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Comparison of Financial Distress Prediction Models: Evidence from Turkey

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Abstract

The purpose of this paper is to explore the differences and similarities between financial distress prediction (FDP) models and to determine which explanatory variables and methodologies are the most effective in prediction of financial distress. For this purpose, 167 manufacturing companies (full sample) listed in Istanbul Stock Exchange (ISE) were used. In total, 27 financial ratios were identified from previous literature studies as potentially significant and they were calculated for the years 2009 and 2010. In the study, logistic regression, artificial neural networks and decision tree methods, which are frequently used in the literature, have been employed. As a result, many of the financial ratios are found to be effective in predicting financial distress. Moreover, logistic regression and artificial neural network methods have indicated better prediction accuracy results of financial distress for classification of companies.

Keywords: Financial Ratios, Financial Distress, Logistic Regression, Artificial Neural Networks, Decision Trees

1. Introduction

In recent years, financial markets in Turkey have been growing rapidly, but the global financial crisis, which led to the bankruptcy of many companies and banks, has also affected Turkey negatively. Due to the crisis, trading volume in financial markets and stock market indices declined. Consequently, financial distress prediction of companies became an important tool for internal and external decision makers (financial institutions, management, shareholders...etc.)

The field of financial distress prediction has many aliases, such as company failure prediction, bankruptcy prediction and business failure prediction. Hereafter, it will be referred to as financial distress prediction (FDP). Financial distress can be defined as the companies' inability to meet the

financial obligations (bankruptcy) or companies having difficulty in paying its liabilities (Beaver, 1966: 71) or in other words, can be defined as cash flow deficiency resulting in inability to meet the financial liabilities. Common causes of financial distress are lack of financial knowledge, failure to set capital plans, poor debt management, inadequate protection against unforeseen events and difficulties in adhering to poor operating discipline in the financial markets (Chen and Du, 2009: 4075).

The purpose of this paper is to explore the differences and similarities between FDP models. This study employs logistic regression, artificial neural networks and decision tree methods, which are frequently used in the literature, to explore these differences and similarities.

2. Previous Research

The development of corporate financial distress prediction models started in America in the mid-1960s. There have been a large number of studies on this subject since 1960. These studies were conducted initially within the boundary of the parametric statistical analysis such as discriminant or logit functions, and later non-parametric models have been developed (Ekşi, 2011: 113). Some of the studies on financial distress prediction are stated below.

In his study, Altman (1968) used multiple discriminant analysis and determined 22 financial ratios to use in his model. After implementing a statistical analysis, the number of variables to be used in the model has been decreased to 5. As a result of this study, Altman derived a model named 'Z-score'. According to the model, 95 percent of the companies were correctly classified as bankrupt or non-bankrupt one year prior to bankruptcy and 72 percent of them were correctly classified two years prior to bankruptcy.

Meyer and Fiber (1970) constructed a model using regression analysis to predict the bankruptcy of banks. For the model, a sample of 78 banks was selected and 32 financial variables were used. According to their model, the companies were 80 percent correctly classified one year and two years prior to bankruptcy.

In his study, Deakin (1972) used discriminant analysis and compared the models of Beaver (1966) and Altman based on the financial statements of the sample companies. The correct classification percentage of the model derived by Beaver was 78 percent. However, in his study Deakin stated that Beaver's model had a better predictive ability over Altman's model.

Moyer (1977) claimed that Altman's (1968) model had a weak predictive ability and he achieved a better classification by using stepwise discriminant analysis. The model correctly classified 85 percent of the companies for one year, 83 percent for two years and 64 percent for three years prior to bankruptcy.

In their study, Casey and Bartczak (1985) derived a model for financial distress prediction using stepwise logistic regression analysis and multiple discriminant analysis. Variables of the model included ratios related with the operating cash flows together with other ratios. The results indicated that the variables related with the cash flows had higher explanatory power in comparison with the variables of promissory digit.

