Journal of Mathematical Extension
Vol. 18, No. 3, (2024) (3)1-29
URL: https://doi.org/10.30495/JME.2024.2869
ISSN: 1735-8299
Original Research Paper

Predict of Financial Distress by Logistic Regression, DEA-R and CAMELS Indicators

M. Shafiee*
Shiraz Branch, Islamic Azad University

H. Saleh
Central Tehran Branch, Islamic Azad University

G.A. Paydar
Shiraz Branch, Islamic Azad University

Abstract. It is very important to choose an appropriate and efficient monitoring system to evaluate the performance of a bank's financial distress, including the most important monitoring systems that have been proposed to evaluate the performance of a bank's financial distress; The use of CAMELS monitoring system, which includes six indicators of capital adequacy, asset quality, management soundness, earning quality, liquidity, market risk sensitivity, so the purpose of this study is to evaluate the financial distress of banks based on CAMELS indicators. In this regard, 12 financial variables based on CAMELS indices have been used, which have been implemented on 17 banks listed on the Tehran Stock Exchange. The sample selected in the model fit includes two groups of healthy and financially distressed, which are separated based on the CAMELS index. The accuracy of both models has been investigated. The results indicate that the overall accuracy of the logistic regression model is higher than the Data Envelopment Analysis model in assessing

Received: 25 September 2023; Accepted: 19 May 2024
*Corresponding Author

financial distress. Also, the results of this study showed that CAMELS financial ratios can be a good assessor for banks' financial distress.

AMS Subject Classification: 90C08; 90B50
Keywords and Phrases: Financial Distress, DEA, DEA-R, Logistic Regression, CAMELS Indicators, Banking Evaluation.

1 Introduction

In today's world, as the number of organizations and commercial institutions continues to rise, economic and commercial relations have become increasingly complex. As a result, enterprises are now operating in a highly competitive and constantly evolving environment. To remain competitive, organizations must adapt their operating conditions to keep pace with the growth and development of leading organizations and advancements in technology. Failure to do so can result in financial distress, and if effective action is not taken, bankruptcy may be inevitable [4]. The possibility of capital losing serves as a foundation for organizations to proactively anticipate their financial state before reaching the verge of bankruptcy, commonly referred to as financial distress. Consequently, the matter of organizational financial distress and failure has always been a challenging and contemplative issue for businesses. Given its significance, accounting and financial experts worldwide are actively seeking methods to predict the financial distress of organizations ([6], [7] [20], [28]). Among the crucial constituents of the financial system, the banking sector serves as a significant economic conduit that connects people's lives. Through its intermediary function, it plays a crucial role in the efficient and consistent allocation of economic resources by mobilizing them for productive activities [4]. Consequently, assessing the performance of the banking sector is of utmost importance to uphold the stability of society, the monetary system, and the public's trust in the entire banking network [26] Hence, it is imperative to provide adequate supervision during times of financial distress or crisis within organizations, particularly in the banking sector of a country. Typically, bank supervisors employ a combination of internal and external monitoring techniques to detect banks that are vulnerable to risk. This enables controllers to predict and identify banks that may face bankruptcy and offer recommendations to mitigate the likelihood of such an outcome. Face-to-face supervision involves physical visits to banks to assess their stability and overall health. However, internal supervision can be expensive due to the labor-intensive nature of the process and the need for daily evaluation of banking operations.

As a result, banking controllers resort to external supervision to keep a check on the performance of banks. This type of supervision involves the use of both econometric and non-econometric methods, providing the controller with a comprehensive understanding of the situation of each bank. This, in turn, allows the contoller to devise strategies to enhance the banks' efficiency. External supervision catalyzes banks to improve their health and stability before internal supervision takes place ([1], [16], [11], [29]) Consequently, one of the ways to identify banks' financial distress is through the development of an external or Off-site Supervisory Rating Systems.

The primary objective of designing such a system is to evaluate the performance of banks at the national and international levels, while also ensuring compliance with legal requirements to keep the bank on track. The complete ranking system is one of the non-economic methods used as an Off-site Supervisory Rating System, which enables controllers to identify financial distressed banks [3]. So, assessing the financial performance of banks and predicting their potential bankruptcy has been the subject of numerous research studies by experts in the field. Chairunesia and Bintara (2019) also investigated the relationship between good corporate governance, financial distress, and earnings management in Indonesian companies [9],. Their study revealed a correlation between corporate governance and financial distress. Similarly, Idrees and Qayyum (2018) explored the impact of financial distress risk on the stock returns of non-financial companies [15]. Their findings indicated that the risk of financial distress has a positive and significant effect on the stock value of the companies studied, and the inefficiency of corporate management in market control plays a crucial role in this study. In another study, Condello et al. (2017) evaluated the effectiveness of data envelopment analysis as a tool for predicting short-term bankruptcy in 283 Italian companies between 2010 and 2016, compared to logistic regression [13]. The study found that DEA was more effective in predicting bankruptcy compared to logistic regression. However, logistic regression analysis was more accurate in predicting healthy companies. Masood et al. (2016) conducted a study to examine the acceptance of CAMELS indicators in Islamic banks in Pakistan [18]. The results indicated that Islamic banks in Pakistan follow and apply CAMELS indicators and guidelines in their strategies. Trivedi and Elahi (2015) evaluated and ranked the performance of public and private banks in India using CAMELS indicators [27]. The study found that private banks had a better performance rating than state-owned banks. Muhmada and Hashima (2015) assessed the performance of Malaysian banks based on CAMEL and logistic regression indices. The results showed that capital adequacy, asset quality, income quality, and liquidity significantly impact the performance of Malaysian banks. For more information, see [19].

Upon examining prior research, it is clear that limited attention has been given to the ranking of banks based on comprehensive vulnerability criteria and the utilization of logistic regression models and DEA as novel and conventional methods for addressing the issue of banks' financial vulnerability. Also, in previous studies, the classical data envelopment analysis model has commonly been employed for predicting financial vulnerability. Although the DEA method is a widely used technique for evaluating the financial stability of banks, the approach employed in this paper differs from traditional DEA models. Rather than identifying the efficiency frontier that distinguishes efficient and inefficient units, the study establishes a bankruptcy or distress frontier. Banks situated on this frontier are deemed financially distressed, while those located beyond it are considered financially nondistressed. Also, the enhanced Russell model with ratio data is favored over classical DEA models. This is primarily because classical DEA models are limited in their ability to handle negative data in input and output indices, as well as their inability to simultaneously reduce inputs and increase outputs.

Furthermore, considering that the CAMELS rating system serves as a diagnostic method for assessing banks' financial distress, this research adopts CAMELS indices as a criterion for evaluating banks' financial helplessness. Subsequently, Consequently, this article follows a sequential structure encompassing a review of pertinent concepts required for further analysis in part 2. A new DEA-R model proposed in section 3, In part 4, the research methodology is discussed, whereas part 5 involves the findings of the research. Subsequently, a comparison is made between the accuracy of these two evaluation methods. Finally, section 6 concludes by summarizing the findings and providing suggestions for future research endeavors.

