Environmental Energy and Economic Research 2023 7(2): S056
DOI 10.22097/EEER.2023.367783.1270

Research Article

Designing an Optimal Model Regarding Early Warning System of Bankruptcy of Banks in Iran Application of Grounded Theory and Econometric Models

Hojjatollah Keshavarz Haddadha, Hamidreza Alipour *, Sina Kheradyar

Department of Management, Rasht Branch, Islamic Azad University, Rasht, Iran

Received: 9 November 2022 /Accepted: 18 January 2023

Abstract
In financial and banking system and macroeconomic conditions develop a comprehensive document for the banking early warning system (BEWS) for monetary and banking policy makers is important. The main objective of the present study is to design and estimate the native model regarding the early warning system of bankruptcy threshold of banks in Iran. Based on the strategy of Grounded Theory, the native model designed. Also, according to the optimization criteria, the optimal model was chosen. The methodology is mixed. In the qualitative part, information is obtained through in-depth interviews by guiding generalities and in a semi-structured way. In the quantitative part, the research hypotheses were tested using data from the panel data for a ten-year period (2011-2020). The results obtained in the qualitative part have shown that capital adequacy, bank competitiveness index and bank stability have been identified as indicators of bankruptcy threshold of banks (dependent variables). Nine variables were identified as explanatory variables. According to the criteria of the optimal model, the third model is the optimal model from the point of view of all the criteria. Moreover, the residual sum of squares of the third model is lower than the other two models. The Durbin-Watson value is much closer to 2, so it is a healthier model and it can be claimed that there is no correlation error in the error term. Finally, in the third model, the value of F statistic is much higher than other models.
Keywords: Early Warning System, Banking, Capital Adequacy, Bank Competitiveness Index, Banking Stability, Grounded Theory

Introduction

In all countries, banks serve as the primary financial intermediaries and offer vital services for mobility and economic growth. Banks require both physical and intellectual assets for this purpose. This implies that a key factor in any country's economic development is the stability of the banking system (Oppong and Pattanayak, 2019). In fact, banks rank among the most significant financial institutions in every country, which have expanded rapidly over the past two decades as a result of the internationalization and liberalization of global banking. The improvement of the efficiency of

* Corresponding author E-mail: alipour@iaurasht.ac.ir

banks has been sought after by numerous bank officials and academic scholars to deal with this competitive environment (Huang et al, 2017). Instability in macroeconomic policies, both in the supervision sector and in the real and financial sectors, causes banks to serve as the last shock absorbers. The need to pay attention to the recent state of the banking network and the instabilities in the macroeconomic conditions makes it inevitable to develop an early warning system document to estimate the probability of downgrading and also to estimate the time of bankruptcy for the country's banking network (Shumway, 2001). In recent years, the challenges faced by the country's banking system, together with the rise in outstanding claims and the lack of liquidity, are becoming a national problem and challenge (Radfar et al., 2019). Numerous financial crises have occurred in different economic sectors of countries during the past few decades, often with disastrous economic, social, and political repercussions. These crises are not limited to the economy of one country, but also spread to the economy of other countries. As a result, international organizations and private sector institutions began to research, develop and provide warning models (EWS) that are designed with the aim of predicting the occurrence of financial crises in different countries. This model was first presented by Kaminsky et al. (1998) for the currency crisis, and then academicians and various private sector institutions have presented early warning system models in other economic sectors in recent years (Gholizadeh, 2020).

The recent crises of the 90s in the financial and banking system and the instabilities in the macroeconomic conditions have made it crucial to develop a comprehensive document for the Banking Early Warning System (BEWS) for monetary and banking policy makers. The central bank's policymakers and its distance monitoring department now place a greater emphasis on the financial health of monetary and credit institutions as a result of the bankruptcy of some financial institutions and the merger of other institutions that have been exposed to bankruptcy. Since, based on international experience, the cost of bank failure in case of occurrence is very high, it is important to identify important factors that have the power to distinguish between bankrupt and healthy banks in the country's banking network, as well as to design a model that has the power to predict bankruptcy in the country's banking network (Komeijani, 2015). The banking crisis is one of the primary causes of economic crises, according to empirical evidence. Banks can experience bankruptcy either individually or collectively, like any other economic enterprise can. However, it is important to keep in mind that the impact of bank bankruptcy is much more severe than that of other commercial enterprises (Whalen, 2016). Shareholders will lose their capital on the one hand, while depositors will lose their savings on the other. Similar to what occurred in America in 2007–2008, such crises in the banking sector typically begin with the appearance of a problem in one or more banks, and with its rapid spread to other banks and affecting the financial markets, the entire economy is quickly affected. Banking crises are accompanied by a decline in trust in the performance of domestic financial institutions, causing a decrease in domestic savings and a large increase in capital outflows. Innovations and deregulation in the banking sector have made banking operations more complicated and riskier than in the past. This issue has created challenges for the department of monitoring the performance of banks (Weibull, 2015).

Atefifar and Fathi (2020) investigated the effectiveness of financial health indicators as symbols of banking financial crisis. They showed that only 4 financial ratios among the CAMEL ratios introduced are effective in the correct ranking of the studied banks based on the combined value of

CAMEL. Also, according to the Delphi technique, the quality of management has the highest priority.

Sadeghi Sharif et al. (2018) investigated the possibility of banks being on the brink of bankruptcy and predicting its timing based on commercial and economic cycles. Also, in this article, the effect of different approaches to defining the threshold of bankruptcy in relation to predicting the time of exposure of banks to bankruptcy in Iran has been investigated by applying the Kaplan-Meier model and the Cox proportional hazards model in the framework of survival analysis. The results show that based on the Akaike criterion (AIC), the Z-Score stability index approach is the best criterion for defining and identifying the bankruptcy threshold of banks compared to the approach of capital adequacy and the ratio of outstanding claims.

Ahmadian and Gorji (2017) presented a bankruptcy prediction model to identify healthy and at-risk banks. In this article, an attempt has been made to identify bankrupt banks by using the financial statements of the country's banks in the period of 2006-2015 and using the banking stability index as a bankruptcy index. To identify bankrupt banks, the kernel function of this index was drawn and its stress point was calculated, in such a way that the banks that are below the stress point were considered bankrupt and otherwise healthy. The results show the accuracy of 87% of the diagnostic analysis model and 98.2% of the logit model in accordance with the environmental conditions of the country's banking network.

Ahmadian and Heydari (2016) designed a quick warning system in the banking network. The results show that the variables of the real sector of the economy such as the added value of the service and industry sectors, the variables of the nominal sector such as the monetary base and the interest rate of the interbank market have a significant effect on moving the possibility of deterioration of the financial health of banks. Filippopoulou et al. (2020) conducted research in this direction in an article titled "An early warning system for predicting systemic banking crises in the Eurozone". The findings showed that most of the risk indicators used from MPDB are important for predicting 1 to 4 years before the onset of a banking system crisis. Also, they found that specific banking variables, which include industry concentration, assets, budget and liquidity, are more important than macroeconomic variables on average. Other indicators such as economic expectations etc. are also significant in this regard. The model is robust to various specifications and performs better when post-crisis observations are not included. The results showed that the financial forecasts related to the indicators of financial health in large companies are relatively better than in smaller companies.