Odom and Sharda (1990) built a model in their study for the prediction of bankruptcy using discriminant analysis and neural network methods. The authors used the Altman (1968) Z-score as the measure. They compared the correct classification performance of the neural network model with the discriminant analysis. As a result, they found that the neural network model's correct prediction percentage of bankrupt companies was 81 percent.

Shirata (1998) employed a multiple discriminant analysis and studied the bankruptcy of the sample companies. 61 financial variables were used in the study and the selected variables were analyzed using the data mining method. The correct classification percentage of the constructed model was calculated as 86 percent.

Atiya (2001) constructed a neural network model for the prediction of corporate bankruptcies. 120 financial ratios were used in the model as variables and these variables were analyzed using a

neural network. The model's correct classification ratio was between 81 percent and 85 percent for each year during a three-year estimation period.

In their study, Yim and Mitchell (2005) compared the corporate distress prediction models. These models were compared using traditional statistical techniques and conventional artificial neural network models. The authors determined 22 ratios to be used in the model. The results suggested that hybrid neural networks performed better than all other models in predicting the companies in financial distress one year prior to the event. The performance of the artificial neural network was improved when the hybridization with discriminant analysis and logit models was considered. The best model was artificial neural network-plogit. This model correctly classified 93 percent of the failure companies and 100 percent of the non-failure companies. For the holdout sample, 89 percent of failure companies and 100 percent of non-failure companies were accurately predicted.

Altaş and Giray (2005) developed a model to detect the companies that have a financial failure risk, employing the factor analysis and logistic regression analysis. The data used in the study belong to the companies listed in Istanbul Stock Exchange and operating in the textile industry. Using the 2001 financial statements of these companies, financial ratios were determined and according to the profits and losses at the period-end, companies were classified into financially successful and financially unsuccessful groups. The correct classification success of the model developed by the authors was calculated as 74 percent.

In their study, Chung et al. (2008) developed an insolvency prediction model using the multivariate discriminant analysis and artificial neural network methods. They employed 36 financial ratios derived from the companies' financial statements. They determined that the financial ratios employed in the model played an important role in determining the financial failure risk. The model's correct classification percentage is calculated as 62 percent.

Gepp and Kumar (2008) developed a financial distress prediction model using the Cox's PH model, discriminant analysis and logistic regression analysis. The authors used a sample consisting of the manufacturing and retail companies listed in AMEX and NYSE. Using the financial statements of these companies, 27 financial ratios were calculated for the analysis. The correct classification percentage of the three methods for the first year is calculated as 96 percent.

Liou (2008) examined the similarities and differences between the models that determine the business failure prediction and fraudulent financial statements using logistic regression, classification tree and neural networks methods. In this study, 52 variables that were employed in previous studies were selected. The results of the study indicated that many variables affected the determination of financial statement frauds and financial failures. Correct classification percentages of logistic regression, artificial neural network and decision tree methods were 99 percent, 91 percent and 95 percent, respectively. Logistic regression and decision tree methods were stated as the most efficient methods in failure prediction.

Chen and Du (2009) developed a financial distress model using artificial neural network and data mining clustering methods. They included 38 financial variables in the analysis. According to their study, artificial neural network approach which had a correct classification percentage of 82, obtained better prediction accuracy than the data mining clustering approach.

Yang et al. (2009) built a model of financial distress prediction using the group method of data handling. The analysis included 24 ratios from 6 different groups (solvency, profitability, operating performance, financial structure, cash flows and growth) and these were analyzed using group method of data handling, discriminant analysis and logistic regression methods. The results of the financial failure prediction model built in the study indicated that the companies lowered their risks and increased their profitability during economic recession periods.

Muzır and Çağlar (2009) tested the performance of 8 different financial distress models that were frequently used in practice and compared their predictive performance as to first year before the failure. In the study, as an alternative to the existing models, 4 new model proposals, named as F-Score (Failure Score) models, developed by using 4 different statistical techniques have been introduced and

the study was enriched by comparing the existing models with F-score models introduced. According to the results, it was stated that none of the currently applied models had a 90 percent or more correct classification percentage. When compared to the other models, it was determined that the O-Score model developed by Ohlson (1980) and Binary Logistic Regression (Log-Reg) F-Score model introduced by Muzır & Çağlar (2009) were more successful, with correct classification percentages of 81 percent and 82 percent respectively.

