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ESSAYS ON PARTICIPATION FINANCE SYSTEM AND STOCK MARKET ANALYSIS

Erdi BAYRAM

Danışman
Prof. Dr. Rabia AKTAŞ

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TAAHHÜTNAME

Bu tezin, Manisa Celâl Bayar Üniversitesi, Lisansüstü Eğitim Enstitüsü, İşletme Ana Bilim Dalında akademik ve etik kurallara uygun olarak yazıldığını ve kullanılan tüm literatür bilgilerinin referans gösterilerek tezde yer aldığını, tamamen kendi çalışmam olduğunu, her alıntıya kaynak gösterdiğimi, tezin yazımında akademik ve etik kurallara aykırı herhangi bir yapay zeka ve program kullanmadığımı beyan ederim.

İmza

Erdi BAYRAM

ÖZET

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Erdi BAYRAM
Manisa Celâl Bayar Üniversitesi
Lisansüstü Eğitim Enstitüsü
İşletme Anabilim Dalı

Danışman: Prof. Dr. Rabia AKTAŞ

Alternatif bir model olarak katılım finans sistemi son dönemde Türk bankacılık sektörü ve sermaye piyasalarında kayda değer bir varlık ve fon büyüklüğüne erişmiş ve farklı kesimlerdeki piyasa katılımcılarının ilgisini çekmiştir. Ayrıca akademik düzeyde çok sayıda teorik ve ampirik çalışmaya konu edilmiştir. Dünyada giderek belirginleşen, temelinde ekonomik ve finansal başarısızlıkların yer aldığı model ve sistem arayışları konvansiyonel yaklaşım ve uygulamalarını gözden geçirmeye zorlamaktadır. Diğer bir deyişle, ekonomide ve modern finansta ana akım paradigma değişmektedir. Farklı düşünce sistematiğine sahip yaklaşımların her biri finansta yeni bir yapılanmaya ihtiyaç olduğunu ifade etmektedir. Bu bağlamda ilk makalede finansın değişen paradigması alternatif yaklaşımlar çerçevesinde incelenmiştir. Finansın yönünü değiştiren teorik ve uygulamadaki yaklaşımlar postmodern finans düşüncesi olarak kavramsallaştırılmış; etik, sosyal ve sorumlu finans, iyi finans, İslami finans, insani finans ve alternatif finans başlıkları altında kavramsal bir inceleme yapılmıştır. Ayrıca makalede katılım finans sistemi tanıtılmış, temel prensipleri ve uygulama alanları açıklanmıştır. Buna ek olarak, Türkiye'de katılım finans sisteminin geleneksel sistem içerisindeki işlevi ve gelecek perspektifi değerlendirilmiş ve tartışılmıştır. Sonuç olarak katılım finans sisteminin belirli sınırlılıklara sahip olmakla birlikte finansın değişen paradigmasıyla uyumlu, kendine özgü ve farklı bileşenleri barındıran bir model olma özeliği taşıdığı düşünülmektedir. İkinci makalede katılım pay piyasasında ampirik bir uygulama yapılmıştır. Makalede Borsa İstanbul Katılım 30 endeksinde yer alan pay senetleri kullanılarak postmodern portföy teorisine dayalı alternatif bir ağırlık belirleme stratejisi önerilmiştir. Makalede optimizasyon yöntemine dayalı iki farklı yaklaşım benimsenmiştir. Birincisi Modern Portföy Teorisiyle uyumlu Sharpe oranı maksimizasyonuna dayalı ağırlık belirleme

yaklaşımıdır. İkincisi Postmodern Portföy Teorisiyle uyumlu Sortino oranı maksimizasyonuna dayalı yaklaşımdır. Her iki optimizasyondan elde edilen ağırlıklar kullanılarak Sharpe ve Sortino portföyleri oluşturulmuş ve portföyler getiri performansı açısından birbiriyle, eşit ağırlıklı portföyle ve pazar endeksi olarak analize dahil edilen Katılım 30 endeksiyle karşılaştırılmıştır. Sonuç olarak kullanılan tekniklerin alternatif bir yatırım stratejisi olarak uygulanabilir olduğu düşünülmektedir. Üçüncü makalede ise Borsa İstanbul'daki katılım ve konvansiyonel endekslerde volatilite tahminini içeren ampirik bir uygulama yapılmıştır. GARCH, TGARCH, EGARCH, APARCH ve EGARCH-M modellerinin kullanıldığı çalışmada model parametreleri tahmin edilerek yorumlanmış ve serilerin volatilite özelikleri incelenmiştir. Ayrıca örneklem dışı dönem için volatilite öngörümlemesi yapılmış ve tahmin modellerinin gün içi beş dakikalık verilerle hesaplanan gerçekleşen volatiliteyi açıklama gücü test edilmiştir. Bu amaçla regresyon denklemleri çözülmüş ve belirlilik katsayılarına (R-kare) göre gerçekleşen volatiliteyi en iyi tahmin eden modelin EGARCH olduğu görülmüştür. Ayrıca Katılım 30 endeksi için diğer endekslerden farklılaşan sonuçlar elde edilmiştir. Üç makaleden oluşan bu tez çalışmasının katılım finans sistemine ilişkin literatüre hem teorik hem de ampirik olarak katkı sunması beklenmektedir.