Huang et al. (2017) designed an early warning method for financial markets based on multiple learning. Their experimental results show that their information-based multiple learning algorithm (IMML) can accurately describe the dynamic financial system and contribute a great deal to investors' information about the state of financial markets.

In response to this issue, banking supervisors have developed new methods and tools to monitor and evaluate banks further. More attention in this field is improving the quality of tests and developing systems that can help observers and identify major changes (Altman, 1968). Iran's banking industry is no exception to this rule. Thus, the researchers try to design a native model of the early warning system of the threshold of bankruptcy of banks and financial institutions admitted to the Tehran Stock Exchange. Therefore, an attempt is made to identify and determine the factors

involved in the bankruptcy of banks and institutions admitted to the Tehran Stock Exchange, based on the views of managers in the banking industry, and finally present it in the form of a local model.

Theoretical Foundations

The recent financial crisis caused bank failures and had a detrimental effect on the real economy. Thus, the consequences of financial instability on the economy have received particular attention (Agnello and Sousa, 2012). Additionally, it is crucial to protect depositors in an environment where market failure is a common occurrence. For that reason, the banking system of every country must identify the sources of bank fragility, because banks are always exposed to many financial risks (Ghenimi et al, 2017). For market policymakers, the financial early warning system is particularly valuable since it enables them to identify economic threats and vulnerabilities and take preemptive measures to lower the risks of financial crises (Berg and Pattillo, 1999). The challenge of designing an effective EWS increased when models developed prior to 2008 were unable to predict the severity and international scope of the recent global crises (Candelon et al, 2014). Due to the significance of the issue, in the early warning systems implemented in developed countries, the theoretical framework of early warning systems can be different depending on the structural and economic conditions of the countries. This framework mainly consists of two stages: applying a suitable statistical model and finally predicting the bank's rating or downgrading the bank's rating. These systems were also used by countries with advanced economies in order to design their ranking system, and these countries have used famous statistical models in this connection. The supervisory rating helps to identify banks that need special supervision. In this type of evaluation, the performance of the bank is evaluated on a comparative basis and the problematic bank is identified. In this type of system, the audited financial statement is used, and this type of evaluation takes into account the change in the financial situation and is more focused on the evaluation of banks at risk (Cole and Wu, 2009).

The financial crisis of 2008 created a lot of potential for designing early warning systems of warning signs and the remarkable stability of these warning signs among sample countries, including developed, emerging and developing countries from 1950 to 2011 for 60 years and all kinds of banking, currency, debt, stock and inflationary crises, has been published in 83 studies (Frankel and Saravelos, 2010). There is a lot of evidence that foreign exchange reserves and exchange rates have been amazing in predicting crises (Laser and Weidner, 2022). The early warning system approach mainly monitors the daily financial markets against abnormal movements, as well as the crisis development hypothesis, which states that the cause of the financial crisis is the mass behavior of investors (Bouri et al, 2022).

In 1980, the American regulatory department introduced the first rating system to the supervisory body through the use of the complete rating system. This led to the introduction of a homologous bank rating method in the United States. Three regulatory bodies, including the Federal Reserve, the Office of the Comptroller of the Currency and the Federal Deposit Insurance Corporation, have used this rating method. In this system, each bank is evaluated by five criteria. These criteria, which include capital adequacy, management quality, asset quality, profitability and liquidity, evaluate the financial performance of banks and their health. The design of the early warning system in different countries depends on the size of the internal and external monitoring

department, control mechanism, reporting and auditing methods, information sources and financial statement data of banks (Sahajawala et al, 2014).

In general, the supervisory systems currently used in most developed countries use four methods to monitor the performance of banks. These four methods include: Bank Regulatory Rating System, Financial Ratio Analysis System, Comprehensive Risk Assessment System and Statistical Modeling. In France, the rating system of banking external supervision, early warning-expected loss models has been experienced in 1997. Also in Germany, the peer group analysis system and financial ratio was implemented in 1997. These two systems have been experienced in Italy as well. External Banking Supervision Rating System in 1993 and Bankruptcy Early Warning and Bankruptcy Time Prediction Models are currently in operation. The Netherlands has the experience of the comprehensive banking risk assessment system in 1999 as well as the analysis system of the peer group and the financial ratio that is currently being implemented (Mayes et al, 2014).

Since 1990, these early warning system models have been used specifically for the banking sector. There are various studies and models in the field of early warning system design. Probit and Logit methods can be mentioned among the common ones which are discussed in the studies of Martin (1977) and Thomson (1991) (Ahmadian, 2015). Kaminsky et al. (1998) evaluated an early warning system for predicting currency crises, tested the empirical evidence of monetary crises and proposed an early warning system for monetary crises. Berg and Pattilo (1999) evaluated and compared the predictive power of three early warning system models, including those designed by Frankel and Rose (1996), Kaminsky et al. (1998). Specifically, they analyzed the models with the following question: If the IMF had used these models in 1996, how well could it have predicted the East Asian crisis? Their results show that the model of Kaminsky et al. (1988) has more predictive power than the other two models. Next, they extended the model of Kaminsky et al. (1998) by adding some new explanatory variables - the level of the ratio of the current account balance and reserves to M2 - and adjusting the sample countries. Also, the variables used in Kaminsky et al. (1998) were placed in a probit model, and they estimated the probabilities of crises. Then, they compared their results with the results of Kaminsky et al. (1998). Apparently, their model provided better results. In the next article, they refined the initial extended profit model and limited the model to five explanatory variables and entered the ratio of short-term debt to reserves as one of the explanatory variables.

From 1990, specifically by applying statistical techniques, the early warning system was designed to identify bankrupt and healthy banks in the banking sector. The first group of studies such as the study by Kaminsky and Reinhart (1999) and Lin and Peng (2022) designed a quick warning system with an indicator. In these patterns, which are called signal patterns and in which univariate statistical technique is used, the probability of bank bankruptcy in the future period is predicted based on the variable time trend effective in causing the past banking crisis. For this purpose, in this method, a threshold is determined for the variable in question, which is lower than the threshold of the variable indicating the occurrence of bank crisis and bankruptcy.

The second group is the multivariable early warning models, based on which the probability of a bank crisis and bankruptcy is estimated according to the indicators included in the system. Among these studies, the study done by Frankel and Saravelos (2010) can be mentioned. Based on these models, the dependent variable is the occurrence of bank bankruptcy and the independent variables are the effective variables in the occurrence of a banking crisis.

The third group of studies have investigated the design of the early warning system by applying the technique of diagnostic analysis, Probit and Logit, Markov switching and non-parametric grouping method. Based on these patterns, it is possible to identify the distinguishing factors between bankrupt and healthy banks, and the probability of bankruptcy is also calculated.

The fourth group of studies have predicted bank bankruptcy by using qualitative variables. According to this group of studies, variables such as bank risk indicators or corporate governance variables have been used to predict banking crisis and as leading indicators.