Salehi and Abedini (2009) investigated the effect of financial ratios for the prediction of financial distress using multiple regression analysis. The correct classification percentage of the model was calculated as 77.

Sori and Jalil (2009) developed a model to predict failure using discriminant analysis. The authors used 64 financial ratios in the study. As a result of the study, it was found that 2 variables were important in failure prediction and the correct classification percentage of the model was computed as 80.

In the study of Çelik (2010), the author compared the predictive powers of discriminant analysis and artificial neural network models and aimed to produce early warning models to predict financial failures of banks. For this purpose, financial ratios of 36 private banks were used to estimate the financial failure probabilities one and two years prior to failure. The correct classification ratio of the discriminant model one and two years before failure is 91 percent. The correct classification ratio of the artificial neural network model was 100 percent for the first year prior to failure and 88 percent for two years before failure.

Yap et al. (2010) developed a model to predict company failure in the sample companies using discriminant analysis. The authors used 16 financial ratios which were analyzed by multiple discriminant analysis. 7 variables were chosen for the discriminant function and the model had a correct classification ratio between 88 percent and 94 percent for each year of the five-year period.

Halim et al. (2011) aimed to determine the factors that affected the failure of a company. The authors determined 17 financial ratios from the selected companies' financial statements. Financial ratios were classified into groups of liquidity, profitability, leverage/gearing and efficiency and were analyzed under each group. According to the results of the analysis, it was stated that financial ratios were powerful factors in determining the failure risk of companies.

Ekşi (2011) used data mining, regression trees (CART) and classification models to determine company failure. In his study, the author determined 15 financial ratios from the financial statements of sample companies. The correct classification ratio of the CART model was calculated as 88 percent.

Yüzbaşıoğlu et al. (2011) used factor analysis and logistic regression method and built a model to determine the financial failure risk of sample companies. The authors determined 22 financial ratios as variables. According to the study, 8 of the factors had 85 percent explanatory power for the first year and 7 factors had 85 percent explanatory power for the second year.

Terzi (2011) developed a model to determine financial failure risk of companies using discriminant analysis. The author selected 19 financial ratios to examine the financial failure of companies. These ratios were subjected to single and multiple statistical analysis and 6 ratios were identified to be included in the model. The model developed in this study has a 90.9 percent correct classification ratio.

3. Research Method

3.1. Sample Selection

The data used in this study are gathered from the financial statements of 167 companies listed in the ISE, operating in manufacturing industry during 2009 and 2010. Companies are classified into two groups (failure vs. non-failure) for the analysis in terms of financial success. The classification of the companies into two groups is made according to the following criteria.

Altman Z-Score criterion (Atiya, 2001; Yüzbaşıoğlu et al. 2011; Terzi, 2011). The formula for the Z-score is as follows (Altman, 1968, p.594):

Z-Score = 1.2 (working capital / total assets) + 1.4 (retained earnings / total assets)
+ 3.3 (earnings before interest and taxes / total assets)
+ 0.6 (market value of equity / book value of total debt)
+ 1.0 (sales / total assets)

The Z-score from the Altman model that is used to determine the financial failure risk is interpreted as follows (Yüzbaşıoğlu et al. 2011: 98):

- If $Z < 1.81$; the company has a significant financial failure risk,
- If $Z > 3$; the company does not have a financial distress and it does not have a financial failure risk.

Since companies with a Z-score lower than 1.81 have a significant financial failure risk, this score ($Z < 1.81$) is chosen as the basis to classify the companies in the analysis.

a) Liquidity shortage and negative equity value. This is the situation where a company's liabilities are greater than its assets. (Deakin, 1972; Chung et al. 2008; Gepp and Kumar, 2008; Sori and Jalil, 2009; Yang et al. 2009).
b) National legal regulations about bankruptcy. (Altman, 1968; Ohlson, 1980; Shirata, 1998; Muzır and Çağlar, 2009; Salehi and Abedini, 2009; Sori and Jalil, 2009). The related regulations on bankruptcy in "Turkish Commercial Code" and "Enforcement and Bankruptcy Law".