Anahtar Kelimeler: Katılım finans sistemi, Paradigma değişimi, Postmodern portföy teorisi, Portföy optimizasyonu, Volatilite tahmin modelleri, Borsa İstanbul.

2024, 85 sayfa

ABSTRACT

PhD Thesis
Erdi BAYRAM
Manisa Celâl Bayar University
Graduate School of Education
Department of Business Administration

Supervisor: Prof. Dr. Rabia AKTAŞ

As an alternative model, the participation finance system has recently achieved substantial asset and fund sizes in capital markets and the Turkish banking sector. This model has attracted participants from various market segments and has been examined in numerous theoretical and empirical studies. The search for models and systems resulting from economic and financial failures, which are becoming increasingly evident worldwide, necessitates a review of the conventional approaches and practices. In other words, the mainstream paradigm is changing. Each approach, with different thought systematics, advocates the implementation of a new financial framework. In this context, the first essay examines the changing paradigm of finance within the framework of alternative approaches. Theoretical and practical approaches that have changed the direction of finance have been conceptualized as postmodern finance. A conceptual review is conducted under the headings of ethical, social, and responsible finance, good finance, Islamic finance, humanitarian finance, and alternative finance. This essay also introduces the participation finance system and explains its fundamental principles and practices in the Turkish finance system. In addition, the function of the participation finance system in conventional finance in Türkiye and its future perspectives are evaluated and discussed. The essay concludes although the participation finance system has certain limitations, it is a model compatible with the changing paradigm of finance and has its own characteristics and remarkable components. The second essay presents empirical research on the stock market in a participation finance system. It proposes an alternative weighting strategy based on postmodern portfolio theory using Borsa Istanbul Participation 30 Index stocks. The study includes two optimization processes. The first is a weighting strategy based on Sharpe ratio maximization in accordance with Modern Portfolio Theory. The

second approach is based on Sortino ratio maximization in line with Postmodern Portfolio Theory. The Sharpe and Sortino portfolios are constructed using weights and compared in terms of return performance. In addition, equally weighted portfolios and market indices were included in the comparison. Consequently, these techniques are applicable as alternative investment strategies. The third essay presents empirical research on volatility forecasting for participation and conventional indices in Borsa Istanbul. The GARCH, TGARCH, EGARCH, APARCH, and EGARCH-M models were used, model parameters were estimated, and the volatility characteristics of the series were analyzed. In addition, volatility forecasting was conducted for the out-of-sample period. Regression equations were solved to analyze the explanatory power of the models for realized volatility, calculated using intraday five-minute data. The model that best predicts volatility according to R-squared coefficients was found to be the EGARCH model. In addition, the findings indicate important results in favor of the Participation 30 Index. This thesis, which consists of three essays, is expected to contribute to the literature on the participation finance system, both conceptually and empirically.

Keywords: Participation finance system, Paradigm shift, Postmodern portfolio theory, Portfolio optimization, Volatility forecasting models, Borsa Istanbul.
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Erdi BAYRAM

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ABBREVIATIONS

AIC	Akaike Information Criterion
APARCH	Asymmetric Power ARCH
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
CAPM	Capital Asset Pricing Model
D-CAPM	Downside Capital Asset Pricing Model
EGARCH	Exponential GARCH
EWMA	Exponentially Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M	GARCH in Mean
HV	Half-Life Volatility
IFSB	Islamic Financial Services Board
LL	Log-Likelihood
LSEG	London Stock Exchange Group
MA	Moving Average
MAR	Minimum Acceptable Return
MSE	Mean Squared Error
PBA	Participation Banks Association of Türkiye
QLIKE	Quasi-Likelihood
TGARCH	Threshold GARCH

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INTRODUCTION

The Islamic financial services industry is growing and developing on a global scale. According to the IFSB (2023) report, the industry asset size was US$ 2.75 trillion in 2020 and calculated to be US$ 3.25 trillion in 2022. The sector is reported to have grown by 6.2% year-on-year, driven by significant improvements in the Islamic banking and Islamic capital market segments. According to 2022 data, based on total assets, the share of Islamic banking in the industry is 69.3%, and the share of capital market instruments is 29.8%. The data shows the central role of the Islamic banking model in Islamic finance.

The participation finance system is essentially based on the principles of Islamic finance, which is defined as an alternative financial system. In this respect, the equivalent of Islamic finance practices in Türkiye is the participation finance system, the main component of which is the participation banking model. This model is defined as Islamic banking in the literature, has a wide range of practices worldwide, and differs from other Islamic financial instruments and services such as Islamic funds, bonds, and insurance in terms of asset size.

There is considerable interest in participation financial institutions and tools that provide an alternative model within the Turkish finance system. Several researchers believe that this interest is predominantly faith-based. In contrast, a consensus has emerged regarding the need to rethink the conventional financial system based on ethics, morality, justice, and social responsibility. Alternative approaches, such as the participation finance system, are at the core of this need for rethinking. The need for restructuring, based on contextually different reasons, affects conventional approaches and changes the paradigm of modern finance in both intellectual and practical dimensions.

