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# Portfolio Selection with AHP and TOPSIS Methods: An Application in BIST

## AHP ve TOPSIS Yöntemleri ile Portföy Seçimi: BİST'de Bir Uygulama

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**ABSTRACT**

In this study, it is aimed to create a portfolio at low-medium-high risk levels with the efficiency analysis of the companies operating in the manufacturing industry sector in 2023 and the multi-criteria decision-making methods AHP and TOPSIS. The sample of the study comprises companies from the basic metal and textile, apparel, and leather industries listed in the BIST manufacturing sector. In the mentioned year, there were 28 firms in the basic metal industry and 27 firms in the textile, apparel, and leather industries. From the overall of 55 companies, data from 48 firms were available for the year 2023 due to recent initial public offerings, and these were included in the analysis. According to the TOPSIS analysis results, groups were categorized as low-risk (6 companies), medium-risk (6 companies), and high-risk (6 companies). According to the risk criteria, T15 falls into the high-risk group, while T1, T2, and others are classified as medium-risk. As indicated by aftermath of the Spearman correlation analysis, a positive correlation was observed amid the TOPSIS scores and the risk groups (r = 0,412); however, this connection is not statistically significant (*p* = ,090).

**JEL Codes:** C44. G11. M21
**Keywords:** Financial Rasios, AHP, TOPSIS

**ÖZ**

Bu çalışmada imalat sanayi sektöründe 2023 yılında faaliyette bulunan şirketlerin etkinlik analizi ile çok kriterli karar verme yöntemlerinden AHP ve TOPSIS ile düşük-orta-yüksek risk seviyelerinde portföy oluşturulması amaçlanmıştır. Çalışmanın örneklemine Bist imalat sanayi sektöründe faaliyette bulunan ana metal sanayi ve tekstil, giyim eşyası ve deri sanayi firmaları alınmıştır. Bahse konu yılda ana metal sanayinde 28, tekstil, giyim eşyası ve deri sanayinde ise 27 firma bulunmaktadır. Toplam 55 firmadan halka yeni arz olmalarından dolayı 2023 yılı için verilerine ulaşabildiğimiz 48 firma analiz kapsamına alınmıştır. TOPSIS analizi sonuçlarına göre az riskli (6 şirket), orta düzeyde riskli (6 şirket) ve yüksek riskli (6 şirket) gruplar belirlenmiştir. Risk kriterlerine göre T15 yüksek risk grubuna girerken, T1, T2 ve diğerleri orta riskli olarak sınıflandırılmıştır. Spearman korelasyon analizi sonuçlarına göre, TOPSIS skorları ile risk grupları arasında pozitif bir ilişki gözlemlenmiştir (r = 0.412), ancak bu ilişki istatistiksel olarak anlamlı değildir (*p* = .090).

JEL Kodları: C44, G11, M21
**Anahtar Kelimeler:** Finansal Oranlar, AHP, TOPSIS

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## Introduction

Creating the most suitable portfolio is recognized as one of the most vital aspects of finance. The ideal distribution of scarce resources at the marketplace scale, the capacity to fulfill the requirements of key players in the market, and the supervision of investment risks are several of the major obstacles faced by current investment markets. Shareholders, particularly in stock markets, rely on structured processes, effective tools, and clear criteria to assess the potential value and risks of investment opportunities. The ideal distribution of existing supplies in the free market, the capability to address the requirements of current investors, and monitoring and minimizing the risk levels of resolutions made or to be made in an investment are always necessary. One way to supervise and reduce existing portfolio risk is to create an investment portfolio and spread risk across all the market instruments within the basket. Consequently, one of the greatest significant issues for investors in capital markets is selecting the optimal share or portfolio in view of return (Thakur et al., 2018; Jing et al., 2023).

Turkey's textile sector is one of the country's largest export sectors, accounting for approximately 10-15% of total exports. Regions such as Europe, America, and the Middle East are among Turkey's primary textile export markets. Particularly, European Union countries hold the largest share in Turkey's textile exports. According to historical data, Turkey's textile exports to Europe increased by 33.8% in 2021, reaching approximately $6 billion. At the same time, Turkey exported $839 million worth of textiles to the United States, indicating that the U.S. is one of Turkey's key target markets. Globally, Turkey ranks among the top 10 textile exporters, significantly contributing to increasing foreign exchange reserves (Turkish Goods, 2021; The Observatory of Economic Complexity, 2022). Turkey's metal sector, especially iron and steel production, plays a vital role in the country's exports. In 2021, Turkey's steel exports reached a record 19.9 million tons, valued at $16.5 billion, representing a 93% revenue increase compared to the previous year. Europe, Latin America, and Southeast Asia are among the major markets for Turkey's steel exports, and the steel sector accounts for 34% of total exports. Additionally, Turkey's iron and steel exports were recorded at $15.7 billion in 2022. The primary export markets include Israel, Italy, Romania, the U.S., and Egypt. The fastest-growing markets for Turkey's steel exports are Romania, Egypt, and Bulgaria (EUROMETAL, 2022; The Observatory of Economic Complexity, 2022). The strong export performance of Turkey's textile and metal sectors, in addition to their influence on the overall economy, have been considered in the portfolio selection process, aiming to create a portfolio in line with global economic dynamics. This study primarily aims to evaluate the financial performance of organizations in Turkey's textile and metal sectors and to make the most appropriate portfolio selection for investors. The study evaluates financial data using multi-criteria decision-making methods (AHP and TOPSIS) to offer a portfolio that optimizes the risk-return balance for investors. Additionally, Data Envelopment Analysis (DEA) is employed to evaluate the effectiveness of the companies. This research integrates multi-criteria decision-making methods including the Analytical Hierarchy Process (AHP), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and Data Envelopment Analysis (DEA) in financial performance and portfolio selection. The AHP method was employed to compute the weights of the criteria, TOPSIS was utilized to rank the companies, and DEA was applied to analyze the companies' efficiency. Finally, companies were categorized into low, medium, and high-risk levels based on the calculated risk ratios and TOPSIS scores, and Spearman correlation analysis was performed using SPSS. The integration of these methods is expected to strengthen the theoretical framework of the study and ensure that portfolio selection is more balanced and reliable.

