us to draw some inferences about BIST firms.

The MFA scores are lower for firms that have an open FX position, and exporting firms have higher scores than non-exporters do. In addition, as the amount of the open FX position of the firms increases, MFA scores decline. In other words, an open FX position makes Turkish firms vulnerable to shocks, which policy makers should give careful consideration.

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 that firms in the distress zone are relatively small, whereas firms in the safe zone are relatively large. More than 30 percent of the firms with an open FX position are in the distress zone, but their assets and open positions comprise less than 20 percent of the total assets and FX exposure of the sample firms. This clearly means that an open FX position poses a greater risk for smaller firms and that large firms are more capable of managing FX risk. In addition, the early warning characteristic of the MFA score allows us to develop a more comprehensive indicator of "debt-at-risk" than the IMF indicator. Using this indicator, we found that the debt share of firms in the distress zone is around 10 percent, and this share rises during turbulent periods.

Finally, the use of the MFA score may lead to further studies, such as on the rating the credit risk of firms, calculating a firm's probability of default, analyzing the effects of policies on the nonfinancial sector, and the response of firm financials to global volatilities. The MFA score might effectively be used in corporate-sector stress testing, in which several different shocks are applied to macro variables under various scenarios to see how firm financials are influenced by these shocks and to measure that influence quantitatively.

## Declaration of competing interest

None.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2020.10.007.

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