Received: 19 November 2022 | Accepted: 24 November 2022
DOI: 10.52898/ijif.2022.7

ORIGINAL ARTICLE

ANALYSIS OF THE FINANCIAL PERFORMANCE OF THE DEPOSIT BANKING SECTOR IN THE COVID-19 PERIOD WITH LMAW-DNMA METHODS

Gülay DEMİR

Abstract

Banks, as one of the most important actors in the money and capital markets, play a critical role in the financial intermediation process for every country's economy. The deposit banking sector is critical to the banking system's effective and efficient operation. The goal of this research is to develop a multi-criteria model for measuring and assessing the performance of the deposit banking sector during the COVID-19 pandemic. In this context, an integrated model consisting of the Logarithm Methodology of Additive Weights (LMAW) and Double Normalization-based Multiple Aggregation (DNMA) methods is proposed. In the first stage of the proposed performance evaluation model, the performance indicators determined based on the previous literature were weighted with the LMAW method. In the second stage, the DNMA method was used to measure and evaluate the financial performance of the deposit banking sector during the COVID-19 pandemic period. In this context, an integrated model consisting of the Logarithm Methodology of Additive Weights (LMAW) and Double Normalization-based Multiple Aggregation (DNMA) methods are proposed. In the first stage of the proposed performance evaluation model, the performance indicators determined based on the previous literature were weighted with the LMAW method. In the second stage, the DNMA method was used to measure and evaluate the financial performance of the deposit banking sector during the COVID-19 pandemic period. When the DNMA ranking findings were analyzed generally, it was determined that the deposit banking sector was severely impacted by the COVID-19 pandemic. This suggests that the sector is inefficient at managing pandemic-related risks. This study's findings may assist bank management, investors, and regulatory and supervisory agencies in making more accurate decisions regarding the stability of the banking system. Various sensitivity analyses were also utilized to verify the model's dependability and robustness within the scope of the study. The results of sensitivity analyses indicate that the suggested methodology generates consistent and reliable sequencing outcomes.

Keywords
LMAW, DNMA, Performance Analysis, Deposit Banking

JEL Classification
C61, C67, G21.

Authors Notes:
Phd., Sivas Cumhuriyet University, Vocational School of Health Services
ORCID: 0000-0002-3916-7639
gulaydemir@cumhuriyet.edu.tr

1. INTRODUCTION

Banks, which mediate the flow of funds between savers and investors in the financial system, considerably contribute to the economic growth of numerous nations. As a result of globalization, banks, one of the most important participants in the financial intermediation process, have assumed important roles in the financial markets. This has resulted in the diversification of bank activities and a rise in competition within the sector (Isik, 2017).

Both financial and nonfinancial crises have a detrimental impact on all participants in the global economy and produce a decline in market confidence and stability. The crisis-induced uncertainty presents both significant opportunities and considerable hazards to all economic units (Kozak, 2021; Ünlü et al.,2022).

The COVID-19 epidemic, which broke out at the end of 2019, disrupted both production and consumption activities, and increased the fragility of financial markets in almost every economy. Central banks and governments have had to make a variety of policy interventions in these unprecedented circumstances. With these interventions, governments tried to facilitate and support the flow of credit to firms in the short term, on the one hand, loosened the restrictions on the use of capital buffers by banks. This has harmed global economic indicators. The banking sector is one of the sectors most affected by the COVID-19 pandemic crisis. The pandemic crisis-related risks caused significant disruptions in the services provided by banks to their customers (Demirgüç-Kunt et al.,2021)

The question of whether the banking sector has been affected by the COVID-19 crisis has been an important research topic that has recently attracted the attention of politicians, practitioners and researchers. As a result, the study intends to assess the performance of the deposit banking sector using various MCDM methods over the course of nine quarters from 2020 to 2022. This study empirically evaluates the effect of the Covid-19 outbreak on the performance of the deposit banking sector in this context.

The main contributions and implications of the current study to the literature can be listed as follows:

i. Subjective criteria weights were determined with LMAW, a relatively new weighting method.

ii. Performance evaluation was carried out at the sector level, rather than the bank level, with the DNMA method, a relatively new ranking method.

iii. The critical performance criteria for deposit banking have been determined within the scope of the performance evaluation model proposed in this study.

iv. This study evaluated how the deposit banking sector was affected by the COVID-19 crisis based on the performance criteria determined differently from the previous literature.

v. Our study provides an analytical framework for a new hybrid MCDM approach for banking sector stakeholders to make better decisions.

vi. A comprehensive sensitivity analysis was used to determine whether the proposed performance assessment model in our study produces robust results.

2. LITERATURE REVIEW

The literature section consists of three parts: (i) studies on the application areas of the LMAW method, (ii) studies on the application areas of the DNMA method, and (iii) studies on MCDM procedures in the banking sector. A summary of some of these studies is presented in Table 1.

Table 1

Literature Review for LMAW and DNMA and the Banking Industry

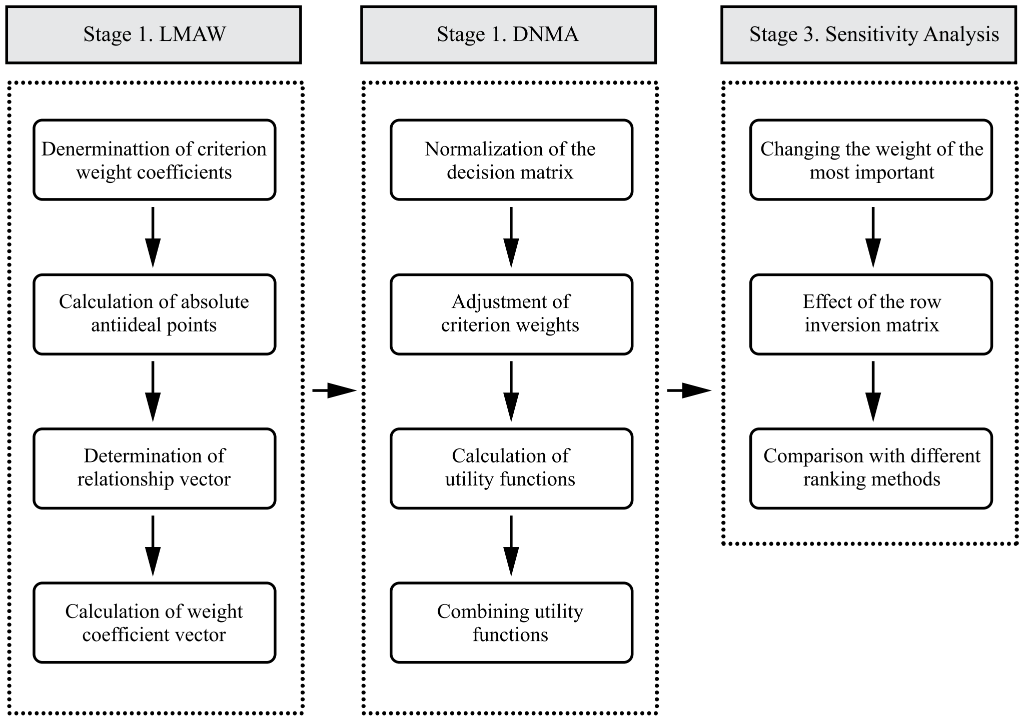
Studies employing LMAW technique	
Author(s)	**Studies**
Pamučar et al. (2021)	Evaluating the operational efficiency of the logistics service provider
Görçün and Küçükönder (2021)	Evaluation of cyber-physical production systems of heavy industries
Puška et al. (2022)	Green supplier selection
Božanić et al. (2022)	Introduction of Fuzzy LMAW
Demir (2022)	Evaluation of the Global Multidimensional Poverty Index
Studies employing DNMA technique	
Author(s)	**Studies**
Liao et al. (2019)	Evaluation of the lung cancer screening process
Nie et al. (2019)	Choosing the location for the shopping center
Lai et al. (2020)	Cloud service providers' selection
Saha et al. (2022)	Healthcare waste treatment method selection
Some Studies using MCDM Methods for the banking sector	
Studies	**Studies**
Wu et al. (2009)	Evaluation of the banking industry in Taiwan
Mandic et al. (2014)	Analysis of commercial banks operating in Serbia
Chaudhuri and Ghosh (2014)	assessment of the performance of deposit banks in India
Siew et al. (2017)	Evaluation of the financial performance of the Malaysian banks
Rezaei and Ketabi (2016)	performance evaluation in Iranian Private Banks
Ünvan (2020)	Financial performance evaluation in Turkish commercial banks
Işık (2019)	Evaluation of the Financial Performance of the Turkish Deposit Banking Sector
Işık (2020)	performance analysis of state-owned development and investment banks
Karadağ et al. (2022)	Evaluation of the performance of development and investment banks in Turkey
Ayçin and Orçun (2019)	Analysis of the performance of deposit banks
Ecer (2013)	Comparison of financial performance of private banks in Turkey
Ecer (2019)	Evaluation of corporate sustainability performance of private banks in Turkey
Ecer and Pamučar (2022)	Sustainability performance assessment of Turkish banks
Aydın (2020a)	Performance evaluation of foreign deposit banks
Aydın (2020b)	Performance Analysis of State-owned Banks
Koşaroğlu (2020)	Evaluation of the performance of banks traded on BIST
Demir (2021a)	Comparison of performance in privately owned deposit banks
Demir (2021b)	Evaluation of the financial performance of the Turkish banking system
Ünlü et al. (2022)	Efficiency and productivity analysis in Turkish deposit banks
Nguyen et al. (2022)	Financial Performance evaluation of Vietnamese Commercial Banks
Sama (2022)	Ranking the Indian private sector banks
Alamoudi and Bafail (2022)	Performance ranking in Saudi Arabian banking industry
İç et al. (2022)	Financial performance measurement for Turkish commercial banks
Özçalıcı et al. (2022)	Long-term performance analysis of Turkish deposit banks
Karbassi Yazdi et al. (2022)	Ranking performance of Iranian banks

