

Comparing Methodologies for Ranking Alternatives: A Case Study in Assessing Bank Financial Performance

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ABSTRACT

The robustness of bank performance rankings is examined by combining three Multi-Criteria Decision-Making (MCDM) procedures. Probability, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Root Assessment Method (RAM), with five objective weighting schemes: Equal, Entropy, Method based on the Removal Effects of Criteria (MERECE), LOGarithmic Percentage Change-driven Objective Weighting (LOPCOW), and Symmetry Point of Criterion (SPC). A panel of nineteen banks is evaluated on seven financial criteria (five benefit-type and two cost-type) following consistent cost/benefit normalization. For each weighting set, the criterion weights are computed and applied within all three ranking procedures; robustness is quantified via a cross-scenario rank-dispersion score (R_{score}) and pairwise Spearman's ρ . The results indicate strong concordance at the extremes of the ordering: the same alternatives occupy the top and bottom positions across methods and weights, whereas mid-range positions exhibit material sensitivity to the choice of the weighting scheme. Across Probability, TOPSIS, and RAM, Entropy yields the lowest R_{score} (highest stability), while SPC yields the highest R_{score} (lowest stability). These findings demonstrate that the selection of objective weights substantially influences the intermediate ranks and identify Entropy as a stability-oriented choice for banking assessments. The study documents all preprocessing and evaluation steps to support reproducibility and outlines extensions involving hybrid objective-subjective weighting and bootstrap-based uncertainty analysis.

Keywords-bank financial performance; weighting; MCDM

I. INTRODUCTION

Financial performance is a holistic construct that captures how effectively a bank deploys capital and assets to generate profit while sustaining operational stability. Beyond accounting aggregates, it reflects risk management, resource optimization, and the bank's contribution to economic development. Comparative assessment is therefore strategically relevant to multiple stakeholders: depositors and investors seeking safety and returns [1], firms selecting reliable financial partners with competitive terms [2], and regulators gauging system health and designing prudential policies [3]. Evaluating bank performance is nontrivial because the underlying criteria (e.g., profitability, asset quality, liquidity, solvency) differ in scale, dispersion, and direction (benefit versus cost) [4]. MCDM has been widely adopted to address such heterogeneity [5]. Early applications often focused on a single MCDM method, which limits its generality. For example, TOPSIS was used for Vietnamese, Chinese, Indian, and Turkish banks, sometimes with subjectively assigned or AHP-derived weights [6–9]. PROMETHEE was applied to five Indian banks [10]. A key limitation of single-method studies is that rankings can change materially across methods [11].

Subsequent work combined multiple methods. In some settings, different MCDM procedures produced identical orderings (e.g., SAW, TOPSIS, VIKOR for Taiwanese banks with AHP weights, VIKOR, TOPSIS, ELECTRE for three Iranian banks) [12, 13]. In other settings, methods diverged: ARAS, TOPSIS, and COPRAS for Borsa Istanbul banks (CRITIC weights) agreed only on the top alternative while differing elsewhere [14]. RAM, PSI, and SRP for 28 Vietnamese banks showed acceptable pairwise concordance but relied solely on Equal weights [15, 16]. EDAS, MOORA, OCRA, and TOPSIS yielded substantially different rankings at Borsa Istanbul [17]. TOPSIS and GRA agreed on each country's top bank but differed markedly over the remaining positions in China, India, Pakistan, and Thailand [18]. These findings collectively motivate factorial evaluations that vary both the ranking procedure and the weighting scheme. Among ranking procedures, TOPSIS is widely used in banking [19]. The Probability method is non-additive and avoids simple summation operators, offering a distinct reliability profile [20]. RAM is a newer, streamlined procedure that balances benefit- and cost-type criteria with fewer steps [21]. Given that the MCDM outcomes depend strongly on criterion weights [22, 23], the selection of weights is pivotal. This study focuses on five objective schemes: Equal, Entropy, MEREC, LOPCOW, and SPC, whose weights are determined solely from the data matrix rather than assessor judgment [16]. The central question is which ranking procedure and which objective weighting scheme yield the most stable and informative ordering of banks.

