Research Article

Analysis of the Financial Performance of Brokerage Houses in the Istanbul Stock Exchange Using the Statistical Variance and Mean Weight-Based MABAC Method

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Abstract: This study analyzes the financial performance of brokerage houses listed on the Istanbul Stock Exchange using the Multi-Attribute Border Approximation Area Comparison (MABAC) method, employing statistical variance and mean weight methods to determine criteria weights. Nine brokerage houses were selected, and their financial performance was evaluated through seven key financial ratios. These include liquidity ratios (current and cash ratios), financial structure ratios (leverage and financial debt ratios), and profitability ratios (return on assets, return on equity, and return on invested capital). The weighting of these criteria was determined through the statistical variance and mean weight methods, providing two distinct rankings that were consolidated using the Borda Count Method for a robust performance assessment. Each brokerage house's financial performance was analyzed on an annual basis from 2017 to 2023. The findings reveal that although there is variability in the rankings of brokerage houses in terms of financial performance, the Borda scores obtained from the rankings of the years helped to reveal high-performing brokerage houses. As a result of the study, OSMEN was found to be a prominent brokerage house in terms of financial performance in the ranking based on total Borda scores. OYYAT ranked second and A1CAP ranked third in terms of financial performance. It is thought that the study can be used as a reliable reference for future performance analyses and can support more effective decision-making in terms of investment decisions in the sector.

Keywords: Brokerage House, Financial Performance, Statistical Variance Method, Mean Weight Method, MABAC Method
Jel Codes: C44, G24, G23

Cite: Gözkonan, Ü. H. & Özbek, G. B. (2025). Analysis of the financial performance of brokerage houses in the Istanbul stock exchange using the statistical variance and mean weight-based MABAC method. *Fiscaoeconomia*, *9*(3), 1305-1322. https://doi.org/10.25295/fsecon.1581399

Submitted: 08.11.2024
Accepted: 27.03.2025

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Borsa İstanbul'da Aracı Kurumların Finansal Performansının İstatistiksel Varyans ve Ortalama Ağırlığa Dayalı MABAC Yöntemiyle Analizi

Öz: Bu çalışmada, Borsa İstanbul'da işlem gören aracı kurumların finansal performansları, istatistiksel varyans ve ortalama ağırlık olarak bilinen kriter ağırlıklandırma yöntemleri kullanılarak, Çok Özellikli Sınır Yaklaşım Alanı Kıyaslaması (MABAC) yöntemi ile analiz edilmiştir. Dokuz aracı kurum seçilmiş ve finansal performansları yedi temel finansal oran üzerinden değerlendirilmiştir. Bunlar likidite oranları (cari ve nakit oranları), finansal yapı oranları (kaldıraç ve finansal borç oranları) ve karlılık oranlarıdır (aktif karlılığı, özsermaye karlılığı ve yatırılan sermaye karlılığı). Bu kriterlerin ağırlıklandırılması istatistiksel varyans ve ortalama ağırlık yöntemleriyle belirlenmiş ve sağlam bir performans değerlendirmesi için Borda Sayım Yöntemi kullanılarak konsolide edilen iki farklı sıralama sağlanmıştır. Her bir aracı kurumun finansal performansı 2017'den 2023'e kadar yıllık bazda analiz edilmiştir. Bulgular, finansal performans açısından aracı kurumların sıralamalarında değişkenlik olmasına rağmen, yıllara göre yapılan sıralamalardan elde edilen Borda skorlarının yüksek performans gösteren aracı kurumların ortaya çıkarılmasına yardımcı olduğunu ortaya koymuştur. Çalışma sonucunda, toplam Borda puanları baz alınarak yapılan sıralamada OSMEN'in finansal performans açısından en başarılı aracı kurum olduğu tespit edilmiştir. Finansal performans açısından ikinci sırada OYYAT, üçüncü sırada ise A1CAP yer almıştır. Çalışmanın gelecekteki performans analizleri için güvenilir bir referans

olarak kullanılabileceği ve sektördeki yatırım kararları açısından daha etkin karar alınmasına destek olabileceği düşünülmektedir.

Anahtar Kelimeler: Aracı Kurum, Finansal Performans, İstatistiksel Varyans Yöntemi, Ortalama Ağırlık Yöntemi, MABAC Yöntemi
Jel Kodları: C44, G24, G23

1. Introduction

Capital markets are long-term financial markets that bring together savers supplying funds and investors seeking funds. Efficient capital markets perform two crucial functions for national economies. The first is to solidify the foundations of economic growth by enabling companies in need of funds for long-term investments to access these funds more easily. The second is to promote widespread economic development and economic prosperity by facilitating the spread of capital ownership. The role of market participants is crucial in achieving an efficient structure for capital markets. One of these key participants is brokerage houses. Brokerage houses play a crucial role in facilitating transactions in capital markets for the parties involved. They assume this intermediary role by executing buy and sell orders in capital markets, providing services during initial public offerings and capital increase processes, offering consultancy services to investors, and conducting activities such as portfolio management and risk management (Shaik, 2014, p. 115-116). In this way, brokerage houses serve as a bridge between savers who provide funds and companies seeking to obtain funds. To operate, brokerage houses must obtain a license and certificate from the Capital Markets Board, and their activities are subject to the Capital Market Law (Capital Market Law, 2012).

Brokerage houses, through the consultancy services and risk management activities they provide, play a crucial role in influencing the investment decisions of savers. Analysts working at these brokerage houses gather and analyze both publicly available and harder-to-access financial information, offering investment recommendations to their clients, and the fund owners (Su et al., 2022, p. 3051). As a result of these recommendations, fund owners aim to achieve at least enough additional returns to cover the commission fees they pay to the brokerage house (Womack, 1996, p. 138). In this context, the performance of brokerage houses and whether they truly generate additional returns for fund owners have been topics of research in the financial literature for many years (Womack, 1996; Ivković & Jegadeesh, 2004; Ryan & Taffler, 2006; Barber et al., 2007). In fact, traditional intermediation theories are built upon transaction costs and asymmetric information. Brokerage houses may promise additional returns to their clients based on the existing information asymmetry. However, particularly in the context of the semistrong form of market efficiency, investment recommendations made using publicly available information do not lead to additional wealth for fund owners. According to the Arrow-Debreu resource allocation model, savers and companies can interact directly through financial markets, where brokerage houses do not play a role within this structure (see Allen & Santomero, 1997 for more discussion). However, the notion that savers and those seeking to obtain funds can interact directly as a result of market efficiency, without brokerage houses playing any role in the financial system, is in contradiction with the practical reality. Despite the diminishing information asymmetry and increasingly accessible financial transaction opportunities due to advancements in technology, brokerage houses have expanded their share within the financial system (Çetin & Oğuz, 2012).

