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Analysis of Efficiency and Productivity of Commercial Banks in Turkey Pre- and during COVID-19 with an Integrated MCDM Approach

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Abstract: Above all, this study is original in that it reveals the efficiency and productivity of banks exposed to the current pandemic situation. The aim of this study is to evaluate bank efficiency and productivity of commercial banks operating in Turkey pre- and during COVID-19 by using a novel integrated multi-criteria decision-making (MCDM) approach. We divided the banks into three groups in order to evaluate the differences in terms of their efficiency and productivity: state banks, foreign banks and private domestic banks. This paper fills a gap in the literature by using a novel integrated MCDM approach including SWARA II as a subjective weighting method, MEREC as an objective weighting method, and MARCOS as a ranking method to evaluate bank efficiency and productivity. The results reveal that banks with foreign investors achieved higher productivity than other bank groups and the productivity of state banks decreased especially during the COVID-19 period. It should also be noted that state banks are restricted to certain political objectives.

Keywords: multi-criteria analysis; bank efficiency and productivity; pre- and during COVID-19; Turkish banking sector; SWARA II; MEREC; MARCOS

MSC: 91-11

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1. Introduction

While the banking sector contributes to the development of the real sector with its intermediary role in the financial system, it is also one of the most important macroeconomic stability indicators for a whole country's economy. Banks do not only exercise money but are also the organizations that produce money. Banks create new money whenever they make loans. Ninety-seven percent of the money in the economy today exists as bank deposits, while just 3% is physical cash [1]. The banking industry in a country works in various ways to make life easier for the public and businesses by providing services such as credit cards, transaction accounts, liquidity creation, and transmission channels. Among a wide range of studies on the banking industry, the performance, efficiency, and productivity of banks have attracted the attention of numerous researchers.

It has been nearly two years since the outbreak of the COVID-19 virus, which was first reported in Wuhan City, China, and has rapidly spread rest of the world. Currently, the number of people affected by the coronavirus pandemic worldwide is more than 455 million [2]. The COVID-19 pandemic has adversely affected individuals, businesses, and communities. Due to this unexpected shock, many markets, especially, financial markets, have experienced substantial losses.

Exogenous shock such as the pandemic creates multiple crises for the banking industry, this is one of the most common reasons for bank failure rates to rise [3]. In crisis times such as the COVID-19 pandemic, customers' withdrawal of deposits reduces the profitability of banks and contributed to weakening credit conditions [4]. The spread of this exogenous shock has already affected the banking industry in many countries of the world [5,6]. Concerns that the banking industry is continuing to carry out the financial intermediation role in the economy have increased [7]. Financial soundness indicators of the Turkish banking sector are given in Table 1.

Table 1. Financial soundness indicators of Turkish banking sector (percent).

	Capitalization Regulatory Capital to Risk-Weighted Assets	Liquidity Liquid Assets to Short-Term Liabilities	Asset Quality Nonperforming Loans to Total Gross Loans	Loan Loss Provisions to Nonperforming Loans	Profitability	
					ROA	ROE
Pre-COVID-19 (December 2019)	18.4	64.8	5.0	65.1	1.4	10.8
Latest 2021 Q3	17.3	70.0	3.4	78.1	1.4	12.2

Sources: IMF, Financial Soundness Indicators database [8].

Compared to the pre-COVID-19 period, banks' capital adequacy ratios and nonperforming loans to total gross loans ratios have fallen slightly; however, it is seen that although the loan loss provisions rates of banks have increased, their profitability has not decreased. The resilience of the Turkish banking sector against the COVID-19 shock could be supported by financial policy measures taken. Thanks to rapid loan growth and postponement of loan payments, banks were able to maintain their asset quality. As mentioned in Table 1, banks' NPL ratios decreased from 5.0 percent in December 2019 to 3.4 percent as of 2021 Q3, and state banks' NPL ratios were lower than other banks. Similar to 2021, in 2022 banks may face a considerable rise in non-performing loans due to an increase in individuals' and businesses' delinquencies.

The COVID-19 pandemic has increased the challenges of digitalization and forced banks to speed up the digital transformations because banks need to make operating model changes: all staff working from home, branches closed. As bank customers now more than ever want customer-centric, easy-to-use, low-cost, and always-accessible financial services, this puts high pressure on banks to change their business models. The developments in the banking sector, which accelerated with the effect of COVID-19, on the one hand have provided an opportunity in terms of competition in the sector with more efficient processes and new products, on the other hand, it further challenged the traditional business models of banks by supporting the entry of new competitors into the system. The long-term impact of digitalization will depend on the prevailing market structure [9–11].

Efficiency can be defined as the level to reach the present aim and productivity is defined as the present sources and the ratio of output to input. Efficiency can be estimated in two ways: output maximization and input minimization, known as "Input orientation" and "Output orientation" [12–14]. When the literature on bank efficiency and productivity is examined [15], there are studies on branch [16–18], comparison [19], deregulation and regulation [20,21], environment and efficiency [22], input–output [23], risk [24,25] and stock performance [26,27]. In the literature, there are two main methodologies, including non-parametric; data envelopment analysis [28–34], free disposal hull [35] and parametric practices; stochastic frontier approach [36–40], distribution-free approach [41,42] and thick frontier approach [43]. In the literature, there are almost no studies on bank efficiency and productivity using MCDM methods [44–47]. In numerous studies, efficiency and productivity variables can be evaluated in three categories [43]; bank-specific variables [33]; macroeconomic variables [48] and regulatory variables [49].

This paper contributes to academic research by exploring the effect of the COVID-19 outbreak on the Turkish banking industry. In the present study, we tried to understand whether exogenous shocks such as the COVID-19 outbreak have an impact on the efficiency and productivity of the Turkish banking sector and whether the ownership structure affects the efficiency and productivity of the banks. In order to investigate the effect of the ownership structure on efficiency and productivity, twelve commercial banks operating in

Turkey were divided into three groups: state banks (Türkiye Cumhuriyeti Ziraat Bankası A.Ş., Türkiye Halk Bankası A.Ş. and Türkiye Vakıflar Bankası T.A.O.), domestic private banks (Akbank T.A.Ş., Türkiye İş Bankası A.Ş., Türk Ekonomi Bankası A.Ş., and Yapı ve Kredi Bankası A.Ş.), and foreign banks (Denizbank A.Ş., HSBC Bank A.Ş., ICBC Turkey Bank A.Ş., QNB Finansbank A.Ş., and Türkiye Garanti Bankası A.Ş.). The purpose of this study is to evaluate the bank efficiency productivity of the commercial banks operating in Turkey pre- and during COVID-19 by using a novel integrated multi-criteria decision-making (MCDM) approach. The contributions of this study are as follows. First, twelve (six for each group) bank-specific variables were determined for efficiency and productivity. Second, the present study fills a gap in the literature by using a different method and period (pre- and during COVID-19) than is commonly used in the previous studies. Another contribution of this study is to apply a novel integrated MCDM approach including SWARA II as a subjective weighting method, MEREC as an objective weighting method, and MARCOS as a ranking method to evaluate the efficiency and productivity of the commercial banks operating in Turkey. The SWARA II method was very recently developed by Keshavarz Ghorabaee [50] to obtain objective weights of criteria. The MEREC method proposed by Keshavarz-Ghorabaee et al. [51] is also a new objective criteria weighting method. The measurement of alternatives and ranking according to compromise solution (MARCOS) method has been recently proposed by Stević et al. [52] for ranking alternatives.

