The comparative study of the power of Logit, Probit, and support machine vector models and discriminant analysis in predicting timely occurrence of the financial distress crisis based on CAMEL ratios in the banks and financial institutions

Abstract

Recent developments in the economics, information and the contract theory have led to a more detailed analysis of the functions of banks and stock markets and other ways of financing of the banks and financial institutions. Financial distress refers to situations in which an organization fails to meet its obligations to creditors or may find it difficult to fulfill those obligations. Thus, predicting the distress has an important and increasing role in the economy. Because it imposes huge costs on companies, shareholders, creditors, and on a macro level the whole economy. The purpose of this study was to evaluate the power of the Logit, Probit, discriminant analysis (discriminant function), and support vector models to predict timely occurrence of the financial distress by 17 banks and financial and credit institutions. In this way we can take steps to formulate a practical template for the early warning system of the distress. Therefore, in this study, five variables of CAMEL model were used to predict the distress of the study population. The results showed that among presented four models, the Logit model was the strongest with 79% prediction accuracy and the support vector machine was the weakest with S circular kernel function and with 53% prediction accuracy for prediction of the financial distress of the banks and financial and credit institutions. The results of this study can be useful for institutional investors to manage their companies. By anticipating the financial crises of their subsidiaries companies (the banks and financial and credit institutions), they can think of the necessary arrangements and prevent these crises to occur.

Keywords: financial distress, CAMEL model, Logit, Probit, discriminant analysis, support vector machine

1. Introduction

Recent developments in economics, information and contract theory have led to a more detailed analysis of the functions of banks and stock markets and other financing ways for the companies. Today, one of the most important dangers that threaten many businesses is their inability to pay obligations, regardless of the size and nature of their business. The available evidence indicates that in the last three decades, the bankruptcy rate of firms has grown significantly compared to the previous decades (Shamoy, 2001). Financial distress is a situation where companies are unable to continue their operations and are not sufficiently able to generate enough cash to meet their needs, such as paying lenders. Given that distress is different from bankruptcy and has been defined as a pre-bankruptcy or liquidation stage, one way to prevent corporate bankruptcy is to predict financial distress (Mansour Far et al., 2016). Over the past two decades, the banking system around the world has experienced significant changes in its operating environment, and the numerous external and internal factors affect on the structure and function of the banking system. However, in spite of all presented changes, the banking system remains the most important source of finance in many

countries and plays a key role in transferring resources from savers to investment units (Hoffman, 2011). Managers of banks and financial institutions, investors, and legislators are all keen to know the causes of a bank collapse and want to be able to predict what bank or credit institution may be in crisis in the future. Depositors and investors also want to be able to identify weak banks and financial institutions in order to safe their assets from risk (Yeganeh et al., 2016). Banking system supervision has different components and can be considered in different ways. The success criterion of a bank or financial and credit institution is not limited to the profitability of its investment projects, but a variety of efficient models and ratios are needed to predict the performance of the bank or financial institution. For this reason, a numerous financial ratios have been designed and presented for monitoring the performance of banks and financial and credit institutions which can be used to determine to some extent the condition of the bank is favorable or unfavorable (Vilen, 2010). By the increasing volume and variety of financial transactions, the banks supervision has become a complex process and requires a great deal of time and expense (Seraj & Taheri, 2012). An early warning system has been introduced to predict the timely occurrence of financial distress and is an effective way to discover the financial health of the banks and financial institutions. The main purpose of the present study is to predict the timely occurrence of financial distress for banks and financial institutions based on the early warning system. In order to apply the early warning system, the financial ratios extracted from the financial statements of the given banks and financial institutions are used. These ratios are compiled to cover five CAMEL features, namely capital adequacy, asset quality, management, profitability and liquidity. After collecting data using Logit, Probit, support machine vector, and the discriminant analysis, the financial distress prediction is done to determine which method in the study population has higher predictive power over financial distress.

2. Review of literature

2.1. The financial distress

The growing empirical literature is rapidly studying the causes and consequences of the bankruptcy of the banks and financial institutions in the contemporary economies. Until recently, research on the banking crisis often relied on experience gained from the crisis of the 19th and early 20th centuries. In particular, the Great Stagnation was the subject of research and study, until a numerous bankruptcy events occurred around the world. The 1990s saw a new wave of the banking crises that gave rise to a new impetus for study (Hobrich, 1990). Banks are the financial intermediaries, often with short-term liabilities. And usually their assets are long-term loans to the businesses and consumers. When the value of their assets falls below their debt value, the banks are unable to pay debt or, in other words, they become distressed (Yeganeh et al., 1986). The value of a bank's assets may fall due to the borrower's inability or unwillingness to pay their debt (credit risk). Sometimes, even in the absence of an increase in deferred claims, if the rate of the return on a bank's assets is lower than the rate required to pay for the liabilities, the bank's balance sheet can be in unsuitable situation (Moshiri, Nadali, 2010). In one of his first studies on financial distress theory, Gordon (1971) defined it as a decline in the power of the company profitability, which increases the likelihood of inability to pay interest rate and the debt principal.