The financial performance of nineteen banks is evaluated using three ranking procedures: TOPSIS, Probability, and RAM, in combination with five objective weighting schemes (Equal, Entropy, MEREC, LOPCOW, and SPC) over seven criteria (five benefit-type and two cost-type). A consistent cost/benefit normalization is adopted, and robustness is assessed across all weight–method combinations using a cross-

scenario R-score and pairwise Spearman's ρ . This study implements a reproducible, factorial pipeline that combines three ranking procedures (TOPSIS, Probability, RAM) with five objective weighting schemes (Equal, Entropy, MEREC, LOPCOW, SPC). Under consistent benefit/cost normalization, robustness is assessed across all weight–method combinations using an R_{score} and pairwise Spearman's ρ . The analysis identifies where ordering is stable (typically at the extremes) and where it is sensitive (in the middle), and relates any sensitivity to the induced weight structure and method mechanics. The dataset, criteria, normalization, weighting schemes, and application steps for the three procedures, together with the robustness metrics, are presented. Additionally, comparative rankings and robustness analyses are reported. Finally, implications for selecting ranking procedures and weighting schemes in banking evaluations are synthesized, while directions for future research are outlined.

II. MATERIALS AND METHODS

A. Bank Financial Performance Data

Table I consolidates the financial performance data for 19 banks, designated from B1 to B19. Seven specific criteria characterize each bank's performance:

- C_1 : Loan-to-asset ratio (total loans / total assets)
- C_2 : Loan-to-deposit ratio (total loans / total deposits)
- C_3 : Equity-to-asset ratio (total equity / total assets)
- C_4 : Net profit-to-asset ratio (net periodic profit / total assets)
- C_5 : Net profit-to-equity ratio (net periodic profit / total equity)
- C_6 : Branch-to-net profit ratio (number of branches / net periodic profit)
- C_7 : Employee-to-net profit ratio (number of employees / net periodic profit)

Criteria C_1 – C_5 are classified as benefit-type criteria (B), meaning that higher values are desirable. Conversely, criteria C_6 and C_7 are cost-type criteria (C), where lower values are preferred [24].

TABLE I. BANK FINANCIAL PERFORMANCE DATA

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7
	max			min			
	0.6363	1.1095	0.1757	0.0558	0.4579	0.0118	0.1301
B1	0.5478	0.7281	0.0876	0.0178	0.2029	0.0428	0.5958
B2	0.5673	0.8457	0.0636	0.0143	0.2245	0.0395	0.7062
B3	0.5556	0.8403	0.1359	0.0437	0.3216	0.0184	0.3788
B4	0.6053	0.7942	0.0645	0.0106	0.1642	0.0704	1.4085
B5	0.581	0.8466	0.1325	0.0508	0.3832	0.0143	0.3169
B6	0.5455	0.8984	0.1139	0.0476	0.4178	0.0152	0.2926
B7	0.5212	0.8249	0.1429	0.0558	0.3908	0.0118	0.2119
B8	0.6007	0.9168	0.0736	0.0286	0.3891	0.0253	0.6634
B9	0.5721	0.8514	0.1036	0.0326	0.315	0.0391	0.7652
B10	0.5427	0.7452	0.0921	0.0407	0.4416	0.04	0.7795
B11	0.6327	0.9294	0.1368	0.0266	0.1943	0.0564	1.1381
B12	0.4423	0.5461	0.0843	0.0342	0.4064	0.0232	0.6126
B13	0.5334	0.8436	0.0879	0.036	0.4099	0.0165	0.7408

