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Araştırma Makalesi (Research Article)

Factors Affecting Portfolios Created With Islamic And Traditional Perspective In Borsa İstanbul: Artificial Intelligence Supported Hybrid Model Proposal*

Diler TÜRKOĞLU[1]
Fatih KONAK[2]

Abstract

This research employs a hybrid artificial intelligence model to attempt to identify the elements influencing the portfolios constructed from the conventional and Islamic viewpoints. By applying the Fama French Five-Factor regression model combined with variables based on accounting and market, it is possible to identify potential differences in the factors influencing the portfolios developed from both a conventional and Islamic perspective. Furthermore, it is found that the effective gene parameters in the portfolios built from various viewpoints differed dependent on the evaluation performed using the hybrid model based on Artificial Neural Networks and developed through the use of Genetic Algorithm optimization. Additionally, it is found that, when combined with the other two models, the hybrid model, which is based on artificial neural networks and produced by genetic algorithm optimization, produces results that are more accurate. As a consequence, it becomes apparent to observe behavioral differences between the portfolios made using the traditional and Islamic perspectives.

Keywords: Islamic Finance, Behavioral Finance, Fama-French, Artificial Neural Networks, Genetic Algorithm.

JEL Codes: G11, G40, G41.

Borsa İstanbul'da İslami ve Geleneksel Perspektifle Oluşturulan Portföyleri Etkileyen Faktörler: Yapay Zeka Destekli Hibrit Model Önerisi

Öz

Bu araştırma geleneksel ve İslami bakış açılarından oluşturulan portföyleri etkileyen unsurları belirlemeye çalışmak için hibrit bir yapay zekâ modeli önermektedir. Muhasebe ve piyasa bazlı değişkenlerle birleştirilmiş Fama French Beş Faktörlü regresyon modeli uygulanarak hem geleneksel hem de İslami bakış açısıyla geliştirilen portföyleri etkileyen faktörlerdeki potansiyel farklılıkların belirlenmesi mümkün olmaktadır. Ayrıca, Yapay Sinir Ağları'na dayalı ve Genetik Algoritma optimizasyonu kullanılarak geliştirilen hibrit model ile yapılan değerlendirmeye bağlı olarak, farklı bakış açılarından oluşturulan portföylerdeki etkili gen parametrelerinin değişiklik gösterdiği, buna ek olarak yapay sinir ağlarına dayalı ve genetik algoritma optimizasyonu ile üretilen hibrit modelin, diğer iki modelle birleştirildiğinde daha doğru sonuçlar verdiği tespit edilmiştir. Sonuç olarak, geleneksel ve İslami bakış açılarıyla oluşturulan portföyler arasındaki davranışsal farklılıkları gözlemlemek mümkün hale gelmektedir.

Anahtar Sözcükler: İslami Finans, Davranışsal Finans, Fama-French, Yapay Sinir Ağları, Genetik Algoritma.

JEL Kodları: G11, G40, G41.

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[1] Sorumlu Yazar (Corresponding Author): Diler TÜRKOĞLU, (Dr. Öğr. Üyesi), Ardahan Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü Öğretim Üyesi, Ardahan/Türkiye, dilerturkoglu@ardahan.edu.tr, ORCID ID: https://orcid.org/0000-0001-5247-1590.

[2] Fatih KONAK, (Prof. Dr.), Hitit Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü Öğretim Üyesi, Çorum/Türkiye, fatihkonak@hitit.edu.tr, ORCID ID: https://orcid.org/0000-0002-6917-5082.

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1. INTRODUCTION

The fundamentals of "Modern Portfolio Theory" were established by Harry Markowitz, whose book "Portfolio Management" suggested that return and risk should be considered together while making investments. Markowitz argues that the standard deviation of historical returns is the only quantitative measure of risk, suggesting that investors should base their decisions on projected return and risk under the presumption that the securities market is efficient and that investors are rational. New hypotheses on the variables influencing stock prices and how stock prices are determined were created in the 1960s and 1970s due to the acceptance of this theory. The premise that "the market is efficient" is central to these ideas.

The Efficient Markets Hypothesis, first proposed by Fama in 1970, states that the stock price represents the information available to all parties. It is further said that this hypothesis holds for all markets, not only the stock market. Presuming rationality among investors, it seems unlikely that securities prices can be accurately predicted. Nevertheless, empirical research carried out in accordance with the demands of the emerging market has led to the emergence of behavioral patterns aiming at abnormal returns with Behavioral Finance. This field is predicated on the theory of expectation and where value is prioritized over expected benefit. This allows the irrational perspective to be effective in financial decisions. The security prices of the information delivered to the markets are presumed to take into account a number of impacts known as anomalies, in addition to the psychological choices and cognitive biases of the market participant. These anomalies could combine with the constraints placed on an investment profile by belief systems inside the context of the psychology of the individual investor. In a nutshell, the investor must make decisions by selecting the best course of action from a range of options and making use of the possibilities at hand to accomplish the goal. Optimization is the process of achieving the optimal outcome given the previously specified options. In the framework of the highest expected return and least risk, optimization may be done using a variety of mathematical expressions with classical approaches. On the other hand, an artificial intelligence model equipped with optimization techniques may solve more complicated issues and streamline procedures.

Key topics that influence significant fields of science and technology in the modern era include artificial intelligence and optimization. Finding the optimal option for the most effective use of resources is the goal of the mathematical field of optimization. The endeavor to provide computer systems intelligence and learning capacities akin to those of humans is known as artificial intelligence. In finance, like in every other field, optimization and artificial intelligence are widely recognized. Forecasting, categorization, and optimization applications commonly employ artificial intelligence applications because of its capacity to provide issue solutions and handle and analyze bigger data sets more quickly than with traditional methods.

The primary goal of the research, conducted within the framework of this theoretical framework, is to compare an artificial neural network-based hybrid model developed with genetic algorithm optimization to the factors influencing the portfolios created with both traditional and Islamic perspectives. This comparison is carried out both within themselves and in the context of a behavioral approach. These factors were obtained from the five-factor model proposed by Fama and French (2015). The evaluation's findings will highlight whether investor groups who make decisions based on their religious beliefs and those that behave rationally differ in terms of the best portfolio selection. By employing the conventional technique that combined with accounting and market-based variables, the results, in particular, show the validity of the Fama and French Five-Factor Model in BIST All and BIST Participation Index. Ultimately, effective models are articulated by taking into account the suitable gene parameters for every one of the 36 portfolios created depending on the primary goal of the research. Since no research has compared artificial neural networks, genetic algorithms, and the FF5F model to design an optimum portfolio with a behavioral structure, this research is anticipated to close a significant gap in the literature. By highlighting the differences between the models, this research will simultaneously assist the decision maker in making a clearer choice and direct them toward the best option in accordance with risk preferences.

In accordance with the research's structure, the literature on the study's theoretical and empirical methods is provided initially, followed by a discussion of the hybrid model's methodology and its application to the Fama-French Five Factor Model. Finally, interpretations and evaluations of the empirical outcomesare provided, together with conventional and Islamic perspectives on suggestions for an AI-supported hybrid model.

2. LITERATURE REVIEW

Empirical research on capital asset pricing models has been more significant with the development of modern portfolio theory. Estimating risk and anticipated return requires creating an ideal portfolio using the mean-variance model and Markowitz diversification. When building the ideal portfolio, artificial intelligence applications are being used more often in addition to capital asset pricing models. According to the goals of the research, artificial intelligence-based optimisation applications are incorporated in addition to the conventional pricing methods that are employed in the literature for optimal portfolio development.

Sharpe (1964) describes the portfolio analysis approach and its benefits in systematically analyzing the relationship between securities, drawing on Markowitz's (1952) work on the optimal portfolio, or minimal risk and highest expected return. His findings led him to the conclusion that the Markowitz approach is a great option for analyzing the connections between securities. Similarly, Vercher, Bermúdez, and Segura (2007) emphasize that the mean-variance model is the optimal technique in their research that aims to offer a fuzzy downside risk approach to handle portfolio selection problems within the framework of risk-return trade-off utilizing interval-valued expectations. However, Markowitz's mean-variance model has been criticized by Kaczmarek, Dymova, and Sevastjanov (2020), who contend that the model does not adequately capture portfolio risk. The results of the research assert that the interval and fuzzy portfolio selection methodology yields higher optimum portfolio building outcomes than standard approaches that are widely used for portfolio selection in fuzzy environments. Examining the matter from an alternative angle, Hanif (2011) finds that equity pricing models are likewise appropriate in the Sharia financial system and tests whether conventional asset pricing models are incompatible with it. Banz (1981) discovered that small businesses often had greater risk-adjusted returns than large businesses using the Capital Asset Pricing Model (CAPM). Comparably, Basu (1983) examined the connection between market capitalization of companies listed on the NYSE and stock returns. The results indicate that while small-company NYSE equities seem to yield considerably greater returns than large-company NYSE stocks, the size advantage almost vanishes when returns are adjusted for variations in risk and earnings-per-share/share price ratios.

Particle swarm optimization was utilized by Chen and Ye (2004) to automatically find the cluster center in a random data set. On four synthetic data sets, the research's findings demonstrated that it performed better than the conventional cluster analysis technique. Similarly, in an effort to create the best risky investment portfolios possible, Kendall and Su (2005) created and evaluated the approach on a range of limited and unconstrained risky investment portfolios. The particle swarm solution displayed excellent computing efficiency in creating the best risky portfolios, according to the research. A heuristic approach based on a Hopfield neural network was created by Fernandez and Gomez (2007) applied to the mean-variance portfolio selection model. Consequently, issue cases requiring suitable portfolios of diversity with minimal investment risk were examined, and it was shown that the neural network model provided superior solutions. Lin and Gen (2007) emphasized that the main goal of portfolio optimization is to maximize anticipated return and minimize portfolio risk with another model approach. They highlighted the significance of applying the multipart decision-based genetic algorithm in portfolio optimization issues. In this approach, they discovered that, in comparison to standard models, the portfolios generated by genetic algorithms using the data of companies included in the NASDAQ 100 Index produced greater success in reaching the optimal value. Similarly, Durmuşkaya and Garayev (2017) created three periods throughout the crisis times in order to incorporate the closing data of 21 equities traded in BIST 30 Index between 2004 and 2016. The goal of the research's genetic algorithmic approach was to maximize expected return while minimizing risk in order to construct a portfolio. Based on the findings, they classified the years 2004-2007 as the pre-crisis period and came to the view that the portfolio was formed with a risk coefficient of 0.22 and a return coefficient of 0.29; the years 2008-2011 as the crisis period and the outcome that the optimal portfolio was formed with a risk coefficient of 0.025 and a return coefficient of 0.034; and the portfolio formed for the years 2012-2016 as the post-crisis period was recommended as the most optimal portfolio by the aforementioned model.