3. METHODS

This study aims to measure and evaluate the performance of the Turkish deposit banking sector in the COVID-19 period (2020-03/P1, 2020-06/P2, 2020-09/P3, 2020-12/P4, 2021-03/P5, 2021-06/P6, 2021-09/P7, 2021-12/P8 and 2022-03/P9). The weights of the criteria were obtained using the LMAW method, one of the new methods that incorporates decision-makers' opinions into the weighting process of the criteria and allows for the use of both qualitative and quantitative data. The necessary analyses were then performed using the DNMA method, a new MCDM method. During the

COVID-19 period, the deposit banking performance scores and success rankings were obtained. The benefit of this proposed model in performance evaluation is that the best alternative can be selected as a result of a combination of LMAW and expert opinions on the one hand and DNMA's use of two normalization techniques and three addition approaches on the other. Figure 1 depicts the study's three stages: the LMAW method in the first stage, the DNMA method in the second stage, and the model flow chart in which sensitivity analysis is performed in the final step.

Figure 2
Flow Chart of the Proposed Model



3.1. LMAW Method

The LMAW method, introduced to the literature by Pamuar et al. in 2021, is one of the most recent methods used in criterion weighting and alternative ranking. This is the section where you find the criterion weight coefficients. This method's implementation steps are as follows: (Pamučar et al. 2021: 365-367):

m alternatives $A = \{A_1, A_2, \dots, A_m\}$ are evaluated compared to n criteria $C = \{C_1, C_2, \dots, C_n\}$ by participation of k experts $E = \{E_1, E_2, \dots, E_k\}$ and according to predefined linguistic scale.

Step 1: Determination of weight coefficients for criteria

Experts in the $E = \{E_1, E_2, \dots, E_k\}$ cluster prioritize the $C = \{C_1, C_2, \dots, C_n\}$ criteria over previously defined linguistic scale values. Prioritization assigns a higher value to the criterion of higher importance while assigning a lower value to the criterion of lower importance on a linguistic scale. By the way, the priority vector $P^e = (\gamma^e_{C_1}, \gamma^e_{C_2}, \dots, \gamma^e_{C_n})$ is obtained.

Here, $\gamma^e_{C_n}$ represents the linguistic scale value assigned by expert e $(1 \leq e \leq k)$ to criterion C_t $(1 \leq t \leq n)$.

Step 1.1: Defining the absolute anti-ideal point Υ_{AIP}

The absolute ideal point Υ_{AIP} should be smaller than the smallest value in the priority vector. It is calculated by;

$$\Upsilon_{AIP} = \frac{\Upsilon_{min}^{e}}{s}$$

equation where Υ_{min}^{e} is the minimum value of the priority vector and s should be greater than the base of logarithmic function. In case of use of Ln function, s value can be selected as 3.

Step 1.2: Determination of relation between priority vector and absolute anti-ideal point

Relation between priority vector and absolute anti-ideal point is calculated by Equation (1);

$$\eta_{Cn}^{e} = \frac{\Upsilon_{Cn}^{e}}{\Upsilon_{AIP}} \tag{1}$$

Thus and so, relation vector $R^{e} = (\eta_{C1}^{e}, \eta_{C2}^{e}, \ldots\ldots, \eta_{Cn}^{e})$ is obtained. In this statement, $\eta_{Cn}^{e})$ represents the value from the relation vector derived from Equation (1) and R^{e} represents the relation vector of $e\ (1 \leq e \leq k)$.

Step 1.3: Determination of the vector of weight coefficients

The vector of weight coefficients $w_j = (w_1, w_2, \ldots\ldots, w_n)^T$ are calculated for expert $e\ (1 \leq e \leq k)$ by Equation (2);

$$w_j^{e} = \frac{\log_A(\eta_{Cn}^{e})}{\log_A(\prod_{j=1}^{n} \eta_{Cn}^{e})}, A > 1 \tag{2}$$

where w_j^e represents the weight coefficients obtained according to evaluations of e^{th} expert and where η_{Cn}^{e} represents the elements of relation vector *R*. These obtained values must meet the $\sum_{j=1}^{n} w_j^e = 1$ condition for the weight coefficients.

By applying the Bonferroni aggregator indicated as Equation (3), aggregated vector of weight coefficients $w_j = (w_1, w_2, \ldots\ldots, w_n)^T$ is determined.

$$w_j = \left(\frac{1}{k.(k-1)} \cdot \sum_{x=1}^{k} \left(w_j^{(x)}\right)^p \cdot \sum_{\substack{y=1 \\ y \neq x}}^{k} \left(w_{ij}^{(y)}\right)^q \right)^{\frac{1}{p+q}} \tag{3}$$

The values of p and q are the stabilization parameters and $p,q \geq 0$. The resulting weight coefficients must meet the condition of $\sum_{j=1}^{n} w_j = 1$.

3.2. DNMA Method

The DNMA method, introduced to the literature in 2019 by Liao and Wu, is one of the new methods for listing alternatives. Two different normalized (linear and vector) techniques are used, as well as three different joining functions (full compensation-CCM, incomplete compensation-UCM, and incomplete compensator-ICM). This method's implementation steps are as follows (Liao and Wu 2019: 7-19; Ecer, 2020: 350-352):

Step 1: Normalization of the decision matrix

The elements of the decision matrix are normalized by linear ($\tilde{x}_{ij}^{1N}$) normalization with Equation (4) and by vector ($\tilde{x}_{ij}^{2N}$) normalization by Equation (5).

$$\tilde{x}_{ij}^{1N} = 1 - \frac{|x^{ij} - r_j|}{max\{\max_i x^{ij}, r_j\} - min\{\min_i x^{ij}, r_j\}} \tag{4}$$

$$\tilde{x}_{ij}^{2N} = 1 - \frac{\left|x^{ij} - r_j\right|}{\sqrt{\sum_{i=1}^{m}(x^{ij})^2 + \left(r_j\right)^2}} \tag{5}$$

The r_j value will be the target value for the c_j criterion and will be considered a $\max_i x^{ij}$ for benefit criteria and $\min_i x^{ij}$ for cost criteria.

Step 2: Determination of Criterion Weights

This step consists of three stages.

Step 2.1: In the first stage, the standard deviation (σ_j) of the criterion c_j is determined by Equation (6) where m is the number of alternatives.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(\frac{x^{ij}}{\max_i x^{ij}} - \frac{1}{m}\sum_{i=1}^{m}\left(\frac{x^{ij}}{\max_i x^{ij}}\right)\right)^2}{m}} \tag{6}$$

Step 2.2: The standard deviation values calculated for the criteria are normalized by Equation (7).

$$w_j^{\sigma} = \frac{\sigma_j}{\sum_{i=1}^{n}\sigma_j} \tag{7}$$

Step 2.3: Finally, the weights are adjusted by Equation (8).

$$\widetilde{w}_j = \frac{\sqrt{w_j^{\sigma}.w_j}}{\sum_{i=1}^{n}\sqrt{w_j^{\sigma}.w_j}} \tag{8}$$

Step 3: Calculation of Aggregation Models

Three aggregation functions (CCM, UCM and ICM) are calculated separately for each alternative.

