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Comparison of the combination model with the structural and accounting model in predicting the financial distress

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Abstract

The current research aims to investigate the power of financial distress prediction models while presenting a combination model, comparing the extracted model with the Merton model and the binary logistic regression model in predicting financial distress. In order to achieve the purpose of the research, the information of 168 distressed companies selected based on the specific criteria of distress and 168 healthy companies admitted to the Tehran Stock Exchange between 2006 and 2019 have been used. After reviewing past studies, 25 variables affecting financial distress, including 17 accounting variables, 4 market variables, and 4 macroeconomic variables, were identified, and by emphasizing the frequency and successful performance of these ratios in past studies and performing statistical tests, the final indicators were selected. To determine the dependent variable, Merton's model was used, and finally, by applying the logit model and determining the relationship between the independent variables and the dependent variable, a composite model was extracted. The research results showed that adding economic and stock market variables to financial variables does not increase the ability to predict financial distress and the combined model has better explanatory power than the Merton model and binary logistic regression. In the present research, to predict financial distress, all three categories of accounting, economic and stock market variables are considered together, and the emphasis is not only on accounting variables, and the combined model is compared with the accounting and market model.

Keywords: Financial distress, combination model, Merton model, macroeconomic variables, stock market variables.
2020 MSC: 34H10, 90C27

1 Introduction

With the increasing expansion of corporations and the diversification of their capital structure on the one hand and the emergence of severe financial crises in micro and macroeconomic dimensions on the other hand, the owners and stakeholders of various companies have sought to create a shield to protect themselves against such risks and this The issue has made them sensitive and aware of the use of forecasting tools and models to evaluate the financial ability of companies. It is very important to find ways to predict the financial distress that happens before bankruptcy [24].

One of the ways to predict the financial distress of companies is to use financial statements, and these statements are considered as sources of extracting financial ratios. Considering that accounting ratios are only obtained based on

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annual information, there is always a risk of trusting historical information. On the other hand, the accounting figures are strongly influenced by the accounting procedures chosen by the manager and sometimes by the profit management, such cases in the current situation have caused many financial statements to lack the necessary predictive power in bankruptcy. Considering that now there are extensive sources of information in the business environment to predict future financial events including bankruptcy, and it is obvious that the company's financial distress cannot be influenced only by financial variables, and the macroeconomic environment and the capital market also affect the companies' business. it seems necessary to identify the position of other information sources in this competition so that, if possible, by putting them together in a prediction model, the possible shortcomings of a single source can be overcome. As Hernandez Tinoco and Wilson [33], Xie et al. [36] and Raghunandan and Subramanyam [26], have shown, considering economic variables and the stock market along with accounting variables is expected to increase the accuracy and power of predicting financial distress. .So far, various models have been presented to predict the financial distress of companies.

If we divide forecasting models into two categories, models based on accounting information and models based on market, the most famous foreign studies based on accounting information are Beaver [5], Altman [2], Springate [32] and Ohlson [22]. Studies based on market models also include: Black and Scholes [7], Merton [21], Hillegeist et al. [13], Bharath and Shumway [6]. Models based on accounting information are retrospective because they use information extracted from financial statements, and market-based models are forward-looking considering market information. Therefore, as shown by the researches of Agarwal and Taffler [1], Bauer [3], Bauer and Agarwal [4], Chava and Jarrow [9], Martin and Peat [19], Shumway [31], it is predicted that the combined model (accounting and market) have more accuracy and predictive power than accounting and market models (individually).

In this research, by examining past studies, variables influencing financial distress, including accounting variables, macroeconomic and market indicators, are identified. Economic and stock market variables are added step by step to the financial variables and the predictive power of the model is measured. Merton's model is also used to determine the dependent variable, and at the end, a combined model is extracted by using the logit model and determining the relationship between the independent variables and the dependent variable. In order to compare the combined model extracted with models based on accounting data from the binary logistic regression model and to compare with the model based on the stock market, the Merton model was used. Most of the past researches have used accounting variables to predict financial distress, and the other two categories, including market and macroeconomic variables, have received less attention. Therefore, in this research, all three groups have been included in the model to determine their effect on financial distress.

2 Theoretical foundations and research background

2.1 Definitions of financial distress

Financial distress refers to a situation where the company cannot fulfill its obligations to its financial providers or has problems in fulfilling these obligations. According to the research of Platt and Platt [23], the occurrence of events such as operating losses for several consecutive years, deferred dividends, financial restructuring, and a period of high unemployment indicate the entry of companies into financial distress.

