



Financial Distress Prediction across Firms

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Abstract

One of the most important events in a firm's life is financial distress, which can propel sectors into financial and sustainable growth problems. Moreover, independent variables in the background of financial distress are accounting ratios, which are extracted from financial statements and macroeconomic variables that are mostly beyond the control of a firm or sector. The current study analysed the information related to a sample of 300 public Iranian companies, during the periods of 2000-2007 and 2009-2016. Logistic regression and decision trees were applied to the prediction of financial distress. It was found that the profitability, liquidity, leverage, interest rate, cash flow, accruals, and GDP were statistically significant in distinguishing distressed from non-distressed firms across sectors. The obtained results showed that the predictive performance of a DT model was more successful than the other model.

Keywords: Prediction of Financial Distress, Accounting ratio, Decision Trees

1 Introduction

The prediction of financial distress is absolutely vital for traders, creditors, and suppliers. To avoid any financial loss, they need to assess the financial risk of a firm before they make any decisions. Financial distress is not the same as bankruptcy. The former occurs while the firm is not able to meet its financial obligations due to a decrease in the firm's operations and excessive costs, while the latter is a very last state in which corporations stop doing commercial enterprise due to financial distress. The bankruptcy needs to be confirmed by a courtroom determination; then, its assets are bought to pay and cover all obligations of creditors (1). Thus, financial distress does not necessarily lead to bankruptcy.

Based on a review of literature, some researchers implicitly suppose that firms' annual statements give an honest and genuine view of the financial state of agencies; although, some annual accounts are indeed unreliable (2). Some studies have stated that despite the fact that the hyperlink between earnings management and financial distress is clear, only few studies have covered such indicators in financial distress prediction (3). Earnings management can be interpreted beneficial, neutral, or pernicious (4, 5). Providing private information on future economic performance through management activities, the beneficial earnings management improves the financial statements of the company. This type of management can be interpreted as neutral if earnings management can be economically efficient for maximizing one's own utility. Finally, earnings management is recognized pernicious when it is about concealing and misrepresenting financial reports of the company.

Furthermore, the stakeholders of a firm are generally concerned about the accuracy of financial distress predictions during business activities. To increase the accuracy of financial distress predictions, some studies have introduced different statistical and artificial intelligence-based models. For example, the multivariate model proposed in (6) was the initial study based on the discriminant analysis approach. Literature contains some artificial intelligence models that can be effectively used in this regard, including Neural Networks (7), Decision Trees (8), and Support Vector Machines (9). Furthermore, to increase the accuracy of the financial distress predictions, not only the financial statements information, but also other available data such as macroeconomic factors and market information are taken into account. To do an empirical study, the performance of a sample of 300 listed Iranian companies, during the periods of 2000-2007 and 2009-2016, was considered. The whole accounting information was extracted from financial reports. Two prediction techniques of logistic regression and decision trees were applied to the research. The rest of the paper is organized as follows. The literature review and hypothesis are presented in Section 2, the methodology in Section 3, and finally, the result of the study and conclusions are presented in Section 4.

2 Literature Review

Financial ratios are vital for predicting financial distress among firms and have been already used by some researchers (6, 10), (11). Every business has its own economic characteristics based on its defined activities. In addition, choosing appropriate

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ratios well matched with the financial condition of any market is the key factor of the study. According to the results of few studies with high accuracy among ratios, accounting and macro ratios are used. Therefore, this study will attempt to answer the following research question:

Research Question: What are the significant determinants of accounting ratios and macroeconomic level variables of financial distress prediction among the listed firms?

2.1. Independent Variables

2.1.1. Accounting Ratios

The financial distress researchers generally focus on the financial reports and market trends of the sectors during specific periods. All factors are collected through reliable available information.