3.2. Detecting Variables

Selected variables used in this study are based on prior research on financial distress prediction. The data related with the variables are gathered from the financial statements of the companies included in the sample. 27 financial variables that are selected for this paper are categorized under four major areas: liquidity, management efficiency, financial structure, and profitability. The selected financial ratios are presented in Table 1 below:

Table 1: Selected financial ratios and their categories

	Variables	Category		Variables	Category
1	Inventories to Sales (INV/SAL)	Man. Eff.	15	Times Interest Earned Ratio (TIER)	Profitability
2	Inventory Turnover (STT)	Man. Eff.	16	Gross Margin (GRM)	Profitability
3	Receivables Turnover (RET)	Man. Eff.	17	Net Profit Margin (NPM)	Profitability
4	Sales to Equity (SAL/EQ)	Man. Eff.	18	Operating Profit Margin (OPM)	Profitability
5	Asset Turnover (AST)	Man. Eff.	19	Operating Expenses to Sales (OE/SAL)	Profitability
6	Return on Assets (ROA)	Man. Eff.	20	Sales Growth Ratio (SALGR)	Profitability
7	Return on Equity (ROE)	Man. Eff.	21	Financial Leverage Ratio (FLR)	Fin. Structure
8	Working Capital to Sales (WC/SAL)	Man. Eff.	22	Debt Turnover (DET)	Fin. Structure
9	Earnings Before Interest and Taxes to Total Assets (EBIT/TA)	Man. Eff.	23	Total Liabilities/Equity (TL/EQ)	Fin. Structure
10	Current Ratio (CUR)	Liquidity	24	Fixed Assets/Equity (FA/EQ)	Fin. Structure
11	Quick Ratio (QUR)	Liquidity	25	Equity to Total Assets (EQ/TA)	Fin. Structure
12	Cash Ratio (CAR)	Liquidity	26	Retained Earnings to Total Assets (RE/TA)	Fin. Structure
13	Working Capital to Total Assets (WC/TA)	Liquidity	27	Long-Term Liabilities to Total Assets (LTL/TA)	Fin. Structure
14	Cash Flow to Total Liabilities (CF/TL)	Liquidity			

3.3. Brief Description of the Methods

For the prediction of financial distress, there are several methods used in the literature. Logistic regression, artificial neural network and decision tree methods are employed in this study, as they are frequently used in previous researches.

Before applying the methods to selected variables, F tests were performed on each variable, using failure and non-failure companies as the grouping variable (Moyer, 1977; Casey and Bartczak, 1985; Lin and McClean, 2000; Yim and Mitchell, 2005; Terzi, 2011). For non-significant differences, the variable is excluded and not used in the models.

F values are used to differentiate the independent variables. The significance levels of the F values are taken into account in this process. Larger F values indicate that the independent variable has superior differentiation power (Chung et al., 2008: 24).

$\mathbf{H_o}$: $\mu_1 = \mu_2 = \ldots = \mu_k$

$\mathbf{H_1}$: $\mu_1 \neq \mu_2 \neq \ldots \neq \mu_k$

where,

μ_1 = mean of ratio 1 across failure and non-failure companies.

μ_2 = mean of ratio 2 across failure and non-failure companies.

μ_k = mean of ratio k across failure and non-failure companies.

If the value of calculated F statistic is significant ($p < 0.05$), the null hypothesis is rejected because there are differences in the means of ratios across failure and non-failure companies. (Chung et al., 2008: 24).

In preparing the data to analysis, the dependent variable is determined as the financially failure and non-failure companies. In the analysis, failure companies are represented by "1" and the non-failure companies are represented by "0". The selected variables according to the F test results and the related information about these variables are presented in Table 2 below.