## Literature

In this section, a summary of studies that applied Data Envelopment Analysis, Analytical Hierarchy Process, and TOPSIS methods in various fields or for different purposes is presented in tabular form.

**Table 1.** *Studies Conducted Using Applied Methods*

| Author(s) | Study |
|---|---|
| Beccali & Ardente (2004) | evaluated renewable energy projects with economic, environmental and social criteria using multi-criteria decision analysis (MCDA) and data envelopment analysis (DEA) methods in energy planning. In the study, MCDA criteria weighting was performed, while DEA measured the efficiency of the projects. As a result, it was shown that the integrated use of these methods allows for a more comprehensive analysis of energy |

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| | projects in terms of efficiency and sustainability. |
| Lozano & Villa (2006) | used data envelopment analysis (DEA) to evaluate mutual fund performance. In the study, fund expenses and risk levels were analyzed as inputs and returns and other performance measures were analyzed as outputs. The results show that DEA is a suitable tool to evaluate the efficiency of mutual funds and to determine performance differences. |
| Lozano & Gutiérrez (2008) | used data envelopment analysis (DEA) and simulation methods to measure the efficiency of port terminals. The study analyzed terminal resources (e.g. labor, equipment) as inputs and loading-unloading volume as outputs. As a result, it was determined that these methods were effective in evaluating terminal efficiency and identifying performance improvement potentials. |
| Azadeh, Ghaderi & Rajabzadeh (2011) | integrated data envelopment analysis (DEA) and analytical hierarchy process (AHP) for performance evaluation and improvement of railway systems. In the study, resource utilization was used as input and carrying capacity and customer satisfaction as output. The results showed that this integration is an effective method to evaluate the system performance and identify areas for improvement. |
| Güngör & Gözgör (2015) | used data envelopment analysis (DEA) and multi-criteria decision making (MCDM) methods for fund selection. In the study, risk and costs were analyzed as inputs, return performance and other financial criteria were analyzed as outputs. The results indicated that these methods were effective in evaluating the performance of funds and determining the best options. |
| Dervişoğlu & Kurt (2017) | used data envelopment analysis (DEA) and TOPSIS methods to compare stock performance in BIST Banking Index. In the study, data such as financial ratios and market indicators were evaluated. The results show that these methods are effective in ranking stock performance and supporting investment decisions. |
| Wei & Zhang (2020) | used data envelopment analysis (DEA) and Markowitz model for performance evaluation and portfolio selection in the Chinese stock market. In the study, risk and costs were analyzed as inputs, return and other performance criteria were analyzed as outputs. The results showed that these methods were effective in portfolio optimization and stock performance evaluation. |
| Bal & Örkcü (2021) | used data envelopment analysis (DEA) and TOPSIS methods to evaluate stock performance in Borsa Istanbul. In the study, data such as financial ratios and market indicators were analyzed. The results revealed that these methods were effective in ranking stock performance and supporting investment decisions. |
| Zolfani et al. (2012) | used a hybrid model combining TOPSIS and VIKOR methods for financial performance evaluation. In the study, financial ratios and performance measures were evaluated. The results showed that this hybrid model is effective for ranking financial performance and determining the best alternatives. |
| Aktaş & Ulusoy (2014) | used the TOPSIS method to evaluate the financial performance of manufacturing firms traded on Borsa Istanbul. In the study, financial ratios and performance measures were analyzed. The results showed that TOPSIS is an effective method to rank the financial performance of |

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| | firms and to determine the best performing firms. |
| Chaweewanchon & Chaysiri (2022) | integrated machine learning methods with Markowitz's mean-variance portfolio optimization for stock selection. The study used stock returns, risk measures, and financial data. The results showed that this integration was effective in improving portfolio performance and making better investment decisions. |
| Figueira et al. (2005) | have comprehensively examined the methods of multi-criteria decision analysis (MCDA). The study addresses the theoretical foundations of MCDA, its application areas and the criteria used. The results show that MCDA provides flexible and effective solutions in complex decision processes with different methods. |
| Ghaffari et al. (2021) | examined methods for dealing with uncertainty in portfolio selection problems. In the study, approaches such as probability-based and robust optimization were considered and financial data were used. The results showed that these methods were effective in optimizing portfolio performance under uncertainty conditions. |
| Hwang & Yoon (1981) | examined the applications of multi-attribute decision making (MADM) methods. In the study, decision alternatives were evaluated with different criteria and weighting methods. The results showed that MADM methods are effective in ranking and selecting alternatives in complex decision processes. |
| Kucukaltan & Aydin (2015) | integrated AHP and TOPSIS methods to evaluate the performance of air traffic controllers. In the study, data such as experience, reaction time and decision-making skills were used. The results showed that this integration is an effective and reliable method in performance evaluation. |
| Markowitz (1952) | developed the theory of portfolio selection and presented an optimization model based on the concepts of mean-return and variance-risk. In the study, stock returns and risk measures were used. The results showed that risk could be minimized and return could be optimized with diversification, and laid the foundation of modern portfolio theory. |
| Meade & Islam (2015) | used artificial neural networks (ANN) and TOPSIS methods to model and predict stock performance. In the study, financial indicators and stock data were analyzed. The results showed that these methods were effective in predicting and ranking stock performance. |
| Peykani et al. (2020) | proposed a two-stage robust portfolio selection and optimization approach. The study used financial data such as stock returns and risk measures. The results showed that this approach is effective for creating more reliable and balanced portfolios under conditions of uncertainty. |
| Ayçin & Çakın (2019) | used MACBETH and COPRAS methods to evaluate the financial performance of companies. In the study, financial ratios and performance indicators were analyzed. The results showed that these methods were effective in ranking financial performance and providing decision support. |
| Yalcin & Unlu (2018) | used the TOPSIS method to evaluate the financial performance of real estate investment trusts in Turkey. In the study, financial ratios and market indicators were analyzed. The results showed that TOPSIS is |