In the first chapter of this study, we evaluate alternative approaches in the context of a changing finance paradigm. The main purpose of this section is to emphasize where the participation finance system is positioned within the changing paradigm of finance. We review what we call postmodern finance thoughts, such as ethical finance, socially responsible finance, humanitarian finance, good finance, and the participation finance system. Additionally, we discuss alternative approaches and their effects on the financial

system in the context of literature. Here, we particularly focus on the participation finance system and its components. The study's conclusion includes a discussion of the function of the participation finance system in Türkiye within the conventional system and its future perspective. Criticisms of mainstream economics and finance assumptions constitute the theoretical basis of this chapter. In this section, we adopt a conceptual analysis as the research method.

Another component of the participation finance system is capital markets. Participation indices and participation funds are important alternative investment instruments. Participation indices are defined as portfolios that are consistent with the Islamic index construction methodology and depend on a set of rules. The stocks included in the indices are consistent with the relevant rules and subject to monitoring. Empirical studies suggest that participation indices and Islamic indices are conservative investment instruments in high-volatility periods. In addition, market participants prefer indices with different investment strategies according to market conditions. These are positioned as faith-based investment alternatives.

In the second chapter of this study, we introduce a portfolio construction method based on postmodern portfolio theory. This section proposes an alternative investment strategy using stocks in the Borsa Istanbul Participation 30 Index (XK030). Unlike modern portfolio theory, we construct portfolios using the Sortino ratio optimization method, which is consistent with downside tools, such as downside volatility, downside beta, and downside CAPM. In addition, as part of traditional approaches, we create portfolios using the Sharpe ratio optimization method and equally weighted strategies. We calculated the portfolio returns for 450 trading days for the four index periods using the daily returns of 52 companies on the Participation 30 Index.

Volatility is one of the main inputs for investment decisions and portfolio management. Volatility modeling and forecasting are important for risk management. Participation indices are theoretically more conservative than conventional indices, a more stable investment alternative during market downturns, and are expected to have a rational risk-return trade-off. In this respect, it is important to compare and reveal the volatility characteristics of participation indices with conventional indices in terms of the

participation finance system. Although different volatility forecasting models have been used in recent studies, the widely preferred method is GARCH-type modeling.

In the third chapter of this study, we investigate the volatility of the four indices using the GARCH family models. The main purpose of this section is to forecast the volatility of participation and conventional indices and compare the forecasting results. The indices are participation indices (XK030 and XK050) and conventional market indices (XU030 and XU100) in Borsa Istanbul. First, we estimate the model parameters using 809 days of data and explain the volatility features of the index return series. Second, we generate a 57-day forecast series for the models. Finally, we measured the explanatory power of the generated conditional variance series to explain the realized volatility calculated using intraday returns.

ESSAY 1. SEEKING A NEW PARADIGM IN FINANCE

1.1. Introduction

Mainstream economics have been intensly criticized, especially since the 2008 financial crisis. The conventional system, which dominates theory and practices, has been contributing factor to financial failures and crises. There is a consensus that the search for a different paradigm necessary (Sun et al. 2011; Saraç, 2017; Acar, 2021). Because of the "*financialization"* (Krippner, 2011) resulting from the increasing weight of financial activities in economies, the theoretical basis, models, and practice of financial systems are criticized, and the necessity for alternative perspectives is emphasized. De Anca (2014) argues that financial deepening has positively affected societies, but that the financial system needs significant reforms due to the serious challenges it has faced since the 2008 crisis. In this respect, this study explores the new paradigm in finance on the basis of alternative and complementary approaches.

How does the paradigm shift within a discipline? To answer this question, we must review some thoughts on this topic. According to Kuhn (1970), the failure of existing rules and methods in a discipline represents a transition process in the search for new rules and methods. The realization of the discrepancies (crises and anomalies) and existing problems in the discipline reaching a level that cannot be ignored, may require a paradigm shift. Popper (2002) defined a paradigm as a collection of assumptions and approaches that shape scientific thought during a particular period. According to Popper, the current paradigm can change if a *black swan* is present. In critical analysis, Gippel (2012) argued that finance has gained a different dimension from the new approaches that challenge the traditional paradigm. Gippel (2012) also emphasizes that disciplines such as neuroscience, cognitive psychology, and evolutionary research, which have been integrated into finance, have caused a paradigm shift in finance. Ernst and Gleissner (2022) build on the framework proposed by Kuhn and stated the need for different approaches to understanding and testing market chaos and complexity. Ardalan (2018) emphasized that different viewpoints affect the current paradigm, and as an inevitable consequence, it is unrealistic to evaluate economic and financial activities in a one-dimensional manner.

In this paper, we primarily present the approaches that we collect under the title of *postmodern finance thoughts* conceptualized by Boulier (2021). Subsequently, we introduce the participation finance system and evaluate its fundamental components. In addition, we provide discussion and assessment for future perspective.

