Corporate Default Prediction among Tehran Stock Exchange's Selected Industries

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Abstract

This study aims to present a model for predicting corporate default among Tehran Stock Exchange's selected industries. To do this, corporate default drivers were identified and selected by referring to previous research findings and using experts' opinions. These drivers were divided into five categories: accounting ratios, market variables, macroeconomic indicators, nonfinancial factors, and earnings quality measures. Structural equation modeling (SEM) technique was used to derive the prediction model. In this technique, corporate default drivers were used as latent independent variables, and their constituent factors were considered as observable indicators of the above variables. In addition, corporate default, as the latent dependent variable, was calculated by a measure based on the Black-Scholes-Merton (BSM) option pricing model. After implementing structural equation modeling (SEM) technique by use of Smart PLS software, a prediction model that contains influential drivers of corporate default was derived and presented for each of the selected industries.

Key Words: *Corporate Default Drivers, Structural Equation Modeling, Black-Scholes-Merton Option Pricing Model.*

1. Introduction

One of the most important matters that financial market participants consider in their financing and investment decisions is access to transparent, accurate and relevant information. If the required information is distributed asymmetrically and unequally among financial market participants, investors increase the bid-ask spread. As a result, due to rising liquidity risk, the cost of capital for issuers of securities increases and market depth decreases.

On the other hand, the success of capital market in allocating financial resources to various industries and sectors efficiently and optimally depends on the fact that suppliers of funds (investors), before investing in a particular firm, have enough information in relation to potential losses of financial distress and the firm’s failure to repay its debts.

Costs and risks inherent in the above event, which can be called corporate default (or corporate failure)[1], caused that the issue has been considered to be a significant one for all stakeholders, including creditors, banks, regulators, managers, auditors, shareholders, governments and credit rating agencies, and various models for predicting and measuring it have been devised and introduced over the past four decades (Wang, 2011).

Default is among the most abrasive events in the life of a corporation. It causes disruptions in productivity through supply chain interruptions and employee attrition, incurs legal and administrative costs, and harms customer retention. Default occurs when a firm’s cash flows are insufficient to cover its debt service costs and principal payments. Default risk increases when a firm’s average cash flow level shifts down and/or its cash flow volatility increases (Xia, 2016).

The occurrence of default imposes significant direct and indirect costs on firms, as well as on the society. Moreover, it has adverse consequences for financial and monetary institutions and the economy as a whole. In recent years, large defaults of big firms such as IndyMac, Hyundai Merchant Marine and Lehman Brothers negatively impacted the interests of their employees, shareholders, creditors, clients and suppliers. In severe cases, corporate default events contribute to a global financial crisis and economic recession fuelling speculation on sovereign default. On the other hand, misspecification of a healthy firm as being in financial distress can cause not only opportunity loss for creditors, but also market value reduction for investors and shareholders (Wang, 2011).

1. In this study, the words of financial distress, corporate default and corporate failure are considered as synonymous.

Accordingly, understanding and predicting corporate default has been an area of extensive research for at least 40 years. The evolving economic environment and advances in research methods have led to the introduction of numerous complex approaches, but there is still neither a common theoretical understanding, nor sufifcient empirical evidence about what triggers corporate default (Hazak & Männasoo, 2007).

The financial crisis of 2008 renewed researchers' interest in predicting corporate default. Timely prediction of failure of a business firm is an important issue in the present economic system, considering the effect of global financial crisis on the world's economy in the past decade (di Donato & Nieddu, 2016). The worldwide financial meltdown highlighted the weaknesses in risk models used in credit risk management (Jorion, 2009). The financial crisis resulted into many companies facing risk of failure around the world. The financial crisis highlighted that even the healthy global firms must frequently observe their financial position and of the firms with which they deal with (Korol, 2013).

When banks and other financial institutions are paying loans to firms, they have to value the risk of those firms. This is where the credit rating industry is giving its contribution (Stenbäck, 2013). In the market view, credit rating agencies are expected to be independent third parties in the borrower/lender relationship, which evaluate the financial condition of the debt issuer (Murcia et.al, 2014). These institutions need a model for predicting and measuring corporate default in order to determine issuer's financial solvency and its credit rating.

In addition, understanding the evaluation methods and driving factors of corporate default could help creditors maximize their profits. It could also help investors and assets managers reduce consequential losses on their portfolios, because an unsatisfactory financial condition would deteriorate a firm's performance (Opler & Titman, 1994). Forecasting corporate default rates accurately is a significant issue for the assessment of financial stability. Therefore, regulators and policymakers could benefit from accurate prediction models. For bankers, a well-preformed default risk prediction model could help avoid profit missing due to suboptimal capital allocation. Governments require an accurate prediction model to mitigate the effects of ill performing companies in terms of short-term operational and fundamental features. Shareholder return is driven by the firm's performance, capital structure and dividend strategy. Lastly, auditors could be empowered to run a more adequate assessment of the firm's health and provide early warning signals through strengthened default prediction processes (Wang, 2011).

Regarding the great importance of corporate default prediction for different stakeholders, this research is to identify its potential drivers and to present a model for predicting this event among the selected industries in Tehran Stock Exchange.

2. Literature Review and Background of the Study

2.1. Measuring Corporate Default

Corporate default, which can be defined as the company's inability to meet its obligations and repay its debts, has been estimated by different measures. The most common ones are accounting-based measures such as Altman's Z-score (Altman, 1968) or Ohlson's O-score (Ohlson, 1980), credit ratings, debt differentials, and market-based measures based on the Black-Scholes-Merton (BSM) option pricing model (Abinzano et al., 2014).

Nevertheless, according to Hillegeist et al., (2004), there are several reasons to question the effectiveness of those measures of default risk that use accounting data. First of all, companies' financial statements are prepared to measure the past performance, and they might not offer much information about the future prospects. Moreover, a company provides its accounting statements on the basis of going concern principle, assuming the company will never go bankrupt.

Another major drawback of these measures is their failure to consider asset volatility, which leads them to conclude that firms with similar ratios will have exactly the same bankruptcy probability. However, volatility is an essential variable in predicting default risk, because it reveals the possibility of company's assets insufficiency to cover its obligations. *Ceteris paribus*, the higher the volatility of a company's asset value, the greater its default risk.

In addition, the use of credit rating as a measure for calculating default risk might be problematic. First of all, a company's credit worthiness can change significantly before readjustment of its credit rating. Secondly, the use of credit rating to determine default risk implies that two companies with similar credit rating will have similar default risk. Nevertheless, as Crosbie and Bohn (2003) have shown, the bonds belonging to a same credit class might have different default rates. Furthermore, it cannot be ignored that there is no available credit rating for some market stocks, particularly the small ones, and that this can lead to a size biased sample.

An alternative for the mentioned default risk estimating methods is a measure using company's market share prices and is used in the Moody's KMV model and in studies of Vassalou and Xing (2004), Byström et al., (2005), Byström (2006), Bottazzi et al., (2011), Li and Xia (2015). These series of studies start

from Merton's (1974) proposal, which considers a company's equity value as a European call option on its assets value and uses the Black-Scholes model (1973) to calculate the value (Abinzano et al., 2014).
Comparing to accounting-based models, the BSM model advantage is that it not only considers past information, but also regards investors' expectations toward stocks performance in the future, using their market prices. This model takes into account asset return volatility as well (Abinzano et al., 2014). Hillegeist et al., (2004) compare the model in this respect with Altman's Z-score (Altman, 1968) or Ohlson's O-score (Ohlson, 1980), and find that the BSM model provides more information about default risk; thus, they recommend the use of it instead of traditional accounting-based measures as a default risk proxy.

Since this model discounts expected future cash flows, therefore, comparing to credit rating as a basis for measuring default risk, the BSM model has the advantage of no time lag between variation in credit worthiness and considering it in the process of risk measurement. BSM is a company-specific model which calculates the value of the company based on its financial situation and capitalization, not on the basis of its credit
Rating; hence, it can present more finely tuned rankings.

As the last advantage, the BSM model uses the least information and measures value for every company, not just those which are credit rated. Finally, we should say that by
using the BSM model, it is possible to overcome some of the shortcomings related to credit spreads as a measure of default risk. We should also consider that it is usually easier to access a company's stock price data than its debt return data (Abinzano et al., 2014).

2.2. Corporate Default Drivers

Given the findings of past studies and by using experts' opinions, corporate default drivers can be divided into five categories: accounting ratios, market variables, macroeconomic indicators, nonfinancial factors and earnings quality measures.

2.2.1. Accounting Ratios

In previous studies, there are more than 185 different accounting ratios with significance in predicting corporate default. Table (1) displays accounting ratios that have shown to be significant in at least four papers published from 1960 to 2010 (Wang, 2011).

Table (1). Accounting Ratios Affecting Corporate Default

Accounting Ratio	Expected Sign
Net Income/Total Assets	Negative
Earnings before Interest and Tax/Total Assets	Negative
Earnings before Interest and Tax/Total Liabilities	Negative
Sales/Total Assets	Negative
Sales Growth Rate	Negative
Cash Flow from Operating Activities/Sales	Negative
Cash Flow from Operating Activities/Short-term and Long-term Loans	Negative
Cash Flow from Operating Activities/Total Liabilities	Negative
Cash Flow from Operating Activities/Total Assets	Negative
Retained Earnings/Total Assets	Negative
Current Assets/Current Liabilities	Negative
Quick Assets/Current Liabilities	Negative
Net Working Capital/Total Assets	Negative
Cash/Current Liabilities	Negative
Quick Assets/Total Assets	Negative
Current Assets/Total Assets	Negative
Current Liabilities/Total Assets	Positive
Cash/Total Assets	Negative
Total Liabilities/Total Assets	Positive
Short-term and Long-term Loans/Total Equity	Positive
Short-term and Long-term Loans/Total Assets	Positive
Market Capitalization/Total Liabilities	Negative
Market Capitalization/ Short-term and Long-term Loans[1]	Negative

Trujillo-Ponce et al., (2014) introduced the ratios of working capital to total assets, retained earnings to total assets, debt to equity, earnings before interest and taxes (EBIT) to total interest payments (interest coverage), and net income to total assets as influencing factors on credit risk in the European market during the period 2002-2009.