2.2 Financial distress prediction models

The researches carried out in the field of predicting financial distress can be divided into the following three groups [14]:

1. The first group is research that has emphasized the issue of theorizing financial distress (such as Wilcox, [35], and Santomero and Vinso, [30]).
2. The second group was formed by researches such as Mensah [20], and Keasey and Watson [15], whose main focus was on identifying the optimal predictor variables of financial distress.
3. The third group also includes researches that have been conducted with the topic of designing and presenting effective models and methods for predicting financial distress, among which Beaver [5], Altman [2], and Ohlson [22], can be mentioned.

Well-known methods such as discriminate analysis and logit analytical approach, which have achieved significant success in predicting financial distress in the past few decades, are the result of the studies of the third group.

2.3 Internal researches

Sadewand and et al. [29], in the article " Examining and comparing the performance of conventional and hybrid models in predicting financial distress " concluded that Altman's Z model has more appropriate predictive power for healthy and distressed companies compared to the combined and Merton models; Meanwhile, for predicting distressed companies, Merton's model and the combined model had better performance compared to Altman's Z.

The research of Vaqfi and Darabi [34], in the article " structural equation model approach in the three-level analysis of financial distress in companies listed on the Tehran Stock Exchange " shows that the effect of risk criteria and corporate governance criteria is greater than accounting performance criteria and macroeconomic variables on financial distress.

The results of the research of Ramoz and Mahmoudi [27], in the article " predicting the risk of financial bankruptcy using a combination model in Tehran Stock Exchange " show that the market model is more accurate than the accounting model.

Fadainejad and Eskandari [12], in a research entitled " designing and explaining the bankruptcy prediction model of companies in the Tehran Stock Exchange " using financial ratios and market data, stated that market data is more effective in predicting bankruptcy than using only financial ratios or a combined Market data with financial ratios.

In all internal studies, by adding economic and stock market variables to the financial variables, the accuracy of the financial distress forecasting model increases, but there are different opinions about whether accounting variables or market variables are better in predicting financial distress.

2.4 Foreign researches

Yuliastari et al. [37], in the article " The Influence of Financial Ratios and Macroeconomic Indicators in Predicting Financial Distress (Empirical Study in the Consumer Goods Sector Companies)" for consumer companies on the Indonesian Stock Exchange in the period of 2014-2018 concluded that current asset turnover, asset turnover and the cash flow of total debts are effective in financial distress. While the days of collection of sales receivables, total debt to total assets, inflation sensitivity and BI rate sensitivity have no effect on financial distress.

Fontaine et al. [28], analyzed financial bankruptcy in corporations using macroeconomic variables. The predicted model was conducted between 2001 and 2014 using the logistic regression technique with panel data. Their presented model with financial and economic variables indicates that financial distress and dissatisfaction are better explained by using explanatory financial and macroeconomic variables.

Doumpos et al. [11], in the article " Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms " concluded that the distance-to-default variable obtained from the structural model, compared to common financial ratios, adds important information. However, when market value is also considered, its power is significantly weakened.

The research results of Hernands Tinoco and Wilson [33], in the article predicting financial distress and bankruptcy of listed companies using accounting, market and macroeconomic variables show the usefulness of combining accounting, market and macroeconomic data in predicting financial distress of companies. The performance of the estimated model (using data combination) has been benchmarked against neural network models (MLP) and Altman's Z-score [2].

Christidis And Gregory [10], in the article " Some new models for financial distress prediction in the UK. Xfi-Centre for Finance and Investment Discussion "concluded that adding market data to the dynamic logit regression model increases the power of models based on accounting variables.

Agarwal and Toffler [1], suggested the use of a model that is not only based on accounting information and based on market information and the current value of the company's assets due to the retrospective nature of accounting information and the great difference between the real value and the book value of assets and the fact that accounting figures are subject to manipulation by managers. They consider it necessary to use it and about the comparison of accounting models against accounting models, they believe that market variables are more suitable for forecasting purposes compared to accounting models.

Hillegeist et al. [13], expanded the Black-Scholes and Merton pricing model and compared the results of this expanded model with the Altman and Ohlson model. The results indicate that the accuracy of the expanded model, which is based on market information, is higher than Altman and Ohlson's model.