The situation is similar for Turkey as well. In Turkey, the origins of brokerage houses trace back to the Ottoman period and the Galata bankers (see Fertekligil, 1993 for more details). After 1980, with the acceleration of financial liberalization policies, the influence

of banks and brokerage houses in financial markets increased significantly. In this context, as in many developing country economies, the level of development of financial markets in the Turkish economy has become interlinked with the growth of banks and brokerage houses. In this regard, the efficient operation of brokerage houses is one of the key factors for financial markets to reach the desired levels of breadth and depth. This will not only facilitate the process for companies in need of funds to participate in capital markets but also encourage households to integrate their savings into the financial system as a result of the trust that is established.

This circumstance also serves as the primary driving force behind the research. Nine Turkish brokerage houses that are listed on the Istanbul Stock Exchange (BIST) had their performance evaluated. The goal is to offer information to fund holders as well as businesses who issue financial instruments. The literature frequently uses multi-criteria decision-making (MCDM) techniques, and national literature has already examined brokerage house performance. The brokerage houses' financial performance was assessed using the MABAC method, one of the MCDM approaches.

The current performance of market participants is a matter of importance for financial decision-makers. In this regard, periodically repeating the performance evaluation of brokerage houses is crucial for ensuring a reliable flow of information to relevant parties. This study not only provides an up-to-date contribution to the literature but also presents findings identified through an alternative evaluation method by employing different techniques from those used in previous studies.

In addition to the MABAC ranking method, the Statistical Variance Method and the Mean Weight Method were used in this research to determine the criteria weights. In this respect, it was aimed to contribute to the literature by using two different objective weighting methods. Afterward, the rankings obtained in the MABAC ranking method, where two different weighting methods were used, were scored with the Borda Count Method and a general ranking was obtained. In this respect, a more robust ranking was obtained by combining the two different objective weighting results.

Following the introduction section, a summary report on previous studies in the literature is presented. This includes both past studies conducted on the relevant topic in the national literature and past studies using related methods in the international literature. In the next stage of the study, information regarding the research dataset and methodology is provided. The subsequent section reports the research findings. Finally, the conclusion section includes evaluations based on the obtained findings.

2. Literature Review

There are numerous studies in the literature that examine the performance of brokerage houses in Turkey through MCDM methods. Kurnaz et al. (2014) analyzed the financial performance of brokerage houses operating under BIST (formerly IMKB) for the period of 2009-2012 using the TOPSIS method and ranked them accordingly. Okay & Köse (2015) analyzed the financial performances of 5 brokerage houses listed on BIST for the period covering 2011-2014 using the TOPSIS method. Günay & Kaya (2017) examined and compared the performance of brokerage houses within BIST for the years 2014 and 2015 using the ELECTRE, ORESTE, and TOPSIS methods. In her study, Tezergil (2018) included all brokerage houses operating in the Turkish financial sector between 2013-2016 and utilized the TOPSIS method to analyze their financial performance. Aras et al. (2018) compared the performances of bank-origin and non-bank-origin brokerage houses between 2005-2016 using the Entropy and TOPSIS methods. According to the research results, they determined that bank-origin brokerage houses exhibited better financial performance. Köse & Akıllı (2021) analyzed the performances of brokerage houses between 2016-2019 using the VIKOR method. Kılıçarslan & Sucu (2022), in their study using the Hirose method, measured the brand value and financial performance of brokerage houses listed on BIST. Pala (2022) examined the performances of brokerage houses in BIST for the year 2021 using the IMV and WASPAS methods and identified ROE

as the most significant indicator influencing financial performance. Şeyranlıoğlu & Kara (2024) analyzed the financial performances of 5 brokerage houses listed on BIST during 2020-2022 and conducted a performance ranking using the Entropy and CODAS methods. Moreover, some studies have measured the efficiency of brokerage houses through data envelopment analysis (Aktaş & Kargın, 2007; Bayram, 2016; Çelik, 2019).

Statistical Variance Method, which is one of the objective weighting methods, was used in several research in the literature. Sharma et al. (2016) introduced a methodology for ranking product recovery alternatives in reverse logistics, combining the Statistical Variance Method for objective weights, the Analytical Hierarchy Process for subjective weights, and the Superiority and Inferiority Ranking (SIR) Method for prioritization. Emovon & Samuel (2017) identified poor maintenance of power equipment as the most critical issue affecting Nigeria's electricity supply. They used an integrated approach combining the Statistical Variance Method and the VIKOR method to prioritize power generation problems, providing a tool for effective problem-solving. Krishankumar et al. (2021) introduced a new decision-making framework using DHHFLTS to improve group decision-making. They employed GMSM operator, DHHFLTS-based statistical variance, Bayesian approximation, and Borda method. Validated on 300 matrices, it enhanced consistency and preference aggregation. Gülençer & Türkoğlu (2020) analyzed financial development performance of 26 developing Asian and European countries from 2013 to 2017 using the OCRA method, utilizing statistical variance procedures. Results showed Asian countries generally have higher financial development levels compared to European counterparts. Altıntaş (2022) examined tax competitiveness performance in European countries using the OCRA method, based on the Statistical Variance Method. The author used a 2021 dataset containing ITCI components for 26 European countries, comparing performance values with other MCDM techniques. Sutrisno et al. (2023) introduced a decision support model for assessing organizational disaster preparedness, combining statistical variance and proximity value index techniques. It enhances evaluation and prioritization of disaster readiness criteria and is applied to a case study involving competing hospitals. Azeem et al. (2024) introduced CFFPMSM operators for MCDM, enhancing efficiency and reducing extreme values. It uses complex Fermatean fuzzy sets and statistical variance methods, demonstrating their superiority over traditional techniques in complex decision-making scenarios.