The rest of the paper is organized into the following sections. In Section 2, a comprehensive review of the relevant literature is given. The methodology is explained in Section 3 by considering the integrated MCDM approach including SWARA II —MEREC—MARCOS and the steps of the evaluation procedure of this study. In Section 4, the new integrated approach presented is applied according to the evaluation procedure explained in the previous subsection to assess and rank efficiency and productivity of commercial banks operating in Turkey pre- and during COVID-19 periods. In addition, a sensitivity analysis is performed through the comparison of the applied model with other MCDM methods, and the calculation of spearman's correlation coefficients are provided at the end of Section 4. Finally, the study is concluded with the directions for future research.

2. Literature Review

MCDM methods are widely used for performance evaluation or determination of the best choice for many businesses and sectors. Although there are many studies in the literature evaluating the financial performance of banks using multi-criteria decision-making models, there are very few studies on efficiency and productivity. The need for these studies is gradually increasing due to technological developments, globalization, and increasing competition. For this reason, in this part of the study, other studies in the literature using MCDM methods that evaluate the financial performance of banks will be included. Wang et al. [28] examined the relationship between intellectual capital (IC) and various performance ratios (BHC) of bank holding companies. In the study, a two-stage DEA model was created using a fuzzy multi-objective programming approach to calculate the productivity score. The created model provides a common scale in order to compare the performances, which facilitates the calculation process and increases the discrimination power. The performance ratios of intellectual capital and bank holding companies were analyzed using the truncated-regression model and a positive relationship was found between them. As a result of the study, a productivity improvement map was proposed. It was recommended to increase the efficiency of the performance ratios of inefficient bank holding companies, which can be detected through the unified decision matrix. Ömürbek et al. [53] have made a sustainable performance analysis of large-scale banks in Turkey, which is considered according to their size. They aimed to make a general ranking by using ARAS, MOOSRA, and COPRAS methods, which are among the MCDM methods. As a result of the sustainable performance ranking of commercial banks in Turkey, it was determined that Ziraat Bank is in the first place, Türkiye İş Bankası is in the second place, and Halkbank is in the third place in all three methods. Vakıfbank had the lowest sustainable financial performance value.

In their study, Dinçer and Yüksel [54] made a balance scorecard-based (BSC) review of new services development (NSD) in the Turkish banking sector. In weighting the criteria, performance rankings were made by using fuzzy ANP (FANP), Monte Carlo simulation, fuzzy TOPSIS (FTOPSIS), and fuzzy VIKOR (FVIKOR) models, respectively. A Monte Carlo simulation was used to calculate the BSC-based dimensions of the NSD. It was determined that the rankings achieved by the FTOPSIS and FVIKOR models depend on the size of the bank. The study is unique because it is one of the rare studies in which the BSC-based NSD analysis is performed for the Turkish banking sector, and it is a study in which FANP, FTOPSIS, FVIKOR, and Monte Carlo simulation techniques are integrated. As a result of the comparative analysis, it was found that the alternative models are consistent in the performance ranking and contribute to the successful acquisition of probabilistic values in the fuzzy environment. In addition, it was observed that the performances of foreign capital banks are worse than private and public banks. For this reason, suggestions were made for banks with foreign capital. It is stated that the comparative advantage of foreign banks compared to other banks can be increased by defining and determining the expectations of customers and developing new services.

In the studies of Ozcalici and Bumin [55], a 2018 performance evaluation of publicly traded Turkish banks traded in Borsa Istanbul was performed. Using quarterly financial statements, a multidimensional data set was obtained by using various financial ratios, personnel and branch network, daily stock market returns, and standard deviations of said daily returns. Many weight combinations were determined for the variables examined using the self-organizing maps technique. EDAS, MOORA, OCRA, and TOPSIS techniques were used because the calculation steps are very close to each other. It was determined that the OCRA technique gave consistent results when compared for different periods. It was determined that the highest correlation with the results of the OCRA method was found in the TOPSIS technique. Puri and Verma [56] aimed to develop an integrated algorithm using the data envelopment analysis (DEA) and multi-criteria decision-making (MCDM) techniques based on the subjective preferences of decision-making units. To prove the feasibility and robustness of the proposed (DEA-MSDM) algorithm, twelve Indian banks were selected and three input and two output variables were determined for the 2018–2019 period. The study is unique as it is the first to combine cross-productivity and subjective decision-making approaches. As a result of the study, it was found that NPAs have a significant effect on the ranking of selected banks and it is very important for bank experts and policymakers to consider the impact of peer review and subjective assessment. Tuysuz and Yıldız [57] presented a hybrid multi-criteria performance evaluation model that combines the subjective judgments of decision-makers and the gray relational analysis (GRA) method. In the study, a real-life application of the proposed performance evaluation model and an application of a private bank operating in the agricultural banking sector in Turkey were conducted in order to show the effectiveness of the model. Considering that the presented hybrid model is based on both probability theory and fuzzy set theory, a highly representative model that handles all dimensions of uncertainty in the decision-making process was obtained. Shakouri et al. [58] presented a stochastic p-robust data envelopment analysis (DEA) model for the efficiency measurement of an Iranian commercial bank. To eliminate the uncertainty of expert opinions, a DEA-based stochastic p-robust model based on both robust and stochastic optimizations is proposed. It was determined that the stochastic p-robust DEA model is an appropriate generalization of the traditional DEA and reaches the desired robustness level. As a result of the study, it was shown with the help of an example that the objective values of the input and output models are not the inverse of each other as in the classical DEA models. It was found that such a proposed model provides better protection against uncertain situations that are often overlooked. This indicates the originality of the study. In her study, Ünvan [59] ranked the performances of the top seven banks in terms of total asset size with TOPSIS and fuzzy TOPSIS methods, using the criteria selected according to the reports received from the Banks Association of Turkey for the 2014–2018 fiscal years. Considering the results of the study, it can be said that both methods give significant results. However, the difference between the two methods in terms of the evaluated period does not allow a one-to-one comparison of the financial performances of banks. Because, while financial performances can be evaluated annually with the TOPSIS method, only the whole of a certain period can be evaluated in the fuzzy TOPSIS method. Sama et al. [60] examined the performance of Indian private sector banks with multi-criteria decision-making techniques. CRITIC, TOPSIS, and GRA decision-making techniques were used in the study. They utilized a combination of MCDM techniques for the first time, namely CRITIC-TOPSIS and CRITIC-GRA. Outputs for Indian private sector banks with selected inputs were examined. As a result, HDFC was the top-performing bank, while Bandhan Bank was ranked second. According to the findings, it was concluded that private sector banks should increase their performance by investing in income-generating areas. Yazdi et al. [61] used Balance Scorecard and MCDM techniques for the performance ranking of Colombian banks. In the study, in which the step-wise weight assessment ratio analysis (SWARA) method was used for the weighting of the decision matrix, the performance indicators were listed by the weighted aggregate product assessment (WASPAS) method. The results of the study revealed that the International Bank of Colombia has a much better performance than other Colombian banks.