2.1.1.1 Profitability

A firm's extreme survival is based on the profitability of its business. In fact, the profitability ratios indicate how well a firm has operated during the fiscal year. The static trade-off theory indicates that profitable firms are likely to have a high tax burden and low cost of bankruptcy (12). Moreover, the profitable firms have more capability to tolerate being indebted since they may be in a position to easily clear their debt on time. This indicator can have a significant role in the bankruptcy investigation. The extant studies on financial distress prediction found a significant relationship between profitability and financial distress (13). Their results suggested that financial distress intensities strongly decrease the level of profitability for all prediction horizons considered. In addition, the authors in (14) and (15) developed a prediction model of financial distress in Iran by Bayesian networks and genetic programming models, respectively. Their findings showed that when a firm has a good profitability level, creditors are sure that their interest's expenses in the firm can be achievable. Moreover, in the context of the Iran economy, the authors in (14) found out that higher profitability makes higher efficiency and better liquidity, hence lowering default risk. Literature widely confirms the existence of a significant relationship between profitability and financial distress prediction (16).

2.1.1.2 Leverage

One of the main variables that explain financial distress is the firm's leverage that can pose a big risk to the firm due to its high costs (17). This proxy demonstrates the risk and capital structure of a firm. Leverage has been investigated by some researchers in terms of its negative effects on the firm performance (18). For example, in (19), a significant negative effect of leverage was explored on the company's risk in the non-financial sector. In addition, the authors in (20) found out that through the use of the agency argument, the benefits of leverage outweigh its cost. The most commonly-used leverage ratio in financial distress prediction is the debt ratio that is measured by dividing the total debt over total assets. Furthermore, some studies have concluded that the debt ratio is a significant factor in identifying the firms' assets to meet the obligations (21).

2.1.1.3 Liquidity

A firm is able to pay off the obligations in a timely manner and indicate its performance improvement when it holds a high liquidity ratio. Therefore, the firms also can pay dividends to

shareholders during activities (22). The ratio of working capital to total assets is a significant factor that considers the liquidity in the firm. If the firm experience operating losses consistently, it will have a shrinkage in current liquidity in relation to total assets. According to literature, insolvency of businesses is instigated by the unsuitable practice of working capital measures, despite optimistic revenues or profitability due to such practices. Thus, it would be uncertain to just concentrate on profitability while overlooking liquidity (23). In addition, in (24), it was found that liquidity plays an important role in the determinants of the financial distress prediction. Alternatively, liquidity is one of the most significant indicators related to financial distress of firms.

2.1.1.4 Earnings Management

In the context of financial distress prediction, banks make lending decisions based on the firms' financial statements disclosed (25-27). Financial information creates a loophole for firms by managing their earnings to obtain loans with more favorable terms. In this regard, the financial statements must provide reliable financial information to the external and internal stakeholders in accordance with International Financial Reporting Standards (IFRS) in a way to be well compared with others' financial statements (28, 29). Collecting, preparing, and publishing the financial information is the managers' responsibility (30, 31). Earnings management as the process of a business uses the generally-accepted accounting procedures for the purpose of altering the earnings figures such as delayed recognition of expenses, premature recognition of revenue, and inventory methods such as last-in, first-out (Lifo) and first-in, first-out (Fifo) (32, 33). Remember that the motivation to manage earnings depends on the nature of the sectors. Various reasons have been suggested in literature for variations in earnings management activities including market development, the structure of ownership, economic factors, initial public offerings, and effective tax rates (34, 35). According to (36, 37), to avoid reporting annual losses, firms use earnings management methods. In addition, firms under financial distress are likely to take different measures in order to decrease the concern of future outcome events or any inherently uncertain conditions such as window-dressing financial statements (38, 39). In this study, the earnings management is discussed in terms of free cash flow of the firm and accruals, which is effective on financial distress prediction among different sectors.

2.1.1.5 Macroeconomic Variables

Macroeconomic factors affect the feasibility of a firm, and these external factors are generally beyond the instant control of sectors (40, 41). Moreover, the macroeconomic variables causing financial distress are the interest rate, inflation, gross domestic product, monetary policy, oil price, financial crisis, and debt crisis. According to the authors in (42-47), macroeconomic indicators affect financial distress prediction. Consistently, an interest rate is the main macroeconomic indicator that affects the corporate success or failure (48). Furthermore, in (49), the interest rate is considered as an important variable that is effective on the company's flexibility and adaptability. It has been also suggested that variation in inflation influences firms because of the rising cost of production or it may generate higher prices that, in turn, causes lower demand. Accordingly, GDP represents the economic performance among sectors and any decline in GDP causes the recession and other financial crises (50, 51). Financial

distress causes significant losses not only to the firms' activities, but also to society as a whole. Thus, the high accuracy of prediction models is very vital to stakeholders, management, and employees as the models provide timely warnings. Generally, macroeconomic conditions have good explanatory power for financial distress prediction and are useful in modeling credit risk (52). In this regard, the current study will apply the three important macroeconomic variables, i.e., the interest rate, inflation, and gross domestic product to accurate prediction of financial distress.