The three-factor asset pricing model proposed by Fama and French (1993) is tested with the market risk (rm-rf), SML and HML factors of NASDAQ NSYE, Amex Indices. The expected returns of 25 portfolios between 1963-1991 are calculated by time series regression method. The analyses revealed that the model outperformed the CAPM. Following this study, Sembiring (2018) aimed to test the ability of the Fama and French Three-Factor Model and the Fama and French Five-Factor Model to explain portfolio returns under market overreaction conditions in the Indonesian Stock Exchange. The research also employed the GARCH econometric model, which was simulated employing monthly data from July 2005 to December 2015. The results of this research indicate that, when the GARCH model is used, profitability (RMW) and investment (CMA) factors have a negative impact on returns, whereas company size (SMB) and firm value (HML) may adequately explain the winning and losing portfolio returns. The Fama-French Three-Factor Model was assessed in the Participation 30 Index for the years 2011-2017 by Çömlekçi and Sondemir (2019). Regression analysis was used to determine if the Fama-French Three-Factor Model was valid for the 25 stocks that had positive equity and were continually listed in the Participation 30 Index between the years under consideration. Kutlu and Kalaycı (2020), on the other hand, used 156 monthly pricing data from 2003 to 2015 to evaluate the French Three-Factor Model and the Fama in BIST 100. Regression analysis and time series analysis yielded results that exhibited a positive and statistically significant association between market risk premium, company size, and abnormal returns in the portfolio. Cao, Leggio and Schniedes (2005) made a comparison of forecasts and predicted the movement of stock prices of companies listed on the Shanghai Stock Exchange using the Artificial Neural Networks approach and the Fama French Three-Factor Model. The results demonstrate how a basic univariate model outperforms a multivariate model in return prediction, and that investors may enhance their forecasting ability in stock selection by utilizing the Artificial Neural Networks model.

Five-factor asset pricing model was first presented by Fama and French (2015) in their paper “A Five-Factor Asset Pricing Model”. Shortly after, research on this paradigm began to appear in the literature. Fama and French proposed that academics include variables related to investment and profitability in the Five-Factor Model. With regard to the Johannesburg Stock Exchange (JSE) returns from 1991 to 2017, Cox and Britten (2019) sought to evaluate how well the Fama and French Five Factor Model explained those returns. Because profitability is more constant than investment, it is inferred that both variables contribute to the explanation of the JSE’s returns.

The purpose of Acaravcı and Karaömer (2018) was to evaluate the Fama-French Factor and CAPM models’ performance in Borsa İstanbul (BIST) from 2005 to 2016. The GRS-F test, which was used to assess performance, revealed that the only Fama-French Factor Models with price inaccuracy were CAPM. Fama-French Factor Models are, in fact, shown to be viable in BIST. Aras et al. (2018) examined the efficacy of multi-factor Fama-French models in a similar manner. The FF3F model outperformed the single-factor CAPM, the FF5F model exceeded the FF3F and other four-factor models, and the FF3F model outperformed other alternative three-factor models, according to the application on Borsa İstanbul. Kaya (2021) aimed to figure out the validity of the CAPM, Fama and French Three-Factor Model, and Fama and French Five-Factor Model in BIST 100 from 2005 to 2017 from the same standpoint. The comparison revealed that the French Five-Factor Model, together with the Fama model, was the best-performing model. Conversely, Zeren et al. (2018) sought to examine the applicability of the Fama-French Five-Factor Model for eighteen firms that were part of the BIST Sustainability Index from 1995 to 2017. It was determined that the BIST Sustainability Index does not accept the Fama-French Five-Factor Model. Furthermore, the Fama and French Six-Factor Models were examined by companies listed at Borsa İstanbul between 2013 and 2021 by Doğan, Kevser, and Leyli Demirel (2022). A total of 9504 portfolios were constructed and incorporated into the model that was expanded to include the momentum element. The results of the research established the validity of the six-factor model in Borsa İstanbul.

The benefits and drawbacks of Verdegay, Zimmermann, and Werners' methodologies were highlighted in Pelitli's (2017) master's thesis in the areas of portfolio selection, implementation, and optimization using fuzzy linear programming. After the portfolios were examined, it was determined that using Werners' and Zimmermann's methods in tandem produced superior outcomes. Liu (2011) addresses the issue of fuzzy portfolio optimisation, in which the asset returns are denoted by fuzzy data. The mean-absolute deviation risk function model is employed as a solution strategy for the fuzzy portfolio optimisation problem. The analysis's results validate the idea that an investor might potentially earn more money the more risk they are prepared to take. Elahi and Abd Aziz (2011) seek to enhance Shariah-compliant portfolio optimization techniques by using a novel fuzzy model. In order to use fuzzy environments to Shariah-compliant portfolio optimization, they therefore suggested an E-S model with a linear combination of risk and reward. In the context of Islamic finance, Abdelwahed and Trabelsi (2021) seek to provide a novel fuzzy theory-based approach for the portfolio selection problem. The fuzzy expectation-dispersion-distortion model is a novel fuzzy (Shariah-compliant) portfolio optimization issue that Abdelwahed and Trabelsi (2021) develop and examine if there is an optimal solution. In a fuzzy environment where rates of return and turnover rates are characterized by fuzzy variables, Liu and Zhang (2013) intended to present a multi-objective portfolio optimization problem for practical portfolio selection. Taking market and liquidity risk into account, they used two probabilistic mean-variance portfolio optimization models. To sum up, a numerical example is provided to demonstrate how the models are applied, and the compared results illustrate that the suggested models cannot be solved by the devised method.

Ma (2023) aimed to put forward various routing strategies and multi-population parallel strategies with the method of improved particle swarm optimisation algorithm, which is the best mutation algorithm in his study. Based on China's financial early warning research, this paper learnt the actual economic and property situation of listed enterprises in China, especially the non-financial indicators and data mining research, thus proposed early warning financial information of listed enterprises, combined with important theoretical and practical knowledge. In addition, Yan (2023) conducts a methodical analysis of the financial asset allocation theory in his research. In order to create a dynamic financial trading platform, he bases his proposal on three new mathematical models: game theory based on particle swarm optimization algorithm, FCM, and PFG technology. The results of the empirical investigations indicate that the TSVL-DPM model is the most effective at predicting asset allocation. In order to enhance neural networks' capacity for financial time series forecasting, Hao et al. (2023) introduced a novel stock forecasting model called APSO-TA-LSTM, which combines temporal attention and adaptive particle swarm optimization with LSTM. By means of a comparison study with similar forecasting models, the experimental findings demonstrate that the APSO-TA-LSTM stock price forecasting model has competitive forecasting accuracy and wide application to various stock datasets.

3. DATA AND METHODOLOGY

By examining the quarterly data in the BIST All and BIST Participation 50 Indices from 2014 to 2021, this research attempts to identify which of the five factors that combined with accounting and market-based variables proposed by Fama and French (2015) is beneficial in whatever kind of portfolio. At this point of view, a thorough testing process has been conducted to determine which elements yield more effective outcomes in certain portfolio types for a hybrid model based on artificial neural networks and genetic algorithm optimization. The investigation also highlights potential disparities in the impact of the portfolios built from the Islamic and conventional views. For each portfolio, a hybrid model incorporating genetic algorithm-based hyperparameter optimizations and neural networks is finally suggested in this research. The only goal here is to provide market players with options for hybrid models that they may employ in conjunction with the generated model, while also revealing the elements impacting portfolios from various angles over the available data. It should be mentioned that classic Fama and French factor model analyses are also taken into consideration in order to create a comparison and add to the literature in this regard, in addition to the hybrid model construction at the research's focal point. The following are the hypotheses that were developed throughout the examination for this purpose:

H_0: The factors influencing the chosen portfolios are not distinct from one another.

H_1: The factors influencing the chosen portfolios differ from one another.

In addition, sub-hypotheses that support the main hypotheses formed in line with this main objective have been formed. These are:

H_{0a}: Fama and French Five-Factor Model is not valid for BIST All Share Index.

H_{0b}: Fama and French Five-Factor Model is not valid for BIST Participation 50 Index.

H_{1a}: Fama and French Five-Factor Model is valid for the BIST All Share Index.

H_{1b}: Fama and French Five-Factor Model is valid for the BIST Participation 50 Index.

H_{0c}: For both indices, there is no difference in the gene parameters that should be used in the hybrid model applied between the portfolios considered.

H_{1c}: For both indices, there is a difference in the gene parameters that should be used in the hybrid model applied between the portfolios considered.

Testing hypotheses H_{0c} and H_{1c} is anticipated to be more crucial in the analyses carried out for the research in order to determine any potential differences in the portfolios formed with the conventional and Islamic perspectives presented in the analyses performed for the purpose of the research, and the research is furthered in this context.