Determining the exact cause or causes of bankruptcy and financial problems is not easy. In many cases, several reasons together lead to bankruptcy. Dunn and Bradstreet (1998) consider the main cause of the bankruptcy to be the financial and economic problems. While Gateman (1998) believes that the first and most important cause of the bankruptcy is mismanagement (Saeedi & Aghaee, 2009).

Rapid alert system is a tool for predicting and identifying bankruptcies from bankruptcies or a way to detect bankruptcies (financially) in the banking system (Seraj & Taheri, 2012).

2.2. Early warning system

Early warning system is a tool for predicting and identifying the bankrupt bank from non-bankrupt one or a way to detect unorganized banks (financially) in the banking system (Seraj & Taheri, 2012). The adverse financial situation of a bank or credit institution undermines the health indicators of the banking system and causes the public mistrust than to the entire banking network. Therefore, it is necessary to design appropriate methods for identifying troubled banks before it has an adverse effect on the entire banking system. The legislators and supervisors of the banking network can deploy an early warning system at least in four of the following ways:

1. Investigate the operation and the function of the bank and discover its violation of the rules of the central bank

2. Check online banking system and evaluate electronic cash transfer

3. Discover the violation of the bank executives and employees of their legal duties and rights

4. Investigation of banks financial status and confirmation or denial of Bank financial health (Gary et al., 1988)

Given that in the Fourth Development Plan as a twenty-year prospect, has emphasized on the privatization, in the twenty-year horizon of national welfare, every Iranian should enjoy factors such as the equal opportunities and the proper income distribution, both of which are achieved through capital market efficiency. Therefore, the need to use the new financial instruments, in particular forecasting and predictive models of the financial distress that contribute to the efficiency of the capital market by disclosing the real situation of the monetary and financial institutions as the main monetary channels of the country, is felt. The recent crises of the 1390s in the financial and banking system of the country and the instability in macroeconomic conditions have also made it important to develop a comprehensive document for the Banking Early Warning System (BEWS) for monetary and banking policy (Ahmadian & Heidari, 2016).

2.3. CAMEL ratios

The CAMEL indicators were applied in October 1987 by the National Credit Union Administration (Babar & Zeb, 2011). The US Reserve Federal also evaluates banks under its supervision on a scale of 1 to 5, using CAMEL indices, each of which monitors one aspect of

the bank's financial health. Rank one indicates strongest performance and the rank five indicates weakest performance. In these credit ratings, profitability and liquidity are among the most important criteria for determining a bank's competence and assessment. To this end, since 1988, the Basel Committee on Banking Supervision has also considered the use of CAMEL indicators to evaluate the financial institutions (Abbasgholi Poor, 2010). The term CAMEL stands for 5 important financial characteristics or indicators that are described below:

1. Capital adequacy: Capital adequacy is a key variable in demonstrating the ability of the banks and financial institutions to stand up against shocks. In other words, the capital adequacy measures the financial ability of the banks and credit institutions (Baral, 2005).
2. Asset Quality: In analyzing the asset quality ratios, the main focus is on the credit risk. Asset quality ratios somehow validate the capital adequacy ratios (Saghafi & Seif, 2005).
3. Quality Management: Introducing a board that plays an important role in identifying, measuring and monitoring the monetary and financial institution's health is another of these indicators.
4. Earning: This indicator preserves the health of a bank or financial institution. Lack of the earning and high earning are both risk factors for a financial organization (Baral, 2005).
5. Liquidity: the banks and credit institutions must have sufficient liquidity to meet short-term liabilities (demand from depositors and lenders), and this has a major impact on the health and stability of the financial system.

2.4. The experimental background

Internal research

- Rasool Zadeh (2001) Research on "The study of the application of Altman Model to investigate bankruptcy of companies listed in Tehran Stock Exchange in two groups of basic Metals and textile industries" to evaluate whether to use Altman Z Model in the Tehran Stock Exchange companies has done well in both groups. In this study, he used the financial information from the financial statements of the above companies between 1996 and 1999. In this research the correct prediction of the bankrupt companies equal to 75% was proved.
- Shakeri (2003) conducted a study called "Investigation the use of Springate model for predicting the bankruptcy of Companies listed on the Stock Exchange". The Springate model, which uses the Multiple Difference Analysis (MDA) statistical method, can predict a company's bankruptcy with 88% confidence two years before it occurs. The question raised in this study is whether the Springate model can predict the exit rate of firms from the capital market over the next two years with a percent of error, according to the criterion of Law 141 of the Business Code.