CCM (complete compensatory model) is calculated by Equation (9).

$$u_1(a_i) = \sum_{j=1}^{n}\frac{\widetilde{w}_j.\tilde{x}_{ij}^{1N}}{\max_i \tilde{x}_{ij}^{1N}} \tag{9}$$

UCM (uncompensatory model) is calculated by Equation (10).

$$u_2(a_i) = \max_j \widetilde{w}_j\left(\frac{1 - \tilde{x}_{ij}^{1N}}{\max_i \tilde{x}_{ij}^{1N}}\right) \tag{10}$$

ICM (incomplete compensatory model) is calculated by Equation (11).

$$u_3(a_i) = \prod_{j=1}^{n} \left(\frac{\tilde{x}_{ij}^{2N}}{\max_i \tilde{x}_{ij}^{2N}} \right)^{\tilde{w}_j} \tag{11}$$

Step 4: Integration of utility values

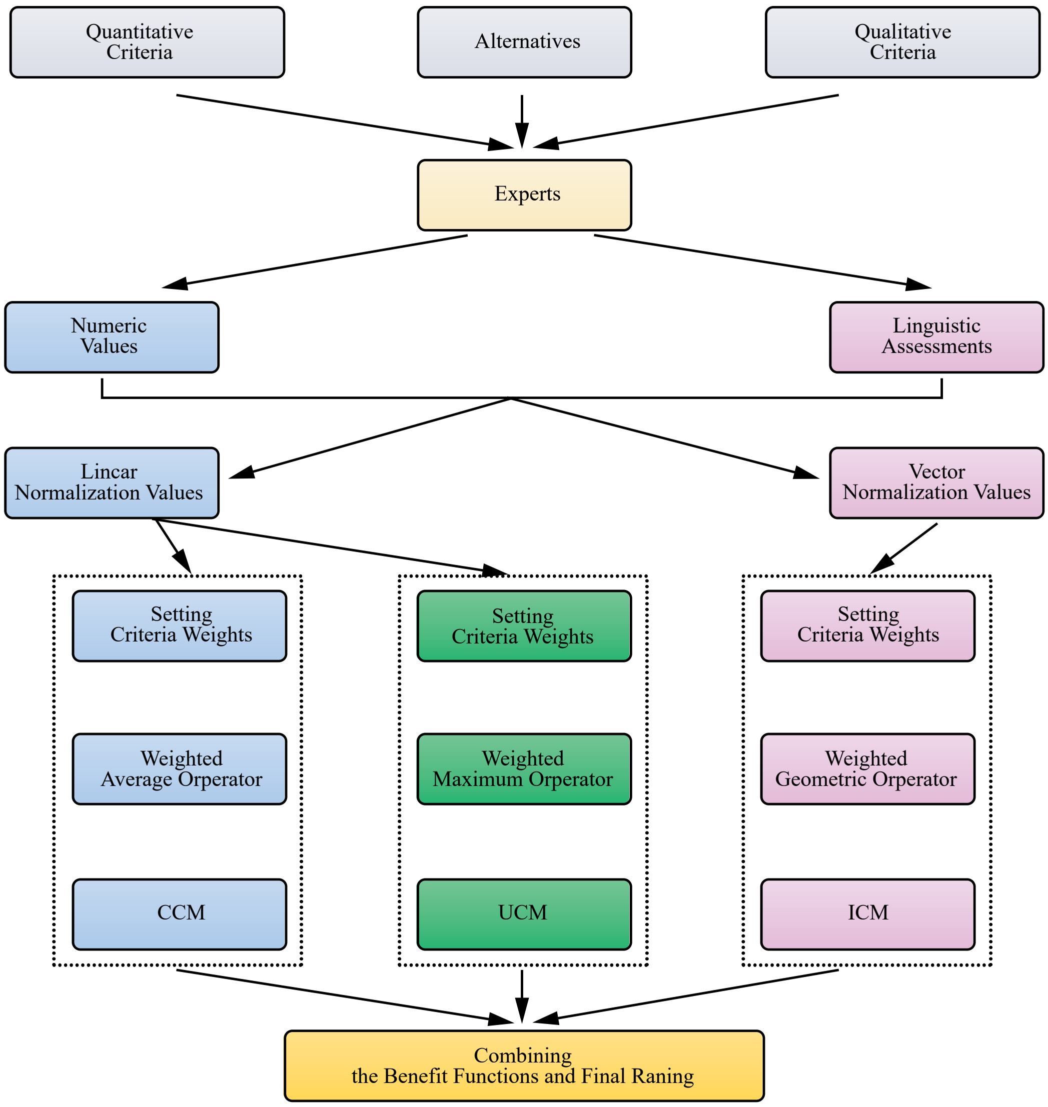
The calculated utility functions are integrated with Equation (12) using the Euclidean distance principle.

$$\begin{aligned} DN_i = {} & w_1 \sqrt{\varphi \left(\frac{u_1(a_i)}{\max_i u_1(a_i)} \right)^2 + (1-\varphi) \left(\frac{m - r_1(a_i) + 1}{m} \right)^2} \\ & - w_2 \sqrt{\varphi \left(\frac{u_2(a_i)}{\max_i u_2(a_i)} \right)^2 + (1-\varphi) \left(\frac{r_2(a_i)}{m} \right)^2} \\ & + w_3 \sqrt{\varphi \left(\frac{u_3(a_i)}{\max_i u_3(a_i)} \right)^2 + (1-\varphi) \left(\frac{m - r_3(a_i) + 1}{m} \right)^2} \end{aligned} \tag{12}$$

$r_1(a_i)$ and $r_3(a_i)$ used in the above formula represent the sequence number for the alternative a_i which is sorted according to the CCM and ICM functions in descending order (the highest value first). On the other hand, $r_2(a_i)$ indicates the sequence number in the order obtained for the UCM utility function in ascending order (smallest value first). The φ coefficient is the relative importance of the subordinate utility values and takes a value in the range of [0,1]. Those who developed the method states that it could be assumed as $\varphi = 0.5$. The coefficients w_1, w_2, w_3 are the importance weights of the CCM, UCM and ICM utility functions respectively. It is determined by the decision makers as the sum of the weights is $w_1 + w_2 + w_3 = 1$. When determining the weights, if the decision maker gives importance to the wide-ranging performance of the alternatives, he can assign the greatest weight to w_1. In case that the decision maker is not willing to take risks, i.e., the chosen alternative should not perform poorly according to some criteria, he can assign the greatest weight to w_2. However, the decision maker can assign the greatest weight to w_3 if he considers both the overall performance and the risks. Finally, the DN values are sorted in descending order, where the alternative with the highest value will be the best. The processing steps of the DNMA method are summarized in Figure 2.

Figure 2

The Procedure of the DNMA Method



Source: Liao and Wu, 2019: 20.

4. IMPLEMENTATION OF THE PROPOSED MODEL FOR ASSESSING THE FINANCIAL PERFORMANCE OF THE DEPOSIT BANKING SECTOR

4.1. Definition of the Problem

The study is based on a quantitative assessment of the deposit banking sector's financial performances, the criteria that define the sector's financial position in the years 2020-2022, and the use of multi-criteria evaluation methods. The criteria used were obtained from the BDDK's monthly banking sector data page, and Table 2 shows the characteristics of these criteria, the periods in which their performance was examined in the study, and the codes used.

Table 2

Criteria Used, Features, Periods Examined and Codes

Symbol	Financial Criteria	Quality
K1	Profit Before Tax (Loss) / Average Total Assets (%)	Benefit
K2	Period Net Profit (Loss) / Average Equity (%)	Benefit
K3	Total Interest Income / Average of Interest-Bearing Assets (%)	Benefit
K4	Net Interest Income (Expense) / Average Total Assets (%)	Benefit
K5	Fee, Commission, and Banking Services Revenues / Total Revenues (%)	Benefit
K6	Total Cash Loans / Total Deposits (%)	Benefit
K7	Legal Equity / Risk Weighted Items Total (%)	Benefit
K8	Non-Performing Receivables (Gross) / Total Cash Loans (%)	Cost
K9	Operating Expenses / Average Total Assets (%)	Cost
K10	Term Deposit / Total Deposit (%)	Cost

4.2. EXPLANATION OF THE DATA

Table 3 shows the financial values of the deposit banking sector in the quarters of 2020-2022.