When the studies related to Mean Weight Method was examined in the literature, it can be seen that there are various study employed this method. Kilic & Çerçioğlu (2016) in their study where they used CRITIC, Standard Deviation, and Mean Weight methods for criteria weighting, evaluated 78 railway line projects using the TOPSIS and VIKOR methods. Vavrek (2019) explored the impact of weighting methods on TOPSIS decision-making outcomes, comparing objective methods like Coefficient of Variation, CRITIC, Mean Weight, Standard Deviation, and Standardized Value Product with subjective methods. The analysis revealed significant variations in the rankings. Kaygın et al. (2019) evaluated the performance of 27 companies operating in the BIST SME Industrial Index using Grey Relational Analysis, one of the multi-criteria decision-making methods. They employed the Mean Weight method for weight allocation. Ardil (2021) employed the Entropic TOPSIS programming method to select three freighter aircraft based on objective performance data. Using multiple criteria decision-making techniques, the Boeing B747-8F was identified as the most suitable candidate, using mean weight and standard deviation methods. Fattouh & Eisa (2023) evaluated four MCDM techniques for robot selection, using five weight allocation methods such as Mean Weight, Standard Deviation, CRITIC, Entropy, and Analytic Hierarchy Process. The study used clean data to assess robot performance across multiple criteria. The authors suggested using multiple MCDM tools to mitigate errors and explore hybrid approaches to address uncertainties in robot selection using intuitionistic fuzzy sets. Trung et al. (2024) examined the use of four MCDM methods to choose the best plastic injection molding machine from five alternatives. The study used ten criteria and two weighting methods such as Mean Weight

and CRITIC, finding all methods equally effective, with JSW J550E-C5 being the top choice.

The MABAC method employed in this research is relatively new among MCDM methods. Some existing researches in the literature on the MABAC method and the areas where it has been applied are as follows. Pamucar et al. (2018) utilized the MABAC method in order to evaluate the universities' websites. Roy et al. (2018) employed the MABAC method in the assessment process of health tourism destinations. Luo and Xing (2019) conducted an application using the MABAC method in the personnel selection decision-making process of an IT company. Adar & Delice (2019) utilized the MABAC method in selecting medical waste disposal technologies. Irvanizam et al. (2020) used an extended version of the MABAC method in an investment selection problem among technology enterprises. Bose et al. (2020) conducted a study using the MABAC method to facilitate appropriate material selection in the manufacture process. Liu & Zhang (2021) developed a MABAC method combined with decision-makers' psychological behaviors and tested it in the supplier selection problem for universities. Büyüközkan et al. (2021) applied the MABAC method in the evaluation and selection of health tourism strategies. Mishra et al. (2021) solved the smartphone selection problem using a new version of the MABAC method, which defined new criterion weights. Üçler (2024) examined the macroeconomic performance of G-7 countries using the MABAC method. Feng (2024) conducted an investment-risk evaluation of green finance projects with the MABAC method.

Additionally, when examining the national literature, it is observed that the MABAC method has increasingly found its place in financial performance evaluation, particularly in recent years (Akbulut, 2020; Çelik, 2020; Işık, 2020; Yıldırım, 2024; Çetin & Karataş, 2024).

3. Data and Methodology

Brokerage houses are among the critical structures that ensure the efficient functioning of financial markets. These institutions, which include brokerage houses, banks, investment firms, portfolio management businesses, and insurance companies, help to move cash around and serve as financial bridges between people and institutions. Therefore, the financial performance of these institutions is crucial for both market stability and investor confidence. Their healthy balance sheets and profitability indicators enhance their lending capacity, while their success in risk management contributes to the mitigation of systemic risks. In addition to supporting economic growth, the performance of brokerage houses has a direct impact on the return and risk balance of individual and institutional investors' portfolios. Therefore, the performance analysis of financial intermediaries is of strategic importance for both regulators and investors.

This study aims to analyze the financial performance of brokerage houses traded in the Istanbul Stock Exchange. The companies included in the study are shown in Table 1.

Table 1. Brokerage House Companies Traded in the Istanbul Stock Exchange

Stock Tickers	Company Name
A1CAP	A1 Capital Yatırım Menkul Değerler A.Ş.
GEDIK	Gedik Yatırım Menkul Değerler A.Ş.
GLBMD	Global MD Portföy Yönetimi A.Ş.
INFO	İnfo Yatırım Menkul Değerler A.Ş.
ISMEN	İş Yatırım Menkul Değerler A.Ş.
OSMEN	Osmanlı Portföy Yönetimi A.Ş.
OYYAT	Oyak Yatırım Menkul Değerler A.Ş.
SKYMD	Şeker Yatırım Menkul Değerler A.Ş.
TERA	Tera Yatırım Menkul Değerler A.Ş.

As seen in Table 1, all brokerage houses traded in the Istanbul Stock Exchange are included in the scope of the study. In this context, this study offers a broader scope than previous studies in the literature.

Previous studies on different sectors and companies have analyzed the financial performance of companies by selecting different financial ratios. However, when the studies are examined in general, it can be seen that there are common financial ratios that are frequently used. In parallel with the previous studies, in addition to some financial ratios that are strong indicators of financial performance, the ROIC (Return on invested capital) ratio, which is expressed as return on invested capital under the profitability rate heading, was also used in this study. Table 2 shows the financial ratios used as criteria for analyzing the financial performance of companies.

Table 2. Financial Ratios for the Financial Performance Analysis

Criteria Codes	Financial Ratios (Criteria)	Formula	Benefit	Cost
DV1	Current Ratio (CR)	Current Assets / Current Liabilities	√	
DV2	Cash Ratio (CsR)	Cash and Cash Equivalents / Short Term Liabilities	√	
DV3	Leverage Ratio (LR)	Total Liabilities / Total Assets		√
DV4	Financial Debt Ratio (FDR)	(S.T. Financial Debt + L.T. Financial Debt) / Total Assets		√
DV5	Return on Assets (ROA)	Net Profit / Total Assets	√	
DV6	Return on Equity (ROE)	Net Profit / Total Equity	√	
DV7	Return on Invested Capital (ROIC)	Net Operating Profit After Tax / Invested Capital	√	

In order to examine the financial performance of brokerage firms, seven distinct financial ratios were identified, as indicated in Table 2. Three profitability ratios—return on equity, return on assets, and return on invested capital—were identified, along with two liquidity ratios—the cash and current ratios—and two financial structure ratios—the leverage and financial debt ratios. While the leverage ratio and financial debt ratio are regarded as cost criteria, the current ratio, cash ratio, return on equity, return on assets, and ROIC are regarded as benefit criteria.