The fifth group of studies is related to statistical methods such as dynamic risk models. Among these studies, the study of Shumway (2001) can be mentioned. Based on these types of patterns, it is possible to estimate the probability of a banking crisis and the timing of a banking crisis.

Methodology

The current research is in the pursuit of designing the native model of the early warning system of bankruptcy threshold of banks and it is trying to explain its relationship with quantitative and qualitative variables and also to provide reliable guidelines in this regard, therefore it is considered practical research. On the other hand, considering the increase in knowledge resulting from the design of the local model and the investigation of the effects of the effective variables in it, this research also has a developmental orientation.

The data and information used in the present study were obtained from two different sources. First, secondary data obtained from books, authentic articles published in domestic and foreign journals, and documents. Also, primary data has been obtained through interviews and the database of responsible organizations. Therefore, from this point of view, the present study is considered among field and library researches.

In qualitative research, knowledge production is based on constructivist philosophy (concepts of lived experiences by individuals) or participatory and biased paradigm (political viewpoints, central controversial issue and cooperation based on mutual trust) or both perspectives. By using research strategies such as grounded theory, new concepts are discovered from texts, discourses, interviews and attitudes, and the researchers collect open data with the aim of enumerating the themes of the opposite point in quantitative research, which are the variables, arising from the data (Creswell, 2018). Mixed researches are researches that are conducted using the combination of two sets of quantitative and qualitative research methods. In mixed research methods, to examine an experimental study problem, the researcher uses a set of methods that are based on different paradigms to enable investigation of an uncertain situation and facilitate its implementation process. Since both qualitative and quantitative research methods have been used in the design and implementation of mixed method research projects, the main characteristics of mixed research methods are influenced by how both quantitative and qualitative methods are used (Bazargan, 2017). In this method, knowledge production relies on constructivist philosophy (concepts of lived experiences by individuals) or participatory and biased paradigm (political viewpoints, central controversial issue and cooperation based on mutual trust) or both viewpoints (Creswell, 2018).

In the qualitative part, the heads of bank branches, investors and university lecturers in the field of banking industry have been invited to participate in order to identify the categories and components that make up the early warning system of bankruptcy threshold of banks. The number

of statistical samples (number of interviews) has continued until reaching the saturation of the categories and it was done with 10 heads of bank branches, senior managers and university lecturers. In the current study, theoretical sampling was used to select the number of statistical samples. The number of heads of bank branches, senior managers and university lecturers continued until the categories were saturated. After extracting the open codes in each interview and comparing them with the new interview codes, the researchers realized that in the tenth interview, all the codes extracted from the interview text are repetitive. Therefore, the interview was terminated. The last stage of the qualitative part is the final writing and editing of the theory. Before this stage, the researchers have done three stages of coding (open, central, selective) and taking notes. At this stage, the picture of the research is clearer than ever for the researchers. The last step is to analyze and interpret what he sees from this image (Strauss and Corbin, 1998).

Finally, it is important to determine whether the researchers' theoretical explanation makes sense and is reasonable to the participants and is an accurate representation of the events and their sequence in the process. In grounded theory, validation is an active part of the research process (Creswell, 2012). In the quantitative section, the research hypotheses were tested using panel data, and a statistical comment was made regarding the acceptance or non-acceptance of each of them. The statistical population in the quantitative section is all banks and financial institutions accepted in the Tehran Stock Exchange. The studied sample is the data from 2011 to 2020. The required data is in the quantitative part of the secondary data type. According to the nature of this research, the library method was used to collect the required information.

Grounded Theory

Grounded Theory is a coherent and integrated set of conceptual hypotheses that emerge from data. In fact, researchers who use the Grounded Theory method identify the main concerns and issues of the participants and find out how these issues can be solved by them. In the Grounded Theory method, instead of using data to test the theory, the data is used to create a theory and the relevant model is created (Glaser, 1998). This method includes coherent steps that lead to the emergence of conceptual categories. These categories are related to each other, providing a theoretical explanation of the actions that are solving the main concern of the participants of the fundamental field under study (Glaser, 2013).

In the past years, the use of Grounded Theory has been greatly expanded. However, the differences between the two founders of the Grounded Theory have led to the formation of two different approaches to this theory: Glaser's method, which is usually referred to as Classical Grounded Theory due to his loyalty to the primary Grounded Theory, and the method of a person named Strauss, which is usually called Straussian Grounded Theory (Glaser and Strauss, 1967).

Findings

In the systematic approach of foundational data theorizing, there are three stages of coding (Creswell and Clark, 2007).

First step - Open coding

In this type of coding, events, actions, and interactions are compared with each other to examine similarities and differences, and are also labeled as concepts.

Second step - Axial coding

The purpose of this stage is to establish a relationship between the concepts produced in the open coding stage. In the following, by examining the concepts and placing close and similar concepts in a class, its central category can be extracted and can be seen in Table 1.

Table 1. Final extracted categories

	Variables		Weight
Dependent variables (Bankruptcy Threshold Measuring Indices)	1. Capital adequacy less than 3%		8
	2. Bank stability		3
	3. Accumulated corporate losses of more than half of the capital		2
	4. Bank stock index drop		2
	5. Bank competitiveness		2
Explanatory variables	1. Bank size		3
	2. The ratio of equity to assets		5
	3. Monetary base	Claims from the government	3
		Lack of independence of the central bank	
	4. Economic downturn		6
	5. Political stability index	Sanctions	9
	6. Profit per share		2
	7. Transparency of financial and economic information	Money laundering	21
		Corporate governance	
		Central bank supervision	
	8. Reputational risk		2
	9. Market risk	Inflation	32
		Exchange rate	
		Interest rate	
	10. Liquidity risk		18
	11. Credit risk		21
	12. Operational risk		7
	13. Country risk		1

Third step - selective coding

In the following, the major categories are related to each other in the form of a paradigmatic model (Figure 1) around the core category. In fact, the drawn model deals with the formal description of the category and its analysis and explanation. This process is called the combination of the core category and refining and decorating the structures resulting from it. The mentioned model can be drawn as a formal model or diagram, but meaningful and conceptual (Figure 2).