To examine the importance of cash flow ratios in determining financially distressed companies, Fawzi et al., (2015) analyzed the data of 52 distressed and 52 non-distressed Malaysian companies for three years prior to distress years between 2009 until 2012. The results found that five cash flow ratios including cash flow from operating activities to total liabilities, cash flow from operating activities to long-term liabilities, cash flow from operating activities to total revenue, cash flow from operating activities plus interest expense to interest expense, and cash flow from investing activities to total liabilities are

1. It is worth noting that in this research the ratios of market capitalization to total liabilities and market capitalization to short-term and long-term loans are categorized as market variables.

significant predictors of financial distress with the overall predictive accuracy of 82.10 percent.

Using a sample of 1,022 German nonfinancial firms with equity listed in Frankfurt in the time period 1991-2015, Mertens et al., (2016) find that four ratios including current book assets divided by book value of total assets, retained earnings divided by book value of total assets, earnings before interest, taxes, depreciation and amortization (EBITDA) divided by book value of total assets, and market equity divided by book value of debt are significantly related to corporate default.

According to Gupta (2017), the ratios of profit after tax to capital employed, profit after tax to net worth, and earnings before interest and taxes (EBIT) to interest expense (interest coverage) are among the predictors of corporate default in India.

Vazifehdust & Zangene (2015) show that the ratios of earnings before interest and taxes (EBIT) to total assets, total liabilities to total assets, quick assets to current liabilities, and financial expenses to gross earnings are final determinants of the firm's bankruptcy in Tehran Stock Exchange.

Combining five accounting ratios (working capital to total assets, retained earnings to total assets, earnings before interest and taxes (EBIT) to total assets, sales to total assets, and total equity to total liabilities) with three market variables, and using artificial neural networks, Ramooz & Mahmoudi (2017) designed a model for predicting bankruptcy of firms listed on Tehran Stock Exchange which significantly outperformed accounting-based and market-based models.

2.2.2. Market Variables

The most commonly used market variables in predicting and measuring corporate default are stock return, stock return volatility, market return and market return volatility. Table (2) presents market variables used and found to be significant in previous studies. These variables can be grouped into six categories: Stock return, stock return volatility, stock price, market capitalization, market to book ratio, and earnings per share (EPS) (Wang, 2011).

Table (2). Market Variables Affecting Corporate Default

Market Variable	**Expected Sign**
Stock Return	Negative
Difference between Stock Return and Market Return (Excess Stock Return over Market Return)	Positive
Standard Deviation of Stock Return	Positive
Stock Price Gap	Positive
Stock Price Trend	Positive
Stock Price	Negative
Log of Stock Price	Negative
Market to Book Ratio	Negative
Log of Firm Market Capitalization	Negative
Log of Firm Market Capitalization over Total Market Capitalization of Listed Firms on Stock Market	Negative
Earnings per Share (EPS)	Negative

Using a sample of 23,218 company-year observations of listed firms during the period 1980-2011, Tinoco & Wilson (2013) found that three market variables including firm's equity price, lagged cumulative security residual return, and the ratio of market capitalization to total debt are powerful and consistent predictors of corporate default two years prior to the observation of this event.

According to Christidis & Gregory (2010), total liabilities over market capitalization, log of excess return (difference between stock return and FTSE All Share Index), cash flow over market value of total assets, standard deviation of stock return over the previous six-month period, stock price, net income over market value of total assets, log of firm market capitalization over total market capitalization of FTSE All Share Index, total liabilities over market value of total assets, working capital over market value of total assets, and book to market ratio are significantly correlated with financial distress.

Fernandez (2012) concluded that stock price, standard deviation of stock price, and the bid-ask spread are among variables that best discriminate between bankrupt and non-bankrupt firms. Li & Xia (2015) showed that firms with more liquid stocks have lower default risk. Brogaard et al., (2017) examined the impact of stock liquidity on firm bankruptcy risk. They found two mechanisms through which stock liquidity reduces firm default risk: improving stock price informational efficiency and facilitating corporate governance by block holders. Moreover, according to their findings, of the two mechanisms, the informational efficiency channel has higher explanatory power than the corporate governance channel.

Feizmohammadi (2014) used 1,025 company-year observations of listed firms on Tehran Stock Exchange during the period 2004-2013 and found that, unlike accounting ratios, market variables contain information that increases the predictability of bankruptcy. Using sixty nine accounting ratios and market variables [including market capitalization, stock price, earnings per share (EPS), and dividend per share (DPS)] as initial predictors, Namazi et al., (2017) confirmed the usefulness of variable selection methods such as T-test, Stepwise Discriminant Analysis, Factor Analysis, Relief, Wrapper and Support Vector Machine (SVM) in financial distress prediction of the firms listed on Tehran Stock Exchange.

2.2.3. Macroeconomic Indicators

Table (3) presents the most significant macroeconomic indicators used in previous studies on corporate default. These indicators can be divided into four categories: stock market information, economic cycle, yield on debt securities and interest rates, and bank lending and investment conditions (Wang, 2011).

Table (3). Macroeconomic Indicators Affecting Corporate Default

Stock Market Information
Stock Market Return
Standard Deviation of Stock Market Return
Economic Cycle
Consumer Price Index (CPI)
Producer Price Index (PPI)
Gross National Product (GNP)
Gross Domestic Product (GDP)
Unemployment Rate
National Income (NI)
Real Imports of Goods and Services
Real Exports of Goods and Services
Industrial Production Index
Yield on Debt Securities and Interest Rates
Effective Federal Funds Rate
Bank Prime Loan Rate
Short-term Certificate of Deposits: Secondary Market Rate
Short-term Treasury Bills: Secondary Market Rate
Midterm Treasury Bills: Constant Maturity Rate
Long-term Treasury Bills: Constant Maturity Rate
Difference between Constant Maturity Rate of Long-term and Midterm Treasury Bills
Moody's Seasoned Aaa Corporate Bond Yield
Moody's Seasoned Baa Corporate Bond Yield
Difference between Moody's Seasoned Aaa and Baa Corporate Bond Yields
Difference between Constant Maturity Rate of Long-term Treasury Bills and Moody's Seasoned Baa Corporate Bond Yield
Bank Lending and Investment Conditions
Total Loans and Leases at Banks
Total Investments at Banks
Total Public Debts
M1 Money Stock
M2 Money Stock

Using a dataset of 859 firms panning across 10 sectors during a ten-year time period from April 1, 2000 to March 31, 2015, Gupta (2017) showed that exchange rate, GDP growth rate, and return on Bombay Stock Exchange (BSE) are among the key predictors that can explain default risk for Indian listed firms. Kim & Sohn (2008) noted that discount rate, unemployment rate and GDP growth rate have high correlations with credit rating downgrades and default probabilities.

Bhattacharjee et al., (2009) introduced volatility of exchange rate and retail price index (RPI) as factors that increase the likelihood of exit of firms. According to Hill et al., (2011), there is a significant relationship between financial distress risk and unemployment rate. Qu (2006) analyzed the relationship between certain macroeconomic factors and the probability of default on an industrial level from April 2000 to September 2005. This study verified, in Sweden, changes in macroeconomic factors such as industrial production index, interest rate spread, exchange rate and stock price[1] affect the probability of default.

Using rating transition and default data of U.S. corporates over the period 1980-2005, Koopman et al., (2009) claimed that GDP growth, short-term interest rates, default spread, and the volatility of the market returns are among significant variables in the duration model. Mishra (2013) examined the link between macroeconomic variables and the corporate health indicator (in the form of Z-scores) of the Indian manufacturing firms under BSE 200 during 1990 to 2009. His findings revealed the existence of a two-way causal relationship between Z-score and GDP, bank rate, wholesale price index (WPI) and trade openness.

Taremi & Khodaverdi (2015) indicated that an increase in inflation rate and bank deposit interest rate leads to an increase in the probability of financial distress. Furthermore, they found that the volume of bank loans, the economic growth, the real stock price index and the real stock return are significantly negatively related to the probability of financial distress in pharmaceutical firms listed on Tehran Stock Exchange. According to Sadeghi et al., (2015), income per capita, economic growth rate and inflation rate are as affecting factors on financial distress.

Payam & Setayesh (2015) evaluated the impact of macroeconomic variables on the bankruptcy risk of firms listed on Tehran Stock Exchange. The study sample consisted of 122 firms over the period 2005-2014. Their findings showed that, among five macroeconomic variables including market discount

1. It is worth noting that in this research stock price is categorized as a market variable.

rate, inflation, change in oil prices, gold coin prices and stock price index, only change in oil prices is significantly correlated with bankruptcy risk.

2.2.4. Nonfinancial Factors

Nonfinancial factors suggested to be significant in previous studies are firm age, the number of firm employees, and firm size (Wang, 2011). However, there are other nonfinancial factors that may affect corporate default.