Maredza et al. [62] examined the internal relations between the banking performance of the Southern African Development Community (SADC) countries and the level of social welfare. In the study, in which the three-stage multi-criteria decision-making (MCDM) approach was used, the criterion weights were determined by the SWARA method without bias, the utility functions in the model were calculated simultaneously with the COPRAS method, and the distances to the ideal solution were simultaneously computed using the TOPSIS method. It was concluded in this study, in which a new non-linear stochastic structural relationship model was used and the internality measurement was made, that the SADC banking performance can reach higher human development index (HDI) values through efficient financial intermediation services, dissemination of good management practices, and other positive spillovers in these countries. Moreira et al. [63], in their study to show that multi-criteria decision-making methods can be applied in the context of information security, examined a large Brazilian bank. A case study using the multi-criteria methodology of decision support—constructivist (MCDA-C) method was applied. As a result of the analyzes made between different categories, it was concluded that the importance of the security continuous monitoring controls category came to the fore. This study also showed that the constructivist method is one of the best methods for a better understanding of risk management. Daiy et al. [64] proposed a hybrid decision model for open banking in their study in which they discussed a local bank and four non-banking service businesses in Taiwan. This hybrid model, which is based on the trust-weighted fuzzy evaluation technique, is the first study to adopt open banking. Reviews were weighted based on information from industry experts. The findings allow the determination of the relative importance of some critical factors in terms of the management and the choice of strategic partners in open banking activities. Ic et al. [65], in their study aiming to measure and compare the performance of banks in Turkey according to their financial ratios, made a performance ranking by integrating regression-AHP and VIKOR methods. The study is the first to analyze bank performance using the regression-AHP-VIKOR combined model. The findings show that an AHP-based VIKOR model contributes to the selection of the best bank in the multi-criteria decision-making process. No et al. [66], identified some branches of a bank in Iran and proposed a new multi-criteria solution procedure under uncertainty. The proposed model combines expert opinions and Shannon's entropy approach to make a new criterion weighting. In addition, in order to eliminate the deficiencies of the intermittent EDAS method in practice, the model was updated and changed for the interval type data. In a study in which mobile banking rankings on seven Indian banks were investigated, Roy and Shaw [67] proposed an m-TOPSIS banking application selection model based on a combined fuzzy best-worst method (fuzzy-BWM) and a fuzzy TOPSIS (fuzzy-TOPSIS). In the analysis, the fuzzy-BWM technique was used to determine the weights of the factors, and the fuzzy-TOPSIS technique was used to rank the m-banking applications. The results show that application functionality, convenience, and performance expectation are significant factors in the selection of an m-banking application, while performance quality, security, and compliance are considered important. Chen et al. [68] examined five major block-chain-based systems with a local bank serving in Taiwan and proposed a hybrid decision model with trust-weighted fuzzy evaluations. They stated that understanding the importance of these factors will contribute to the determination of the ideal business strategy for the bank and that the most important dimension is not the technical capacity of the banks but the relevant policies and regulations. Abdel-Basset et al. [69], in their study where they proposed a plitogenic-based model to evaluate the performance of Egyptian commercial banks, evaluated the top ten Egyptian commercial banks on the basis of three main criteria and 19 sub-criteria, including financial, customer satisfaction, and qualitative evaluation. The importance levels of the selected criteria were determined by the AHP technique. The ideal solution was obtained using the three MCDM methods including TOPSIS, VIKOR, and COPRAS. Thus, the performances of the top ten Egyptian banks were ranked comparatively. The authors concluded that CIB had the highest performance among the top 10 commercial banks in Egypt, while Faisal Islamic Bank and Bank Audi had the lowest performance.

3. Methods

The methodology of this study presents a new integrated MCDM approach comprising three MCDM tools. These tools are SWARA II as the subjective weighting method, MEREC as the objective weighting method, and MARCOS as the ranking of alternatives. These tools are delineated in the following subsections, and the procedure of the presented approach is described in the last subsection. Since the presented approach is applicable in dealing with MCDM problems, in all parts of this section, it is supposed that there is an initial decision matrix with m alternatives and n criteria, which presents the performance rating of i-th alternative on j-th criterion. The decision matrix X of a decision problem including multiple criteria can be described as follows:

$$X = \begin{array}{c c} & \begin{array}{cccc} w_1 & w_2 & \cdots & w_n \\ C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad (1)$$

3.1. Stepwise Weight Assessment Ratio Analysis II (SWARA II)

In order to determine the subjective weights of criteria in an MCDM problem, several methods such as AHP, ANP, SWARA (step-wise weight assessment ratio analysis), BWM (best–worst Method), FUCOM (full consistency method), and LBWA (level-based weight assessment) can be applied [70–76]. In this study, a novel subjective criteria weighting technique namely SWARA II proposed in 2021 by Keshavarz-Ghorabaee [51], which is a modified version of the SWARA method, was used. The overall structure of this new method is similar to the original one. Its procedure also uses a procedure that includes the ordering and preferences of the criteria just like the original one. Since the SWARA II method becomes easier and more practical for decision-makers because of modifications in its structure, it was preferred to be used in this study.

The steps of SWARA II to determine subjective criteria weights are as follows [50]:

Step 1: Sort the criteria in descending order of importance, i.e., the first criterion in the sorted list has the highest importance. Let us denote by t_j the position or rank of the j-th criterion in the sorted list ($t_j \in \{1, 2, \ldots, n\}$).

Step 2: Ask the decision-maker to express the relative preference (RP) concerned with each criterion by comparing it with the next criterion in the sorted list of the first step.

The question "How much more important is the t_j-th criterion than the t_j+1-th criterion?" could be used to elicit the preferences of the decision-maker. In order to answer this question, linguistic variables and the Likert scale can be utilized. The linguistic variables and their corresponding values given in Table 2 are used in this study.

Table 2. Linguistic variables and their corresponding values [50].

Linguistic Variable	Value
VVL (very very low)	1
VL (very low)	2
L (low)	3
ML (medium–low)	4
M (medium)	5
MH (medium–high)	6
H (high)	7
VH (very high)	8
VVH (very very high)	9

Step 3: Determine the preference degree (PD) of each criterion. To determine the values of PD, it is necessary to quantify the relative preferences of Step 2 first. If the quantified value of the relative preference of the t_j-th criterion is denoted by $P_{[t_j]}$, the values of PD can be defined as follows.

$$PD_{[t_j]} = u\left(P_{[t_j]}\right) \tag{2}$$

where u is a utility function that turns the quantified values of the relative preferences into some scaled values in the range [0, 1], and therefore $0 \leq PD_{[t_j]} \leq 1$. In this study, Equation (3) is utilized as a nonlinear utility function; nevertheless, this function can be defined according to decision-makers' opinions and the characteristics of the problem.

$$u(x) = \left(\frac{x}{10}\right)^2 \tag{3}$$

Step 4: Calculate relative weighting coefficients. These coefficients are calculated based on the position of each criterion in the sorted list and the values of PD. Let $V_{[t_j]}$ denote the values of relative weighting coefficients. Starting from the n-th criterion, the following equation is used for the calculation.

$$V_{[t_j-1]} = \left(1 + PD_{[t_j-1]}\right) \times V_{[t_j]} \tag{4}$$

where $1 \leq V_{[t_j]} \leq 2$ and $V_n = 1$

Step 5: Determine the subjective weights of criteria. The subjective weights are determined by scaling the values of relative weighting coefficients + using Equation (5).

$$w_j^s = \frac{V_{[t_j]}}{\sum_{t_j=1}^{n} V_{[t_j]}} \tag{5}$$

3.2. Method Based on the Removal Effects of Criteria (MEREC)

There are several methods such as entropy, CRITIC, and standard deviation (SD) used to determine objective criteria weights. Recently, a new objective weighting method called MEREC (method based on the removal effects of criteria) was introduced to the literature by Keshavarz-Ghorabaee et al. [51]. In order to determine the importance of criteria, the MEREC method uses their removal effects in the decision matrix. This method differs from other methods in that it uses the removal effects of each criterion on the overall performance of the alternatives while calculating criteria weights. Since MEREC is a fairly new method, there are few studies using this method in the literature [50,77]. Therefore, the MEREC method was utilized to obtain the objective weights of bank efficiency and productivity criteria pre- and during COVID-19 in this study.