1.2. Postmodern Finance Thoughts

Increasing criticism of the conventional financial systems has led to the emergence of alternative approaches. One approach concerns the necessity of revisiting financial instruments and products. A second approach includes practices developed to restructure finance based on ethical and moral principles. A third rejects a system based on endless borrowing and interest as not sustainable and suggets restructuring according to new norms. These approaches reflect the perspectives of different economic thoughts regarding the economy and the financial system. These thoughts seem to be internally consistent, and the common idea is the necessity of a new perspective on the financial system. In this context, we present *ethical, social, and responsible finance* as an umbrella concept.

1.2.1. Ethical, Social, and Responsible Finance

Thinkers such as Zaman (2009), Shiller (2012), and Chapra (2014) stated that participants and institutions in the financial system have turned into units that pursue only self-interest and have no sense of responsibility towards the environment and society. Therefore, financial markets play an important role in creating an inhumane system and faulty distribution structure in economies. The absence of ethical and moral principles in the system, coupled with the relentless pursuit of economic agents to gain under any circumstances, has resulted in financial failures (Looft, 2014; Saraç, 2017). Looft (2014) argues it is feasible to establish and uphold strong ethical and moral obligations in finance, but it necessitates embracing a paradigm change in our approach to the production and distribution of financial products, particularly for those who are economically disadvantaged. Ryszawska (2017) states that green finance and sustainable finance and its practices, contrary to the traditional role of finance, have grown rapidly. Ethically and socially responsible finance refers to financial activities and investments consistent with a set of ethical principles that support social and environmental sustainability. In other words, the responsible finance approach illustrates that units are accountable for the

environment, society, and people in their economic and financial activities. The literature on the *ethics-embedded nature of finance*[1] uses key concepts. These concepts are illustrated in Figure 1.1.

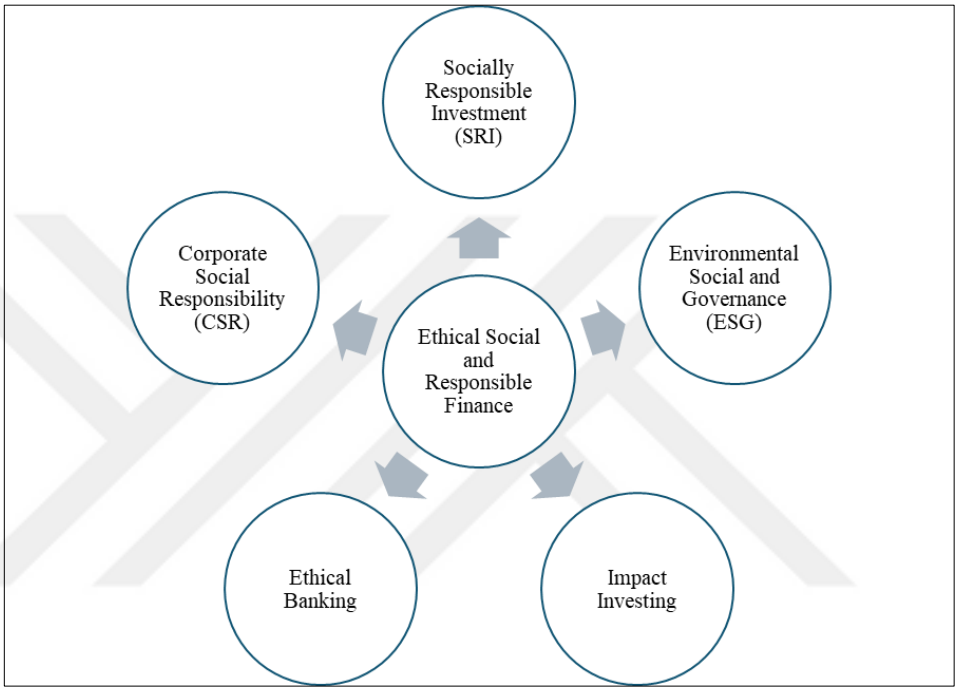


Figure 1.1: Components of Ethical Social and Responsible Finance
(Source: Created by Author)

Ethical, social, and responsible finance can be approached from two different perspectives (Figure 1.2). The first is investment and financing decisions related to corporate finance in terms of real assets and financial markets. The corporate finance aspect of ethical and socially responsible investing is represented by companies and the ecosytems in which companies are a component. The second approach is fund and portfolio management from the perspective of individual and institutional investors. In other words, the formation of *ethical and social financial markets* is related to supply and demand. The demand side consists of retail and institutional investors in ethical and social finance ecosystems. In addition to their expectations for financial returns, investors

[1] The notion belongs to Erragraguy et al. (2014).

demand that their investments have a positive impact on society (Cooper et al., 2016). On the supply side are sustainable projects, social enterprises, and companies with socially responsible investments, eager to obtain financing from entities within the same ecosystem.

