

Iranian Private Commercial Banks' Financial Performance Analysis: A DEA Approach

Bitá Mashayekhi^{1*}, Samira Ghasemi Dashtaki², Hosseyn Ahmadi³, Zabihollah Rezaee⁴

Abstract

The purpose of this study is to analyze the performance efficiency of Iranian private commercial banks. A sample comprising 15 private banks, which disclosed their financial statements in accordance with standardized protocols spanning the period from 2020 to 2023, has been meticulously chosen for examination. The study employs Data Envelopment Analysis (DEA) models, specifically the Constant Returns to Scale (CCR) with input orientation and the Variable Returns to Scale (BCC) with input orientation, to scrutinize performance efficiency relative to the banking sector's average efficiency ratio. The findings indicate that the performance of Decision Making Units (DMU) is superior in BCC models when contrasted with CCR models. Nevertheless, given the regulatory framework governed by the Central Bank of Iran, CCR-I was employed for performance estimation. The CCR-I analysis spanning the years 2020 to 2023 reveals that only two banks consistently demonstrated full efficiency performance, attaining a 100% efficiency score across all years. The observed fluctuations in banks' efficiency performance are attributed to disparities between the growth or reduction in inputs and the corresponding augmentation or diminution in outputs.

Keywords: Data Envelopment Analysis (DEA), Constant Returns to Scale (CCR), Variable Returns to Scale (BCC), commercial Banks, Iran, Islamic Economy.

1. Introduction

The development of the financial system is greatly aided by the banking sector, which serves as the primary source of financial intermediation and a payment system conduit [1]. These days, a nation's financial market plays a major part in its development. It makes it easier for savings and investments to flow directly into the financial system at a reasonable cost, which facilitates capital accumulation and the production of services and goods [2]. The banking industry is just one of the crucial sectors of the economy that support consumers, increase investment, and help businesses grow financially [3]. An essential part of the financial system is played by commercial banks. In order to enable the banking industry to act more effectively, commercial banks assist in lowering the cost of acquiring information regarding savings and borrowing opportunities and going forward, more effectively [4]. Commercial banks can accommodate the needs of individual banking customers, but they primarily service corporations or businesses. Commercial banks have the same lending capabilities as retail banks, in addition to providing deposit accounts, foreign banking, and payment processing. In general, commercial banks offer a variety of services. For

¹ Professor of Accounting, Department of Accounting and Auditing, Faculty of Management, University of Tehran, Tehran, Iran. Email: mashayekhi@ut.ac.ir (* Corresponding Author)

² MSc in Auditing, Department of Accounting and Auditing, Faculty of Management, University of Tehran, Tehran, Iran. Email: Ghs.samira@gmail.com

³ Bachelor of Chemical Engineering, Arak University, Arak, Iran. Email:ahmdi.hoseiyn@gmail.com

⁴ Professor of Accounting, Fogelman College of Business and Economics, University of Memphis, United States; Email: Zrezaee@memphis.edu

instance, a commercial bank may lend money for business equipment or real estate, charging interest and other costs to borrowers just for the ability to borrow the money [5].

Precise financial projections, emphasizing both internal financial variables and the economic climate, are now essential components of the decision-making process. Future expectations are crucial to the nature of predicting. Forecasts play a crucial role in the financial planning process of the banking industry, enabling the effective use of available resources to accomplish organizational goals. With so many different ways to obtain and utilize money and a growing emphasis on high-profit margins and expansion rather than safety, financial decisions in the banking sector have gotten more and more complicated. A bank's financial process forecasting is a complex function that examines possible portfolio choices over a certain planning horizon. Typically, this function would need to forecast the external economic climate that each bank will face in the future as well as internal financial factors. The choices made in the past to invest deposits and monies from other sources in alternative investment options, such as bonds and loans, have resulted in a bank's current financial situation. The choices a bank makes now about raising and investing money will have an impact on the bank's financial situation later on [6].

Any nation's ability to generate jobs and expand its economy is largely dependent on how productive its banks are; Iran is no different in this sense. The Iranian Central Bank has recently taken the task of evaluating and enhancing the effectiveness of the country's banking sector very seriously (CBI). An organization's director can use performance evaluation as a benchmarking tool to assess operational activity, assess goal attainment, determine the company's position within the industry, and provide recommendations for improving underperforming units [7]. The effectiveness and standard of services provided by banks not only play a crucial role in a country's economic development but also have an influence on various aspects of people's everyday lives. In order for banks to remain competitive, they must significantly enhance their performance given the rise in both domestic and international competition as well as the range of services and goods they offer [8]. Commercial banks must therefore evaluate their past, current, and future performance in relation to the operational capacity of other banks.