The calculation steps of MEREC are as follows [50,51]:

Step 1: Construct the decision matrix. Suppose that there is a decision matrix like Equation (1) and $x_{ij} > 0$.

Step 2: Normalize the decision matrix and transform all values into the minimization type. n_{ij}^x denotes the normalized matrix elements. If B^S shows the set of beneficial criteria, and C^S represents the set of non-beneficial criteria, Equation (6) can be used for normalization.

$$n_{ij}^x = \begin{cases} \frac{\min\limits_k x_{kj}}{x_{ij}} \; if\ j \in B^S \\ \frac{x_{ij}}{\max\limits_k x_{kj}} \; if\ j \in C^S \end{cases} \tag{6}$$

Step 3: Calculate the performance of the alternatives (S_i) using a logarithmic measure. These values can be calculated using Equation (7).

$$S_i = \ln\left(1 + \left(1/m \sum_j \left|\ln\left(n_{ij}^x\right)\right|\right)\right) \tag{7}$$

Step 4: Calculate the performance of the alternatives by removing each criterion. If the performance of *i*-th alternative concerning the removal of the *j*-th criterion is symbolized by S'_{ij}, the values of S'_{ij} can be calculated using Equation (8).

$$S'_{ij} = \ln\left(1 + \left(1/m \sum_{k,k\neq j} |\ln(n_{ik}^x)|\right)\right) \tag{8}$$

Step 5: Obtain the removal effect of the *j*-th criterion by computing the summation of absolute deviations related to the values resulted from Steps 3 and 4 of the method. Let us denote by the removal effect of the *j*-th criterion. Using Equation (9), the values of ε_j can be calculated.

$$\varepsilon_j = \sum_i \left|s'_{ij} - S_i\right| \tag{9}$$

Step 6: Determine the objective weights of criteria using the values of removal effects (ε_j) obtained in the previous step. If w_j^O stands for the objective weight of the *j*-th criterion, Equation (10) can be used for calculating.

$$w_j^O = \frac{\varepsilon_j}{\sum_k \varepsilon_k} \tag{10}$$

.

3.3. Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS)

The MARCOS (measurement alternatives and ranking according to compromise solution) method developed in 2020 by Stević et al. for decision-making analysis is based on defining the relationship between alternatives and reference values (ideal and anti-ideal alternatives). The utility functions representing the position of the alternatives with respect to the ideal and anti-ideal solution are defined and a compromise ranking is obtained. The best alternative is the one closest to the ideal and farthest from the anti-ideal [78]. After being introduced to the literature in 2020, the MARCOS method has been used in many practical decision-making problems [52,76,78–87].

The MARCOS method is performed through the following steps [55]:

Step 1: Construct an initial decision-making matrix. Suppose that there is a decision matrix like Equation (1).

Step 2: Construct an extended initial matrix. In this step, the extension of the initial matrix is performed by defining the ideal (*AI*) and anti-ideal (*AAI*) solution as in Equation (11).

$$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \cdots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{22} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \end{array} \tag{11}$$

The anti-ideal solution (*AAI*) is the worst alternative while the ideal solution (*AI*) is an alternative with the best characteristic. Depending on the nature of the criteria, *AAI* and *AI* are defined by applying Equations (12) and (13).

$$AAI = \min_i x_{ij} \; if \; j \in B \; and \; \max_i x_{ij} \; if \; j \in C \tag{12}$$

$$AI = \max_i x_{ij} \; if \; j \in B \; and \; \min_i x_{ij} \; if \; j \in C \tag{13}$$

where B represents a benefit group of criteria, while C represents a group of cost criteria.

Step 3: Normalize the extended initial matrix. The elements of the normalized matrix $N = \left[n_{ij}\right]_{m \times n}$ are obtained by applying Equations (14) and (15).

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \; if \; j \in C \tag{14}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \; if \; j \in B \tag{15}$$

where elements x_{ij} and x_{ai} represent the elements of the extended initial matrix.

Step 4: Determine the weighted matrix $V = \left[v_{ij}\right]_{m \times n}$. The weighted matrix V is obtained by multiplying the normalized matrix N with the criteria weights (w_j) as in Equation (16).

$$v_{ij} = n_{ij} \times w_j \tag{16}$$

Step 5: Calculate the utility degree of alternatives K_i. The utility degrees of an alternative in relation to the anti-ideal and ideal solution can be calculated by applying Equations (17) and (18).

$$K_i{}^{-} = \frac{S_i}{S_{aai}} \tag{17}$$

$$K_i{}^{+} = \frac{S_i}{S_{ai}} \tag{18}$$

where S_i (i = 1, 2, … , m) represents the sum of the elements of the weighted matrix V, Equation (19).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{19}$$

Step 6: Determine the utility function of alternatives $f(K_i)$. The utility function is the compromise of the observed alternative in relation to the ideal and anti-ideal solution. The utility function of alternatives is defined using Equation (20).

$$f(K_i) = \frac{K_i{}^{+} + K_i^{-}}{1 + \frac{1 - f(K_i{}^{+})}{f(K_i{}^{+})} + \frac{1 - f(K_i{}^{-})}{f(K_i{}^{-})}} \tag{20}$$

where $f(K_i^-)$ represents the utility function in relation to the anti-ideal solution, while $f(K_i^+)$ represents the utility function in relation to the ideal solution.

Utility functions in relation to the ideal and anti-ideal solutions are determined using Equations (21) and (22).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{21}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{22}$$

Step 7: Rank the alternatives. The ranking of the alternatives is based on the final values of utility functions. It is desirable that an alternative has the highest possible value of the utility function.

3.4. The Evaluation Procedure of the Study

In the present study, an evaluation procedure (Figure 1) was proposed to evaluate and rank the efficiency and productivity of the commercial banks operating in Turkey based on a new integrated MCDM approach comprising SWARA II-MEREC-MARCOS. The explanation of each phase is given in the following sections.

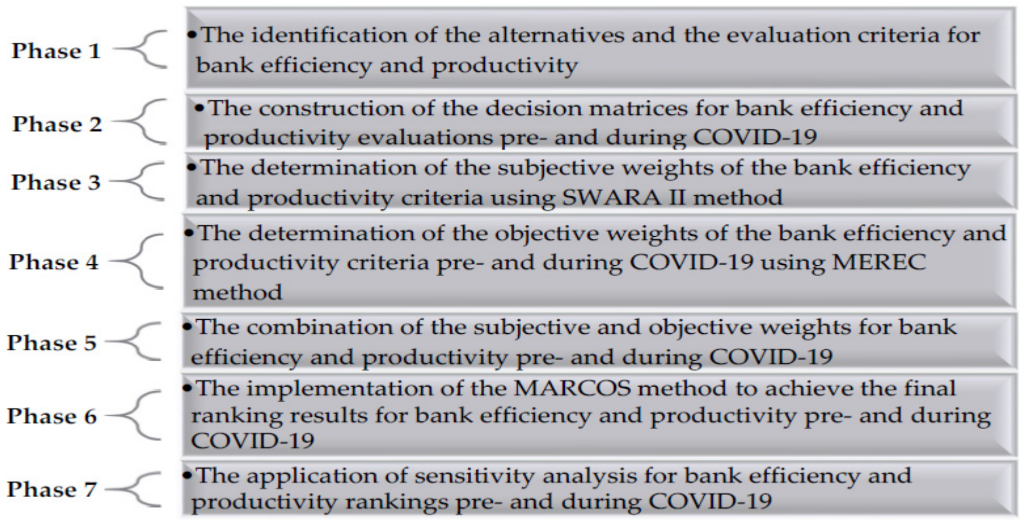

Figure 1. The evaluation procedure of the study.