Table 3

Data Defining the Financial Values of the Deposit Banking Sector

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0,4159	3,1635	2,3802	1,2051	12,0526	104,0565	17,3871	5,3193	0,4492	26,0685
P2	0,7780	6,0217	4,4246	2,2462	11,1125	106,1731	19,0887	4,7296	0,8862	30,8879
P3	1,0951	8,8329	6,4496	3,2617	10,9388	102,5272	19,0215	4,3667	1,2529	31,6239
P4	1,3377	10,8996	8,5999	4,0391	10,7657	103,1265	18,3243	4,3579	1,6567	31,3058
P5	0,2979	2,5693	2,2515	0,7133	9,0974	102,2916	17,6423	4,0771	0,3836	30,9007
P6	0,5908	5,3315	4,6589	1,4753	10,5283	99,8524	17,3906	3,9121	0,7740	32,0519
P7	1,0361	9,1081	7,2817	2,4529	10,9255	96,9429	16,8249	3,7834	1,1581	32,4930
P8	1,6341	15,0023	10,1002	3,9031	9,8671	90,5252	18,0570	3,3655	1,5830	37,7197
P9	0,9113	8,0279	2,6154	1,2206	9,1425	90,2258	20,1277	3,0428	0,3945	36,5702

4.3. LMAW Method Application

To calculate the values of the weight coefficients of the criteria, the four experts prioritized the criteria according to the scale in Table 4.

Table 4.

Prioritization Scale

Linguistic Variables	Prioritization Score
Absolutely Low (AL)	1
Very Low (VL)	1.5
Low (L)	2
Medium (M)	2.5
Equal (E)	3
Medium High (MH)	3.5
High (H)	4
Very High (VH)	4.5
Absolutely High (AH)	5

Source: Pamučar et al., 2020: 369.

Given that the assessment was carried out by four experts, four priority vectors have been identified.

$$E^1 = (H, AH, H, E, MH, MH, H, VH, E, L)$$

$$E^2 = (VH, VH, MH, H, H, MH, AH, AH, L, VL)$$

$$E^3 = (E, MH, VH, AH, AH, H, E, E, H, E)$$

$$E^4 = (MH, E, E, VH, AH, E, AH, H, H, L)$$

The absolute anti-ideal point (Υ_{AIP}) is arbitrarily defined as $\Upsilon_{AIP} = 0.5$. Based on the data obtained from the expert priority vectors and $\Upsilon_{AIP} = 0.5$., the relationship between the elements of the priority vector and the absolute anti-ideal point (Υ_{AIP}) is determined by means of Equation (1). The following section presents the relationships between the elements of the priority vector and (Υ_{AIP}).

The elements of the vector R^1 are obtained by applying Equation (3) as follows.

$$\eta^1_{K_1} = \frac{4}{0{,}5} = 8, \eta^1_{K_2} = \frac{5}{0{,}5} = 10, \eta^1_{K_3} = \frac{4}{0{,}5} = 8, \eta^1_{K_4} = \frac{3}{0{,}5} = 6, \eta^1_{K_5} = \frac{3{,}5}{0{,}5} = 7,$$

$$\eta^1_{K_6} = \frac{3{,}5}{0{,}5} = 7, \eta^1_{K_7} = \frac{4}{0{,}5} = 8, \eta^1_{K_8} = \frac{4{,}5}{0{,}5} = 9, \eta^1_{K_9} = \frac{3}{0{,}5} = 6, \eta^1_{K_{10}} = \frac{2}{0{,}5} = 4.$$

$$R^1 = (8, 10, 8, 6, 7, 7, 8, 9, 6, 4)$$

The elements of the remaining vectors R^2, R^3 and R^4 are obtained similarly.

$$R^2 = (9, 9, 7, 8, 8, 7, 10, 10, 4, 3)$$

$$R^3 = (6, 7, 9, 10, 10, 8, 6, 6, 8, 6)$$

$$R^4 = (7, 6, 6, 9, 10, 6, 10, 8, 8, 4)$$

To calculate the weight coefficients vector, the elements of the first expert's vector w_j^1 are obtained by applying Equation (2) as follows.

$$w^1_1 = \frac{\ln(8)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}1061 \quad w^1_2 = \frac{\ln(10)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}1175$$

$$w^1_3 = \frac{\ln(8)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}1061 \quad w^1_4 = \frac{\ln(6)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}0914$$

$$w^1_5 = \frac{\ln(7)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}0993 \quad w^1_6 = \frac{\ln(7)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}0993$$

$$w^1_7 = \frac{\ln(8)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}1061 \quad w^1_8 = \frac{\ln(9)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}1121$$

$$w^1_9 = \frac{\ln(6)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}0914 \quad w^1_{10} = \frac{\ln(4)}{\ln(8.10.8.6.7.7.8.9.6.4)} = 0{,}0707$$

$$w^1_j = (0{,}1061; 0{,}1175; 0{,}1061; 0{,}0914; 0{,}0993; 0{,}0993; 0{,}1061; 0{,}1121; 0{,}0914; 0{,}0707)$$

Obtained values of weight coefficients here meet the condition $\sum_{j=1}^{9} w^1_j = 1$. The remaining elements of vectors w^2_j, w^3_j and w^4_j are calculated in similar manner.

$w_j^2 = (0{,}1125; 0{,}1125; 0{,}0996; 0{,}1064; 0{,}1064; 0{,}0996; 0{,}1179; 0{,}1179; 0{,}0710; 0{,}0562)$

$w_j^3 = (0{,}0893; 0{,}0969; 0{,}1095; 0{,}1147; 0{,}1147; 0{,}1035; 0{,}0893; 0{,}0893; 0{,}1035; 0{,}0893)$

$w_j^4 = (0{,}0989; 0{,}0911; 0{,}0911; 0{,}1117; 0{,}1171; 0{,}0911; 0{,}1171; 0{,}1057; 0{,}1057; 0{,}0705)$

Applying the Equation (3), the aggregate vector of the weighting coefficients is obtained.

$w_j = (0{,}1017;\ 0{,}1045;\ 0{,}1017;\ 0{,}1061;\ 0{,}1095;\ 0{,}0985;\ 0{,}1076;\ 0{,}1062;\ 0{,}0927;\ 0{,}0715)^T$

As an example, the value of $w_1 = 0{,}1017$ is calculated by average values of w_j^e ($1\leq e\leq 4$) for each expert where $w_1^1 = 0.1061$, $w_1^2 = 0.1125$, $w_1^3 = 0.0893$ and $w_1^4 = 0.0989$ as follows.

$$w_1 = \{0{,}1061\ \ 0{,}1125\ \ 0{,}0893\ \ 0{,}0989\}^{p,q=1}$$
$$= \sqrt{\frac{0{,}1061^1.0{,}1125^1 + 0{,}1061^1.0{,}0893^1 + 0{,}1061^1.0{,}0989^1 + \cdots + 0{,}0989^1.0{,}1061^1 + 0{,}0989^1.0{,}1125^1 + 0{,}0989^1.0{,}0893^1}{4(4-1)}}$$
$$= 0{,}1017$$

The remaining values of the vectors of the weight coefficients are obtained similarly.

4.4. DNMA Method Application

The results of linear normalization by applying Equality (4) to the data in Table 3 are given in Table 5.

Table 5
Linear Normalization Results

Alternatives	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0,0883	0,0478	0,0164	0,1479	1,0000	0,8673	0,1702	0,0000	0,9485	1,0000
P2	0,3592	0,2777	0,2769	0,4609	0,6819	1,0000	0,6854	0,2591	0,6052	0,5864
P3	0,5966	0,5038	0,5349	0,7663	0,6231	0,7714	0,6651	0,4184	0,3172	0,5232
P4	0,7781	0,6700	0,8089	1,0000	0,5645	0,8090	0,4540	0,4223	0,0000	0,5505
P5	0,0000	0,0000	0,0000	0,0000	0,0000	0,7566	0,2475	0,5457	1,0000	0,5853
P6	0,2192	0,2222	0,3067	0,2291	0,4842	0,6037	0,1713	0,6181	0,6934	0,4865
P7	0,5524	0,5259	0,6409	0,5231	0,6186	0,4212	0,0000	0,6747	0,3916	0,4486
P8	1,0000	1,0000	1,0000	0,9591	0,2605	0,0188	0,3730	0,8583	0,0579	0,0000
P9	0,4590	0,4390	0,0464	0,1525	0,0153	0,0000	1,0000	1,0000	0,9915	0,0987

The vector normalization results by applying Equality (5) to the data in Table 3 are given in Table 6.