B14	0.4716	0.6609	0.0731	0.0124	0.1693	0.0563	1.3010
B15	0.5656	0.7648	0.0742	0.0238	0.3199	0.1584	2.2814
B16	0.4436	1.1095	0.0474	0.0217	0.4579	0.0296	0.5734
B17	0.6363	0.9184	0.0881	0.0208	0.2359	0.0266	0.8488
B18	0.5976	1.0592	0.0678	0.0179	0.2635	0.0321	0.8248
B19	0.5463	0.7063	0.1757	0.0488	0.2781	0.0604	0.8705

Visual inspection alone is insufficient to derive a defensible ordering from Table I, because the criteria differ in direction and scale. A principled ranking requires (i) determining criterion weights and (ii) aggregating the normalized criteria via MCDM procedures. This study adopts consistent benefit-cost normalization and employs five objective weighting schemes (Equal, Entropy, MEREC, LOPCOW, and SPC) in Section II-B, together with three ranking procedures (Probability, TOPSIS, and RAM) in Section II-C, to produce the final rankings.

B. Methods Used

Criterion weights are computed using five objective methods: Equal, Entropy, MEREC, LOPCOW, and SPC. These procedures derive weights directly from the decision matrix without requiring assessor input; detailed step-by-step formulas are provided in [25, 26]. Equal assigns uniform weights, Entropy emphasizes the criteria with higher information divergence, MEREC penalizes the criteria whose removal minimally perturbs performance, LOPCOW integrates logarithmic transformations with pairwise comparisons, and SPC adjusts weights by standardized proportional contributions. To enable ranking, the present study constructs a decision matrix x_{ij} over m alternatives and n criteria. Each element x_{ij} denotes the observed value of criterion j for alternative i ($i = 1, 2, \dots, m, j = 1, 2, \dots, n$). It also defines the weight vector $w=(w_1, \dots, w_n)$ and the index sets B and C for benefit-type and cost-type criteria, respectively. These are used in the subsequent normalization and aggregation steps.

C. Probability Method

To rank the alternatives using the Probability method, this work proceeds through the following steps [20].

- Step 1: Probability of a favorable outcome

For benefit-type criteria, the probability of a favorable outcome in the decision-making process increases linearly and is calculated using:

$$P_{ij} \propto x_{ij}, \quad P_{ij} = \alpha_j x_{ij}, i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \quad (1)$$

where α_j is the normalization coefficient for the j -th benefit criterion, calculated as:

$$\alpha_j = \frac{1}{\sum_{i=1}^m x_{ij}} \quad (2)$$

For cost-type criteria, the probability of a favorable outcome in the decision-making process is also a linear function and is calculated using:

$$P_{ij} \propto (x_{jmax} + x_{jmin} - x_{ij})$$

$$P_{ij} = \beta_j (x_{jmax} + x_{jmin} - x_{ij}) \quad (3)$$

where $i = 1, 2, \dots, m, j = 1, 2, \dots, n, \beta_j$ is the normalization coefficient for the j cost criterion, calculated as:

$$\beta_j = \frac{1}{m(x_{jmax} + x_{jmin} - \frac{\sum_{i=1}^m x_{ij}}{m})} \quad (4)$$

- Step 2: Overall favorable probability:

$$P_i = \prod_{j=1}^n (P_{ij})^{w_j} \quad (5)$$

- Step 3: Alternatives are ranked based on the principle that the best alternative is the one with the highest overall probability of success.

D. TOPSIS Method

To rank alternatives using the TOPSIS method, the following steps are applied [27]:

- Step 1: Calculate the normalized values using:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (6)$$

- Step 2: Determine the weighted normalized values considering the criterion weights using:

$$y_{ij} = w_j \cdot n_{ij} \quad (7)$$

- Step 3: Positive-ideal and negative-ideal solutions (A^+ and A^-). These are identified for each criterion using:

$$A^+ = \{y_1^+, y_2^+, \dots, y_j^+, \dots, y_n^+\} \quad (8)$$

$$A^- = \{y_1^-, y_2^-, \dots, y_j^-, \dots, y_n^-\} \quad (9)$$

where y_j^+ and y_j^- denote, respectively, the best and worst weighted-normalized values for j .