4. Analysis and Results

In this study, the performance of the twelve commercial banks operating in Turkey was evaluated in terms of the efficiency and productivity perspective pre-COVID-19 (2019) and during COVID-19 (2020) by using an integrated decision-making approach including SWARAII-MEREC-MARCOS. The evaluation framework represented in the methodology of the study is explained in the following phases.

Phase 1. The identification of the alternatives and the evaluation criteria for bank efficiency and productivity: In the first phase of the study, firstly, both private and public commercial banks acting in Turkey were determined. Although there are thirteen commercial banks, twelve commercial banks were considered in this study due to the lack of data on one commercial bank (Şekerbank A.Ş.). In this context, twelve commercial banks of Turkey, Türkiye Cumhuriyeti Ziraat Bankası A.Ş. (B1), Türkiye Halk Bankası A.Ş. (B2), Türkiye Vakıflar Bankası T.A.O. (B3), Akbank T.A.Ş. (B4), Türkiye İş Bankası A.Ş. (B5), Türk Ekonomi Bankası A.Ş. (B6), Yapı ve Kredi Bankası A.Ş. (B7), Denizbank A.Ş. (B8), HSBC Bank A.Ş. (B9), ICBC Turkey Bank A.Ş. (B10), QNB Finansbank A.Ş. (B11), and Türkiye Garanti Bankası A.Ş. (B12) were identified as alternatives. In order to evaluate the efficiency and productivity of the commercial banks, the evaluation criteria were established from efficiency and productivity perspectives.

There is little consensus among researchers about the measurement and definition of efficiency and productivity due to the nature and functions of the banks. Therefore, it has been endeavored to determine the ratios considered meaningful for the efficiency and productivity of the banking sector in this study [36,45–47,88,89]. Thus, these ratios, in other words, efficiency and productivity criteria for banks were determined. As seen in Table 3, six efficiency criteria and six productivity criteria for the banks are defined by considering the opinions of decision-makers. The two efficiency criteria (E5 and E6) are non-beneficial and the remaining four (E1, E2, E3, and E4) are beneficial; all six productivity criteria are beneficial.

Table 3. Bank efficiency and productivity criteria.

Efficiency criteria
E1: Equity/(Credit + Market + Operational Risk Basis)
E2: Total Loans/Total Assets
E3: Interest Income/Interest Expenses
E4: Net Interest Income/Total Assets
E5: Loans Received/Total Assets
E6: Non-performing Loans/Total Loans
Productivity criteria
P1: Profit (Loss) Before Taxes/Total Assets
P2: Net Profit(Loss)/Equity
P3: Total loans and receivables/Branches
P4: Net fees and Commission Incomes/Total Assets
P5: Total Assets/Number of Employees
P6: Profit (Loss) Before Taxes from continuing operations/Total Assets

Phase 2. The construction of the decision matrices for bank efficiency and productivity evaluations pre- and during COVID-19: In the second phase, the decision matrices of the twelve commercial bank alternatives regarding the efficiency and productivity criteria were constructed. Therefore, the initial set of data pre-COVID-19 (2019) and during COVID-19 (2020) of the commercial banks were collected from the Banks Association of Turkey website (http://www.tbb.org.tr, accessed on 10 March 2022).

The decision matrices constructed for evaluating bank efficiency and productivity pre-and during COVID-19 periods are shown in Tables 4 and 5, respectively.

Table 4. The efficiency criteria values of banks pre- and during COVID-19.

	Pre-COVID-19						**During COVID-19**					
Banks	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**
B1	17.020	64.915	2.833	68.946	162.824	2.907	18.220	64.145	2.313	63.724	199.291	2.257
B2	14.332	68.036	5.149	67.654	129.381	1.294	15.226	70.481	3.762	66.136	153.603	1.751
B3	16.614	62.271	5.928	69.641	144.785	1.133	16.440	59.009	3.969	62.883	172.645	1.162
B4	20.973	56.636	7.289	56.542	183.600	2.208	21.843	58.896	6.834	56.785	240.248	2.253
B5	17.865	64.990	5.991	64.479	179.438	2.464	18.684	71.893	4.223	59.217	220.667	2.107
B6	16.948	56.814	6.529	61.796	185.662	3.732	18.509	57.290	5.573	61.546	246.125	3.868
B7	17.814	55.058	7.600	62.056	170.605	1.539	18.231	56.174	6.410	63.787	205.369	1.528
B8	17.685	55.368	10.449	67.614	161.961	1.206	18.670	54.488	8.861	67.761	234.481	0.540
B9	20.415	44.959	4.027	50.271	185.717	1.792	16.868	41.853	2.366	60.413	211.524	3.240
B10	18.635	23.129	1.847	49.959	143.021	0.844	19.479	18.824	0.457	40.097	163.551	1.611
B11	15.732	59.782	6.955	65.484	170.395	3.218	16.439	56.646	6.111	65.723	240.527	3.131
B12	19.567	58.518	6.887	64.212	192.109	1.341	18.538	58.959	4.565	63.938	276.579	1.919

Table 5. The productivity criteria values of banks pre- and during COVID-19.

Banks	Pre-COVID-19						During COVID-19					
	P1	P2	P3	P4	P5	P6	P1	P2	P3	P4	P5	P6
B1	1.177	9.708	254.825	0.006	13.790	0.952	1.149	9.581	342.842	0.0033	14.182	0.830
B2	0.431	5.620	307.364	0.006	18.854	0.376	0.475	6.922	443.974	0.0038	19.912	0.382
B3	0.861	9.131	309.747	0.009	17.853	0.717	0.921	12.603	469.538	0.0049	17.893	0.668
B4	1.887	11.034	264.376	0.013	16.537	1.503	1.781	10.686	353.797	0.0087	17.115	1.405
B5	1.317	11.001	146.960	0.012	19.011	1.296	1.107	11.143	182.268	0.0095	19.451	1.147
B6	1.469	11.175	227.572	0.013	18.924	0.997	1.491	10.755	297.899	0.0083	19.167	0.841
B7	1.120	8.979	284.236	0.014	19.658	0.929	1.425	11.447	351.168	0.0114	19.206	1.105
B8	0.944	8.057	1041.585	0.023	17.343	0.900	1.049	8.832	2366.326	0.0137	17.144	0.854
B9	1.722	15.630	228.160	0.011	106.000	1.345	1.348	13.090	341.153	0.0078	111.000	0.990
B10	0.451	3.431	211.351	0.005	26.169	0.233	0.354	4.508	255.618	0.0053	25.299	0.225
B11	1.750	16.778	226.614	0.015	17.000	1.443	1.320	13.852	314.439	0.0104	18.718	1.094
B12	1.998	12.262	275.401	0.016	23.023	1.575	1.753	10.769	353.234	0.0121	23.392	1.266

Phase 3. The determination of the subjective weights of bank efficiency and productivity criteria using the SWARA II method: In the third phase, the subjective weights of efficiency and productivity criteria were determined based on the judgements of decision-makers. In this phase, the calculation steps of the SWARA II method and the obtained results are given in Tables 6 and 7 for efficiency and productivity criteria, respectively.