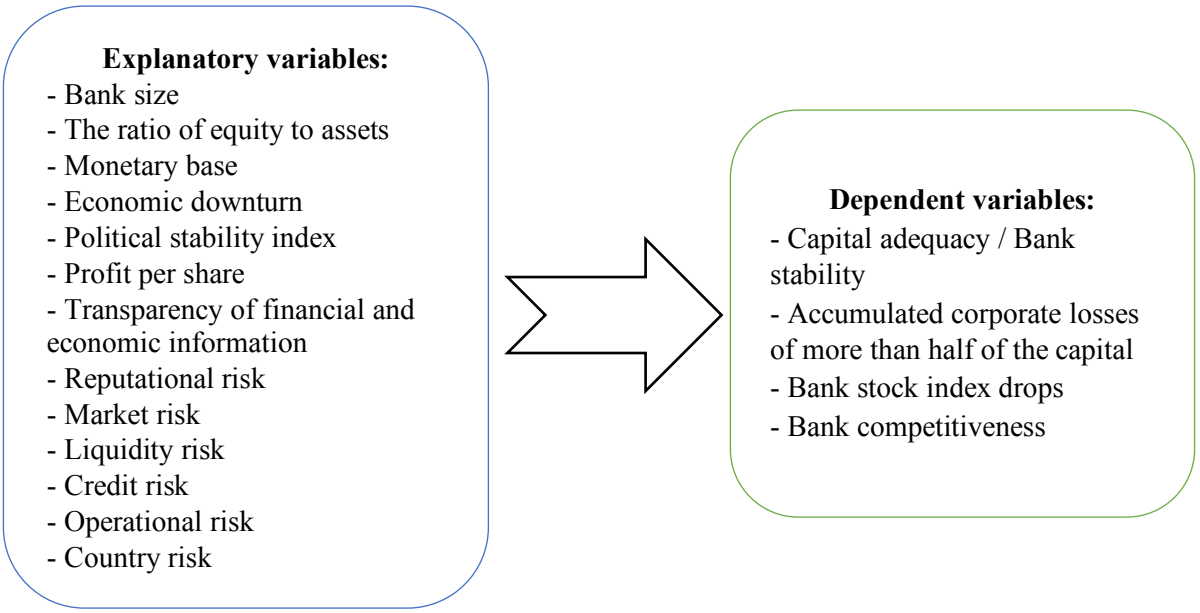

Figure 1. Paradigm Model

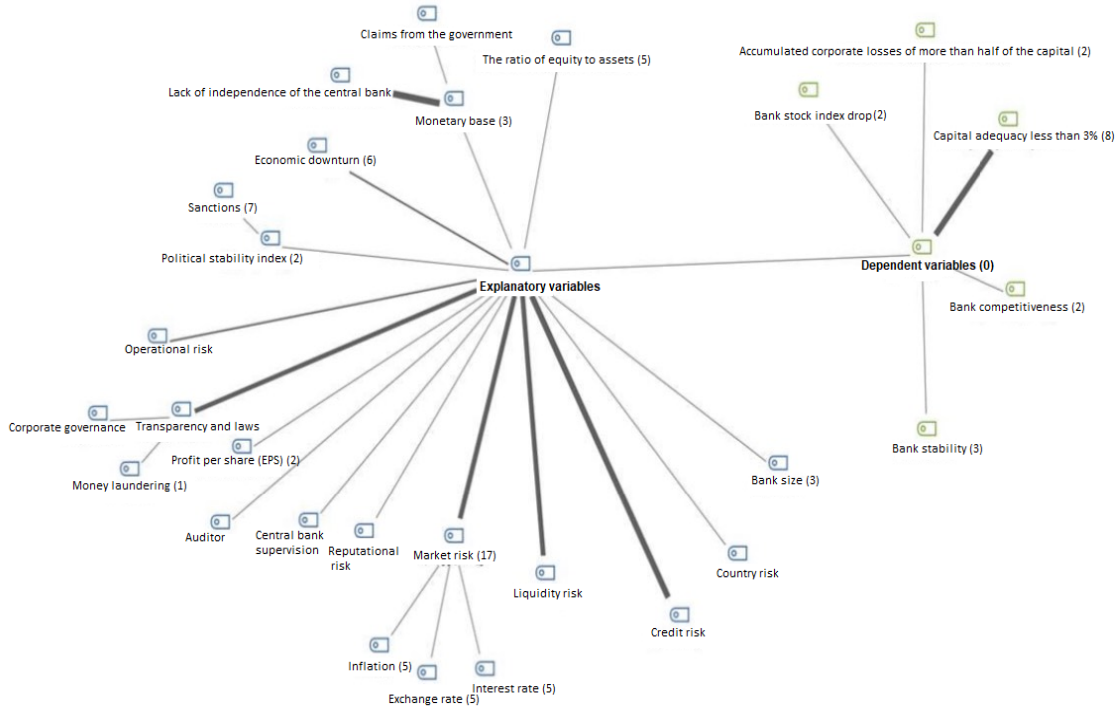

Figure 2. Final Model

Validation of the theory

After formulating a theory, the theorists of Grounded Theory validate the process by comparing it with the existing processes found in the specialized background (Danaeifard and Emami, 2007). For this purpose, before presenting the final model, the theoretical foundations for each of the components are presented in Table 2.

Table 2. Number of studies conducted in relation to categories

Final categories	Instance	Number of studies
Capital adequacy less than 3%	Almanidis and Sickles (2016), Lepetit And Sroble (2015), Sahajawala et al. (2014), Claessens and Kose (2013), Ivicic (2008), Diamond and Dybvig (1983), Sadeghi Sharif et al. (2018), Mabkhot and Al-Wesabi (2022), Atefifar and Chen et al. (2022).	12
Bank stability	Shumway (2001), Tatom (2012), Sadeghi Sharif et al. (2018)	3
Accumulated corporate losses of more than half of the capital	Betz et al. (2014)	1
Bank stock index drop	Bats et al. (2011)	1
Bank competitiveness	Almanidis and Sickles (2016), Komeijani (2015), Kaminsky et al. (1998), Atefifar and Chen et al. (2022).	4
Bank size	Babajide et al. (2015), Li et al. (2022), Lepetit and Sroble (2015), Ivicic (2008), Bakeri et al. (2020)	6
The ratio of equity to assets	Cole and Wu (2009), Sahajawala et al. (2014), Bakeri et al. (2020), Seraj and Taheri (2011)	4
Monetary base	Li et al., (2022), Lepetit and Sroble (2015), Kaminsky et al. (1998), Ivicic (2008), Ahmadian and Heydari (2016).	5
Economic downturn	Filippopoulou (2020), Almanidis and Sickles (2016), Komeijani (2015), Li et al. (2022), Lepetit and Sroble (2015), Cole and Wu (2009), Ivicic (2008), Fratzscher and Bussiere (2003), Kaminsky et al. (1998), Mabkhot and Al-Wesabi (2022), Sadeghi Sharif et al. (2018), Ahmadian and Heydari (2016), Mahmoudinia and Borhani (2022).	16
Political stability index	Ahmadian and Heydari (2016), Mabkhot and Al-Wesabi (2022)	3
Profit per share	Mayes et al. 2014	1
Transparency of financial and economic information	Huang et al. (2017), Altman (1968), Weibull (2015), Komeijani (2015), Shirinpour et al. (2022), Sahajawala et al. (2014), Mayes et al. (2014), Dincer et al. (2022), Chen et al. (2022), Botta et al. (2022)	10
Reputational risk	---	0
Market risk	Filippopoulou (2020), Mayes et al. (2014), Li et al. (2022), Betz et al. (2014), Tatom (2012), Cole and Wu (2009), Ivicic (2008), Fratzscher and Bussiere (2003), Kaminsky et al. (1998), Patel and Sarkar (1998), Gholizadeh et al. (2020), Mabkhot and Al-Wesabi (2022), Ahmadian and Heydari (2016), Mahmoudinia and Borhani (2022)	18
Liquidity risk	Filippopoulou (2020), Sahajawala et al. (2014), Mayes et al. (2014), Lepetit and Sroble (2015), Tatom (2012), Kaminsky et al. (1998), Radfar et al. (2019), Atefifar and Fathi (2020), Ahmadian (2015).	10
Credit risk	Babajide et al. (2015), Hammond et al. (2022), Mayes et al. (2014), Betz et al. (2014), Samad and Armstrong (2022), Cole and Wu (2009), Kaminsky et al. (1998), Radfar et al. (2019), Mabkhot and Al-Wesabi (2022), Sadeghi Sharif et al. (2018), Ahmadian and Heydari (2016), Ahmadian (2015), Mahmoudinia and Borhani (2022), Seraj and Taheri (2011).	15
Operational risk	Babajide et al. (2015), Hammond et al. (2022), Mayes et al. (2014), Li et al. (2022), Betz et al. (2014), Gerged et al. (2022), Mabkhot and Al-Wesabi (2022), Sadeghi Sharif et al. (2018), Ahmadian (2015), Botta et al. (2022)	10
Country risk	---	-