The companies included in the study and their financial data were obtained from the Fintables database. Within the scope of the study, annual financial statement data between 2017 and 2023 were used. Due to the incomplete financial statement data of some brokerage houses, 2017 was determined as the starting year. Since the year 2024 has not yet been completed and the annual financial statements of 2024 have not yet been published, the year 2023 has been determined as the end year.

In this study, the weights of the criteria used in the ranking method were obtained by the Statistical Variance and Mean Weight methods. The MABAC method was used to obtain financial performance rankings of companies. Finally, the Borda Count Method was used to obtain an overall ranking based on the performance rankings for each year.

3.1. Statistical Variance Method

One objective weighting technique is the statistical variance method (Zardari et al., 2015, p. 35). According to Özcan Buckley & Türkoğlu (2022, p. 323), the weights of the criteria in this approach are established by their variances. Compared to the entropy method put out by Jee & Kang (2000) and Shanian & Savadogo (2006), the idea of statistical variance—which establishes the objective weights of the attributes—is comparatively easier (Rao & Patel, 2010, p. 4740). As stated by Rao & Patel (2010), Demir et al. (2021), and Altıntaş (2022), the statistical variance approach has the following stages:

Step 1: Creating the decision matrix:

$$X = [x_{ij}]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \dots & k_{1n} \\ x_{21} & x_{22} & \dots & k_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

In the matrix consisting of m decision alternatives (stocks) and n criteria, x_{ij} indicates the value of decision alternative i. within the scope of criterion j.

Step 2: Calculation of criteria variance: Equation 2 is used to calculate the variance of the criteria.

$$V_k = \left(\frac{1}{m}\right)\sum_{k=1}^{m}\left(x_{ij} - \overline{x_{ij}}\right)^2 \quad (2)$$

Where $\overline{x_{ij}}$ is the average or mean value of x_{ij}, and V_k is the statistical variance of the data corresponding to the *k*th attribute. The dispersion of a collection of data points around their mean values is measured by the statistical variance. The mean squared deviations from the mean is a mathematical expectation. The variance examines every data point before determining its distribution, in contrast to statistical techniques that focus on the extremes. As a result, in a lot of statistical and experimental scenarios, the variance offers crucial insights about the data distribution.

Step 3: Calculation of criteria weights: Equation 3 is used to calculate the weights of the criteria.

$$w_j = \frac{v_k}{\sum_{k=1}^{n} v_k} \quad (3)$$

The *k*th attribute's objective weight, w_j, is determined by dividing its statistical variance by the sum of the statistical variances of the 'n' number of characteristics. Table 3 displays the year-based criteria weights that were determined using the Statistical Variance Method.

Table 3. Weights obtained by statistical variance method (by years)

Years	DV1	DV2	DV3	DV4	DV5	DV6	DV7
2017	0,330	0,423	0,068	0,122	0,003	0,034	0,020
2018	0,390	0,401	0,052	0,112	0,003	0,034	0,007
2019	0,114	0,529	0,036	0,110	0,008	0,186	0,017
2020	0,071	0,378	0,026	0,067	0,026	0,316	0,116
2021	0,116	0,305	0,044	0,059	0,023	0,354	0,098
2022	0,206	0,148	0,064	0,024	0,026	0,367	0,165
2023	0,463	0,226	0,079	0,029	0,014	0,160	0,030

3.2. Mean Weight Method

The mean weight calculation, which is predicated on the idea that each criterion is equally significant, represents the decision maker's impartiality and the allocation of equal weights to the criteria. Such an attitude is often thought to ensure the fairness of the assessment procedure. In the mean weight method, weights are calculated using the simple formula in Equation 4 (Diakoulaki et al., 1995, p. 766). Table 4 shows the criteria for all years with equal weights.

$$w_j = \frac{1}{m} \quad (4)$$

Table 4. Weights obtained by mean weight method (all years)

Years	DV1	DV2	DV3	DV4	DV5	DV6	DV7
2017-2023	0,143	0,143	0,143	0,143	0,143	0,143	0,143

3.3. Multi-Attribute Border Approximation Area Comparison (MABAC) Method

Finding the distance between each alternative's criteria function and the border approximation region is the foundation of the MABAC approach. The MABAC technique is a valuable, practical, and trustworthy mathematical instrument for logical decision-making because of its simple and uncomplicated calculation process and consistent solution generation. To ensure that the outcome is thorough, the technique also accounts for any benefits and losses. To put it another way, the main goal of this approach is to compute the probable benefits and losses in order to get the most accurate results (Ecer, 2020, p. 282). There are six steps in the MABAC approach (Pamučar & Ćirović, 2015; Ecer, 2020; Demir et al., 2021).

Step 1: Creating the initial decision matrix: The initial matrix X obtained as a result of the evaluation of m alternatives according to n criteria is shown in Equation 5.

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & k_{1n} \\ x_{21} & x_{22} & \dots & k_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{5}$$

Table 4. Decision Matrix

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
A1CAP	1,500	0,150	0,640	0,136	0,004	0,010	-0,103
GEDIK	1,120	0,420	0,870	0,230	0,028	0,210	0,077
GLBMD	1,430	0,210	0,654	0,225	0,043	0,127	0,089
INFO	1,910	0,420	0,495	0,086	0,025	0,045	0,002
ISMEN	1,140	0,710	0,873	0,562	0,022	0,250	0,039
OSMEN	1,870	1,260	0,528	0,217	0,100	0,196	0,024
OYYAT	1,260	0,670	0,788	0,446	0,049	0,238	0,162
SKYMD	1,210	0,760	0,744	0,304	0,030	0,108	0,001
TERA	1,260	0,430	0,710	0,591	0,001	0,005	0,019

It is uncommon to find negative values in the decision matrix of MCDM analyses. Criterion Crt.7 of alternative Alt.1 has a negative value, as can be observed in the decision matrix in Table 4. The decision matrix's elements must be changed to positive values in this situation since negative values cannot be a part of the normalized matrix. The Z-score standardization method, which Zhang et al. proposed, was applied in this study to change the decision matrix's negative values into positive ones. The processes involved are shown below (Zhang et al., 2014, p. 3)

First, the elements of the decision matrix are transformed using Equation 6.

$$x_{ij} = \frac{X_{ij} - \bar{X}_\iota}{S_i} \tag{6}$$

x_{ij} denotes the standardized data for index i in area j. X_{ij} denotes the original data; $\bar{X}_\iota$ and S_i denote the arithmetic mean and standard deviation, respectively.

