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Deep Analysis of Financial Indicators Affecting Bank Efficiency Using the Monte Carlo Simulation Technique

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Abstract

In today's competitive environment, evaluating bank branch performance is crucial to managerial decision-making. Inefficient branches continuously strive to improve, while efficient ones seek to maintain their superior positions. Discriminant Analysis is a common classification method in banking, used to predict the status of new branches based on data from existing ones. However, predictions from this method often involve uncertainty. This study introduces a confidence-level metric to more accurately assess the status of new branches. Using a Monte Carlo simulation-based sensitivity analysis, the impact of various financial indicators on this confidence level is assessed, identifying key indicators that influence the classification of branches as efficient or inefficient. The results reveal that long-term deposits are of significant importance. In contrast, variables such as the number of personnel, overdue receivables, and Qarz al-Hasna deposits have negligible effects on efficiency classification. These findings provide valuable insights for bank managers in establishing and managing new branches and enable targeted planning to reform and guide inefficient units toward greater efficiency.

Keywords: Monte Carlo simulation, Discriminant analysis, Confidence level, Sensitivity analysis, Bank branch efficiency.

1 | Introduction

The banking system plays an important role in economic stability by facilitating the implementation of monetary policies. For this reason, the profitability and income of banks have always been a concern for experts and the general public alike, as the optimal functioning of banks significantly impacts the country's economic growth and development. In recent years, threats and pressures arising from globalization and the growth of non-bank financial and credit institutions have forced banks to improve their performance to

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survive and compete in the market. Globalization has led to the establishment of research centers and to comparative research on their situation relative to other banks. Performance measurement is one of the most effective ways for banks to obtain information for decision-making purposes. Many studies have been conducted to measure bank efficiency and rank banks, and numerous models from mathematics, statistics, and operations research have been developed to evaluate banks accurately. However, many of these models are classical and cannot be evaluated thoroughly or optimally, paving the way for more complex models to enter this field. One basic approach to setting up productivity and efficiency improvement programs at the bank level is for each bank to examine its future situation, identify the factors affecting the inefficiency of its branches, and plan accordingly to guide inefficient units towards improvement [1].

Discriminant analysis can be applied to many decision-making problems. Since Fisher introduced his model, most subsequent models have been deterministic, whereas in practice, most variables are uncertain [2]. One important feature of banking is uncertainty in banking parameters and indicators, which can affect bank efficiency [3]. One relatively new approach to optimization under data uncertainty is simulation. Banking indicators are often subject to high levels of uncertainty due to measurement errors, limited information, and an incomplete understanding of the factors that affect them. Incomplete knowledge reduces confidence in the model output. This study aims to investigate which of the considered banking indicators, such as the number of personnel, types of deposits, types of facilities, overdue claims, and banking fees, have the greatest impact on the ranking of the bank branch in question. The results can help banking managers and experts to identify effective performance evaluation indicators and facilitate decision-making [4].

2 | Confidence Level

Discriminant analysis is a decision-making tool for predicting the classification of new observations and assigning them to previously defined categories. In this method, a group of observations whose membership in different groups is known is used to estimate the weights of a discriminant function. Mangasarian introduced a linear discriminant function based on linear programming for the case of two linearly separable sets of observations [5]. Later studies developed linear programming methods using criteria such as minimizing the sum of deviations or maximizing the minimum deviation from the discriminant function, in the case where the two sets are not linearly separable [6], [7].

In several studies, they combined discriminant analysis and goal programming to introduce various models, considering criteria such as minimizing maximum deviation, maximizing minimum deviation, minimizing the sum of internal deviations, minimizing the sum of deviations, minimizing misclassified observations, and maximizing the ratio of internal to external deviations [8–10]. In these models, where the membership of observations in groups is known, a hyperplane is defined that separates the two groups using a set of weights and a threshold. This hyperplane can then be used to predict the group to which new observations belong.

