Forecasting Credit Risk in Banks Listed on Tehran Stock Exchange

Ammar Feyzi
Young Researchers and Elites Club ,Saveh branch ,Islamic azad university ,Saveh ,iran.
(Corresponding author)
ammar.f@stu.iau-saveh.ac.ir

Mohammadreza Ghorbanian
Faculty Member, Department of Accounting, University of Shahre-Ghods, Tehran, Iran.
m.ghorbanian@godsiau.ac.ir

Valalioalah Berangi
PH.D Business Administration International Tendencies, Islamic Azad University Science and Research Branch of Tehran, Instructor at Islamic Azad University, Central Tehran Branch, Iran Expert1392@chmail.ir

ABSTRACT

The present study aim is to offer a systematic method of assessing the credit risk of banks and also to identify key indicators using Decision Making Trial and Evaluation Laboratory (DEMATEL) technique as well as using Logit Regression in order to predict the credit risk of listed banks. The population of the study consists of the legal clients of the bank (Ansar Bank, Bank Saderat Iran, Bank Mellat, Parsian Bank, Bank Pasargad, Post Bank of Iran, Tejarat Bank, Sina Bank, Krafarin Bank, and Eghtesad Novin Bank), who have been granted facilities. The results of the study show that, implementing DEMATEL technique, the variable of asset turnover ratio is the most influential indicator among the examined indicators in predicting the credit risk of banks. In addition, the variables of cash ratio, free cash flow ratio, and current ratio are among the most effective variables, respectively, and the current ratio is the indicator mostly affected compared to other indicators. And according to the prediction made by Logit Model, 207 of the 276 clients, who were prompt in paying their dues, have been categorized properly. This indicates 70% of the dependent variables (y =0) have been predicted properly. Furthermore, 100 of the 176 clients, who were delinquent in paying dues, have been categorized properly. This means that 57% of the variables (y=1) have been predicted properly.

Keywords:

Credit Risk Bank,Tehran Stock Exchange, Logit Model, DEMATEL technique

1. Introduction

The review of the international economic system highlights the fact that there is always a close relationship between investment and economic development level of the county. This means that countries with efficient capital allocation to various sectors of the economy often enjoy economic development and as a result higher social welfare (Alipour, et al, 2015).

Over the past two decades, assets and liabilities of banks grew very fast in developing countries that were followed by banking crises. Studies show that banking crises have resulted in consequences such as halt in economic activities, reduced access to bank credit and monetary policy passivity. Therefore, banks have mainly focused on risk management in recent years. Bank managers have founded that effective risk management enables banks to avoid the risks that endanger their financial health, in addition to controlling risks they are willing to take, and establish a reasonable balance in this area (Leavy et al., 2015).

In a market where banks' profit margins are continuously reducing due to intensified competition and there is always pressure to further reduce costs, credit risk models will create a relative advantage for banks and credit institutions by predicting the losses of defaults on the repayments of loans. Credit risk models can provide asset pricing by measuring risk and making a reasonable relationship between risk and return. Also, credit risk models will make possible to optimize the composition of the credit portfolio and determine banks' economic capital to reduce capital costs (Tehrani and Falah Shams, 2005).

Commercial banks in each country pave the way for economic growth with collecting resources and national capitals and allocating them to various economic sectors. Efficient allocation of resources to achieve this goal is of particular importance. If banks, regardless of geographical area, have a valuable system to assess their clients, they can allocate their resources efficiently to them (Asgharzadeh, 2006; Bahrami, 2007).

The Iranian banking system in recent years has experienced a significant growth in outstanding claims. Statistics show that the growth rate is still rising (Cheng et al, 2007). What may undermine banks is the large number of unpaid loans by clients or payments with delay and they may even lead to bankruptcy of a bank due to their high volume. Despite the use of innovative technologies for credit management in the world, including, credit risk management, credit ranking, credit scoring, etc. and the growing volume of outstanding and bad debts in monetary and credit institutions (banks, financial and credit institutions, leasing companies, etc.), unfortunately, the allocation of credit to credits applicants is still measured by a traditional and non-metric method, especially in recent years.

These credit deviations, which often occur along with recession in the housing market, money market, fall in the capital market and international crises, are continued without providing any strategy considering the lack of working knowledge in trustees and banking and monetary authorities (ShirinBakhsh, Yoosefi and Ghorbanzad, 2011). There are different forms of risk in a monetary and credit institution, including credit risk, interest rate fluctuation risk, the risk of fluctuations in foreign currency (convertible), liquidity risk, the risk of return, investment risk, the risk of new competitors, and the risk of government's economic and political decisions, but given the main and operational activities of monetary and credit institutions "credit risk" is considered the most important risk due to centrality, the volume of operations and particularly its sensitivity. Credit risk management is of great importance. Taking advantage of credit risk models to predict losses due to non-repayment of loans will be an advantage for lenders (Alipour et al., 2015).

Credits are still allocated to applicants in Iran without any measurement. This necessitates a thorough knowledge about the sources of risk, determination and measurement methods for banks. Therefore, changes in implementation methods and use of more appropriate methods ensure that, rather than using the current methods, newer methods can be used to guarantee the return of resources and prevent further delay of the banking resources (Rabizadeh, 2007).

The reasons listed above suggest that indicators to assess the credit risk of banks should be identified and the most important of them should be distinguished and introduced to managers and decision-makers in the banking industry. Despite the importance of this subject, little research has been conducted on the identification of these indicators and their ranking that adds to the necessity and importance of the current research.

Fundamental questions of this study are:

1) What indicators should be used to identify credit risk?
2) What are the key indicators to predict banks' credit risk by DEMATEL technique?
3) How is the prediction of banks' credit risk by logit regression model?

This research aimed to provide a systematic way to predict credit risk, identify key indicators and evaluate the relationships between variables to identify and evaluate the interrelationship between criteria and mapping network connections and weighting and prioritizing by DEMATEL technique and using logit regression model to estimate the credit risk of banks listed on the Stock Exchange of Tehran. The results can provide the experts, financial/credit managers of banks and financial institutions, and researchers and academics with a more accurate credit allocation to banks and it also provides insights for future research.

2. Literature Review

The risk of default or delayed payment of principal and interest of loans granted by banks and other debt instruments from clients is called credit risk. A model was designed by John Mowry in 1909 for the first time for measuring and rating credit risk on bonds (Leavy et al, 2015). Weak supervision for granting of credits and supervision through traditional methods are the main causes of the increase in credit risk. Due to the complexity of modern banking, changes in credit and supervision procedures are inevitable. Identification of clients as much as possible for granting credits to them is one of the cases that should be considered to address weaknesses in the current supervision practices in the banking system(Lee, 2007). Working capital of projects is one of the most damaging factors to credits resulting in increased credit risk that no appropriate control and supervision tool is defined to detect it. In addition to the number of external supervisors and the failure to integrate them, the main problems for banks' supervision are factors including:

- ✓ Unproportionate balance between organizational structure of banks and the volume of domestic supervisors;
- ✓ Poor training of supervisory personnel;
- ✓ Banking technology advances faster than the appropriate monitoring mechanisms on them;
- ✓ The large number of banks' credit clients, etc.