Financial indices, which [9] claims are inadequate performance indicators, were mostly used in the past to analyze bank performance. This situation altered as a result of developments in operational research methods, including Data Envelopment Analysis (DEA), which is now one of the most widely used methods for analyzing an organization's efficiency [10]. DEA's advantages include the following: It can operate with inputs and outputs at many measurement scales [11]; it is efficient in handling complicated industrial processes [12]; It may run the optimization process for every decision-making unit (DMU) in the sample, allowing for the individual analysis of each DMU and comparison with other DMUs [13] [14]. It can also identify inefficient DMUs and provide a benchmarking signal for them. A thorough and recognized tool for assessing performance in the banking sector, DEA has been utilized in numerous applications and is well recognized [15]. mostly due to the model's utilization of various inputs and outputs and suitability for investigating nonlinear interactions in investigations [16, 17].

The purpose of this study is to present a thorough analysis of the effectiveness of the Iranian banking sector. This study is the first of its kind in Iran to offer a framework for forecasting commercial bank performance. The study's authors anticipate that the DEA model and machine

learning approach for prediction performance would be helpful references for research on the banking sector.

The remainder of this paper is organized as follows: Section 2 provides brief literature review of the related studies. Section 3 presents the research methodology. Section 4 discusses the results, and Section 5 concludes.

2. Literature review

Since policymakers rely heavily on the evaluation of performance in many economic sectors, it is a topic of interest to a wide range of stakeholders, including academic researchers, government officials, and regulatory agencies [18]. Because the banking industry is seen as an essential component of the modern economy, its effectiveness is crucial. Banks need to be thoroughly studied and assessed in order to guarantee a sound financial system and a productive economy [19].

The study of commercial banks has made considerable use of DEA for efficiency measurement [20]. Additionally, a number of scholars have suggested that the management component of CAMELS(Capital adequacy, Asset quality, Management capability, Earnings, Liquidity, and Sensitivity to market risk) employs DEA efficiency measurements as the basis for evaluation [21]. The outcomes show where the operational performance stands and are useful in organizing upcoming initiatives to raise performance. Because it is crucial for policymaking, the assessment of performance in different economic sectors is a topic of interest for a wide range of people, including academic researchers, government officials, and regulatory agencies.

The evaluation of efficiency in the banking sector has been evaluated by empirical research through the traditional DEA model and various developments. In their study, Shi et al. (2023) suggested an enhanced slacks-based DEA model (SBM) that incorporated undesirable outputs and utilized a by-production framework. The research was conducted on 36 commercial banks in China, covering the period from 2016 to 2021. The outputs are divided into two categories in the first stage: interest revenue and non-interest income. These two types of income are shared and regarded as final outputs. Non-performing loans are considered undesirable outputs in the second stage. The research's empirical findings demonstrate that modifications in stage 2 were primarily responsible for shifts in the banks' overall efficiency. Additionally, this method offers a wealth of data to support decision-making. [22]

Wang et al. (2022) evaluated the performance of the banking sector in Vietnam using the DEA Malmquist model and the grey prediction GM (1, 1) to calculate the relative efficiency index, which represents the performance scores of all Vietnamese commercial banks and can be broken down into changes in technical and technological efficiency. The management implications of this model's findings provide a framework for sustainable development by providing an overall assessment of the performance of the leading commercial bank in Vietnam. [4]

Appiahene et al. (2020) evaluated bank performance and efficiency utilizing 444 Ghanaian bank branches, or Decision-Making Units (DMUs), by combining a combined DEA with three machine learning techniques. The outcomes were contrasted with the DEA's comparable efficiency ratings. Lastly, a comparison was made between the three machine learning algorithm models' prediction accuracies. The decision tree (DT) with its C5.0 algorithm appeared to be the most effective prediction model, according to the findings. The random forest algorithm came next to the DT, and then the neural network came last. According to the study's conclusion, banks in Ghana can utilize the findings to estimate their individual efficiencies [23].

Minh et al. (2013) calculated and contrasted the efficiency performance of thirty-two Vietnamese commercial banks from 2001 to 2005, and they also determined potential determinants of this efficiency performance. Assuming variable returns to scale (VRS), efficiency was quantified using a DEA model and super-efficiency through a slacks-based model (SBM). They discovered that, in contrast to small banks, big banks do not always guarantee high super-efficiency scores and that there are relatively few efficient banks [24].

In order to analyze operational quality and operational profitability metrics, Marie et al. (2013) used a parallel DEA model on the banking industry in Dubai. Within both models, they compared the Islamic and commercial banks. They discovered that the operational-profitability model does not statistically distinguish between Islamic and commercial banks. [25].

Kao et al. (2004), used their financial projections, which are based on ambiguous financial data that are expressed as ranges rather than as single numbers, to make advanced predictions about the performances of 24 commercial banks in Taiwan. For interval data, a DEA model was developed to forecast the efficiency. The efficiency scores that were computed using the data in the financial statements that were later made public were all discovered to fall within the appropriate projected ranges of the efficiency scores that were computed using the financial projections. The findings also demonstrated that this study may be used to forecast in advance even the poor performance of the two banks that the Financial Restructuring Fund of Taiwan took over [26].