Table 6
Vector Normalization Results

Alternatives	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0,5888	0,5359	0,5747	0,6307	1,0000	0,9929	0,9499	0,8175	0,9793	1,0000
P2	0,7450	0,6948	0,7250	0,7912	0,9702	1,0000	0,9813	0,8648	0,8584	0,9522
P3	0,8357	0,7866	0,8200	0,9066	0,9640	0,9876	0,9798	0,8891	0,7486	0,9441
P4	0,9050	0,8525	0,9228	1,0000	0,9556	0,9890	0,9650	0,8818	0,6095	0,9445
P5	0,5263	0,5140	0,5498	0,4973	0,8901	0,9848	0,9484	0,8990	1,0000	0,9457
P6	0,6283	0,6201	0,6852	0,6102	0,9398	0,9731	0,9389	0,9075	0,8597	0,9283
P7	0,7821	0,7632	0,8307	0,7526	0,9510	0,9566	0,9200	0,9133	0,7103	0,9166
P8	1,0000	1,0000	1,0000	0,9770	0,8921	0,9173	0,9451	0,9579	0,5023	0,8331
P9	0,6287	0,6048	0,3227	0,3674	0,8354	0,9040	1,0000	1,0000	0,9940	0,8212

Then, in order to adjust the criterion weights, the standard deviations of the criteria are first calculated by Equation (6) and given in Table 7.

Table 7

Standard Deviations of Criteria

$\sigma 1$	$\sigma 2$	$\sigma 3$	$\sigma 4$	$\sigma 5$	$\sigma 6$	$\sigma 7$	$\sigma 8$	$\sigma 9$	$\sigma 10$	Total
0,4322	3,9092	2,8561	1,2300	0,9644	5,7946	1,0449	0,6904	0,4938	3,3876	20,80309

The standard deviation values are normalized by Equation (7) and given in Table 8.

Table 8

Normalized Standard Deviation Values

w_1^σ	w_2^σ	w_3^σ	w_4^σ	w_5^σ	w_6^σ	w_7^σ	w_8^σ	w_9^σ	w_{10}^σ	Total
0,0208	0,1879	0,1373	0,0591	0,0464	0,2785	0,0502	0,0332	0,0237	0,1628	1,0000

The adjusted weight values are obtained by Equation (8) and given in Table 9.

Table 9

Adjusted Weight Values

$\tilde{w}_1$	$\tilde{w}_2$	$\tilde{w}_3$	$\tilde{w}_4$	$\tilde{w}_5$	$\tilde{w}_6$	$\tilde{w}_7$	$\tilde{w}_8$	$\tilde{w}_9$	$\tilde{w}_{10}$	Total
0,0506	0,1543	0,1301	0,0872	0,0785	0,1824	0,0810	0,0654	0,0517	0,1188	1,0000

The values obtained using Equations (9), (10) and (11) respectively for the calculation of the utility functions CCM, UCM and ICM are given in Table 10.

Table 10

CCM, UCM and ICM Values

Alternatives	CCM	Descending Order	UCM	Ascending Order	ICM	Descending Order
P1	0,4451	7	0,1469	6	0,0863	7
P2	0,5466	5	0,1115	4	0,1998	4
P3	0,7697	1	0,0766	2	0,2864	3
P4	0,6569	3	0,0534	1	0,3296	1
P5	0,3149	9	0,1543	7	0,0523	8
P6	0,5788	4	0,1200	5	0,1013	6
P7	0,7132	2	0,1056	3	0,1857	5
P8	0,5319	6	0,1790	8	0,3029	2
P9	0,3208	8	0,1824	9	0,0278	9

The performance scores of the alternatives are obtained by integration of calculated utility functions with Equation (12) which is based on Euclidean distance. The values for φ, w_1, w_2 and w_3 are deemed appropriate by the experts to consider as $\varphi = 0.5$ $w_1 = 0.6$ $w_2 = 0.1$ and $w_3 = 0.3$. The calculated performance values and the ranking of the alternatives are given in Table 11.

Table 11
Performance Values and Ranking of Alternatives

Alternatives	DN	Rank
2020Q1	0,1409	7
2020Q2	0,2452	5
2020Q3	0,4613	1
2020Q4	0,3655	3
2021Q1	0,0444	9
2021Q2	0,2894	4
2021Q3	0,4045	2
2021Q4	0,1595	6
2022Q1	0,0536	8

According to the information in Table 11, the most successful period of the deposit banking sector in terms of selected performance indicators was 2020-Q4, while the most unsuccessful period of the said sector was determined as 2021-Q1.

5. SENSITIVITY ANALYSIS

Sensitivity analysis was applied by changing the criterion weights, checking the effect of the row inversion matrix and comparing it with other MCDM methods.

5.1. Change of Criteria Weights

In the first phase of the sensitivity test, the effect of changing the three most important criteria K5, K7 and K8 on the ranking results was analyzed. A total of 30 scenarios were created using Equality (13) (Vrtagić et al., 2021 11).

$$w_{n\beta} = (1 - w_{n\alpha})\frac{w_\beta}{(1 - w_n)} \quad (13)$$

The scenarios are based on three different groups of 10 sets each. In the first group of scenarios, the K5 criterion was changed, in the second group the K7 criterion, and in the third group, the K8 criterion was changed.

If Equality (13) is observed, $w_{n\beta}$ represents the corrected value of the criteria K1, K2, K3, K4, K6, K7, K8, K9, K10 followed by K1, K2, K3, K4, K5, K6, K8, K9, K10 and K1, K2, K3, K4, K5, K6, K7, K9, K10, respectively, according to the groups. $w_{n\alpha}$ represents the reduced value of the criteria K5, K7 and K8, respectively, according to the groups, the original value of the criterion considered w_β, and the original value of the criteria w_n, in which case the value K5, K7 and K8 are reduced. In the first scenario, the value of the K5 criterion was reduced by 5%, while the values of the remaining criteria were adjusted proportionally by applying Equation (13). In each subsequent scenario, the value of criterion K5 was reduced, while the values of the remaining criteria were corrected, so that the condition $\sum_{j=1}^{n} w_j^m = 1$ was met. The obtained weights are calculated and sorted by the DNMA method and given in Figure 3.

Figure 3

Comparison of Initial Results with S1–S10 Scenarios

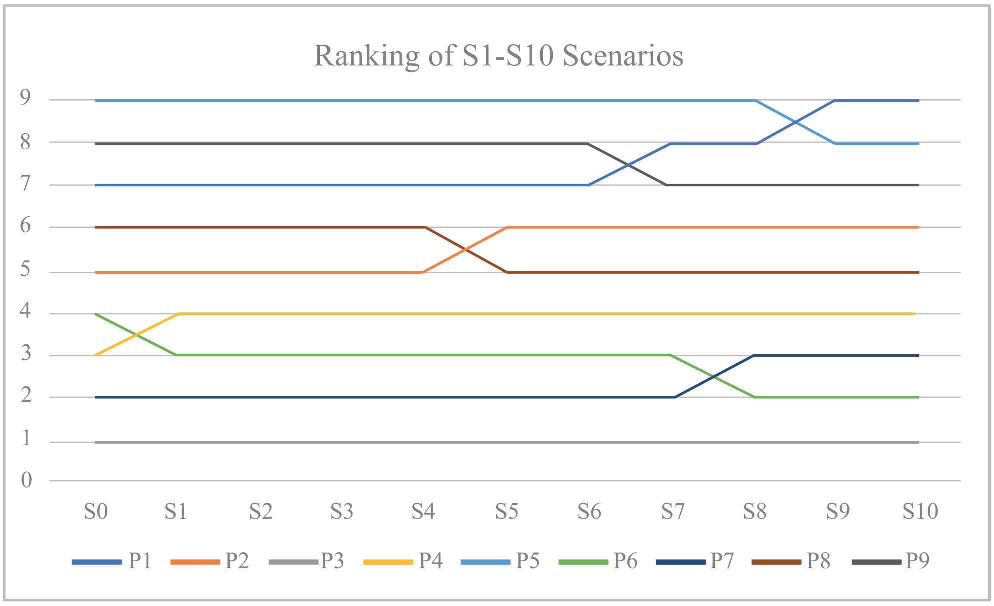


Figure 3 shows the obtained order of the alternatives and the comparison of the initial results with the results in the first scenario group, i.e., S1–S10. The change in the weight of the first criterion appears to have affected the performance ranks of the deposit banking sector. While the P3 alternative in the first place was in first place in all scenarios, there were differences in the rankings of the other alternatives.

The rankings calculated by using the weights obtained with scenarios S11-S20 to sort again by DNMA method are given in Figure 4.

Figure 4.