Today in the banking system, decisions are common that have adverse effects, including the growing banks' debts and the lack of social and economic justice (Padeganeh, 2006).

Providing financial credits is considered as one of the important activities of the banking system. For granting credits, the credit rating and ability to repay the principal and interest of the amount of credit should be determined. The possibility that the borrower fails to repay the loan is known as credit risk or the risk of non-repayment of loans (Sinky, 1992). According to Basel Committee, Switzerland, the definition of credit risk is as follows: "Credit risk is the potential that a borrower or his counterparty is not able to fulfill his obligations to the bank within a specified period" (Basel Committee, 2000). The management of credit risk is also of great importance. Risk management includes identifying, analyzing, managing and systematic planning for dealing with risky effects and appreciating its positive effects. The risk management process includes: (1) Risk management planning, (2) Risk identification, risk qualitative evaluation, (3) Risk quantitative evaluation, and (4) Reactive and control planning of risk (Amiri, 2002).

Credit risk: It is the probability of postponement, doubtful or bad debts in a part of monetary institution's credit portfolio due to internal factors (such as: poor credit management, internal controls, follow up and supervision) or external factors (economic recession, crisis, etc.). Credit risk is important in monetary and credit institutions because resource allocations are, in fact, monetary institution debt (lender) to shareholders, people and banks so that freezing or lack of liquidity flows would weaken accreditation power and also debt payment power of monetary institution (lender) (Falah Shams, 2002).

Credit risk models: Many tools in scientific fields of mathematics, statistics, econometrics and operations research such as mathematical programming, probabilistic and deterministic simulation, neural networks, survival analysis, game theory, audit analysis, logistic analysis (logit) and probit analysis have been involved in the development of accurate measurement of credit risk, also financial market theories such as arbitrage, option pricing and pricing model of capital assets have played an effective role in the development of more accurate models to measure credit risk (Roy, 1991).

In general, the most common risk measurement techniques include:

1) **Econometric techniques:** such as multivariate regression models, audit analysis, probit analysis, in which the probability of non-repayment of loans or loss premium of non-repayment of loans as the dependent variable and financial ratios and other quantitative and qualitative factors such as competition management etc. are considered as independent variables.
2) **The neural networks:** are computer-based systems which try to imitate human brain function as a network of neurons connected in the decision-making process.
3) **Optimization models:** are mathematical programming techniques used for optimal weighting for loan and borrower characteristics to minimize loss of non-repayment and maximize profits.
4) **Expert or rule-based systems:** try to imitate structured methods and decision making process of experienced professionals.
5) **Hybrid systems:** use simulation, estimation and calculation techniques to extract causal relationships between independent variables and the probability of non-repayment of loans. In these systems, model parameters are determined based on estimation techniques. KMV is an example of these systems. This model uses theoretical formulas of option for explaining the relationship between estimates (Rose, 1999).

Application domain of risk models: credit risk models are used widely in many domains among which the most important ones are:

- **Credit approval:** is one of the main applications of credit risk models to decide the approval or rejection of loan application from clients. Such models are used more for approving small or medium loans, and generally, other systems are also used for approving larger loans in addition to credit risk model.
- **Credit rating:** few models are used to determine the rating of different types of bonds and loans. The rank of credit instruments represents the degree of credit risk, or, in other words, the probability of non-repayment of principal and interest determined at maturity. Credit ratings will be used to determine loan limits and credit portfolio.
- **Credit pricing:** it determines credit risk models with estimation of the probability of non-repayment and the size of potential loss of non-repayment, the risk premium on bonds and all loans and thereby provides the possibility of pricing and interest rate.

Credit quality criteria: the first step for verifying clients' credit is to identify the main factors affecting credit risk. Different definitions and criteria are known for evaluation of client's risk around the world, including criterion C5, criterion P5, standard LAPP, Rytan model etc. which some of them are presented here:

Criterion C5: It was used for the first time in 2001 by Bryant to assess the risk of agricultural credits. In criterion C5, five parameters are evaluated to assess clients' credit quality:

1) **Character:** Evaluation of commitment and performance in the past financial activities and social reputation. (In evaluation of legal clients, in addition to assessing the organization, the character of organization's management should be examined.)
2) **Capacity:** Evaluation of applicant's income and business management to meet commitments.
3) **Capital:** Evaluation of applicant's capital and financial statements status.
4) **Collateral:** Client's assets deposited in the bank to cover the losses resulting from non-fulfillment of obligations.
5) **Conditions:** Evaluation of environmental conditions, which are out of control, affecting the applicant's performance.

Criterion P5

1) **People:** Evaluation of public opinion regarding the economic unit, including efficiency in production, trade and managers' age, insurance coverages, the profits from capital and assets, evaluation and

control of assets, the desire to fulfill commitments, the place in the industry or economic sector.

2) **Product:** Profitability, quality and quantity of value, availability, marketing goals, insurance coverages, etc. are evaluated.
3) **Support:** Questions such as “Are there internal supports based on financial statements?”, “Is there liquidity or other collaterals available?”, “Is there external support such as bank guarantee?” are evaluated.
4) **Payments:** Cases such as “Is there the problem of unpaid credits or not?” and information related to past payments etc. are evaluated.
5) **General perspective of future:** A case such as whether the company has specific strategy and program for the future or is new in this field, etc. is evaluated. These evaluations will make the credit decision-makers be able to comment on granting credits, the credit limit, and the control practices as well as the time and method of repayment (Turvey, 1991).

DEMATEL technique

Decision Making Trial and Evaluation Laboratory (DEMATEL) technique was presented by Fontela and Gabus in 1971. DEMATEL, which is one of the decision-making methods based on pairwise comparison, provides a hierarchical structure of system’s factors with relations of mutual interaction with the benefit of experts’ judgment in the extraction of factors in a system and systematic structuring by using principles of graph theory so that it determines the severity of effect of these relations as a numerical score. DEMATEL is used to identify and assess the mutual relationship between the criteria and the mapping of network relations. Directed graphs can better show the elements relations in a system, DEMATEL is based on graphs that can divide involved factors into two groups and makes their relationship an understandable structural model. DEMATEL was developed generally for very complex global issues. It is also used to structure a sequence of given information such that it can examine the intensity of relationships with scoring, investigating feedbacks and their importance, and accepting inalienable relations.