Based on external studies, the combination of financial, economic and stock market variables, as well as the combination of financial variables with economic variables or the combination of financial variables with stock market variables, works better than the application of individual variables, and the distance-to-default variable obtained from the structural equation model in Forecasting financial distress is useful and combined models have a high power in predicting financial distress. According to the results of the studies, the research hypotheses are stated as follows.

2.5 Research hypotheses

1) The ability to predict the financial distress model increases with the combination of financial, economic and stock market variables.

2) The combined model's ability to predict financial distress is greater than Merton's model.

3) The ability to predict financial distress of the combined model is higher than the binary logistic regression model.

2.6 Distress exit model

The initial models of Altman, Springate and Zmijewski do not have much ability to identify financially helpless and bankrupt companies in Iran, and the adjusted models with 93% accuracy have more ability to achieve the goal. The model provided by the audit analysis method, the variables used and the range of separation of companies into healthy, helpless and bankrupt are as follows:

Model (1):

$$\begin{array}{l} (MDA) = 0.626X_1 + 0.137X_2 + 0.679X_3 - 0.583X_4\,,\ \text{Localized Kurdistan -Tatli model} \\ X_1:\ \text{Accumulated profit(loss) on total assets} \\ X_2:\ \text{Operating profit(loss) to total assets} \\ X_3:\ \text{Net profit(loss) to total assets} \\ X_4:\ \text{Total liabilities to total assets} \\ \begin{cases} \text{Bankruptcy range helpless range Healthy range models} \\ TK \le -0.5 \qquad -0.5 < TK < -0.3 \quad TK \ge -0.3 \qquad \text{Audit analysis} \end{cases} \end{array} \tag{2.1}$$

2.7 The impact of macroeconomic factors and management system on financial distress

The logit model predicts the rank of each sample company by assigning weights to independent variables. This rank is used to determine the probability of membership in a certain group (successful or unsuccessful). The probability of success or failure (or any other dual qualitative rating) in this model is calculated using the following cumulative distribution function (model 2):

Model (2):

$$p_i = E\left(Y = 1|X_i\right) = \left(1/1 + e^{-Z}\right) = \left(1/\left(1 + e^{-a-\sum_{i=1}^{k} b_i X_i}\right)\right) \tag{2.2}$$

In this Pi model; Probability of occurrence 1 = Y, Xi. The independent variable, a and bi are also parameters of the model estimation. The probability of Pi is always a number between zero and one. If Z moves to negative infinity, Pi tends to zero. If Z tends to the positive side of infinity, Pi tends to the number one.

When Z is equal to zero, the resulting probability is equal to 0.5.

The dependent form of relation (2.2) can be expressed by simple mathematical operations in the form of relation (2.3):

Model (3):

$$\log\left[p_i/(1 - p_i)\right] = Z = a + \sum_{i=1}^{k} b_i X_i \tag{2.3}$$

Equation (2.3) is known as the general equation of logit regression and can be estimated. In this study, the dependent variable (z); The logarithm is the ratio of the probability of financial distress of companies to their lack of financial distress, independent variables (Xi) also include macroeconomic variables and the management system of companies. To evaluate the effect of changing each of the independent variables (Xi) on the probability of financial distress (E(Y=1IXi)), it should be derived from the cumulative distribution function (relation (2.2)) with respect to Xi. In this case, the following function is obtained, which is known as the final effect or marginal effect function.

Model (4):

$$\frac{\partial p_i}{\partial X_j} = b_j \left(\left(e^{a+\sum_{i=1}^{k} b_i X_i} \right) / \left(1 + e^{a+\sum_{i=1}^{k} b_i X_i} \right)^2 \right) \tag{2.4}$$

2.8 Financial distress risk

Altman is the first person who presented multivariate bankruptcy prediction models. By applying the method of multiple audit analysis and using financial as independent variables, he sought to predict the bankruptcy of companies. He presented his famous model called Z-score model, which is famous in the field of bankruptcy prediction. Among the twenty two financial ratios, Altman selected five ratios and included them in his model, which in his opinion were the best variables for predicting bankruptcy [25].