3.1. Fama and French Five Factor Methodology

The Capital Asset Pricing Model (CAPM) uses historical data on average returns for different asset classes to focus on historical average returns. In light of this, it is possible to argue that the CAPM was created to explain why different assets have different risk premiums. Variations in the riskiness of asset returns are the cause of these discrepancies. According to the model, beta is the appropriate riskiness metric. The Capital Asset Pricing Model (CAPM) calculates the predicted risk premium for an asset based on its beta and risk-free rate (Jagannathan and McGrattan, 1995). In addition to size and value considerations, Fama and French (2015) indicate that investment and profitability factors may also be useful in understanding the variation in the return above the risk-free interest rate. The five-factor model was formulated as follows by Fama and French (2015):

$$R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW + c_i CMA_t + e_{it} \quad (1)$$

These factors can be explained as follows (Fama & French, 2015):

R_{it}= portfolio return at time t,

R_{Ft}= risk-free return at time t,

R_{Mt}-R_{Ft}= The difference between the market return and the risk-free interest rate, also referred to as the market risk premium at time t,

SMB_t= The return difference between the portfolios composed of stocks with small and large market capitalisation at time t,

HML_t= The return difference of the portfolios composed of stocks with high and low PD/DD ratios at time t,

RMW_t= The return difference of the portfolios composed of stocks with strong and weak profitability at time t,

CMA_t= It expresses the return difference of the portfolios composed of stocks with conservative and aggressive investment approach at time t.

In the research conducted by Fama and French (2015), the factors were prioritized by taking into account their median values for the 2x3 form employed in the Five-Factor Model while creating portfolios. Two groups of the size factor (SMB) were created, and intersecting portfolios with the other factor were assembled. First, the value factor (HML) ranking requirements were followed to produce the portfolios for SH, SN, SL, BH, BN, and BL. Then, portfolios for the profitability (RMW) factor were created for SR, SN (SM), SW, BR, BN (BM) and BW. Ultimately, 18 portfolios, totaling 540 portfolios for each quarter and 1080 portfolios overall for both indexes, were created for the investment (CMA) component. These portfolios included SC, SN (SM-), SA, BC, BN (BM-), and BA. The average returns of the created portfolios above the risk-free interest rate were taken into account to calculate the SMB, HML, CMA, and RMW values for each period. Also, the intercept coefficient ai is zero for all securities and i portfolios, while the coefficients b_i, s_i, h_i, r_i, and c_i in Model 1 capture all variance in anticipated returns (Fama and French, 2015).

3.2. Artificial Neural Network Based Hybrid Model Generated by Genetic Algorithm Optimisation

The 1940s Artificial Neural Cell Model, inspired by the structure of organic nerve cells, demonstrated that logic operations like "and, or, not" could be numerically modeled. As a result, studies in a variety of domains now frequently focus on Artificial Neural Networks (ANN) models, which function similarly to the biological nervous system. ANN properties are distinct from those of conventional information processing models (Şen, 2004). Given that artificial neural networks (ANN) are employed to address problems in a variety of fields, including learning, association, classification, generalization, feature determination, and optimization, it is evident that ANNs are capable of producing answers to a wide range of contemporary issues. In theory, the most fundamental objective of an artificial neural network (ANN) is to identify an output set that can match to an input set displayed to it when it is trained with instances of network-related events and given the capacity to generalize (Öztemel, 2012). Hence, the most precise definition of an artificial neural network (ANN) is a structure that was created by modeling the human brain, featuring neural cell processing components and having the ability to process data distributedly and in parallel (Yılmaz, 2022).

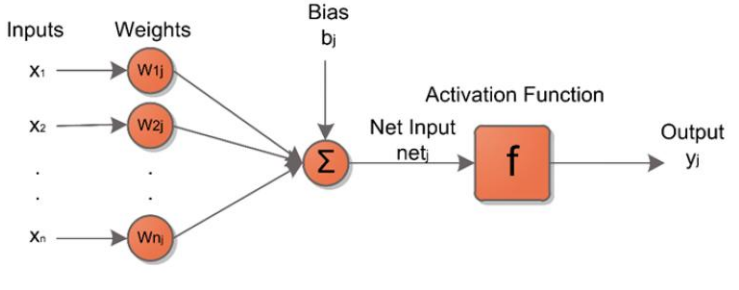

Figure 1. Neuron Structure

for the data network coming to each neuron cell is multiplied by the weights determined by the network. The results obtained are sent to the summation function in the neuron, where the bias value is added to the values summed with each other. The bias value allows the activation function to be shifted. By adding the bias value, a net input is obtained for the neuron. The net input value obtained for the neuron is passed through the activation function and the net output is obtained for that neuron cell (Bülbül et al., 2022).

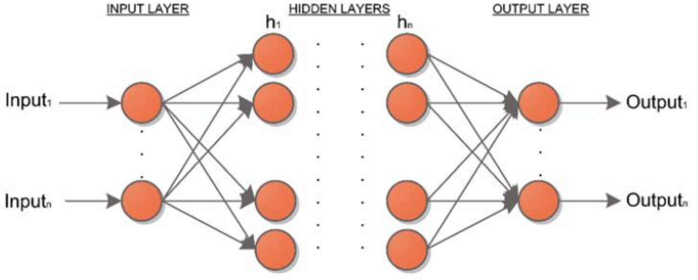

Figure 2 Artificial Neural Network Structure

Figure 2 demonstrates a feed-forward back-propagation ANN construction. An artificial neural network model with feed-forward and backpropagation is planned applying the desired optimal model. The input layer's inputs serve as the subsequent layer's input data. As a result, the artificial neural network's performance and efficiency are significantly influenced by the number of layers and neurons. Artificial neural networks employ activation functions at every layer (Bülbül & Öztürk, 2021).

The University of Michigan's Jonh Holland et al. (1975) conducted the first development of the research, which was later formalized in the book "Adaptation in Natural and Artificial System". As per the findings of the research, the Genetic Algorithm (GA) technique is employed to tackle very challenging issues that conventional optimisation approaches are unable to effectively address. The most appropriate one in an individual is carried over into later generations, according to genetic theory, which impacts problem resolution. Character binary sequences that match to chromosomes make up the population that makes up every generation. To put it another way, GA explores the solution space of a problem by beginning with a population of randomly generated solutions known as candidates. A fixed number of individuals or solutions make up the first candidate set, and each is represented by a genetic sequence with changeable information (Yang, 2016; Jaiswalet al., 2019).

Complex optimization issues are solved employing GA technology, which first finds random starting solutions to the problems. Better performing solutions are then generated by matching these solutions with one another. In this manner, the ongoing solutions are combined to seek for new ones. This procedure is repeated until the optimal outcome is achieved and it is agreed upon that it should be inherited by the subsequent solution and applied to the new solutions found in the first solutions. According to Öztemel (2012) the components of genetic algorithms are chromosome and gene, solution pool, crossover, mutation, and fitness function.

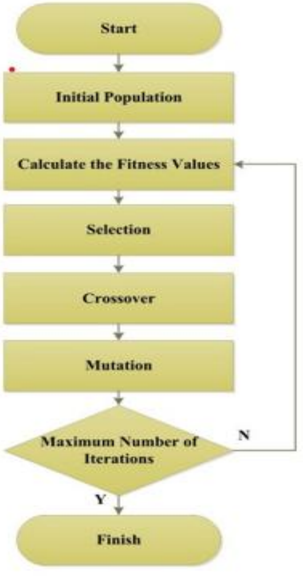

Figure 3 Genetic Algorithm Flow Diagram

4. FINDINGS

With a hybrid model based on Artificial Neural Network generated by Genetic Algorithm optimisation using quarterly data between 2014 and 2021, the goal of the research is to determine which of the five criteria defined by Fama and French (2015) provide more effective outcomes in which sorts of portfolios. Additionally, the research highlights the potential distinctions between the elements influencing the portfolios created from the traditional and Islamic viewpoints. This component of the research first examinations, employing the traditional technique, the validity of the French Five-Factor model and Fama model applied to both participation and conventional stock market indexes. Subsequently, portfolios generated applying the French Five Factor Model and Fama criteria are subjected to an Artificial Neural Network based hybrid model through the use of Genetic Algorithm Optimization.

4.1. Fama and French Five-Factor Model Findings

The 159 firms in the Borsa İstanbul All Index that were left out of the financial sector because of their high leverage ratios, firms with negative equity values, and firms that had no data continuity from the data set were evaluated in the first step of the application phase of the Fama and French Five-Factor Model. A reexamination of the companies listed in the Borsa İstanbul Participation 50 Index was carried out. Applying the same procedure to the eliminations resulted in the inclusion of 29 out of 50 enterprises in the Borsa İstanbul Participation 50 Index data set. The HML (High Minus Low) variable, or firm value, is calculated as the ratio of market value to book value (PD/BV). By considering the total assets of the businesses, the investment component CMA (Conservative Minus Aggressive) is incorporated in the study. The profitability measure, known as RMW (Robust Minus Weak), was derived by dividing the EBIT by the total assets. Lastly, since there are no risks associated with non-repayment, liquidity, maturity, or reinvestment in the ri-rf nominal interest rate, government domestic debt securities (GDDS) were included in the computation of the portfolio returns that exceed the risk-free interest rate (Sayılgan, 2019).

To begin with, the research employs datastream and Finnet programs to acquire company data for both indexes. Subsequently, quarterly variables were obtained from company data separately for each index. Using the variables obtained, the median of the calculated quarterly returns of the firms and the median of the SMB variable were taken and divided into two groups. Then, based on their median returns, the HML, RMW, and CMA variables were split into portfolios of 30%,40%, and 30%. Afterwards, permutations between the SMB variable and every other variable were created to create portfolios. Every quarter, this procedure was used. For each period, the SBM, HML, CMA, RMW, and ri-rf variables were derived using the average returns from the constructed portfolios. In addition, the data set for every quarter includes the rm-rf variable that was calculated from the BIST 100 market portfolio.

Initially, the average returns, descriptive statistics, and correlations of the portfolios produced from both BIST All and BIST Participation 50 Index of 18 distinct portfolios were examined in order to assess the validity of these factors in BIST All and BIST Participation 50 Index. As the Durbin Watson result from the test was higher than the necessary threshold, OLS tests were performed throughout the remainder of the investigation, and the Prais-Weinstein test was used to alleviate the autocorrelation problem. Panel Data Analysis was employed to examine how the determinants affected the created portfolio returns over the risk-free interest rate. Hausman tests, the Breusch Pagan Test, and the panel data model selection criteria F (chow) were then used. After applying the random effect model to the findings, it was possible to examine how the independent factors affected the dependent variable. It is investigated whether there is an issue with variance variation, autocorrelation, and inter-unit correlation using the fundamental presumptions associated with panel data models. Ultimately, autocorrelation and inter-unit correlation issues were found, and robust estimators were used to complete the examination.