- - Fallah Pour (2004) predicted the financial distress of listed companies in Tehran Stock Exchange with the help of the artificial neural networks and compared the results of his work with the results of discriminant analysis. The population consisted of 80 companies. In this study, he concluded that the ANN approach was significantly more accurate in predicting the financial distress than in the discriminant analysis method.
- Makian (2010) used a neural network model to compare the two methods of logistic regression and discriminant analysis to predict the financial crisis. The overall result of the study confirmed the priority of the neural network model over two other statistical methods.
- In his research, Saroui (2010) investigated the performance of the Springate, Zmijewski, and Ohlson models in both the pharmaceutical and textile industries, and the results showed that in the three years studied, the Springate model showed better results.
- Nadali, Mohammad (2013), in a study entitled "Calculating the Stress Index in the Money Market of the Iranian Economy", has calculated the Money Market Stress Index in the Iranian Economy during the period (1970-2009). The results of Nadali's research show that in some periods of time, the Iranian economy has been experiencing high fluctuations in the money market stress index, indicating the likelihood of the banking crisis occurring; however, due to the government structure governing the banks, these conditions have not led to an obvious banking crisis.
- Panahi, Hossein et al. (2014) conducted a study entitled "Five-Year Forecast of the Financial Bankruptcy for the Companies Listed in Tehran Stock Exchange".In their research, they have presented a model for the bankruptcy prediction, which is predicted within five years before a bankruptcy occurs. Model estimation is done in three ways: the linear probability model, Logit model and Probit model.

External Research

- Altman is the first one who proposes the multivariate bankruptcy models. He sought to predict the bankruptcy of firms by employing the multiple discriminant analysis and using the financial ratios as the independent variables. He introduced his famous model, the Z-Score, which is known as the commercial bankruptcy prediction. By this way, he chose 5 out of the 22 financial ratios that he thought were the best ratios to predict the bankruptcy. By combining these five ratios, Altman presented a model that he considers to be the best performance among the other financial ratios. In the years that followed, the criticisms of the Z –Score were introduced. The analysts, accountants, and even executives believed that the Z-Score applies only to the public institutions. Throughout his studies, Altman succeeded in correcting and modifying the model and presented a new model (Cited by Altman, 1968).

- Springate (1978) continued Altman's studies and used the discriminant analysis to select four appropriate financial ratios, including working capital to total assets, earnings before the interest rate and taxes to total assets, pre-tax profits to current debt, sale to all assets among the 19 ratios that were best ratios for identification of the healthy and bankrupt companies. After testing it in 40 companies, he presented a model that achieved 92.5% correct prediction.

-Ohlson (1980) used a logistic analysis method to create his model and tested his sample in 105 bankrupt countries and 2058 non-bankrupt companies, using 9 independent variables in his model. His model achieved 85.1% correct prediction.

- Zimijewski (1984) used the financial ratios of the liquidity, leverage, and performance to provide an appropriate model. These ratios were not theoretically selected, but rather based on his experience in the previous studies. Zimijewski's model was based on a sample of the 40 bankrupt and 800 non-bankrupt companies and achieved 86.14% of the correct prediction.

- Wallace (2004) in his research designed a model using neural network method. In his model, he used the key financial ratios that were reported as the best ratios in past bankruptcy studies. The Wallace model had an overall accuracy of 94% and examined 65 different financial ratios in previous studies.

-Cochrane et al. (2006) investigated the bankruptcy among internet companies using Cox PH technique. Their research results show that the net profit parameters to total assets, the cash flow to total liabilities, and the total assets are three key elements in prediction of the corporate bankruptcy. In addition, they found that for a year before the bankruptcy, the liquidity is the most important criterion for predicting the bankruptcy; while for three years before bankruptcy, the profitability is the more important parameter for predicting the bankruptcy. They used data from 225 companies in the 1997-2001, including 26 bankrupt companies. In addition, they used both the market variables and the accounting ratios to formulate their model.

- Wu et al. (2008) proposed a probabilistic neural network approach in their research. They compared this method with multiple discriminant analysis. The study 48 Chinese public companies and 7 financial ratios have been used including: Profitability Ratio, Total Debt to Total Asset Ratio, Goods Inventory Ratio, Accounts Receivable Ratio, Total Assets Turnover, Profit Index and Cash Flow Index. The results show that both the probabilistic neural network method and the multiple discriminant analysis provide good classification but the neural network method has more predictive accuracy than the multiple discriminant analysis and do not require the multivariate normality of the data.

- Chen (2009), based on the operating rules of the listed companies in the Taiwan Stock Exchange, considered their scope of analysis to be stopped or suspended companies. In their study they used the financial ratios, the non-financial ratios, and factor analysis to extract appropriate variables. The methods used were the artificial neural networks and the data mining. The results show that the prediction accuracy of the ANN is higher than the DM clustering method.