There are some empirical research studies analyzing the efficiency level in the Iranian banking industry specifically. Aghakarimi et al. used the CAMELS indicators (Capital adequacy, Asset quality, Management, Earning, Liquidity, and Sensitivity to market risk) to assess the financial soundness of 11 Iranian commercial banks. The Decision-Making Units' (DMUs') efficiency score was determined using Data Envelopment Analysis (DEA). PCA, or principal component analysis, was utilized to verify the DEA findings. Iranian private banks do the best when it comes to management and capital adequacy indicators, and the worst when it comes to asset quality, according to the findings of statistical tests and sensitivity analysis. Additionally, the authors offer suitable tactics for enhancing the banking system's performance by utilizing the Strengths-Weaknesses-Opportunities-Threats (SWOT) matrix [27].

Omrani et al (2023) created a multi-objective DEA model in order to determine three different types of efficiencies—namely profitability, operational, and transactional—in the context of a real case involving 45 Agriculture bank branches located in West Azerbaijan, Iran, where ambiguous data is For an actual scenario of 45 Agriculture bank branches located in West Azerbaijan, Iran, Omrani et al. (2023) built a multi-objective DEA model to compute three sorts of efficiencies:

profitability, operational, and transactional when there are ambiguous data. Their primary objective was to compute four distinct scenarios' worth of bank branch efficiencies. The outcomes demonstrated that the suggested model is capable of generating precise results in many contexts. In order to identify benchmark branches as well as inefficient branches, they also carried out a comparative analysis of each efficiency factor [28].

Mahmoudabadi et al. (2019) evaluated 37 branches of one of the biggest commercial banks in Iran for operational efficiency, service effectiveness, and social effectiveness all at the same time using a network Slacks-Based Measure (SBM) DEA model. The findings demonstrated that the suggested model outperforms conventional black box models in terms of discriminating power. Furthermore, the efficiency of the system is actually the weighted average of the efficiency of its constituent parts [8]. An empirical study by Zagherd et al. (2017) examines the Iranian banking industry's performance evaluation from 2007 to 2015 using the CAMELS framework. According to the research model's findings, the return on assets of banks in the Iranian banking sector is directly and significantly impacted by capital adequacy, liquidity quality, management quality, liquidity quality, asset quality, and sensitivity to market risk indicators; however, the impact of earnings quality on this return is rejected [29].

A fuzzy multi-criteria decision model is proposed by Amile et al. (2012) to assess the performance of 10 branches of three banks. Using standard questionnaires in Iran. After consulting experts' opinions and doing library research, the influencing factors at two financial and non-financial levels were determined and looked into. Expert opinions indicate that, as a result of the findings, profitability at the financial level and service quality at the non-financial level have become increasingly significant. Private banks ranked first overall in the ranking of management performance, followed by partially private and private banks, which ranked second and third, respectively [30].

Data envelopment analysis was utilized by Mansoury et al. (2011) to assess the effectiveness of the Industrial and Mine Bank in Iran. This approach has allowed each branch's rank to be determined based on its various efficiency levels. Lastly, a ranking system has been devised and all of the branches have been ranked based on the average efficiency, kind of returning to scale, frequency of each branch as a pattern, efficiency, and inefficiency. This approach divides branches into six categories: excellent, superior, and degrees ranging from 1 to 4 [31].

In all of these papers, only efficient decision-making units are identified. In fact, data envelopment analysis is only used to identify efficient units, and how inefficient units can be efficient. These are important issues that can be investigated in data envelopment analysis. The important aim of this paper is to use the DEA method in rankings and to formulate a bank grading system based on efficiency. In all of these papers, only historical data of banks were used and they focused on a specific bank in Iran. This paper focused on both the historical and future performance of 15 Iranian private commercial banks.

3. Methodology

3.1 DEA Model

One nonparametric technique for evaluating the production and efficiency of economic units is the DEA Model. Under Cooper's supervision, Rhodes' PhD thesis served as the impetus for this approach[32]. Then, in 1984, Banker et al. produced updated versions of the principles and versions of data envelopment analysis[33]. Data envelopment analysis is actually a variation of linear programming for observable data and is thought to be a new approach for empirically estimating the efficiency frontier. A kind of mathematical programming called DEA is used to assess how well decision-making units operate. As long as the organization follows a methodical procedure, data envelopment analysis can be handled by a manager, boss, or supervisor of an organizational unit or an individual organization. In other words, a variety of production factors are employed to produce a variety of goods. Data envelopment analysis is utilized for efficiency frontier estimation because of its experimental character and ability to shed problematic assumptions. Two approaches are used to consider DEA theoretical versions: Banker, Charnes, and Copper (BCC) and Charnes, Cooper, and Rhodes (CCR)

CCR version [32]:

This model was created in 1978 with the assumption of constant returns to scale (CRS) in order to assess the technical efficacy of a particular observed decision-making unit (DMU). Stated differently, if one moves from one point on the frontier curve to another, the change in inputs will always have an impact on the outputs. Regarded as a worldwide exemplar of pure technological efficiency is the CCR model. The formulation of linear programming included many inputs and multiple outputs. Nonetheless, there are two types of the CCR model: input-oriented (CCR-I) and output-oriented (CCR-O).