- Step 4: Determine the S_i^+ and S_i^- values using:

$$S_i^+ = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^+)^2} \quad i = 1, 2, \dots, m \quad (10)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2} \quad i = 1, 2, \dots, m \quad (11)$$

- Step 5: Determine the C_i values using:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \dots, m; \quad 0 \leq C_i^* \leq 1 \quad (12)$$

- Step 6: Alternatives are ranked based on the principle that the best alternative is the one with the most significant C_i value.

E. RAM Method

The steps for using the RAM method to rank alternatives are [21]:

- Step 1: Normalize the raw data using:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (13)$$

- Step 2: Calculate the weighted normalized values for each criterion using:

$$y_{ij} = w_j \cdot r_{ij} \tag{14}$$

- Step 3: Determine the total weighted normalized score using:

$$S_{+i} = \sum_{j=1}^n y_{+ij} \quad \text{if } j \in B \tag{15}$$

$$S_{-i} = \sum_{j=1}^n y_{-ij} \quad \text{if } j \in C \tag{16}$$

- Step 4: Calculate each alternative's final score using:

$$RI_i = \frac{2+S_{-i}}{\sqrt{2+S_{+i}}} \tag{17}$$

- Step 5: Rank the alternatives in descending order based on their calculated scores.

To compare the various MCDM methods and weighting techniques, two primary metrics were employed: the R_{score} coefficient and the Spearman's rank correlation coefficient (hereafter referred to as the Spearman coefficient). The R_{score} coefficient reflects the stability of alternative rankings when generated by a specific MCDM method. A lower R_{score} value indicates greater stability in the rankings. For the Probability, TOPSIS, and RAM methods, this coefficient is calculated using [28]:

$$R_{score} = \frac{\max(P_i)}{\min(P_i)}, \quad i = 1 \div m \tag{18}$$

$$R_{score} = \frac{\max(C_i)}{\min(C_i)}, \quad i = 1 \div m \tag{19}$$

$$R_{score} = \frac{\max(RI_i)}{\min(RI_i)}, \quad i = 1 \div m \tag{20}$$

The Spearman coefficient, on the other hand, measures the consistency of alternative rankings either when evaluated by different MCDM methods or when evaluated by a single MCDM method but with varying criterion weighting techniques. This coefficient is computed using (21) [25], where D_i denotes the difference between the ranks assigned to alternative i by the two orderings under comparison.

$$S = 1 - \frac{\sum_{i=1}^m D_i^2}{m(m^2-1)} \tag{21}$$

III. RESULTS AND DISCUSSION

Table II reports the weights obtained from the five objective schemes (Equal, Entropy, MEREC, LOPCOW, SPC). Weight magnitudes vary substantially across the schemes: the range for C_1 spans a 10.15× factor and for C_7 a 9.48× factor, while even the least variable criterion (C_3) changes by 2.03×. This dispersion underscores the importance of comparing the weighting schemes before ranking the alternatives. A notable contrast emerges between Entropy and SPC: criteria that receive small weights under Entropy often receive large weights under SPC. For example, C_1 is the smallest in terms of

Entropy and the largest in terms of SPC. Conversely, C_6 attains its most significant SPC weight (0.4228) but its smallest Entropy weight (0.0949). The following subsections examine whether these weight-structure differences result in materially different rankings of banks.

Using the Probability procedure, the current study computes the overall probabilities P_i via (1)–(5) under each weighting scheme. This yields five sets of P_i scores and ranks, consolidated in Table III.

Applying TOPSIS, the closeness coefficients C_i are obtained via (6)–(12), again five times—once per weighting scheme. The resulting C_i values and ranks are summarized in Table IV.

For RAM RI_i computed via (13)–(17) under all five weighting schemes. The complete RI_i scores and ranks are reported in Table V.