Switzer et al., (2016) found that there is a positive and significant relationship between firm age and default risk. Nevertheless, according to Atsu & Costantini (2015), firm age is significantly negatively correlated with corporate failure of UK public listed firms. Wijn & Bijnen (2001) showed that the number of firm employees affects its probability of financial distress. Pervan & Visic (2012) and Situm (2014) introduced firm size as a relevant predictor for bankruptcy. Giordani et al., (2014) noted that firm size (log of total sales) has a negative impact on bankruptcy risk, but the relationship between firm age and bankruptcy risk is hump-shaped. Aleksanyan & Huiban (2016) suggested that smaller and younger firms are more vulnerable to bankruptcy. Amendola et al., (2015) showed that some characteristics, such as age, legal form and size of the firm inlfuence its probability of being inactive and liquidated.

Gilson (1989) found that senior management change has a relationship with default action. According to Lussier & Halabi (2010), total years of education, difficulty of staffing, whether they have specific plan and professional advice are key variables in measuring a small business success. Camacho-Miñano & Moreno (2016) analyzed the content of management reports of the bankrupt listed firms in Spain in two moments of time, the last year just before entering into the legal bankruptcy procedure and five years earlier. Their findings showed that two textual characteristics of management reports, i.e., length and negative references could function as a warning of bankruptcy situations. Gitman (1998), Berryman (1983), Gaskill et al., (1993), Ooghe & De Prijcker (2008), Pretorius (2009), Wu (2010) and Arasti (2011) believed that one of the most important reasons for bankruptcy is poor management.

Banerjee et al., (2008), Kale & Shahrur (2007) and Titman (1984) argued that a firm with customer-supplier relationships often must undertake relationship-specific investments, which will in turn, lead to higher financial distress costs. According to Wang (2012), firm's dependence on small number of major customers/suppliers affects its probability of financial distress. Cornaggia et al., (2017) found that firms with higher ability managers obtain more favorable credit ratings.

Mardani et al., (2016) found that firm size has a statistically significant relationship with financial distress. However, there is no correlation between firm age and financial distress. Namazi & Ghadiryian Arani (2014) stated that there is a negative correlation between firm size and bankruptcy risk. Hozhabri (2016) indicated that firm life cycle is significantly related to financial distress. According to Hajeb et al., (2014), the higher the managerial ability, the lower the firm's probability of going bankrupt. Karami (2017) showed that managerial ability and financial flexibility are significantly negatively related to financial distress.

2.2.5. Earnings Quality Measures

Earnings quality is a concept which has different aspects, and hence various definitions and criteria have been proposed in relation to it. Earnings quality is an important aspect of evaluating an entity's financial health, yet investors, creditors, and other financial statements users often overlook it.

According to Bellovary et al., (2005), earnings quality refers to the ability of reported earnings to reflect the firm's true earnings, as well as the usefulness of reported earnings to predict future earnings. It also refers to the stability, persistence, and lack of variability in reported earnings. Schipper & Vicent (2003) defined earning quality as the degree to which reported earnings of entity truly reflects the Hicksian income. Earnings quality is, under this definition, measured with reference to Hicksian income where the closeness of earnings to Hicksian income infers higher quality. Srinidhi et al., (2011) described earnings quality as the ability of current reported earnings to reflect the future cash flow and earnings. In this context, earnings quality refers to how best current reported earnings can predict future performance of an entity.

According to Francis et al., (2004) and Li et al., (2013), the most important criteria for assessing earnings quality are accrual quality, persistence, predictability, smoothness, value relevance, timeliness, and conservatism. These researchers characterized the first four criteria as accounting-based because they are typically measured using accounting information only, and the last three criteria as market-based because proxies for these constructs are typically based on relations between market data and accounting data.

Charitou et al., (2011) showed that the relation between earnings quality and financial health is not monotonic. Distressed firms have a low level of earnings timeliness for bad news and a high level for good news, and manage earnings toward a positive target more frequently than healthy firms. On the other hand, healthy firms have a high level of earnings timeliness for bad news. Ke (2012) investigated the role of earnings quality in the prediction of financial distress and found that earnings quality is positively associated with the informativeness of both accounting- and price-based distress predictors, and negatively associated with distress risk, itself. Furthermore, he showed that incorporating the impact of earnings quality improves prediction models' out-of-sample performance, especially when the forecast horizon is longer than one year.

Persakis & Iatridis (2015) examined earnings quality by using conservatism, value relevance, accruals quality, earnings persistence, earnings predictability, loss avoidance analysis, and earnings smoothness, and indicated that during the global 2008 financial crisis, earnings quality is decreased. Li et al., (2013) investigated the relation between earnings quality and stress levels of Chinese firms listed on Shanghai and Shenzhen stock exchanges from 2003 to 2007 by classifying them as financially stressed and bankrupt (SB), financially stressed and not bankrupt (SNB), and not financially stressed and not bankrupt (NSNB) firms. These researchers measured earnings quality by four separate attributes: accruals quality, earnings persistence, earnings predictability, and earnings smoothness. They found that earnings quality levels are parallel to firm's stress levels: the SB firms have the lowest earnings quality measured by each of the four earnings attributes, the SNB firms have a lower earnings quality compared with the SB firms, and the NSNB firms have the highest earnings quality.

Using a large sample of UK bankrupt firms, García Lara et al., (2009) showed that failed firms manage earnings upwards in four years prior to the failure. This manipulation is achieved in two ways: (1) through accounting (accruals) manipulation; and (2) by implementing real operating actions that deviate from normal practice. They indicated that these two types of manipulation lead to reduced earnings reliability. According to Li et al., (2014), accruals quality, earnings predictability, and earnings smoothness are significantly different between healthy and bankrupt firms. Howe & Houston (2016) examined the propensity of distressed firms to manage earnings and the impact of their earnings management on investor response to earnings. They found that distressed firms manage earnings upward and downward more than non-distressed firms. Moreover, their results suggested that earnings management by distressed firms lowers earnings quality and weakens investor response. Fischinger (2017) analyzed the relationship between earnings quality and credit access on a balanced sample of 4,715 public and private European companies over a seven-year period (2009-2015). Her findings suggested that firms with high-quality earnings and financial reporting are less informationally opaque, their bankruptcy costs are lower, and thus benefit from enhanced access to external credit.

Kordestani & Tatli, (2014) showed that bankrupt firms have the lowest, and healthy firms have the highest earnings quality. According to Ebrahimi et al., (2017), earnings persistence and earnings predictability are significantly correlated with financial crisis of firms. Mashayekhi & Ganji (2014) and Delkhosh & Malek (2016) stated that earnings quality is an effective factor in predicting corporate bankruptcy. Ahmadpour et al., (2016) confirm the significant impact of accrual quality, earnings persistence, and earnings predictability on the bankruptcy risk. Mehrani et al., (2017) asserted that financially distressed firms have a lower earnings quality compared with healthy firms.

3. Research Methodology

To present a model for predicting corporate default in Tehran Stock Exchange, by choosing the period 2005-2016, three industries that are more exposed to the attention of market participants (in terms of trading volume and turnover) and have the largest number of listed firms were selected (apart from industries such as banks and credit institutions, insurance and pension funds, investments, industrial conglomerate and other financial intermediaries, whose unusual features of capital structure and their different financial reporting practices can distort data related to corporate default and its potential drivers). These industries are: (1) automotive and auto parts manufacturing industry, (2) pharmaceuticals industry, and (3) cement, lime and plaster industry.

Firms in each industry were sampled by the systematic exclusion method. Sampling conditions were as follows: (a) sampled firms need to be listed and quoted on Tehran Stock Exchange prior to 2005, (b) their fiscal year should conclude on March 20, (c) during the period 2005-2016, their fiscal year should not be changed, (d) in the period 2005-2016, their shares need to be traded for at least three months in each year, (e) they should not be considered as an investment or holding company, and (f) in the abovementioned period, their financial statements should be published on the Codal system.

After considering these conditions, 24 firms in automotive and auto parts manufacturing industry, 18 firms in pharmaceuticals industry, and 15 firms in cement, lime and plaster industry were selected.

3.1. Sources, Methods and Tools for Collecting Data

In this study, after conducting library research in order to identify and extract the drivers and factors affecting corporate default, experts' opinions about these drivers were obtained through the fuzzy Delphi method and questionnaire (in two rounds). Then, data related to corporate default and its drivers, among accounting ratios, market variables, macroeconomic indicators, nonfinancial factors, and earnings quality measures (according to experts' opinions) were extracted from the parent company's financial statements, the official website of Tehran Stock Exchange Technology Management Company (TSETMC), the Codal system and the official website of Iran Central Bank. After collecting the required data, a model for predicting corporate default in each industry was derived and presented using structural equation modeling (SEM) technique.

3.2. Research Questions

The first question: How is the corporate default prediction model?
The second question: Which accounting ratios affect corporate default in each of the selected industries?
The third question: Which market variables affect corporate default in each of the selected industries?
The forth question: Which macroeconomic indicators affect corporate default in each of the selected industries?
The fifth question: Which nonfinancial factors affect corporate default in each of the selected industries?
The sixth question: Which earnings quality measures affect corporate default in each of the selected industries?

3.3. Corporate Default Drivers Identified Using the Fuzzy Delphi Method

By conducting the fuzzy Delphi method in two rounds, it was revealed that, according to experts' opinions, of the 65 drivers of corporate default identified in previous studies,
33 drivers are known as factors affecting the prediction of this event in Iran. These factors are classified in Table (4)[1].

1. It is worth noting that in structural equation modeling (SEM) technique, the variables can be either latent or observable. Here, corporate default is the latent dependent variable which is considered as the second-order construct. Accounting ratios, market variables, macroeconomic indicators, nonfinancial factors, and earnings quality measures are latent independent variables, which are considered as the first-order constructs. Corporate default drivers are observable or manifest variables, which are regarded as indicators of latent independent variables.