The basic formula of the input-oriented CCR model:

$$\text{Maximize } \frac{\sum_{r=1}^s u_r y_{ro}}{\sum_{i=1}^m v_i x_{io}} = \theta_o x \text{ subject to } \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, j = 1, 2, \dots, n, x$$

$$u_r \geq 0, v_i \geq 0, \forall r, i.$$

Input-oriented CCR model :

$$\text{Maximize } \sum_{i=1}^m u_r y_{rj}$$

$$\text{subject to } \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, j = 1, 2, \dots, n,$$

$$\sum_{r=1}^s v_i x_{ij} = 1 \quad u_r \geq 0, v_i \geq 0, \forall r, i.$$

Output-oriented CCR model:

$$\text{Minimize } \sum_{i=1}^m v_i x_{io}$$

$$\text{subject to } \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, j = 1, 2, \dots, n,$$

$$\sum_{r=1}^s u_r y_{ro} = 1 \quad u_r \geq 0, v_i \geq 0, \forall r, i.$$

BCC version [33]:

By extending the CCR paradigm, BCC models enable variable returns to scale [34]. They are designed to assess a decision-making unit's (DMU) technical efficacy under the assumption of variable returns to scale (VRS). This approach takes a localized pure technological efficiency into account. The input-oriented (BCC–I) and output-oriented (BCC–O) versions of the BCC model are separated [35].

Input-oriented BCC model:

$$\begin{aligned} & \text{maximize } \sum_{r=1}^s u_r y_{ro} - u_o, x \text{ subject to } \sum_{i=1}^m v_i x_{io} = 1, x & \sum_{r=1}^s u_r y_{rj} - \\ & \sum_{i=1}^m v_i x_{ij} - u_o \leq 0, j = 1, \dots, n, x & u_r, v_i \geq 0, r = 1, \dots, s; i = 1, \dots, m. \end{aligned}$$

Output-oriented BCC model:

$$\begin{aligned} & \text{Minimize } \sum_{i=1}^m v_i x_{ij} + v_o, x \text{ subject to } \sum_{i=1}^m u_r y_{ro} = 1, x & \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} - v_o \\ & \leq 0, j = 1, \dots, n, x & u_r, v_i \geq 0, r = 1, \dots, s; i = 1, \dots, m. \end{aligned}$$

3.2 The difference between input-oriented and output-oriented applications:

The input-oriented model measures the ineffectiveness of the evaluated DMU from the perspective of input. It focuses on the degree to which the technical effective inputs should be reduced without reducing output. The output-oriented model measures the ineffectiveness of the evaluated DMU from the perspective of output. It focuses on the degree to which the technical effective outputs should be reduced without increasing input to the extent of the increase.

3.3 Anderson Peterson model:

Anderson-Peterson model, or the super-efficiency method, which makes it possible to determine the most efficient unit, was proposed by Anderson and Peterson in 1993[36] to rank efficient units. In this method, the score of efficient units can be more than 1, and in this way, efficient units can be rated like inefficient units. The larger the coefficient of a unit, the more efficient the unit is.

Input-oriented formula for calculating super efficiency:

$$\text{Max } e_p = \Sigma_i^n = 1^{u_i y_{ip}}$$

$$\Sigma_i^m = 1^{v_i x_{ip}} = 1$$

$$\Sigma_i^n = 1^{u_i y_{ij} - \Sigma_i^m} - \Sigma_i^m = 1^{v_i x_{ip} \leq 0}$$

$$j = 1, 2, \dots, k, j \neq p$$

$$u_i \geq 0, v_i \geq 0$$

3.4 Decision-Making Units (DMUs) Selection

Appropriately choosing the decision-making units (DMUs) is another essential step in the study procedure. These topics, which are representative of the whole Iranian banking sector, are those on which the data will be collected. As a result, the banks whose yearly financial statements were made public were chosen by the writers. It is important to note that this study evaluated the performance of Iran's banking industry during the years 2020 to 2023. Fifteen commercial banks in all have been chosen. The largest commercial banks listed on the Iranian stock exchange provided their yearly financial statements, which were used to create the statistics.