Model (5):

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{2.5}$$

where:

$$X_1 : \frac{\text{Working capital}}{\text{Total assets}},\ X_2 : \frac{\text{Retained}}{\text{Total assets}}, X_3 : \frac{\text{Profit before interest and tax}}{\text{Total assets}},$$
$$X_4 : \frac{\text{Market value of equity, book}}{\text{Value of total liabilities}},\ X_5 : \frac{\text{Sale}}{\text{Total assets}}.$$

Model (6):

$$Z^{'} = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \tag{2.6}$$

where:

$$X_4 : \frac{\text{Book value of equity, book}}{\text{Value of total liabilities}}$$

In this model, the lower the Z-score, the greater the financial distress of the company. Companies with a Z-score higher than 2.9 are considered healthy and safe, and those with a Z-score less than 1.23 are classified as bankrupt companies. A Z-score between 1.23 and 2.9 is considered a zone of doubt and should be interpreted with caution. Altman achieved 94% correct prediction with this model.

3 Research methodology

3.1 Population and statistical sample

The statistical population investigated in this research is the companies admitted to the Tehran Stock Exchange. The time domain of this research is from 2006 to 2019.

The "general criteria" for sample selection are as follows:

The information required to calculate the research variables about those companies is available during the research period and the company's financial year ends on March 29 and the company has not changed its financial year during the study period, as well as financial intermediary companies such as investments and banks are excluded due to their special nature.

The "specific criteria" for selecting helpless companies are as follows [18]:

Specific criteria for financial distress	Number of companies
-1 Three consecutive years of losses	43
-2 More than 40% decrease in annual cash profit compared to last year	11
3- Less than 80% of the profit before interest, tax and depreciation of the interest expense for two consecutive years.	77
4-Negative stock returns with a decrease of more than 30% along with negative sales growth	151
5- The book value of each share is smaller than the par value of stock.	52
Total	334

Out of 334 companies, 166 companies are eliminated due to duplication because the mentioned 166 companies had more than one scale of financial distress. After determining 168 samples of distressed companies, peer companies have been selected as non-distressed (healthy) companies as much as possible based on industries and market values close to distressed companies.

3.2 Research process

First step: document study to extract financial distress variables identified in previous years. These variables are placed in three categories: 1. Accounting ratios 2. Market variables 3. Macroeconomic variables.

The second step: measuring the probability of financial distress using Merton's model

The third step: applying the step-by-step regression method to identify variables affecting financial distress

The fourth step: applying logit analysis to provide a combination model to predict financial distress in the Tehran Stock Exchange.

The fifth step: measuring financial distress by applying the binary logistic regression model, where the economic variables and the stock market were added step by step to the financial variables.

Sixth step: testing the validity and accuracy of combined financial distress prediction models, Merton and binary logistic regression for each of the selected companies admitted to the Tehran Stock Exchange.

3.3 Variables and how to measure

The independent variables in the combined model are classified into three groups: fundamental or financial variables, market variables and macroeconomic variables.

The financial ratios of this research are: working capital to total assets, debt ratio, current ratio, gross return on assets, return on assets, asset turnover, current ratio, accumulated profit to total assets, operating profit to sales (operating profit margin), firm size, return on equity, profit to sales (net profit margin), coverage ratio, debt to equity, operating cash flow to total liabilities, investing cash flow to total liabilities, financing cash flow to total liabilities.

The economic variables of this research are: inflation rate, GDP growth, pertol price, gold price.

The variables based on the stock market of the current research are: P/S, P/B, market added value and value index (value of entity to profit).

Dependent variable: Financial distress has been investigated as a dependent variable. A value of one is assigned to companies that are determined to be financially distress based on the specific criteria mentioned, and a value of zero is assigned to other companies.

β_1 until the β_{17} Financial Ratio β_{18} to β_{21} Macroeconomic variables and β_{22} to β_{25} The variables are based on the stock market.

4 Data analysis

4.1 Accounting model to predict financial distress

One of the most common models for measuring financial distress is the regression model. In the logistic regression (LR) technique, a concept called the superiority ratio (the ratio of the probability of occurrence pi to the probability of non-occurrence 1-Pi) is used, and the logarithm of this ratio is calculated based on the following relationship. This model is known as the logit model.

$$L_i = \ln\left(\frac{p_i}{1-p_i}\right) = Z_i = \beta_0 + \beta_i x_i \tag{4.1}$$