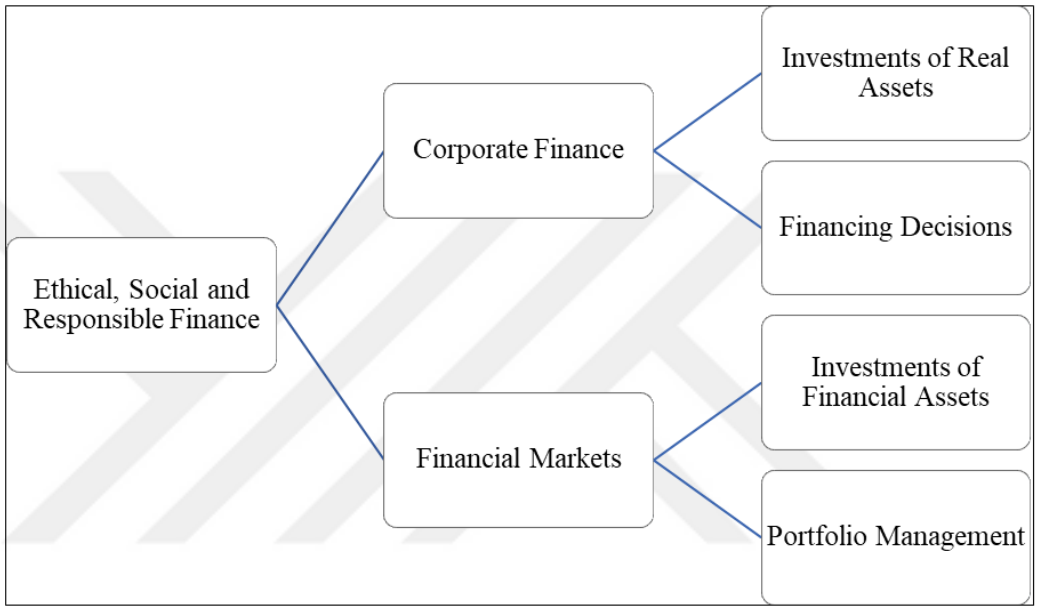


Figure 1.2: Dimensions of Ethical Social and Responsible Finance
(Source: Created by Author)

In Widyawati's (2020) systematic review of ethical and responsible finance approaches, Socially Responsible Investment (SRI) is discussed as the integration of finance with ethical values and explained as the investor's ability to achieve financial gain by investing in companies that comply with ethical values and principles. In his literature review, Camilleri (2021) emphasized that individual investor, institutional investors, and portfolio managers integrate social and environmental priorities into their investment management perspectives in line with the SRI approach. According to the SRI approach, decision units follow certain strategies by conducting both negative and positive screenings. Negative screening aims to exclude companies in certain sectors from their investment portfolios that do not comply with ethical standards. In particular, investors may prefer to avoid firms in industries such as arms, tobacco and fossil fuels that have

negative social and environmental impacts. This approach reflects investors' ethical values in their financial decisions. Positive screening involves decision makers favoring companies with practices that are beneficial to the environment and society. Investments based on the SRI approach can be directed toward companies that produce renewable energy, adopt sustainable methods, and/or apply ethical trade principles. It is believed that achieving socially beneficial outcomes in addition to financial returns is feasible through this approach.

Environmental, Social, and Governance (ESG) refers to the three main components that assess companies' environmental, social, and governance performance. These components are effective for assessing the sustainability and ethical practices of businesses (Figure 1.3). In addition, ESG is used as a measurement tool and is considered important for financial decision makers who want to evaluate the sustainability performance of companies. Empirical studies use ESG scores in addition to traditional measures. For example, Duque-Grisales and Aguilera-Caracuel (2021) examined the relationship between ESG scores and traditional financial indicators.

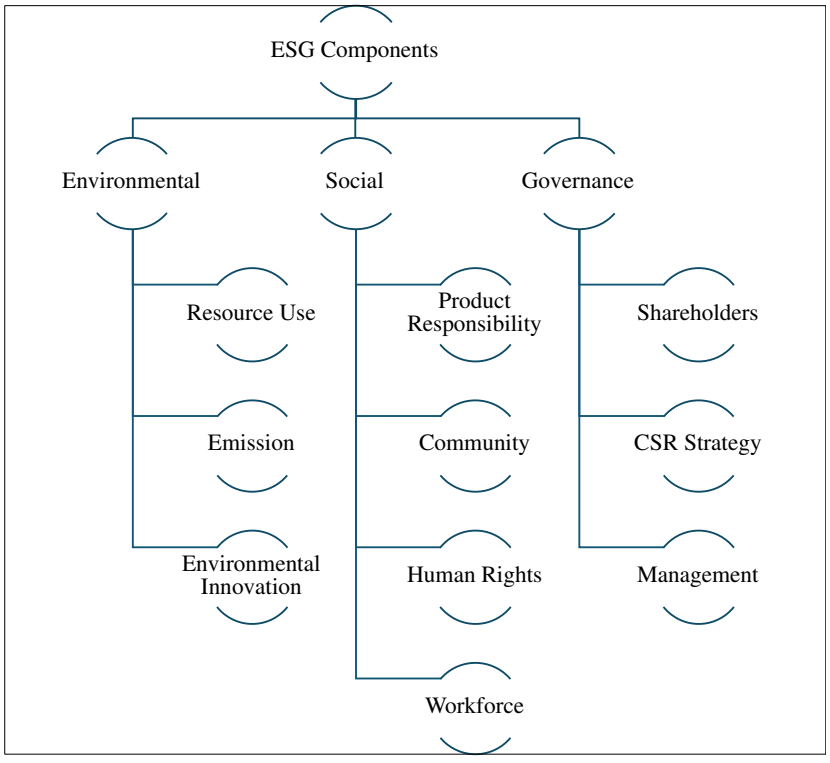


Figure 1.3: Fundamental Components of ESG
(Source: LSEG, 2023)