Table 6. Calculations of the subjective weights of bank efficiency criteria.

Sorted Criteria (C_j)	t_j	RP	$P_{[tj]}$	$PD[t_j]$	$V_{[tj]}$	w_j^S
E5	1	L	3	0.09	2.115	0.211
E3	2	ML	4	0.16	1.941	0.194
E4	3	VVL	1	0.01	1.673	0.167
E6	4	VVL	1	0.01	1.656	0.165
E1	5	VH	8	0.64	1.640	0.164
E2	6	–	–	–	1	0.100

Table 7. Calculations of the subjective weights of bank productivity criteria.

Sorted Criteria (C_j)	t_j	RP	$P_{[tj]}$	$PD[t_j]$	$V_{[tj]}$	w_j^S
P2	1	ML	4	0.16	1.888	0.220
P6	2	VL	2	0.04	1.628	0.189
P4	3	VL	2	0.04	1.565	0.182
P1	4	H	7	0.49	1.505	0.175
P3	5	VVL	1	0.01	1.010	0.117
P5	6	-	-	-	1	0.116

Phase 4. The determination of the objective weights of the bank efficiency and productivity criteria using the MEREC method: In the fourth phase, the objective weights of bank efficiency and productivity criteria were established through the calculation steps of the MEREC method. The results are given in Tables 8 and 9 for objective weights of bank efficiency and productivity criteria for pre-and during COVID-19, respectively.

Table 8. The objective weights of bank efficiency criteria pre-and during COVID-19.

Pre-COVID-19						During COVID-19					
w_1^O	w_2^O	w_3^O	w_4^O	w_5^O	w_6^O	w_1^O	w_2^O	w_3^O	w_4^O	w_5^O	w_6^O
0.090	0.096	0.281	0.095	0.107	0.330	0.050	0.084	0.248	0.128	0.096	0.392

Table 9. The objective weights of bank productivity criteria pre-and during COVID-19.

Pre-COVID-19						During COVID-19					
w_1^O	w_2^O	w_3^O	w_4^O	w_5^O	w_6^O	w_1^O	w_2^O	w_3^O	w_4^O	w_5^O	w_6^O
0.183	0.196	0.126	0.141	0.088	0.264	0.212	0.150	0.147	0.157	0.085	0.249

Phase 5. The combination of the subjective and objective weights: In this phase, the objective weights, w_j^O, obtained from MEREC were combined with subjective weights, w_j^S, obtained using the SWARA II method. The calculation of the subjective-objective weights, w_j^{SO}, is formulated as follows:

$$w_j^{SO} = \frac{w_j^S w_j^O}{\left(\sum_{j=1}^{n} w_j^S w_j^O\right)} \tag{23}$$

In this phase, the subjective-objective weights of bank efficiency and productivity criteria were determined by Equation (23). The obtained results are given for subjective–objective weights of bank efficiency criteria in Table 10 and subjective-objective weights of bank productivity criteria in Table 11 pre-and during COVID-19.

Table 10. The subjective-objective weights of the efficiency criteria pre- and during COVID-19.

Pre-COVID-19						During COVID-19					
w_1^{SO}	w_2^{SO}	w_3^{SO}	w_4^{SO}	w_5^{SO}	w_6^{SO}	w_1^{SO}	w_2^{SO}	w_3^{SO}	w_4^{SO}	w_5^{SO}	w_6^{SO}
0.086	0.056	0.317	0.093	0.132	0.318	0.048	0.049	0.281	0.125	0.119	0.378

Table 11. The subjective-objective weights of the productivity criteria pre- and during COVID-19.

Pre-COVID-19						During COVID-19					
w_1^{SO}	w_2^{SO}	w_3^{SO}	w_4^{SO}	w_5^{SO}	w_6^{SO}	w_1^{SO}	w_2^{SO}	w_3^{SO}	w_4^{SO}	w_5^{SO}	w_6^{SO}
0.182	0.245	0.084	0.146	0.058	0.284	0.215	0.191	0.100	0.165	0.057	0.272

Phase 6. The implementation of the MARCOS method to achieve the final ranking results for bank efficiency and productivity pre- and during COVID-19: In this phase, the calculation steps of the MARCOS method were given only for bank efficiency pre-COVID-19 era as an example. According to the MARCOS method, the first step is to construct an initial decision-making matrix given in Table 4 for bank efficiency pre-COVID-19 period. The second step involves the construction of an extended initial matrix by defining the ideal (AI) and anti-ideal (AAI) solutions by using Equation (1). AAI and AI are defined by applying Equations (2) and (3) depending on the nature of the criteria. In this example, benefit criteria are C1, C4, C5, and C6; cost (non-beneficial) criteria are C2 and C3. The extended initial matrix, normalized decision matrix, and weighted normalized decision matrix are given in Table 12, Table 13, and Table 14, respectively. Finally, bank efficiency ranking results pre- and during COVID-19 are depicted in Table 15. By applying the similar calculation steps, bank productivity ranking results pre- and during COVID-19 are also given in Table 16.

Table 12. The extended initial matrix of bank efficiency for pre-COVID-19.

Banks	E1	E2	E3	E4	E5	E6
AAI	14.332	68.036	10.449	49.959	129.381	0.844
B1	17.020	64.915	2.833	68.946	162.824	2.907
B2	14.332	68.036	5.149	67.654	129.381	1.294
B3	16.614	62.271	5.928	69.641	144.785	1.133
B4	20.973	56.636	7.289	56.542	183.600	2.208
B5	17.865	64.990	5.991	64.479	179.438	2.464
B6	16.948	56.814	6.529	61.796	185.662	3.732
B7	17.814	55.058	7.600	62.056	170.605	1.539
B8	17.685	55.368	10.449	67.614	161.961	1.206
B9	20.415	44.959	4.027	50.271	185.717	1.792
B10	18.635	23.129	1.847	49.959	143.021	0.844
B11	15.732	59.782	6.955	65.484	170.395	3.218
B12	19.567	58.518	6.887	64.212	192.109	1.341
AI	20.973	23.129	1.847	69.641	192.109	3.732

Table 13. The normalized decision matrix of bank efficiency for pre-COVID-19.

Weight	**0.086**	**0.056**	**0.317**	**0.093**	**0.132**	**0.318**
Banks	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**
AAI	0.683	0.340	0.177	0.717	0.673	0.226
B1	0.812	0.356	0.652	0.990	0.848	0.779
B2	0.683	0.340	0.359	0.971	0.673	0.347
B3	0.792	0.371	0.312	1.000	0.754	0.303
B4	1.000	0.408	0.253	0.812	0.956	0.592
B5	0.852	0.356	0.308	0.926	0.934	0.660
B6	0.808	0.407	0.283	0.887	0.966	1.000
B7	0.849	0.420	0.243	0.891	0.888	0.412
B8	0.843	0.418	0.177	0.971	0.843	0.323
B9	0.973	0.514	0.459	0.722	0.967	0.480
B10	0.889	1.000	1.000	0.717	0.744	0.226
B11	0.750	0.387	0.266	0.940	0.887	0.862
B12	0.933	0.395	0.268	0.922	1.000	0.359
AI	1.000	1.000	1.000	1.000	1.000	1.000

Table 14. The weighted matrix of bank efficiency for pre-COVID-19.