- Zhang and Lin (2009) examined and tested the predictive ability of the four most commonly used financial distress prediction models that provide reliable prediction models for Taiwanese companies. The multiple discriminant analysis, Logit, Probit and the artificial neural networks are selected by them between 1998 and 2005. In this study, 20 variables were used to create models to predict the financial distress. The results show that the Logit, Probit and ANN models have higher prediction accuracy and are reliable.

- Cho et al. (2009) proposed a coherent strategy on how to effectively and efficiently integrate the artificial intelligence techniques and the statistical techniques that are also applicable. By integrating the multiple discriminant analysis, the logistic regression, the neural networks and the decision tree introduced a coherent model based on learning neural networks to predict the bankruptcy. The strength of their proposed model stems from the differentiation of the source methods weights for each of the themes in the experimental dataset. The results show that the proposed model can increase the prediction accuracy compared to the source methods.

- Premachandra et al. (2009 introduced data covering analysis as a quick and easy tool in their research work for assessing the company bankruptcy compared to the logistic regression. Their statistical population includes 50 bankrupt and 910 non-bankrupt companies between 1991 and 2004. They used 9 variables (2 outputs and 7 inputs) in their studies. The results of this study show that the logistic regression performs well in the internal samples while the data covering analysis performs well in the external samples. The data covering analysis model also performed very well in identifying the bankrupt companies, while the logistic regression model performed better in identifying non-bankrupt companies than the DEA.

Chiaramonte and Casu (2016) have investigated the relationship between the capital, the liquidity ratios and the financial crisis for the European banking industry. Using a large-scale database of the large banks, they test the relationship between the structural liquidity and the capital ratios defined in the Basel Committee on the bankruptcy probability. The model developed by them by estimating several versions of the logistic likelihood model has shown that the probability of the financial failure and distress decreases with increasing the liquidity sources, while the impact of the capital ratios is significant only for the large banks.

- Cleary and Hebb (2016) have designed an efficient and the practical model to predict bank distress in and out of the sample evidence. They analyzed the failures of 132 US banks between 2002 and 2009 and developed a model based on the data from their study that could guarantee the bank efficiency in preventing the financial distress with high accuracy.

- Caggiano et al. (2016) compare the Logit-based early warning systems. Their main question was whether the period of the systemic banking crisis mattered. And accordingly, they have compared the Logit models of the binomial and polynomials to construct the warning systems for the systemic bank crises. The results of their research demonstrate the advantages of multiple Logit models in a large sample of the world economy.

- Dawood et al. (2017) conducted a study entitled “prediction of the independent debts crisis with a warning system approach”. Pointing to the challenge of designing warning systems for the independent debt crisis, they aimed to provide a prediction model that has empirically evaluated its power more than prediction econometric models. They have proposed a crisis prediction model, the results of which have reported a more accurate estimation for the prediction of the independent debt crisis.

3- Research Method

This research is a descriptive-causal research in terms of method and it's an applied research in terms of purpose. In order to achieve the main aim of the research, first, it is necessary to examine the ratios used in the research and then introduce the models that are used to predict the timing of distress (rapid alert system).

1-3 Introducing CAMEL Ratios for banks and financial and credit institutions

Various financial ratios have been used to cover CAMEL's features in internal and external researches. Due to the lack of access to all statistics of the country's banking system some of the ratios cannot be calculated. Therefore, in selecting ratios used to measure CAMEL features, consider to: access the information needed to calculate selected ratios, validation of ratios used by experts and financial distress experts in banking industry and the choice of ratios that cover all CAMEL indices is essential. In the present study, the ratios presented in Table 1 will be used to measure the CAMEL indices by taking into account the availability and calculation of these ratios.

Table 1. Selected financial ratios

Row	Financial ratio	CAMEL feature
1	Equity / Assets	Capital adequacy
2	Allowance for suspicious receivables / total receivables and financial assets	
3	Total Assets / Equity	Adequacy of assets
4	Operating profit / operating cost	Management
5	Total Cost / Total Income	
6	Profit after-tax / total staff	
7	The total for Net interest income and operating income / average earnings	
8	Earnings from concessional facilities/ total income	Profitability
9	Pre-tax profit / average total assets	
10	Profit after-tax / average total assets	
11	Profit after-tax / average shareholders' equity	
12	Bank service fee income / total income	
13	Administrative and Public Expenses / Total Expenses	
14	Credits and seller concessions/ Total Bank Deposits	Liquidity
15	Cash Assets / Total Assets	
16	Long Term Deposits / Total Assets	
17	Deduction of Current Debt from Current Assets / Total Assets	

In this study, the value of each financial ratio is calculated for 17 banks and financial institutions based on statistics published in the Balance Sheet, Profit and Loss Statement and other information in a 5-year period from 2012 to 2016. In fact, the secondary analysis

method will be used to collect information. Finally, each of the presented models is used to timely prediction of a financial distress in order to measure their ability to predict the financial distress of banks and financial and credit institutions. In the following, each of these models is introduced.