2 Literature Review

2.1 Explain the concept of financial helplessness in banks

Banks serve as financial intermediaries, with short-term deposits comprising most of their liabilities and long-term loans to businesses and consumers forming the bulk of their assets. Consequently, if a bank's debts exceed the value of its assets, it may face financial difficulties and become unable to meet its obligations. This can occur when borrowers default on their debts (credit risk), causing the value of the bank's assets to decline. Additionally, even in the absence of an increase in accrued receivables, if the rate of return on the bank's assets is lower than the rate of interest on its liabilities, the bank's balance sheet may become unfavorable [8]. Changes in exchange rates can lead to a disproportionate rate of return, particularly when banks borrow in foreign currency and repay in domestic currency. If bank deposits are uninsured and the quality of the portfolio deteriorates, depositors may withdraw their funds before the bank goes bankrupt. This sudden outflow of deposits can have similar effects to a bank run, which can occur after a period of short-term foreign capital inflows, as seen in Latin America, Asia, and Eastern Europe in the 1990s. In countries where banking supervision is weak despite the banking sector's freedom of action, looting can cause banking crises and financial distress to spread. Therefore, it is crucial to assess the situation of investable banks to protect their capital and prevent helplessness. This assessment process is described below.

2.2 CAMELS rating system

As profit-driven institutions, banks need to maximize their profits, which is why financial criteria are necessary to evaluate their performance. However, assessing the performance of banks can be complex. In recent years, various solutions have been proposed to evaluate the financial and international financial institutions, including the National Bank and the Ball or Ballet Committee. One such solution is to use comprehensive indicators that consider credibility, profitability, and reliability as the most important criteria for measuring activity and determining competency. The CAMELS rating system was first approved by the Federal Financial Institutions Supervisory Board (FFIEC) in the United States in 1979 and is now used by US banking industry regulators and large rating agencies. The acronym CAMELS stands for capital adequacy (C), asset quality (A), management (M), earnings (E), liquidity (L), and market risk sensitivity (S), which was added in 1996 to create a risk-focused rating system. According to Roman and Sargu (2013), the capital adequacy index, management quality index, profit and profitability index, liquidity index, and market risk sensitivity index are the main determinants in identifying the potential of banks and financial intermediaries in managing banks [25]. The capital adequacy index and availability are crucial in identifying a bank's potential, while the management quality index indicates the ability to maintain the bank's position among competitors. The profit and profitability index measures the management's ability to use resources and capital effectively, while the liquidity index shows the bank's ability to deal with economic and financial situations. Finally, the market risk sensitivity index measures a bank's position relative to other banks and the views of market factors and depositors towards it.

2.3 Logistic regression pattern

Logistic regression has been used in the life sciences since the early twentieth century and has since gained popularity in other fields, particularly in the social sciences. This statistical model is used to demonstrate the impact of quantitative or qualitative variables on a two-dimensional dependent variable. While logistic regression analysis is similar to linear regression analysis, the dependent variable in logistic regression is qualitative and two-dimensional, as opposed to a small variable in linear regression. Additionally, independent qualitative variables must either be a two-dimensional variable or become a two-dimensional apparent variable in logistic regression. Therefore, the dependent variable in logistic regression is a two-dimensional dependent variable, and the role of each independent variable on the probability of occurrence of a specific class of dependent variables is shown. Logistic regression is used when the dependent variable is binary, nominal, or sequential, and there are no restrictions for independent variables [14].

3 Data Envelopment Analysis Model

The Data Envelopment Analysis method is a non-parametric method for performance analysis. In this study, the research path has changed from performance analysis to financial distress assessment. This study therefore presents a new type of DEA application for assessing and predicting financial distress. Several studies have utilized DEA to forecast financial distress and bankruptcy. For instance, Celine et al. (2004) employed the CCR model to predict bankruptcy [12]. However, the CCR model [10]cannot use negative data for inputs, while financial ratios commonly used in bankruptcy forecasting may have negative values. Consequently, the use of classic DEA models has been limited. Additionally, the BCC [5] and CCR models are input or output-oriented models and are not suitable for considering simultaneous changes in input and output. Although the Additive model solves this problem, it cannot provide an efficiency score with a suitable scale. One of the types of non-radial models is the modified Russell model, which was presented by Pastor et al. (1999) [23]. Based on this measure, unlike radial models, changes in each input and each output are considered independent of other inputs and outputs. In other words, input shrinks with a factor of , and output expands with a rate of . As a result, the enhanced Russell model was introduced as the (1) model.

$$
\begin{aligned}
&Re = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\theta_i}{\frac{1}{s}\sum_{r=1}^{s}\varphi_r} \\
&s.t \\
&\sum_{j=1}^{n}\lambda_j x_{ij} \leq \theta_i x_{i0}, \quad i=1,\ldots,m, \\
&\sum_{j=1}^{n}\lambda_j y_{ij} \leq \varphi_r y_{r0}, \quad r=1,\ldots,S, \\
&\theta_i \leq 1, \quad i=1,\ldots,m,\ \varphi_r \geq 1, r=1,\ldots,S, \quad \lambda_j \geq 0, \quad j=1,\ldots,n
\end{aligned}
\tag{1}
$$

In specific situations, we encounter certain types of data, such as percentages, which represent ratios. As a result, if at least one input or output is a ratio, the standard DEA models are not appropriate. Therefore, researchers have explored DEA models to create versions suitable for ratio data. In this section, our focus is on the enhanced Russell model, which incorporates ratios in both inputs and outputs.

3.1 Enhanced Russell model with ratio data

Suppose that $DMU_j, \quad j=1,\ldots,n$ by consuming $x_j=(x_j^v, x_j^R), \quad j=1,\ldots,n$ produce $y_j=(y_j^v, y_j^R), \quad j=1,\ldots,n$. So that $x_{ij}^v, i\in I^v$ and $y_{rj}^v, r\in O^v$ denote the volume input and output and $x_{ij}^v, i\in I^v$ and $y_{rj}^v, r\in O^v$ show the ratio input and output respectively. Also: $O^v \cup O^R = \{1,\ldots,r\}$ and $I^v \cup I^R = \{1,\ldots,m\}$.
Olesen et al. (2015) demonstrate that adjustments are required to the standard axioms established by Banker et al. (1984) for VRS technology when dealing with ratio measures as inputs or outputs [22]. Specifically, the axiom of convexity is substituted with the axiom of selective convexity, as proposed by Podinovski (2005) [24].

This issue assumes that when DMUs have the same vectors of ratio inputs and outputs, it is possible to achieve convex combinations. However, suppose the vectors of ratio inputs and outputs of the combined DMUs are not identical. In that case, aggregation is still feasible but necessitates a different approach to handling volume and ratio measures. So selective convex combination, with volume and ratio data, is developed as (2)-(6).