Table 5. Standardized decision matrix

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
A1CAP	0,298	-1,211	-0,443	-0,965	-1,018	-1,264	**-1,882***
GEDIK	-0,976	-0,412	1,259	-0,446	-0,194	0,809	0,589
GLBMD	0,063	-1,034	-0,343	-0,471	0,335	-0,055	0,753
INFO	1,672	-0,412	-1,522	-1,237	-0,300	-0,905	-0,444
ISMEN	-0,909	0,448	1,280	1,384	-0,389	1,225	0,060
OSMEN	1,538	2,077	-1,272	-0,516	2,255	0,660	-0,147
OYYAT	-0,506	0,329	0,648	0,743	0,523	1,094	1,750
SKYMD	-0,674	0,596	0,322	-0,036	-0,116	-0,248	-0,461
TERA	-0,506	-0,382	0,072	1,543	-1,096	-1,315	-0,217

Min value: -1,882

Second, the elements of the decision matrix are made positive using Equation 7.

$$x'_{ij} = x_{ij} + A \rightarrow A > \left|\min x_{ij}\right| \quad (7)$$

x'_{ij} denotes the standard value after transformation and must be greater than zero. The minimum value in the decision matrix is -1,882. In Equation 7, the value of A is taken as 1,961.

Table 6. Positive Decision Matrix

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
A1CAP	2,259	0,750	1,518	0,996	0,944	0,697	0,079
GEDIK	0,985	1,550	3,220	1,515	1,767	2,770	2,550
GLBMD	2,025	0,927	1,618	1,490	2,296	1,906	2,714
INFO	3,633	1,550	0,439	0,724	1,661	1,056	1,517
ISMEN	1,052	2,409	3,241	3,346	1,572	3,186	2,022
OSMEN	3,499	4,039	0,689	1,445	4,216	2,621	1,814
OYYAT	1,455	2,290	2,609	2,704	2,484	3,055	3,711
SKYMD	1,287	2,557	2,284	1,925	1,845	1,713	1,500
TERA	1,455	1,579	2,033	3,504	0,865	0,646	1,744

Step 2: Normalization of the initial decision matrix: Criteria are normalized depending on whether they are costs or benefits. Equation 8 is used to normalize benefit-based criteria and Equation 9 is used to normalize cost-based criteria. In the equations, x_i^+ indicates the maximum value and x_i^- indicates the minimum value. Thus, the normalized matrix in Equation 10 is obtained.

$$n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \quad (8)$$

$$n_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \quad (9)$$

$$N = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} n_{11} & n_{12} & \dots & n_{1n} \\ n_{21} & n_{22} & \dots & n_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ n_{m1} & n_{m2} & \dots & n_{mn} \end{bmatrix} \end{array} \quad (10)$$

Table 7. Normalized decision matrix

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
A1CAP	0,481	0,000	0,615	0,902	0,023	0,020	0,000
GEDIK	0,000	0,243	0,007	0,715	0,269	0,836	0,680
GLBMD	0,392	0,054	0,579	0,725	0,427	0,496	0,725
INFO	1,000	0,243	1,000	1,000	0,238	0,161	0,396
ISMEN	0,025	0,505	0,000	0,057	0,211	1,000	0,535
OSMEN	0,949	1,000	0,911	0,741	1,000	0,777	0,478
OYYAT	0,177	0,468	0,226	0,288	0,483	0,949	1,000
SKYMD	0,114	0,550	0,342	0,568	0,293	0,420	0,391
TERA	0,177	0,252	0,431	0,000	0,000	0,000	0,458

Step 3: Weighting of the normalized matrix: Each element of the normalized matrix is weighted according to the criteria weights. The weighted matrix (V) is calculated by Equation 11. Thus, the matrix in Equation 12 is obtained. The criteria weights used here are obtained from the Statistical Variance and Mean Weight Method.

$$v_{ij} = w_i n_{ij} + w_i \quad (11)$$

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & x_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} \quad (12)$$

The weighted values obtained through Equations 11 and 12 are shown in Table 8. The table shows the weighted matrix according to the criteria weights obtained by the statistical variance method for 2017.

Table 8. Normalized Matrix Weighted by Statistical Variance Method

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
w_i	**0,330**	**0,423**	**0,068**	**0,122**	**0,003**	**0,034**	**0,020**
A1CAP	0.489	0.423	0.109	0.232	0.003	0.035	0.020
GEDIK	0.330	0.525	0.068	0.210	0.004	0.063	0.033
GLBMD	0.460	0.445	0.107	0.211	0.005	0.052	0.034
INFO	0.660	0.525	0.135	0.244	0.004	0.040	0.028
ISMEN	0.339	0.636	0.068	0.129	0.004	0.069	0.030
OSMEN	0.644	0.845	0.129	0.213	0.006	0.061	0.029
OYYAT	0.389	0.620	0.083	0.157	0.005	0.067	0.040
SKYMD	0.368	0.655	0.091	0.192	0.004	0.049	0.028
TERA	0.389	0.529	0.097	0.122	0.003	0.034	0.029

Similarly, the weighted values obtained through Equations 11 and 12, but this time using the mean weight method, are shown in Table 9.