Table (4). Factors Affecting the Prediction of Corporate Default in Iran

Latent Dependent Variable	Latent Independent Variables	Observable or Manifest Variables (Indicators)
Corporate Default	Accounting Ratios	Net Income/Total Assets Earnings before Interest and Tax/Total Assets Earnings before Interest and Tax/Total Liabilities Sales/Total Assets Sales Growth Rate Retained Earnings/Total Assets Current Assets/Current Liabilities Quick Assets/Current Liabilities Net Working Capital/Total Assets Cash/Current Liabilities Current Liabilities/Total Assets Total Liabilities/Total Assets Short-term and Long-term Loans/Total Equity Short-term and Long-term Loans/Total Assets Cash Flow from Operating Activities/Sales Cash Flow from Operating Activities plus Interest Expense/Interest Expense Cash Flow from Operating Activities/Earnings before Interest and Tax Cash Flow from Operating Activities/Short-term and Long-term Loans Cash Flow from Operating Activities/Total Liabilities Cash Flow from Operating Activities/Current Liabilities
	Market Variables	Market Value/Book Value Earnings per Share Market Capitalization/Total Liabilities Market Capitalization/Short-term and Long-term Loans
	Macroeconomic Indicators	Changes in Exchange Rate Changes in Consumer Price Index Changes in Term Deposit Rate Gross Domestic Product Growth Rate Changes in Bank Loan Interest Rate
	Nonfinancial Factors	Dependence on Small Number of Principal Customers
	Earnings Quality Measures	Earnings Persistence Earnings Predictability Earnings Smoothness

3.4. Measuring Corporate Default Probability

In this study, using Black-Scholes-Merton (BSM) option pricing model, and through the method of Hillegeist et al., (2004), corporate default probability was measured in SAS software.

An important observation in the BSM model is that equity can be viewed as a call option on the value of the ifrm's assets. Equity holders are the residual claimants to the ifrm's assets and are only subject to limited liability when the ifrm is bankrupt. Thus, the payoffs to equity mimic the payoffs for call options. Under the BSM framework, the strike price of the call option is equal to the face value of the ifrm's liabilities and the option expires at $t = T$ when the debt matures. At time T, equity holders will exercise their option and pay off the debt holders if the value of the ifrm's assets is greater than the face value of its liabilities. Otherwise, the equity holders will let their call option expire when the value of the assets is not sufficient to fully repay the ifrm's debts. In this case, the ifrm ifles for bankruptcy; ownership of the firm is assumed to be transferred costlessly to the debt holders, and the payoff for equity holders is zero. The probability of each outcome, of course, is an important determinant of the value of the call option, and these probabilities are embedded in the BSM model (Hillegeist et al., 2004).

The BSM equation for valuing equity as a European call option on the value of the ifrm's assets is given in Eq (1) below. This equation is modiifed for dividends and relfects that the stream of dividends paid by the ifrm accrues to the equity holders.

$$(1)\ V_E = V_A e^{-\delta T} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-\delta T}) V_A$$

Where $N(d_1)$ and $N(d_2)$ are the standard cumulative normal of d_1 and d_2, respectively, and

$$(2)\ d_1 = \frac{\ln\left[\frac{V_A}{X}\right] + (r - \delta + \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}$$

$$(3)\ d_2 = d_1 - \sigma_A \sqrt{t} = \frac{ln\left[\frac{V_A}{X}\right] + (r - \delta - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}$$

V_E is the current market value of equity; V_A is the current market value of assets; X is the face value of the liabilities maturing at time T; r is the continuously-compounded risk-free rate; δ is the continuous dividend rate expressed in terms of V_A, and σ_A is the standard deviation of assets returns (Hillegeist et al., 2004).

Under the BSM model, the probability of bankruptcy is simply the probability that
the current market value of assets, V_A, is less than the face value of the liabilities, X, at time T (i.e., $V_A(T) < X$). The BSM model assumes that the natural log of future asset values is distributed normally as follows, where μ is the continuously-compounded expected return on assets:

$$(4)\ \ln V_A(t) \sim N\left[\ln V_A + (\mu - \delta - \frac{\sigma_A^2}{2})t, \sigma_A^2 t\right]$$

As shown in McDonald (2002), the probability that $V_A(T) < X$ is as follows:

$$(5)\ N\left(-\frac{\ln\left[\frac{V_A}{X}\right] + \left(\mu - \delta - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right) = BSM - Prob$$

Eq (5) shows that the probability of bankruptcy is a function of the distance between the current market value of the ifrm's assets and the face value of its liabilities ($\frac{V_A}{X}$) adjusted for the expected growth in asset values ($\mu - \delta - \frac{\sigma_A^2}{2}$) relative to asset volatility (σ_A) (Hillegeist et al., 2004).

To empirically calculate *BSM-Prob* from Eq (5), the current market value of assets, V_A, assets returns volatility, σ_A, and the expected return on assets, μ, need to be estimated, since these values are not directly observable. As described below, ifrs, V_A and σ_A are simultaneously estimated, then, these values are used to estimate μ. Once these steps are completed, using Eq (5), corporate default probability is calculated according to the BSM model (Hillegeist et al., 2004).

In the ifrst step, the values of V_A and σ_A are estimated by simultaneously solving the call option equation [Eq (1)] and the optimal hedge equation [$\sigma_E = \frac{V_A e^{-\delta T} N(d_1)\sigma_A}{V_E}$] in SAS software. The starting values are determined by setting $V_A = V_E + X$, and $\sigma_A = \frac{\sigma_E V_E}{V_E + X}$. The iterative process uses a Newton search algorithm that ends when the pair of values solves both equations. In almost all cases, the process converges within ifve iteration (Hillegeist et al., 2004).

V_E is set equal to the total market value of equity based on the closing price at the end of the ifrm's fiscal yea. σ_E is computed using daily return data over the entire ifscal year. The strike pri.. X is set equal to the sum of current liabilities and one-half of long-term liabilities, T equals to one year, and r is the public participation bonds rate. The dividend rate, δ, is the sum of the prior year's common dividends divided by the approximate current market value of assets[1].

In the second step, the expected return on assets, μ, is estimated based on the actual return on assets during the previous year. This process is based on the estimates of V_A that were computed in the previous step. In many cases, the actual return on assets is negative. Since expected returns cannot be negative, the expected growth rate is set equal to the risk-free rate in these cases. Thus, $\mu(t)$ is calculated as follows:

$$(6)\ \mu(t) = max\left[\frac{V_A(t) + dividends - V_A(t-1)}{V_A(t-1)}, r\right]$$

Where dividends is the sum of the common dividends declared during the year.

Finally, the values for V_A, σ_A, μ, δ, T, and X are used to calculate *BSM-Prob* for each firm-year via Eq (5) (Hillegeist et al., 2004).

3.5. Structural Equation Modeling (SEM)

Regression-based analysis has drawbacks that limit its application in some cases. The main drawbacks of this approach, as also summarized in Titman and Wessels (1988), are as follows. First, in the case that there is more than one possible proxy for a particular attribute, choosing a single indicator as proxy may lead to biased parameter estimates and invalid test statistics. Second, it is often difficult to find measures of particular attributes that are unrelated to other attributes. Third, since the observed variables are proxies of the attributes, their use in regression analysis introduces an errors-in-variable (EIV) problem which will cause biased parameter estimates. Finally, measurement errors in the proxy variables may be correlated with measurement errors in the dependent variables, creating spurious effects (Chen & Jiang, 2001).

Because many attributes identiifed as the determinants and drivers of corporate default are often indirectly observed variables or latent variables, in this study, instead of regression model, structural equation modeling (SEM) technique, which lacks abovementioned drawbacks, was used. Also, the Smart PLS software was applied to implement this technique.

1. It is computed as the sum of current liabilities and one-half of long-term liabilities, X, plus the total market value of equity, V_E.

Very briefly, this technique assumes that, although the relevant attributes or factors are not directly manifested, we can observe a number of indicators that are linear functions of one or more attributes and a random error term (Chen & Jiang, 2001). Since SEM is designed for working with multiple related equations simultaneously, it offers a number of advantages over some more familiar methods, and therefore provides a general framework for linear modeling. SEM allows great flexibility on how the equations are specified. The development of an evocative graphical language has accompanied the development of SEM as a statistical method. Due to this language, complex relationships can be presented in a convenient and powerful way to others not familiar with SEM (Monecke & Leisch, 2012).

The entire structural equation model can be divided into two parts: The structural model and the measurement model. The structural model, also called inner model, is the part that relates latent variables (constructs) with each other according to substantive theory. The measurement model or outer model is the part which relates latent variables to their measured, observable or manifest variables (indicators) (Monecke & Leisch, 2012).

The main advantage of structural equation modeling (SEM) technique is that it provides a unique analysis that simultaneously considers questions of both measurement and structural relations. Unlike exploratory factor analysis which is guided by intuitive and ad hoc rules, the measurement model casts a factor analysis in the tradition of hypothesis testing with explicit tests of both the overall quality of measurement and the specific factor loadings composing the model. Unlike the multiple regression analysis that is exploring the statistical relationship among only observed variables, the structural model allows the specification and testing of complex path or structural relations (Chen & Jiang, 2001).