Banks	E1	E2	E3	E4	E5	E6
AAI	0.059	0.019	0.056	0.066	0.089	0.072
B1	0.070	0.020	0.206	0.092	0.112	0.248
B2	0.059	0.019	0.114	0.090	0.089	0.110
B3	0.068	0.021	0.099	0.093	0.099	0.096
B4	0.086	0.023	0.080	0.075	0.126	0.188
B5	0.073	0.020	0.098	0.086	0.123	0.210
B6	0.069	0.023	0.090	0.082	0.127	0.318
B7	0.073	0.023	0.077	0.083	0.117	0.131
B8	0.072	0.023	0.056	0.090	0.111	0.103
B9	0.083	0.029	0.145	0.067	0.127	0.153
B10	0.076	0.056	0.317	0.066	0.098	0.072
B11	0.064	0.022	0.084	0.087	0.117	0.274
B12	0.080	0.022	0.085	0.085	0.132	0.114
AI	0.086	0.056	0.317	0.093	0.132	0.318

Table 15. The bank efficiency ranking pre- and during COVID-19.

	Pre-COVID-19						During COVID-19					
Banks	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	**Rank**	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	**Rank**
B1	2.072	0.747	0.265	0.735	0.682	1	2.105	0.534	0.202	0.798	0.508	5
B2	1.332	0.480	0.265	0.735	0.438	10	1.735	0.440	0.202	0.798	0.418	9
B3	1.319	0.476	0.265	0.735	0.434	11	1.530	0.388	0.202	0.798	0.369	11
B4	1.603	0.578	0.265	0.735	0.527	7	2.014	0.511	0.202	0.798	0.486	6
B5	1.690	0.609	0.265	0.735	0.556	5	1.950	0.494	0.202	0.798	0.470	8
B6	1.966	0.709	0.265	0.735	0.647	2	2.672	0.677	0.202	0.798	0.644	1
B7	1.397	0.504	0.265	0.735	0.460	9	1.703	0.432	0.202	0.798	0.411	10
B8	1.263	0.455	0.265	0.735	0.415	12	1.384	0.351	0.202	0.798	0.334	12
B9	1.676	0.604	0.265	0.735	0.551	6	2.495	0.633	0.202	0.798	0.602	3
B10	1.900	0.685	0.265	0.735	0.625	3	2.660	0.675	0.202	0.798	0.642	2
B11	1.797	0.648	0.265	0.735	0.591	4	2.383	0.604	0.202	0.798	0.575	4
B12	1.438	0.518	0.265	0.735	0.473	8	2.007	0.509	0.202	0.798	0.484	7

Table 16. The bank productivity ranking pre- and during COVID-19.

	Pre-COVID-19						During COVID-19					
Banks	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	**Rank**	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	**Rank**
B1	2.641	0.484	0.155	0.845	0.471	9	2.431	0.493	0.169	0.831	0.477	10
B2	1.436	0.263	0.155	0.845	0.256	11	1.489	0.302	0.169	0.831	0.292	11
B3	2.381	0.436	0.155	0.845	0.424	10	2.475	0.502	0.169	0.831	0.485	9
B4	3.909	0.716	0.155	0.845	0.697	4	3.760	0.762	0.169	0.831	0.737	2
B5	3.342	0.612	0.155	0.845	0.596	5	3.160	0.641	0.169	0.831	0.619	7
B6	3.224	0.591	0.155	0.845	0.575	7	3.022	0.613	0.169	0.831	0.592	8
B7	2.845	0.521	0.155	0.845	0.507	8	3.480	0.706	0.169	0.831	0.682	4
B8	3.307	0.606	0.155	0.845	0.589	6	3.390	0.687	0.169	0.831	0.664	6
B9	4.236	0.776	0.155	0.845	0.755	3	3.453	0.700	0.169	0.831	0.677	5
B10	1.076	0.197	0.155	0.845	0.192	12	1.161	0.235	0.169	0.831	0.228	12
B11	4.292	0.787	0.155	0.845	0.765	1	3.502	0.710	0.169	0.831	0.686	3
B12	4.251	0.779	0.155	0.845	0.758	2	3.837	0.778	0.169	0.831	0.752	1

When the bank efficiency ranking results belonged to the pre- and during COVID-19 periods, given in Table 16, are examined, the change in the efficiency of banks during the COVID-19 era is as follows: those with increased efficiency are B2, B4, B6, B9, B10, and B12; those with decreased efficiency were B1, B5, and B7; and those with unchanged efficiency were B3, B8, and B11. The most efficient bank was B1 pre-COVID-19 and B6 during the COVID-19 period. However, B8 was the least efficient bank in both pre- and during the COVID-19 periods.

When the ranking results regarding bank productivity obtained pre- and during the COVID-19 pandemic period, given in Table 17, are examined, the change in the productivity of banks in terms of during the COVID-19 is as follows: B3, B4, B7, and B12 were the banks with increased productivity; B1, B5, B6, B9, and B11 were the banks with decreased productivity; B2, B8, and B10 were the banks with unchanged productivity. While B11 was the most productive bank pre-COVID-19, B12 became the most productive bank during the COVID-19 period. However, B10 was the least efficient bank in both pre- and during the COVID-19 periods.

Table 17. Results of the comparative analysis for bank efficiency pre- and during COVID-19.

	Pre-COVID-19								
Banks	**MARCOS**	**EDAS**	**VIKOR**	**TOPSIS**	**ARAS**	**COPRAS**	**WASPAS**	**CODAS**	**PI**
B1	1	1	1	1	1	2	1	1	1
B2	10	8	11	9	10	9	10	10	8
B3	11	10	10	10	11	11	11	11	10
B4	7	7	6	7	7	7	7	7	7
B5	5	5	5	4	6	6	6	5	5
B6	2	2	2	2	3	3	2	2	2
B7	9	11	9	11	9	10	9	9	11
B8	12	12	12	12	12	12	12	12	12
B9	6	4	4	5	5	5	5	6	4
B10	3	6	8	6	2	1	3	3	6
B11	4	3	3	3	4	4	4	4	3
B12	8	9	7	8	8	8	8	8	9
(r_s)	-	*0.916*	*0.881*	*0.937*	*0.965*	*0.993*	*0.986*	*1.000*	*0.916*
	During COVID-19								
Banks	**MARCOS**	**EDAS**	**VIKOR**	**TOPSIS**	**ARAS**	**COPRAS**	**WASPAS**	**CODAS**	**PIV**
B1	5	4	4	4	5	4	5	5	3
B2	9	8	9	8	9	9	9	9	8
B3	11	10	11	10	11	11	11	11	10
B4	6	9	8	9	8	8	8	6	9
B5	8	7	6	5	7	7	7	7	7
B6	1	2	1	2	3	3	3	1	2
B7	10	11	10	11	10	10	10	10	11
B8	12	12	12	12	12	12	12	12	12
B9	3	1	2	1	2	2	2	3	1
B10	2	3	7	6	1	1	1	2	4
B11	4	5	3	3	4	5	4	4	5
B12	7	6	5	7	6	6	6	8	6
r_s	-	*0.923*	*0.860*	*0.846*	*0.951*	*0.958*	*0.958*	*0.993*	*0.902*

When the results of the rankings obtained in terms of bank efficiency and productivity are examined, it is seen that the efficient bank was not productive or in contrast, the productive bank was not efficient. The ranking results between the efficiency and productivity of the banks pre-COVID-19 are as follows: the banks with higher efficiency compared to their productivity were B1, B2, and B10; the banks whose efficiency was lower than their productivity B3, B4, B6, B7, B8, B9, B11, and B12; the bank with the same efficiency and productivity was B5. Similarly, when the ranking results between the efficiency and productivity of banks pre-COVID-19 are analyzed, the results are as follows: the banks with higher efficiency compared to their productivity were B1, B2, B6, and B10; the banks whose efficiency was lower than their productivity were B3, B4, B5, B7, B8, B9, B11, and B12.