(1) Taking into account the interactions: The advantage of this method over network analysis is its clarity in the reflection of interactions among wide ranges of components, so that experts can express their views on the effects (direction and intensity of effects) among factors. It should be noted that the resulting matrix of DEMATEL (matrix of internal relationships) is indeed forming a part of super matrix, in other words, DEMATEL does not operate independently, but operates as a subsystem of a larger system such as ANP.

(2) Structuring complex factors in the causal groups: This is one of the most important functions and one of the main reasons for its frequent application in problem solving processes, as with classification of a wide range of complex factors in a group of causal groups it puts the decision maker in better conditions to understand the relationships. This leads to a greater understanding of the place of factors and their role in the process of mutual influence.

DEMATEL steps include:

- Designing questionnaire and collecting data about relative dependence of project risk parameters from experts;
- Calculating the direct correlation matrix (Z);
- Calculating normal direct relationship matrix (S);
- Calculating total relationships matrix (direct and indirect dependence) (T);
- Calculating total relationships normal matrix with acceptance threshold;
- Mapping network relationships based on two vectors D and R.

The general structure of diagram for relationship between criteria is according to Figure (1). In this matrix, pairwise comparisons will be conducted to calculate the effect of row factor on the column. Comparative figures include: (0, 1, 2, 3 and 4), which represent “no effect” to “great effect”, respectively. The following matrix elements, also called direct relationship matrix, will be formed based on the effect of criteria i on j.

$$A = \begin{vmatrix} a_{11} & \dots & a_{1j} & \dots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{vmatrix}$$

Figure 1: Diagram of direct relationship between criteria

Equations (1) and (2) are used to normalize the direct relationship matrix.

$$S = m.A \tag{1}$$

$$m = \min\left[\frac{1}{\max_i \sum_{j=1}^{n}|a_{ij}|}, \frac{1}{\max_j \sum_{i=1}^{n}|a_{ij}|}\right] \tag{2}$$

Total relationships matrix T is calculated by matrix S through equation (3) in which I is the unit matrix.

$$T = S(I - S)^{-1} \tag{3}$$

Two vectors A and R are used for network relationship mapping, i.e. they are, respectively, the sum of rows and columns of matrix T and their calculation is presented in Equations (4) and (5):

$$D = \left[d_i\right]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{4}$$

$$R = \left[r_j\right]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{5}$$

d_i means the sum of i^{th} row of the matrix T and represents the sum of direct and indirect effects of criterion i on other criteria. Also r_j means the sum of j^{th} column of the matrix T and represents the sum of direct and indirect effects of other criteria on criterion j.

$(d_i + r_i)$ represents the main effect of factor i in the problem. If $(d_i - r_i)$ is positive, it means that other factors are affected by factor i. Conversely, when $(d_i - r_i)$ is negative, other factors affect factor i, and thus network relationships mapping will be made (Li et al, 2014).

Logit model

The model used in this research is the logistic model (logit). This model is one of the most common models used in the analysis of credit risk. The advantage of logit model to other models, such as linear probability, audit analysis, tree classification method and artificial neural network is that logit regression can be used in cases in which the response variable has only two states: zero and one, i.e. zero state: for clients who have not defaulted in repayment (creditworthy clients) and one state for clients who have defaulted in repayment (uncreditworthy clients). In logit regression, there is no limitation for normality of independent variables and equality of variances of two groups. In this model, it is enough to know the target phenomenon has happened or not. For example, the company has fulfilled its commitment on the due date or not. In this case a discrete dependent variable, such as zero and one can be used to show the mentioned phenomenon.

Since the probability values can be between 0 and 1, the values predicted in the logit regression should be between 0 and 1. Also, because the relationship between independent and dependent variables is nonlinear, the conventional linear regression cannot be used for estimation and the relationship cannot be considered in a normal regression as normal regression requires assumptions that in this case they cannot be developed. First, errors related to discrete values follow the binomial distribution rather than the normal distribution. Therefore, all tests related to it are invalid. Second, the variance of discrete variables is not constant.

This leads to a phenomenon called heteroscedasticity. Given the non-linear nature of logit conversion in it, the method of maximum likelihood is used (this phenomenon is developed when changes or variance of the dependent variable are not equal with a level of independent variables with changes or variance of the dependent variable on another level of the independent variables.

However, in the logistic regression, such as multivariate regression, the independent variables coefficients are estimated, but the way it works is quite different. The least squares method is used in multivariate regression. In this method, the sum of differences squared between actual and predicted values of dependent variable is minimized. However, the coefficients estimation method is similar to normal regression in many respects. The logistic model follows logistic curve. Thus, this curve is fitted based on real data. According to the fact that the target phenomenon has occurred or not, the actual data have one of the two states: zero or one. The occurrence or non-occurrence of the phenomenon is determined due to the different levels of linear combinations of independent variables.

Cumulative distribution function can be used to explain the logistic regression model. Cumulative distribution functions create a set of changes in the independent variable that put P value in equation (6) in the distance between zero and one. These functions have uniform properties (i.e. they are monotonically increasing or decreasing functions). We assume that a standard normal distribution is selected to express the probability:

$$P(\frac{Y}{X}) = \Phi(b'X) = \int_{-\infty}^{b'x} \Phi(z)dz \qquad (6)$$

X = Explanatory variables vector
P = Cumulative probability of event occurrence
b' = Coefficients vector
$\Phi(z)$ = Standard normal density function

This function is known as Probit model. If a logistic density function is used instead of the standard normal density function to express cumulative probability of event occurrence it will lead to logistic model. In this case, we have:

$$P(\frac{Y}{X}) = \Phi(b'X) = \int_{-\infty}^{b'x} \eta(z)dz = \frac{1}{1+e^{-\beta' x}} = \frac{e^{\beta' x}}{1+e^{\beta' x}} \qquad (7)$$

where:

$$1-P_i = \frac{1}{1+e^{\beta' x}}$$

In above equation $\eta(z)$ is the logistic density function. The dependent variable is defined as zero and one in logit and probit models and has a binomial distribution. The ratio of $\frac{P}{1-P}$ is the ratio of event occurrence probability to event non-occurrence probability, as seen in equation (8):

$$\frac{P}{1-P} = e^{\beta_0+\beta_1 x_1+...+\beta_n x_n} \qquad (8)$$

In this equation, we have:
P = Phenomenon occurrence probability
1-P = Phenomenon non-occurrence probability
$\beta_0+\beta_1 x_1+...+\beta_n x_n$ = Linear combination of independent variables
e = Base of natural logarithm or Euler's Number
The ratio of $\frac{P}{1-P}$ is the ratio of event occurrence probability to event non-occurrence probability and is called the odds ratio. Due to the non-linearity of Equation (9), linear conversion of this function is used as follows. By taking logarithm, Equation (8) is rewritten as Equation (9):

$$L = Ln(\frac{P}{1-P}) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n \qquad (9)$$

Thus, the relationship which is called the logarithm of the odds ratio or logit is linear with respect to independent variables and thus variables coefficients can be estimated.