3.2 Logit model: This model is one of the most effective models of rapid alert system for predicting the financial status of banks and financial institutions. In this model, usually zero number represents the unfavorable situation and one number represents a desirable situation. In this method, the probability of y occurring is not a linear function of the research variables but it is a function of the logistic distribution (Hill, et al., 2008).

$$P(y=1|X)=\Lambda(X\beta)=\frac{1}{1+e^{-X\beta}} \qquad (1)$$

Since in this model the coefficients are nonlinearly correlated with the dependent variable, therefore, linear estimators such as least squares cannot be used to estimate it. For this reason, the maximum likelihood estimator is used to estimate this model. The main advantage of the Logit model is that the estimated value for the probability of the dependent variable in this model will necessarily be in the range of {0, 1}.

3.3 Probit Model: The Probit model is exactly the same as the Logit model except the probability of the dependent variable occurring has a standardized normal distribution (Trinn, 2003).

$$P(y=1|X)=\Phi(X\beta)=\int_{-\infty}^{X\beta}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}u^2}du \qquad (2)$$

3.4 Audit Analysis Model: In cases where the dependent variable is nominal and the independent variables are quantitative or qualitative, the audit analysis method is used to predict the dependent variable (group membership) through independent variables (Sarmad, et al., 1387). In other words, the dependent variable takes only two variables of zero and one, and thus in the audit analysis, the dependent variable is a qualitative variable with two values (Azar and Momeni, 2005). In scientific literature, audit analysis has many synonyms such as detection function, discriminant function and audit analysis. Analysis based on detection function is in fact a reverse multivariate analysis of variance which means that in the audit analysis, considered the independent predictor variables and dependent variables. The detection function, also called focal root, is defined as follows. In fact, this equation is used to predict future group membership.

Z or D = b1x1+ ……+bixi+c (3)

3-5 Support-Vector Machine Model: is one of the machine learning methods based on statistical learning in the 90's developed by Wipnik et al. The support vector machine or SVM is actually a two-way classifier. This method tries to create a hyper plane for two floors with the maximum distance of each floor to the hyper plane. The point data closest to the hyper plane is used to measure this distance. Hence, this point data called support vectors

(Wipnik, 1995). In this method, model building involves two stages of training and testing. At the end of the training phase, the generalizability of the trained model is evaluated using the experimental data.

Support-Vector Machines have the following properties:
1- Designing a classifier with maximum generalization
2. Reaching a global optimal point of function
3. Automatic determining the optimal structure and topology for the classifier
4- Modeling nonlinear differentiation functions using nonlinear kernels and the concept of inner product space in Hilbert spaces.

In this method, the kernel functions are used in the training phase, and Table 2 presented the popular kernel functions that are commonly used in support vector machine learning.

Table 2: Kernel Functions of Support Vector Machine Training

Kernel function	الگوریتم
Linear function	$k(x_i, x_j) = x_i^T . x_j$
Polynomial function	$k(x_i, x_j) = (\gamma x_i^T . x_j + r)^d$
RBF function	$k(x_i, x_j) = exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) = \exp(-\gamma\|x - x_i\|^2), \gamma = \frac{1}{2\sigma^2}$
Circular function	$k(x_i, x_j) = \tanh\ (\gamma x_i^T . x_j + r)$ $\tanh(x) = \frac{e^x}{e^x + 1}$

2- Results

In this section, we will present methods for categorizing banks and credit institutions in Iran into two categories of healthy and helpless. In the state of distress, the institutions' inability to pay debt is temporary and it's permanent in the state of bankruptcy. In bankruptcy, the business ceases to operate and the company fails to meet its predetermined goals, which means it will be died and take no action to improve the company. In fact, bankruptcy is the last stage of the life cycle of the institution. But in a state of distress, the institution shows signs of financial distress and has not yet died, and the institution can be improved by restructuring. Distress is pre-bankruptcy, and companies that are helpless do not necessarily go bankrupt.

4.1 Research variables: As mentioned earlier, the following five financial ratios have been used in distress model in this study.
1- Capital adequacy (x_1)
2- Asset quality (x_2)
3- Management Quality (x_3)
4- Profitability (x_4)
5- Liquidity (x_5)

In this section, before estimating the model and analyzing the results, the mean and variance of the financial ratios of helpless banks and financial and credit institutions are compared with those of healthy banks and financial institutions. The results are presented in Table 3.