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| | an effective method in ranking performance and determining the best performing companies. |
| Zavadskas, Turskis & Kildienė (2014) | have comprehensively studied the multi-criteria decision making (MCDM) methods used in economics. The study has examined the theoretical frameworks and application areas of different MCDM methods. The results have shown that these methods are effective in evaluating and ranking alternatives in solving economic problems. |
| Zopounidis & Doumpos (2013) | examined the multi-criteria decision analysis (MCDM) methods used for financial performance and portfolio selection. In the study, financial indicators and portfolio data were considered. The results showed that MCDM methods are effective in supporting investment decisions and evaluating financial performance. |

## Material and Methods

To calculate the efficiency of these 48 firms, a data envelopment analysis was conducted using MATLAB software, and as a result, 18 efficient firms were selected as a sample. In order to measure firm efficiency, 14 criteria used in the study conducted by Roodposhti et al. (2018) were used and input-output values were formed from these criteria. In addition, the financial ratios used for efficiency analysis consist of financial ratios frequently used in the literature. Three indicators - total asset turnover, receivables turnover and inventory turnover - were selected as input measures for the analysis, while sales growth and ROA were selected as output indicators. The financial measures used in the study were obtained from the Public Disclosure Platform (KAP). Table 2 presents the financial ratios used in the analysis and the weights of the relevant criteria obtained using the AHP method. These weights represent the relative importance of each criterion in the decision-making process. In Table 2. Weight (Wj) represents the criteria importance levels obtained from the opinions of experts (experts. academicians. industry professionals. etc.) to determine the relative importance levels of the criteria. The consistency ratio (CR) of the pairwise comparison matrix was calculated as 0.0. ensuring that the weight assignments are consistent.

**Table 2.** *Variables and Criteria Weights Used in the Study*

| Financial Indicators (Ratio) | | Weight (Wj) |
|---|---|---|
| **Liquidity Ratios** | X8(Net Sales / Total Assets) | 0.181 |
| | X9(Net Sales / Average Receivables) | 0.136 |
| **Financial Structure Ratios** | X12(Total Debt / Total Assets) | 0.090 |
| **Profitability Ratios** | X5(Net Profit / Net Sales) | 0.072 |
| | X6(Net Profit / Total Assets) | 0.109 |
| | X7(Net Profit / Equity) | 0.063 |
| **Activity Ratios** | X10(Inventory Turnover) | 0.090 |
| **Risk Ratios** | X11(Beta-Coefficient showing market risk) | 0.045 |
| **Valuation Ratios** | X13(Share Price / Earnings Per Share) | 0.036 |
| | X14(Share Price / Book Value) | 0.054 |
| **Growth Ratios** | X1(Sales Growth Rate) | 0.027 |
| | X2(Net Profit Increase / Decrease Rate) | 0.045 |
| | X3(Earnings Per Share Growth Rate) | 0.036 |
| | X4(Net Profit / Number of Shares) | 0.009 |

In portfolio selection, risk measures such as the Beta coefficient and the Total Debt/Total Assets ratio were used. Sharpe (1964) first introduced the Beta coefficient in the circumstance of the Capital Asset Pricing Model (CAPM). Beta is a risk measure that indicates how sensitive an asset is to market fluctuations. The Beta value calculates how much risk an investment carries compared to the overall market. A Beta value of 1 means that the stock's performance parallels the market in both direction and intensity. A Beta higher than 1 demonstrates that the stock is more susceptible to volatility than the market and, therefore, carries a higher risk. A Beta less than 1 indicates that the stock is less volatile than the market, implying lower risk. A Beta less than 0 suggests the stock behaves inversely to the market (Investopedia, 2023; Corporate Finance Institute, 2023).

Modigliani and Miller (1958) considered debt ratios as part of a firm's risk structure in their work. The Total Debt/Total Assets ratio shows how much of the firm's operations are financed through debt and how much of that debt is covered by the assets. This ratio is a critical indicator of a company's financial leverage and its reliance on debt. It is also widely used to assess the company's financial risk. If this ratio is less than 0.30, firms in this group are considered low-risk and financially more reliable. This means that the firm primarily uses equity financing and has a lower debt burden. Such firms are generally less likely to struggle with debt payments during economic downturns (Investopedia, 2023).

For firms in the medium-risk group, this ratio should be between 0.30 and 0.60. A moderate level of debt indicates that the firm maintains a balanced structure between debt and equity, meaning that debt is strategically used to finance growth and expansion opportunities (Investing Answers, 2023). For high-risk firms, this ratio should be greater than 0.60. Firms in this group continue their operations with higher levels of debt. A higher ratio implies an increased debt service burden, which reduces the firm's financial flexibility. This situation increases potential risks for the company and can threaten its ability to repay debts (Investing, 2023).

**Data Set**

This study aims to construct portfolios categorized into low, medium, and high-risk levels for companies operating in the manufacturing sector in 2023 using efficiency analysis and multi-criteria decision-making methods, namely AHP and TOPSIS. The sample includes companies from the BIST manufacturing sector, specifically in the basic metal and textile, clothing, and leather industries. In the mentioned year, there were 28 companies in the basic metal industry and 27 companies in the textile, clothing, and leather industries. Out of a total of 55 companies, data from 48 firms were available for the year 2023 due to recent initial public offerings, and these firms were incorporated into the analysis. Table 3 shows the companies included in the analysis.