It should be noted that if the odds ratio $\frac{P}{1-P}$ can be calculated in logistic regression, the above equation can be estimated by the least squares method, but in other cases, logit model coefficients can be estimated by the general method of maximum likelihood.
As mentioned before, the dependent variable is a binary state variable (0 and 1) in the logistic regression. If we assume that Y is a random variable that can adopt values of zero and one, in this case the probability of Y occurrence can be considered as Equation (10):

$$P(Y=1) = P = \frac{e^{\beta' x}}{1+e^{\beta' x}}$$

$$P(Y=0) = (1-P) = \frac{1}{1+e^{\beta' x}} \qquad (10)$$

where β' is the row vector of coefficients and X is the column vector of independent variables. The above equation can be also considered as follows:

$$\ln \frac{P}{1-P} = \beta' X$$

In logistic regression, the concept of odds is used for the dependent variable value. The probability varies between zero and one, while the odds may be more than one. The keyword in structural logistic regression analysis is called logit which is natural logarithm of the odds. Logistic regression is defined as Equation (11) (Tehrani and Falah Shams, 2005):

$$Z_i = Ln(\frac{P_i}{1-P_i}) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \quad (11)$$

In the above equation, Ln indicates the natural logarithm. In logistic regression model, the event occurrence probability (non-repayment of loan by client) is calculated according to Equation (12):

$$P_i = \pi_i (x_1, x_2, ..., x_k) = \frac{e^{\beta_0 + \sum_{i=1}^{k} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{k} \beta_i x_i}} \quad (12)$$

Research background

Otsuki (2015) conducted a study entitled "the effect of macroeconomic risks on credit risk in the loan portfolio of banks in Serbia". For this purpose, political rate, GDP, household credit risk, business credit risk, exchange rate fluctuations, investments, assets and liquidity were considered. The researcher investigated 32 banks in Serbia with a sample member of 398 by logit regression. The prediction period of credit risk was considered from 2008 to 2012. The results show that the business cycle in banks of Serbia is deteriorating and currency depreciation rate is worsening, and the loan portfolio of banks in Serbia is observed lower than expected.

Shin et al. (2012) in an article entitled "the efficiency and risk in European banking" used financial variables, corporate governance variables and cash flow variables and logit regression methods and neural networks to create a model for warning about fraudulent and non-fraudulent companies. The results showed that the ratio of debt and equity ratio are two important variables to distinguish between the two groups. Logit regression has also outperformed neural networks.

Silachi et al. (2010) in an article entitled "credit risk assessment based on company's performance" used the logit regression and data envelopment analysis (DEA) for the credit risk in a sample of companies in textile, wood and paper, computer industries and research and development in France to find an estimated efficiency in each industry. The results show the important role of non-financial criteria in assessing credit risk. Inefficient management and profitability are also important predictors for companies' financial risk.

Karbassi Yazdi, Fatehi and Nabizadeh (2014), conducted a study entitled "measuring the risk of credits granted to legal clients of banks using logit model (case study: Bank Sepah)". Using logit analysis of cross-sectional data, this study examined the role of financial and non-financial data in developing a model to determine the credit risk. The statistical population included legal persons who received credits from Bank Sepah between 2006 and 2011 and their number totaled 346 companies by screening. The statistical sample consisted of 180 companies (114 creditworthy and 66 uncreditworthy companies) that received credits from Bank Sepah, the sample size was obtained by Cochran formula. According to the research objectives, considering statistics and econometric models, logit model was selected. The findings suggest that the current ratios of financial assets to total assets, the ratio of cash to total assets, long-term debts to total assets, total short and long-term loans to total debts were introduced as potential predictors for determining credit risk of legal clients. The research showed that this model can predict the probability of non-repayment of bank financial credits granted with 89.9% probability.

Feyzi and Hashemi (2013) conducted a study entitled "providing a model to assess banks' credit risk (case study: banks listed on the Tehran Stock Exchange)". The researchers believed that when banks, regardless of geographic location, use a valuable system for assessing their clients, they can allocate their resources efficiently to them. They stated that their study aimed to provide a formalized method for assessing banks' credit risk, identifying key indicators using fuzzy analytic hierarchy process and using Altman model Z to measure the credit risk of banks, which are Stock Exchange members. The research statistical population included the legal clients of Banks (Ansar, Saderat Iran, Melat, Parsian, Pasargad, Post Bank of Iran, Tejarat, Sina, Karafarin and Eghtesad novin) that had received credits. The results of the study showed that Altman's credit risk measurement is more accurate for two-year periods than four-year periods. Altman's model was not proposed for the measurement of banks' credit risk for periods of more than two years, but it has a high accuracy for two-year periods.

Using financial ratios to identify the economic unit status has been considered from past to present and is known as a conventional method. Although information about client status by financial ratios has significant acceptance, there is no consensus on determining the type and value of financial ratios. Accordingly, most researchers have preferred to use a set of financial ratios. Today, accredited rating institutions, such as Moody's, and Standard and Poor's use specific methodologies for rating bonds and other types of credit issues. Close similarity of banks' credits to bonds attracted the attention of some researchers to rating the credit risk of banks' credits i.e. measuring the risk of non-repayment of principal and banks' efficiency. The use of financial ratios and bankruptcy prediction was considered in the early twentieth century.

Altman (1968) measured the credit risk of corporate bonds by the multivariable scoring model known to Z score model. Altman was trying to evaluate the success of American manufacturing companies by audit analysis method. In this method, 22 financial ratios were used. Variables included liquidity ratio, profitability, leverage, debt repayment adequacy and activity ratio. Altman considered the liquidity ratio in the first place of importance and investment ratios in the second place, but he did not consider activity ratios appropriate for differentiation. The use of such a model in the bank will lead the loan application to be rejected or more control be applied for increasing the safety of concessional lending if the Z-score of company is lower than the critical value, thereby losses due to failure to repay loans will be minimal. In this way, the higher is Z, the lower will be the risk of non-repayment of loans classification. Therefore, low or negative value of Z indicates that the borrower will be in a high risk of non-repayment of loans classification. Saunders and Alan (1995) used Altman model Z to predict the credit risk of borrowers and concluded that this model has a high power for predicting the credit risk.