The binary logistic regression model of the present study is as follows:

$$P(DISTRESS) = 1/\left\{1+\exp\left[-\left(\begin{array}{l}\beta_0+\beta_1 WC/TA+\beta_2 DR+\beta_3 CR+\beta_4 EBIT/TA\\ +\beta_5 ROA+\beta_6 ATR+\beta_7 AR+\beta_8 RE/TA+\beta_9 OIM\\ +\beta_{10} FIRMSIZE+\beta_{11} ROE+\beta_{12} NI/S+\beta_{13} ICR\\ +\beta_{14} TD/TE+\beta_{15} OCF/TL+\beta_{16} ICF/TL\\ +\beta_{17} FCF/TL+\beta_{18} IR+\beta_{19} GDPC+\beta_{20} PP\\ +\beta_{21} PGC+\beta_{22} P/B+\beta_{23} P/S+\beta_{24} MVA+\beta_{25} VP\end{array}\right)\right]\right\} \tag{4.2}$$

Table 1: introduction of research variables

type	Variables	Explanation and how to calculate variables
	P(DISTRESS)	The probability that a company will experience financial distress
	DISTRESS	1 if the company is financially distress and 0 otherwise
	Exp	exponential function
Financial ratio	WC/TA	Working capital to total assets
	DR	A debt ratio that equals total liabilities to total assets
	CR	A current ratio that equals current assets to current liabilities
	EBIT/TA	Earnings before interest and taxes on total assets
	ROA	Return on assets, which is equal to the net profit of total assets
	ATR	Turnover of total assets which is equal to sales to total assets
	AR	acid ratio
	RE/TA	Retained earnings on total assets
	OIM	Operating income to sales (operating income margin)
	FIRMSIZE	with the natural logarithm of the total assets of each firm
	ROE	Return on equity, which is equal to net profit to equity
	NI/S	Net income to sales (net profit margin)
	ICR	Earnings before interest and taxes on interest expense
	TD/TE	Total debt to total equity
	OCF/TL	Operating cash flow to total liabilities
	ICF/TL	Investing cash flow to total liabilities
	FCF/TL	Financing cash flow to total liabilities
Macroeconomic variable	IR	Inflation rate
	GDPG	GDP growth
	PP	petrol prices
	PGC	gold price
Stock market variable	P/B	Market price to the book value of per share
	P/S	Market price to sell
	MVA	market value (MV) - capital employed in the company (Capital) market value = book value of liabilities + market value of equity (market value of per share x number of company shares))
	VP	value to profit $\frac{(Total\ shares\ \times\ shares\ price)\ +\ debt-cash-quick\ transaction\ of\ capital\ transfer}{\text{Net profit + financial expense}}$

4.2 A market-based model (structural) of predicting financial distress

Merton's approach [21], follows the logic of the Black-Scholes option pricing method; In this way, the company's equity is considered as a European call option, whose basic asset is the company's total assets, its agreed price is equal to the nominal value of the company's total debts, and the date of its application is the maturity of the company's debts (T). At time T, if the value of the company's assets is greater than the nominal value of its debts, the shareholders exercise their purchase option and pay the company's creditors; Otherwise, that is, when the value of the company's assets is not enough to pay its debts, shareholders do not exercise their purchase option and financial distress occurs [13]. Merton's approach is referred to as "structural approach"; Because the company's capital structure is relied to model credit risk.

Due to the unobservability of asset market value variables and asset volatility and the difficulty and inaccuracy of simultaneous equation calculations of two unknowns, the criterion proposed in this article to estimate the default probability is the model of Li and Andreeva [17], which is a simple approach of the model It is a structure of Black and Schulz-Merton and calculates the probability of default according to the following relations:

$$\sigma_{\mathrm{D}}= 0.05 + 0.25\sigma_{\mathrm{E_{it}}} \tag{4.3}$$

$$\sigma_{V_{it}} = \frac{E_{it}}{E_{it}+F_{it}}\sigma_{E_{it}} + \frac{F_{it}}{E_{it}+F_{it}}\sigma_D \tag{4.4}$$

$$P_{edf\ \ it} \ = N\ (-\frac{\ln\left(\frac{E_{it}+F_{it}}{F_{it}}\right)+\left(r_{i\ t-1}-\frac{\sigma_{vit}^2}{2}\right)}{\sigma v_{it}\sqrt{T}} \tag{4.5}$$

E_{it}= The market value of the company's shares at the end of the year t

$\sigma_{V_{it}}$= Approximate volatility of company value at the end of the year t

F_{it}= The nominal value of the company's debts at the end of year t (equal to the sum of short-term debt and *50%* of long-term debt)

N (0) = Cumulative probability of normal distribution

T= Maturity period (considered equal to one year)

$r_{i\ t-1}$= Annual return on stock of company i per year t-1

$\sigma_{E_{it}}$= Volatility of stock returns of company i in year t (calculated using the standard deviation of monthly stock returns of the company in year t-1.