Li et al. (2024) examined the relationship between corporate environmental responsibility (CER) and corporate financial performance (CFP) and found that CFP has a positive and significant effect on CER. In another study by Barber et al. (2020), investors were willing to invest in funds with both financial and social or environmental outcomes (impact investing). According to the literature, impact investing can be defined as an investment approach in which investors aim to create positive social and environmental changes in addition to financial returns. Jeffers et al. (2024) examined the risk-return characteristics of impact investing funds and concluded that such funds have low exposure to market risk. Liang and Renneboorg (2020) argue that Corporate Social Responsibility (CSR) practices in companies affect financial decisions and that activities should be analyzed not only in terms of financial results but also in terms of their impact on society, the environment, and stakeholders.

Ganzo's (2014) research establishes eco-social-transparent banks as the basis of ethical banking practices. Furthermore, Ganzo (2014) states that some aspects of these banks merge with the interest-free banking model. First, these banks determine which projects they will and will not provide loans to based on a set of ethical criteria used in ethical banking practices. This is similar to the criteria and procedures in the interest-free banking model. Ganzo emphasizes that the interest-free principle is implemented as a requirement for ethical and responsible financing. Paulet et al. (2015) put forward the thesis that the banking industry evolved towards two types of banking models after the 2008 crisis and emphasized that the *"banking with ethics"* approach constitutes an alternative to traditional banking.

Some comments by Serrats (2014) and Erragraguy et al. (2014) on the need for ethical, social, and responsible approaches to finance are of interest.

- Banks and financial institutions have started to lose their reputation in the public, leading to a serious loss of trust.
- Institutes need to prioritize re-engaging with customers and regain their lost reputations.
- Customers often feel cheated by the financial industry. The existence of unethical behavior is known, even expected, and attributed to human nature.

- The lack of ethical, moral, and real rules of conduct for companies to act in a socially responsible manner poses a *dilemma*.

1.2.2. Good Finance

The crises of capitalism from the past to the present and the collateral damage caused by these crises are directly related to the deterioration of the financial structure. Akgiray (2019) argues that a new social contract between policymakers, financial markets, and people is necessary, particularly after the 2008 financial crisis. Akgiray (2019) formulated the concept of *good finance* as a unique approach that offers a new perspective on risk, governance, and conventional financial instruments. Financial systems should redefine and demonstrate the place of finance in real economic life and be compatible with the main objectives of economic policy. Good finance, as a financial model, should consider environmental, social, and governance issues and be structured based on responsibility. Akgiray (2019) offers the following regarding the regulation of the financial system: *"The first step towards good finance is to break the growing vicious cycle of credit and debt. Short of this, regulation can never save the system, and it will always have to save to firms at the expense of the people. In a properly regulated industry, fates of firms are determined in free markets, not by governments. A functional approach to regulation is much needed."(p. 136).*

1.2.3. Humanitarian Finance

Researchers who proposed rethinking financial mechanisms and the system's functioning using a faith-based approach introduced the concept of *humanitarian finance* in the literature. Humaniratian finance is a new idea that promotes economic activities in line with human nature and defends the opinion that access to financial resources and opportunities is a fundamental right for all humanity (Korkut & Kar, 2018; Hazıroğlu, 2021). Although the origins of the concept are based on the principles and practices of Islamic finance, humanitarian finance is considered a broad definition and umbrella concept. There is no clear distinction in the literature in terms of positioning the financial system as humanitarian and non-humanitarian. However, it is also clear that a humanitarian finance system should be align with an ethical, social, and responsible

investment approach, care about the social and environmental impacts of finance, have effective risk-sharing and management tools, and be integrated with real assets. This concept is both integrative and inclusive.

1.2.4. Islamic Finance

The criticisms in Asutay's (2007) study are important in considering Islamic finance as an alternative approach. Asutay (2007) states that the basis of economics and finance is represented by individual values that are part of the social structure and that economic-financial relations are formed around these values. In this respect, it is possible to suggest that Islamic finance is a new conception of the system, which is faith-based and is part of the Islamic religion. This emphasizes that production, consumption, and distribution activities should be conducted in accordance with the Islamic ethos. Instead of a system positioned in opposition to existing practices, Asutay (2007) emphasizes that Islamic finance should foreground partnership-based banking models, microfinance, socially responsible investments, and similar practices such as social and ethical banking models that have already been experienced (El-Gamal, 2006, as cited in Asutay, 2007, p.16).