As can be seen, for most of the concepts extracted from the text of the interviews, as well as in relation to all the categories, several studies have been conducted, which show the validity of the categories. The following graph shows the number of studies related to categories.

Among the five indicators for measuring the bank's bankruptcy threshold, there are the following items in order: Capital adequacy (12 observations); Bank competitiveness (4 observations); Bank stability (3 observations); Bank stock index drop (1 observation) and accumulated corporate losses of more than half of the capital (1 observation). Therefore, it can be concluded that Capital adequacy indicators, Bank competitiveness index and Bank stability have the necessary validity. However, the Bank stock index drop and the Accumulated corporate losses of more than half of the capital do not have the necessary validity.

Model specification

AC, BS, BC = f (BZ, MB, ED, PS, TR, MR, LR, CR, OR)
Check Table 3 for Definition of used variables; In which:

AC: Adequacy of capital; *BS*: Bank stability; *BC*: Bank competitiveness; *BZ*: Bank size;
MB: Monetary base; *ED*: Economic downturn; *PS*: Political stability index;
TR: Transparency of financial and economic information; *MR*: Market risk;
LR: Liquidity risk; *CR*: Credit risk; *OR*: Operational risk

First model:
$$AC_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

Second model:
$$BS_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

Third model:
$$BC_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

Model estimation

Estimation of the first model:
The purpose of the following regression estimation is to examine the factors affecting capital adequacy of banks as one of the components of the early warning system of bankruptcy threshold of banks.

$$AC_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

First, to determine the presence or absence of a separate intercept for each bank, as presented in chapter three, the Lemer test and the Hausman test must be examined (Table 4). (Rastogi and Kanoujiya, 2022)

Table 3. Definition of variables

Variable	Definition
Capital adequacy ratio	The ratio of capital adequacy resulting from the division of basic capital to total assets weighted by risk coefficients in percentage terms $CAR = \frac{Tier\ 1\ capital + Tier\ 2\ capital}{Risk\ weighted\ assets}$
Bank stability	The Z index is the most common measure to measure bank stability, and with its increase, the probability of bank bankruptcy decreases. This index is as follows: $Z=(k+\mu)/\delta$ k: It is the ratio of capital to assets, which is obtained by dividing the cash capital by the total financial assets of the bank. μ: Ratio of yield to bank assets. δ: The standard deviation of an asset's return is an approximation for the frequency of changes in returns (return risk).
Intensity of competitiveness	In order to measure the competitiveness of banks in this research, the index of the ratio of the total bank assets to the total assets of the banks accepted in Tehran Stock Exchange is used.
Bank size	It represents the size of banks and financial institutions and is obtained from the natural logarithm of the total assets of banks and financial institutions.
Monetary base (high-powered money)	Commercial bank deposits with the central bank, plus cash in circulation in the hands of the public, plus cash physically held in banks.
Economic downturn	If economic growth is negative, it means economic downturn.
Political stability index	It is a variable that accepts values between 2.5 and +2.5. The data of the country's political instability index were extracted from the WGI website.
Transparency of financial and economic information	The data related to the transparency of financial and economic information was extracted from the website of Standard and Poor's Institute.
Operational risk	The average of the following variables is used to measure operational risk. - Fluctuations in asset return rates - Stock return rate - Equity to assets
Liquidity risk	LR index = (debt to the central bank to savings deposits + current + short-term deposits) (cash + net coin balance in the account with the central bank to deposit with other banks + bonds purchased from other banks + balance with domestic banks after settlement) / total assets
Credit risk	Credit risk is obtained by dividing non-current facilities by total bank facilities. Non-current facilities include passed, overdue and doubtful loans.
Market risk	To calculate the beta coefficient, stock returns of sample companies (Ri) and market portfolio returns (Rm) have been used. $MR = \frac{cov(Ri, Rm)}{\delta^2 Rm}$

Table 4. LM test output in the first model

Effect Test	Statistic	d.f	Prob.
Cross-Section F	6.07	14.126	0.00
Cross-Section Chi-squre	77.34	14	0.00

As can be seen, the combined method is not accepted. Therefore, there is a difference in the intercept of cross-sectional units (Table 5).

Table 5. The output of the Hausman test of the first model

Effect Test	Statistic	d.f	Prob.
Cross-Section random	29.74	5	0.00

According to the results of the Hausman test and the estimated probability is less than 0.05, therefore, the model is of the fixed effects type. Therefore, the regression was estimated using the fixed effects method, and the model estimation results are as described in the Table 6.

Table 6. The output of the first model after fixing the autocorrelation of the error term

Variable	FIXED		
	Coefficient	t Value	Prob
C	0.66	12.97	0.00
BZ	-0.03	-14.79	0.00
MB	-2.8e-5	-1.78	0.07
ED	-0.005	-3.23	0.00
PS	-0.004	-0.59	0.55
TR	0.0003	3.54	0.00
MR	-1.8e-6	-0.003	0.99
LR	-0.0009	-2.62	0.00
CR	-0.04	-3.66	0.00
OR	0.11-	2.48-	0.01
AR (1)	0.77	17.56	0.01
Adjusted R-squared=0.84		R-squared=0.86	
F=30.63		Prob=0.00	
D.W=2.07			

According to the estimation results of the first model, the first native model of the fast-warning system of bankruptcy threshold of banks is as described in the following equation:

$$AC_t = 0.66 - 0.03 * BZ_t - 2.8e65 * MB_t - 0.005 * ED_t + 0.0003 * TR_t - 0.0009 * LR_t - 0.04 * CR_t - 0.11 * OR_t$$

Estimation of the second model:

The purpose of estimating the second regression is to examine the factors affecting the stability of the country's banking system as one of the components of the early warning system of bankruptcy threshold of banks (Table 7).

$$BC_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

Table 7. LM test output in the second model

Effect Test	Statistic	d.f	Prob.
Cross-Section F	1.81	14.126	0.04
Cross-Section Chi-squre	27.59	14	0.01

As can be seen, the combined method is not accepted. Therefore, there is a difference in intercept of cross-sectional units (Table 8).