**Table 3.** *Companies Included in DEA Analysis*

| Analysis Codes | Textile Company Code | Analysis Codes | Metal Company Code |
|---|---|---|---|
| T1 | ATEKS | M4 | BRSAN |
| T2 | ARSAN | M10 | CUSAN |
| T3 | BLCYT | M14 | ERCB |
| T5 | BRMEN | M16 | ISDMR |
| T6 | BOSSA | M17 | IZMDC |
| T10 | ENSRI | M18 | KRDMD |
| T15 | LUKSK | M19 | KCAER |
| T16 | MEGAP | M20 | PNLSN |
| T24 | YUNSA | M22 | TUCLK |

**Data Envelopment Analysis (DEA)**

As a non-parametric method based on computational modeling, Data Envelopment Analysis (DEA) is a sufficient approach to test the performance level of a Decision-Making Unit (DMU) by considering input and output parameters. This method is rooted in the work on efficiency conducted by Farrell in 1957 (Farrell, 1957; Charnes et al., 1989; Charnes et al., 1978; Thanassoulis et al., 2008). The principal benefit of using the DEA technique is its ability to create a ranking among the DMUs under analysis. This technique automatically assigns weights to the criteria being analyzed and processes raw data. In terms of weights, the analysis often assigns a zero weight to certain criteria in some DMUs, identifying the efficient criteria. However, the possibility of ignoring a particular criterion is considered a disadvantage of the method (Oliveira et al., 2023). The DEA approach is one of the most significant techniques for evaluating the financial productivity of assets of different sizes. The design of the method allows for variations in models incorporating constant and varying returns to scale. This flexibility enables comprehensive analyses to identify assets with the highest level of financial efficiency. The results received also form the premise for evaluating significant proposals for assets described by severely worse financial conditions (Smętek et al., 2022). The DEA approach submitted by Charnes et al., 1978) is formulated as follows:

$$\boldsymbol{makh_k} = \frac{\sum_{r=1}^{s} u_{rk} \cdot Y_{rk}}{\sum_{r=1}^{s} v_{ik} \cdot x_{ik}} \tag{1}$$

$h_k$: Efficiency of decision-making unit (DMU) k,
s: Number of outputs,
r: r-th output,
i: Number of inputs,
$u_{rk}$ : Weight assigned by DMU k for the r-th output,
$Y_{rk}$ : Amount of r-th output produced by DMU k,
$v_{ik}$ : Weight assigned by DMU k for the i-th input,
$x_{ik}$ : Amount of i-th input used by DMU k.

**AHP and TOPSIS**

The Analytic Hierarchy Process (AHP) was first evolved by Saaty in 1980 and is broadly utilized in the literature. Saaty introduced a scale of crucial, ranging from 1 to 9, to be used during the pairwise comparison phase of the analysis. However, since most real-world decisions involve uncertain outcomes, meaning they are subjective, fuzzy AHP is used instead of the traditional AHP (Saaty, 1980). In the AHP method, the criteria affecting the decision-making process are generally categorized into two groups: objective and subjective criteria. The weights of the criteria were calculated using pairwise comparisons, and their impact on the final decision was evaluated. Objective criteria are those that can be directly evaluated based on quantifiable and tangible outcomes. These criteria are used to minimize ambiguity and provide an objective assessment during decision-making. Objective criteria are based on measurable data, such as financial indicators, performance metrics, and other numerical information (Saaty, 1980; Ho, 2008). In this study, objective criteria were preferred during the decision-making process. The general structure of AHP can be outlined as follows formulas (Saaty, 1980). The pairwise comparison matrix highlights the relative priority of decision criteria:

$$a_{ij=}\frac{w_i}{w_j} \tag{2}$$

Here:
$a_{ij}$: The relative importance of criterion $\mathbf{i}$ compared to criterion j**,**
$w_i$ : The weight of criterion i**,**
$w_j$: The weight of criterion j**.**

The weight $\boldsymbol{w_i}$ for each criterion is calculated from the pairwise comparison matrix,

$$w_i = \frac{\sum a_{ij}}{n} \tag{3}$$

Here:
$w_i$: The weight of criterion $\mathbf{i}$,
$a_{ij}$: Elements of the pairwise comparison matrix,
n: The number of criteria.

To evaluate the consistency of the comparisons, the consistency ratio (CR) is calculated. CR is obtained by dividing the consistency index (CI) by the random index (RI).

$$CR= \frac{CI}{RI} \tag{4}$$

CI: Consistency index,
RI: Random index (determined from a table based on the number of criteria).

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a classical representation of a multi-criteria decision-making method. It ranks alternatives judged by their nearness to the positive ideal solution and the negative ideal solution The positive ideal solution is defined as the one that seeks to maximize benefit criteria and reduce cost criteria, while the negative ideal solution does the opposite, maximizing cost criteria and minimizing benefit criteria. TOPSIS incorporates both the positive and negative ideal solutions, and the best options are ranked based on Their affinity to the positive ideal solution and their distance from the negative ideal solution. This ranking method prevents alternatives from being similar to both the positive and negative benchmark solutions Judged by the relative nearness to the ideal outcome (Benitez et al., 2007; Seçme et al., 2009). The general structure of the TOPSIS method can be expressed by the following formulas (Hwang & Yoon, 1981). First, for TOPSIS normalization and the weighted decision matrix:

$$r_{ij=}\frac{x_{ij}}{\sqrt{\sum_i^m = x_{ij}^2}} \tag{5}$$

Here:
$r_{ij}$: The normalized value of the i-th alternative under the j-th criterion.
$x_{ij}$: The original (raw) value of the i-th alternative under the j-th criterion.
m: The number of alternatives (the total number of all alternatives under that criterion).

The number of alternatives (the total number of all alternatives under that criterion);

$$v_{ij=}\, w_i.\, r_{ij} \tag{6}$$

Here:
$v_{ij}$ : Weighted decision matrix element,
$w_i$: The weight of the j-th criterion,
$r_{ij}$: Normalized decision matrix element.

For TOPSIS distance calculation:

$$D_{\mathrm{i}}^{+} = \sqrt{\sum(v_{ij} + A^{+})}^{\,2} \tag{7}$$

$$D_{\mathrm{i}}^{-} = \sqrt{\sum(v_{ij} + A^{-})}^{\,2}$$

Here:
$A^{+}$: Positive ideal solution,
$A^{+}$: Negative ideal solution,
$D_{\mathrm{i}}^{+}$: Distance to the positive ideal solution,
$D_{\mathrm{i}}^{-}$: Distance to the negative ideal solution.

For TOPSIS score calculation:

$$S_i = \frac{D_{\mathrm{i}}^{-}}{D_{\mathrm{i}}^{+} + D_{\mathrm{i}}^{-}} \tag{8}$$

Here:
$S_i$: Alternative TOPSIS score.
For risk-based portfolio selection (Markowitz, 1952):

$$P_{risk} = \frac{\Sigma(R_i.W_i)}{\Sigma W_i} \tag{9}$$

Here:
$P_{risk}$ : Portfolio's risk score,

$R_i$: Risk score of the i-th company,

$W_i$: Weight of the i-th company.