In addition, it would be beneficial to mention some critiques of Islamic finance. Rudnyckyj (2017) argues that researchers who accept Islamic finance as a moral project think of an alternative form of capitalism and see Islamic finance as a way to realize this alternative representation. A fundamental problem with Islamic finance is the extent to which it can offer a moral alternative to market capitalism or whether it essentially replicates the basic moral structures of the market. The morality of market actions is a recurring question for proponents and practitioners of Islamic finance. Tunç (2016) argues that integrating non-interest instruments into the conventional system is extremely shallow in nature and lacks utility. In this respect, Hazıroğlu (2016, 2018) argues that putting the word “Islamic” at the beginning of the concepts in the conventional finance system’s practices is simplistic and that concepts that can address the whole of humanity are needed to build a different system. In parallel, Hazıroğlu (2018) introduced the concepts of participation economics and participation finance into the literature.

1.2.5. Alternative Finance

Here, we refer to alternative financing methods as alternative finance. Technological developments are leading to the growth of alternative finance. Alternative finance covers crowdfunding, microfinance, peer-to-peer lending, venture capital, and angel investing, whose business models and practices are closely followed by the finance literature. Crowdfunding, which can be defined as the financing of a project or venture by many people through a specific platform, has become popular in recent years. As stated in Shneor's (2020) research, crowdfunding platforms have common features such as partnership, participation, donation, and transparency, which shows that they differ from conventional tools. Additionally, intermediary-free fund transfer transactions such as peer-to-peer (P2P) applications contribute to the *democratization of the finance* approach, as described by Shiller (2012). In addition, it is important that these practices become widespread in the development of new social contracts, as emphasized by Akgiray (2019). The microfinance method, which has different examples in practice, is a good solution to the problem of *financial exclusion* (Ganzo, 2014, p. 20). Microfinance projects, which are generally direct non-profit organizations, carry out activities that prioritize communal and social benefits on issues such as the fight against poverty and the economic and social development of low-income groups. Venture capitalists and angel investors are also important for the development and application of alternative financing and the sustainability of these models. Alternative models emphasize equity financing rather than debt financing. These models are also referred to as entrepreneurial finance (Drover et al., 2017).

1.3. The Implementation of Islamic Finance in Türkiye: Participation Finance System

The participation finance system may describe the Turkish implementation of thoughts and practices, defined as postmodern finance approaches. The participation finance model, which was formed based on the principles of Islamic finance, has a structure that integrates ethical, social, and responsible finance understandings. The basic principles and rules of the participation finance system, which is also called the humanitarian finance model (GPAS Istanbul, 2018), examining its convergence and

divergence from the conventional system, and its unique banking model are the main topics in the literature.

1.3.1. The Principles of Participation Finance System

The participation finance model, adopted as an alternative, despite its position in the traditional financial system, is the Turkish experience of the practice known in the literature as Islamic finance.

In the context of the basic principles of the model, markets and institutions operate within the framework of the idea of participation. The choice of the concept of *participation* takes the participation finance model beyond a faith-based perspective and universalizes the system. It is possible to list the characteristics (principles) of the participation finance system as follows (Habib, 2018, p. 3-4):

Faith-based Approach

In participation finance, the functioning of financial institutions and markets is based on faith-based regulations. The model refers to religious norms. This set of rules applies not only to the financing model, but also to the general economic, social, political, and cultural life of the society.

The Principle of Interest-Free

The participation-banking model takes part in the participation finance system and operates according to the interest-free principle. The practice of *riba*, which involves making money from money, is prohibited by religious decrees. Theoretically, participation banks are based on profit-loss sharing when accepting deposits and providing loans. Depositors receive a share of a bank's trading and investment profits. On the other hand, the bank makes payments with the yield it deserves from the projects it finances (Kuran, 2018, p. 1307). Losses may occur. This model is based on profit- and loss-sharing, which shares business risks.

Link to Real Assets

In a participation finance system, financial transactions occur through real assets. In other words, financial resources are directed toward the production of goods and

services and make a profit is made in this way. Theoretically, financial institutions deal with open and transparent transactions defined by real assets.

Collaboration and Profit-Loss Sharing

In accordance with articles on partnership, there is collaboration between the economic units that provide funds to the system and the institutions that use these funds. Based on this cooperation, the risks, profits, and losses arising from business activities are fairly shared.

Cautious Choices

The participation finance system encourages economic agents to be cautious when providing and using funds. Because it will ultimately be a cooperation or partnership, potential risks and losses are borne by all parties.

The Focus on Production and Investment

This system is sensitive to socially beneficial initiatives and projects. Owing to the negative consequences of money trade, such as increasing inequality and poverty, it is desirable to convert funds into production and investment.

Uncertainty and Prohibition of Speculation

In the participation finance system, making uncertain transactions (such as not knowing what to buy or sell), taking excessive risks, and speculative behaviors that cause social harm are ethically and morally criticized.

The participation finance system (or participation finance model) aims to conduct economic and financial transactions within the framework of the aforementioned principles, thus maximizing social welfare and minimizing social unrest. In the literature, the basic principles of this system are discussed primarily in the context of Islamic economics and finance. However, there are various arguments that this system is an alternative and complementary to the traditional structure.

The participation finance system, an original implementation of the Islamic finance model in Türkiye, consists of markets, institutions, and organizations. The four major components of the participation finance system are participation finance

institutions, participation capital markets, participation social finance, and participation insurance. On the side of financing institutions are participation banks and savings financing companies. Instruments based on the participation finance model, such as stocks, Islamic bonds (sukuk), investments, and pension funds, can be prioritized in terms of capital markets. Microfinance, karz-ı hasen (interest-free loans), and similar financial instruments can be referred to as the social financing tools of the system. Participation insurance (takafûl) is another component of the insurance sector.