σ_D= Deviation of debts which was calculated through equation (4.3)

Equations (4.3), (4.4) and (4.5) have been used to calculate the distance to default. Debt volatility is estimated according to equation (**??**) and company volatility is estimated as the weighted average of equity value and debt volatility is estimated according to equation (4.4).

The above model is programmed using SAS 9,1 software.

4.3 A combination model to predict financial distress

In an effort to increase the predictive power of a company's financial distress, this article presents a combination model that combines two sets of information: the information obtained from the fundamental model and the information obtained from the market-based model. In the present study, it is believed that the combination of these two approaches may increase the predictive power of the combined model; Because each approach contains information about the company's specific credit risk that is not considered by the other approach. Li and Miu [16], confirm that many studies have shown that investors and financial institutions rarely use a single approach to make decisions, but combine different sources of information to achieve their credit risk assessment.

In the design of the combined model in this study, the binary logistic regression model is combined with the Merton model. To achieve this combination, the default probability variable obtained from the Merton model is added to the independent variables used in binary logistic regression.

The combined model of the current research is as follows:

$$P(Y_{it+1} = 1/Y_{it+1} = 0) = \frac{1}{1 + \exp(-\alpha_t - \beta x_{it})} \tag{4.6}$$

$$P(DISTRESS) = 1/\left\{1 + \exp\left[-\left(\begin{array}{l}\alpha_t + \beta_1 FINR_{i,t} + \beta_2 MARK_{i,t} + \\ \beta_3 MACRO_{i,t} + \beta_4 P_{def\ it}\end{array}\right)\right]\right\} \tag{4.7}$$

P (DISTRESS) = The probability of financial distress

$FINR_{i\ t}$= Financial ratios in company i for time period t

$MARK_{i\ t}$ =Market variables in company i for time period t

$MACRO_{it}$= Macroeconomic variables in company i for time period t

$P_{def\ it}$ = Default probability of company i for time period t

5 Findings

Before testing the main hypotheses of the research, using the Mann-Whitney test, the correctness of separating the companies into two distress and non-distress groups was investigated. The results of test show the difference is significant. This shows the correctness of the specific criteria used to separate the companies into distress and non-distress.

After determining the correctness of separating the companies into two distress and non-distress groups, it has been explained and prioritized the indicators affecting financial distress using step-by-step regression.

The selected independent variables were implemented in the form of binary logistic regression and Merton and combination statistical methods using Excel 2016, SAS 9.1, SPSS 25 and R software.

5.1 Collinearity test of variables

As can be seen in table (2), the values of the variance inflation factor are all less than 5 and the tolerance values are all greater than 0.2, and this indicates the absence of collinearity problems between the selected independent variables.

Table 2: Test collinearity of variables

	Variance inflation factor	tolerance
Gross return on assets	1/626	/0615
return on assets	1/622	/0616
Investment cash flow to total liabilities	1/009	/0991
gold price	1/005	/0995

5.2 Binary logistic regression model

According to table (3), the Coefficient of Determination model despite financial variables 24.5% and despite financial and economic variables 24.5% and despite financial, economic and stock market variables is 24.3%; This means that 24.5, 24.5 and 24.3 percent of financial distress can be predicted using model variables. Considering that the calculated probability value of the model is less than 0.05, therefore the model is statistically significant and suitable.

According to the probability values in the above table, despite the financial variable, the variables of intercept, asset return and net profit margin are not significant in the model, and the independent variables of working capital, total assets, total asset turnover, gross asset return have negative power. which shows the opposite effect of these variables on the probability of default. The variable of investment cash flow and total liabilities have a positive effect on the probability of default.

Despite the financial and economic variable, the asset return variable, total asset turnover, net profit margin, and width from the origin are not significant in the model, and the independent variables, gross asset return, total assets working capital have negative power, which indicates the opposite effect of these variables. It is on the probability of default and the variable of investment cash flow to total liabilities have a positive effect on the probability of default.