Comparison of initial results with S11–S20 scenarios

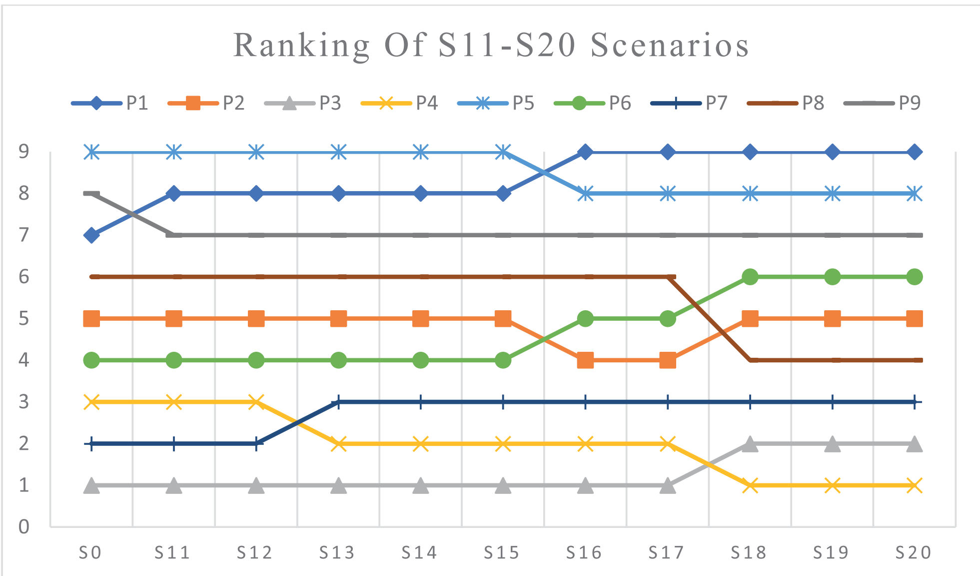
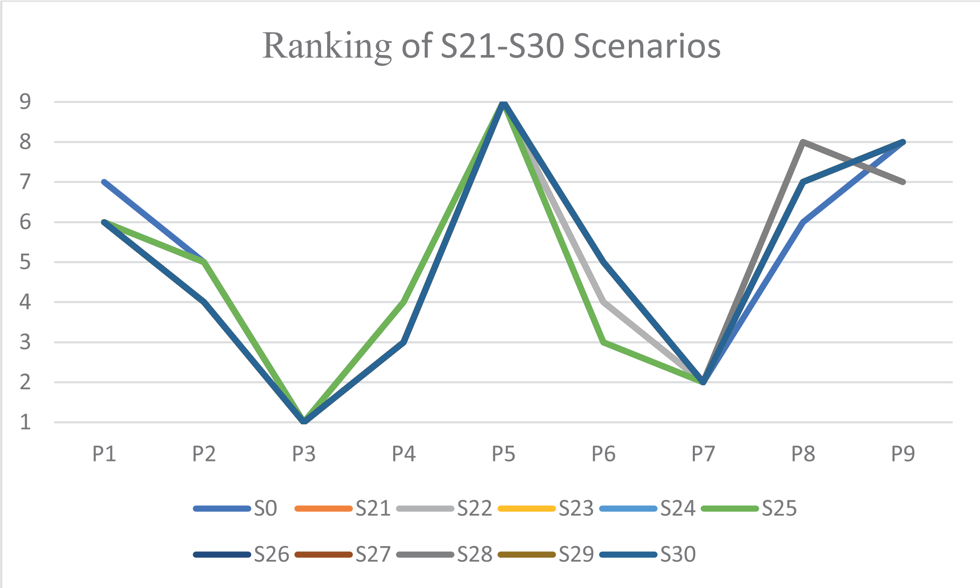


Figure 4 shows the obtained order of the alternatives and the comparison of the first results with the results in the second scenario group, namely S11–S20. In Figure 4, it can be noticed that there are small changes in the order of alternatives between scenarios.

Finally, the rankings calculated by using the weights obtained with the S21-S30 scenarios to sort by the re-DNMA method are given in Figure 5.

Figure 5
Comparison of initial results with S21–S30 scenarios



In Figure 5, it can be noticed that there are also some changes in the order of alternatives between the scenarios. Despite minimizing the impact of the most important criterion, alternative P3 remains in the first place, while P5 remains in last place. There have been changes in the rankings of other alternatives.

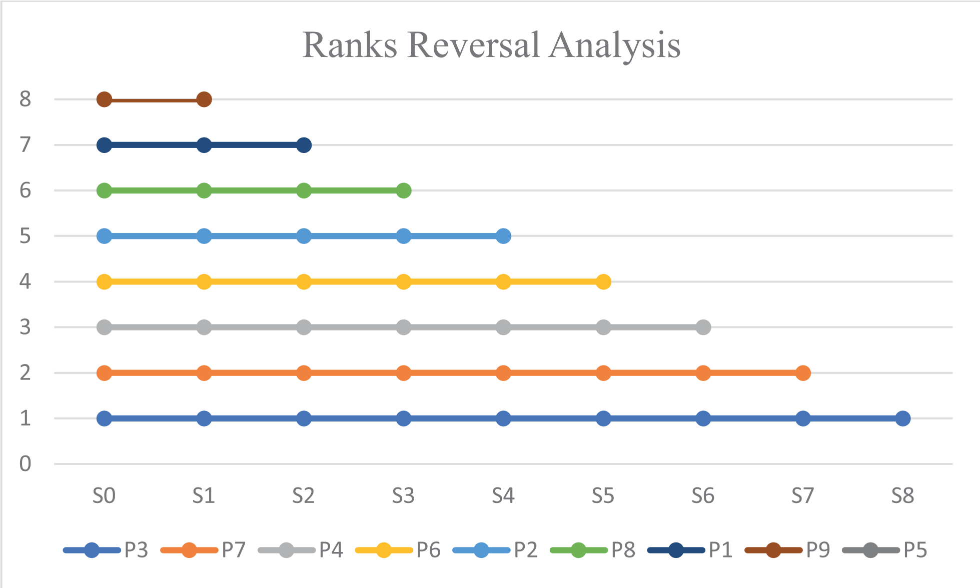
5.2. Effect of Rank Reversal Matrix

Adding new alternatives to the original cluster or removing weak alternatives from the cluster is one way to test the stability of MCDM methods. In such cases, the MCDM method is unlikely to significantly alter the ranking of alternatives. This phenomenon is known as the sequence inversion problem and has received a lot of attention in the literature (Mukhametzyanov and Pamuar, 2018; Pamuar et al., 2017).

Creating dynamic matrices and then analyzing the solutions that the model offers under the newly created conditions is one method for testing the validity of the model's results for decision-making. If the solutions contain some logical contradictions, such as undesirable changes in the order of alternatives, one may be concerned that there is a problem with the mathematical apparatus of the method used. For this purpose, a test was carried out in which the resistance of the model to the row inversion problem was taken into account. In the test, 8 scenarios were created in which the change in the elements of the decision matrix was simulated. As a rule, 8 scenarios should be created (one less than the total number of alternatives). After the first experiment, DNMA method is applied, and the deposit is sorted according to the results shown in scenario S0 of the banking system (original ranking). In the following scenario (S1), the period that reaches the fewest rankings is eliminated. After that, the remaining 7 periods are sorted again. Thus, a total of 8 scenarios (S1–S8) are created, whereby the worst-ranked period from the set in each subsequent scenario is eliminated, and the rankings are given in Figure 6.

Figure 6

Results of Ranks Reversal Analysis



It can be noted from Figure 6 that the DNMA model provides valid results in a dynamic environment and that the model has a strong resistance to the problem of rank reversal.