3.5 Inputs and Outputs Selection

Finding the input and output elements that will be taken into account for the analysis comes after the significant DMUs have been chosen. These elements must have a significant effect on the banks' performance. The following factors, which are frequently taken into account by earlier studies [36], have been chosen by the authors to be taken into account:

- Operating costs (input, million USD): These are the costs associated with the regular day-to-day operations of a business, like employee salaries and office supplies.
- Deposits (input, million USD): A customer deposit indicates that money will be credited to the account. It could be money that a business gets before making money from a client.
- Assets (as input, million USD): The aggregate assets and values of all the goods that small firms own are referred to as the total assets.
- Liabilities (input, million USD): The total amount of debts and commitments that a person or business owes to other parties is known as its liabilities. any of the company's

possessions are listed as assets, and any amounts owed for upcoming commitments are included as liabilities.

- Loans (output, million USD): To manage finances for scheduled or unforeseen occurrences, one or more people or businesses may borrow money from banks or other financial organizations.
- Revenue (output, million USD): the entire amount of money received by the company from the sale of goods and services associated with its main business activities.

4. Results and Discussion

The source of research data for this study is from the financial statements of Iranian private commercial banks. The selected banks are namely in Table 1.

Table 1. Banks used in the study

Banks	DMU
Middle east Bank	DMU1
Pasargad Bank	DMU2
Bank Mellat	DMU3
Karafarin Bank	DMU4
Export Development Bank of Iran	DMU5
Tejarat Bank	DMU6
EN Bank	DMU7
Sina Bank	DMU8
Tourism Bank	DMU9
Parsian bank	DMU10
Shahr Bank	DMU11
Sarmaye Bank	DMU12
Refah Bank	DMU13
Saman Bank	DMU14
Day Bank	DMU15

One output (i.e., revenues) measure is used in this study. According to the descriptive statistics of our data which is presented in Table 2, the distribution is highly skewed to the right, indicating that a few banks have a considerably larger revenue compared to most banks. This is reflected in the large gap between the mean and median values.

Table 2. Descriptive Statistics

Variables	n	Mean	Standard deviation	Median
<i>Output</i>				
Revenues	15	232,124,438	234,616,856	152,084,822
<i>Input</i>				
Operating costs	15	48,772,454	62,114,317	23,017,282
Deposits	15	1,681,482,899	1,599,188,692	1,239,021,142
Assets	15	2,310,179,297	2,475,522,424	1,330,560,514

Liabilities	15	2,466,083,193	2,447,708,703	1,529,028,097
Loans	15	1,393,287,962	1,732,114,051	738,619,969

4.1. Comparative Analysis of CCR and BCC Models.

The DEA models' assumptions have been applied before operating the CCR and BCC models. First, the input/output variable selected is greater than or equal to zero. Second, there are significant positive correlation between inputs and outputs greater than 50%. Third, homogeneity DMUs refer to identical used input/output variables for DMUs. Four, the sample size selected (sample = 15) is greater than or equal to the multiply of input (5 variables) with output (1 variable). Five, also the sample size selected (sample = 15) is greater than or equal to the multiplied by (3*input*output). Finally, the full efficiency rate (100%) for DMUs is not greater than or equal to the third sample size ((1/3) *15 = 5). The CCR and BCC models are applied after the above conditions.

The comparison between CCR and BCC models is explained in Table 3. We can observe that the performance of DMU is better in BCC models compared to CCR models for several reasons: (i) we find banks could improve their performance from a minimum of 0.49 in CCR-I to a minimum of 0.74 in BCC-I. (ii) The number of efficient DMUs in BCC models is more than in CCR models.

Table 3: Comparison between CCR and BCC models.

Models	No. of DMU	Efficient	Non-efficient	Average score	Max	Min
BCC-I	15	9	6	0.9363	1	0.7495
CCR-I	15	3	12	0.8631	1	0.4941

4.2. BCC-I

The average efficiency and slacks for input-oriented BCC-I models from 2020 to 2023 are shown in Table 4. The banks should decrease the input variables to approximate the performance efficiency to 100%. For instance, DMU 5 should reduce, on average, Operating cost to 38,252,077 IRR, Deposits to 0.00 IRR, assets to 360,385,832 IRR, Liabilities to 509,359,204 IRR, and Loans to 0.00 IRR, if we assume CRR. Indeed, the input-oriented DEA model is considered a good efficiency performance if the efficiency rate is close to one.