**Findings**

In this part of the study, the financial results of the companies in the basic metal and textile, clothing and leather sectors for 2023 were calculated and the findings obtained through risk-based portfolio selection were interpreted. The importance levels of each criterion for the

At this stage, in order to evaluate the importance levels of each criterion, criteria weights were created using pairwise comparison matrices in consultation with experts including academics, bankers and industry executives.

**Evaluation of Financial Performance**

The financial ratios used in this study were determined based on the research conducted by Jing et al. (2023). In the related study, the importance levels of the criteria were calculated implementing multi-criteria decision-making strategies like AHP and TOPSIS for portfolio selection. In this study, 18 companies from two different sectors and 14 evaluation criteria (financial ratios) were used. Table 4 presents the normalized decision matrix values.

**Table 4.** *Normalized Decision Matrix companies considered in the analysis were determined using the AHP method*

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 | X14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| T1 | 0.817 | 0.788 | 0.811 | 0.796 | 0.820 | 0.821 | 0.821 | 0.838 | 1.000 | 0.967 | 0.883 | 0.835 | 0.000 | 0.857 |
| T2 | 0.000 | 0.004 | 0.004 | 0.008 | 0.006 | 0.002 | 0.002 | 0.002 | 0.023 | 1.000 | 0.003 | 0.002 | 0.013 | 0.003 |
| T3 | 0.001 | 0.000 | 0.000 | 0.072 | 0.001 | 0.002 | 0.005 | 0.080 | 1.000 | 0.610 | 0.006 | 0.020 | 0.282 | 0.046 |
| T5 | 0.510 | 0.488 | 0.492 | 0.378 | 0.000 | 0.528 | 0.525 | 0.561 | 0.634 | 1.000 | 0.558 | 0.564 | 0.452 | 0.608 |
| T6 | 0.655 | 0.371 | 0.305 | 0.434 | 0.434 | 0.435 | 0.432 | 0.452 | 1.000 | 0.468 | 0.447 | 0.453 | 0.000 | 0.644 |
| T10 | 0.000 | 0.001 | 0.000 | 0.008 | 0.000 | 0.021 | 0.046 | 0.212 | 0.002 | 0.001 | 0.000 | 0.000 | 0.011 | 1.000 |
| T15 | 0.025 | 0.000 | 0.010 | 0.041 | 0.035 | 0.035 | 0.035 | 0.082 | 0.307 | 0.211 | 0.056 | 0.039 | 1.000 | 0.090 |
| T16 | 0.489 | 0.999 | 0.997 | 0.000 | 0.526 | 0.531 | 0.497 | 0.636 | 1.000 | 0.866 | 0.607 | 0.624 | 0.085 | 0.749 |
| T24 | 0.000 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.001 | 0.004 | 0.002 | 0.002 | 0.012 | 1.000 |
| M4 | 0.000 | 0.000 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0.001 | 0.001 | 0.007 | 1.000 |
| M10 | 0.000 | 0.168 | 0.210 | 0.410 | 0.043 | 0.024 | 0.028 | 0.042 | 0.298 | 0.334 | 0.100 | 0.037 | 1.000 | 0.208 |
| M14 | 0.002 | 0.000 | 0.000 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 1.000 | 0.002 | 0.003 | 0.002 | 0.057 | 0.013 |
| M16 | 0.513 | 0.445 | 0.451 | 0.505 | 0.512 | 0.512 | 0.512 | 0.546 | 1.000 | 0.718 | 0.576 | 0.549 | 0.000 | 0.555 |
| M17 | 0.015 | 0.009 | 0.000 | 0.016 | 0.016 | 0.016 | 0.016 | 0.019 | 0.070 | 0.064 | 0.023 | 0.017 | 1.000 | 0.120 |
| M18 | 0.023 | 0.000 | 0.004 | 0.041 | 0.023 | 0.024 | 0.025 | 0.072 | 0.310 | 0.241 | 0.035 | 0.037 | 1.000 | 0.112 |
| M19 | 0.000 | 0.065 | 0.048 | 0.233 | 0.016 | 0.022 | 0.034 | 0.263 | 0.846 | 0.818 | 0.047 | 0.068 | 1.000 | 0.206 |
| M20 | 0.006 | 0.074 | 0.100 | 0.284 | 0.022 | 0.000 | 0.020 | 0.058 | 0.426 | 1.000 | 0.030 | 0.081 | 0.970 | 0.207 |
| M22 | 0.000 | 0.012 | 0.018 | 0.156 | 0.043 | 0.031 | 0.039 | 0.090 | 0.756 | 0.398 | 0.012 | 0.047 | 1.000 | 0.234 |

Table 4 shows the normalized decision matrix, which is one of the critical steps in the TOPSIS method. The normalization process allows all criteria to be brought to a comparable scale and allows the analysis of the criteria without distorting their relative importance. The values in this table are calculated by applying the vector normalization method to the raw financial data of the companies. This transformation makes the financial performances of the companies fairly comparable in the multi-criteria decision-making process. The normalized values range from 0 to 1, with higher values indicating better performance in the relevant criterion.