Table 2: The Test of Equality of Group Means

	Mean		**Std. Deviation**		
Variables	**1**	**0**	**1**	**0**	**F (*)**
Inventories to Sales (INV/SAL)	0.172	0.390	0.141	1.224	2.963
Inventory Turnover (STT)	18.474	6.319	84.305	10.013	1.479
Receivables Turnover (RET)	6.881	6.937	5.788	14.970	0.001
Sales to Equity (SAL/EQ)	1.857	0.711	1.712	15.750	0.496
Asset Turnover (AST)	0.986	0.742	0.538	0.481	**9.245**
Return on Assets (ROA)	0.065	-0.038	0.089	0.099	**50.136**
Return on Equity (ROE)	0.101	1.071	0.118	6.045	2.449
Working Capital to Sales (WC/SAL)	0.463	-64.212	1.048	479.183	1.734
Earnings Before Interest and Taxes to Total Assets (EBIT/TA)	0.073	-0.007	0.081	0.083	**38.888**
Financial Leverage Ratio (FLR)	0.342	0.976	0.182	1.741	**12.446**
Debt Turnover (DET)	8.845	5.491	5.651	3.815	**18.846**
Total Liabilities/Equity (TL/EQ)	0.675	-2.430	0.616	45.987	0.434
Fixed Assets/Equity (FA/EQ)	0.726	-2.538	0.284	37.907	0.706
Equity to Total Assets (EQ/TA)	0.658	0.024	0.182	1.741	**12.446**
Retained Earnings to Total Assets (RE/TA)	0.131	-1.139	0.165	4.218	**8.619**
Long-Term Liabilities to Total Assets (LTL/TA)	0.085	0.214	0.082	0.318	**14.438**
Current Ratio (CUR)	3.091	1.175	2.900	1.231	**27.626**
Quick Ratio (QUR)	2.389	0.751	2.678	0.668	**25.688**
Cash Ratio (CAR)	1.099	0.171	2.352	0.546	**10.739**
Working Capital to Total Assets (WC/TA)	0.277	-0.297	0.152	1.724	**10.448**
Cash Flow to Total Liabilities (CF/TL)	0.213	-0.016	0.916	0.267	**4.234**
Times Interest Earned Ratio (TIER)	4.889	0.325	6.461	2.473	**32.297**
Gross Margin (GRM)	0.210	0.167	0.135	0.265	1.929
Net Profit Margin (NPM)	0.021	-12.161	0.664	75.875	2.453
Operating Profit Margin (OPM)	0.028	-8.777	0.544	53.341	2.593
Operating Expenses to Sales (OE/SAL)	-0.142	-0.915	0.087	3.720	**4.106**
Sales Growth Ratio (SALGR)	0.231	0.093	0.290	0.344	**7.929**

(*) The selected variables according to the F test results ($p<0.05$) are written in bold.

According to the F test results, some of the variables are determined to be in a significant relationship with financial failure risk. Therefore, variables with high statistical significance are included in the model. These variables are AST, ROA, EBIT/TA, FLR, DET, EQ/TA, RE/TA, LTL/TA, CUR, QUR, CAR, WC/TA, CF/TL, TIER, OE/SAL and SALGR. Some of the ratios are not included in the model since they are not statistically significant.

Logistic regression analysis is a regression method which helps making classification and assignment. This method does not have the normality of distribution and continuity assumptions. The effect of independent variables on the dependent variable is given as a probability by the method, thus the risk factors can be determined as probabilities (Hosmer and Lemeshow, 2000: 2-4). In selecting the variables to be included in the model, forward stepwise (Wald) regression procedures with the significance level boundaries for entry and removal set to 5% and 10% are used (Geep and Kumar, 2008: 19).