Table 1 in the Appendix displays the average returns of the portfolios that make up the BIST All and BIST Participation Index. Analyzing the table reveals that the outcomes of the Fama and French (2015) research demonstrate the size effect, which indicates that companies with smaller market capitalization might offer better average returns than companies with larger market capitalization. Therefore, the firm size impact found by Banz (1981) and Fama and French (2015) is revealed by the data obtained for both indices. Due to the research's low correlation between its independent variables, multicollinearity and spurious regression issues may be avoided in the model (Doğan et al., 2022). Because of the limited temporal dimension in the data set, stationarity analysis was not performed in accordance with Yerdelen Tatoğlu (2018a).

The Pooled OLS test is utilized to investigate the impact of the parameters of the model on the created portfolios. Given that it is usually accepted to be the strongest test against first-order autocorrelation, the Durbin-Watson (1950) outcome should fall between 1.5 and 2.5 when being used to measure autocorrelation (Öztürk 2006; Bartels and Goodhew, 1981). Autocorrelation in the series was found by the Durbin-Watson test conducted in the research. Because of this, the identified autocorrelation was eliminated using the Prais-Winsten (1954) test. According to research, this test works well and is repeated using the sum of error squares that minimizes the estimation of the autocorrelation coefficient (Park & Mitchell, 1980; Bottomley, Ooko, Gasparrini, & Keogh, 2023). Tables 2 and 3 in the Appendix display the Prais-Weinsten test results of the portfolios created inside the indices within the context of this structure. Upon analysis of all Prais-Weinsten test findings, it becomes apparent that there is a substantial difference between the BIST All and BIST Participation 50 Index scores. In portfolios built using the conventional viewpoint, the rm-rf and hml factors are effective, whereas in portfolios made using the Islamic perspective, the rm-rf, smb, rmw, and cma factors are effective at various levels. When all of the results are analyzed, it becomes clear that, while there is a general difference in the factor efficiency of the factors chosen on the portfolios created by considering various criteria from the traditional and Islamic perspectives, one of the research's main hypotheses, hypothesis H_0, is rejected, and hypothesis H_1 is accepted.

To provide light on the potential impacts of the elements used in the Five-Factor Model on the BIST All and BIST Participation 50 Indexes, Fama and French generally also carried out a panel data analysis as part of the research. In this case, it was determined which model was more suited for which index within the framework of panel data model selection criteria after descriptive statistics and correlation analysis were completed for both indices. For both indexes, fundamental assumption tests were used to evaluate the findings' validity. The research efforts were finished by choosing the suitable robust estimator in order to yield more valid results, in accordance with the findings. Descriptive statistics and correlation matrix of these indices are presented in the appendix. When the results are analysed, it does not constitute a risk since it is below the critical value of 0.80 suggested by Gujarati and Porter (2009). The results shown in the correlation matrix table, which shows the relationship between the dependent and independent variables and the direction of their relationship, do not pose any risk since the correlation coefficients between the independent variables are below the critical value.

Panel data model selection criteria and assumption tests for model selection to be used in the analysis are given in Table 4 in the Appendix. When the table in question is examined, Levene, Brown and Forsythe (1974) tests were applied to determine whether there is a problem of changing variance in the random effects model and the test statistics (W0, W50, W10) were compared with the free-order Snedecor F table (Yardelen Tatoğlu, 2018b). There is heteroskedasticity in the model for BIST All Index, while there is no heteroskedasticity for BIST Participation Index. In order to determine the autocorrelation problem, Bhargava et al. (1982) Durbin Watson test was applied to both indices. No critical value is given in the literature on these tests, but a value less than 2 is interpreted as an autocorrelation problem (Yardelen Tatoğlu, 2018b). Therefore, the test results of 0.912 and 0.631 for BIST All and BIST Participation, respectively, indicate that there is an autocorrelation problem. Baltagi-Wu (1999)'s LBI test results support this. Finally, Frees test was applied to examine the correlation between units. When the Frees (1995, 2004) test statistic is compared with the critical values given at 90%, 95% and 99% confidence intervals, the test statistic is greater than the confidence levels, indicating the presence of inter-unit correlation.

According to the results obtained, it is concluded that the appropriate model is the random effects model. For this reason, hypothesis H_0 was accepted for both indices and the necessity of applying the random effects model was revealed.

Table 5. Results of Random Effects Model Analysis and Robust Estimator

	BIST All Share Index				BIST Participation 50 Index			
	Coeff.	Std. Error	T Stat.	P>t	Coeff.	Std.Error	T Stat.	P>t
sml	1.1605	0.3181	3.6500	0.000***	0.7675	0.4078	1.8800	0.06*
hml	0.3126	0.3258	0.9600	0.3370	-3.0519	0.3070	-9.9400	**0.000*****
cma	0.2735	0.4125	0.6600	0.5070	-0.6113	0.4918	-1.2400	0.2140
rmw	-2.7462	0.3201	-8.5800	0.000***	-0.4984	0.2193	-2.2700	0.023**
rmrf	0.9645	0.0060	160.8300	0.000***	0.9814	0.0076	129.470	0.000***
cons	0.0538	0.0127	4.2300	0.000***	-0.0293	0.0098	-3.010	0.003***
Sigma_u	0.0000				Sigma_u 0.0000			
Sigma_e	0.1634				Sigma_e 0.1952			
Rho	0.0000				Rho 0.0000			

	BIST All Share Index		BIST Participation 50 Index	
	Huber Eicker White Test	FGLS	Huber Eicker White Test	FGLS
SML	1.1604	2.7958	0.7675476	0.3801
	(0.000)***	(0.000)***	(0.0347)**	(0.343)
HML	0.3126	0.2733	-3.051862	-2.894946
	(0.000)***	(0.3209	(-3.8594)	(0.000)***
CMA	0.2735	2.0920	-0.6112562	-1.1623
	(0.000)***	(0.000)***	(-1.3005)	(0.019)**
RMW	-2.7462	-2.119089	-0.4984367	-0.2589
	(0.000)***	(0.000)***	(-0.7140)	(0.214)
RMRF	0.9644	0.9704	0.9814093	0.9790
	(0.000)***	(0.000)***	(0.9658)	(0.000)***

	BIST All Share Index				**BIST Participation 50 Index**			
	Coeff.	Std. Error	T Stat.	P>t	Coeff.	Std.Error	T Stat.	P>t
sml	1.1605	0.3181	3.6500	0.000***	0.7675	0.4078	1.8800	0.06*
C	0.0538	0.0235				-0.0293275	-0.0296	
	(0.000)***	(0.010)***					(-0.0423)(*.000)***	

***, ** and * denote significance at 1%, 5% and 10% level, respectively.

The outcomes of the random effects model research indicate that, at the 1% level, the RIRF dependent variable is significantly and positively affected by the SML and RMRF components in Table 5. At the 1% level, the RMW factor's influence is also significant and negative. The other two components additionally exhibit positive impacts, although these benefits are not statistically significant. The SML factor is significant at the 10% level, the RMRF factor is significant at the 1% level, and both variables have a positive influence in the BIST Participation 50 Index. It has been noted that the RMW factor has a 5% negative effect while the HML factor has a 1% negative effect.

The Huber Eicker White test, which was developed by Huber (1976), Eicher (1976), and White (1980) and makes panel data analysis robust to the heteroskedasticity problem, was employed to determine the robust standard errors in Table 5. The literature (Vaz de Melo Mendes and Pereira Câmara Leal, 2005; Perret-Gentil and Victoria-Feser, 2005; Karakoç, 2022) proposes estimators that are resistant to autocorrelation, inter-unit correlation, and shifting variance concerns. Following the test, it was found that, with the exception of the RMW variable, every variable for the BIST All Index had an impact on return above the risk-free interest rate at the 1% significance level.

Upon examination of the portfolios generated inside BIST Participation 50, it was discovered that alone the SML component had statistical significance at the 5% level and exhibited a positive trend. With the exception of the HML variable in the BIST All Index, all other variables are significant at the 1% level, according to the findings of the "Feasible Generalised Least Squares Test (FGLS)" used in the instance of AR(1) correlation between and within units in Table 5. HML, CMA, and RMRF variables are significant at 1% negative, 5% negative, and 1% positive levels, respectively, when the BIST Participation 50 Index is analyzed. It is evident that the portfolios created using the two views differ from one another. Consequently, the primary hypothesis, H_0, is rejected based on the Panel Data Analysis Model's findings.

Finally, the GRS-F (Gibbons, Ross and Shanken, 1989) test is applied to compare the performance of asset pricing models. In the study, following Fama and French (2015), it is suggested that the performance of regression models with low GRS and A|ai| and high A(R2) values are optimal (Aras et al., 2018). As Fama and French (2015) emphasise in their study, capital asset pricing models provide propositions about expected returns and the models can be rejected as a result of the tests applied. However, rather than whether other models are rejected or not, it is essential to estimate their performance evaluated using GRS-F and other statistics. These tests aim to identify the best performing model for expected returns and are shown in Table 6.