Table 8. The output of the Hausman test of the second model

Effect Test	Statistic	d.f	Prob.
Cross-Section random	19.61	5	0.00

According to the results of the Hausman test and that the estimated probability is less than 0.05, therefore, the model is of the fixed effects type. Therefore, the regression was estimated using the fixed effects method, and the model estimation results are as described in the Table 9.

Table 9. The output of the second model after fixing the autocorrelation of the error term

Variable	FIXED		
	Coefficient	Value t	Prob.
C	247.10	3.80	0.00
BZ	-8.05	-4.51	0.00
MB	-0.02	-0.92	0.35
ED	-13.02	-3.43	0.00
PS	34.65	1.95	0.05
TR	-0.12	-0.44	0.65
MR	-0.37	-0.32	0.74
LR	-3.34	-2.88	0.00
CR	-16.95	-1.04	0.29
OR	-191.53	-4.20	0.00
AR (1)	-0.16	-0.89	0.37
Adjusted R-squared=0.21		R-squared=0.35	
F=2.53		Prob=0.00	
D.W=2.26			

According to the estimation results of the current model, the second native model of the early warning system of bankruptcy threshold of banks is as described in the following equation:

$$BS_t = 247.10 - 8.05 * BZ_t - 13.02 * ED_t + 34.65 * PS_t - 3.34 * LR_t - 191.53 * \beta_9 OR_t$$

Estimation of the third model

The purpose of the third regression estimation is to examine the factors affecting the bank competitiveness as one of the components of the early warning system of bankruptcy threshold of banks (Table 10).

$$BC_t = \beta_0 + \beta_1 BZ_t + \beta_2 MB_t + \beta_3 ED_t + \beta_4 PS_t + \beta_5 TR_t + \beta_6 MR_t + \beta_7 LR_t + \beta_8 CR_t + \beta_9 OR_t + \varepsilon_t$$

Table 10. LM test output in the third model

Effect Test	Statistic	d.f	Prob.
Cross-Section F	54.69	14.110	0.00
Cross-Section Chi-squre	280.07	14	0.00

As can be seen, the combined method is not accepted. Therefore, there is a difference in intercept of cross-sectional units (Table 11 and 12).

Table 11. Output of Hausman test of the third model

Effect Test	Statistic	d.f	Prob.
Cross-Section random	5.16	5	0.00

Table 12. The output of the third model after fixing the autocorrelation of the error sentence

Variable	FIXED		
	Coefficient	Value t	Prob.
C	-0.46	-9.21	0.00
BZ	0.02	12.81	0.00
MB	-5.6e-5	-5.04	0.00
ED	-0.003	-1.96	0.05
PS	0.03	3.33	0.00
TR	0.0003	2.07	0.03
MR	0.0001	0.36	0.71
LR	0.0007	1.20	0.23
CR	-0.01	-2.81	0.00
OR	0.01	1.34	0.18
AR(1)	0.01	1.88	0.06
Adjusted R-squared=0.97		R-squared=0.98	
F=259.77		Prob=0.00	
D.W=1.99			

According to the estimation results of the current model, the third native model of the early warning system of bankruptcy threshold of banks is as described in the following equation:

$$BC_t = -0.46 + 0.02 * BZ_t - 5.6e-5 * MB_t - 0.003 * ED_t + 0.03 * PS_t + 0.0003 * TR_t - 0.01 * CR_t - 0.01 * OR_t$$

Early warning system models of bankruptcy threshold of banks

According to the results of the analysis of the interviews, three patterns were introduced. After estimating the models, the following results were obtained:

$$AC_t = 0.66 - 0.03 * BZ_t - 2.8e65 * MB_t - 0.005 * ED_t + 0.0003 * TR_t - 0.0009 * LR_t - 0.04 * CR_t - 0.11 * OR_t$$

$$BS_t = 247.10 - 8.05 * BZ_t - 13.02 * ED_t + 34.65 * PS_t - 3.34 * LR_t - 191.53 * \beta_9 OR_t$$

$$BC_t = -0.46 + 0.02 * BZ_t - 5.6e-5 * MB_t - 0.003 * ED_t + 0.03 * PS_t + 0.0003 * TR_t - 0.01 * CR_t - 0.01 * OR_t$$

By replacing the values of the explanatory variables, it is possible to identify the threshold of bankruptcy of the banks accepted in the Tehran Stock Exchange. In the following, the optimal model is introduced:

Table 12. Optimal model selection criteria

Criteria	First Model	Second Model	Third Model
R-squared	0.86	0.35	0.98
Adjusted R-squared	0.84	0.21	0.97
S.D. dependent var	0.07	18.23	0.05
Durbin-Watson stat	2.07	2.26	1.99
Sum squared reside	0.08	28673	0.008
F-statistic	30.63	2.53	259.77

Table 13. Choosing the optimal model

Criteria	First Model	Second Model	Third Model
R-squared	×	×	✓
Adjusted R-squared	×	×	✓
S.D. dependent var	×	×	✓
Durbin-Watson stat	×	×	✓
Sum squared reside	×	×	✓
F-statistic	×	×	✓

As can be seen from the results of Tables 12 and 13, the third model is the optimal model from the point of view of all criteria. This means that it has the highest coefficient of determination and adjusted coefficient of determination. It has the lowest standard deviation. Also, the residual sum of squares of the third model is lower than the other two models. The value of Watson's camera is much closer to 2, so it is a healthier model. It can be claimed that there is no correlative error. Finally, in the third model, the value of F statistic is much higher than other models.

Conclusion

The results obtained in the qualitative part have shown that capital adequacy, bank competitiveness index and bank stability have been identified as indicators of bankruptcy threshold of banks (dependent variables). Nine variables were identified as explanatory variables.

These variables are bank size, monetary base (high-powered money), economic downturn, political stability index, transparency of financial and economic information, operational risk, liquidity risk, credit risk and market risk. Also, in the quantitative part, the obtained results show that all research variables are at the stationary level, only the monetary base variable became stationary at level one, this means that it is entered into the model after one differentiation. In all three models, according to both the Pedroni test (PP) and the Advanced Dickie-Fuller (ADF) method, the null hypothesis of non-collinearity between the model variables was rejected. These

results show that the variables in both tests form a long-term equilibrium relationship in the models. Also, all the classical assumptions were true in all three models.

The results of the estimation of the first model showed that bank size, economic downturn, transparency of financial and economic information, liquidity risk, credit risk and operational risk have a significant relationship with capital adequacy. The coefficient of determination is 86% and the adjusted coefficient of determination is 84%, which indicates the high explanatory power of the independent variables.

The value of Watson's camera statistic is equal to 2.07 and is not far from 2, so it can be claimed that the error values are not autocorrelated and the model is healthy.