Table 9. Normalized Matrix Weighted by Mean Weight Method

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7
w_i	**0.143**	**0.143**	**0.143**	**0.143**	**0.143**	**0.143**	**0.143**
A1CAP	0.212	0.143	0.231	0.272	0.146	0.146	0.143
GEDIK	0.143	0.178	0.144	0.245	0.181	0.262	0.240
GLBMD	0.199	0.151	0.226	0.246	0.204	0.214	0.246
INFO	0.286	0.178	0.286	0.286	0.177	0.166	0.199
ISMEN	0.146	0.215	0.143	0.151	0.173	0.286	0.219
OSMEN	0.278	0.286	0.273	0.249	0.286	0.254	0.211
OYYAT	0.168	0.210	0.175	0.184	0.212	0.278	0.286
SKYMD	0.159	0.221	0.192	0.224	0.185	0.203	0.199
TERA	0.168	0.179	0.204	0.143	0.143	0.143	0.208

Step 4: Creation of boundary approach area matrix: The elements of this matrix are the geometric mean of the column elements of the weighted matrix and are calculated using Equation 13. This results in the boundary approach area matrix G shown in Equation 14. Each element of the matrix G represents a boundary approach area according to the relevant criterion.

$$g_i = \left(\prod_{j=1}^{m} v_{ij} \right)^{\frac{1}{m}} \quad (13)$$

$$G = \begin{matrix} C_1 & C_2 & \dots & C_n \end{matrix} \\ [g_1 \quad g_2 \quad \cdots \quad g_n] \quad (14)$$

For 2017, the boundary approximation area matrix according to the statistical variance weighting method through Equations 13 and 14 is presented in Table 10.

Table 10. Boundary Approximation Area Matrix by Statistical Variance Method

G	DV1	DV2	DV3	DV4	DV5	DV6	DV7
g_i	6.59428E-05	0.000666425	7.56659E-11	2.82278E-08	3.92406E-23	2.45101E-13	1.95382E-15

Similarly, for 2017, the boundary approximation area matrix according to the mean weight method through Equations 13 and 14 is presented in Table 11.

Table 11. Boundary Approximation Area Matrix by Mean Weight Method

G	DV1	DV2	DV3	DV4	DV5	DV6	DV7
g_i	3,50387E-08	3,84623E-08	6,36086E-08	1,15134E-07	2,93272E-08	8,8146E-08	1,02549E-07

Step 5: Calculation of distances of alternatives to the boundary approximation area matrix: As shown in Equation 15, the distance matrix Q is obtained by subtracting the boundary approximation area matrix G from the weighted matrix V.

$$Q = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \cdots & v_{1n} - g_n \\ v_{21} - g_1 & x_{22} - g_2 & \cdots & v_{2n} - g_n \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} - g_1 & v_{m2} - g_2 & \cdots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ q_{m1} & q_{m2} & \cdots & q_{mn} \end{bmatrix} \quad (15)$$

The boundary approximation area (G), the upper approximation area (G^+) or the lower approximation area (G^-) can be where each choice alternative (A_i) is situated. The majority of the criteria values must fall inside the upper approximation range (G^+) for a choice alternative to be considered the best option. The approximation areas are shown in Figure 1.

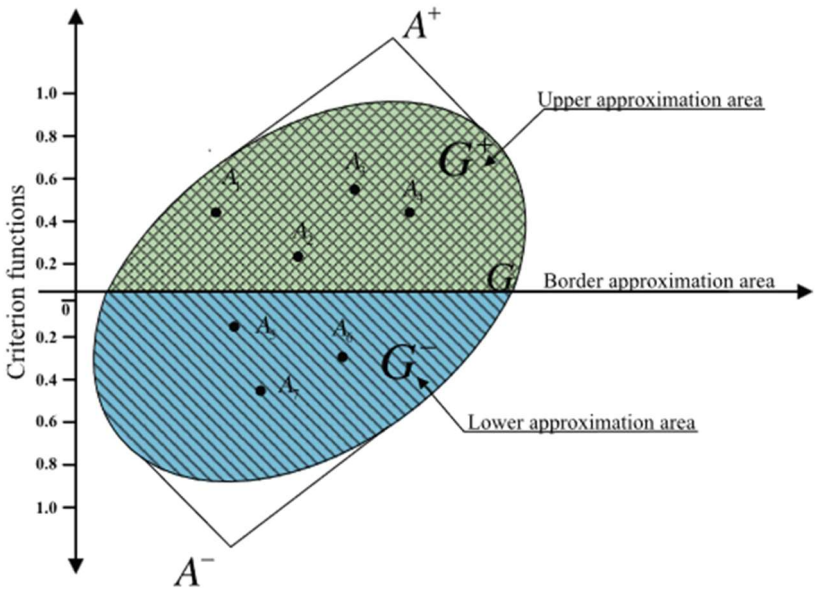

Figure 1. Border Approximation Areas (Pamučar & Ćirović, 2015)

Equation 16 shows that if $q_{ij} > 0$, the alternative A_i is close to the ideal alternative, and if $q_{ij} < 0$, the alternative A_i is close to the negative ideal alternative.

$$A_i \in \begin{cases} G^+ \; if \; q_{ij} > 0 \\ G \;\; if \; q_{ij} = 0 \\ G^- \; if \; q_{ij} < 0 \end{cases} \tag{16}$$

Step 6: Ranking of alternatives: Using Equation 17, the sum of the distances to the boundary approach areas for each alternative is calculated. According to the total results, the alternatives are ranked in descending order.

$$S_i = \sum_{j=1}^{n} q_{ij}, \quad j = 1, 2, \dots, n, \qquad i = 1,2, \dots, m \tag{17}$$

Table 12. Distances of Alternatives to the Boundary Approximation Area Matrix and Ranking of Alternatives (for the year 2017)

Tickers/ Criteria	DV1	DV2	DV3	DV4	DV5	DV6	DV7	SVM S_i	MW S_i
A1CAP	0.489	0.422	0.109	0.232	0.003	0.035	0.020	1.311	1,292
GEDIK	0.330	0.525	0.068	0.210	0.004	0.063	0.033	1.233	1,393
GLBMD	0.460	0.445	0.107	0.211	0.005	0.052	0.034	1.312	1,486
INFO	0.660	0.525	0.135	0.244	0.004	0.040	0.028	1.636	1,577
ISMEN	0.338	0.635	0.068	0.129	0.004	0.069	0.030	1.274	1,333
OSMEN	0.644	0.844	0.129	0.213	0.006	0.061	0.029	1.927	1,837
OYYAT	0.389	0.620	0.083	0.157	0.005	0.067	0.040	1.360	1,513
SKYMD	0.368	0.654	0.091	0.192	0.004	0.049	0.028	1.385	1,382
TERA	0.389	0.528	0.097	0.122	0.003	0.034	0.029	1.203	1,188

SVM – S_i; refers to scores based on the statistical variance-based MABAC method.
MW – S_i; refers to scores based on the mean weight-based MABAC method.