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i^v, \; i \in I^v, \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r^v, \; r \in O^v, \tag{3}$$

$$\lambda_j (x_{ij}^R - x_i^R) \leq 0, i \in I^R, \quad j = 1, \ldots, n, \tag{4}$$

$$\lambda_j (y_{ij}^R - y_r^R) \geq 0, \; r \in O^R, \quad j = 1, \ldots, n, \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \tag{6}$$

By considering selective convexity, a modified Russell model is developed for ratio data such as model (7).

$$\begin{aligned}
& Re = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \theta_i}{\frac{1}{s}\sum_{r=1}^{s} \varphi_r} \\
& s.t \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i^v, \; i \in I^v, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r^v, \; r \in O^v, \\
& \lambda_j (x_{ij}^R - x_i^R) \leq 0, i \in I^R, \quad j = 1, \ldots, n, \\
& \lambda_j (y_{ij}^R - y_r^R) \geq 0, \; r \in O^R, \quad j = 1, \ldots, n, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \theta_i \leq 1, i = 1, \ldots, m, \; \varphi_r \geq 1, r = 1, \ldots, n, \lambda_j \geq 0, \; j = 1, \ldots, n
\end{aligned} \tag{7}$$

It is evident that model (7), because of $\lambda_j(y_{rj}^R - \varphi_r y_{ro}^R) \geq$ and $\lambda_j(x_{ij}^R - \theta_i x_{io}^R) \leq 0$ is a nonlinear model.These inequalities are rewritten in equivalent form as (8). It is easy to show that $\lambda_j(x_{ij}^R - \theta_i x_{io}^R) \leq 0$ is equivalent to the relations (9)-(10).

$$\lambda_j = 0, \; or \; \left[x_{ij}^R - \theta_i x_{io}^R \leq 0 and (y_{rj}^R - \varphi_r y_{ro}^R) \geq 0 \right], \quad j = 1, \ldots, n, \tag{8}$$

Now based on Olesen et al (2017) and using $\delta_j \in \{0, 1\}$, condition (8) is replaced by inequalities (9)-(11).

$$\lambda_j \leq \delta_j, \quad j = 1, \ldots, n \tag{9}$$

,

$$(x_{ij}^R - \theta_i x_{io}^R) \leq M_i(1 - \delta_j), \quad j = 1, \ldots, n, \; i \in I^R \tag{10}$$

and

$$(\varphi_r y_r^R - y_{rj}^R) \leq N_r(1-\delta_j),\ j=1,\dots,n,\ r \in O^R \tag{11}$$

Theorem 3.1. *Suppose that:* $\bar{x}_{ij}^R = \max\{x_{ij}^R | j = 1,\dots,n\}$ $i \in I^R$ *and* $\bar{y}_{rj}^R = \max\{y_{rj}^R | j=1,\dots,n\}, r \in O^R$ *. So for any scalers that satisfy in relation:* $\bar{x}_{ij}^R \leq M_i$, $\bar{y}_{rj}^R \leq N_r$ *and* $L = \max\{M_i, N_r | i \in I^R, r \in O^R\}$, *constraints* (8) *is equivalent to constraints* (9), (12) *and* (13) *as follows.*

$$(x_{ij}^R - \theta_i x_{io}^R) \leq L(1-\delta_j), j=1,\dots,n,\ i \in I^R \tag{12}$$
$$(\varphi_r y_r^R - y_{io}^R) \leq L(1-\delta_j),\ j=1,\dots,n,\ r \in O^R \tag{13}$$

Proof. *If* $\delta_j = 0$ *then* $\lambda_j = 0$ *. We know that:*

$$x_{ij}^R \leq \bar{x}_{ij}^R \leq M_i \leq L \tag{14}$$

Also:

$$\theta_i x_{io}^R \geq 0 \Longrightarrow -\theta_i x_{io} \leq 0 \tag{15}$$

Therefore by adding (14) *and* (15), *we have:* $x_{ij}^R - \theta_i x_{io}^R \leq L$ *.So the constraint* $x_{ij}^R - \theta_i x_{io}^R \leq L(1-\delta_j)$ *is redundant.*
If $\delta_j = 1$ *then* $\lambda_j \leq 1$ *and* $x_{ij}^R - \theta_i x_{io}^R \leq 0$ *. So the constraint* $\lambda_j \leq \delta_j$ *is redundant.*
Similarly, $\lambda_j(y_{rj}^R - \varphi_r y_{ro}^R) \geq 0,\ r \in O^R,\ j=1,\dots,n$ *can presented by* (9) *and* (13).
Based on the above discussion and Theorem 1, model (7) *converts to model* (16). □

$$\begin{aligned}
&Re = \min \frac{\frac{1}{m}\sum_{i=1}^m \theta_i}{\frac{1}{s}\sum_{r=1}^s \varphi_r}\\
&s.t\\
&\sum_{j=1}^n \lambda_j x_{ij} \leq \theta_i x_{io}^v,\ i \in I^v,\\
&\sum_{j=1}^n \lambda_j y_{rj}^v \geq \varphi_r y_{ro}^v,\ r \in O^v,\\
&\lambda_j \leq \delta_j,\ j=1,\dots,n\\
&(x_{ij}^R - \theta_i x_{io}^R) \leq L(1-\delta_j),\ j=1,\dots,n, i \in I^R\\
&(\varphi_r y_r^R - y_{rj}^R) \leq L(1-\delta_j),\ \ j=1,\dots,n,\ r \in O^R\\
&\sum_{j=1}^n \lambda_j = 1,\\
&\theta_i \leq 1, i=1,\dots,m,\ \varphi_r \geq 1, r=1,\dots,n, \lambda_j \geq 0, \delta_j \in \{0,1\},\ j=1,\dots,n
\end{aligned} \tag{16}$$

4 Research Methodology

This research method is correlational, i.e., the study of the relationship and correlation between variables through regression and post-event research methodology (using past information). Also, according to the division of scientific research from different perspectives, this research is based on the quasi-experimental nature based on the analysis of capital market data and is of the correlational type and applied in terms of purpose. Its decision has been reviewed by the statistical population. Also, the study's statistical population is 17 banks listed on the Tehran Stock Exchange during 2020, 2018 and 2017, and according to the 3 years, a total of 51 bank years have been examined. Since the whole statistical population was used, no sampling was done, so the statistical sample is equal to the statistical population and includes all banks present in the statistical population, which is described in Table 1. The research employed a combination of field and library data collection methods. The study focused on banks and utilized the financial statements of participating banks in the Tehran Stock Exchange to collect data related to research variables. The financial statement information was obtained from various sources including Tadbir Pardaz and Rahavard Novin software databases, audited financial statements of listed companies available at the library of the Tehran Stock Exchange Organization, and the comprehensive database of listed companies (Tehran Stock Exchange website). The financial ratios were calculated based on CAMELS indicators, and two models, logistic regression and data coverage analysis, were used to measure financial distress. The accuracy of the evaluation model was determined using SPSS, Excel, and WinQsb software for data analysis.