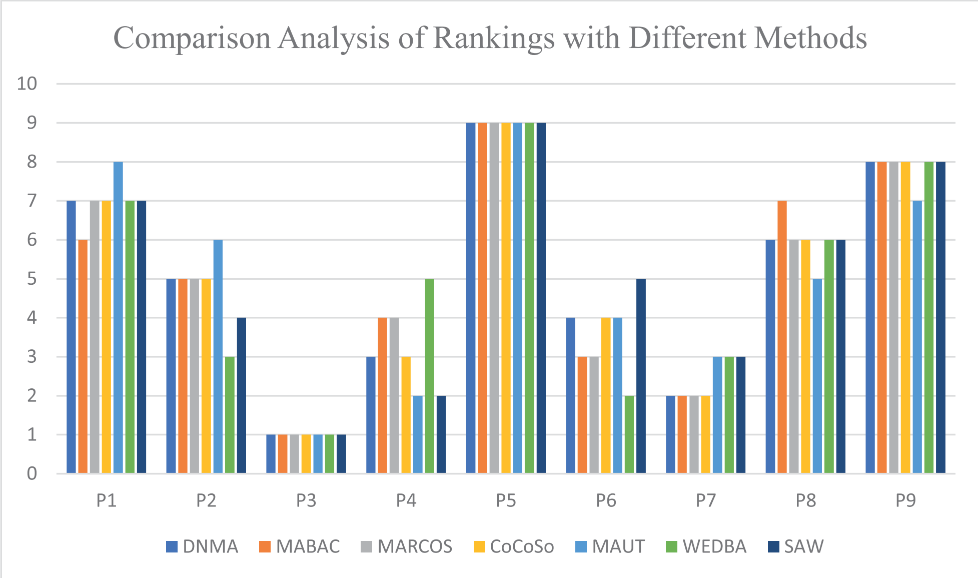
5.3. Comparison Analysis Based on Different Ranking Methodologies

In many complex decision environments, sensitivity analysis is performed by comparing the result of a model with other available and well-structured methods to examine the robustness and reliability of the ranking scores of the alternatives. It clarifies how different MCDM anatomies can produce similar or different ranking scores. In addition, the high correlation coefficient between ranking scores can also provide a pragmatic confirmation and agreement pathway. This can also be considered a global strategy for comparing the decision results of applications in practice.

To calculate the stability of the ranking, a comparative analysis is performed with multi-criteria decision-making methods based on different ranking methodologies. In many complex decision environments, the robustness and reliability of the ranking scores of alternatives are examined by comparing the result of one model with other available and established methods. A similar ranking comparison was made with some commonly used methods such as MABAC, MARCOS, CoCoSo, MAUT, WEDBA, and SAW to select the best alternative and explain the reliability of the proposed LMAW-DNMA-based model. These methods were chosen because of their various advantages, wide application, and potential to efficiently sort out alternatives in a multi-criteria selection environment. The resulting ranking results are given in Figure 7.

Figure 7

Ranking of Alternatives by Different MCDM Methods



According to Figure 7, among the quarters in which the activities of the deposit banking sector took place, the third quarter of 2020 ranked first in all methods. The third quarter of 2021 ranked last in all methods. There were slight differences in the rankings of the other quarters according to the methods. Spearman Sequence Correlation was used to determine this relationship between the results obtained by different methods. A comparison of the rankings by applying Spearman Order Correlation is given in Table 10.

Table 12

Sequence Correlation Values of the Obtained Methods

	DNMA	MABAC	MARCOS	CoCoSo	MAUT	WEDBA	SAW
DNMA	1,000	0,967	0,983	1,000	0,950	0,895	0,967
MABAC		1,000	0,983	0,967	0,867	0,929	0,900
MARCOS			1,000	0,983	0,917	0,946	0,917
CoCoSo				1,000	0,950	0,895	0,967
MAUT					1,000	0,812	0,933
WEDBA						1,000	0,845
SAW							1,000

The proposed model's ranking with an average correlation value of 0.960 between the other six MCDM techniques and the DNMA approach used is confirmed and can be said to be reliable.

6. CONCLUSION

The COVID-19 pandemic caused the worst social and economic crisis since the 2007-2009 global financial crisis. It slowed down the functioning of both real sector companies and financial institutions, including banks. Banks, considered among the most important actors in financial markets in developing economies such as Turkey, are a vital source of funds for the activities of the real sector.

This study aims to measure and evaluate the financial performance of the Turkish deposit banking sector during the COVID-19 pandemic period, with bank-specific financial data covering the period 2020-2022. For this purpose, 9 quarterly data on the deposit banking sector were used in the study.

LMAW-DNMA decision model was used to measure and evaluate the performance of the deposit banking sector. In the first stage of the proposed model, the subjective weights of the selected criteria were calculated with the LMAW technique. In the second stage, the alternatives were ranked based on the DNMA technique.

According to the LMAW subjective weighting method, the three most critical financial criteria during the COVID-19 pandemic period are the ratio of fee, commission, and banking services revenues to total revenues, the ratio of total cash loans to total deposits, and the ratio of non-performing it has been determined that there are receivables (gross) to total cash loans, respectively.

Based on the findings obtained using the DNMA technique, it was determined that the most successful period of the deposit banking sector was the third quarter of 2020, while the most unsuccessful period was the first quarter of 2021.

When the results of the suggested performance evaluation are evaluated in general, it can be stated that the performance of the deposit banking sector decreased sharply with the onset of the pandemic, but improved in the next 6 months. However, the results indicate that the performance gradually deteriorated by the last quarter of 2020. Between the first quarter and the third quarter of 2021, a significant improvement was observed in financial performance due to the decrease in COVID-19 cases and deaths. However, the financial performance of the deposit banking sector started to decline again in the last quarter of 2021 and the first quarter of 2022. As a result, it can be stated that the observed ups and downs in the performance of the sector are that the deposit banks are not adequately prepared to manage the pandemic crisis and, therefore they are unsuccessful in crisis management.

Various sensitivity analyzes were carried out to test the reliability of the results of the bank performance evaluation model proposed within the scope of the study. The first of these is the sensitivity analysis based on changing the weights. The other two are sensitivity analyses based on evaluating the effect of the Rank Reversal Matrix and comparing it with other MCDM techniques, respectively. Empirical findings from different sensitivity analyzes reveal that the results of the proposed hybrid model in performance evaluation are reliable and valid.

This study has some limitations. The results of this study can only be evaluated in terms of the deposit banking sector, but cannot be generalized to other sectors. This study uses only financial data related to the COVID-19 period as inputs for the performance evaluation model. In future studies, the performance of the participation banking sector, which has been mentioned frequently recently, can be measured with newer hybrid methods. In addition, the decision model proposed in this study can be used to evaluate the performance of other sectors.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researchers' Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There are no potential conflicts of interest in this study

REFERENCES

Alamoudi, M. H., & Bafail, O. A. (2022). BWM-RAPS Approach for Evaluating and Ranking Banking Sector Companies Based on Their Financial Indicators in the Saudi Stock Market. Journal of Risk and Financial Management, 15(10), 467. https://doi.org/10.3390/jrfm15100467

Ayçin, E., & Orçun, Ç. (2019). Mevduat bankalarının performanslarının ENTROPİ ve MAIRCA yöntemleri ile değerlendirilmesi. Balıkesir Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 22(42), 175-194. https://doi.org/10.31795/baunsobed.657002

Aydın, Y. (2020a). A hybrid multi-criteria decision-making (MCDM) model consisting of SD and COPRAS methods in performance evaluation of foreign deposit banks. Equinox Journal of Economics Business and Political Studies, 7(2), 160-176.

Aydın, Y. (2020b). Bütünleşik CRITIC ve MAIRCA Yöntemleri ile kamu sermayeli bankalarının performans analizi. Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 5(4), 829-841. https://doi.org/10.29106/fesa.834217

Božanić, D., Pamučar, D., Milić, A., Marinković, D., & Komazec, N. (2022). Modification of the logarithm methodology of sdditive weights (LMAW) by a triangular fuzzy number and its application in multi-criteria decision making. Axioms. 11(3):89. https://doi.org/10.3390/axioms11030089

Chaudhuri, T. D., & Ghosh, I. (2014). A multi-criterion decision-making model based approach for evaluation of the performance of commercial banks in India. IUP Journal of Bank Management, 13(3), 23-33.

Demir, G. (2022). Küresel çok boyutlu yoksulluk endeksinin bulanık LMAW yöntemi ile değerlendirilmesi. Sosyal Bilimlerde Nicel Araştırmalar Dergisi, 2(1), 67-77.

Demir, G. (2021a). Özel sermayeli mevduat bankalarında performans analizi: SWARA-RAFSI bütünleşik model uygulaması. Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, 35(4), 1359-1382. https://doi.org/10.16951/atauniiibd.897065

Demir, G. (2021b). Türk bankacılık sisteminin finansal performansının ROC-ITARA-CODAS yöntemleriyle analizi. Gümüşhane Üniversitesi Sosyal Bilimler Dergisi, 12(3), 831-847.

Demirgüç-Kunt, A., Pedraza, A., & Ruiz-Ortega, C. (2021). Banking sector performance during the COVID-19 crisis. Journal of Banking & Finance, 133, Article 106305. https://doi.org/10.1016/j.jbankfin.2021.106305

Ecer, F., & Pamučar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. Omega, Article 102690. https://doi.org/10.1016/j.omega.2022.102690

Ecer, F. (2020). Multi-criteriad Decision-making comprehensive approach from past to present. Seçkin Publications.