In this particular case, the structural model describes the relationships between corporate default (as latent dependent variable or the second-order construct) and its various attributes (as latent independent variables or the first-order constructs), including accounting ratios, market variables, macroeconomic indicators, nonfinancial factors, and earnings quality measures. As well, the measurement model identifies the relationships between the attributes and their indicators or proxy variables, such as the ratio of net income to total assets, the ratio of sales to total assets, earnings per share, gross domestic product growth rate, earnings predictability, etc.[1]

1. These indicators are listed in Table (4).

3.6. General Model for Predicting Corporate Default

Eq (7) shows the general model for predicting corporate default in each of the selected industries in Tehran Stock Exchange.

$$(7)\ BSM - Prob_{i,t} = \beta_1 ACCR_{i,t-1} + \beta_2 MARK_{i,t-1} + \beta_3 MACRO_{t-1} + \beta_4 NFIN_{i,t-1} + \beta_5 QUAL_{i,t-1}$$

Where $BSM - Prob_{i,t}$ is corporate default probability in the industry *i* for the time period *t*, $ACCR_{i,t-1}$ represents accounting ratios in the industry *i* for the time period *t-1*, $MARK_{i,t-1}$ represents market variables in the industry *i* for the time period *t-1*, $MACRO_{t-1}$ represents macroeconomic indicators for the time period *t-1*, $NFIN_{i,t-1}$ represents nonfinancial factors in the industry *i* for the time period *t-1*, and $QUAL_{i,t-1}$ represents earnings quality measures in the industry *i* for the time period *t-1*.

In this study, according to Charalambakis et al., (2009), González-Aguado & Moral-Benito (2013), and Medhat (2015), the independent variables are lagged one year to ensure that they are observable prior to the event of corporate default, and to allow for one-year prediction.

It is worth noting that currently, there are several general methodological approaches or frameworks within which researchers conduct linear panel analysis. One stems from the econometric tradition, and focuses most explicitly on the problem of the unobservables in the causal system. Another approach to panel analysis stems from structural equation modeling (SEM). The SEM approach is often extended by including additional equations to model random measurement error in observed indicators of the exogenous and endogenous variables, resulting in a set of measurement equations linking latent variables with one or more error-filled indicators, and a set of structural equations linking the latent variables together in the presumed causal system. Such models may also be extended to test alternative causal lag structures in the model, such that variables may be presumed to exert causal influence on endogenous variables either simultaneously (i.e., at the same wave of observation), or lagged by one or more time periods (Finkel, 2007). In addition, according to Eriksson & Pesämaa (2007), Leung et al., (2008), and Xiong (2015), SEM can handle longitudinal designs when time lag variables are involved.

3.7. Assessing the Accuracy of Corporate Default Prediction Model

The accuracy of corporate default prediction model in each of the selected industries is tested as follows:

In the first step, a sample of financially distressed firms, as well healthy firms is selected in each industry. In this study, financially distressed firms are those that have suffered unfavorable financial performance in two or more consecutive years, and for this reason, they have been delisted from Tehran Stock Exchange and transferred to the base market of Iran Fara Bourse, or those that are currently listed on Tehran Stock Exchange, but have at least one of the following specific criteria:

(1) They experience losses (negative pre-tax operating income or net income) over at least three consecutive years (Denis & Denis, 1995),

(2) They have negative retained earnings and poor performance over at least a few consecutive years (Gilbert et al., 1990),

(3) Their book value of equity is lower than their paid-in capital (Gilbert et al., 1990),

(4) Their earnings before interest, taxes, depreciation and amortization (EBITDA) is lower than their financial expenses over two consecutive years (Pindado et al., 2008), or in any of two consecutive years, their EBITDA is lower than 80% of their financial expenses (Asquith et al., 1994),

(5) Their dividend payments are omitted or reduced more than 40% compared to the previous year over three consecutive years (Lau, 1987; Jantadej, 2006),

(6) They have negative cash flow from operating activities in two or three consecutive years (Platt, 2010),

(7) They experience negative stock returns and negative growth in sales over two consecutive years (Opler & Titman, 1994),

(8) Their sales and net profit margin or gross profit margin are decreasing over two or three consecutive years (Hamilton, 2014),

(9) Their cash balances are relatively low, and their inventory levels are escalating over two or three consecutive years (Evans, 2015).

In the second step, using corporate default prediction model derived via structural equation modeling (SEM) technique, default probability of financially distressed firms and healthy firms in each selected industry is measured in 2017.

In the final step, default probability measured in the second step is compared with the specified range for default probability of financially distressed firms [between 0.33 (exclusive) and 1.00 (inclusive)] and healthy firms [between 0.00 (inclusive) and 0.33 (inclusive)] (Fadaeinejad et al., 2015).

4. Research Findings

4.1. Automotive and Auto Parts Manufacturing Industry

4.1.1. Descriptive Statistics

Table (5) presents summary descriptive statistics for indicators of latent independent variables.

Table (5). Descriptive Statistics for Indicators of Latent Independent Variables

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	240	-0.26	0.28	0.05	0.08
	Earnings before Interest and Tax/Total Assets (EBITTA)	240	-0.32	0.35	0.09	0.08
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	240	-0.21	0.79	0.14	0.14
	Sales/Total Assets (STA)	240	0.02	5.14	1.08	0.62
	Sales Growth Rate (SG)	240	-0.93	2.50	0.16	0.37
	Retained Earnings/Total Assets (RETA)	240	-0.77	0.39	0.05	0.15
	Current Assets/Current Liabilities (CACD)	240	0.46	3.15	1.16	0.37
	Quick Assets/Current Liabilities (QACD)	240	0.12	1.97	0.62	0.27
	Net Working Capital/Total Assets (WCTA)	240	-0.48	0.58	0.06	0.19
	Cash/Current Liabilities (CASHCD)	240	0.001	0.56	0.06	0.07
	Current Liabilities/Total Assets (CDTA)	240	0.22	1.10	0.64	0.15
	Total Liabilities/Total Assets (TDTA)	240	0.29	1.57	0.72	0.19
	Short-term and Long-term Loans/Total Equity (TLEQ)	240	-4.15	5.74	1.06	1.24
	Short-term and Long-term Loans/Total Assets (TLTA)	240	0.00	0.89	0.28	0.15
	Cash Flow from	240	-0.43	1.13	0.10	0.18

Latent Independent Variable	**Indicator**	**Count**	**Min**	**Max**	**Mean**	**Standard Deviation**
	Operating Activities/Sales (CFOS)					
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	240	-5.23	5.93	1.84	1.70
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	240	-4.20	5.82	0.81	1.37
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	240	-1.33	4.52	0.47	0.69
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	240	-0.51	2.17	0.14	0.22
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	240	-0.54	2.30	0.16	0.24
Market Variables (MARK)	Market Value/Book Value (MVBV)	240	-3.00	6.73	1.18	1.12
	Earnings per Share (EPS)	240	-0.14	3.38	2.05	1.01
	Market Capitalization/Total Liabilities (MCTD)	240	0.03	4.97	0.59	0.56
	Market Capitalization/Short-term and Long-term Loans (MCTL)	240	0.05	6.88	1.69	1.45
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	10	-0.03	1.047	0.151	0.32
	Changes in Consumer Price Index (DCPI)	10	0.104	0.347	0.19	0.087
	Changes in Term Deposit Rate (DDRATE)	10	-0.035	0.065	0.007	0.03

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
	Gross Domestic Product Growth Rate (GDPG)	10	-0.077	0.067	0.02	0.04
	Changes in Bank Loan Interest Rate (DLRATE)	10	-0.02	0.085	0.005	0.03
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	240	0.00	1.00	0.99	0.09
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	240	-2.43	4.73	0.27	0.69
	Earnings Predictability (PRED)	240	0.01	0.11	0.04	0.02
	Earnings Smoothness (SMOOTH)	240	0.02	6.99	2.01	1.63

Table (6) presents summary descriptive statistics for latent dependent variable.

Table (6). Descriptive Statistics for Latent Dependent Variable

Latent Dependent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
DEFAULT	BSM-Prob	240	0.00	0.99	0.04	0.14

4.1.2. Inferential Statistics

In Table (7), path coefficient, t-statistic and its p-value are listed for each indicator.

Table (7). Path Coefficient, T-Statistic and P-Value for Indicators

Latent Independent Variable	Indicator	Path Coefficient	T-Statistic	P-Value
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	0.684*	2.977	0.003
	Earnings before Interest and Tax/Total Assets (EBITTA)	-0.671*	-2.937	0.004
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	-0.069	-1.123	0.262
	Sales/Total Assets (STA)	-0.067	-1.107	0.269
	Sales Growth Rate (SG)	-0.089*	-2.061	0.040
	Retained Earnings/Total Assets (RETA)	-0.359*	-2.314	0.022
	Current Assets/Current Liabilities (CACD)	-0.040	-0.781	0.435
	Quick Assets/Current Liabilities (QACD)	-0.010	-0.214	0.830
	Net Working Capital/Total Assets (WCTA)	-0.039	-0.706	0.480
	Cash/Current Liabilities (CASHCD)	-0.060	-1.586	0.113
	Current Liabilities/Total Assets (CDTA)	0.087	1.369	0.172
	Total Liabilities/Total Assets (TDTA)	0.700*	3.103	0.002
	Short-term and Long-term Loans/Total Equity (TLEQ)	0.008	0.116	0.908
	Short-term and Long-term Loans/Total Assets (TLTA)	-0.080*	-2.349	0.020
	Cash Flow from Operating Activities/Sales (CFOS)	-0.013	-0.416	0.678
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	0.069	1.541	0.124
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	-0.006*	-2.852	0.005
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	-0.046	-1.391	0.165
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	-0.210*	-2.046	0.042
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	-0.260*	-2.338	0.020

Latent Independent Variable	Indicator	Path Coefficient	T-Statistic	P-Value
Market Variables (MARK)	Market Value/Book Value (MVBV)	-0.009	-0.372	0.710
	Earnings per Share (EPS)	-0.041	-1.667	0.097
	Market Capitalization/Total Liabilities (MCTD)	-0.024	-1.753	0.081
	Market Capitalization/Short-term and Long-term Loans (MCTL)	-0.025	-1.624	0.105
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	-0.017	-1.562	0.120
	Changes in Consumer Price Index (DCPI)	0.034	1.147	0.253
	Changes in Term Deposit Rate (DDRATE)	-0.067	-0.989	0.324
	Gross Domestic Product Growth Rate (GDPG)	0.027	1.397	0.164
	Changes in Bank Loan Interest Rate (DLRATE)	-0.055	-1.621	0.106
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	0.029	1.111	0.268
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	0.034	0.885	0.377
	Earnings Predictability (PRED)	0.087	0.862	0.390
	Earnings Smoothness (SMOOTH)	0.094	1.059	0.291

** Significant at the 95% Confidence Interval*

According to Table (7), the ratios of net income to total assets (NITA), earnings before interest and tax to total assets (EBITTA), sales growth rate (SG), retained earnings to total assets (RETA), total liabilities to total assets (TDTA), short-term and long-term loans to total assets (TLTA), cash flow from operating activities to earnings before interest and tax (CFOEBIT), cash flow from operating activities to total liabilities (CFOTD) and cash flow from operating activities to current liabilities (CFOCD) are significantly related to corporate default.