In the logistic regression model, the dependent variable is a binary [0, 1] discontinuous variable; the risk is represented by 1 (failure) and 0 (non-failure).

$$E(y) = \frac{e^{\beta_0 + \beta_1 X_1 + - + \beta_k X_k}}{1 + e^{\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k}}$$

The parameters in this model are:

y= The frequency of the investigated event (for y= 1 Failure, for y= 0 Non-Failure)

β_0 = The value of the dependent variable when independent variables are zero (constant value)

$\beta_1, \beta_2, \ldots, \beta_k$= The regression coefficients of the independent variables

$X_1, X_2, \ldots, X_k$= Independent variables

k= The number of independent variables

e= 2.71

Where Failure = 1 if Failure discovered group, 0 otherwise. Probability to fail (y=1);

$$\text{Failure} = \beta_0 + \beta_1(\text{AST}) + \beta_2(\text{ROA}) + \beta_3(\text{EBIT/TA}) + \beta_4(\text{FLR}) + \beta_5(\text{DET}) + \beta_6(\text{EQ/TA}) + \beta_7(\text{RE/TA}) + \beta_8(\text{LTL/TA}) + \beta_9(\text{CUR}) + \beta_{10}(\text{QUR}) + \beta_{11}(\text{CAR}) + \beta_{12}(\text{WC/TA}) + \beta_{13}(\text{CF/TL}) + \beta_{14}(\text{TIER}) + \beta_{15}(\text{OE/SAL}) + \beta_{16}(\text{SALGR}) + \varepsilon$$

Artificial neural network, consisting of a number of neurons or nodes, emulate the human brain to classify and predict data. The artificial nodes receive scalar data from several other nodes and they combine the information into a single output signal. The interconnections are weighted, and the weights are modified as the network operates on training data (Liou, 2008: 654). The neurons are arranged into layers. A layered network consists of at least an input (first) and an output (last) layer. Between the input and output layer, there may exist one or more hidden layers (Kirkos et al. 2007: 999). The input layer consists of 16 nodes, one for each of the ratios. The hidden layer consists of 8 nodes. The output layer consists of only one neuron with a response of 0, representing non-failure, and a response of 1, representing failure. The network classifies the data on a scale between 0 and 1. Companies with output below 0.5 are classified as failure and companies with output greater than 0.5 are classified as non-failure. In this study, implementing a back-propagation neural network has been chosen.

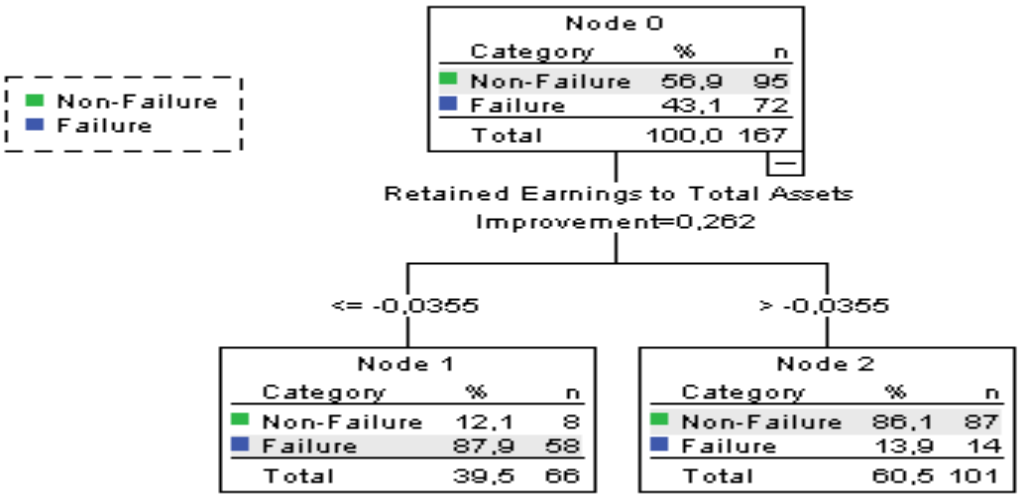
Decision tree is a type of decision-making process, which depends on using the induction method to sample data with known classifications. A decision tree is a structure where large records are divided into very small groups by applying simple decision-making steps. With every successful division, the elements of the resulting group become more similar to the others (Albayrak and Yılmaz, 2009: 39). Decision tree methods generate a decision tree that properly classifies the training sample. This is an inductive learning model and produces a set of IF - THEN rules (Lin and McClean, 2000: 50). In this study, one of the decision tree methods, namely the Classification and Regression Tree (CART) method, is applied (Shirata, 1998; Kirkos et al. 2007).