TABLE II. CRITERION WEIGHTS

Method	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Equal	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Entropy	0.1809	0.1926	0.1116	0.0920	0.1535	0.0949	0.1745
MEREC	0.0381	0.0722	0.1137	0.1673	0.1061	0.2755	0.2270
LOPCOW	0.1562	0.0931	0.1672	0.2321	0.1173	0.2051	0.0289
SPC	0.0178	0.0261	0.0824	0.1110	0.0658	0.4228	0.2740
max/min	10.15	7.37	2.03	2.52	2.33	4.45	9.48

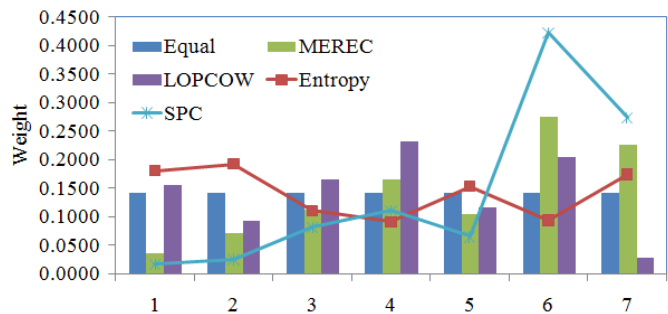


Fig. 1. Criterion weights chart.

An examination of Table III reveals that when the Probability method is employed for ranking banks, the ranks exhibit minimal changes despite using five different sets of criterion weights. As shown in Table II, the criterion weights themselves varied considerably. Despite this, consistently top-ranked banks were identified regardless of the weighting method used. Specifically, B7 consistently ranked 1st, B5 2nd, B6 3rd, and B3 4th. Furthermore, the lowest-ranked banks, B15 (19th) and B4 (18th), also remained consistent across all five weighting methods. This partially demonstrates the advantage of the Probability method in ensuring ranking stability when various weighting methods are applied to the criteria.

TABLE III. P_i SCORES AND RANKS OF ALTERNATIVES USING THE PROBABILITY METHOD

Alt.	Equal		Entropy		MEREC		LOPCOW		SPC	
	P_i	Rank	P_i	Rank	P_i	Rank	P_i	Rank	P_i	Rank
B1	0.0446	15	0.0456	15	0.0455	15	0.0426	15	0.0483	14
B2	0.0428	16	0.0450	16	0.0430	16	0.0398	16	0.0462	15
B3	0.0614	4	0.0596	4	0.0636	4	0.0630	4	0.0637	4
B4	0.0350	18	0.0371	18	0.0325	18	0.0335	18	0.0338	18

...
B18	0.0473	14	0.0496	12	0.0465	14	0.0448	14	0.0486	13
B19	0.0566	5	0.0540	8	0.0557	7	0.0604	5	0.0524	10

TABLE IV. C_i SCORES AND RANKS OF ALTERNATIVES USING THE TOPSIS METHOD

Alt.	Equal		Entropy		MEREC		LOPCOW		SPC	
	C_i	Rank	C_i	Rank	C_i	Rank	C_i	Rank	C_i	Rank
B1	0.6151	14	0.6329	13	0.7101	13	0.580	15	0.7662	13
B2	0.5940	16	0.6153	16	0.6956	14	0.563	16	0.7641	14
B3	0.8204	4	0.8037	4	0.8872	4	0.832	4	0.9208	4
B4	0.4267	18	0.4089	18	0.4947	18	0.443	18	0.5418	18
...
B18	0.6188	13	0.6307	15	0.7116	12	0.605	14	0.7814	10
B19	0.6723	10	0.6400	12	0.6730	16	0.706	8	0.6680	16