Table 1: Formulation of Independent Variables

Variables	Formulation
Accounting Variables	
Profitability	EBIT /Total Asset
Liquidity	Working Capital / Total Assets
Leverage	Current Liabilities / Total Equity
Earning Management	
Free cash flow	Operating cash flow -- capital expenditure
Accrual	Net income-cash-dividends /Total Asset
Macroeconomic level	
Interest rate	Central Bank of Iran
GDP	Per capita
Inflation	Consumer Price Index (CPI)

1.2 Dependent Variable

Dependent variable of financial distress is also a dummy variable, and if the value of the financial distress variables gets 1 in a year, it is considered that the firm was unable to settle the debt on that given year, or it has gone into financial distress on that year (Central Bank of Iran, 2014). The criterion for classifying firms into their financial conditions such as normal or distressed firms is based on the listed firm that is specially treated (ST) by the Teheran Stock Exchange. According to the Iran Business Law, Article 141, if the accumulated losses of a firm are more than 50% of stockholder equity, the firm is considered as a distressed firm (53).

3 Methodology

Technological advancements and a rise in the availability and power of computerization in the 1990s enabled researchers of financial distress prediction to resort to a more extensive range of methods. Today, financial distress prediction models are utilizing both statistical analyses and artificial intelligence to upgrade the decision support tools and to enhance the decision-making processes (54). Logistic regression and decision trees are applied to the current study. The Logistic regression studies the outcome of several independent variables to predict the relationship

between independent variables and dependent variable classes. There are two main applications of logistic regression. First, this method forecasts the category membership. The logistic regression determines the likelihood of non-distressed over the probability of distressed, and the results of the analysis are presented in the form of a probability ratio. Second, this method verifies the associations and strengths among the variables. Coefficients of regression can be used to evaluate odds ratios for all of the independent variables separately (55). Decision trees are one of the most popular methods for classification and forecasting. The main reason behind their recognition is their easiness and transparency as well as interpretability. The accuracy of classification or prediction in different applications is a crucial factor. For instance, in credit scoring applications, the model's ability to demonstrate the reasons is extremely critical as it affects the decisions to predict credit scoring. In this regard, in comparison with some statistical and data mining techniques, a decision tree is able to depict rules of classification. Thus, this technique is more attractive in order to classification applications (56). The main difference between decision trees and linear and logistic regression is that regarding the decision trees, models commence by generating classification of observation into groups and continue by obtaining a score for each group. However, in the logistic regression methods, first, a score is generated; then, a classification is done based on a discriminant rule. In order to present the idea and estimate the probability of financial distress of the firm, let us start by considering the following model of logit regression; where the Logit of π is the probability of firm failure, and X_1 through X_n represent any of the independent variables used to predict firm failure.

$$\text{Logit}(\pi) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k$$

$$P = \frac{1}{e + 1 - (\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}$$

As the decision tree (DT) is a non-parametric and preliminary procedure, it can learn from samples by a process of generalization (Figure 1). Commonly, DT refers to binary trees that comprise a set of subdivisions (paths from roots to leaf nodes), leaf nodes (objects classes), and nodes (decision rules), which categorize objects based on their characteristics (57).