Siyoshi presented a new model of discriminant analysis that combines the collective model of data envelopment analysis and discriminant analysis, and uses objective programming [11], [12]. This model is known as the DEA/DA method. One problem with existing discriminant analysis methods is that they only classify new observations, without providing information about the degree of confidence of their membership in the specified group. To address this issue, this study defines a degree of confidence for the new observation, providing more detail to inform better decision-making. In the DEA/DA model, the classification of the new observation is determined by solving two models. In order to determine the degree of confidence, first determine the state in which the new observation $r_o=(r_{1o},\ldots,r_{mo})^T$ belongs to the first group. The hyperplane produced in the first stage $\sum_{i=1}^{m} \lambda_i^* r_{io} = a_o^*$ is, so the distance r_o is obtained from this hyperplane. Suppose $\lambda^* = (\lambda_1^*, \ldots, \lambda_m^*)$ Therefore, the distance $r_o=(r_{1o},\ldots,r_{mo})^T$. And this hyperplane is obtained from the following relationship:

$$\bar{\bar{d}}_1 = \frac{\|\lambda^*. r_o - a_o^*\|_p}{\|\lambda^*\|_p}. \quad (1)$$

For simplicity, *Eq. (1)* in the second norm is written as follows:

$$\bar{\bar{d}}_1 = \frac{|\lambda^*.r_o - a_o^*|}{\sqrt[2]{{\lambda_1^*}^2 + \cdots + {\lambda_m^*}^2}}. \tag{2}$$

The distance of all observations of the first group from the hyperplane $\sum_{i=1}^{m} \lambda_i^* r_{io} = a_o^*$ is calculated as follows:

$$\tilde{d}_{1j} = \frac{|\lambda^*.r_j - a_o^*|}{\sqrt[2]{{\lambda_1^*}^2 + \cdots + {\lambda_m^*}^2}}, \qquad j \in G_1. \tag{3}$$

And the distance of the farthest point from this hyperplane is equal to $\hat{d} = \max\{\tilde{d}_{1j} | j \in G_1\}$. Therefore, to normalize the value of $\bar{\bar{d}}_1$, it is divided by the maximum distance.

$$d_1 = \frac{\bar{\bar{d}}_1}{\hat{d}}.$$

Similarly, the observation distance from the hyperplane generated in the second step $\sum_{i=1}^{m} \mu_i^* r_{io} = c^*$, called d2, is calculated.

In this study, the distance from both hyperplanes is used to determine the degree of confidence. For this reason, the degree of confidence is defined as follows:

$$d = d_1 \times d_2. \tag{4}$$

A confidence level close to 1 indicates that the observation belongs to the group with high confidence, while a confidence level close to 0 indicates that the observation belongs to the group with low confidence. If the new observation is the most distant from the hyperplane, the values $d_1=1$ or $d_2=1$ are considered, meaning the new observation is also included in the set of observations used to calculate the confidence level. Similarly, if the new observation belongs to the second group, the confidence level is obtained in the same way.

3 | The Role of Financial Indicators Using Monte Carlo Simulation

In this section, the role of financial indicators affecting the degree of confidence is examined. For this purpose, suppose that the new observation is represented as $r_o = (r_{1o},\ldots,r_{mo})^T$, whose parameters are independent and have a probability density function *f*, so it is represented as follows [13]:

$$d = f(r_o), \qquad r_o = (r_{1o}, r_{2o}, \ldots, r_{mo}) \in K^m \equiv [0,1]^m. \tag{5}$$

The sensitivity index is obtained by decomposing the function f into additive sums in the following form [14]:

$$f(r_o) = f(r_{1o}, r_{2o}, \ldots, r_{mo}) = f_c + \sum_{i=1}^{m} \sum_{q_1 < \cdots < q_i} f_{q_1,\ldots,q_i}(r_{q_1}, r_{q_2}, \ldots, r_{q_i}), \tag{6}$$

where f_c is the median value of the function, and the integral of each sum over its variables is zero. Therefore:

$$\int_{U^n} f_{i_1,\ldots,i_t} f_{j_1,\ldots,j_q} \, dr_o = 0, \ \ (i_1, \cdots, i_t) \neq (j_1, \cdots, j_q). \tag{7}$$