Table 6. GRS-F Test Results for the Validity of the Five-Factor Model Constructed within the Scope of BIST All Index

		GRS-F	A|ai|	$A(R^2)$			GRS-F	A|ai|	$A(R^2)$
Panel A: Size - PD/DD Portfolio					Panel B: Size-Profitability Portfolio				
1	Rm-Rf	3.31**	0.0976	0.57	1	Rm-Rf	7.53***	0.0321	0.58
2	Rm-Rf SMB HML (FF3F)	1.02	0.0210	0.62	2	Rm-Rf SMB HML (FF3F)	5.559***	0.0209	0.66
3	Rm-Rf SMB RMW	2.59**	0.0498	0.36	3	Rm-Rf SMB RMW	1.41**	0.0498	0.74
4	Rm-Rf SMB CMA	2.12*	0.0244	0.72	4	Rm-Rf SMB CMA	6.75***	0.0243	0.59
5	Rm-Rf HML RMW	3.06**	0.0808	0.78	5	Rm-Rf HML RMW	1.70	0.0808	0.83
6	Rm-Rf HML CMA	2	0.0182	0.76	6	Rm-Rf HML CMA	4.28***	0.0182	0.62
7	Rm-Rf RMW CMA	3.47**	0.0650	0.67	7	Rm-Rf RMW CMA	1.58	0.0650	0.78
8	Rm-Rf SMB HML RMW	1.87**	0.0527	0.66	8	Rm-Rf SMB HML RMW	1.33	0.0526	0.71
9	**Rm-Rf SMB HML CMA**	1.42*	0.0200	0.81	9	Rm-Rf SMB HML CMA	5.07***	0.0200	0.64
10	Rm-Rf SMB HML RMW CMA (FF5F)	1.72**	0.0539	0.75	10	**Rm-Rf SMB HML RMW CMA (FF5F)**	1.20**	0.0328	0.76

	GRS-F	A|ai|	$A(R^2)$	GRS-F	A|ai|	$A(R^2)$	
1	Rm-Rf			3.22**			
2	Rm-Rf SMB HML (FF3F)	2.13*	0.0209	0.62	2	**Rm-Rf SMB HML (FF3F)**	1.29**
3	Rm-Rf SMB RMW	1.47	0.0497	0.71	3	Rm-Rf SMB RMW	2.58*
4	Rm-Rf SMB CMA	1.85	0.0244	0.69	4	Rm-Rf SMB CMA	1.72
5	Rm-Rf HML RMW	2.20*	0.0807	0.81	5	Rm-Rf HML RMW	3.67*
6	Rm-Rf HML CMA	1.94**	0.0181	0.85	6	Rm-Rf HML CMA	1.25
7	Rm-Rf RMW CMA	1.61	0.0649	0.73	7	Rm-Rf RMW CMA	2.72*
8	Rm-Rf SMB HML RMW	1,73	0.0526	0.68	8	Rm-Rf SMB HML RMW	1.41*
9	Rm-Rf SMB HML CMA	1.87**	0.0200	0.63	9	Rm-Rf SMB HML CMA	1.10**
10	**Rm-Rf SMB HML RMW CMA (FF5F)**	1.56**	0.0338	0.81	10	Rm-Rf SMB HML RMW CMA (FF5F)	1.35*

***, ** and * denote significance at 1%, 5% and 10% level, respectively.

In Panel A of Table 6, where the performance of asset pricing models constructed within the scope of BIST All Index is measured, significant results are obtained for CAPM at 5% level. According to the results obtained, GRS-F test result is 3.31, A|ai| is 0.0976 and A(R2) value is 0.57. Although insignificant results were obtained for the FF3F model, a GRS-F result of 1.72 and significant at 5% level was obtained in the FF5F Model. A|ai| result is 0.0539 and A(R2) result is 0.75. When the panel is analysed, the fact that the four-factor model consisting of Rm-Rf, SMB, HML, CMA variables yields a GRS-F test result of 1.42, A|ai| result of 0.0200 and A(R2) of 0.81 at the 10% significance level reveals that this model should be considered as the most optimal asset pricing model in the size-PD/DD ratio portfolio. In Panel B, which shows the results for the Size-Return Portfolio, although the CAPM and FF3F model results are significant, the 1.20 GRS-F test result, 0.0328 A|ai| and 0.76 A(R2) obtained from the FF5F model indicate that the model with the highest explanatory power in explaining stock returns is FF5F. The results of Panel C, which tests the size-investment portfolio, again suggest that the explanatory power of the FF5F model is stronger. Finally, in Panel D, the analysis is applied for 18 intersection portfolios. As a result, the findings suggest that the FF3F model, which yields lower GRS-F test and A|ai| and higher A(R2) results than the others, is optimal.

Table 7. GRS-F Test Results for the Validity of the Five-Factor Model Constructed within the Scope of BIST Participation Index

		GRS-F	A|ai|	A(R^2)			GRS-F	A|ai|	A(R^2)
Panel A: Size - PD/DD Portfolio					Panel B: Size-Profitability Portfolio				
1	Rm-Rf	3.47*	0.0101	0.56	1	Rm-Rf	3.68*	0.0705	0.66
2	Rm-Rf SMB HML (FF3F)	3.49*	0.0102	0.73	2	Rm-Rf SMB HML (FF3F)	4.41*	0.0902	0.78
3	Rm-Rf SMB RMW	2.48*	0.0035	0.65	3	Rm-Rf SMB RMW	2.59*	0.0682	0.71
4	Rm-Rf SMB CMA	3.36	0.0143	0.59	4	Rm-Rf SMB CMA	3.86*	0.0839	0.69
5	Rm-Rf HML RMW	2.44	0.0096	0.72	5	Rm-Rf HML RMW	3.95	0.0726	0.61
6	Rm-Rf HML CMA	3.56	0.0036	0.82	6	Rm-Rf HML CMA	4.26*	0.0858	0.75
7	Rm-Rf RMW CMA	2.60	0.0102	0.79	7	Rm-Rf RMW CMA	2.28	0.0631	0.68
8	Rm-Rf SMB HML RMW	2.43*	0.0081	0.66	8	**Rm-Rf SMB HML RMW**	2.43***	0.0306	0.74
9	**Rm-Rf SMB HML CMA**	1.33*	0.0012	0.61	9	Rm-Rf SMB HML CMA	2.98**	0.0779	0.71
10	Rm-Rf SMB HML RMW CMA (FF5F)	2.29**	0.0100	0.78	10	Rm-Rf SMB HML RMW CMA (FF5F)	3.40**	0.0507	0.81
		GRS-F	A|ai|	A(R^2)			GRS-F	A|ai|	A(R^2)
Panel C: Size - Investment Portfolio					Panel D: 18 Cross-Section Portfolio				
1	Rm-Rf	4.81	0.0100	0.74	1	Rm-Rf	2.43	0.0705	0.66

2	Rm-Rf SMB HML (FF3F)	3.892*	0.0103	0.62	2	Rm-Rf SMB HML (FF3F)	1.38*	0.0902	0.78
3	Rm-Rf SMB RMW	4.96**	0.0381	0.61	3	Rm-Rf SMB RMW	2.16*	0.0682	0.71
4	Rm-Rf SMB CMA	2.63*	0.0143	0.76	4	Rm-Rf SMB CMA	1.65	0.0839	0.69
5	Rm-Rf HML RMW	3.72	0.0955	0.79	5	Rm-Rf HML RMW	3.19	0.0726	0.61
6	Rm-Rf HML CMA	4.71*	0.0355	0.64	6	Rm-Rf HML CMA	2.21*	0.0858	0.75
7	Rm-Rf RMW CMA	2.71*	0.0101	0.72	7	**Rm-Rf** **RMW** **CMA**	1.08**	0.0631	0.68
8	Rm-Rf SMB HML RMW	1.90***	0.0082	0.57	8	Rm-Rf SMB HML RMW	3.38*	0.0306	0.74
9	**Rm-Rf** **SMB** **HML** **CMA**	1.59**	0.0012	0.59	9	Rm-Rf SMB HML CMA	1.54*	0.0779	0.71
10	Rm-Rf SMB HML RMW CMA (FF5F)	2.61*	0.0101	0.76	10	Rm-Rf SMB HML RMW CMA (FF5F)	1.12**	0.0507	0.81

***, ** and * denote significance at 1%, 5% and 10% level, respectively.

In Table 7, the performances of asset pricing models constructed within the scope of BIST Participation 50 Index are compared. According to the results obtained, the validity of the four-factor model obtained from Rm-Rf, SMB, HML and CMA factors was determined when the results of the size-PD/DD ratio portfolio in Panel A and Panel C Size-Investment portfolio were analysed, and the validity of the four-factor model obtained from Rm-Rf, SMB, HML and RMW variables in Panel B Size-Profitability Portfolio was determined. Finally, the validity of the three-factor model in which Rm-Rf, RMW and CMA factors are effective is observed in the findings obtained from the evaluation of 18 segment portfolios.

When Table 6 and Table 7 are analysed together, significance is found in all CAPM, FF3F, FF5F models in both BIST All Index and BIST Participation 50 Indexes. Therefore, the validity of all models in Borsa İstanbul has been tested and significant findings have been reached. When the two indices are compared, it is observed that the Fama and French Five-Factor regression model has the highest performance in the size-PD/DD panel. In the size-profitability panel, while the five-factor model is also valid in the BIST All Index, the four-factor regression model consisting of RMRF, SMB, HML and RMW factors is accepted in the Participation 50 Index. In another panel, the size-investment panel, the five-factor model is again valid for the BIST All Index, while the four-factor model consisting of RMRF, SMB, HML and CMA factors is the most optimally performing model for the Participation 50 Index. Finally, in the panel consisting of 18 certain portfolios, the three-factor model is valid in both indices; however, these factors vary. While the Fama and French Three-Factor model was determined as the optimal model in the BIST All Index, the performance of the regression model consisting of the factors that make up the five factors, namely the RMRF, RMW and CMA factors in the Participation 50 Index was found to be superior. As a result, the validity of the Fama and French Five-Factor model in the BIST All Index and BIST Participation 50 Index has been proven, and the sub-hypotheses H_{0a} and H_{0b} of the study have been rejected. In addition, the findings obtained again indicate that the differentiation in the factors that are effective in both the BIST All Index, which includes the portfolios formed with the traditional perspective, and the BIST Participation 50 Index, which includes the portfolios formed with the Islamic perspective, points to the rejection of the main hypothesis H_0.