4.1 Identification and operational definition of logistic regression independent variables

In this research, a thorough examination of the existing literature in the field was conducted, and the opinions of experts were reviewed to identify the most relevant independent variables. After careful consideration, a total of 12 variables were selected and incorporated into the logistic regression model, as outlined in Table 2. Based on the selected independent variables and the dependent variable, a conceptual model of financial distress was developed using logistic regression, as illustrated in Figure 1.

4.2 Identify and define the indicators of the model of data envelopment analysis

The Data Envelopment Analysis Model is a non-parametric method for performance analysis based on performance frontier. In this research, the research path has been changed from performance analysis based on efficiency threshold to assessment of financial helplessness threshold. This study therefore presents a new type of DEA application for assessing and predicting financial distress. Therefore, the definitions of input and output indicators are also different. Generally, In the context of financial distress assessment, financial ratios are classified as inputs and outputs as follows [3]:

Table 1: List of banks evaluated in the research

No	Name	Type
1	Medal	Private
2	Eghtesead Novin	Private
3	Ansar	Private
4	IranZamin	Private
5	Parsian	Private
6	Pasargad	Private
7	Tejarat	Private
8	Hekmat Iranian	Private
9	Day	Private
10	Saman	Private
11	Sarmaye	Private
12	Sina	Private
13	Saderat Iran	Private
14	Karafarin	Private
15	Gardeshgari	Private
16	Melat	Private
17	Postbank	Govermental

Table 2: CAMELS indices used in logistic regression model

Financial Ratio	Defining a variable
Asset Quality	1-Debt Ratio=A=totaldebt/total asset 2-Non-current receivables in total facilities=B= Non-current receivables/total facilities
Management Quality	1-Proportion of total bank expenses to total bank revenues=C=total bank expenses/total bank revenues 2-Ratio of operating profit to operating costs=D=operathing profit/operating costs
Capital Adequacy	1-Ratio of capital to risk-weighted assets (capital adequacy)=E=capital base/Assets weighted at risk 2-Ratio of equity to total assets (ownership)=F=Sum of equity/Total Assets
Liquidity coverage	1-Ratio of Cash balance, Deposit to the central bank and bank account=G= Bank account balance and cash flow with the Central Bank/Total deposits 2-Deposit retention ratio=H= Investment deposits = (sight deposits + savings deposits)/Escape deposit
Earnings	1-Return Of Asset(R.O.A)=I=Net Income/Total Assets 2-Return Of Equity=J=Net Income/Total Equity
Sensitivity to market risk	1-The beta ratio of bank shares on the stock exchange 2-Interest rate sensitivity ratio=K= Sensitive assets/ Sensitive Debts

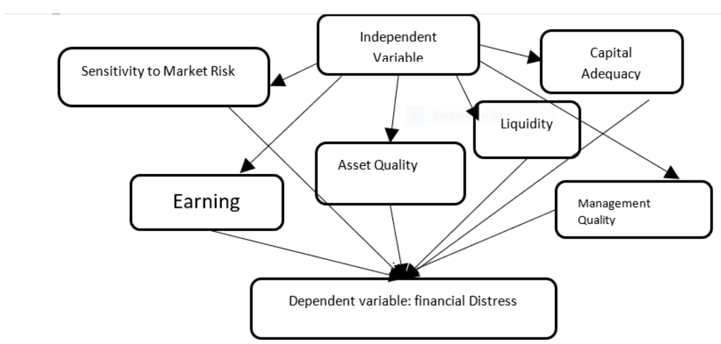

Figure 1: Conceptual model of financial distress by logistic

Table 3: Input and output of the DEA model based on CAMELS

Inputs	Outputs
X_1 =Ratio of operating profit to	
X_2 = capital Adequacy	Y_1 = Debt Ratio
X_3 = Ratio of ownership	Y_2 = Non-current receivables in total facilities
X_4 =Liquidity coverage	Y_3 = Proportion of total bank expenses to total bank revenue
X_5 = Deposit retention ratio	
X_6 = Return Of Asset(R.O.A)	
X_7 = Return Of Equity	
X_8 = The beta ratio of bank shares on the stock exchange	
X_9 = Interest rate sensitivity ratio	

- **Inputs**: are financial indicators that are presented in the form of financial ratios, the reduction of which leads to a situation of imbalance or more severe financial stress.

- **Output variables**: are financial indicators that are presented in the form of financial ratios, the increase of which leads to bankruptcy or financial crisis.

Therefore, according to the mentioned points, previous financial research and the opinion of experts, the input and output of the research are described in Table 3. As can be seen, some indictors are ratio data. So traditional DEA model is not suitable for this issue and DEA-R model such as enhanced Russell model with ratio data need to be applied. Hence, based on the input and output indicators, the conceptual framework depicting financial distress is derived through the utilization of data envelopment analysis, as presented in Figure 2.

This research focuses on evaluating a total of 17 banks which serve as the decision-making units.

4.3 Modeling

In this study, the model of Data Envelopment Analysis has been used to predict bankruptcy. It is then compared with the logistic regression model, which is an economic approach, to evaluate the success rate in predicting the bankruptcy and financial distress of the banks evaluated in the study.

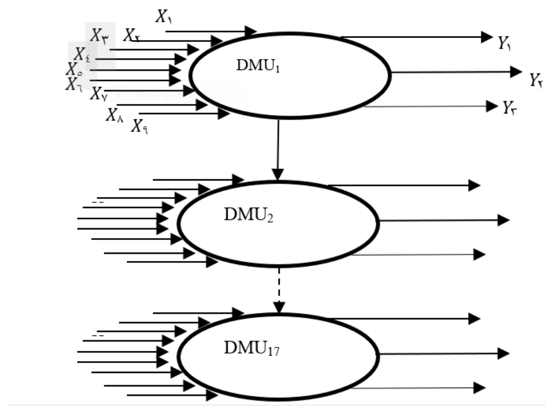

Figure 2: Conceptual model of financial distress through Data Envelopment Analysis

4.3.1 Data envelopment analysis

4.3.1.1 Bankruptcy frontier

In the data envelopment analysis model based on the production aspect, a key aspect is the construction of the efficiency frontier. This frontier aims to optimize efficiency by achieving higher output levels with reduced input requirements. The present research follows an unconventional approach, challenging the conventional methods. Notably, the definition of the bankruptcy probability set shares similarities with that of the production possibility set. However, a distinguishing feature is observed in the bankruptcy boundary, where an increase in input may correspond to a decrease in output.

4.3.2 Calculation of critical and non-critical probabilities

Initially, the enhanced Russell with ratio data model is solved by utilizing the WinQSB software to analyze all banks individually. Subsequently, the bankruptcy frontier is delineated, which allows for the identification of each bank's position based on its efficiency score in relation to the bankruptcy frontier. In the case that all slacks equate to zero in an optimal scenario, the bank is considered to be on the brink of bankruptcy. Conversely, if at least one slack value is positive, the bank does not align with the frontier. Figure 3 visually portrays the bankruptcy frontier, uniquely using the symbol O to denote non-bankrupt banks and the symbol X to signify banks that have succumbed to bankruptcy.