These are calculated using the following multidimensional integrals:

$$f_c = \int_{K^m} f(r_o)\, dr_o, f_i(r_{io}) = -f_c + \int_0^1 \cdots \int_0^1 f(r_o) dr_{o\sim i}, \ f_{ij}(r_{io}, r_{jo}) = -f_c - f_i(r_{io}) - f_j(r_{jo}) + \int_0^1 \cdots \int_0^1 f(r_o) dr_{o\sim(ij)}, \tag{8}$$

denote the integral over all variables except r_{io}, r_{io}, and r_{jo}, respectively. To calculate the sensitivity where $dr_{o\sim(ij)}$ and $dr_{o\sim i}$ index, SI_i, the variance of the confidence level must be obtained as follows:

$$V_d = \int_{K^m} f^2(r_o)\, dr_o - f_c^2. \quad (9)$$

By squaring *Eq. (8)* and integrating over K^m and using the property given in *Eq. (7)*, we obtain:

$$V_d = \sum_i V_i + \sum_{i<h} V_{ih} + \sum_{i<h<k} V_k + \cdots + V_{1,2,\cdots,m}. \quad (10)$$

$$V_i = V[E(d|r_{io} = r_{io}^*)]. \quad (11)$$

This expression yields the sensitivity of d to the r_{io} factor. Accordingly, the sensitivity index is defined as follows:

$$SI_i = \frac{V_i}{V_d}. \quad (12)$$

Initially, this section classifies the 78 Mellat Bank branches with more than 20 employees using a collective model to assess efficiency. Next, the efficiency or inefficiency of a new branch is predicted. According to the method presented in this study, the degree of confidence in this new branch is calculated. Finally, the sensitivity of this new branch's efficiency to the bank's indicators is evaluated. When classifying these branches, the number of employees, interest paid, and overdue receivables are considered inputs, while facilities, long-term deposits, current deposits, Qarz-ol-Hasana deposits, short-term deposits, interest received, and fees received are considered output variables. Using this collective model, 45 of the 78 branches studied are considered efficient, while 33 are considered inefficient.

The values of the weighted estimates of the discriminant functions obtained in both stages are given in *Table 1*. To address the imbalance between the data and the differing importance of efficient and inefficient data, the second-stage DEA-DA assigns weights w to the groups. In this section, the correctly classified data are more important, so w is set to 1. Consider now the new observation A, whose information is given in *Table 2*. Using the results of the first stage of DEA-DA, it is found to be within the overlap, and the second stage concludes that it is inefficient. Using *Table 1*, the obtained confidence level is 0.0283, corresponding to the overlap of this observation. Given the low confidence level of this observation, it should be classified as inefficient with caution. Also, greater care should be taken when collecting or estimating its data.

Sensitivity analysis using the Monte Carlo method relies on repeated random sampling to calculate the results [12]. The Monte Carlo method uses random numbers to simulate the parameters. In other words, by taking into account the Coefficient of Variation (COV) for each parameter, a set of random numbers is generated whose mean equals the exact value of the variable. The COV indicates the amount of dispersion around the mean value and is defined as follows:

$$COV = \frac{\sigma}{\mu}. \quad (13)$$

In this context, σ represents the standard deviation, and μ represents the mean. The following pattern is used to generate random variables relating to each parameter:

$$r_{ij} = \mu_{r_{ij}} \left(1 + COV_{r_{ij}} \alpha_l\right), \quad (14)$$

where $\mu_{r_{ij}}$ and $COV_{r_{ij}}$ express the mean values and coefficients of variation of random parameters, respectively, and α_l is a random parameter with a mean of zero that is used in a Monte Carlo simulation. A large amount of uncertainty usually accompanies the collection of banking data, so the COV of these variables plays an important role in efficiency changes. However, because obtaining the COV requires extensive research in banking, which is beyond the scope of this study, we set the COV for all variables to 0.05 in this section. The indicators' sensitivity to changes in confidence levels is examined using the Monte Carlo method. The results of the sensitivity analysis for different parameters are shown in *Fig. 1*. These results show the extent to which changes or uncertainties in each parameter affect the confidence in the desired observation. This diagram shows the relative contribution of each parameter to changes in the degree of confidence.

The total sensitivity index across parameters is approximately 99%, so the higher-order indices have very small values, meaning their effect on the degree of confidence is negligible; therefore, their calculation has been omitted. The results given in *Fig. 1* indicate that the impact of long-term deposits on changes in the degree of confidence is 65%, and changes in the three indicators of the number of personnel, Qarz-ul-Hasana deposits, and overdue claims have the least effect on changes in the degree of confidence. Therefore, the most important source of uncertainty in the degree of confidence is long-term deposits and interest received, and their values should be collected and estimated more accurately.

Table 1. Hyperplane weights obtained from DEA-DA.

Index	First stage	Second Stage
personnel	-0.86752	-0.00100
Facilities	-0.00100	0.001833
Long-term deposits	0.001747	0.038314
Current deposits	0.001031	0.002730
Qarz al-Hasana deposits	0.002191	0.008920
Short-term deposits	0.001000	0.010257
Interest paid	-0.02534	-0.47351
Interest received	0.060138	0.001000
Commission received	0.039035	-0.043627
Deferred claims	-0.00100	-0.02617

Table 2. New observation information.

Index	C
personnel	29
Facilities	$10^8 \times 899$
Long-term deposits	$10^8 \times 259$
Current deposits	$10^8 \times 390$
Qarz al-Hasana deposits	$10^8 \times 90$
Short-term deposits	$10^8 \times 201$
Interest paid	$10^8 \times 22$
Interest received	$10^8 \times 13$
Commission received	$10^6 \times 2016$
Deferred claims	$10^8 \times 103$

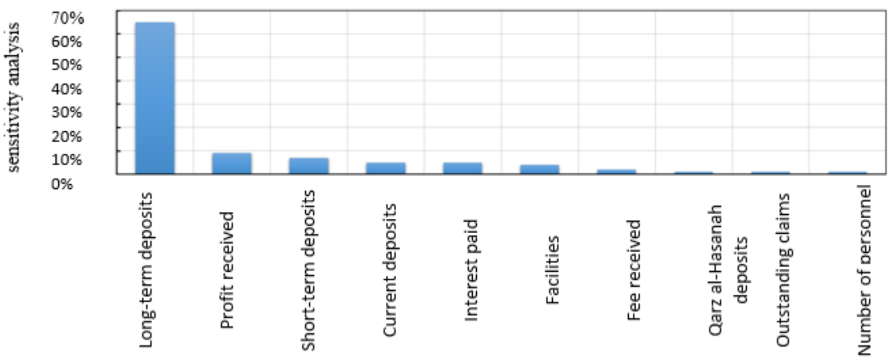

Fig. 1. Results of sensitivity analysis on new observation.

4 | Conclusion

Classification models assign observations whose group membership is unknown to specified groups using a set of parameters dependent on each observation. Discriminant analysis is one such model used to predict an observation's membership. This study introduces a two-stage discriminant analysis model in which the first stage determines the presence of overlap, and the second stage reclassifies observations within this area. A limitation of the discriminant analysis method is that it can only assign a new observation to a category. However, it is often necessary to have more information about the new observation. Therefore, this study introduces a degree of confidence based on the distance of the observation from the hyperplane.