Altman could achieve good results on companies' bankruptcy in 1968 based on financial ratios. He investigated the prediction of agencies' bankruptcy by using multiple audit analysis and financial ratios as independent variables. He provided his usage pattern as model Z known as commercial bankruptcy prediction. Using this method, he selected five ratios from 22 financial ratios for bankruptcy prediction that he believed they were the best. According to Equation (1), Altman with combination of these five ratios provided a good model for bankruptcy.

$$Z = 1.\ 2x1 + 1.\ 4x2 + 3.\ 3x3 + 0.\ 6x4 + 0.\ 99x5 \tag{13}$$

X_1 = Working capital/total assets
X_2 = Retained earnings/total assets
X_3 = Earnings before interest and taxes/total assets
X_4 = Market value of equity/book value of debt
X_5 = Total sales/total assets
In this model, Z value limits are according to Table (1):

Table 1: Altman Z value limits

Bankruptcy probability	Z range
Too much	$Z \leq 1.\ 8$
Weak	$Z \leq 2.\ 99 \leq 1.\ 8$
-	$Z > 2.\ 99$

Years later, some critics were raised on model Z. Credit analysts, accountants and even corporate managers believed that model Z was only applicable for public manufacturing enterprises (listed) and Altman continued his studies and modified model Z. In the new model, which Altman called it Ź, the most important modification was that the market value of equity was replaced by the book value of equity (x_4). The variation of coefficients is presented in Equation (14).

$$Ź = 0.\ 717x1 + 0.\ 874x2 + 3.\ 1x3 + 0.\ 42x4 + 0.\ 998x5$$

With this change, the model was able to predict bankruptcy of listed and private manufacturing companies. In this model, Ź value limits are according to Table (2).

Table 2: Altman Ź value limits

Bankruptcy probability	Ź range
Too much	$Ź \leq 1.\ 21$
Weak	$Ź \leq 2.\ 99 \leq 1.\ 21$
-	$Ź > 2.\ 99$

Altman had a special attention to manufacturing companies in the design of these two models, therefore designed model Ź̋ for predicting the bankruptcy of non-manufacturing and services companies. The main difference of model Ź̋ with two previous models is the elimination of the ratio of sales to total assets (x_5), according to Equation (15).

$$\H{Z} = 6.5 x1 + 3.26x2 + 6.27x3 + 1.05x4 \qquad (15)$$

In this model, Ž value limits are according to Table (3).

Table 3: Altman Ž value limits

Bankruptcy probability	Ž range
Too much	Ž ≤ 1. 1
Weak	Ž ≤ 2. 6 ≤1. 1
-	Ž > 2. 6

Bankrupt and non-bankrupt companies were predicted correctly by Altman model Z, model Ź and model Ž, 94% and 97%, 91% and 97%, and 91% and 94%, respectively.

In the late 1970s, linear probability models and multiple-probable situation (Logit, Probit) were proposed for predicting companies' bankruptcy. Also, using mathematical programming models was addressed in many studies in 1980 and 1990. The main purpose of these methods was to remove the assumptions and limitations of previous techniques, improve the reliability and accuracy of the classification. In early 1990, Decision Support System (DSS) was used in combination with Multi Criteria Decision Making (MCDM) to solve the problems of financial classifications. For example, Roy used Electre and Dimitras model in 1991 and used Rough Set Model in 1999, Morgan used validation model design in 1998 and Treacy used value at risk model design in 1998 to estimate the probability density function of non-repayment. William Beaver (1996) provided multivariate logistic regression model (legit regression) as the first model to determine companies' bankruptcy. He found that a number of indicators can separate companies in terms of ability and disability for continuing activities and play a special role in differentiation. He conducted a research on 20 companies and with comparing 13 financial ratios concluded that the return on capital ratio and debt-to-equity ratio are the best ratios for differentiation. Emel et al. (2003) proposed a credit rating methodology based on data envelopment analysis. For credit rating, they used current financial data of 82 manufacturing/industrial companies that constituted the credit portfolio of one of the largest Turkish banks. In this study, based on the literature, 42 financial ratios were selected, among which six were considered. After validation of the model with regression analysis, Emel et al. found that DEA is able to estimate companies' credit ratings and has efficiency needed for credit scoring. Min and Lee (2007) in a study titled "A practical approach to credit scoring" used an approach based on DEA for credit scoring. For credit rating, they used the proposed methodology of Emel et al. on a much broader statistical population including current financial data of 1061 manufacturing companies and the credit portfolio of one of the largest credit guarantee organizations. Today, using the Basel Committee (supervision committee for banking regulations, Bank for International Settlements), many studies are conducted by researchers and credit institutions to design an accurate model for credit risk measurement. Many models are also used by econometric techniques and neural and fuzzy networks for measuring credit risk in banks and credit institutions. Although the quantification of banks' credit risk has started nearly two decades in developed countries such as America and Europe, few studies have been conducted in Iran on prediction and quantification of banks' credit risk.

Here, the most important studies on banks' credit risk will be provided. Table (4) shows a summary of these studies.

3. Methodology

The present study is an applied research in terms of objective and is a descriptive survey research in terms of data collection method. To collect data, in addition to studying articles and books, two researcher-made questionnaires that were also used (to measure the relationships between indicators and weighting). Validity and reliability of questionnaires were confirmed by a survey of banking experts and academics. The validity of the instrument was confirmed according to professors and experts. Cronbach's alpha was used to confirm its reliability. Cronbach's alpha value is 0.921 for the questionnaire of indicators relationships measurement that in this method, if the alpha value is more than 0.7, the questionnaire has an acceptable reliability. The statistical population of this study consisted of legal clients of banks (Ansar, Saderat Iran, Melat, Parsian, Pasargad, Post Bank of Iran, Tejarat, Sina, Karafarin and Eghtesad novin) that received credits between 2009 and 2014 including 452 companies listed on the

Stock Exchange based on information in Rahavard Novin. The research sample consists of 20 companies listed on the Stock Exchange that received credits from the mentioned banks. SPSS-22, EXCEL-2013, DEMATEL calculations and logit regression were used for data analysis. Figure (2) shows conceptual model from Altman, et al. (2001).