To establish the bankruptcy threshold, a demarcation line is drawn, resulting in the formation of four distinct categories:

A. Bankrupt banks on the verge of bankruptcy.

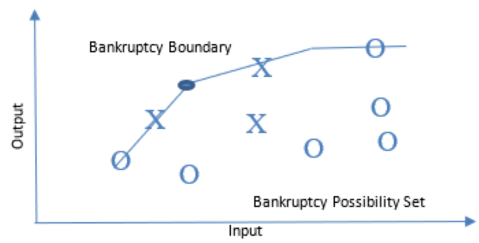

Figure 3: Bankruptcy Frontier and Bankruptcy Probability Set

B. Bankrupt banks that are not on the verge of bankruptcy.

C. Non-bankrupt banks that are not on the brink of bankruptcy.

D. Non-bankrupt banks that are on the brink of bankruptcy.

Proceeding further, the member banks within each of these four groups are identified, and probabilities are computed according to Table 4. When a research hypothesis is rejected, if the first type of error occurs, and when a hypothesis contrary to the research hypothesis is accepted, if it is false; The second type of error has occurred. The wrong classification is identified by the second probability P(NBR/BR) as the first type error and the fourth probability number P(BR/NBR) as the second type error. The correct classification rate is determined by the probability of the third number P(NBR/NBR) and the probability of the number one P(BR/BR). This study considers that if a bank is on the verge of bankruptcy, the bank belongs to the bankruptcy status.

4.3.3 Logistic regression model

Logistic regression stands as a highly useful generalized model utilized for examining the connection between one or more explanatory variables and a nominal response variable. Logistic analysis, a prevalent approach, explores the probability of a dichotomous outcome about a collection of potential predictors. The fundamental equation for logistic regression can be represented as 17.

$$\log \frac{p}{(1-p)} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \tag{17}$$

In the above relation, p is the probability of occurrence of the event, β_0 is the width of the origin and β_k is the coefficient related to the exponent x. The dependent variable is the logarithm of the probability of occurrence of an event to the probability of its non-occurrence. In this type of regression, independent variables can be both quantitative and nominal scale, but the dependent variable is nominal and two-level scale. These two levels usually refer to membership and non-membership in a group.

Table 4: Calculation of critical and non-critical probabilities

Possibility	**How to measure it**
$P(\frac{BR}{BR}) =$ The number of critical banks on the verge of bankruptcy divided by the total number of critical banks	$\frac{A}{A+B}$
$P(\frac{NBR}{BR}) =$ The number of critical banks that are not on the verge of bankruptcy is divided by the total number of critical banks	$\frac{B}{A+B}$
$P(\frac{NBR}{NBR}) =$ The number of non-critical banks that are not on the verge of bankruptcy divided by the total number of non-critical banks	$\frac{C}{C+D}$
$P(\frac{BR}{NBR}) =$ The number of non-critical banks on the verge of bankruptcy, divided by the total number of non-critical banks	$\frac{D}{C+D}$

Table 5: Bank health level intervals

Ranking criteria of CAMELS	**Banking health rating**
Rated less than $\sigma - 0.842\bar{x}$	Too strong
Ranks within the range $\sigma - 0.253\bar{x},\ \sigma - 0.842\bar{x}$	Strong
Ranks within the range $\sigma + 0.253\bar{x},\ \sigma - 0.253\bar{x}$	Medium
Ranks within the range $\sigma + 0.842\bar{x},\ \sigma + 0.253\bar{x}$	Weak
More ratings than $\sigma + 0.842\bar{x}$	Very weak

Logistic regression maximizes the probability of an event occurring instead of minimizing the square of the errors (which is done in normal regression). Hypothesis zero in the logistics test will be as 18.

$$H_0 : \beta_1 = \beta_2 = ... = \beta_k = 0 \tag{18}$$

$$H_1 : \beta_1 \neq \beta_2 \neq ... \neq \beta_k \neq 0 \tag{19}$$

To analyze logistic regression and evaluate its efficiency, significant tests of coefficients (parent test), model likelihood ratio, Nigel crack or Kassel and Snell determination coefficient, luck ratio and Hosmer–Lemeshow test are used, which are described in the following.

5 Research findings

5.1 Ranking of banks to assess financial distress by CAMELS method

To determine the health level intervals of the banks evaluated in the research, Table 5 has been used. Within the provided table, we encounter the following variables: x, denoting the average of combined ranks, and , representing the standard deviation of the sample comprising these combined ranks. The ranking criterion is established under the assumption of normal distribution, with equal distribution and dispersion observed across all levels, encompassing 20% of the banks. Within the framework of a normal distribution, the sample's standard deviation displays a mean of $\pm 0.253\sigma$ with a deviation of ± 0.842 on either side. To accomplish this, we initially computed the financial ratios associated with each indicator, subsequently assigning rankings to CAMELS sub-indicators based on their influence on financial distress. We then determined the average of combined ratings for each of the 6 groups. Additionally, the research data reveals that the average of combined rankings is 8.20 for the year 2020, 8.34 for 2018, and 8.31 for 2017. The standard deviation of the average sample of combined classes in 2020 is equal to 1.91, in 2018 is equal to 2.23 and in 2017 is equal to 2, and finally, the final rank of each bank was obtained based on perfect criteria, which are described in Table 6.

Table 6: Bank health level intervals

Bank name	**Health level in the year (t = 2020)**	**Health level in the year (t - 2 = 2018)**	**Health level in the year (t - 3 = 2017)**
Melal	Weak	Very Weak	Very Weak
Eghtesad Novin	Weak	Weak	Medium
Ansar	Very Weak	Very Weak	Weak
IranZamin	Very Weak	Very Weak	Very Weak
Parsina	Very Weak	Weak	Very Weak
Pasargad	Very Strong	Very Strong	Very Strong
Tejarat	Strong	Medium	Strong
Hekmat Iranian	Very Strong	Very Strong	Strong
Day	Strong	Weak	Strong
Saman	Strong	Weak	Strong
Sarmaye	Strong	Weak	Medium
Sina	Strong	Very Strong	Very Strong
Saderat Iran	Very Weak	Strong	Very Weak
Karafarin	Strong	Very Strong	Very Strong
Gardeshgary	Weak	Weak	Very Weak
Mellat	Very Strong	Strong	Strong
Posbank	Weak	Weak	Weak

After determining the health range of the studied banks during the mentioned years, the financial distress of the banks has been addressed by the DEA model and logistic regression, which is discussed below.