Meanwhile, the ratio of total liabilities to total assets (TDTA) with path coefficient of 0.700 is the most important, and the ratio of cash flow from operating activities to earnings before interest and tax (CFOEBIT) with path coefficient of -0.006 is the least important predictor of corporate default.

It was also found that as expected, the relationships between the ratios of earnings before interest and tax to total assets (EBITTA), sales growth rate (SG), retained earnings to total assets (RETA), cash flow from operating activities to earnings before interest and tax (CFOEBIT), cash flow from operating activities to total liabilities (CFOTD) and cash flow from operating activities to current liabilities (CFOCD) with corporate default probability are negative, and the relationship between the ratio of total liabilities to total assets (TDTA) and corporate default probability is positive. However, it was observed that, contrary to expectations, the ratio of net income to total assets (NITA) has a positive impact, and the ratio of short-term and long-term loans to total assets (TLTA) has a negative impact on corporate default probability.

Moreover, it was revealed that in other categories, including market variables, macroeconomic indicators, nonfinancial factors, and earnings quality measures, none of the indicators has a significant relationship with corporate default probability.

4.1.3. Evaluating Collinearity

In this study, variance inflation factor (VIF) is used to evaluate collinearity among indicators. VIF values for all indicators of each first-order construct (latent independent variable) are less than 5.00, and indicate that there is no collinearity problem.

4.1.4. Final Model for Predicting Corporate Default and Assessing Its Accuracy

Eq (8) shows final model for predicting corporate default in automotive and auto parts manufacturing industry.

(8) $BSM - Prob_{i,t} = 0.684NITA_{i,t-1} - 0.671EBITTA_{i,t-1} - 0.089SG_{i,t-1} - 0.359RETA_{i,t-1} + 0.7TDTA_{i,t-1} - 0.08 TLTA_{i,t-1} - 0.006CFOEBIT_{i,t-1} - 0.21CFOTD_{i,t-1} - 0.26CFOCD_{i,t-1}$

Where $BSM - Prob_{i,t}$ is corporate default probability in the firm *i* for the time period *t*, $NITA_{i,t-1}$ represents the ratio of net income to total assets in the firm *i* for the time period *t-1*, $EBITTA_{i,t-1}$ represents the ratio of earnings before interest and tax to total assets in the firm *i* for the time period *t-1*, $SG_{i,t-1}$ represents sales growth rate in the firm *i* for the time period *t-1*, $RETA_{i,t-1}$ represents the ratio of retained earnings to total assets in the firm *i* for the time period *t-1*, $TDTA_{i,t-1}$ represents the ratio of total liabilities to total assets in the firm *i* for the time period *t-1*, $TLTA_{i,t-1}$ represents the ratio of short-term and long-term loans to total assets in the firm *i* for the time period *t-1*, $CFOEBIT_{i,t-1}$ represents the ratio of cash flow from operating activities to earnings before interest and tax in the firm *i* for the time period *t-1*, $CFOTD_{i,t-1}$ represents the ratio of cash flow from operating activities to total liabilities in the firm *i* for the time period *t-1*, and $CFOCD_{i,t-1}$ represents the ratio of cash flow from operating activities to current liabilities in the firm *i* for the time period *t-1*.

The method used to test the accuracy of final model for predicting corporate default is that, at the end of the fiscal year 2017, a sample of financially distressed firms[1], as well healthy firms in automotive and auto parts manufacturing industry is selected. Default probability threshold is considered 0.33. It means, all of the firms with default probabilities above 0.33 are assumed to be financially distressed and those with default probabilities equal to or below 0.33 are assumed to be healthy (Fadaeinejad et al., 2015). Then, using the derived model, default probability for each of these firms is measured. In the end, by comparing these two default probabilities (for each company) and calculating percentage of accurate prediction, the credibility level of the derived model is determined.

1. The procedure for identifying financially distressed firms is described in section 3-7.

Table (8) shows the accuracy of final model for predicting corporate default in automotive and auto parts manufacturing industry.

Table (8). Accuracy of Final Model for Predicting Corporate Default in the Group of Financially Distressed and Healthy Firms

Industry	Percentage of Accurate Prediction	
	Financially Distressed Firms	**Financially Healthy Firms**
Automotive and Auto Parts Manufacturing	81/25	71/43

4.2. Pharmaceuticals Industry

4.2.1. Descriptive Statistics

Table (9) presents summary descriptive statistics for indicators of latent independent variables.

Table (9). Descriptive Statistics for Indicators of Latent Independent Variables

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	180	0.01	0.48	0.18	0.09
	Earnings before Interest and Tax/Total Assets (EBITTA)	180	0.02	0.53	0.24	0.10
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	180	0.03	1.43	0.40	0.23
	Sales/Total Assets (STA)	180	0.23	1.49	0.78	0.19
	Sales Growth Rate (SG)	180	-0.59	2.15	0.26	0.30
	Retained Earnings/Total Assets (RETA)	180	0.00	0.45	0.21	0.11
	Current Assets/Current Liabilities (CACD)	180	0.66	2.96	1.36	0.34
	Quick Assets/Current Liabilities (QACD)	180	0.35	1.51	0.88	0.23
	Net Working Capital/Total Assets (WCTA)	180	-0.22	0.56	0.18	0.14
	Cash/Current Liabilities (CASHCD)	180	0.00	0.61	0.06	0.07
	Current Liabilities/Total Assets (CDTA)	180	0.29	0.87	0.60	0.12
	Total Liabilities/Total Assets (TDTA)	180	0.35	0.88	0.64	0.12
	Short-term and Long-term Loans/Total Equity (TLEQ)	180	0.00	4.96	1.06	0.87
	Short-term and Long-term Loans/Total Assets (TLTA)	180	0.00	0.68	0.30	0.15
	Cash Flow from Operating Activities/Sales	180	-0.22	1.10	0.16	0.16

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
	(CFOS)					
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	180	-1.85	6.92	2.47	1.82
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	180	-3.02	3.43	0.56	0.66
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	180	-6.09	5.96	0.65	1.11
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	180	-0.24	1.45	0.22	0.24
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	180	-0.24	1.62	0.24	0.26
Market Variables (MARK)	Market Value/Book Value (MVBV)	180	0.88	6.43	2.91	1.11
	Earnings per Share (EPS)	180	0.00	3.86	3.12	0.38
	Market Capitalization/Total Liabilities (MCTD)	180	0.45	6.93	1.90	1.27
	Market Capitalization/Short-term and Long-term Loans (MCTL)	180	0.59	6.84	2.18	1.47
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	10	-0.03	1.047	0.151	0.32
	Changes in Consumer Price Index (DCPI)	10	0.104	0.347	0.19	0.087
	Changes in Term Deposit Rate (DDRATE)	10	-0.035	0.065	0.007	0.03
	Gross Domestic Product Growth Rate	10	-0.077	0.067	0.02	0.04

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
	(GDPG)					
	Changes in Bank Loan Interest Rate (DLRATE)	10	-0.02	0.085	0.005	0.03
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	180	0.00	1.00	0.99	0.07
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	180	-1.90	2.12	0.18	0.54
	Earnings Predictability (PRED)	180	0.00	0.13	0.03	0.02
	Earnings Smoothness (SMOOTH)	180	0.12	6.87	2.14	1.72

Table (10) presents summary descriptive statistics for latent dependent variable.

Table (10). Descriptive Statistics for Latent Dependent Variable

Latent Dependent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
DEFAULT	BSM-Prob	180	0.00	0.88	0.01	0.08

4.2.2. Inferential Statistics

In Table (11), path coefficient, t-statistic and its p-value are listed for each indicator.