Despite the financial, economic and stock market variables, the variables of asset return and investment cash flow to total liabilities and intercept are not significant in the model, and the independent variables of working capital total assets and gross asset return have negative power which shows the opposite effect of these variables on the probability of default.

5.3 Merton model

According to table (4), the probability of the model is smaller than 0.05, so the model is statistically significant and appropriate. In the year of distress, according to the probability values, the width variable is not significant, but the probability of default is significant. The determination coefficient of the models in the year of distress is calculated to be 4.2%; This means that 4.2% of financial distress can be predicted using the default variable.

5.4 Combination model

According to table (5), the determination coefficient of the model is calculated as 22.8% in the year of distress. Considering that the calculated probability value of the model is less than 0.05, therefore the model is statistically suitable. According to the probability values in the above table, in the year of distress, the variables of intercept and asset return and gold price are not significant. The independent variable of gross return on assets has a negative power, which indicates the inverse effect of this variable on the probability of default. That is, with the increase of this variable, the probability of default decreases and inverse. The variable of investment cash flow and total debt has a positive effect on the probability of default. This means that with the increase of this variable, the probability of default also increases and inverse.

Test of the first hypothesis

According to tables (3) and (6), the coefficient of determination and percentage of correct prediction of the logistic model is 24.5% and 70.1% with the presence of better financial variables, and after adding economic variables, the

Table 3: Binary logistic regression model

Financial variable		**Variable**	**Coefficient**	**The standard deviation**	**wald statistics**	**significant**	**odds ratio**
	the level 12	Working capital to total assets	572/0-	0/173	10/909	0/001	0/771
		Gross return on assets	652/0-	0/221	8/723	0/003	0/521
		return on assets	-3/77	0/272	1/919	0/166	0/686
		Total asset turnover	-0/244	0/143	2/930	0/087	0/783
		Net profit margin	-141/299	90/550	2/435	0/119	0/000
		Investment cash flow to total liabilities	2/864	1/509	3/603	0/058	17/535
		intercept	-7/814	5/026	2/417	0/120	0/000
		The coefficient of determination	0/245				
		Probability model	0/000				
Financial and economic variable		Variable	Coefficient	The standard deviation	wald statistics	significant	odds ratio
	the level 16	Working capital to total assets	-0/572	.0/173	10/909	0/001	0/771
		Gross return on assets	-0/652	0/221	8/723	0/003	0/521
		return on assets	-0/377	.0/272	1/919	0/166	0/686
		Total asset turnover	-0/244	0/143	2/930	0/087	0/783
		Net profit margin	-141/299	90/550	2/435	0/119	0/000
		Investment cash flow to total liabilities	2/864	1/509	3/603	0/058	17/535
		intercept	-7/814	5/026	2/417	0/120	0/000
		The coefficient of determination	0/245				
		Probability model	0/000				
Financial, economic and stock market variable		Variable	Coefficient	The standard deviation	wald statistics	significant	odds ratio
	the level 9	Working capital to total assets	-0/664	0/194	11/778	0/001	0/943
		Gross return on assets	-0/585	0/288	4/123	0/042	0/557
		return on assets	-0/688	0/409	2/827	0/093	.503
		Investment cash flow to total liabilities	3/162	1/697	3/472	0/062	23/620
		intercept	0/066	0/190	0/122	0/727	1/068
	The coefficient of determination		0/243				
	Probability model		0/000				

coefficient of determination and percentage of correct prediction is still 24.5%. and it is 70.1%, and by adding stock market variables, the coefficient of determination and percentage of correct prediction decreases to 24.3% and 68.5%. Considering that with the addition of economic variables, the coefficient of determination and the percentage of correct prediction remained constant and with the addition of stock market variables, the coefficient of determination and the percentage of correct prediction decreased, the first hypothesis of the research is to increase the ability to predict the financial distress model by combining financial variables. , economic and stock market, is rejected.