According to the estimation results of the first model, the first native model of the early warning system of bankruptcy threshold of banks is as described in the following equation:

$$AC_t = 0.66 - 0.03 * BZ_t - 2.8e65 * MB_t - 0.005 * ED_t + 0.0003\ TR_t - 0.0009 * LR_t - 0.04 * CR_t - 0.11 * OR_t$$

The results of the estimation of the second model showed that bank size, economic downturn, political stability index, liquidity risk, and operational risk have a significant relationship with the stability of the banking system at the level of 99 percent of the banks. The coefficient of determination is 35% and the adjusted coefficient of determination is 21%, which indicates the high explanatory power of the independent variables. The value of Durbin Watson's statistic is equal to 2.26 and it is not far from 2, so it is possible to claim the lack of autocorrelation of the error values and the health of the model.

According to the estimation results of the second model, the first native model of the early warning system of bankruptcy threshold of banks is as described in the following equation:

$$BS_t = 247.10 - 8.05 * BZ_t - 13.02 * ED_t + 34.65 * PS_t - 3.34 * LR_t - 191.53 * \beta_9 OR_t$$

The results of the estimation of the third model have shown that bank size, monetary base, economic downturn, political stability index, variable of transparency of financial and economic information and credit risk have a significant relationship with the competitiveness of banks. The coefficient of determination is 97% and the adjusted coefficient of determination is 98%, which indicates the high explanatory power of the independent variables. The value of Watson's camera statistic is equal to 1.99 and it is not far from 2, so it is possible to claim the absence of autocorrelation of error values and the health of the model.

According to the estimation results of the third model, the first native model of the early warning system of bankruptcy threshold of banks is as described in the following equation:

$$BC_t = -0.46 + 0.02 * BZ_t - 5.6e - 5 * MB_t - 0.003 * ED_t + 0.03 * PS_t + 0.0003 * TR_t - 0.01 * CR_t - 0.01 * OR_t$$

According to the criteria of the optimal model, the third model is the optimal model from the point of view of all the criteria. This means that it has the highest coefficient of determination and adjusted coefficient of determination. It has the lowest standard deviation. Also, the sum of squared residuals of the third model is lower than the other two models. Watson's camera value is much closer to number 2, so it is a safer model. It can be claimed that there is no correlative error. Finally, in the third model, the value of F statistic is much higher than other models.

References:

Agnello, L., and Sousa, R. M. (2012). How do banking crises impact on income inequality?. Applied Economics Letters, 19(15), 1425-1429.

Ahmadian, A. (2015). Designing an early warning system to predict the time of exposure to bankruptcy of banks, Quarterly Journal of Applied Theories of Economics, 2(4), 119-144.

Ahmadian, A., and Gorji, M. (2017). Explanation of bankruptcy prediction model to identify healthy and at-risk banks, Scientific-research quarterly of Asset Management and Financing, 5(3), 1-18.

Ahmadian, A., and Heydari, H. (2016). Designing a quick warning system in the banking network, the 26th annual monetary and exchange policy conference, Tehran, Monetary and Banking Research Institute.

Almanidis, P., and Sickles, R. C. (2016). Banking crises, early warning models, and efficiency. In Advances in Efficiency and Productivity, Springer.

Atefifar, A., and Fathi, Z. (2020). Effective investigation of financial health indicators as symbols of banking financial crisis by using multivariate logit models (case study of listed banks), Financial Engineering and Securities Management Quarterly, 42, 361-333.

Babajide, A. A., Olokoyo, F. O., and Adegboye, F. B. (2015). Predicting bank failure in Nigeria using survival analysis approach. Journal of South African Business Research, 2015, 965940.

Bakeri, A., Rezazadeh, J., Haghighat, H., and Kordestani, G. (2020). A Resilience-Based Model for Performance Assessment of Companies Listed in Tehran Stock Exchange During Economic and Environmental Crisis. Environmental Energy and Economic Research, 4(2), 135-153.

Bats, J. V., Giuliodori, M., and Houben, A. C. (2022). Monetary policy effects in times of negative interest rates: What do bank stock prices tell us?. Journal of Financial Intermediation, 101003.

Bazargan, A. (2017). An introduction to qualitative and mixed research methods; Common Approaches in Behavioral Sciences. Tehran: Didar Publications.

Berg, A., and C. Pattillo. (1999). Predicting Currency Crises: The Indicator Approach and an Alternative. Journal of International Money and Finance, 18(4), 561-586.

Betz, F., Oprica, S., Peltonen, T. A., and Sarlin, P. (2014). Predicting distress in European banks. Journal of Banking and Finance, 45, 225-241.

Botta, A., Caverzasi, E., and Russo, A. (2022). When complexity meets finance: A contribution to the study of the macroeconomic effects of complex financial systems. Research Policy, 51(8), 103990.

Bouri, E., Demirer, R., Gabauer, D., and Gupta, R. (2022). Financial market connectedness: The role of investors' happiness. Finance Research Letters, 44, 102075.

Candelon, B., Dumitrescu, E.-I., and Hurlin, C. (2014). Currency crises early arning systems: why they should be dynamic. International Journal of Forecast, 30(4), 1016-1029.

Chen, Q., Goldstein, I., Huang, Z., and Vashishtha, R. (2022). Bank transparency and deposit flows. Journal of Financial Economics, 146(2), 475-501.

Chen, T. H., Lee, C. C., and Shen, C. H. (2022). Liquidity indicators, early warning signals in banks, and financial crises. The North American Journal of Economics and Finance, 62, 101732.

Claessens, S., and Kose, M. A. (2013). Financial Crises: Explanations, Types, and Implications, IMF Working Paper, No WP/13/28.

Cole, R. A., and Wu, Q. (2009). Is hazard or probit more accurate in predicting financial distress? Evidence from US bank failures. Munich Personal RePEc Archive, Paper No. 29182.

Creswell, J.W., and Clark, V.L. (2007). Designing and conducting mixed methods research, Thousand Oaks. CA: SAGE publication.

Creswell, J. W., and Creswell, J. D. (2018). Research Design: Quantitative and Mixed Methods Approaches. CA: SAGE Publications.

Creswell, J.W. (2012). Educational research: Planning, conducting, and evaluating quantitative and qualitative research. 4th Edition. Boston: Pearson Publication

Danaeifard, H., and Emami, S. M. (2007). Qualitative Research Strategies: A Reflection on Grounded Theory. Management Thought, 1(2), 97-69.

Diamond, D., and Dybvig, P. (1983). Bank runs, liquidity, and deposit insurance. Journal of political Economy, 91(3), 401-419.

Dincer, N., Eichengreen, B., and Geraats, P. (2022). Trends in monetary policy transparency: further updates. International Journal of Central Banking, 18(1), 331-348.

Filippopoulou, C. H., Galariotis, E., and Spyrou, S. (2020). An early warning system for predicting systemic banking crises in the Eurozone: A logit regression approach. Journal of Economic Behavior and Organization, 172, 344-363.

Frankel, J. A., and Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. Journal of International Economics, 41(3-4), 351-366.