Table (11). Path Coefficient, T-Statistic and P-Value for Indicators

Latent Independent Variable	Indicator	Path Coefficient	T-Statistic	P-Value
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	-0.088	-1.667	0.097
	Earnings before Interest and Tax/Total Assets (EBITTA)	0.121*	2.871	0.004
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	-0.363*	-3.209	0.001
	Sales/Total Assets (STA)	-0.100	-1.186	0.237
	Sales Growth Rate (SG)	-0.021*	-2.454	0.014
	Retained Earnings/Total Assets (RETA)	-0.785*	-3.423	0.001
	Current Assets/Current Liabilities (CACD)	-0.023	-1.616	0.108
	Quick Assets/Current Liabilities (QACD)	-0.040	-1.576	0.117
	Net Working Capital/Total Assets (WCTA)	0.657*	2.421	0.016
	Cash/Current Liabilities (CASHCD)	-0.028*	-2.010	0.045
	Current Liabilities/Total Assets (CDTA)	0.099	1.415	0.158
	Total Liabilities/Total Assets (TDTA)	0.688*	2.327	0.021
	Short-term and Long-term Loans/Total Equity (TLEQ)	0.011*	1.999	0.046
	Short-term and Long-term Loans/Total Assets (TLTA)	0.060	1.856	0.064
	Cash Flow from Operating Activities/Sales (CFOS)	0.065	1.294	0.196
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	0.069	1.202	0.230
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	-0.041	-1.342	0.180
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	-0.019	-0.922	0.357
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	0.471*	2.067	0.040
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	-0.248*	-2.351	0.020
Market Variables	Market Value/Book Value	-0.090	-1.864	0.063

Latent Independent Variable	Indicator	Path Coefficient	T-Statistic	P-Value
(MARK)	(MVBV)			
	Earnings per Share (EPS)	-0.007	-0.448	0.654
	Market Capitalization/Total Liabilities (MCTD)	-0.045	-1.423	0.156
	Market Capitalization/Short-term and Long-term Loans (MCTL)	-0.004	-0.092	0.927
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	0.116*	2.768	0.006
	Changes in Consumer Price Index (DCPI)	0.102*	2.100	0.037
	Changes in Term Deposit Rate (DDRATE)	-0.012	-0.229	0.819
	Gross Domestic Product Growth Rate (GDPG)	-0.108*	-2.361	0.019
	Changes in Bank Loan Interest Rate (DLRATE)	-0.031	-1.268	0.205
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	0.009	0.683	0.495
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	0.050	0.806	0.421
	Earnings Predictability (PRED)	0.061	0.736	0.462
	Earnings Smoothness (SMOOTH)	-0.058	-1.063	0.289

** Significant at the 95% Confidence Interval*

According to Table (11), among accounting ratios, the ratios of earnings before interest and tax to total assets (EBITTA), earnings before interest and tax to total liabilities (EBITTD), sales growth rate (SG), retained earnings to total assets (RETA), net working capital to total assets (WCTA), cash to current liabilities (CASHCD), total liabilities to total assets (TDTA), short-term and long-term loans to total equity (TLEQ), cash flow from operating activities to total liabilities (CFOTD), and cash flow from operating activities to current liabilities (CFOCD), and among macroeconomic indicators, changes in exchange rate (DCUR), changes in consumer price index (DCPI), and gross domestic product growth rate (GDPG) are significantly related to corporate default.

Meanwhile, the ratio of retained earnings to total assets (RETA) with path coefficient of -0.785 is the most important, and the ratio of short-term and long-term loans to total equity (TLEQ), with path coefficient of 0.011 is the least important predictor of corporate default.

It was also found that as expected, the relationships between the ratios of earnings before interest and tax to total liabilities (EBITTD), sales growth rate (SG), retained earnings to total assets (RETA), cash to current liabilities (CASHCD), cash flow from operating activities to current liabilities (CFOCD), and gross domestic product growth rate (GDPG) with corporate default probability are negative, and the relationships between the ratio of total liabilities to total assets (TDTA), the ratio of short-term and long-term loans to total equity (TLEQ), changes in exchange rate (DCUR), and changes in consumer price index (DCPI) with corporate default probability are positive. However, it was observed that, contrary to expectations, the ratios of earnings before interest and tax to total assets (EBITTA), net working capital to total assets (WCTA), and cash flow from operating activities to total liabilities (CFOTD) positively affect corporate default probability.

Moreover, it was revealed that in other categories, including market variables, nonfinancial factors, and earnings quality measures, none of the indicators has a significant relationship with corporate default probability.

4.2.3. Evaluating Collinearity

VIF values for all indicators of each first-order construct (latent independent variable) are less than 5.00, and indicate that there is no collinearity problem.

4.2.4. Final Model for Predicting Corporate Default and Assessing Its Accuracy

Eq (9) shows final model for predicting corporate default in pharmaceuticals industry.

$$(9)\ BSM-Prob_{i,t} = 0.121EBITTA_{i,t-1} - 0.363EBITTD_{i,t-1} - 0.021SG_{i,t-1} - 0.785RETA_{i,t-1} + 0.657WCTA_{i,t-1} - 0.028CASHCD_{i,t-1} + 0.688TDTA_{i,t-1} + 0.011TLEQ_{i,t-1} + 0.471CFOTD_{i,t-1} - 0.248CFOCD_{i,t-1} + 0.116DCUR_{t-1} + 0.102DCPI_{t-1} - 0.108GDPG_{t-1}$$

Where $EBITTD_{i,t-1}$ represents the ratio of earnings before interest and tax to total liabilities in the firm *i* for the time period *t-1*, $WCTA_{i,t-1}$ represents the ratio of net working capital to total assets in the firm *i* for the time period *t-1*, $CASHCD_{i,t-1}$ represents the ratio of cash to current liabilities in the firm *i* for the time period *t-1*, $TLEQ_{i,t-1}$ represents the ratio of short-term and long-term loans to total equity in the firm *i* for the time period *t-1*, $DCUR_{t-1}$ represents changes in exchange rate for the time period *t-1*, $DCPI_{t-1}$ represents changes in consumer price index for the time period *t-1*, and $GDPG_{t-1}$ represents gross domestic product growth rate for the time period *t-1*.

Table (12) shows the accuracy of final model for predicting corporate default in pharmaceuticals industry.

Table (12). Accuracy of Final Model for Predicting Corporate Default in the Group of Financially Distressed and Healthy Firms

Industry	Percentage of Accurate Prediction	
	Financially Distressed Firms	Financially Healthy Firms
Pharmaceuticals	87/50	80/00

4.3. Cement, Lime and Plaster Industry

4.3.1. Descriptive Statistics

Table (13) presents summary descriptive statistics for indicators of latent independent variables.

Table (13). Descriptive Statistics for Indicators of Latent Independent Variables

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	150	-0.02	0.63	0.21	0.12
	Earnings before Interest and Tax/Total Assets (EBITTA)	150	0.02	0.67	0.23	0.13
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	150	0.02	2.66	0.48	0.41
	Sales/Total Assets (STA)	150	0.06	1.38	0.62	0.28
	Sales Growth Rate (SG)	150	-0.55	5.21	0.20	0.47
	Retained Earnings/Total Assets (RETA)	150	0.00	0.69	0.23	0.15
	Current Assets/Current Liabilities (CACD)	150	0.22	3.51	0.91	0.51
	Quick Assets/Current Liabilities (QACD)	150	0.04	2.15	0.38	0.32
	Net Working Capital/Total Assets (WCTA)	150	-1.17	0.59	-0.08	0.24
	Cash/Current Liabilities (CASHCD)	150	0.00	0.41	0.08	0.08
	Current Liabilities/Total Assets (CDTA)	150	0.17	0.81	0.39	0.13
	Total Liabilities/Total Assets (TDTA)	150	0.24	0.90	0.56	0.15
	Short-term and Long-term Loans/Total Equity (TLEQ)	150	0.00	6.71	0.82	0.87
	Short-term and Long-term Loans/Total Assets (TLTA)	150	0.00	0.69	0.26	0.17
	Cash Flow from Operating	150	0.07	1.37	0.42	0.16

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
	Activities/Sales (CFOS)					
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	150	0.85	6.94	2.48	1.80
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	150	0.35	5.53	1.14	0.50
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	150	0.10	6.80	1.44	1.46
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	150	0.07	2.19	0.50	0.38
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	150	0.08	2.76	0.66	0.41
Market Variables (MARK)	Market Value/Book Value (MVBV)	150	0.86	6.36	2.29	1.27
	Earnings per Share (EPS)	150	-0.01	3.97	3.01	0.44
	Market Capitalization/Total Liabilities (MCTD)	150	0.07	6.06	2.03	1.43
	Market Capitalization/Short-term and Long-term Loans (MCTL)	150	0.49	6.81	2.26	1.69
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	10	-0.03	1.047	0.151	0.32
	Changes in Consumer Price Index (DCPI)	10	0.104	0.347	0.19	0.087
	Changes in Term Deposit Rate (DDRATE)	10	-0.035	0.065	0.007	0.03
	Gross Domestic Product Growth Rate	10	-0.077	0.067	0.02	0.04

Latent Independent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
	(GDPG)					
	Changes in Bank Loan Interest Rate (DLRATE)	10	-0.02	0.085	0.005	0.03
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	150	0.00	1.00	0.81	0.40
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	150	-1.52	1.24	0.24	0.48
	Earnings Predictability (PRED)	150	0.01	0.15	0.05	0.03
	Earnings Smoothness (SMOOTH)	150	0.08	6.18	1.47	1.07

Table (14) presents summary descriptive statistics for latent dependent variable.

Table (14). Descriptive Statistics for Latent Dependent Variable

Latent Dependent Variable	Indicator	Count	Min	Max	Mean	Standard Deviation
DEFAULT	BSM-Prob	150	0.00	0.80	0.04	0.13

4.3.2. Inferential Statistics

In Table (15), path coefficient, t-statistic and its p-value are listed for each indicator.