Table 3: Mean and Variance of Research Variables separately sorted by helpless and healthy banks and institutions

Variables	**Healthy**		**distress**	
	Variance	**average**	**Variance**	**average**
Capital adequacy	0.15	0.04	11.85	11.7
Asset quality	0.12	0.05	4.61	0.63
Management Quality	0.15	0.16	0.89	0.005
Profitability	0.98	0.52	0.95	0.15
Liquidity	1.12	0.91	1.09	0.81

According to Table 3, the mean capital adequacy variable for helpless banks and financial institutions is higher than healthy banks and institutions. This means helpless banks and institutions are failing to utilize their capital adequately. In contrast, the mean of other variables for healthy banks and institutions is higher than helpless banks and institutions. Also, the mean of two variables of capital quality and asset quality in helpless firms is being negative. Considering that the distance between the occurrence of distress and the intended time for the research variables is five years, it is expected that the means of two groups not significantly different. In fact, many signs and symptoms of financial distress have not been disclosed over the five years before distress, so there should be no difference between financial ratios of two groups. Table 4 shows the results of the equality test of the mean of two variables. The means equality for the capital adequacy is not excluded as a result the means of two groups is not significantly different in these ratios. But for the other variables there is a significant difference between the means of two groups at the 10% level.

H_0(Healthy average - helpless average)			
H_a: mean(diff)$\neq$ 0		**H_a**	
x_1	0.45 : probability measure	H_a: mean(diff)>0	Pr= 0.16
x_2	*0.08 : probability measure	H_a: mean(diff)>0	Pr= 0.04
x_3	*0.09 : probability measure	H_a: mean(diff)>0	Pr= 0.05
x_4	**0/002 : probability measure	H_a: mean(diff)>0	Pr= 0.001
x_5	0.47 : probability measure	H_a: mean(diff)>0	Pr= 0.32

(**) indicates significance at 5% level and (*) indicates significance at 10% level of model estimation results

4-2 Implementation of distress prediction models

In the following, there are the models for diagnosis of distress relating to the statistical sample of 17 banks and credit institutions.

1-2.4 Logit model

In this model, in this model the coefficients are nonlinearly correlated with the dependent variable, therefore, linear estimators such as least squares cannot be used to estimate it. For this reason, the maximum likelihood estimator is used to estimate this model. The estimation results are shown in Table 5.

Table 5: Results of Logit Model Estimation to Predict Distress

Logit Model	
۰/۸۰۷ *** (۰/۲۰۵)	x_1
۳/۳۱۵ *** (۰/۶۵۹)	x_2
– –	x_3
۳/۱۵۱ *** (۰/۷۳۲)	x_4
۲/۰۶۲ *** (۰/۵۸)	x_5
۱/۸۵۲ *** (۰/۷۸۱)	Constant
Prob = ۰/۰۰	Significance of the whole regression
۰/۲۵	$R^۲$
۰/۰ ۷۹	correctpredicting percentage of model for the sample

Logit Model	
x_1	0/807 *** (0/205)
x_2	3/315 *** (0/659)
x_3	- -
x_4	3/151 *** (0/732)
x_5	2/062 *** (0/58)
Constant	1/852 *** (0/781)
Significance of the whole regression	Prob = 0/00
$R^۲$	25/0
correctpredicting percentage of model for the sample	79 0/0

(*) Significance at the level of ten percent, (**) Significance at the level of five percent, (***) Significance at the level of one percent

Any financial ratios whose coefficient was not significant were excluded from the model and only the results of the final model are reported in the table. Since in this study, if the company is helpless, the dependent variable will have a value of zero and if it is healthy, the dependent variable will have a value of one, if the coefficient of any of ratios is positive, it indicates that the higher the financial ratio, the lower the likelihood of being helpless. In the second column of Table 5, the results of Logit model estimation are presented. The asset quality factor (x_3) is not significant, so it is removed from the model. Also the correctpredicting percentage of model for the sample is 0.079.

2-2-4 Probit Model

The Probit model is exactly the same as the Logit model except the probability of the dependent variable occurring has a standardized normal distribution. The results of the implementation of this model are presented in Table 6.

Table 6: Results of Probit Model Estimation to Predict Distress

Probit Model	
x_1	0/561 *** (0/381)
x_2	2/251 *** (0/325)
x_3	- -
x_4	2/724 *** (0/315)
x_5	0/483 ** (0/236)
Constant	1/23 *** (0356)
Significance of the whole regression	Prob = 0/00
R^2	27/0
Correct predicting percentage of model for the sample	76 0/0

(*) Significance at the level of ten percent, (**) Significance at the level of five percent, (***) Significance at the level of one percent

In the second column of Table 6, the model estimation results are presented by Probit method. Again, it is not significant according to the asset quality factor (x_3). Therefore, this variable is removed from the model. Also, coefficient signs are completely expected and in terms of significance, all of the coefficients are significant at 1% level. The model was able to predict the degree of distress of the sample members with an accuracy of 76%. It can be considered in terms of the power of prediction for the sample members, the Logit model is the most accurate and the Probit model is then adopted. Of course, their difference in prediction accuracy is 3%.