Test of the second hypothesis

According to tables (4) and (6), the coefficient of determination and percentage of correct prediction of the combined

Table 4: Merton model

		Coefficient	The standard deviation	Wald statistics	significant	odds ratio
the level 1	probability of default	0/75	0/24	10/04	0/00	2/13
	intercept	-0/17	0/14	1/45	0/22	84/0
	coefficient of determination	0/042				
	Probability model	0/00				

Table 5: Combined model

		Coefficient	**The standard deviation**	**wald statistics**	**significant**	**odds ratio**
the level 19	Gross return on assets	26/1-	0/38	10/87	0/00	28/0
	Return on assets of investment cash flow to total debt	82/0-	0/49	2/82	09/0	28/0
	Return on assets of invested cash to total debt	7/52	2/49	9/09	00/0	1.84
	gold price	0/26	0/15	3/03	0/08	1/30
	intercept	0/13	0/24	30/0	58/0	1/14
	The coefficient of determination	228/0				
	Probability model	0/000				

model is 22.8% and 70.6%, and Merton BetterTib is 0.042% and 58%. The higher coefficient of determination and percentage of correct prediction of the combined model compared to the Merton model indicates that the distress prediction ability of the combined model is more than the Merton model. As a result, the second hypothesis related to the comparison of the combined model with the Merton model is confirmed.

Test of the third hypothesis

According to tables (5) and (6), the coefficient of determination and correct prediction percentage of the combined model is 22.8% and 70.6% and the best binary logistic regression model is 24.3% and 68.5%. Due to the higher coefficient of determination of the binary logistic regression model and the high percentage of correct prediction of the combined model, it is not possible to make a comparison between the combined model and the binary logistic regression model.

5.5 Prediction accuracy

The prediction accuracy of the aforementioned statistical methods is based on table (6).

Table 6: Percentage of correct predictions of the models

Model	Correct prediction percentage
Logistic regression with financial variables	1/70
Logistic regression with financial and economic variables	1/70
Logistic regression with financial, economic and stock market variables	5/68
Merton	0/58
combination	6/70

Based on the above table, the combined model has the highest percentage of correct prediction compared to the Merton model and logistic regression.

5.6 Comparison test of models

R programming software was used to compare the models. The summary of the results is as described in table (7).

Table 7: Comparison of models

	difference	probability value	Result
Combined model with Merton	40/3	000/0	combined> merton
Mixed model with logistic regression	-8/047	05/0<	Logistic regression = combined

Based on the difference between the models and their probability value, the combined model is better than the Merton model, but a comparison between the combined model and the binary logistic regression model cannot to perform comparison.

6 Discussion

Considering the importance of predicting financial distress, in this research, while presenting a combination model, in order to compare the said model with the models based on accounting data, the binary logistic regression model was used and to compare with the market-based model, the Merton model was used. In order to achieve the goal of the research, three hypotheses have been developed and tested. By adding economic variables to financial variables, the coefficient of determination and percentage of correct prediction remain constant, and by adding stock market variables to financial variables, the coefficient of determination and percentage of correct prediction decrease, as a result, adding economic variables and the stock market to financial variables dos not increases the ability to predict the financial distress of companies. which is in agreement with the research results of Yuliastari et al. [37], and against the research results of Fontaine et al. [28]. The coefficient of determination and percentage of correct prediction of the combined model is higher than that of Merton's model, which indicates that the combined model's ability to predict distress is greater than that of Merton's models. The comparison of the models with the R software also confirms this result. As a result, the greater ability of the combined model to predict financial distress compared to the Merton model is confirmed. A mixed model and logistic regression were performed. The high power of combination models has been confirmed in the studies of Bauer and Agarwal [4], charalamram Bakis et al. [8]. In general, it can be concluded that the combined model has better explanatory power than the Merton model and the binary logistic regression model. Considering that the overall performance of Merton's model, which is based on market variables, is weaker than the other two models, which are mainly composed of financial or accounting ratios, and also considering the results of past researches about proving the inefficiency of the stock market in Iran, it is suggested that in Future research in the field of predicting financial distress should use the combined model of the current research and the accounting model, and due to the existence of hidden values in companies, intellectual capital indicators and other non-financial variables affecting distress should be taken into consideration, along with financial variables. Also, improved structural models and other statistical methods such as genetic algorithm and adaboost were used and compared with the results of the combined model of the present study. The main limitation of the current research is the selection of healthy companies from companies in the same industry as financially distress companies. Due to the fact that in some industries there were not necessarily healthy companies in the number of financially distress companies, companies from other industries were inevitably used and due to the influence of non-financial variables such as intellectual capital, non-financial reporting and social responsibility, etc. on financial distress. companies, the non-financial variables in the current research cause the predictive power of the models to be lower.

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