**Table 5.** *Weighted Standard Decision Matrix*

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 | X14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| T1 | 0.149 | 0.107 | 0.074 | 0.058 | 0.090 | 0.052 | 0.075 | 0.038 | 0.036 | 0.053 | 0.024 | 0.038 | 0.000 | 0.008 |
| T2 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.055 | 0.000 | 0.000 | 0.000 | 0.000 |
| T3 | 0.000 | 0.000 | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 | 0.004 | 0.036 | 0.033 | 0.000 | 0.001 | 0.010 | 0.000 |
| T5 | 0.093 | 0.067 | 0.045 | 0.027 | 0.000 | 0.034 | 0.048 | 0.026 | 0.023 | 0.055 | 0.015 | 0.026 | 0.016 | 0.006 |
| T6 | 0.119 | 0.051 | 0.028 | 0.032 | 0.047 | 0.028 | 0.039 | 0.021 | 0.036 | 0.026 | 0.012 | 0.021 | 0.000 | 0.006 |
| T10 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.001 | 0.004 | 0.010 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.009 |
| T15 | 0.005 | 0.000 | 0.001 | 0.003 | 0.004 | 0.002 | 0.003 | 0.004 | 0.011 | 0.012 | 0.002 | 0.002 | 0.036 | 0.001 |
| T16 | 0.089 | 0.136 | 0.091 | 0.000 | 0.057 | 0.034 | 0.045 | 0.029 | 0.036 | 0.047 | 0.017 | 0.028 | 0.003 | 0.007 |
| T24 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.009 |
| M4 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.009 |
| M10 | 0.000 | 0.023 | 0.019 | 0.030 | 0.005 | 0.002 | 0.003 | 0.002 | 0.011 | 0.018 | 0.003 | 0.002 | 0.036 | 0.002 |
| M14 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.036 | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 |
| M16 | 0.093 | 0.061 | 0.041 | 0.037 | 0.056 | 0.033 | 0.047 | 0.025 | 0.036 | 0.039 | 0.016 | 0.025 | 0.000 | 0.005 |
| M17 | 0.003 | 0.001 | 0.000 | 0.001 | 0.002 | 0.001 | 0.001 | 0.001 | 0.003 | 0.003 | 0.001 | 0.001 | 0.036 | 0.001 |
| M18 | 0.004 | 0.000 | 0.000 | 0.003 | 0.003 | 0.002 | 0.002 | 0.003 | 0.011 | 0.013 | 0.001 | 0.002 | 0.036 | 0.001 |
| M19 | 0.000 | 0.009 | 0.004 | 0.017 | 0.002 | 0.001 | 0.003 | 0.012 | 0.031 | 0.045 | 0.001 | 0.003 | 0.036 | 0.002 |
| M20 | 0.001 | 0.010 | 0.009 | 0.021 | 0.002 | 0.000 | 0.002 | 0.003 | 0.015 | 0.055 | 0.001 | 0.004 | 0.035 | 0.002 |
| M22 | 0.000 | 0.002 | 0.002 | 0.011 | 0.005 | 0.002 | 0.004 | 0.004 | 0.027 | 0.022 | 0.000 | 0.002 | 0.036 | 0.002 |

Table 5 shows the weighted standard decision matrix obtained by multiplying the normalized values with the criteria weights determined by the AHP method. This table allows for a better analysis of the contribution of each criterion to the performance of the companies. In the next step, the relative performances of the companies were evaluated by calculating the ideal and negative ideal solutions. This process helps to rank the companies in terms of their financial strength and supports the optimal portfolio choices of investors. The ideal negative-positive solution results after normalized decision matrix and weighted decision matrices are shown. The ideal negative-positive solution results after normalized decision matrix and weighted decision matrices are shown.

**Table 6.** *Ideal (A+) and Negative Ideal (A−) Solutions*

| Criterion | Tex (T) A+ | Tex (T) A- | Met (M) A+ | Met (M) A- |
|---|---|---|---|---|
| X1 | 0.817 | 0.000 | 0.513 | 0.000 |
| X2 | 0.999 | 0.000 | 0.445 | 0.000 |
| X3 | 0.997 | 0.000 | 0.451 | 0.000 |
| X4 | 0.796 | 0.000 | 0.505 | 0.001 |
| X5 | 0.820 | 0.000 | 0.512 | 0.001 |
| X6 | 0.866 | 0.000 | 0.576 | 0.001 |
| X7 | 0.607 | 0.001 | 0.549 | 0.001 |
| X8 | 1.000 | 0.001 | 1.000 | 0.001 |
| X9 | 1.000 | 0.001 | 0.846 | 0.001 |
| X10 | 1.000 | 0.001 | 1.000 | 0.001 |
| X11 | 1.000 | 0.000 | 1.000 | 0.000 |
| X12 | 0.835 | 0.000 | 0.970 | 0.000 |
| X13 | 1.000 | 0.000 | 1.000 | 0.000 |
| X14 | 1.000 | 0.003 | 1.000 | 0.003 |

Upon reviewing Table 6, it is noticeable that the textile sector has higher A+ (ideal solution) values than the metal sector in most criteria. This shows that the best companies perform better in the textile sector. The metal sector shows lower values than the textile sector, particularly in certain financial performance indicators (such as X4 and X5). It is understood that there are performance differences in both sectors, that is, some companies perform quite well while others perform poorly.

Table 7 presents the TOPSIS score rankings for companies in the basic metal and textile, clothing, and leather industries for the year 2023, ordered from highest to lowest.

**Table 7.** *Company Rankings Based on TOPSIS Scores*

| Companies | TOPSIS Score | Companies | TOPSIS Score |
|---|---|---|---|
| T1 | 0.755 | M4 | 0.229 |
| T2 | 0.571 | M10 | 0.225 |
| T3 | 0.431 | M14 | 0.141 |
| T5 | 0.427 | M16 | 0.074 |
| T6 | 0.425 | M17 | 0.061 |
| T10 | 0.399 | M18 | 0.055 |
| T15 | 0.324 | M19 | 0.045 |
| T16 | 0.303 | M20 | 0.039 |
| T24 | 0.277 | M22 | 0.032 |

Upon reviewing at Table 7, it is understood that the textile sector has generally higher TOPSIS scores than the metal sector. This means that textile companies are in a better position than metal companies in terms of performance. The metal sector, on the other hand, presents a weak picture in terms of performance. No metal company has achieved a TOPSIS score close to the best performing companies of the textile companies. The score differences indicate a significant performance difference between the two sectors. While textile companies generally have stronger financial or operational criteria, it is acknowledged that metal companies have significant performance deficiencies.