Table 4: The average efficiency rate and slacks for BCC-I during 2020-2023

DMU	Efficiency	Rank	Operating cost (\$)	Deposit (\$)	Asset (\$)	Liability (\$)	Loan (\$)
M U1	1	2	0.00	0.00	0.00	0.00	0.00
M U2	1	7	0.00	0.00	0.00	0.00	0.00
M U3	1	14	0.00	0.00	0.00	0.00	0.00
M U4	1	4	0.00	0.00	0.00	0.00	0.00
M U5	0.8580	15	38,252,057	0.00	360,385,832	509,359,204	0.00
M U6	1	13	0.00	0.00	0.00	0.00	0.00
M U7	0.9433	11	29,595,218	159,583,168	0.00	3,944,302,728	73,060,813
M U8	1	6	0.00	0.00	0.00	0.00	0.00
M U9	1	5	0.00	0.00	0.00	0.00	0.00

M	U10	0.7515	8	696,493	0.00	144,297,148	221,985,299	0.00
M	U11	0.9239	10	8,779,073	354,120,513	0.00	352,987,437	0.00
M	U12	1	1	0.00	0.00	0.00	0.00	0.00
M	U13	0.7495	12	35,315,904	0.00	35,063,495	56,422,514	0.00
M	U14	0.8190	9	2,235,427	6,473,167	0.00	102,032,114	0.00
M	U15	1	3	0.00	0.00	0.00	0.00	0.00

4.3 CRR-I

The average efficiency and slacks for input-oriented CRR-I models from 2020 to 2023 are shown in Table 5. The banks should decrease the input variables to approximate the performance efficiency to 100%. For instance, DMU 5 should reduce, on average, Operating cost to 71,348,816 IRR, Deposits to 0.00 IRR, assets to 231,056,598 IRR, Liabilities to 571,406,049 IRR and Loans to 0.00 IRR, if we assume CCR.

Table 5: The average efficiency rate and slacks for CCR-I during 2020-2023

DMU	Efficiency	Rank	Operating cost (\$)	Deposits (\$)	Assets (\$)	Liabilities (\$)	Loans (\$)
DMU1	0.9719	3	0.00	50,476,110	6,740,101	0.00	15,788,059
DMU2	1	1	0.00	0	0.00	0.00	0.00
DMU3	0.8342	8	122,765,341	0.00	624,261,808	698,351,069	1,111,395,782
DMU4	1	1	0.00	0.00	0.00	0.00	0.00
DMU5	0.7545	10	71,348,816	0.00	231,056,598	571,406,049	0.00
DMU6	0.8408	7	53,021,659	0.00	0.00	488,247,907	0.00
DMU7	0.9172	5	17,170,230	0.00	0.00	3,859,259,933	77,910,349
DMU8	0.9761	2	6,547,188	90,324,758	0.00	0.00	23,036,288
DMU9	1	1	0.00	0.00	0.00	0.00	0.00
DMU10	0.7451	11	2,612,409	0.00	145,890,189	246,095,384	0.00
DMU11	0.9029	6	584,553	241,673,658	0.00	359,180,736	0.00
DMU12	0.4941	13	1,598,642	37,003,042	0.00	198,458,118	0.00
DMU13	0.7400	12	36,792,080	0.00	28,824,352	65,354,067	0.00
DMU14	0.8175	9	1,736,536	0.00	0.00	102,725,881	0.00
DMU15	0.9518	4	3,089,124	0.00	52,863,348	116,244,779	0.00

Since the banks in Iran are operating under the same conditions as the bank's rates are notified by the Central Bank of Iran, we decided to rank the banks under the CCR model.

4.4 Super Efficiency

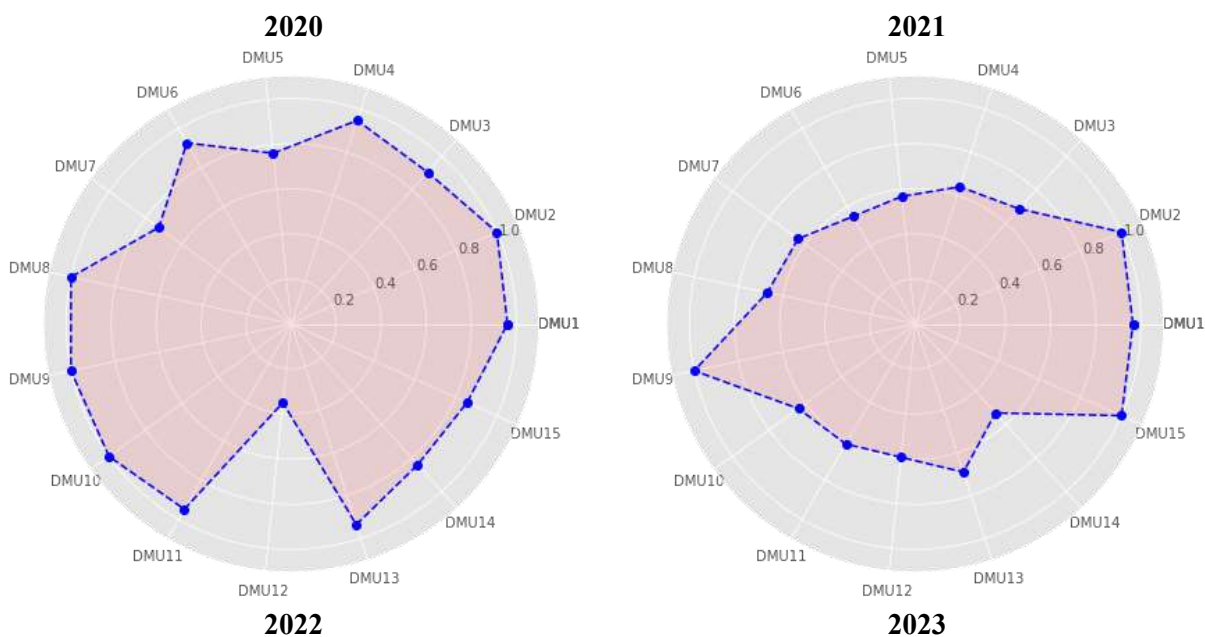
One of the issues associated with the DEA model is that we may receive more than one efficient unit and to rank the efficient units, Anderson Anderson-Peterson model can be used. The average efficiency and super efficiency for input-oriented in CCR-I models from 2020 to 2023 are shown in Table 6. Based on the average performance of these 15 banks, DMU9 (Tourism Bank) ranked in first place and Sarmaye Bank ranked last in terms of efficiency.