3.4. Borda Count Method

The Borda voting system developed by Jean-Charles Borda (1770) is used to obtain integrated solutions in MCDM problems. In this context, in the set of tools and processes called the Borda method, the rank value a_{ik} of alternative i in the ranking k is converted into the Borda score given in Equation 18 (Aytekin, 2023, p. 504).

$$B_i = \sum_{k=1}^{r} m - a_{ik} \tag{18}$$

In Equation 18, m is the number of alternatives. The ranking of alternatives is carried out according to their B scores, from higher to lower. The Borda method has an understandable and easy-to-apply structure that provides effective results in most decision-making problems (Aytekin, 2023, p. 504).

Table 13. Borda Scores of Alternative Rankings According to the MABAC Method Based on Statistical Variance and Mean Weighting

Tickers/ Criteria	SVM-B_i	MW-B_i	Total-B_i
A1CAP	35	40	75
GEDIK	22	23	45
GLBMD	8	12	20
INFO	26	24	50
ISMEN	35	32	67
OSMEN	52	52	104
OYYAT	38	42	80
SKYMD	14	8	22
TERA	22	19	41

Table 13 shows the Borda scores of the rankings obtained according to each weighting method for each year. SVM-B_i is the Borda score according to the statistical variance method, MW-B_i is the Borda score according to the mean weighting and Total-B_i is the total Borda score obtained from the two weighting methods.

4. Findings

In the study, the financial performance of 9 brokerage houses traded in the Istanbul Stock Exchange was analyzed using the MABAC method. The weights used in the MABAC method were determined by two different methods. Statistical Variance Method and Mean Weight Method were used to find the weights. The financial performance rankings obtained according to the two different weighting methods used are shown in Table 14 on a yearly basis.

Table 14. Rankings of Alternatives According to the MABAC Method Based on Statistical Variance and Mean Weighting (by years)

Tickers	2017		2018		2019		2020		2021		2022		2023	
	S.	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**
A1CAP	6	8	3	1	8	5	5	2	3	2	1	1	2	4
GEDIK	8	5	5	5	4	4	3	5	7	7	7	7	7	7
GLBMD	5	4	9	6	9	9	9	9	9	9	8	9	6	5
INFO	2	2	2	3	7	7	6	7	6	6	5	5	9	9
ISMEN	7	7	6	8	3	3	2	3	5	5	2	3	3	2
OSMEN	1	1	1	2	1	1	1	1	2	3	4	2	1	1
OYYAT	4	3	7	4	2	2	4	4	1	1	3	4	4	3
SKYMD	3	6	8	9	6	8	7	8	8	8	9	8	8	8
TERA	9	9	4	7	5	6	8	6	4	4	6	6	5	6

S; refers to rankings based on the statistical variance-based MABAC method.
M; refers to rankings based on the mean weight-based MABAC method.

In 2017, according to the statistical variance-based MABAC method, OSMEN ranked first, INFO ranked second and SKYMD ranked third. Other alternatives were ranked as OYYAT, GLBMD, A1CAP, ISMEN, GEDIK, and TERA, respectively. According to the mean weight-based MABAC method, OSMEN ranked first, INFO ranked second and OYYAT ranked third. Other alternatives were ranked as GLBMD, GEDIK, SKYMD, ISMEN, A1CAP, and TERA, respectively.

In 2018, according to the statistical variance-based MABAC method, OSMEN ranked first, INFO ranked second and A1CAP ranked third. Other alternatives were ranked as TERA, GEDIK, ISMEN, OYYAT, SKYMD, and GLBMD respectively. According to the mean weight-based MABAC method, A1CAP ranked first, OSMEN ranked second and INFO ranked third. Other alternatives were ranked as OYYAT, GEDIK, GLBMD, TERA, ISMEN, and SKYMD, respectively.

In 2019, according to the statistical variance-based MABAC method, OSMEN ranked first, OYYAT ranked second and ISMEN ranked third. Other alternatives were ranked as GEDIK, TERA, SKYMD, INFO, A1CAP, and GLBMD respectively. According to the mean weight-based MABAC method, OSMEN ranked first, OYYAT ranked second and ISMEN ranked third. Other alternatives were ranked as GEDIK, A1CAP, TERA, INFO, SKYMD, and GLBMD, respectively.

In 2020, according to the statistical variance-based MABAC method, OSMEN ranked first, ISMEN ranked second and GEDIK ranked third. Other alternatives were ranked as OYYAT, A1CAP, INFO, SKYMD, TERA, and GLBMD respectively. According to the mean weight-based MABAC method, OSMEN ranked first, A1CAP ranked second and ISMEN ranked third. Other alternatives were ranked as OYYAT, GEDIK, TERA, INFO, SKYMD, and GLBMD, respectively.

In 2021, according to the statistical variance-based MABAC method, OYYAT ranked first, OSMEN ranked second and A1CAP ranked third. Other alternatives were ranked as TERA, ISMEN, INFO, GEDIK, SKYMD, and GLBMD respectively. According to the mean weight-based MABAC method, OYYAT ranked first, A1CAP ranked second and OSMEN ranked third. Other alternatives were ranked as TERA, ISMEN, INFO, GEDIK, SKYMD, and GLBMD, respectively.

In 2022, according to the statistical variance-based MABAC method, A1CAP ranked first, ISMEN ranked second and OYYAT ranked third. Other alternatives were ranked as OSMEN, INFO, TERA, GEDIK, GLBMD, and SKYMD respectively. According to the mean weight-based MABAC method, A1CAP ranked first, OSMEN ranked second and ISMEN ranked third. Other alternatives were ranked as OYYAT, INFO, TERA, GEDIK, SKYMD, and GLBMD, respectively.

In 2023, according to the statistical variance-based MABAC method, OSMEN ranked first, A1CAP ranked second and ISMEN ranked third. Other alternatives were ranked as OYYAT, TERA, GLBMD, GEDIK, SKYMD, and INFO respectively. According to the mean weight-based MABAC method, OSMEN ranked first, ISMEN ranked second and OYYAT ranked third. Other alternatives were ranked as A1CAP, GLBMD, TERA, GEDIK, SKYMD, and INFO, respectively.