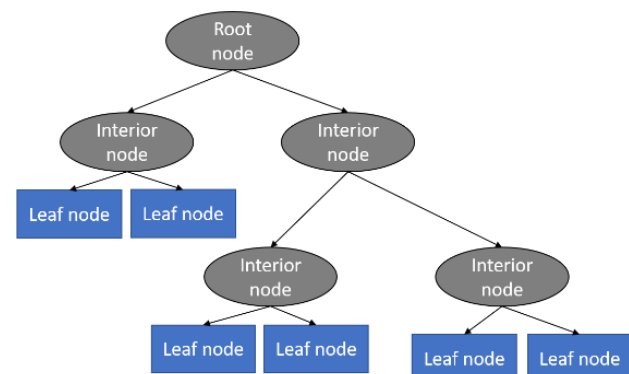


Figure1: Structure of Decision Trees

4 Empirical Results

This study examined the significant financial distress determinants of Iranian firms listed on the Tehran Stock

Exchange (TSE) across non-financial sectors. This study executes a sector-wise analysis of 300 non-financial Iranian firms across sectors. The selected firms were chosen from a dataset for periods of 2000-2007 and 2009-2016 across sectors. In addition, the current study extracted the financial information from the firms based on the Commercial Law, Act 141 of Tehran Stock Exchange, which classifies firms as distressed if the retained losses are more than 50% of their capital. As discussed, the following equation provides the association between the accounting and macroeconomic factors using logistic regression analysis.

$$FD = \beta_0 + \beta_1 PROF_{it} + \beta_2 LEV_{it} + \beta_3 LIQ_{it} + \beta_4 FCF_{it} + \beta_5 ACR_{it} + \beta_6 (INF) + \beta_7 (INT) + \beta_8 (GDP) + \epsilon_i$$

Table 2: Model summary of accounting and macroeconomic level determinants based on logistic regression

Predicted				
Status	Non Distress		Distress	Percentage
	Non Distress	988	25	90.4
Status	Distress	37	145	60.1
	Overall Percentage			83.3

The model effectively grouped 83.3% of determinants of financial distress across firms, which is higher than half, while the examination was directed without the independent factors that are utilized in the model. Table 3 exhibits log likelihood ratio, Cox & Snell R Square and Nagelkerke R Square.

Table 3: Classification of overall independent variables

-2Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1196.345a	0.317	0.445

Table 4: Estimation results of logit analysis of independent variables

Ind. Variable	β	S.E.	Wald Df	Sig
PROF	-2.118	0.709	10.516	0.031
LEV	21.051	3.257	15.314	0.040
LIQ	9.324	3.751	11.623	0.045
FCF	25.310	0.415	5.312	0.130
ACR	14.346	1.254	5.271	0.203
GDP	0.684	0.852	2.321	0.052
INF	2.361	3.523	14.501	0.058
INT	6.052	8.321	21.301	0.054

Table 4 exhibits the overall analysis based on firm and macroeconomic level determinants. The independent variables are profitability (PROF), leverage ratio (LEV), liquidity (LIQ), free cash flow (FCF), accrual (ACR), inflation (INF), interest rate (INT), and gross domestic product (GDP). Based on Table 4, the

profitability and liquidity are negatively associated with financial distress. In addition, leverage ratio and free cash flow are positively associated with financial distress. Moreover, accrual variable is found statistically significant and finally, interest rate, inflation rate, and GDP are persistently maintained significant to the probability of financial distress across sectors. In general, the significant relationship between accounting and macroeconomic factors and the probability of financial distress across sectors show that firms among sectors tend to affect the probability of financial distress by its determinants.

Table 5: Classification of decision tree model of overall independent variables

Overall		Predicted		
		Non Distress	Distress	Percentage
status	Non Distress	975	31	87.4
	Distress	42	141	50.1
Overall Percentage		86	24	85.1

Table 5 shows the classification table of the practical results using the decision tree model. It is observed that the classification shows the overall analysis of firm and macroeconomic level determinants; it has correctly classified with 85.1% accuracy.

5 Conclusion

Financial distress prediction is the inevitable phenomenon that has been a hot topic of corporate finance literature. The consequences of financial distress affect negatively the social and economic states of any country in general. Therefore, appropriate prediction tools are needed to be proposed. Furthermore, to keep track of firm business activities, minimize the risk of failure, and make an effective decision, the prediction models can help managers analyse important trends of the market. In addition, financial distress models assist the creditors to assess the risk of the firm in order to issue a new loan, and they may warn the auditor of the firm to monitor the performance of the financial activities. Accordingly, the results of this study showed that a DT model outperforms the other models in terms of predicting financial distress.

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