Ecer, F., (2019). Özel sermayeli bankaların kurumsal sürdürülebilirlik performanslarının değerlendirilmesine yönelik çok kriterli bir yaklaşım: Entropi-ARAS bütünleşik modeli. Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi, 14(2), 365-390. https://doi.org/10.17153/oguiibf.470336

Ecer, F., (2013). Türkiye'deki özel bankaların finansal performanslarının karşılaştırılması: 2008-2011 dönemi. Abant İzzet Baysal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 13(2),171-189.

Görçün, Ö. F., & Küçükönder, H. (2021). Evaluation of the transitions potential to cyber-physical production system of heavy industries in Turkey with a novel decision-making approach based on the bonferroni function. Verimlilik Dergisi, 1-16. https://doi.org/10.51551/verimlilik.983133

Işık, Ö. (2020). SD tabanlı MABAC ve WASPAS yöntemleriyle kamu sermayeli kalkınma ve yatırım bankalarının performans analizi. Uluslararası İktisadi ve İdari İncelemeler Dergisi, (29), 61-78. https://doi.org/10.18092/ulikidince.705148

Işık, Ö. (2019). Türk mevduat bankacılığı sektörünün finansal performanslarının ENTROPİ tabanlı aras yöntemi kullanılarak değerlendirilmesi. Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 4(1), 90-99. https://doi.org/10.29106/fesa.533997

Isık, O. (2017). Internal determinants of profitability of state, private and foreign owned commercial banks operating in Turkey. Journal of Economics Finance and Accounting, 4(3), 342-353. https://doi.org/10.17261/Pressacademia.2017.701

İç, Y. T., Yurdakul, M., & Pehlivan, E. (2022). Development of a hybrid financial performance measurement model using AHP and DOE methods for Turkish commercial banks. Soft Computing, 26(6), 2959-2979. https://doi.org/10.1007/s00500-021-06589-1

Karadağ Ak, Ö., Hazar, A., & Babuşcu, Ş. (2022). Evaluation of the financial performance of development and investment banks with entropy-based ARAS method. Macroeconomics and Finance in Emerging Market Economies, 1-21. https://doi.org/10.1080/17520843.2022.2035523

Karbassi Yazdi, A., Spulbar, C., Hanne, T., & Birau, R. (2022). Ranking performance indicators related to banking by using hybrid multicriteria methods in an uncertain environment: a case study for Iran under COVID-19 conditions. Systems Science & Control Engineering, 10(1), 166-180.

Koşaroğlu, Ş. M. (2020). BİST'te işlem gören bankaların performanslarının SD ve EDAS yöntemleriyle değerlendirilmesi. Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 5(3), 406-417. https://doi.org/10.29106/fesa.758281

Kozak, S. (2021). The impact of COVID-19 on bank Equity and Performance: The case of central eastern south european countries. Sustainability, 13(19), 11036. https://doi.org/10.3390/su131911036

Lai, H., Liao, H., Šaparauskas, J., Banaitis, A., Ferreira, F. A., & Al-Barakati, A. (2020). Sustainable cloud service provider development by a Z-number-based DNMA method with Gini-coefficient-based weight determination. Sustainability, 12(8), 3410. https://doi.org/10.3390/su12083410

Liao, H., Long, Y., Tang, M., Streimikiene, D., & Lev, B. (2019). Early lung cancer screening using double normalization-based multi-aggregation (DNMA) and Delphi methods with hesitant fuzzy information. Computers & Industrial Engineering, 136, 453-463. https://doi.org/10.1016/j.cie.2019.07.047

Liao, H., & Wu, X. (2020). DNMA: A double normalization-based multiple aggregation methods for multi-expert multi-criteria decision making. Omega, 94, 102058. https://doi.org/10.1016/j.omega.2019.04.001

Mandic, K., Delibasic, B., Knezevic, S., & Benkovic, S. (2014). Analysis of the financial parameters of Serbian banks through the application of the Fuzzy AHP and TOPSIS Methods. Economic Modelling, 43, 30-37. https://doi.org/10.1016/j.econmod.2014.07.036

Mukhametzyanov, I., & Pamučar, D. (2018). A sensitivity analysis in MCDM problems: A statistical approach, Decision-making: Applications in Management and Engineering, 1(2), 51-80. https://doi.org/10.31181/dmame1802050m

Nie, S., Liao, H., Wu, X., Tang, M., & Al-Barakati, A. (2019). Hesitant fuzzy linguistic DNMA method with cardinal consensus reaching process for shopping mall location selection. International Journal of Strategic Property Management, 23(6), 420-434. https://doi.org/10.3846/ijspm.2019.10851

Nguyen, P. H., Tsai, J. F., Hu, Y. C., & Ajay Kumar, G. V. (2022). A hybrid method of MCDM for evaluating financial performance of Vietnamese commercial banks under COVID-19 impacts. in shifting economic, Financial and Banking Paradigm (pp. 23-45). Springer, Cham. https://doi.org/10.1007/978-3-030-79610-5_2

Özçalıcı, M., Kaya, A., & Gürler, H. E. (2022). Long-term performance evaluation of deposit banks with multi-criteria decision-making tools: The case of Turkey. Pamukkale University Journal of Social Sciences Institute, 50: 87-114. https://doi.org/10.30794/pausbed.975901

Pamučar, D., Žižović, M., Biswas, S., & Božanić, D. (2021). A new Logarithm Methodology of additive weights (LMAW) for multi-criteria decision-making: application in logistics. Facta Universitatis Series: Mechanical Engineering, 19(3), Special Issue: 361-380. https://doi.org/10.22190/FUME210214031P

Pamučar, D., Božanić, D., & Ranđelović, A. (2017). Multi-criteria decision-making: An example of sensitivity analysis, Serbian Journal of Management, 11(1), 1-27. https://doi.org/ 10.5937/sjm12-9464

Puška, A., Božanić, D., Nedeljković, M., & Janošević, M. (2022). Green supplier selection in an uncertain environment in agriculture using a hybrid MCDM model: Z-Numbers–Fuzzy LMAW–Fuzzy CRADIS model. Axioms, 11(9), 427. https://doi.org/10.3390/axioms11090427

Rezaei, M., & Ketabi, S. (2016). Ranking the banks through performance evaluation by integrating Fuzzy AHP and TOPSIS Methods: A study of Iranian Private Banks. International Journal of Academic Research in Accounting, Finance and Management Sciences, 6(3), 19-30. http://dx.doi.org/10.6007/IJARAFMS/v6-i3/2148

Saha, A., Mishra, A.R., Rani, P., Hezam, I.M., & Cavallaro, F. (2022). A q-Rung orthopair Fuzzy FUCOM double normalization-based multi-aggregation method for healthcare waste treatment method selection. Sustainability, 14, 4171. https://doi.org/10.3390/su14074171

Sama, H. R., Kosuri, S. V. K., & Kalvakolanu, S. (2022). Evaluating and ranking the Indian private sector banks-A multi-criteria decision-making approach. Journal of Public Affairs, 22(2), e2419. https://doi.org/10.1002/pa.2419

Siew, L. W., Fai, L. K., & Hoe, L. W. (2017). Evaluation of the financial performance of Malaysian banks with the TOPSIS model. American Journal of Service Science and Management, 4(2), 11-16.

Ünlü, U., Yalçın, N., & Avşarlıgil, N. (2022). Analysis of efficiency and productivity of commercial banks in turkey pre-and during COVID-19 with an integrated MCDM approach. Mathematics, 10(13), 2300. https://doi.org/10.3390/math10132300

Ünvan, Y. A. (2020). Financial performance analysis of banks with TOPSIS and fuzzy TOPSIS approaches. Gazi University Journal of Science, 33(4), 904- 923. https://doi.org/10.35378/gujs.730294

Vrtagić, S., Softić, E., Subotić, M., Stević, Ž., Dordevic, M., & Ponjavic, M. (2021). Ranking road sections based on MCDM model: New improved Fuzzy SWARA (IMF SWARA). Axioms, 10(2), 1-23. https://doi.org/10.3390/axioms10020092

Wu, H. Y., Tzeng, G. H., & Chen, Y. H. (2009). A fuzzy MCDM approach for evaluating banking performance based on a Balanced Scorecard. Expert systems with applications, 36(6), 10135-10147. https://doi.org/10.1016/j.eswa.2009.01.005

How to cite this article: Demir, G. (2022). Analysis of the financial performance of the deposit banking sector in the Covid-19 period with LMAW-DNMA methods. *International Journal of Insurance and Finance, 2*(2), 17-36. https://doi.org/10.52898/ijif.2022.7