**Table 8.** *Portfolio Grouping Based on Risk Measures*

| Companies | TOPSIS Score | Beta and Debt/Asset Risk Group |
|---|---|---|
| T1 | Low Risk | Medium Risk |
| T2 | Low Risk | Medium Risk |
| T3 | Low Risk | Medium Risk |
| T5 | Medium Risk | Medium Risk |
| T6 | Low Risk | Medium Risk |
| T10 | Medium Risk | Medium Risk |
| T15 | Low Risk | High Risk |
| T16 | Medium Risk | Low Risk |
| T24 | Medium Risk | Medium Risk |
| M4 | Low Risk | Low Risk |
| M10 | Medium Risk | Low Risk |
| M14 | Medium Risk | Low Risk |
| M16 | High Risk | Low Risk |
| M17 | High Risk | Low Risk |
| M18 | High Risk | Low Risk |
| M19 | High Risk | Low Risk |
| M20 | High Risk | Low Risk |
| M22 | High Risk | Low Risk |

When looking at Table 8, the textile sector shows a more balanced distribution according to Beta risk, many companies are in the low and medium risk group. However, according to debt/asset ratios, most companies appear to be at medium risk. In terms of debt management, companies need to control their financial risks. Especially T15 draws attention with both low market risk and high debt risk. Although the metal sector is low risk according to metal companies' debt/asset ratios, it is concluded that it is at high risk according to Beta values. Especially M16, M17, M18, M19, M20 and M22 companies are considered among the companies that investors should pay attention to, even if they are at high market risk and have low debt levels.

The risk groups in Table 8 were determined based on the TOPSIS scores, Beta coefficients and Debt/Asset ratios of the firms. However, it is observed that some firms are in the low risk group despite having a low TOPSIS score or vice versa. This situation shows that risk is determined not by a single factor but by the interaction of more than one variable (Sharpe, 1964; Modigliani and Miller, 1958). Since textile sector firms generally operate with low debt levels, they seem to be more reliable in terms of financial risk. On the other hand, metal sector firms carry higher risk due to their high capital requirements and sensitivity to market fluctuations. Spearman Correlation Analysis (r = 0.412, $p$ = .090) conducted in the study shows that there is a positive relationship between TOPSIS scores and risk groups, but it was determined that this relationship was not statistically significant. This situation reveals that there is no definite relationship between the financial performances of firms and their risk levels and that different risk factors should be taken into consideration.

## Conclusion and Recommendations

Portfolio selection is a critical process that aims to ensure that investors make optimum investment decisions by balancing risk and return. While traditional methods focus solely on financial ratios, considering the multidimensional nature of investment decisions, the use of multiple criteria decision making (MCDM) methods has become increasingly important. Analytical Hierarchy Process (AHP) and TOPSIS methods provide investors with the opportunity to make more conscious and objective choices by systematically evaluating different criteria that affect investment decisions. Considering global economic fluctuations and uncertainties in financial markets, the use of such methods paves the way for investors to make more reliable and sustainable decisions. Therefore, portfolio selection is of strategic importance in investment management for both individual and institutional investors.

In general, when the inter-sectoral evaluation is made, it is seen that the textile sector ("T" coded companies) generally performs better and falls into the low-risk group. In contrast, a greater number of companies in the metal industry (companies with the code "M") are classified as high-risk. The results indicate that firms in the metal sector tend to carry higher risks, signaling that the sector is more volatile. As a general investment strategy, the textile sector appears ideal for safe and long-term investments, offering opportunities for investors to diversify their portfolios with low-risk firms. The metal industry, by comparison, is more applicable for investors seeking short-term speculative opportunities, particularly those with a high-risk tolerance.

Firms with high TOPSIS scores are typically witnessed in the low and medium-risk categories, indicating that these companies perform better financially and are more attractive to investors. High-risk companies tend to have lower TOPSIS scores, suggesting they struggle to balance risk and return. For investors, these results highlight that low and medium-risk companies show strong performance and offer more reliable investment opportunities, while high-risk firms carry significant risks despite the potential for higher returns. Reviewing studies from different years, such as Yüksel & Canöz (2015), Doğan (2016), Küçük & Büyükbaş (2017) and Çetin & Yıldırım (2018), We find that our outcomes are in accordance with their findings, where the textile sector demonstrates more stable performance, while the metal sector is more volatile and risky.

The addition of this research enhances the existing literature is reflected in its example application of combining Data Envelopment Analysis (DEA), AHP, and TOPSIS methods for portfolio selection. The integration of these three methods provides a robust structure for both criterion weighting and company performance ranking. Analyzing and comparing the textile and metal sectors offer insights into how risks in different sectors affect investor decisions. Additionally, the insights provided on evaluating a company's financial structure and its impact on the risk-return balance are foreseen to provide to the financial risk management literature.

The limitations of this study include its focus solely on companies in the textile and metal sectors in Turkey. The exclusion of other sectors could make it harder to apply the results broadly across all markets. Furthermore, the exclusion of potential factors, such as environmental or social considerations, could be viewed as another limitation. Future studies could incorporate time series analysis to examine how companies' performance changes over the years. Long-term analyses could help better understand trends in the sector. Additionally, similar analyses could be conducted across a broader range of industries.

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**Genişletilmiş Özet**

Türkiye'nin tekstil ve metal sektörlerindeki güçlü ihracat performansı ve genel ekonomiye etkisi, çalışmanın portföy seçim sürecinde dikkate alınmış ve küresel ekonomik dinamiklerle uyumlu bir portföy oluşturulması amaçlanmıştır. Bu çalışmanın temel amacı Türkiye'de tekstil ve metal sektörlerindeki firmaların finansal performanslarını analiz ederek, yatırımcılar için en uygun portföy seçimini gerçekleştirmektir. Çalışma finansal verileri çok kriterli karar verme yöntemleri (AHP ve TOPSIS) ile değerlendirerek, yatırımcılara risk-getiri dengesini optimize edecek bir portföy sunmayı hedeflemektedir. Bunun yanında, Veri Zarflama Analizi (DEA) kullanılarak firmaların etkinliği değerlendirilmiştir. Bu çalışma, finansal performans ve portföy seçiminde Analitik Hiyerarşi Süreci (AHP), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ve Veri Zarflama Analizi (DEA) gibi çok kriterli karar verme yöntemlerini entegre ederek gerçekleştirilmiştir. AHP yöntemi ile kriterlerin ağırlıkları belirlenmiş, TOPSIS ile firmalar sıralanmış ve DEA ile firmaların verimliliği analiz edilmiştir. Son olarak hesaplanan risk oranları ve TOPSIS skorları kullanılarak firmalar düşük-orta-yüksek risk durumlarına göre sıralanmış ve SPSS'te Spearman korelasyon analizi yapılmıştır. Bu yöntemlerin birlikte kullanımı, çalışmanın teorik altyapısını güçlendirmiş ve portföy seçiminin daha dengeli ve güvenilir olması sağlanmıştır.