Table 7: Evaluation of the significance of the variables in the model

Variables	**the amount of Coefficient**	**standard error**	**Wald statistics**	**Degrees of freedom**	**Probability value**
Capital Adequacy	9165	47.39	0.000	1	0.001
Ratio Risk	109	57.95	0.000	1	0.000
y-intercept	-502	26.39	0.000	1	0.000

5.2 Implementation of logistic regression model and its results

The regression models used to investigate are:

$$\begin{aligned} z_i = \beta_0 &+ \beta_1 capitalAdequacy_i + \beta_2 RatioRETA_i + \beta_3 DebtRatio_i + \beta_4 RatioNCSF_i \\ &+ \beta_5 Liquidity_i + \beta_6 RatioDR_i + \beta_7 RatioTCTI_i + \beta_8 RatioOPOC_i \\ &+ \beta_9 RatioROA_i + \beta_1 0 RatioROE_i + \beta_1 1 RatioRisk_i + \beta_1 2 RatioRIS_i + E_i \end{aligned} \tag{20}$$

The forward lR imaging method is used in logistics regression. When both variables are modeled, then using the method of removal and elimination of the variables, which do not have a meaning in the model, is based on the maximum number of parts, the best model is provided. The results are given in Table 7. Therefore, according to Table 7 and Forward lR step method, the best model in fiscal year (t), i.e. 2020, is equal to:

$$z_i = \beta_0 + \beta_1 capitalAdequacy_i + \beta_1 1 RatioRisk_i + E_i \tag{21}$$

In the following, the regression model of the research is tested.

5.3 Fitting the logistic regression model to determine the factors affecting the financial distress of the bank

According to Table 8, the null hypothesis is rejected and this means that the presence of independent variables in the equation is statistically appropriate and significant. The probability value of the holistic test is 0.00. The null hypothesis is rejected with a 95% probability, and as a result, the significance of the coefficients is confirmed.

Table 8: Holistic test (general, omnibus) significance of model coefficients

	The amount of chi-square statistics	**Degrees of freedomr**	**Probability value**
Model	23.508	2	0.000

Accordingly, there is a significant relationship between the independent variables considered to predict financial distress.

Table 9: Summary of logistic regression model

Statistics	**Proofreading logarithm**	**Cox and Snell coefficient**	**Nigel crack determination coefficient**
Amount of statistics	0.000	0.749	1

The coefficient of determination of Cox and Snell is 749. and the coefficient of Nigel crack is equal to 1, which means that approximately 74 to 100% of the changes in the response variable can be described by independent variables.

Table 10: Hosmer–Lemeshow Fit Test

Statistics	**Probability value**	**Degrees of freedom**	**The amount of chi-square statistics**
Amount of statistics	4.150	7	0.762

The probability value related to the model fit study (Hosmer–Lemeshow test) is equal to 0. 762 and it is larger than 0.05. So it is not rejected with a 95% probability of model fit and adequacy.

5.4 Checking the accuracy of the logistic regression model based on the predictions made

As can be seen in Table 11, the accuracy of the model during the financial years under study shows that the model with 100% accuracy in the fiscal year 2020 and 82.4% accuracy in the two years before the year of helplessness and accuracy of 64.7% In the three years before the year of helplessness, correctly predicted the financial helplessness of the banks evaluated by the research.

Table 11: Assessing the accuracy of the regression model in the studied years

observed	Predicted (in 2020)		
	Distressed	Non-distressed	Correct percentage
	1	0	
Financially distressed 0	8	0	100
Healthy 1	0	9	100
Overall percentage			100
observed	Predicted (in 2018)		
	Non-distressed	Distressed	Correct percentage
	1	0	
Financially distressed 0	9	1	90
Healthy 1	2	5	71.4
Overall percentage			82.4
observed	Predicted (in 2017)		
	Non-distressed	Distressed	Correct percentage
	1	0	
Financially distressed 0	6	3	66.7
Healthy 1	3	5	62.5
Overall percentage			64.7

5.5 Results of logistic regression forecast in fiscal year (t), (t-2) and (t-3)

To predict financial distress and select the best forecasting year for banks listed on the Tehran Stock Exchange, the fiscal year 2020 was first selected and the financial distress of banks was predicted based on the CAMELS index.

Table 12: Results of logistic regression forecast in 2020, 2018, 2017

Logistic regression results in fiscal year (t-3)	**Logistic regression results in fiscal year (t-2)**	**Logistic regression results in fiscal year (t)**	
17	17	17	Total number of sample banks
1.125	1.42	0.88	The ratio of helpless to healthy banks
9	10	8	Number of helpless banks
8	7	9	Number of healthy banks
33.3	10	0	The first type of error
37.5	28.6	0	The second type of error
64.7	82.4	100	Correct classification rate
35.3	17.6	0	Incorrect classification rate

Table 13: Prediction of financial distress with the enhanced russell model with ratio data healthy banks

Healthy banks			Helpless banks		
No.	Bank	efficiency	No.	Bank	efficiency
1	Pasargad	0.5691	1	Melal	1
2	Hekmat	1	2	Eghtesad Novin	0.6862
3	Mellat	0.1303	3	Gardeshgary	1
4	Tejarat	1	4	Postbank	1
5	Day	1	5	Ansar	1
6	Sarmaye	1	6	Iranzamin	1
7	Sina	1	7	Parsina	1
8	Karafarin	0.1982	8	Saderat Iran	1
9	Saman	1			

Then, with real information and based on the final model of logistic regression in 2020 and the identification of final variables, two years before 2020 and three years before were predicted and then the best financial year in predicting financial distress was estimated, the results in Table 12 Come. As can be seen from Table 12, the best year to predict financial distress is the fiscal year 2020, which had the best forecast compared to two years before financial distress and three years before financial distress. Then, the best year of forecasting for the assessment of helplessness was selected by the model of data envelopment analysis, the results of which are given below.

5.6 Results of predicting financial distress by data envelopment analysis model

According to the results of Table 6, the sample studied in 2020 has 9 healthy banks and 8 financially helpless banks. Also, in Table 13, the results of forecasting the financial distress of banks with the enhanced Russell model with ratio data and including inputs and outputs are shown that out of 17 banks surveyed, 13 banks have one efficiency or in other words, they are on the verge of financial distress. Then, according to Table 14, the values of four groups A, B, C and D were calculated. In the next step, the number of banks belonging to these four groups was determined, and then according to Table 4, the ratios of critical and non-critical probabilities were calculated. Type error and type II error were found this information is given in Table 15.

Table 14: Frequency and percentage of banks based on border protection

	Total banks	Banks that are not on the verge of financial distress		Banks on the brink of financial distress	
		Percentage	frequency	Percentage	frequency
Financially helpless banks	8	12	1	88	7
Healthy banks	9	34	3	66	6
Total banks	17	4	4	13	13

Table 15: First and second type errors

Row	**Ratio**	**Amount %**
1	P(BR/BR)	88
2	P(NBR/BR)	12
3	P(NBR/NBR)	34
4	P(BR/NBR)	66

According to Table 15, rows one and three show the correct classification, row two indicates the first type of error and row four indicates the second type of error. These two types of errors are equal to 12% and 66%, respectively. Which indicates a wrong prediction. In general, it can be said that 61% of the predictions by the data analysis technique were correct and 39% of them were incorrect. The information is given in Table 16.