Table (15). Path Coefficient, T-Statistic and P-Value for Indicators

Latent Independent Variable	Indicator	Path Coefficient	T-Statistic	P-Value
Accounting Ratios (ACCR)	Net Income/Total Assets (NITA)	-0.468*	-3.209	0.002
	Earnings before Interest and Tax/Total Assets (EBITTA)	-0.222*	-3.076	0.003
	Earnings before Interest and Tax/Total Liabilities (EBITTD)	-0.282	-1.777	0.078
	Sales/Total Assets (STA)	-0.025*	-3.053	0.003
	Sales Growth Rate (SG)	-0.289*	-2.449	0.015
	Retained Earnings/Total Assets (RETA)	-0.408*	-3.555	0.001
	Current Assets/Current Liabilities (CACD)	-0.121	-1.449	0.149
	Quick Assets/Current Liabilities (QACD)	-0.114	-1.375	0.171
	Net Working Capital/Total Assets (WCTA)	-0.080*	-2.621	0.010
	Cash/Current Liabilities (CASHCD)	0.443*	2.357	0.020
	Current Liabilities/Total Assets (CDTA)	0.063	1.058	0.292
	Total Liabilities/Total Assets (TDTA)	0.501*	3.883	0.000
	Short-term and Long-term Loans/Total Equity (TLEQ)	0.097	1.539	0.126
	Short-term and Long-term Loans/Total Assets (TLTA)	0.323*	2.956	0.004
	Cash Flow from Operating Activities/Sales (CFOS)	-0.512*	-2.006	0.047
	Cash Flow from Operating Activities plus Interest Expense/Interest Expense (CFOII)	0.162	1.467	0.144
	Cash Flow from Operating Activities/Earnings before Interest and Tax (CFOEBIT)	-0.082	-1.689	0.093
	Cash Flow from Operating Activities/Short-term and Long-term Loans (CFOTL)	0.119	0.992	0.323
	Cash Flow from Operating Activities/Total Liabilities (CFOTD)	0.028	0.863	0.390
	Cash Flow from Operating Activities/Current Liabilities (CFOCD)	0.305*	2.267	0.025
Market Variables (MARK)	Market Value/Book Value (MVBV)	0.023	0.846	0.399

Latent Independent Variable	**Indicator**	**Path Coefficient**	**T-Statistic**	**P-Value**
	Earnings per Share (EPS)	0.011	1.662	0.099
	Market Capitalization/Total Liabilities (MCTD)	0.026*	2.014	0.046
	Market Capitalization/Short-term and Long-term Loans (MCTL)	0.006	1.127	0.262
Macroeconomic Indicators (MACRO)	Changes in Exchange Rate (DCUR)	0.055	1.235	0.219
	Changes in Consumer Price Index (DCPI)	0.005	0.224	0.823
	Changes in Term Deposit Rate (DDRATE)	0.225	1.347	0.180
	Gross Domestic Product Growth Rate (GDPG)	-0.076	-0.995	0.321
	Changes in Bank Loan Interest Rate (DLRATE)	0.029	0.563	0.574
Nonfinancial Factors (NFIN)	Dependence on Small Number of Principal Customers (PCUS)	0.041	1.567	0.119
Earnings Quality Measures (OUAL)	Earnings Persistence (PERS)	-0.044	-1.480	0.141
	Earnings Predictability (PRED)	-0.035	-1.208	0.229
	Earnings Smoothness (SMOOTH)	-0.055	-0.991	0.323

** Significant at the 95% Confidence Interval*

According to Table (15), among accounting ratios, the ratios of net income to total assets (NITA), earnings before interest and tax to total assets (EBITTA), sales to total assets (STA), sales growth rate (SG), retained earnings to total assets (RETA), net working capital to total assets (WCTA), cash to current liabilities (CASHCD), total liabilities to total assets (TDTA), short-term and long-term loans to total assets (TLTA), cash flow from operating activities to sales (CFOS), cash flow from operating activities to current liabilities (CFOCD), and among market variables, the ratio of market capitalization to total liabilities (MCTD) are significantly related to corporate default.

Meanwhile, the ratio of cash flow from operating activities to sales (CFOS) with path coefficient of -0.512 is the most important, and the ratio of sales to total assets (STA) with path coefficient of -0.025 is the least important predictor of corporate default.

It was also found that as expected, the relationships between the ratios of net income to total assets (NITA), earnings before interest and tax to total assets (EBITTA), sales to total assets (STA), sales growth rate (SG), retained earnings to total assets (RETA), net working capital to total assets (WCTA), and cash flow from operating activities to sales (CFOS) with corporate default probability are negative, and the relationships between the ratios of total liabilities to total assets (TDTA), and short-term and long-term loans to total assets (TLTA) with corporate default probability are positive. However, it was observed that, contrary to expectations, the ratios of cash to current liabilities (CASHCD), cash flow from operating activities to current liabilities (CFOCD), and market capitalization to total liabilities (MCTD) positively affect corporate default probability.

Moreover, it was revealed that in other categories, including macroeconomic indicators, nonfinancial factors, and earnings quality measures, none of the indicators has a significant relationship with corporate default probability.

4.3.3. Evaluating Collinearity

VIF values for all indicators of each first-order construct (latent independent variable) are less than 5.00, and indicate that there is no collinearity problem.

4.3.4. Final Model for Predicting Corporate Default and Assessing Its Accuracy

Eq (10) shows final model for predicting corporate default in cement, lime and plaster industry.

(10) $BSM - Prob_{i,t} =$
$-0.468NITA_{i,t-1}$ $-0.222EBITTA_{i,t-1}$ $-0.025STA_{i,t-1}$ $-0.289SG_{i,t-1}$ $-0.408RETA_{i,t-1}$ -0.08
$WCTA_{i,t-1}$ $+0.443CASHCD_{i,t-1}$ $+0.501TDTA_{i,t-1}$ $+0.323TLTA_{i,t-1}$ $-0.512CFOS_{i,t-1}$ $+0.305$
$CFOCD_{i,t-1}$ $+0.026MCTD_{i,t-1}$

Where $STA_{i,t-1}$ represents the ratio of sales to total assets in the firm *i* for the time period *t-1*, $CFOS_{i,t-1}$ represents the ratio of cash flow from operating activities to sales in the firm *i* for the time period *t-1*, and $MCTD_{i,t-1}$ represents the ratio of market capitalization to total liabilities in the firm *i* for the time period *t-1*.

Table (16) shows the accuracy of final model for predicting corporate default in cement, lime and plaster industry.

Table (16). Accuracy of Final Model for Predicting Corporate Default in the Group of Financially Distressed and Healthy Firms

Industry	Percentage of Accurate Prediction	
	Financially Distressed Firms	Financially Healthy Firms
Cement, Lime and Plaster	100/00	85/71

5. Conclusion

In this study, a model for predicting corporate default in three selected industries in Tehran Stock Exchange, including automotive and auto parts manufacturing industry, pharmaceuticals industry, and cement, lime and plaster industry was presented.

In automotive and auto parts manufacturing industry, among accounting ratios, the ratios of net income to total assets, earnings before interest and tax to total assets, sales growth rate, retained earnings to total assets, total liabilities to total assets, short-term and long-term loans to total assets, cash flow from operating activities to earnings before interest and tax, cash flow from operating activities to total liabilities, and cash flow from operating activities to current liabilities are significantly related to corporate default. These findings are consistent with Christidis and Gregory (2010), Trujillo-Ponce et al., (2014), Vazifehdust & Zangene (2015), Mertens et al., (2016), and Ramooz & Mahmoudi (2017). In addition, final corporate default prediction model's accuracy in the group of financially distressed firms is 81.25% and in the group of healthy firms is 71.43% in the fiscal year 2017.

In pharmaceuticals industry, among accounting ratios, the ratios of earnings before interest and tax to total assets, earnings before interest and tax to total liabilities, sales growth rate, retained earnings to total assets, net working capital to total assets, cash to current liabilities, total liabilities to total assets, short-term and long-term loans to total equity, cash flow from operating activities to total liabilities, and cash flow from operating activities to current liabilities, and among macroeconomic indicators, changes in exchange rate, changes in consumer price index, and gross domestic product growth rate have significant relationships with corporate default. These findings are consistent with Qu (2006), Bhattacharjee et al., (2009), Koopman et al., (2009), Christidis and Gregory (2010), Fernandez (2012), Tinoco & Wilson (2013), Trujillo-Ponce et al., (2014), Fawzi et al., (2015), Taremi & khodaverdi (2015), Sadeghi et al., (2015), Vazifehdust & Zangene (2015), Mertens et al., (2016), Ramooz & Mahmoudi (2017), and Gupta (2017). In addition, final corporate default prediction model's accuracy in the group of financially distressed firms is 87.50% and in the group of healthy firms is 80.00% in the fiscal year 2017.

In cement, lime and plaster industry, among accounting ratios, the ratios of net income to total assets, earnings before interest and tax to total assets, sales to total assets, sales growth rate, retained earnings to total assets, net working capital to total assets, cash to current liabilities, total liabilities to total assets, short-term and long-term loans to total assets, cash flow from operating activities to sales, and cash flow from operating activities to current liabilities, and among market variables, the ratio of market capitalization to total liabilities are significantly related to corporate default. These findings are consistent with Christidis and Gregory (2010), Fernandez (2012), Trujillo-Ponce et al., (2014), Fawzi et al., (2015), Vazifehdust & Zangene (2015), Mertens et al., (2016), and Ramooz & Mahmoudi (2017). Moreover, final corporate default prediction model's accuracy in the group of financially distressed firms is 100.00% and in the group of healthy firms is 85.71% in the fiscal year 2017.

As it might be seen, in automotive and auto parts manufacturing industry, accounting ratios, in pharmaceuticals industry, accounting ratios and macroeconomic indicators, and in cement, lime and plaster industry, accounting ratios and market variables are introduced as corporate default drivers, and other potential drivers (according to previous research findings and experts' opinions) including nonfinancial factors and earning quality measures do not play a role in predicting corporate default.

In addition to credit rating agencies that have recently been licensed as the ninth financial institution under the supervision of Securities and Exchange Organization of Iran (SEO), the money, capital and insurance markets authorities, banks, creditors, investors, asset managers, insurance companies, auditors and the government can also use the derived model for predicting corporate default in these three industries to assess the financial health of their listed firms with more details.

In future studies, researchers can design and present the corporate default prediction model in other industries in Tehran Stock Exchange, using other statistical techniques or prediction models such as conditional probability models, advanced choice models, hazard intensity survival models and artificial intelligence methods.

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