4.2. Artificial Neural Network Based Hybrid Model Generated by Genetic Algorithm Optimisation Findings

In order to determine the degree of influence of the aforementioned factors on the portfolios determined by taking into account different factors, the hybrid model built in this section optimizes the number of hidden layers, the number of neurons in the hidden layer, the number of hidden layer activations, the number of neurons in the output layer, and the learning function. For both the BIST All Index and the BIST Participation Index, eighteen distinct efficient model recommendations for eighteen distinct portfolios are provided. This might aid in the process of elucidating the variables influencing the portfolios that will be created by market participants or in the course of future research. In addition to the originality of these model outputs, it is thought that this model will contribute to the literature in terms of comparing the portfolios formed with a conventional and Islamic perspective both within each other and with the findings that can be obtained from different studies. Based on this motivation and focus, the portfolios of the companies operating in the BIST All Index and the BIST Participation 50 Index were evaluated with the ANN-based hybrid model created by Genetic Algorithm optimization using quarterly data between 2014 and 2021. In the study, return in excess of risk-free interest rate (ri-rf) is used as output. Firm size (SMB), firm value (HML), investment (CMA), profitability (RMW) and finally risk premium (rm-rf) are used as inputs.

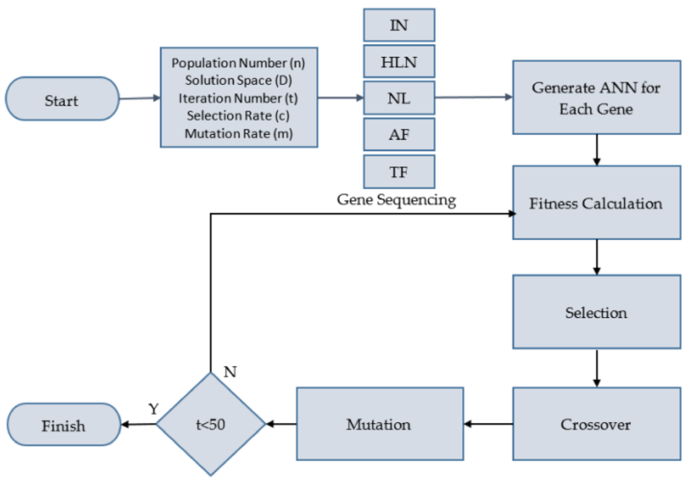

Figure 4. Hybrid Flow Diagram

In the flowchart of the hybrid structure shown in Figure 4, the first step is the initial population for the GA and each individual in the GA forms an ANN structure within itself. Here, each individual consists of network parameters that directly affect the performance of the ANN. In the proposed hybrid structure, the initial population is created as the first step of GA. Through the created hybrid structure, it is aimed to optimize the network parameters to produce the most successful result (Bülbül et al., 2022). As a first step, the genetic algorithm parameters of the hybrid structure were determined as presented in Table 8 and a random population was created.

Table 8. Genetic Algorithm Parameters

Genetic Algorithm Parameters	Values
Population Number (n)	20
Solution Space (D)	5
Selection Rate (c)	0.9

The most successful results were obtained by applying GA in the five-dimensional solution space to identify the ANN network parameters illustrated in Table 8. The success of the proposed hybrid model in obtaining accurate results from the same type of data can be influenced by various factors such as the number of hidden layers, activation functions in the layers, and variation of the parameters in the learning functions (Bülbül and Öztürk, 2022). The Mean Square Error (MSE) is a metric used to quantify every individual's success. The data set is split into two categories: 70% for training and 30% for testing, which are used in the network structure that each individual creates. The roulette wheel approach is employed in the hybrid model's selection process to boost the odds of survival for those who get the best possible results. By using crossover and mutation processes, a single generation was finished for every individual in the model. Based on the parameters, the Genetic Algorithm operated for 50 generations. Hyperparameter optimization was implemented to generate the network parameters in the individual with the highest MSE value in the final generation. The most successful gene parameters found within the parameters of the employed hybrid model are displayed in Tables 9 and 10.

Table 9. Most Successful Gene Parameters for BIST All Index

	Portfolio	Input	Number of Hidden Layers	Hidden Layer Neuron Numbers	Hidden Layer Act.Function	Number of Output Layer Neurons	Output Layer Act. Function	Learning Function	MSE Value
1	BA	RMW, SMB, HML, RMRF	1	3	radbas	1	purelin	trainbfg	0,0057
2	BM-	RMRF, CMA, HML, RMW	1	8	radbas	1	purelin	trainrp	0,0002
3	BC	SMB, RMW, RMRF, CMA, HML	1	7	tansig	1	purelin	trainbfg	0.000009
4	SA	CMA, RMRF, SMB, RMW	3	7-6-4-7-7	'logsig''purelin' 'tansig	1	purelin	traingda	0.001
5	SM-	RMW, RMRF, SMB, CMA, HML	2	6-1-5-8-2	'tansig' 'logsig'	1	purelin	trainbfg	0.000009
6	SC	SMB, RMRF, CMA, HML, RMW	5	7-7-6-5-4-7-4-7-3	'tansig''purelin' 'purelin' 'tansig''tansig'	1	purelin	trainbfg	0.0014

7	BM	HML, RMRF, RMW, SMB, CMA	2	8-6-4	'tansig' 'tansig'	1	purelin	trainbfg	0.000009
8	BR	SMB, HML, CMA, RMRF	5	8-5-8-2 7-4-5-7	'radbas''radbas'	1	purelin	trainbfg	0.002
					'radbas''purelin' 'radbas'				
9	BW	RMRF, CMA, HML, SMB, RMW	2	8	'radbas' 'logsig'	1	purelin	trainbfg	0.000009
10	SW	SMB, RMRF, CMA, RMW	3	5-8-7-7	'tansig' 'radbas'	1	purelin	trainbfg	0.000009
					'radbas'				
11	SM	RMRF, SMB, RMW, HML	4	8	'radbas' 'logsig'	1	purelin	trainbfg	0.000009
					'radbas''radbas'				
12	SR	RMW, RMRF, CMA, HML, SMB	3	3-8	'logsig' 'tansig'	1	purelin	trainbfg	0.0002
					'radbas'				
13	BL	RMW, SMB, CMA, HML, RMRF	1	7	'radbas'	1	purelin	traincgf	0.0043
14	BN	SMB, CMA, RMRF, RMW	1	7-6-4	'radbas'	1	purelin	trainbfg	0.0001
15	BH	RMW, CMA, HML, RMRF	3	7-7-6-1-5-8-2	'logsig''purelin'	1	purelin	trainbfg	0.000009
					'radbas'				
16	SH	RMRF, SMB, RMW, HML	1	7-7	'logsig'	1	purelin	trainbfg	0.0003
17	SN	HML, RMRF, RMW, SMB	1	6-5-4-7-4	'radbas'	1	purelin	trainbfg	0.00009
18	SL	RMRF, RMW, CMA, SMB	3	7-3	'purelin' 'logsig'	1	purelin	trainbfg	0.002

Table 10. Most Successful Gene Parameters for BIST Participation Index

	Portfolio	Input	Number of Hidden Layers	Hidden Layer Neuron Numbers	Hidden Layer Act.Function	Number of Output Layer Neurons	Output Layer Act. Function	Learning Function	MSE Value
1	BA	HML, SMB, CMA, RMW, RMRF	2	7-3	'radbas' 'logsig'	1	purelin	trainbfg	0.0003
2	BM-	RMW, CMA, SMB, RMRF	5	8-7-2-6-1	'radbas' 'logsig' 'purelin' 'tansig" logsig'	1	purelin	trainbfg	0.000007
3	BC	CMA, RMRF, RMW, HML	2	7-3	'logsig"radbas'	1	purelin	traincgb	0.001
4	SA	HML, RMRF, SMB	2	8-3	'radbas"purelin'	1	purelin	trainrp	0.003
	SM-	RMRF, HML, CMA, SMB	1	8	'tansig'	1	purelin	trainscg	0.002
5	SC	HML, RMRF, RMW	4	8-4-6-1	'logsig"radbas' 'tansig"purelin'	1	purelin	trainbr	0.000007
6	BW	RMRF, RMW, HML, CMA	2	7-3	'radbas' 'logsig'	1	purelin	trainrp	0.0001
	BM	RMW, HML, RMRF	1	8	'logsig'	1	purelin	trainbfg	0.0008
	BR	RMW, HML, RMRF	1	8	'logsig'	1	purelin	trainbfg	0.002
7	SW	RMW, HML, RMRF	1	8	'logsig'	1	purelin	trainrp	0.001
8	SM	RMW, SMB, RMRF, HML, CMA	4	8-4-3-3	'radbas"purelin' 'tansig' 'logsig'	1	purelin	trainbfg	0.00005
	SR	HML, RMRF, CMA, RMW, SMB	2	5-8	'purelin' 'tansig'	1	purelin	trainbfg	0.000009
	BL	RMW, SMB, HML, CMA, RMRF	1	8	'logsig'	1	purelin	trainscg	0.0002
9	BN	CMA, HML, RMW, SMB, RMRF	1	8	'radbas'	1	purelin	trainrp	0.0003
10	BH	SMB, CMA, RMW	4	6-7-6-6	'tansig"logsig' 'radbas' 'tansig'	1	purelin	trainbfg	0.000005

	SH	RMW, CMA, RMRF, HML	2	6-6	'purelin' 'tansig'	1	purelin	traincgb	0.002
11	SN	RMW, HML, RMRF	3	7-3-4	'tansig''tansig' 'logsig'	1	purelin	trainbr	0.000009
	SL	HML, SMB, RMW, RMRF	2	4-7	'radbas' 'tansig'	1	purelin	trainbfg	0.000009
12	BA	HML, SMB, CMA, RMW, RMRF	2	7-3	'radbas' 'logsig'	1	purelin	trainbfg	0.0003
	BM-	RMW, CMA, SMB, RMRF	5	8-7-2-6-1	'radbas' 'logsig' 'purelin' 'tansig'' logsig'	1	purelin	trainbfg	0.000007
13	BC	CMA, RMRF, RMW, HML	2	7-3	'logsig''radbas'	1	purelin	traincgb	0.001
14	SA	HML, RMRF, SMB	2	8-3	'radbas''purelin'	1	purelin	trainrp	0.003
15	SM-	RMRF, HML, CMA, SMB	1	8	'tansig'	1	purelin	trainscg	0.002
	SC	HML, RMRF, RMW	4	8-4-6-1	'logsig''radbas' 'tansig''purelin'	1	purelin	trainbr	0.000007
16	BW	RMRF, RMW, HML, CMA	2	7-3	'radbas' 'logsig'	1	purelin	trainrp	0.0001
17	BM	RMW, HML, RMRF	1	8	'logsig'	1	purelin	trainbfg	0.0008
18	BR	RMW, HML, RMRF	1	8	'logsig'	1	purelin	trainbfg	0.002