Table 16: Accuracy assessment based on model prediction (enhanced Russell model with ratio data)

Observed	**0**	**1**	**Correct percentage**
Financially helpless 0	7	1	88
Healthy 1	6	3	34
Overall percentage	13	4	61

5.7 Assessing the accuracy of predicting financial distress in the LR-DEA model

Paired comparison test (T) was used to evaluate the performance and accuracy of both patterns of coverage analysis, data and logistic regression in the year of helplessness. Since assuming that there is a normal distribution for the statistical population, the statistical distribution related to the test statistic in this case has a "t-distribution", this test is known as "mating samples". The pairwise comparison test is used when we want to examine the similarity of the mean of two societies. Of course, provided that both communities are completely similar in other respects. The test hypothesis is as follows:

$$H_0 : M_1 - M_2 = 0 \tag{22}$$

$$H_1 : M_1 - M_2 \neq 0 \tag{23}$$

Therefore, if the test statistic is greater than 0.5 the desired statistic is meaningless, and if the test statistic is smaller than 05., there is significance at level 0.5 and if it is less than 0.1, there is significance at level 0.1. Therefore, using this test, the performance of both has been investigated, the results of which are shown in Table 17. As can be seen from Table 17, the classification performance of the logistic regression model with a 95% confidence level is better than the data analysis model. In other words, the logistic regression model works better than the data envelopment analysis model in assessing the helplessness of banks admitted to the Tehran Stock Exchange. The results of this study emphasize the need to predict financial distress, which in this regard is consistent with the results of research by Alfianti et al. [2], Chironiza and Bintara [9] and Idris and Qayyum [15]. The results of this study also confirm the need to pay attention to the international indicators of CAMELS. These findings are similar to the results obtained by Massoud et al. [18], Triodi and Elahi [27], Mahmada and Hashima [19], Ramezani et al. [9]. Also, the results of this study showed that it is possible to formulate a financial health model based on CAMELS indices in Iranian banks. The results of this study are consistent with the research of Candello et al. [13] and Celine [12] in terms of merely using data analysis as a tool to predict financial distress. To use the logistic regression model in predicting financial

Table 17: Results of paired comparison test

	LR	**DEA**
The average correct classification rate	0.5294	0.2353
Standard classification rate deviation	0.51450	0.43724
T parameter	-3.771	
P value	0.000	

distress with the research of Candello et al. [13], Mahmada and Hashima [19].

6 Conclusion

Anticipating banks' financial distress is a crucial concern within the realm of economics and finance. It prompts timely decision-making and enables suitable resource allocation adjustments. Accurate prediction of financial vulnerability, followed by effective problem identification and resolution, can yield highly satisfactory outcomes. Predicting banks' financial distress holds immense significance for multiple stakeholders, including investors, creditors, managers, auditors, the government, and particularly the central bank. Banks and credit ranking institutes commonly rely on these models to make informed credit decisions and assign rankings. Therefore, the development of statistical models to predict health as well as the risk of bankruptcy of banks is very necessary. In this regard, the purpose of this study is to test the ability of CAMELS indexes to provide a model for evaluating and predicting the health of banks listed on the Tehran Stock Exchange. To cover the characteristics of 6 CAMELS indices, 12 selected financial ratios were introduced. Then, CAMELS indicators were used to assess the risk of financial distress of banks and the separation of healthy and helpless banks evaluated by the research and healthy and helpless banks was determined. The results of this study in the superior fiscal year (t = 2020) showed that in terms of the capital adequacy index, Sarmaye Bank and Bank Day are in first place. Also in terms of asset quality index; Hekmat Iranian Bank and Sina Bank are in the first place. In terms of liquidity index, all banks except Iranzamin Bank are in the first place. In terms of management quality index; Bank Mellat and Bank Hekmat Iranian are in the first place. In terms of the profitability index, Sarmaye Bank is in the first place and terms of the market risk and sensitivity index, Saman Bank and Bank Melal are in the first place. Also, in this study, as mentioned, the health level of each bank was determined by CAMELS indicators, among which banks; Pasargad, the Hekmat Iranians, and the Mellat were in a very strong range.

Also, banks; Tejarat, Day, Sarmaye, Sina, karafarin, and Saman were in a strong range. Credit banks of Melal, Eghtesad Novin, Gardeshgari, and Postbank were in a weak range and banks Ansar, Iranzamin, Parsian, and Saderat Iran were in a very weak range.
This study suggests that the worst banks (those with poor and very poor financial performance) should improve their position in terms of capital adequacy, asset quality, management efficiency, liquidity and market risk sensitivity to those with banks. Those who have good financial performance, are equal. Therefore, banks; Pasargad, Hekmat Iranian, Meli, Tejarat, Day, Sarmaye, Sina, Karafarin, and Saman as Healthy Banks and Banks; Credit of Melal, Eghtesad Novin, Gardeshgari, postbank, Ansar, Iranzamin, Parsian, Saderat Iran were identified as financially helpless banks and also logistic regression models and data analysis were used to predict the financial distress of banks. In this way, while presenting the prediction model of financial distress in the field of banks based on the CAMELS index and extracting the most important CAMELS indices, various models of financial distress risk assessment were presented and then, in the next step, the model that had the best prediction; Was identified from different models. A retrospective approach will be used for this purpose. Thus a fiscal year for which real information is available; Like the fiscal year ending 1399/12/29, banks with financial distress were identified based on the CAMELS index. Then, with real information and based on the final variables of the determined fiscal year, two years before and three years before the year of financial distress, the CAMELS-based forecasting model was designed and then using logistic regression and data envelopment analysis, the fiscal year 2020 was estimated. It was then compared with actual data to determine which of the two models of regression and data envelopment analysis were better predictors. On the other hand, in this study, enhanced Russell model with a different approach was used. Thus, the analysis path of the research was changed based on the financial helplessness of banks instead of the efficiency limit of banks and the results showed that out of 17 banks surveyed in the top fiscal year (t = 2020), 13 banks are ranked first and this means being These banks are on the verge of financial helplessness. Then the critical and non-critical probabilities were calculated and it was found that the forecast accuracy of financially helpless banks is 88% and the forecast accuracy of healthy banks is 34%. The forecast of helpless and healthy banks in the top financial year (t = 2020) was 100%, which indicates that the data analysis model cannot be a good alternative to the ability of the statistical model of logistic regression. The results showed that the overall accuracy of the logistic regression model is higher than the DEA model in assessing financial distress. Also, the results of this study showed that CAMELS financial ratios can be a good assessor for banks' financial distress. Therefore, banks and credit institutions can use the financial ratios used in this study in the ranking process of their subsidiaries. In general, it can be said that by using the results of this study as a first step, it is possible to prevent banks from suffering from financial helplessness and eventually bankruptcy, as well as its consequences. Of course, after the prediction, the root of the problem is traced and its causes are traced. In conclusion, to conduct applied research in the future, the following suggestions are presented:

1. The limitation of the present study is that it is limited to the analysis of

banks listed on the Tehran Stock Exchange. The CAMELS indicators, the data envelopment analysis and the logistic regression of the research can be used to study the financial performance of public and non-listed banks as well as non-bank financial companies for further analysis.