Table 6: The average efficiency and super efficiency rate for CCR-I during 2020-2023

DMU	Efficiency	Rank	DMU	Efficiency	Rank
DMU1	0.9719	3	DMU1	0.9719	5
DMU2	1	1	DMU2	1.2148	2
DMU3	0.8342	8	DMU3	0.8342	10
DMU4	1	1	DMU4	1.0371	3
DMU5	0.7545	10	DMU5	0.7545	12
DMU6	0.8408	7	DMU6	0.8408	9
DMU7	0.9172	5	DMU7	0.9172	7
DMU8	0.9761	2	DMU8	0.9761	4
DMU9	1	1	DMU9	1.5022	1
DMU10	0.7451	11	DMU10	0.7451	13
DMU11	0.9029	6	DMU11	0.9029	8
DMU12	0.4941	13	DMU12	0.4941	15
DMU13	0.7400	12	DMU13	0.7400	14
DMU14	0.8175	9	DMU14	0.8175	11
DMU15	0.9518	4	DMU15	0.9518	6

4.5 The analysis of CCR-I from 2020 to 2023

Figure 1 shows the dynamic CCR-I efficiency performance of each bank over the years from 2020 to 2023. The Pasargad Bank and the Tourism Bank have a full efficiency performance of 100% in all years.



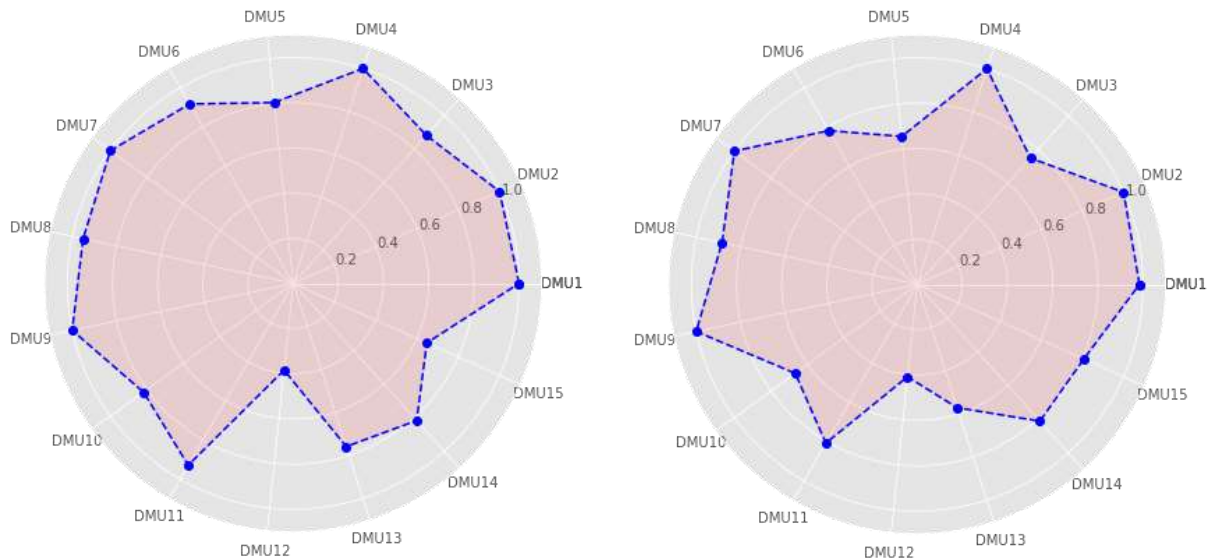


Figure1: The CCR-I efficiency performance of each bank over the years from 2020 to 2023