TABLE V. R_i SCORES AND RANKS OF ALTERNATIVES USING THE RAM METHOD

Alt.	Equal		Entropy		MEREC		LOPCOW		SPC	
	R_i	Rank	R_i	Rank	R_i	Rank	R_i	Rank	R_i	Rank
B1	1.4213	15	1.4222	15	1.4150	14	1.4221	15	1.4099	14
B2	1.4209	16	1.4221	16	1.4143	16	1.4215	16	1.4093	16
B3	1.4279	4	1.4276	4	1.4225	4	1.4300	4	1.4171	4
B4	1.4170	18	1.4183	18	1.4082	18	1.4184	18	1.4018	18
...
B18	1.4225	13	1.4236	13	1.4155	13	1.4235	14	1.4103	12
B19	1.4253	6	1.4249	9	1.4177	10	1.4283	5	1.4100	13

Table IV also exhibits that the top-ranked banks remain consistent when using the TOPSIS method, even with varying weights for the criteria. Specifically, TOPSIS consistently identified B7 as 1st, B5 as 2nd, B6 as 3rd, and B3 as 4th across all five weighting methods. Similarly, the two lowest-ranked banks, B15 (19th) and B4 (18th), were also consistently identified. A notable observation is that the four best-performing and two worst-performing banks were consistently identified across both the Probability and TOPSIS methods.

When applying the RAM method to rank alternatives, the top-ranked banks, B7 (1st), B5 (2nd), B6 (3rd), and B3 (4th), were consistently identified, regardless of the weighting method used. The two lowest-ranked banks, B4 (18th) and B15 (19th), also showed consistent rankings across different weighting methods. A thorough review of Tables III, IV, and V reveals a highly significant finding: the best- and worst-performing banks consistently maintained their ranks, regardless of the criterion weighting method or the alternative ranking method employed. Specifically, B7 consistently ranked 1st, B5 2nd, B6 3rd, B3 4th, B15 19th, and B4 18th across all methods.

Therefore, in terms of identifying the highest and lowest-ranked banks, the Equal, Entropy, MEREC, LOPCOW, and SPC weighting methods exhibit comparable performance. Similarly, the Probability, TOPSIS, and RAM alternative ranking methods are also deemed to have equivalent performance in this regard. However, when considering the overall ranking of all banks, numerous rank changes are observed when different weighting methods or alternative ranking methods are used. Hence, to ensure the stability of bank rankings, it is crucial to conduct comparative analyses among the criterion weighting methods and among the alternative ranking methods.

Applying (18-20), the R_{score} coefficients were calculated for all performed scenarios, as summarized in Table VI.

It is evident that when the Entropy method is used for criterion weighting, the R_{score} coefficient consistently exhibits the lowest value compared to other weighting methods, regardless of whether Probability, TOPSIS, or RAM are used for ranking. Conversely, employing the SPC method for criterion weighting consistently yields the highest R-squared coefficient, regardless of the ranking method. This outcome indicates that among the five criterion weighting methods examined, the Entropy method provides the highest stability in alternative rankings. In contrast, the SPC method yields the lowest ranking stability. This is not a critique of SPC. Among Equal, Entropy, MEREC, LOPCOW, and SPC, Entropy is recommended as the preferred objective weighting scheme to achieve higher stability in the resulting rankings.

Equation (21) was applied to calculate the Spearman coefficients between the weighting methods for each case using the Probability, TOPSIS, and RAM methods for ranking alternatives. These results are compiled in Tables VII-IX.