In terms of financial distress prediction, the accuracy of the prediction is measured by two quantities: Type I Error Rate and Type II Error Rate. Type I Error Rate means that the error rate for

risk can't categorize the non-failure company as a non-failure company. Type II Error Rate means that the error rate for risk can't categorize a failure company (Chen and Du, 2009: 4080).

Each possible path of the decision tree, from the root node to the leaf node, represents a sequence of classification rules. When the bottom leaf node is reached, then the classification process ends. The sequence continues until an optimal prediction model is reached. The classification tree algorithm does not specify whether the variables are the most significant or not (Liou, 2008: 654).

Figure 1: The structure of the generated decision tree model



SPSS (Statistical Package for Social Science) statistical program is used for the F test, logistic regression, artificial neural network and decision tree methods employed in this study to build the model.

4. Empirical Findings and Discussion

The averages of the ratios are examined (F test) and it is found that some of the variables are significant at 5 percent significance level. It indicates that there are significant differences between failure companies and non-failure companies. The findings demonstrate that the "financial ratios significantly affect the determination of financial failures of companies operating in the manufacturing industry *(H_o: $\mu_1 = \mu_2 = \ldots = \mu_k$)*" hypothesis is accepted.

ROA ($p<0.000$) and EBIT/TA ($p<0.000$) show that failure companies are less profitable compared to non-failure companies in terms of the resources they use. Furthermore, LTL/TA ($p<0.000$) ratio shows that failure companies continue their operations usually with short term liabilities and EQ/TA ($p<0.001$) ratio shows that failure companies are usually financed through debt. One of the most important ratio groups in differentiating failure and non-failure companies is the liquidity ratios. Failure companies have liquidity shortages and because of the fact that they resort to lending, their times interest earned ratios (TIER) are lower than non-failure companies. This also indicates that the profitability ratios of the failure companies are lower. The results of the study are consistent with prior literature (Beaver, 1966; Altman, 1968; Deakin, 1972; Ohlson ,1980; Casey and Bartczak, 1985; Altaş and Giray, 2005; Chung et al. 2008; Gepp and Kumar, 2008; Liou, 2008; Chen and Du, 2009; Yap et al. 2010; Terzi, 2011). In these prior studies, it was found that failure companies had liquidity shortages, they could not generate enough return from the assets employed in the business and they usually raised money in the form of debt rather than equity financing.

4.1. Logistic Regression

In the application of the logistic regression analysis, forward stepwise (Wald) method is used and AST, EQ/TA, RE/TA and WC/TA variables are included in the model. Companies with low asset turnover, low equity to total assets, low retained earnings to total assets, and low working capital to total assets ratios are more likely to fail according to the results of the stepwise logistic regression.

AST (β= -8.176; $p < 0.002$), EQ/TA (β= -26.266; $p < 0.001$), RE/TA (β= -25.772; $p < 0.000$), and WC/TA (β= -11.582; $p < 0.006$) have a significant negative effect. This means that companies with high asset turnover have an increased probability of being classified within the non-failure companies. These results are consistent with prior literature (Altman, 1968; Chung et al. 2008; Gepp and Kumar, 2008; Salehi and Abedini, 2009; Yap et al. 2010; Terzi, 2011).

The validity of the model is tested using the Hosmer Lemeshow test (Hosmer and Lemeshow, 2000; Yim and Mitchell, 2005).

H_0: Estimation equation is significant.

H_1: Estimation equation is not significant.