Table 4: The most important studies on banking credit risk

Title	Researcher-year	Conclusion
Efficiency and risk in European banking	Shin et al. (2012)	They used financial variables, corporate governance variables, cash flow variables, logit regression and neural-network techniques to create a model for warning about fraudulent and non-fraudulent companies
Credit risk assessment based on company's performance	Silacci et al. (2010)	They used data for the credit risk in a sample of companies in textile, wood and paper, computer and R & D in France to find an estimated efficiency in each industry. The results show the important role of non-financial criteria in assessing credit risk. Inefficient management and profitability are important predictors for companies' financial risk
Measuring the risk of credits granted to legal clients of banks using logit model (case study: Bank Sepah)	Karbassi Yazdi, Fathi and Nabizadeh (2014)	The results indicate that the financial ratios of current assets to total assets, the ratio of cash to total assets, long-term debts to total assets, total short and long-term loans to total debts were introduced as potential predictors for determining credit risk of legal clients
Providing a model to assess banks' credit risk (case study: banks listed in the Tehran Stock Exchange)	Feyzi and Hashemi (2013)	Researchers believed that if banks, regardless of geographical area, have a valuable system to assess their clients, they can allocate their resources efficiently to them. Researchers stated that their study aimed to provide a formalized method for assessing banks' credit risk, identifying key indicators using fuzzy analytic hierarchy process technique and using Altman model Z to measure credit risk of banks, which are Stock Exchange members
Evaluating the relationship between interest rate of bank credits and deferred items and the effectiveness role of marketing	Esmaeili et al. (2012)	This study assessed the interest rate of bank credits to deferred items of Bank Mellat between 2003 and 2010 and variables such as past due receivables, outstanding claims, doubtful debts and bad debts were studied. The results showed that there is a significant relationship between the interest rate of bank credits and increased doubtful debts in different sectors
Factors affecting banks' lending and rating with FAHP technique (case study: Melli, Mellat and Refah Banks)	Dariush and Shirazifar (2012)	Identified criteria included applicant's quality characteristics, technical feasibility, organization's profile and financial analysis. The researchers used confirmatory and exploratory factor analysis to identify sub-criteria and prioritized criteria and sub-criteria with fuzzy AHP technique of Chang and Moun.

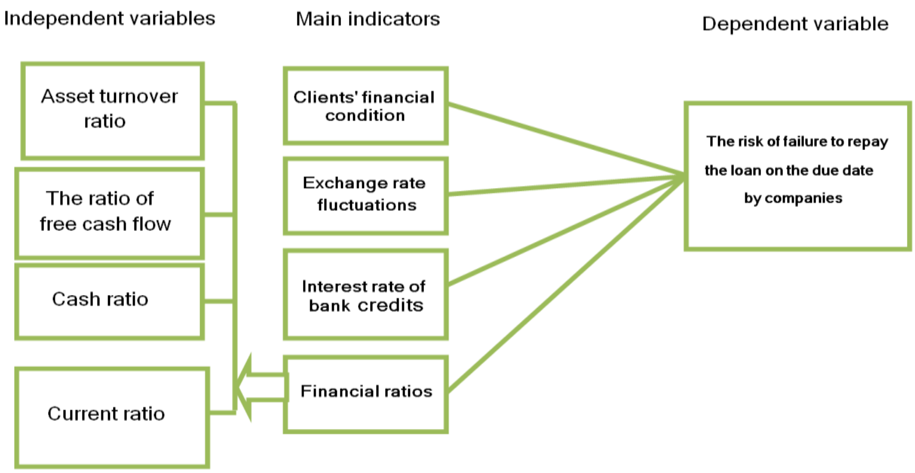

Figure 2: Research conceptual model (Altman et al., 2001)

4. Results

4.1 A Study on Intensity of Relationships among Bank Credit Risk Assessment Indicators using DEMATEL

Firstly, indicators identified from the literature affecting the prediction of banks' credit risk were measured by banking experts, professors and questionnaires and were ranked by DEMATEL. After verifying the validity and reliability, questionnaire one was forwarded to experts in order to study the intensity of interconnectedness among bank credit risk assessment indicators. The items are scored from zero to 4. DEMATEL algorithm has 9 steps as follows:

Step 1: Determining the system elements

Four indicators were identified after studying the literature review and theoretical principles concerning assessment indicators for bank risk credit using experts` opinions:

Step 2, 3, and 4: Determining the elements located in diagram, vertex and the relationships governing them

DEMATEL is employed to determine the relationship and intensity of credit risk assessment indicators in banks listed on Iran Stock Exchange.

In the second step:

The assumed elements are located in vertexes of a diagram and the relationships governing the indicators (vertexes) are clarified. Like for instance, what is the impact of CR on ATR, or vice versa? , or interconnectedness?

Pairwise comparison is performed. Judgment of experts is used only for direct link among the elements. It means that potential direct relationship between CR, ATR, CACD, etc. is judged.

In the second step, we studied the governing relationship among the assumed elements located at diagram vortexes by experts. The vertexes are assessment indicators of bank credit risk mentioned in the first step. Evaluating the indicators and their relationships can be performed multiple times by banking experts in order to facilitate the access to an organized study.

In the third step:

We clarify the group decision-making in order to reach a consensus among experts for the potential relationship between CR and ATR (for example, the majority of votes).

In the fourth step:

We requested the intensity of final relationships from the experts. The intensity of items is scored from zero to 4. Then, we calculate the median of scores, or the geometric mean using percentage for CR and ATR and display on the diagram.

Figure3 shows the governing relationship of vertexes and the intensity of effectiveness between risk credit assessment indicators (Asset Turnover Ratio(ATR), The Ratio of Free Cash Flow (RFCF), Cash Ratio (CR), Current Ratio (on the diagram RC), in banks listed on Iran Stock Exchange.

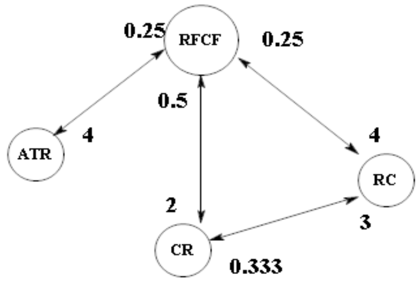

Figure 3: Diagram for credit risk assessment indicators

Total sum of diagram vertexes is as follows:

$$N = \{ATR, RFCF, CR, RC\}$$

Step 5: Showing the final scores through a matrix

Final scores, shown in step 4, are shown through a matrix ($\hat{M}$).

We show the relationship in the diagram through a system relationship intensity matrix (1)

$$\hat{M} = \begin{array}{r|cccc|} & ATR & RFCF & CR & RC \\ ATR & 0 & 0.25 & 0 & 0 \\ RFCF & 4 & 0 & 2 & 4 \\ CR & 0 & 0.5 & 0 & 3 \\ RC & 0 & 0.25 & 0.333 & 0 \end{array}$$

Matrix 1: Intensity matrix of system relationships

The input in each intersection (for example number 4 in the second row and the first column) shows the intensity of impact of the row on the columns (RFCF and ATR). Zero shows lack of relationship between the elements in the intersection.