When the year-based rankings obtained for the two different weighting methods are analyzed, it is seen that there are alternatives with similar rankings in both methods as well as alternatives with different rankings. This shows that the weighting methods used in the MABAC method are effective in financial performance rankings. The alternatives with different rankings according to their weightings and years were scored with the Borda Count method and the rankings obtained from two different methods were converted into a single ranking. Table 15 shows the Borda scores calculated on a yearly basis based on the rankings of the alternatives and their overall scores and total scores according to both weighting methods.

Table 15. Borda Scores of Alternative Rankings According to the MABAC Method Based on Statistical Variance and Mean Weighting

Tickers	**2017**		**2018**		**2019**		**2020**		**2021**		**2022**		**2023**		S-B_i	M-B_i	T-B_i
	S.	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M.**	**S.**	**M**	**S.**	**M.**	
A1CAP	3	1	6	8	1	4	4	7	6	7	8	8	7	5	35	40	75
GEDIK	1	4	4	4	5	5	6	4	2	2	2	2	2	2	22	23	45
GLBMD	4	5	0	3	0	0	0	0	0	0	1	0	3	4	8	12	20
INFO	7	7	7	6	2	2	3	2	3	3	4	4	0	0	26	24	50
ISMEN	2	2	3	1	6	6	7	6	4	4	7	6	6	7	35	32	67
OSMEN	8	8	8	7	8	8	8	8	7	6	5	7	8	8	52	52	104
OYYAT	5	6	2	5	7	7	5	5	8	8	6	5	5	6	38	42	80
SKYMD	6	3	1	0	3	1	2	1	1	1	0	1	1	1	14	8	22
TERA	0	0	5	2	4	3	1	3	5	5	3	3	4	3	22	19	41

S; refers to the Borda Score based on the statistical variance-based MABAC method.
M; refers to the Borda Score based on the mean weight-based MABAC method.
S-B_i; refers to the total Borda Score based on the statistical variance-based MABAC method.
M-B_i; refers to the total Borda Score based on the mean weight-based MABAC method.
T- B_i; refers to the total Borda Score based on the statistical variance and mean weight-based MABAC method.

According to the total Borda scores in Table 14, OSMEN ranked first, OYYAT ranked second and A1CAP ranked third in terms of financial performance according to the MABAC method based on statistical variance and mean weight methods. Subsequently, ISMEN ranked fourth, INFO fifth, GEDIK sixth, TERA seventh, SKYMD eighth and GLBMD ninth in terms of financial performance.

5. Conclusion

This study analyzed the financial performance of 9 brokerage houses traded in the Istanbul Stock Exchange between 2017 and 2023 with the MABAC method and used statistical variance and mean weight methods to determine the criteria weights. In the analysis, seven key financial ratios based on liquidity, financial structure and profitability indicators were taken into consideration. A consistent performance ranking throughout time is produced by combining the Borda Count Method with the rankings derived from various weighting techniques for each year. This approach allowed for an objective assessment of different financial structures in the sector.

The findings of the study reveal that there are significant fluctuations in the financial performance of brokerage houses over the years. While OSMEN has ranked at the top in many years, GLBMD has consistently underperformed. It is observed that INFO and SKYMD have shown a declining performance over the years, whereas TERA, A1CAP, and ISMEN exhibit an upward performance trend. Additionally, it is noted that whether the institutions are bank-origin or not does not create a significant difference in their performance. This result suggests that while some institutions maintain their competitive edge in the sector and display a stable performance, others are more sensitive to market conditions. These differences in annual performance rankings reflect the diversity in financial stability and growth strategies of brokerage houses. Additionally, the rankings in the study's findings show similarities (in overlapping years) with the rankings in previous studies that have examined brokerage houses using different evaluation methods in the literature (Pala, 2022; Şeyranlıoğlu & Kara, 2024).

According to the Statistical Variance Method, one of the criteria weighting methods used in the study, the criterion weights have shown significant changes over the years. While the Current Ratio, which held the second-highest weight in 2017 and 2018, declined relatively in 2019, 2020, and 2021, it became the criterion with the highest weight in 2023. The Cash Ratio had the highest weight until 2020. Among profitability ratios, ROE gained significant importance after the first two years. On the other hand, the weight of the Financial Debt Ratio, one of the financial structure ratios, experienced a noticeable decline, particularly after 2019.

When the criterion weights are examined in general, liquidity ratios hold the largest weight. This underscores the importance of cash flow and cash management for companies (as cash flow insufficiency is a major cause of corporate bankruptcies, particularly in Turkey). Profitability ratios follow liquidity ratios in terms of weight, while financial structure ratios remain relatively less significant compared to other ratio groups.

In particular, the fact that the performance of brokerage houses has changed over the years reveals the impact of market fluctuations on these institutions. The findings show how institutions' liquidity management, leverage ratios and profitability levels affect their performance and indicate that some institutions may face difficulties in these areas. This situation emphasizes the importance of ensuring stability in the financial structures of brokerage houses in order to gain and maintain the trust of investors.

Moreover, the MABAC method and weighting techniques used in this study provide an objective framework for understanding competition in the sector. Analyzing the performance of brokerage houses over the years provides a strategic tool for investors and regulators to assess the competitive position of institutions in the market. By identifying the strengths and weaknesses of brokerage houses, such analyses can contribute to the development of policy recommendations to support their sustainability in the sector.

In conclusion, this study provides a comprehensive methodology for understanding the financial performance of brokerage houses in Turkish capital markets. The findings suggest that brokerage houses adopt different strategies to maintain or improve their position in the sector. This study not only contributes to the literature's relevance on a topic critical to financial decision-makers but also differentiates itself from similar studies by using two different weighting and voting methods that have not been applied before in this research area. The methodological framework presented in the study can be used

as a reliable reference for future performance analyses and can support more effective decision-making processes in the industry.

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Conflict of Interest: None.

Funding: None.

Ethical Approval: None

Author Contributions: Ümit Hasan GÖZKONAN (50%), Gökhan Berk ÖZBEK (50%)

Çıkar Çatışması: Yoktur.

Finansal Destek: Yoktur.

Etik Onay: Yoktur.

Yazar Katkısı: Ümit Hasan GÖZKONAN (%50), Gökhan Berk ÖZBEK (%50)