Çalışmada imalat sanayi sektöründe 2023 yılında faaliyette bulunan şirketlerin verimlilik analizi ve çok kriterli karar verme yöntemleri AHP ve TOPSIS ile düşük-orta-yüksek risk seviyelerinde portföy oluşturulması amaçlanmıştır. Çalışmanın örneklemine BIST imalat sanayi sektöründe faaliyette bulunan ana metal sanayi ve tekstil, giyim eşyası ve deri sanayi firmaları alınmıştır. Bahse konu yılda ana metal sanayinde 28, tekstil, giyim eşyası ve deri sanayinde ise 27 firma bulunmaktadır. Toplam 55 firmadan halka yeni arz olmalarından dolayı 2023 yılı için verilerine ulaşabildiğimiz 48 firma analiz kapsamına alınmıştır.

Bu 48 firmanın verimliliklerini hesaplamak için MATLAB yazılımı kullanılarak bir veri zarflama analizi yapılmış ve bu analizin sonucunda 18 verimli şirket seçilerek örneklem belirlenmiştir. Verimlilik analizi değerleri ise Roodposhti vd. (2018) araştırmasına dayanarak, şirketlerin verimliliğini ölçmek için 14 kriter ve bu kriterler içinden girdi-çıktı değerleri belirlenmiştir. Bu kriterler arasından üç gösterge girdi (toplam varlıkların cirosu, alacak devir hızı, stok devir hızı) ve iki gösterge çıktı (satış büyümesi ve ROA) alınarak verimlilik analizi yapılmıştır. Çalışmada kullanılan finansal oranları hesaplamak için KAP (Kamuoyu Aydınlatma Platformu)'dan faydalanılmıştır.

Çalışmanın tutarlılık oranı (CR) 0.0 olarak hesaplanmıştır. Spearman Korelasyon sonuçlarına göre risk grubu ile TOPSIS skoru arasında orta düzeyde pozitif bir ilişkinin olduğu ($r=0.412$), ancak bu ilişkinin kalıcı olarak anlamlı olmadığı ($p=0,090$) görülmektedir. Genel sektör karşılaştırması olarak değerlendirildiğinde; tekstil sektörü (T kodlu firmalar), bu sektörde yer alan firmaların genel olarak daha iyi performans gösterdikleri ve düşük risk grubunda yer aldıkları görülmektedir. Bu çalışılan dönem ve kullanılan finansal oranlara göre tekstil sektörünün genel olarak daha güvenli bir yatırım alanı sunduğu anlamına gelmektedir. Metal sanayi (M kodlu firmalar) için ise, riskli firmaların sayısının daha fazla olduğu görülmektedir. Analiz sonuçlarına göre metal sektöründeki firmalar genellikle daha yüksek risk taşımaktadır ve bu durum sektörün daha volatil olduğuna işaret etmektedir. Genel olarak yatırım stratejisi yapıldığında, tekstil sektörünün güvenli ve uzun vadeli yatırımlar için ideal olduğu ve düşük riskli firmalarla yatırımcılara portföylerini çeşitlendirme imkânı sunmaktadır. Metal sanayi sektörünün ise, kısa vadeli spekülatif fırsatlar arayan yatırımcılar için daha uygun olduğu ve yüksek risk toleransına sahip yatırımcılar için fırsatlar bulunduğu görülmektedir.

Yüksek TOPSIS skoruna sahip firmaların genellikle düşük ve orta risk gruplarında yer alan firmalar olduğu görülmektedir. Bu da bu firmaların daha iyi finansal performans sergilediklerini ve yatırımcılar için daha cazip olduğunu göstermektedir. Yüksek risk grubundaki firmalar, daha düşük TOPSIS skorlarına sahip olma eğilimindedirler, bu da risk ve getirinin dengelenmesinde daha zayıf olduklarını göstermektedir. Yatırımcılar için bu sonuçlar, düşük ve orta riskli firmaların yüksek performans gösterdiği ve daha güvenilir yatırım fırsatları sunduğu anlamına gelirken, yüksek riskli firmaların ise daha yüksek getiri beklentisi sunmakla beraber önemli riskler taşıdığına işaret etmektedir. Literatürde farklı yıllarda yapılan çalışmalara bakıldığında, Yüksel ve Canöz (2015), Doğan (2016), Küçük ve Büyükbaş (2017), Çetin ve Yıldırım (2018) çalışmamızın sonuçlarının uyumlu olduğu, tekstil sektörünün daha istikrarlı performans gösterirken, metal sektörünün ise daha volatil ve riskli olduğu kanısına varmışlardır.

Çalışmanın literatüre katkısı ise, Veri zarflama analizi (DEA), AHP ve TOPSIS yöntemlerinin birleştirilerek kullanıldığı portföy seçimlerine ilişkin örnek bir uygulama olmasıdır. Üç yöntemin bir arada kullanılması, hem kriter ağırlıklandırılması hem de firmaların performans sıralaması açısından güçlü bir yapı sunmaktadır. Tekstil ve metal sektörlerinin karşılaştırmalı olarak analiz edilmesinin, farklı sektörlerdeki risklerin yatırımcı kararlarını nasıl etkilediğini anlamaya yönelik bir katkı sunacağı düşünülmektedir. Ayrıca çalışmada yatırımcılar için firmanın finansal yapısının nasıl değerlendirileceği ve bu yapıların risk-getiri dengesi üzerindeki etkileri hakkında yapılan yorumların, finansal risk yönetimi literatürüne katkı sağlayacağı umulmaktadır.