Frankel, J. A., and Saravelos, G. (2010). Are leading indicators of financial crises useful for assessing country vulnerability? Evidence from the 2008-09 global crisis (No. w16047). National bureau of economic research.

Fratzscher, M., and Bussiere, M. (2003). Towards a new early warning system of financial crises. In: Royal Economic Society Annual Conference (No. 81). Royal Economic Society.

Gerged, A. M., Marie, M., and Elbendary, I. (2022). Estimating the Risk of Financial Distress Using a Multi-Layered Governance Criterion: Insights from Middle Eastern and North African Banks. Journal of Risk and Financial Management, 15(12), 588.

Ghenimi, A., Chaibi, H., and Omri, M. A. B. (2017). The effects of liquidity risk and credit risk on bank stability: Evidence from the MENA region. Borsa Istanbul Review, 17(4), 238-248.

Gholizadeh, A., Falahshams, M., and Afsharkazemi, M. A. (2020). Designing a quick warning system for the occurrence of a financial crisis in the Tehran Stock Exchange with the approach of Logit and Probit models. Scientific Journal of Financial Science of Securities Analysis, 13(48), 135-148.

Glaser, B., and Strauss, A. (1967). The discovery of grounded theory. Chicago: Aldine Publishing Company.

Glaser, B. (1998). Doing grounded theory: Issues and discussions. CA: Sociology Press.

Glaser, B. (2013). What is grounded theory. Online at: http: //www.groundedtheory.com /what-is-gt.aspx

Glaser, B., Bailyn, L., Fernandez, W., Holton, J. A., and Levina, N. (2013). What Grounded Theory Is…. In: Academy of management proceedings, Briarcliff Manor, NY 10510: Academy of Management.

Hammond, P., Opoku, M. O., and Kwakwa, P. A. (2022). Relationship among corporate reporting, corporate governance, going concern and investor confidence: Evidence from listed banks in sub Saharan Africa. Cogent Business and Management, 9(1), 2152157.

Huang, Y., Kou, G., and Peng, Y. (2017). Nonlinear manifold learning for early warnings in financial markets. J. European Journal of Operational Research, 258, 692-702.

Ivičić, L., Kunovac, D., and Ljubaj, I. (2008). Measuring bank insolvency risk in CEE countries. In: The Fourteenth Dubrovnik Economic Conference.

Kaminsky, G., and Lizondo, S., and M. Reinhart. (1998). Leading Indicator of Currency Crises. IMF Staff Papers, 45, 1-48.

Kaminsky, G. L., and C. M. Reinhart. (1999). The Twin crises: The causes of banking and balance of payments problems. American Economic Review, 89 (3), 473-500.

Komeijani, A. (2015). The role of banking system in Iranian Economy. Role of public relations in the banking industry, Conference in Central Bank of Iran (In Persian).

Laser, F. H., and Weidner, J. (2022). Currency compositions of international reserves and the euro crisis. Open Economies Review, 33, 917-944.

Lepetit, L., and Strobel, F. (2015). Bank insolvency risk and Z-score measures: A refinement. Finance Research Letters, 13, 214-224.

Li, Z., Yang, C., and Huang, Z. (2022). How does the fintech sector react to signals from central bank digital currencies?. Finance Research Letters, 50, 103308.

Lin, X., and Peng, Y. (2022). Research on the early warning system of regional financial risk. International Journal of Industrial and Systems Engineering, 41(3), 404-415.
Mabkhot, H., and Al-Wesabi, H. A. H. (2022). Banks' Financial Stability and Macroeconomic Key Factors in GCC Countries. Sustainability, 14(23), 15999.
Mahmoudinia, D., and Borhani, L. (2022). The Twin Crises in the Iranian Economy and Its Determination during 1980–2018. Iranian Economic Review, 26(1), 183-197.
Martin, D. (1977). Early warning of bank failure: A logit regression approach. Journal of banking and finance, 1(3), 249-276.
Mayes, D.G., and Hanno, S. (2014). The effectiveness of capital adequacy measures in predicting bank distress. Vienna: SUERF - The Europe. Money and Finance Forum.
Oppong, G.K., and Pattanayak, J.K. (2019). Does investing in intellectual capital improve productivity? Panel evidence from commercial banks in India, Borsa-Istanbul Review, (http://creativecommons.org/licenses/bync-nd/4.0/)
Patel, S., and Sarkar, A. (1998). Crises in Developed and Emerging Stock Markets. Federal Reserve Bank.
Radfar, H., Shahchera, M., and Sabouri, B. (2019). The simultaneous effect of liquidity risk and credit risk on the stability of banks admitted to the Tehran Stock Exchange, 7(27), 191-214.
Rastogi, S., and Kanoujiya, J. (2022). Corporate disclosures and financial distress in banks in India: the moderating role of competition. Asian Review of Accounting, 30(5), 691-712.
Sadeghi Sharif, J., Talebi, M., Alemtabriz, A. and Katouzian, M. (2018). Comparison of indicators for determining the financial crisis threshold of banks in the early warning system based on the factor of business cycles, Monetary and Banking Research Quarterly, 11(38), 501-534.
Sadeghi sharif, J., Talebi M., Alemtabriz A., and Katouzian M. (2018). Comparison of indicators for determining the financial crisis threshold of banks in the early warning system based on the factor of business cycles, Monetary and Banking Research Quarterly, 11(38), 534-501.
Sahajawala, R., and Bergh, P. Van den. (2014). Supervisory risk assessment and early warning systems. Basel committee on banking supervision working papers, No 4.
Samad, A., and Armstrong, V. S. (2022). Bootstrap-DEA management efficiency and early prediction of bank failure: Evidence from 2008-2009 US bank failures. Central Bank Review, 22(3), 119-127.
Seraj, S., and Taheri, M. (2011). Banking supervision based on the early warning system, using CAMEL ratios in the form of logit model, scientific research journal of monetary-banking research, 4(12), 45-70.
Shirinpour, M., Haji, G., Sarlak, A., and Alipour, H. (2022). Asymmetric Effects of Oil Price, Exchange Rate and Money Volume on Stock Returns of Tehran Stock Exchange. Environmental Energy and Economic Research, 7(1), S049.
Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. The journal of business, 74(1), 101-124.
Strauss, A., and Corbin, J. (1998). Basics of qualitative research: Grounded theory procedures and techniques, 2nd ed. Thousand Oaks, CA: SAGE Publication.
Tatom, J. (2012). Predicting failure in the commercial bank industry. Munchin Personal RePEc Archive, Paper No. 34608.
Thomson, J. B. (1991). Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland Economic Review, 27(1), 9-20.
Weibull, W. (2015). A statistical theory of the strength of materials. In: Ingeni¨ors Vetenskaps Akademien Handlingar, vol. 151. Stockholm: Generalstabens Litografiska Anstalts Forlag.
Whalen, G. (2016). A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool, Federal Reserve Bank of Cleveland Economic Review. Quarter 1, 9-20.
Zaghdoudi, T. (2016). Bank failure prediction with logistic regression. International Journal of Economics and Financial Issues. 3(2), 537-543.