3.2.2 Audit Analysis Model

The final model was obtained by the stepwise method in two steps and Wilks' lambda values have been calculated for each stage (Wilks' lambda ratio is a value that shows the

differentiation power of a detection function. This ratio is undisclosed variance to the total variance. The smaller the variance, the higher the power of the function's detection). The data analyzer software removes the nonsignificant variables that have the least or no effect on the prediction of the dependent variable in each step, respectively. The remained variables are those have the greatest impact on the prediction of the dependent variable, means they have the continuity of activity. Also the final value of lambda in the second step is 0.838 and its F value is 50.9 , both values are significant at 95% confidence level.

Table 7: Wilks' Lambda

Test of Function	Wilks' Lambda	Chi-square	df	Sig
1	0.838	94.241	16	0.000

In the final model in Table 7, the Wilks' Lambda value is 0.838 which is the least value compared to the previous steps and the chi-square value for the model is equal to 94.224 which according to the specified critical value, the pattern is significant. According to the coefficients obtained from the audit analysis, it was found that the capital adequacy coefficient is 0.159, the quality of assets in the audit function is 0.94, the quality of management is 0.804, the profitability is 0.04 and the liquidity is 0.04. Thus, the focal detection function (Fisher's linear function) is obtained as follows:

$$Z=+0/159X1 + 0/94X2 +0/804X3 + 0/04 X4+0/104X5 \qquad (4)$$

Critical points: To assign individuals to groups, it is necessary to identify a critical point In order to assign individuals to groups, it is necessary to identify a critical point by which classify them. The critical point is the midpoint between the mean of two statistical populations. If the value of the detection function for one individual exceeds the critical point, it is assigned to one group, and if the individual score falls below, it is assigned to another group. Table 8 presented the critical values and the type of decision about the type of activity or inactivity of banks and financial and credit institutions:

Table 8: Critical values for the classification of banks and institutions

The type of decision	Critical values
Bank or institution is helpless	Less than -0.378
Can't comment	Between -0.378 to 0.378
Bank or institution is healthy	More than 0.378

Correct prediction rate: Based on the critical points, the level of correct recognition of healthy and helpless banks and financial and credit institutions is presented. When data on 5 independent variables are put into function, a certain value is obtained that predicts the activity of the company (bank or institution) if compared with the critical points. The correct

prediction rate of active companies is about 47% and the correct prediction rate of passive companies is 30% which is 77% of the total classified correctly.

By the help of z test we can check the quality of 77%. As we know, the probability of distress and continuity of activity is equal to one, and when the probability of an event is equal, the random distribution leads to a correct classification of 50% in each group. This means that the probability of companies being in the group 0 is 50% and the probability of being in the group 1 is 50%. The difference between the percentage of classification obtained from the audit analysis function and the 50 percent random for each group indicates the quality of the audit function model. The importance of this difference is revealed by calculating the z test. According to the n = 85 (5-year period), the calculated value of z test is as follows:

$$z = \frac{0.77-0.5}{\sqrt{(0.5\times0.5/85}} = 4.059$$

This value is greater than the standard value of 1.96 at the 5% error level, which means that by using a Discriminant Analysis model with a 95% confidence level, we can make a better discrimination than a purely accidental process.

4-2-4 Support Vector Machine Model

If D = $\{(x_i, y_i)\}_i^l$ =l be a dataset containing L sample x_i with the labels of $y_i \in \{0,1\}$ of two classes (helpless and non helpless) and to discriminant these two classes Linearly we are looking for an optimal separator plane so that it has the least segmentation error. The most appropriate choice is the one with the most margins between two sides. The margin can be the sum of the closest points from both floors to the separator plane. The equilibrium between the margin and error of the misclassified samples can be controlled by predetermined the positive value of C. The decision function here can be as follows.

$$f(x) = sign\left[\sum_{i=1}^{l} \lambda_i y_i x^T x_i + b\right]$$

λ_i is called the Lagrangian coefficient. Data whose corresponding Lagrangian coefficient is nonzero, called the support vector that is being on the boundary between two classes. In practice, the use of linear classifiers to separate nonlinear data reduces performance significantly. Therefore, it is advisable to use a nonlinear classifier, which is easily achieved by depicting data in a higher dimensional feature space, that means:

$$x \in R^d \quad \rightarrow \quad z(x) = (\emptyset_1(x), \dots, \emptyset_n(x)) \in R^n$$

Now we can write the relationships of linear classifiers in this new space. As a result, the decision function for this case is as follows:

$$f(x) = sign\left[\sum_{i=1}^{l} \lambda_i y_i z^T(x) z(x_i) + b\right]$$

A key point about the support vector machine is for calculating the decision functions the only value to be calculated is the Dot Product $z^T(x)\ z(x_i)$. For convenience, the kernel function is introduced as follows:

$$z^T(x)z(x_i) = \sum_{i=1}^{\infty} \alpha_i \varphi_i(x)\varphi_i(y) = K(X,Y)$$

Where $\{\varphi_i\}_{i\infty} = 1$ and $\{\alpha_i\}_{i\infty} = 1$ are a series of real numbers and functions, respectively. Thus the decision function becomes:

$$f(x) = sign\left[\sum_{i=1}^{l} \lambda_i y_i K(x,x_i) + b\right]$$

Table 2 lists the popular kernel functions commonly used in support vector training. In the following, the results of the model implementation presented in Table 9 using above four functions for the research data.