The degree of confidence is then demonstrated using a numerical example of a new observation within the overlap. Next, a Monte Carlo sensitivity analysis is conducted to assess the effects of input indicators on output changes. The sensitivity analysis results showed that long-term deposit indicators have the greatest effect. In contrast, the number of personnel is the lowest, indicating that increasing it has a minimal impact on changes in the degree of confidence. It is worth noting that, since the results of the sensitivity analysis depend on the COV, appropriate studies must be conducted to determine the parameter variances to obtain a valid COV for the sensitivity analysis.

Author Contribution

Joorbonyan designed the research framework, developed the two-stage discriminant analysis model, performed the Monte Carlo sensitivity analysis, analyzed and interpreted the results, and prepared the manuscript.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

References

[1] Coccorese, P. (2017). Banking competition and economic growth. In *Handbook of competition in banking and finance* (pp. 230–263). Edward Elgar Publishing. https://doi.org/10.4337/9781785363306.00020

[2] Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of eugenics*, *7*(2), 179–188. https://doi.org/10.1111/j.1469-1809.1936.tb02137.x

[3] Peykani, P., Mohammadi, E., Jabbarzadeh, A., & Jandaghian, A. (2016). Utilizing robust data envelopment analysis model for measuring efficiency of stock, a case study: Tehran Stock Exchange, *1*, 15–24. https://b2n.ir/mm8921

[4] Karimi, T., Ahmadian, M., & Shahbazi, M. (2024). Performance evaluation of bank branches in the atmosphere of grey uncertainty. *Journal of modelling in management*, *19*(6), 2300–2319. https://doi.org/10.1108/JM2-09-2023-0206

[5] Mangasarian, O. L. (1965). Linear and nonlinear separation of patterns by linear programming. *Operations research*, *13*(3), 444–452. https://doi.org/10.1287/opre.13.3.444

[6] Freed, N., & Glover, F. (1981). Simple but powerful goal programming models for discriminant problems. *European journal of operational research*, *7*(1), 44–60. https://doi.org/10.1016/0377-2217(81)90048-5

[7] Olfati, M., Krömer, P., Fanati Rashidi, S., Mirjalili, S., & Snášel, V. (2025). A goal programming-based algorithm for solving multi objective optimization problems. *Annals of operations research*, 1–26. https://doi.org/10.1007/s10479-025-06646-0

[8] Banks, W. J., & Abad, P. L. (1991). An efficient optimal solution algorithm for the classification problem. *Decision sciences*, *22*(5), 1008–1023. https://doi.org/10.1111/j.1540-5915.1991.tb01904.x

[9] Glover, F. (1990). Improved linear programming models for discriminant analysis. *Decision sciences*, *21*(4), 771–785. https://doi.org/10.1111/j.1540-5915.1990.tb01249.x

[10] Retzlaff-Roberts, D. L. (1996). A ratio model for discriminant analysis using linear programming. *European journal of operational research*, *94*(1), 112–121. https://doi.org/10.1016/0377-2217(95)00196-4

[11] Sueyoshi, T. (1999). DEA-discriminant analysis in the view of goal programming. *European journal of operational research*, *115*(3), 564–582. https://doi.org/10.1016/S0377-2217(98)00014-9

[12] Sueyoshi, T. (2001). Extended DEA-discriminant analysis. *European journal of operational research*, *131*(2), 324–351. https://doi.org/10.1016/S0377-2217(00)00054-0

[13] Hasan, S., & Elwakil, E. (2021). Knowledge-driven stochastic reliable modeling for steel bridge deck condition rating prediction. *Journal of structural integrity and maintenance*, *6*(2), 91–98. https://doi.org/10.1080/24705314.2020.1862965

[14] Saltelli, A., Chan, K., & Scott, E. M. (2000). Sensitivity analysis: Gauging the worth of scientific models. John Wiley & Sons. https://B2n.ir/pn8336