As a result of the Hosmer Lemeshow test ($p < 0.999$) H_0 hypothesis is accepted. The examination of the classification success of the logistic model for financial distress prediction indicates that the logistic regression model's correct classification ratio is 94.6 percent. In other words, the model correctly estimates 94.6 percent of the companies correctly. This ratio is an indicator that the equation is significant. According to this analysis, 5 of the non-failure companies are falsely classified into the other group and 4 of the failure companies are falsely classified as non-failure.

Table 3: Classification Performance of Logistic Regression

Observed	Predicted		
	Non-Failure	Failure	Percent Correct
Non-Failure (Type I Error)	91	4	95.8%
Failure (Type II Error)	5	67	93.1%
Overall Percentage			94.6%

4.2. Artificial Neural Network

The results of the artificial neural network analysis are presented in Table 4. As shown in the training phase of the table, the model correctly classifies 95.7 percent of the observations correctly and 4.3 percent incorrectly. At the testing (validation) data set, the model achieves a good performance and correctly classifies all 30 observations with a correct prediction percentage of 100.

Table 4: Classification Performance of Artificial Neural Network

Sample	Observed	Predicted		
		Non-Failure	Failure	Percent Correct
Training Set	Non-Failure (Type I Error)	64	1	98.5%
	Failure (Type II Error)	4	47	92.2%
	Overall Percent	58.6%	41.4%	95.7%
Testing Set	Non-Failure (Type I Error)	30	0	100.0%
	Failure (Type II Error)	3	18	85.7%
	Overall Percent	64.7%	35.3%	94.1%

4.3. Decision Tree

The decision tree model constructed was shown in Figure 1 and the performance of the model is shown in Table 5 below. The model correctly classifies 86.8 percent of the observations correctly and 11.2 percent incorrectly.

Table 5: Classification Performance of Decision Tree

Observed	Predicted		
	Non-Failure	Failure	Percent Correct
Non-Failure (Type I Error)	87	8	91.6%
Failure (Type II Error)	14	58	80.6%
Overall Percentage	60.5%	39.5%	86.8%

As presented in Figure 1, the tree splits at the root with RE/TA variable. If the RE/TA ratio is greater than -0.0355, the company is classified as failure. This means that companies with RE/TA ratio greater than -0.0355 is very likely to fail. This result is consistent with similar studies (Chung et al. 2008; Gepp and Kumar, 2008; Salehi and Abedini, 2009; Yap et al. 2010).

5. Conclusion and Future Research

The purpose of this paper is to determine the differences and similarities between financial distress prediction models, and to determine the most effective explanatory variables and methodologies in prediction of financial distress. 167 manufacturing companies from Istanbul Stock Exchange are used in the study and 27 financial ratios are identified from previous literature studies as potentially significant.

In classification of the sample companies, Altman Z score, negative equity value and legal regulations are used as basis. 27 financial ratios are determined to examine the financial success of the companies. As a result of the analysis, only 16 of these ratios are found to be significant in discriminating the failure and non-failure companies. These variables are included in the study through logistic regression, artificial neural networks and decision tree models that are widely used in the literature.

Findings indicate that selected financial ratios are related with financial distress. Moreover, according to the results of the analysis, liquidity, management efficiency, financial structure and profitability ratios are found to play an important role in determining the financial success of the companies. Findings of this study are also consistent with the previous studies.

Logistic regression, artificial neural network and decision tree methods correctly classify most of the failure companies. In this study, the least successful method in classifying the companies is determined as the decision tree method.

This paper has demonstrated that logistic regression and artificial neural network are appropriate methods for predicting company failures because the classification successes of the two methods are high and close to each other.

The financial distress prediction models used in the study might be useful in their evaluations for managers, financial analysts, investors and other stakeholders. Additionally, these models may be helpful for auditors in their activities, as they will have an opportunity to determine additional audit procedures and to state an appropriate opinion about the financial statements.

This study may provide an insight for future studies about the determination of financial failure. In the future studies:

- Including the interim financial information of the companies in the analysis together with the annual financial information,

- Using data for longer time periods,
- Including qualitative factors together with financial (quantitative) data in the models

would increase the accuracy in the determination of financial failure risk.

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