Table 9: Prediction Percentage of distress for support vector machine using different kernels

	Kernel type	Prediction percentage of distress
Prediction percentage	RBF	21/64
	Polynomial	37/64
	Circular S	57/53
	Linear	45/54

For this research, as you can see from the above table, the polynomial kernel has the best prediction for the support vector machine than the other kernels.

5-2-4 Comparing the models

In the following and table 10, the results of the predicting of different models for banks and credit institutions are presented.

Table 10: Comparison of model prediction percentages

Correct prediction percentage	Model
79 0/0	Logit model
76 0/0	Probit model
77 0/0	Audit Analysis Model
21/64 0/0	support vector machine model with RB kernel
37/64 0/0	support vector machine model with polynomial kernel
57/53 0/0	support vector machine model with circular S kernel
45/54 0/0	support vector machine model with linear

	kernel

According to Table 10, the Logit model by the prediction percentage of 79% is in the first rank of predicting distress of banks and credit institutions. On the other hand, the support vector machine model by circular S kernel with 0.57.57 has the least prediction power of distress in this statistical sample.

3. Conclusions and Suggestions

The purpose of this study was to evaluate the power of Logit, Probit, Audit Analysis and Support Vector Machines models in predicting distress occurrence of bank and financial and credit institutions. The results indicated that all models used had the ability to predict the timing of financial distress. But to achieve a rapid alert system in discussing bank financial distress and financial and credit institutions needed to compare the strengths and capabilities of these models and determine the strongest model in the prediction. The results showed that the Logit model with 79% predictive ability and accuracy was in the first rank among the investigated models. It should be noted that in this study the variables introduced in CAMEL model were used to measure the ability of the evaluated models and the results are based on data and information collected according to CAMEL model variables from 17 banks and financial and credit institutions. The results of Logit model in this study were consistent with the results of Siraj and Taheri's (2012) research on "Banking surveillance Based on Rapid Alert System Using CAMEL Ratios in Logit Model". In this study, Logit model was used to create a rapid alert system in the banking system in order to predict financial distress and its results indicated that profitability ratio along with capital adequacy ratio were more effective in the discussion of preventing financial distress in the studied banks. The results of applying the Probit model are consistent with the results of Panahi et al. (2014). In this study, model estimation is done in three ways: linear probability model, Logit model and Probit model based on Altman model indices. The selected sample involved 134 companies listed in the Stock Exchange and the evaluated model was able to accurately predict the status of these companies in 2008. Results of applying Audit Analysis Model (Recognition Function) consistent with the results of Yeganeh and Sayadi Research (2011) by the topic: "Using Audit Analysis (Detection Function) to Predict the Continuity of Corporate Activity Using Some Figures from The underlying financial statements (balance sheet, profit and loss statement and cash flow statement) correspond to the application of the audit analysis model (the recognition function). Regarding the results of the support vector machine model it should be noted that in this study used four models: RBF, Polynomial, Circular S and Linear Kernel for predicting the timing of financial distress of studied banks and financial and credit institutions. The results showed that all the used models were able to predict the timing of financial distress. But among these four models, the polynomial kernel model is more capable than the other subset models of support vector machine. This model was able to correctly predict financial distress with a capacity of 64%. The results obtained in this section of the study are consistent with those of Mansourfard ,et al. (2013). The results also showed that kernel functions, polynomial functions in the year of distress, one or two years before have the highest predictive power. Also, the results of this part of the study are consistent with the

results of Feng Hui & Sun (2006) and Sun & Li (2012) in that both studies investigate the use of support vector machine in predicting financial distress and the results emphasized on effective use of this model in predicting the timing of financial distress. It should be noted that one of the concerns of investors and creditors is investing in companies that eventually go bankrupt due to the poor performance, and thus lose their expected capital and profits. Using the performed models in this study can help investors in optimizing their portfolio and help creditors avoid lending to banks and financial and credit institutions that are more likely to go bankrupt. The results of this study can be particularly useful for institutional investors involved in corporate finance, to anticipate the possible financial crises of the subsidiaries (banks and financial institutions and credit institutions), to take the necessary precautions and to prevent these crises occurring.

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