TABLE VI. R_{score} COEFFICIENT VALUES

Method	R_{score}				
	Equal	Entropy	MEREC	LOPCOW	SPC
Probability	2.7678	2.5141	4.9441	2.5588	7.6535
TOPSIS	5.5911	5.0883	11.1875	5.6596	23.8572
RAM	1.0119	1.0103	1.0181	1.0124	1.0223

TABLE VII. SPEARMAN CORRELATION COEFFICIENTS USING THE PROBABILITY METHOD FOR RANKING ALTERNATIVES

Method	Entropy	MEREC	LOPCOW	SPC
Equal	0.9596	0.9842	0.9947	0.9246
Entropy		0.9526	0.9491	0.9193
MEREC			0.9789	0.9632

LOPCOW				0.9140
Average	0.9699			

TABLE VIII. SPEARMAN CORRELATION COEFFICIENTS USING THE TOPSIS METHOD FOR RANKING ALTERNATIVES

Method	Entropy	MEREC	LOPCOW	SPC
Equal	0.9474	0.9491	0.9702	0.9123
Entropy		0.9421	0.8842	0.8930
MEREC			0.8842	0.9825
LOPCOW				0.8404
Average	0.9205			

TABLE IX. SPEARMAN CORRELATION COEFFICIENTS USING THE RAM METHOD FOR RANKING ALTERNATIVES

Method	Entropy	MEREC	LOPCOW	SPC
Equal	0.9719	0.9509	0.9877	0.9105
Entropy		0.9596	0.9404	0.9439
MEREC			0.9246	0.9860
LOPCOW				0.8772
Average	0.9453			

Across Tables VII-IX, all Spearman coefficients between any two weighting methods are notably high, exceeding 0.8. This suggests that all sets of bank rankings are considered appropriate [29]. However, a more detailed analysis reveals that the Spearman coefficient between any two weighting methods consistently performs better when the Probability method is used for ranking compared to TOPSIS and RAM. When the Probability method ranks alternatives, the minimum Spearman coefficient is 0.9140 (between LOPCOW and SPC). For TOPSIS, the minimum is 0.8404 (also between LOPCOW and SPC), and for RAM, it is 0.8772 (again, between LOPCOW and SPC). This partially indicates that the highest level of ranking stability for alternatives is achieved when the Probability method is used. Within this dataset, TOPSIS yields the least stable rankings across weighting schemes, which is consistent with prior evidence indicating that it is comparatively sensitive to criterion weights [30]. Furthermore, the average Spearman coefficient among weighting methods is 0.9699 when using the Probability method for ranking, 0.9205 when utilizing the TOPSIS method, and 0.9453 when employing the RAM method. This further reinforces the conclusion that the highest level of ranking stability is ensured by the Probability method, followed by RAM, and then TOPSIS.

IV. CONCLUSION

Evaluating a bank's financial performance is a complex and consequential process for competition, transparency, and informed managerial decision-making. Rankings depend materially on both the weighting scheme and the ranking procedure. In this study, five objective weighting methods: Equal, Entropy, MEREC, LOPCOW, and SPC, and three ranking procedures: Probability, TOPSIS, and RAM, were compared on nineteen banks and seven criteria under consistent benefit and cost handling. An inverse pattern was observed between Entropy and SPC: the criteria assigned smaller weights by Entropy tended to receive larger weights under

SPC, and vice versa. The extremes of the ordering proved stable across all combinations of weighting and ranking, with B7, B5, B6, and B3 consistently occupying the top four positions, and B15 and B4 consistently occupying the bottom two. Considering the cross-scenario stability, Entropy produced the lowest R_{score} values across procedures in this dataset. In contrast, SPC produced the highest, indicating that Entropy yields the most stable rankings and SPC the least stable. In terms of concordance across weighting schemes, Probability achieved the highest Spearman coefficients on average, followed by RAM, whereas TOPSIS showed the most extraordinary sensitivity to the choice of weights.

These findings suggest that when stability is a priority, Entropy is a suitable objective weighting choice, and Probability is an effective default ranking procedure, with RAM as a close alternative. TOPSIS remains useful but should be accompanied by sensitivity checks when weighting schemes vary. The analysis is limited to objective weights, without eliciting expert judgment on the importance of the criteria. Future work can incorporate subjective or hybrid weighting methods, such as SIWEC, PIPRECIA, and ROC, and extend robustness assessment through bootstrap or cross-temporal validation to strengthen the practical evaluations of bank performance.

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