In the first year, 4 banks Sina Bank, Tourism Bank, Pasargad Bank, and Parsian Bank were ranked 1st to 4th respectively with a full efficiency performance of 100%. Conversely, Sarmaye Bank occupied the final position, displaying a comparatively lower efficiency performance with a score of 0.35. In the second fiscal year of 2021, a discernible decline in efficiency was observed across all banks, with the notable exception of Middle East Bank, Day Bank, and Sarmaye Bank. The primary factor contributing to this decrease emanated from a substantial expansion in inputs relative to the marginal increase in outputs. For the aforementioned trio of banks, which bucked the trend of reduced efficiency, the augmentation in inputs nearly mirrored the escalation in outputs, resulting in a nominal alteration in their efficiency percentages.

It Is imperative to underscore that, excluding Sarmaye Bank and Refah Bank, along with those banks that consistently maintained a 100% efficiency rating throughout all evaluated years, the remaining financial institutions exhibited their lowest efficiency levels in the second year in comparison to other periods. Noteworthy among these is Karafarin Bank, which exhibited nearly optimal efficiency in 2020, and achieved a 100% efficiency performance in both 2022 and 2023, but experienced a decline in efficiency in 2021 attributed to a substantial surge in operational costs and loan portfolios.

In the year 2022, a notable enhancement in efficiency performance was observed across all banks, with the exception of Sarmaye Bank and Day Bank, which registered a decline in output despite an increase in input quantities. Middle East Bank, Karafarin Bank, and EN Bank demonstrated optimal efficiency, achieving a full performance rating of 100% during this period. Additionally, Tejarat Bank, Sina Bank, and Shahr Bank were positioned closely to be ranked as efficient banks, further underscoring their commendable efficiency metrics in the same year.

In the year 2023, a discernible reduction in efficiency performance was observed among all banks, excluding those that consistently maintained full efficiency, namely Sarmayeh Bank and Day Bank. The proportionate relationship between escalating inputs and output played a pivotal role in sustaining the efficiency percentages of these banks. Notably, Middle East Bank was excluded

from the cohort of effective banks due to an insufficient increase in revenue (output) relative to the magnitude of input expansion during this period.

Table 7 shows the ranks of each DMU from 2020 to 2023 based on the Super Efficiency.

Table 7: The rank based on super efficiency rate for CCR-I during 2020–2023

DMU	2020	2021	2022	2023
DMU1	5	4	3	5
DMU2	3	3	4	2
DMU3	10	6	9	11
DMU4	7	9	2	3
DMU5	13	13	12	13
DMU6	9	14	8	10
DMU7	14	8	5	4
DMU8	1	7	6	6
DMU9	2	2	1	1
DMU10	4	10	10	12
DMU11	6	11	7	8
DMU12	15	12	15	15
DMU13	8	5	13	14
DMU14	12	15	11	7
DMU15	11	1	14	9

5. Conclusion

In this research endeavor, we have successfully introduced a method for estimating the performance efficiency of Iranian private commercial banks. The study focuses on banks that disclose their financial statements adhering to standards between the years 2020 and 2023. Employing Data Envelopment Analysis (DEA) models, specifically the Constant Returns to Scale (CCR) and the Variable Returns to Scale (BCC), the analysis centers on evaluating performance efficiency using the average efficiency ratio of the sector.

The findings indicate that the performance of Decision Making Units (DMUs) is superior in the BCC models compared to the CCR models for several reasons. The sector's performance shows potential improvement, ranging from a minimum efficiency score of 0.49 in CCR to a minimum of 0.74 in BCC. Furthermore, the number of efficient DMUs is greater in BCC models than in CCR models. Despite these insights, considering the uniform regulatory environment in Iran, where banks operate under the same conditions with rates dictated by the central bank, the decision was made to rank the banks using the CCR model.

The CCR-I analysis spanning the years 2020 to 2023 reveals that Pasargad Bank and Tourism Bank consistently achieve full efficiency performance at 100% throughout all years. In the initial year, Sina Bank, Tourism Bank, Pasargad Bank, and Parsian Bank secured the top four positions

with perfect efficiency scores of 100%. However, in the subsequent year, the efficiency of all banks, except Middle East Bank, Day Bank, and Sarmaye Bank, witnessed a notable decline. Conversely, in 2022, the efficiency performance of all banks, excluding Sarmaye Bank and Day Bank, exhibited an increase. Noteworthy, Middle East Bank, Karafarin Bank, and EN Bank achieved full efficiency performance at 100% during this period.

In 2023, the efficiency performance of all banks, excluding those already operating at full efficiency (Sarmayeh Bank and Day Bank), experienced a decrease compared to the preceding year. This fluctuation in efficiency is primarily attributed to the misalignment between the growth/decrease in inputs and the corresponding increase/decrease in outputs within the banking sector.

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