Step 6: Multiplying each matrix input by the inverse of maximum sum of the same matrix row

After forming the score matrix for each indicator, total sum of each row is calculated. Then, the maximum values are inversed and they are selected as α coefficient. Matrix (2) shows this operation.

$$\hat{M} = \begin{array}{r|ccccc|} & \text{ATR} & \text{RFCF} & \text{CR} & \text{RC} & \sum \text{R} \\ \text{ATR} & 0 & 0.25 & 0 & 0 & 0.25 \\ \text{RFCF} & 4 & 0 & 2 & 4 & \mathbf{10} \\ \text{CR} & 0 & 0.5 & 0 & 3 & 3.5 \\ \text{RC} & 0 & 0.25 & 0.333 & 0 & 0.583 \end{array}$$

Matrix 2: Matrix of total sum of rows

According to matrix 2, the maximum value is for RFCF row (10). Therefore, it is inversed, leading to($\alpha = \frac{1}{10} = 0.1$). Now, each of $\hat{M}$ entries (1) are multiplied by α .Matrix 3 shows the result of this multiplication.

$$M = 0.1 \times \hat{M} = \begin{array}{r|cccc|} & \text{ATR} & \text{RFCF} & \text{CR} & \text{RC} \\ \text{ATR} & 0 & 0.025 & 0 & 0 \\ \text{RFCF} & 0.4 & 0 & 0.2 & 0.4 \\ \text{CR} & 0 & 0.05 & 0 & 0.3 \\ \text{RC} & 0 & 0.025 & 0.033 & 0 \end{array}$$

Matrix 3: Relative intensity governing the direct relationships

Step 7: calculating the total sum of unlimited sequence of the direct and indirect effects of the elements on each other

Total sum of unlimited effects of direct and indirect effects of the elements, along with possible feedbacks, are calculated through a geometric progression based on the existing rules of graphs. Calculating this sum requires the use of $(I\text{-}M)^{-1}$ matrix. Indirect effects are convergent to the inversion matrix because indirect effects are constantly decreasing along the chain of diagrams.

Matrix (4), inversion matrix (3), shows the possible intensity of direct and indirect relationships. Matrix (5) shows total sum of rows (R) and total sum of column (J).

$$(I - M)^{-1} = \begin{array}{r|cccc|} & \text{ATR} & \text{RFCF} & \text{CR} & \text{RC} \\ \text{ATR} & 21.68 & 2.5 & -3.33 & -15.02 \\ \text{RFCF} & 40 & 0 & 0 & 0 \\ \text{CR} & -30.03 & 0 & 0 & 3.03 \\ \text{RC} & -6.67 & 0 & 3.33 & 0 \end{array}$$

Matrix 4: Possible intensity of direct and indirect relationships

$$M \times (I\text{-}M)^{-1} = \begin{array}{r|ccccc|} & \text{ATR} & \text{RFCF} & \text{CR} & \text{RC} & \text{R} \\ \text{ATR} & 0 & 0.063 & 0 & 0 & 0.063 \\ \text{RFCF} & 16 & 0 & 0 & 0 & 16 \\ \text{CR} & 0 & 0 & 0 & 9.009 & 9.009 \\ \text{RC} & 0 & 0 & 0.111 & 0 & 0.111 \\ \text{J} & 16 & 0.063 & 0.111 & 9.009 & \end{array}$$

Matrix 5: R and J values for direct and indirect relationship matrix

Step 8: Calculating the possible intensity of indirect relationships

Matrix 6 shows the results of possible intensity calculation from indirect relationships.

$$M^2 (I - M)^{-1} = \begin{array}{r|cccc|} & \text{ATR} & \text{RFCF} & \text{CR} & \text{RC} \\ \text{ATR} & 0.217 & 0 & 0 & 0 \\ \text{RFCF} & 0 & 0 & 0 & 0 \\ \text{CR} & 0 & 0 & 0 & 0.601 \\ \text{RC} & 0 & 0 & 0 & 0 \end{array}$$

Matrix 6: Relative intensity of indirect relationships

The results are according to Table (5). This step differentiates possible hierarchy or structure from the elements. The influence order of assumed elements of a problem on other elements or being influenced by them will determine the possible structure from those elements hierarchy in improving or solving the problem.

Table 5: The influence order of indicators affecting the prediction of banks' credit risk with DEMATEL

The order of elements	Based on the maximum total row (R)	The order of elements	Based on the maximum total column (J)	The order of elements	Based on R+J	The order of elements	Based on R-J
The Ratio of Free Cash Flow(RFCF)	16	Asset Turnover Ratio(ATR)	16	Asset Turnover Ratio(ATR)	16.063	The Ratio of Free Cash Flow(RFCF)	15.938
Cash Ratio(CR)	9.009	Current Ratio (RC)	9.009	The Ratio of Free Cash Flow(RFCF)	16.063	Current Ratio (RC)	0.049
Current Ratio (RC)	0.111	Cash Ratio(CR)	0.111	Current Ratio (RC)	0.174	Cash Ratio(CR)	-0.049
Asset Turnover Ratio(ATR)	0.063	The Ratio of Free Cash Flow(RFCF)	0.063	Cash Ratio(CR)	0.174	Asset Turnover Ratio(ATR)	-15.938

Also, We have figure(4) shown result of DEMATEL technique.

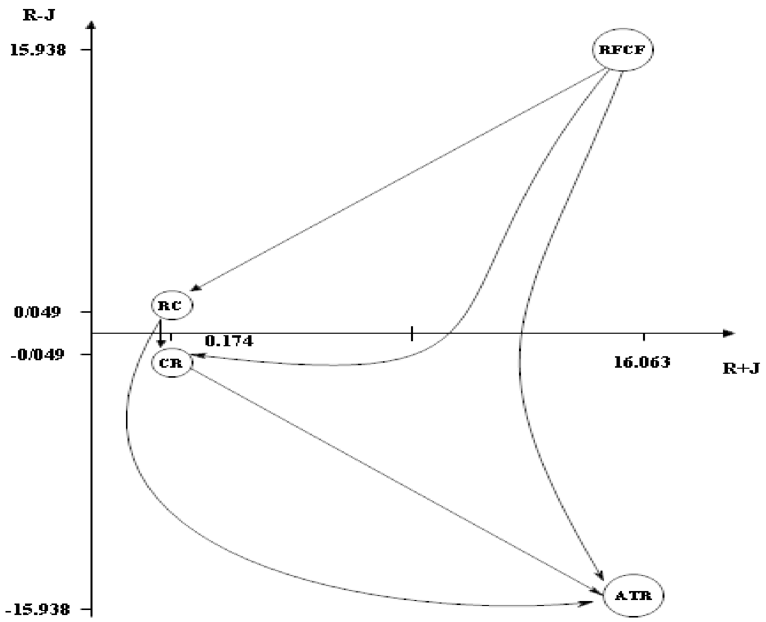

Figure 4: Resulting of DEMATEL analysis for indicators of banks' credit risk

According to data from Table (5) and figure (4), the variable of The Ratio of Free Cash Flow (RFCF) has the highest value in the total row and thus is the most influential indicator among indicators examined in the prediction of banks' credit risk. Also, the variables of Cash Ratio, Asset Turnover Ratio(ATR) have the maximum influence and the current ratio is the most influenced indicator.