The present research goes beyond the artificial neural network (ANN), which is often used in the literature with standard parameters, and optimizes each parameter that is encountered in the ANN independently using the evolutionary algorithm. After individually optimizing the inputs, hidden layers, number of neurons, output layer, and learning algorithms to be utilized in the ANN, the best ANN model was chosen and applied to the relevant portfolios. The Mean Square Error (MSE) numbers should also be considered in addition to these values. This is accurate because the MSE method offers a trustworthy way to gauge the degree of uncertainty related to the two-stage estimator. Moreover, as the number of small areas approaches 0, it can provide asymptotically valid confidence intervals on the small area mean, in other words, the closer the MSE value is to zero, the better the network's success in learning. Therefore, it is possible to determine the success of the networks created by each gene based on MSE values (Prasad and Rao, 1990; Bülbül, 2022).

In this framework, it can be seen from Tables 9 and 10 that the number of inputs, number of hidden layers, number of neurons, learning functions and MSE values differ for each portfolio. For example, the BA portfolio under the BIST All Index has 4 inputs, 1 hidden layer, 3 hidden layer neurons, radbas hidden layer activation, trainfg learning function and 0.0057 MSE, while the BA portfolio under BIST Participation 50 has 5 inputs, 2 hidden layers, 7-3 hidden layer neurons, radbas and logsis hidden layer activation, trainfg learning function and 0.0003 MSE. Similarly, in the SL portfolio formed within the BIST All Index, 4 inputs, 3 hidden layers, 7-3 hidden layer neuron counts, purelin, logsis and radbas hidden layer activations, trainfg learning function and 0.002 MSE value were determined; while in the SL portfolio formed within the BIST Participation 50, 4 inputs, 2 hidden layers, 4-7 hidden layer neuron counts, radbas and tansing hidden layer activations, trainfg learning function and 0.00009 MSE value were determined.

The efficient portfolios created with various factors from the traditional perspective differ from the efficient portfolios created with the Islamic perspective, according to the findings of the analyses carried out using the models established separately for a total of 36 portfolios obtained from the quarterly data of the firms operating in the BIST All Index and the BIST Participation Index between 2014 and 2021. As a consequence, the primary hypothesis H_{0c} is rejected based on the variations in the most effective gene characteristics of the portfolios built from various viewpoints.

5. CONCLUSION

This research aims to reveal the differences in the factors affecting the portfolios formed by market participants investing in companies listed in the Borsa İstanbul All and Borsa İstanbul Participation 50 Index within the framework of conventional and Islamic Law guidelines, both within themselves and in the context of behavioral approach with the hybrid artificial intelligence model developed. The methodology of the five factor model developed by Fama and French (2015) between 2014 and 2021 is followed. For this reason, 18 portfolios were made for each of the indices, and these were compared both inside and between the parameters of the two models that were used.

SMB, HML, CMA, and RMW values are derived for each period by calculating the average returns of the created portfolios. The Prais-Weinsten test is used to determine how factor values affect the created portfolios and to solve the series' autocorrelation issue. When all of the results are analyzed, it becomes clear that, while factor efficiency is generally different between the portfolios created by considering different factors from both the traditional and Islamic perspectives, one of the research's main hypotheses, hypothesis H_0, is rejected and hypothesis H_1 is accepted. Panel data analysis was also carried out as part of the research to uncover potential impacts of the factors chosen in the Fama and French Five Factor Model on the BIST All Index and BIST Participation 50 Index. The validity of the random effects model was evaluated as part of the panel data model selection criteria, and robust estimators from Huber Eicker White and FGLS were employed to address issues with shifting variance, autocorrelation, and cross-sectional dependency. These tests demonstrate that the factors impacting the portfolios created from the two perspectives are different, which leads to the rejection of the primary hypothesis, H_0.

Subsequently, the performance of asset pricing models is compared using the GRS-F (Gibbons, Ross, and Shanken, 1989) Test. Thus, the research's sub-hypotheses H_{0a} are disproved and the validity of the Fama and French Five-Factor model for the BIST All Index is established. The findings are similar to those of Fama and French (2015); Cox and Britten (2019); Aras et al. (2018); Acaravcı and Karaömer (2018); Kaya (2021). Likewise, the validity of the Fama and French Five-Factor Model in the BIST Participation 50 Index was determined and the null hypotheses H_{0a} and H_{0b} were rejected. These results contradict Zeren et al. (2018) but are comparable to Hanif's (2011) conclusion that the CAPM equity pricing model may be used in the Sharia financial system. Furthermore, the outcomes indicate a rejection of the main hypothesis H_0 and an acceptance of hypothesis H_1, as they point to the differentiation of the factors that are effective in both the BIST All Index, which includes portfolios created with a traditional perspective, and the BIST Participation 50 Index, which includes portfolios created with an Islamic perspective.

The research proceeded on to examine which portfolio types, employing an ANN-based hybrid model optimized with genetic algorithms, had the best results when every factor included in the French Five and Fama factors were combined. The roulette wheel method was used for the hybrid model's selection process, increasing the chances of survival for those who get successful outcomes. By using crossover and mutation processes, a single generation was finished for every individual in the model. Based on the parameters, the Genetic Algorithm operated for 50 generations. Hyperparameter optimization was used to generate the network parameters in the individual with the highest MSE value in the final generation. As a result of the analysis, not forgetting the fact that all parameters are optimized and all portfolios are efficient, the portfolios with the lowest MSE value differ in both the BIST All Index and the BIST Participation 50 Index. In addition, it is also observed that the most successful gene parameters determined in the efficient portfolios created with different criteria from the traditional point of view and the efficient portfolios created from the Islamic point of view differ, and accordingly, the main hypothesis H_{0c} is rejected.

Since the results of the artificial neural network-based hybrid model created with genetic algorithm optimization produce more specific outputs, it is thought to present more remarkable findings by market participants. In terms of performance comparison in studies conducted with ANN and GA optimization in the literature, Cao, Leggio and Schniedes (2005); Kendall and Su (2005); Lin and Gen (2007); Durmuşkaya and Garayev (2017); Abdelwahed and Trabelsi (2021) found that these models provide superior results to asset pricing models. It can be said that the findings of this study are similar to the aforementioned studies.

The results obtained from the study are expected to guide market participants in making investments by taking gene parameters into account. At the same time, for researchers, the results are also instructive in terms of comparing the portfolios created with both conventional and Islamic perspectives with the studies to be conducted within the scope of conventional and artificial intelligence models. Furthermore, it might be argued that the creation of web-based apps would make it easier for market participants to employ these models.

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APPENDICES

Table 1. Average Returns of Portfolios Formed within BIST All and BIST Participation 50 Index

	BIST All Share Index			BIST Participation Index		
ri-rf	Average	Median	Std. Dev.	Average	Median	Std. Dev.
SH	-0.4869	-0.4869	0.0372	-0.4920	-0.4902	0.0320
BH	-0.4915	-0.4918	0.0357	-0.4931	-0.4965	0.0308
SN	-0.4896	-0.4883	0.0317	-0.4796	-0.4842	0.0384
BN	-0.4938	-0.4918	0.0296	-0.4801	-0.4901	0.0380
SL	-0.4913	-0.4915	0.0344	-0.4906	-0.4933	0.0302
BL	-0.4962	-0.4960	0.0319	-0.4916	-0.4965	0.0289
SR	-0.4915	-0.4918	0.0358	-0.4905	-0.4876	0.0333
BR	-0.4963	-0.4962	0.0335	-0.4915	-0.4965	0.0323
SM	-0.4896	-0.4869	0.0336	-0.4837	-0.4850	0.0342
BM-	-0.4938	-0.4915	0.0317	-0.4843	-0.4904	0.0335
SW	-0.4865	-0.4869	0.0339	-0.4876	-0.4933	0.0352
BW	-0.4913	-0.4907	0.0321	-0.4885	-0.4965	0.0344
SC	-0.4854	-0.4845	0.0363	-0.4888	-0.4901	0.0295
BC	-0.4902	-0.4891	0.0349	-0.4897	-0.4965	0.0282
SM-	-0.4891	-0.4901	0.0330	-0.4878	-0.4902	0.0362
BM	-0.4933	-0.4920	0.0311	-0.4886	-0.4911	0.0355
SA	-0.4932	-0.4918	0.0338	-0.4849	-0.4842	0.0366
BA	-0.4980	-0.4980	0.0310	-0.4857	-0.4904	0.0360