2. In the present study, perfect criteria have been used to measure the financial performance of banks. It is suggested that in future research, other criteria such as stock returns, Q-Tobin criterion, etc. be used to measure the financial performance of banks.

References

[1] M. A. Ahmad, and H. M. Alrabba, The role of external auditing in activating the governance for controlling banking risk, *Corporate Ownership and Control*, 14 (2017), 96-112.

[2] M. H. Alfiyanti, C. R. Damayanti, and F. Nurlaily, Analisis Financial Distress Dengan Menggunakan Metode Altman Z-Score Dan Springate S-Score (Studi pada EmitenSektorIndustri Barang Konsumsi Sub Sektor Food and Beverages yang Terdaftar di Bursa Efek IndonesiaTahun 2014-2018), *JurnalAdministrasi-Bisnis*, 78(2020), 76-85.

[3] D. Al-Najjar, and H. F. Assous, Key determinants of deposits volume using CAMEL rating system: The case of Saudi banks, *Plos one*, 16(2021), e0261184.

[4] P. K. Aspal, and S. Dhawan, Financial performance assessment of banking sector in India: A case study of old private sector banks, *The Business and Management Review*, 5(2014), 196.

[5] R. D. Banker, A. Charnes, and W. W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management science*, 30(1984), 1078-1092.

[6] D. E. Y. Bernardin, and T. Tifani, Financial distress predicted by cash flow and leverage with capital intensity as moderating, *Jurnal Apresiasi Ekonomi*, 7(2019), 18-29.

[7] A. Bhunia, S. S. Mukhuti, S. G. Roy, D. Harbour, W. Bengal, and N. Delhi, Financial performance analysis-A case study,*Current Research Journal of Social Sciences*, 3(2011), 269-275.

[8] M. Brei, C. Borio, and L. Gambacorta, Bank intermediation activity in a low-interest-rate environment, *Economic Notes*, 49(2020), e12164.

[9] W. Chairunesia, and R. Bintara, The Effect of Good Corporate Governance and Financial Distress on Earnings Management in Indonesian and Malaysia Companies Entered in Asean Corporate Governance Scorecard, International Journal of Academic Research in Accounting, *Finance and Management Sciences*, 9(2019), 224-236.

[10] A. Charnes, W. W. Cooper, E. Rhods, Measuring the efficiency of decision-making units, *European Journal of Operational Research*, 2(1978) 429-444.

[11] S. Chupradit, D. Yannan, H. W. Kamran, S. S. Soudagar, A. M. Shoukry, and J. A. Khader, Measuring technical efficiency associated with environmental investment: does market competition and risk matters in banking sector, *Environmental Science and Pollution Research*, 28(2021) 66575-66588.

[12] A. Cielen, L. Peeters, and K. Vanhoof, Bankruptcy prediction using a data envelopment analysis, *European Journal of Operational Research*, 154(2004), 526-532.

[13] S. Condello, A. Del Pozzo, and S. Loprevite, Potential and Limitations of DEA as a Bankruptcy Prediction Tool in the Light of a Study on Italian Listed Companies, *Applied Mathematical Sciences*, 11(2017), 2185 – 2207.

[14] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, Introduction to the logistic regression model, *Applied logistic regression*, 2(2000) 1-30.

[15] S. Idrees, and A. Qayyum, The impact of financial distress risk on equity returns: A case study of non-financial firms of Pakistan Stock Exchange, *Journal of Economics Bibliography*, 5(2018), 49-59.

[16] A. H., Khan, and H. Dewan, Who should supervise banks for the banking sector stability?, *Applied Economics Letters*, 20(2013), 1531-1537.

[17] H. Li, and J. Sun, Predicting business failure using an RSF-based case-based reasoning ensemble forecasting method, *Journal of Forecasting*, 32(2013), 180-192.

[18] O. Masood, S. M. K. Ghauri, and B. Aktan, Predicting Islamic banks performance through CAMELS rating model, *Banks and bank systems*, 11(2016), 37-43.

[19] S. N. Muhmada, and H. Hashima, Using the camel framework in asessing bank performance in Malaysia, *International Journal of Economics, Management and Accounting*, 23(2015), 109-127.

[20] M. Nii, T. Okabe, H. Ito, S. Morita, Y. Yasuda, and J. Yoshimura, Bankruptcy is an inevitable fate of repeated investments with leverage, *Scientific Reports*, 9(2019), 1-5.

[21] O. B. Olesen, N. C. Petersen, and V. V. Podinovski, Efficiency analysis with ratio measures, *European journal of operational research*, 245(2015), 446-462.

[22] O. B. Olesen, N. C. Petersen, and V. V. Podinovski, Efficiency measures and computational approaches for data envelopment analysis models with ratio inputs and outputs, *European journal of operational research*, 261(2017), 640-655.

[23] J. T. Pastor, J. L. Ruiz, and I. Sirvent, An enhanced DEA Russell graph efficiency measure, *European Journal of Operational Research*, 115(1999), 596-607.

[24] V.V. Podinovski, Selective convexity in DEA models, *European Journal of Operational Research*,161(2005), 552–563.

[25] A. Roman, and A. C. Şargu, Analysing the financial soundness of the commercial banks in Romania: an approach based on the camels framework, *Procedia economics and finance*, 6(2013), 703-712.

[26] O. V. Savchina, E. A. Sidorina, O. V. Savchina, and P. S. Shcherbachenko, Financial Sustainability Assessment of the Largest Systemically Important Credit Institutions in the Context of the Global Instability, *International Journal of Financial Research*, 12(2021), 10-26.

[27] A. R. Trivedi, and Y. A. Elahi, A comparative analysis of performance of public and private sector banks in India through camel rating system, *International journal of applied financial management perspectives*, 4(2016), 1724-1736.

[28] R. L. Wilson, Organizational resilience as a human capital strategy for companies in bankruptcy. *Work*, 54(2016), 309-323.

[29] H. Yin, J. Yang, and X. Lu, Bank globalization and efficiency: Host-and home-country effects. *Research in International Business and Finance*, 54(2020) 101305.

Morteza Shafiee
Department of Industrial Management
Associat Professor of Industrial Management
Shiraz Branch, Islamic Azad University
Shiraz, Iran
E-mail: ma.shafiee277@gmail.com

Hilda Saleh
Department of Mathematics
Assistant Professor of Mathematics
Central Tehran Branch, Islamic Azad University
Tehran, Iran
E-mail: hilda˙saleh@yahoo.com

Gholam Abbass Paydar
Department of Accounting
Assistant Professor of Accounting
Shiraz Branch, Islamic Azad University
Shiraz, Iran
E-mail: abbas.paidar@gmail.com