4.2. Credit risk estimation by logistic

To design an optimal model for measuring the credit risk for legal clients of banks listed on the Tehran Stock Exchange, four main indicators were selected as the important variables affecting companies' credit risk. Then, financial and non-financial information relating to these variables were extracted by financial statements of 452 legal clients and processed by Excel. To achieve an optimal model of credit scoring, first all variables were entered the model and the significance of their coefficients were examined by Wald statistic and the significance of total regression was evaluated by LR statistic (at 95% confidence level) and also the accuracy of model specification. Finally, different combinations of four variables were confirmed after testing, and the logistic model of credit risk is as follows:

- Asset turnover ratio
- The ratio of free cash flow
- Cash ratio
- Current Ratio

$$Ln(\frac{P}{1-P}) = \beta_0 + \beta_1 ATR + \beta_2 RFCF + \beta_3 CR + \beta_4 CACD$$

The logistic model aims to distinguish between two companies that will/will not repay their loans. Therefore, in this research, before fitting the logit model by the mean difference test, the possibility of separating these two groups based on financial ratios has been tested.

The results of the mean difference test of two groups (companies that have repaid/have not repaid their loans) are shown in Table 6.

According to Table (6), given the significance level (less than 0.05), at 95% confidence level, all variables were different in two groups.

In logistic regression, like normal regression, the significant coefficient of an independent variable can be tested by the assumption that zero coefficient has no effect on the success probability of the dependent variable. Significant coefficient of an independent variable is tested through t-statistic in a normal regression. But in the logistic regression another statistic is used called "Wald statistic". For each coefficient like normal regression, Wald statistic shows the significance of the relevant coefficient. This statistic has χ^2 distribution with one degree of freedom. Table (7) shows the results of the model fitting using Wald statistic (w).

Table 6: Results of the mean difference of two groups

Independent variable	T-statistic	Degrees of freedom	Significance level	95% confidence level	
				Lower limit	Upper limit
Asset turnover ratio	9.52	325	0.000	0.41	0.68
The ratio of free cash flow	6.51	325	0.002	0.38	0.49
Cash ratio	5.79	325	0.000	0.27	0.69
Current ratio	10.62	325	0.006	0.47	0.89

Table 7: Results of the logit model fitting

Variable	Beta coefficient	Standard deviation	Wald statistic	Degrees of freedom	Significance level
Constant value	-0.659	0.314	-1.479	1	0.000
Asset turnover ratio	-0.547	0.374	-1.470	1	0.026
The ratio of free cash flow	1.479	0.214	-1.63	1	0.000
Cash ratio	4.719	0.496	4.558	1	0.000
Current ratio	-2.238	0.515	3.14	1	0.038

Wald statistic calculated for each variable and the calculated error level represent significant coefficients in the model. The likelihood for this model is 051.322, which indicates the high ability of model for predicting the credit risk. Logistic model, designed to predict the credit risk based on financial ratios coefficients (independent variables), is defined as follows:

$$Z_i = Log_e(\frac{p_i}{1-p_i}) = 0.659 - 0.547X_1 + 1.479X_2 + 4.719X_3 - 2.238X_4$$

Also, Z value limits by statistical data are according to Table (8):

Table 8: Z value in non-repayment cases

Non-repayment probability	Z range
Too much	$Z \leq 1/458$
Weak	$1/458 \leq Z \geq 5/943$
Zero (normal situation)	$Z \geq 5/943$

Based on the fitted model, the probability of non-repayment of loans by the client is calculated as follows:

$$1\text{-}p_i = 1-\pi(x_1,\dots,x_4)=$$

$$1-\frac{e^{-0.659-0.547X_1+1.479X_2+4.719X_3-2.238X_4}}{1+e^{-0.659-0.547X_1+1.479X_2+4.719X_3-2.238X_4}}$$

The number of creditworthy and uncreditworthy clients is calculated by examining the model's prediction power at the threshold (0.5). Table (9) shows the prediction power of the logistic model at the threshold (0.5).

Table 9: Examining the model's prediction power by data at the threshold of 0.5

Y=0 (creditworthy)	Y=1 (uncreditworthy)	the threshold of 0.5
207	76	$P(Y) \leq 0.5$
69	100	$P(Y) > 0.5$
276	176	Total

As shown in Table (9), from a total of 276 creditworthy clients, 207 cases have been classified correctly (75%), the dependent variables (y=0) have been correctly predicted, and from a total of 176 uncreditworthy clients, 100 cases have been classified correctly (57%), the dependent variables (y=1) have been correctly predicted.

The above table is known as classification table in the statistical literature. The ratio of observations, Y=1, that has been correctly predicted is called sensitivity degree and the ratio of observations Y=0 that has been correctly predicted is called detection degree of model. The sensitivity degree of model is 75% and the detection degree is 57%.

Discussion and Conclusions

Evaluation and measurement of banks' credit risk is one of the most interesting and important fields of study in finance. In this study, various models of banks' credit risk and prediction models were evaluated and then the logit regression model was selected by literature review. Then influential indicators for predicting credit risk of banks' legal clients were detected.

The results of this study are consistent with the results of Karbassi Yazdi, et al. (2014) in terms of indicator, but the strength point of the present study to the mentioned article is using DEMATEL for weighting and determining the severity of effects and influence of indicators. The results of this study show that 75% of creditworthy clients and 57% of uncreditworthy clients have been classified correctly. Considering the research of Feyzi and Hashemi (2013), who predicted banks' credit risk by Altman's model Z, there is more probability to predict banks' credit risk by this model compared to the logit regression model with four-year limitation period. As a result, the researchers suggest that it is better to use Altman model Z instead of logit regression as it has a higher prediction power.

In the end, some suggestions are provided for other researchers:

1) Evaluating the credit risk by fuzzy artificial neural network and rating of key indicators by VIKOR.
2) It is recommended that manufacturing companies review their financial status by this model and in the case of bankruptcy, perform appropriate measures to prevent the event.
3) Using the model by the Stock Exchange to list companies helps the market to predict companies investigated more accurately.
4) It is recommended that neural networks and artificial intelligence be used for predicting and measuring banks' credit risk over a five-year period.
5) It is recommended that fuzzy multi-criteria decision making be used for measuring the importance of indicators in the assessment of banks' credit risk.

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