Table 2. Prais-Weinsten Test Results for the Portfolios Formed within the BIST All Index

ri-rf	α	β	smb	hml	rmw	cma	DW	A.R²
SH	0.0310	0.968	4.077	1.201	-2.278	3.116	2.94	0.42
	(0.422)	(0.000)***	(0.002)***	(0.315)	(0.024)**	(0.049)**	(2.24)	(0.000)***
SN	0.0304	0.975	4.398	0.749	-2.351	3.639	2.94	0.38
	(0.462)	(0.000)***	(0.002)***	(0.555)	(0.029)**	(0.033)**	(2.22)	(0.000)***
SL	0.030	0.969	4.096	0.189	-2.275	3.129	2.94	0.36
	(0.433)	(0.000)***	(0.002)***	(0.873)	(0.024)**	(0.047)**	(2.25)	(0.000)***
BH	0.029	0.969	3.068	1.191	-2.260	3.137	2.94	0.51
	(0.441)	(0.000)***	(0.016)**	(0.316)	(0.024)**	(0.046)**	(2.26)	(0.000)***
BN	0.030	0.975	3.476	0.749	-2.358	3.634	2.94	0.48
	(0.458)	(0.000)***	(0.012)**	(0.555)	(0.029)**	(0.033)**	(2.21)	(0.000)****
BL	0.0304	0.968	3.049	0.204	-2.262	3.124	2.94	0.59
	(0.429)	(0.000)***	(0.017)**	(0.863)	(0.025)**	(0.048)**	(2.25)	(0.000)***
SR	0.0331	0.972	4.314	0.712	-1.813	3.353	2.92	0.65
	(0.401)	(0.000)***	(0.002)***	(0.556)	(0.072)*	(0.039)**	(2.23)	(0.000)***
SM	0.025	0. 969	4.017	0.711	-2.282	3.248	2.97	0.33
	(0.523)	(0.000)***	(0.003)***	(0.559)	(0.027)**	(0.046)**	(2.25)	(0.000)***
SW	0.033	0. 972	4.317	0. 712	-2.808	3.355	2.92	0.36
	(0.401)	(0.000)***	(0.002)***	(0.556)	(0.008)***	(0.038)**	(2.37)	(0.000)***
BR	0.0332	0.972	3.270	0.711	-1.812	3.352	2.92	0.57
	(0.400)	(0.000)***	(0.013)**	(0.557)	(0.072)***	(0.039)**	(2.23)	(0.000)***
BM	0.025	0.969	3.103	0.710	-2.284	3.248	2.97	0.48
	(0.523)	(0.000)***	(0.018)**	(0.560)	(0.027)**	(0.046)**	(2.25)	(0.000)***
BW	0.0333	0.972	3.268	0.711	-2.817	3.351	2.92	0.51
	(0.399)	(0.000)***	(0.013)**	(0.557)	(0.008)***	(0.039)**	(2.23)	(0.000)***
SC	0.032	0.972	4.128	0.779	-2.257	3.633	2.96	0.41
	(0.408)	(0.000)***	(0.002)***	(0.513)	(0.026)**	(0.024)**	(2.26)	(0.000)***
SM-	0.026	0.969	4.345	0.592	-2.375	3.629	2.90	0.38
	(0.508)	(0.000)***	(0.002)***	(0.635)	(0.026)**	(0.031)**	(2.20)	(0.000)***
SA	0.032	0.972	4.128	0.779	-2.257	2.638	2.96	0.68
	(0.408)	(0.000)***	(0.002)***	(0.513)	(0.026)**	(0.093)**	(2.26)	(0.000)***
BC	0.032	0.972	3.080	0.779	-2.261	3.634	2.96	0.66
	(0.405)	(0.000)***	(0.017)**	(0.514)	(0.026)***	(0.024)	(2.26)	(0.000)***
BM-	0.027	0. 969	3.427	0.591	-2.380	3.628	2.90	0.48
	(0.506)	(0.000)***	(0.011)**	(0.636)	(0.026)**	(0.031)**	(2.20)	(0.000)***
BA	0.032	0.972	3.080	0.779	-2.261	2.630	2.96	0.54
	(0.405)	(0.000)***	(0.017)**	(0.514)	(0.026)**	(0.094)**	(2.26)	(0.000)***

Table 3 Prais-Weinsten Test Results for the Portfolios Formed within the BIST Participation 50 Index

ri-rf	α	β	smb	hml	rmw	cma	DW	A.R²
SH	-0.00243	0.998	0.817	-1.123	0.487	-1.190	2.61	0.56
	(0.919)	(0.000)***	(0.516)	(0.185)	(0.449)	(0.461)	(2.01)	(0.000)***
SN	-0.007	0.994	0.580	-1.516	0.367	-1.693	2.63	0.74
	(0.744)	(0.000)***	(0.0638)	(0.072)*	(0.560)	(0.290)	(2.08)	(0.000)***
SL	-0.002	0.998	0.817	-2.101	0.487	-1.190	2.61	0.56
	(0.919)	(0.000)***	(0.516)	(0.018)**	(0.449)	(0.461)	(2.01)	(0.000)***
BH	-0.002	0.998	-0.206	-1.103	0.488	-1.184	2.61	0.47
	(0.921)	(0.000)***	(0.869)	(0.193)	(0.448)	(0.464)	(2.00)	(0.000)***
BN	-0.007	0. 994	0. 371	-1.513	0.363	-1.707	2.63	0.58
	(0.739)	(0.000)***	(0.764)	(0.073)*	(0.564)	(0.286)	(2.08)	(0.000)***
BL	-0.002	0.998	-0.020	-2.12	0.488	-1.184	2.61	0.45
	(0.921)	(0.000)***	(0.869)	(0.017)**	(0.448)	(0.464)	(2.00)	(0.000)***
SR	-.0796	0.931	-0.970	-5.808	-0.637	-2.948	2.07	0.38
	(0.173)	(0.000)***	(0.696)	(0.004)***	(0.629)	(0.334)	(1.95)	(0.000)***
SM	-.0765	0.936	-0.325	-5.194	-0.830	-2.426	2.10	0.32
	(0.161)	(0.000)***	(0.890)	(0.006)***	(0.505)	(0.401)	(1.94)	(0.000)***
SW	-0. 0726	0.939	-0.636	-5.372	-1.497	-2.644	2.12	0.42
	(0.172)	(0.000)***	(0.782)	(0.004)***	(0.225)	(0.351)	(1.95)	(0.000)***
BR	-.0782	0.933	-1.933	-5.722	-0.595	-2.889	2.08	0.52
	(.173)	(0.000)***	(0.432)	(0.004)***	(0.646)	(0.337)	(1.95)	(0.000)***
BM	-0.075	0.937	-1.225	-5.138	-0.812	-2.387	2.11	0.36
	(0.160)	(0.000)***	(0.600)	(0.006)***	(0.511)	(0.405)	(1.94)	(0.000)***
BW	-0.070	0.941	-1.596	-5.273	-1.493	-2.582	2.13	0.46
	(0.173)	(0.000)***	(0.483)	(0.004)***	(0.217)	(0.355)	(1.95)	(0.000)***
SC	-0.001	0.997	0.689	-1.476	0.401	-0.895	2.62	0.66
	(0.950)	(0.000)***	(0.580)	(0.082)*	(0.527)	(0.574)	(2.05)	(0.000)***
SM-	-0.009	0.995	0.814	-1.762	0.527	-1.33	2.61	0.31
	(0.692)	(0.000)***	(0.519)	(0.042)**	(0.413)	(0.409)	(1.98)	(0.000)***
SA	-0.001	0.997	0.683	-1.474	0.398	-1.881	2.62	0.68
	(0.948)	(0.000)***	(0.583)	(0.083)*	(0.530)	(0.243)	(2.05)	(0.000)***
BC	-0.001	0.997	-0.340	-1.471	0.398	-0.876	2.62	0.48
	(0.953)	(0.000)***	(0.784)	(0.083)*	(0.530)	(0.582)	(2.05)	(0.000)***
BM-	-0.001	0.997	-0.334	-1.473	0.401	-1.891	2.62	0.52
	(0.955)	(0.000)***	(0.787)	(0.082)	(0.527)	(0.240)	(2.06)	(0.000)***
BA	-0.001	0.997	-0.334	-1.473	0.401	-1.891	2.62	0.54
	(0.955)	(0.000)***	(0.787)	(0.082)	(0.527)	(0.240)	(2.06)	(0.000)***

Table 4. Panel Data Model Selection Criteria aand Basic Assumption Tests

Panel data selection criteria for BIST All Index

Applied Tests	**Test Stat.**	**Prob.**	**Hypotheses**	**Outcome**
F (Chow) Testi	0.20	0.997	H_0: Pooled model is valid. H_1: Fixed effects model is valid.	H_0 accepted: The classical model is valid.
Breusch Pagan Testi	1675.7	0.000***	H_0: Pooled model is valid. H_1: Random effects model is valid.	H_0 reject: Random model valid.
Hausman Testi	14.32	0.724	H_0: Random effects model is valid. H_1: Fixed effects model is valid.	H_0 accepted: Random model valid.

Panel data selection criteria for BIST Participation Index

Applied Tests	**Test Stat.**	**Prob.**	**Hypotheses**
F (Chow) Testi	0.42	0.9802	H_0: Pooled model is valid. H_1: Fixed effects model is valid.
Breusch Pagan Testi	397.88	0.000***	H_0: Pooled model is valid. H_1: Random effects model is valid.
Hausman Testi	7.65	0.876	H_0: Random effects model is valid. H_1: Fixed effects model is valid.

Basic Assumption Tests gor Panel Data for BIST All Index

Assumptions	**Uygulanan Test**	**Test Stat.**	**Prob.**	**Outcome**
Heteroscadasticity	Levene, Brown and Forsythe Tests	Wo: 0.0473 W50: 0.0464 W10: 0.0460	0.0137** 0.0128** 0.0121**	There is a Problem of Heteroscadasticity
Autocorrelation	Bhargava vd.DW Baltagi-Wu LBI	0.912 0.979	- -	There is a Problem of Autocorrelation
Cross-Sectional Dependence	Frees*	15.98	- -	There is a Problem of Cross-Sectional Dependence

*The table critical values for the Frees test at 1%, 5% and 10% significance levels are 0.0861, 0.111 and 0.159, respectively.

Basic Assumption Tests gor Panel Data for BIST Participation Index

Heteroscadasticity	Levene, Brown and Forsythe Tests	Wo: 0.501 W50: 0.392 W10: 0.430	0.952 0.986 0.978	There is not a Problem of Heteroscadasticity
Autocorrelation	Bhargava etc. DW Baltagi-Wu LBI	0.631 0.683	- -	There is a Problem of Autocorrelation
Cross-Sectional Dependence	Frees**	13.325	-	There is a Problem of Cross-Sectional Dependence

**Table critical values for Frees test at 1% and 5% significance level are 0.159 and 0.111, respectively.