Phase 7. The application of sensitivity analysis for bank efficiency and productivity rankings pre- and during COVID-19: In the last phase, the ranking results obtained with MARCOS were compared with other MCDM methods namely the evaluation based on distance from average solution (EDAS) [90] Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [91], technique for order preference by similarity ideal solution (TOPSIS) [92], additive ratio assessment (ARAS) [93], complex proportional assessment (COPRAS) [94], weighted aggregated sum product assessment (WASPAS) [95], combinative distance-based assessment (CODAS) [96] and proximity indexed value (PIV) [97]. The results of the sensitivity analysis and Spearman's correlation coefficient (r_s) between the results of the proposed approach and the other comparison methods are presented for bank efficiency and productivity pre-and during COVID-19 periods in Tables 17 and 18, respectively. As seen in Tables 17 and 18, since all the correlation values are greater than 0.80

showing a very strong relationship [50,98], it can be deduced that the proposed approach gives results consistent with the results of other MCDM methods.

Table 18. Results of the comparative analysis for bank productivity pre- and during COVID-19.

	Pre-COVID-19								
Banks	**MARCOS**	**EDAS**	**VIKOR**	**TOPSIS**	**ARAS**	**COPRAS**	**WASPAS**	**CODAS**	**PIV**
B1	9	9	9	9	9	9	9	9	9
B2	11	11	11	11	11	11	11	11	11
B3	10	10	10	10	10	10	10	10	10
B4	4	4	4	4	4	4	4	4	4
B5	5	6	5	5	6	6	6	5	6
B6	7	7	6	6	7	7	7	7	7
B7	8	8	8	8	8	8	8	8	8
B8	6	5	7	7	5	5	5	6	5
B9	3	1	3	3	1	1	1	3	1
B10	12	12	12	12	12	12	12	12	12
B11	1	2	1	1	2	3	3	1	2
B12	2	3	2	2	3	2	2	2	3
r_s	-	0.972	0.993	0.993	0.972	0.965	0.965	1.000	0.972
	During COVID-19								
Banks	**MARCOS**	**EDAS**	**VIKOR**	**TOPSIS**	**ARAS**	**COPRAS**	**WASPAS**	**CODAS**	**PIV**
B1	10	10	10	9	10	10	10	9	10
B2	11	11	11	11	11	11	11	11	11
B3	9	9	9	10	9	9	9	10	9
B4	2	4	2	2	3	4	2	2	3
B5	7	7	6	6	7	7	7	7	7
B6	8	8	8	8	8	8	8	8	8
B7	4	5	4	3	5	5	4	4	5
B8	6	1	7	7	1	1	5	6	1
B9	5	3	5	5	4	3	3	5	4
B10	12	12	12	12	12	12	12	12	12
B11	3	6	3	4	6	6	6	3	6
B12	1	2	1	1	2	2	1	1	2
(r_s)	-	0.846	0.993	0.979	0.867	0.846	0.951	0.993	0.867

5. Conclusions

Banks are commercial institutions that make up a large part of the financial market, especially the money market. In a financial system, the power of the banking sector and thus its profitability make positive contributions to the financial system. From this point of view, efficiency and productivity in the banking system are very important for all service units and parties in the economy. The efficiency and productivity of the banking system bring the efficient and effective operation of the financial system. However, the damage caused by the COVID-19 pandemic that emerged in December 2019 in the financial system and the changes in the global financial system need to be followed and understood. For this purpose, many academic studies have been carried out in a short period. With this motivation, this study was carried out to analyze the banks, which are of great importance in the financial markets, in terms of bank efficiency and productivity before and during the COVID-19 pandemic.

Accordingly, the aim of this study is to evaluate the efficiency and productivity of commercial banks operating in Turkey by using a new integrated multi-criteria decision analysis approach, taking into account the period pre- and during COVID-19 comparatively. In the present study, it has been endeavored to observe whether there has been an impact of exogenous shocks such as the COVID-19 outbreak, and the ownership structure of banks on the efficiency and productivity of the commercial banks operating in Turkey. In this context, the efficiency and productivity of twelve commercial banks with different ownership structures (public banks, domestic private banks, and foreign banks) pre- and during COVID-19 were analyzed with the integrated approach proposed for the first time in this study. According to the results obtained, while Türkiye Cumhuriyeti Ziraat Bankası A.Ş (state bank) was the most efficient bank pre-COVID-19, Türk Ekonomi Bankası A.Ş. (domestic private bank) became the most efficient bank during the COVID-19. However, Denizbank A.Ş. (foreign bank) was the least efficient bank in both pre- and during COVID-19 periods. QNB Finansbank A.Ş. (foreign bank) was the most productive bank pre-COVID-19, whereas Türkiye Garanti Bankası A.Ş. (foreign bank) became the most productive bank during the COVID-19 period. According to the findings from the present study, it turned out that the banks with foreign investors achieved higher productivity than other bank groups. However, foreign banks are more likely to be less exposed to COVID-19 shocks as they operate in different parts of the world and are familiar with the epidemic policies of different countries. It was observed that the productivity of the state banks decreased especially during the COVID-19 period. These results should be carefully evaluated by regulators, policymakers, and bank managers.

The contributions of this study can be given as follows. First, bank-specific variables were determined for bank efficiency and productivity. Second, the study covers the pre- and during COVID-19 pandemic period. It also fills an important gap in the literature by using a novel integrated MCDM approach including SWARA II as a subjective weighting method, MEREC as an objective weighting method, and MARCOS as a ranking method to evaluate bank efficiency and productivity. SWARA II and MEREC are very new objective criteria weighting methods proposed recently. The proposed approach of this study has taken into account both subjective and objective weights of the criteria. The combination of these weights provides much more accurate weights for the MARCOS method to analyze the efficiency and productivity of banks pre- and during COVID-19. In order to test the proposed approach based on some MCDM methods, the ranking results obtained were compared with the results determined using the EDAS, VIKOR, TOPSIS, ARAS, COPRAS, WASPAS, CODAS, and PIV methods. In the calculating procedures of all eight MCDM methods, the same weights of the criteria obtained by applying the SAWARA II-MEREC were utilized. The obtained correlation values show that the results of the proposed approach are valid. Thus, the reliability and stability of the proposed approach have been fully confirmed. The proposed integrated SWARA II-MEREC-MARCOS model has proven to be extremely successful in the efficiency and productivity analysis of commercial banks in Turkey. The SWARA II-MEREC-MARCOS model is simple to use, useful, and dynamic as it includes subjectivity and objectivity. For future studies, the proposed model can be applied in other areas such as bank performance evaluation, supplier selection, personnel selection, and information technologies.

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