1.3.2. Participation Banking

Participation banking is a significant component of a participation finance system. Although its practice in the world is known as Islamic banking, it is not adequate to describe this banking form in religious norms and terms only. Especially from the Turkish banking system point of view, this banking form seems worth examining. On the other hand, it appears that different banking models (such as ethical banking) around the world also developed in line with the participation banking approach. We argue that the business models and methods for these banking types' coincide with participation banking practices.

The financial system is based on the regulatory framework of different councils such as central banks, capital market boards, and securities exchanges. Although institutions in the participation finance system are obliged to comply with the same regulations, the most important point where the system differs from the conventional model is according to its own principles. In this respect, the participation banking business model is based on the principle of interest-free banking and ethical norms. Participation banks offer three main functions: fund collection, fund allocation and general banking services. Unlike conventional systems, these activities are conducted within the framework of their principles (Table 1.1).

Table 1.1: The Differences Between Participation and Conventional Banking

Aspect	Participation Banking	Conventional Banking
Business Model	The business model is based on profit-loss sharing arising from commercial activities. It is alternatively referred to as interest-free banking model.	The business model is based on intermediation of fund transfer among economic units with interest. This could also be called money trading.
Funding	Banks typically use a method called murabaha. This method involves the purchase of goods from the supplier and the sale of the goods to the customer by adding profit.	Banks provide personal and commercial loans, creating a debt-credit relationship.
Credit Policy	Banks funding mechanisms are based on specific principles and indicators of financial stability (solvency), such as credit scores. The main objective is to fund real economic activities.	Banks consider indicators of financial solvency for the provision of funds.
Regulations	Banks function under the framework of the banking law. In addition, the advisory board (shariah board) decides on the eligibility of banks' activities.	Banks operate purely in accordance with banking law.
Banking Services	Banks develop financial products and services comparable to conventional banks. Additionally, there is monitoring of the product and services development and launch process. Therefore, bank products and services are limited and less competitive.	Banks are highly competitive, market-oriented, and a develop products and services faster.

(Source: Created by author)

As Orhan (2018) states, the participation banking business model is based on profit-loss partnership projects. Although the supply of basic banking services and the provision of services similar to conventional banking are critical issues, the financing of real economic activities is considered to be a distinctive feature of this model. In addition, the conviction that a project will not be beneficial or may even be harmful to people, society, and the environment, could result in failure to provide financing for the relevant project. In this respect, it can be concluded that participation banks comply with an alternative approaches within the Turkish financial system.

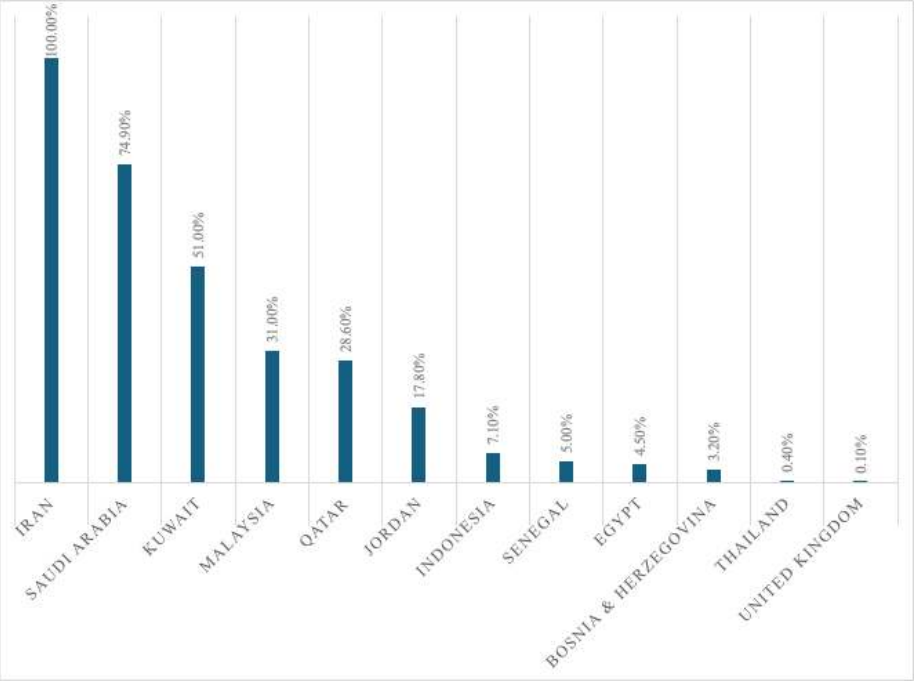
It is possible to associate participation banking with ethical banking, as defined in Paulet et al. (2015) and Vigano (2021). Indeed, there are certain connections and similarities between these two banking models. Considering that the general tendency is to compare participating banks with conventional banks, the extent to which alternative models converge to conventional models is debated. Another issue that must be evaluated is the link between alternative models. We argue that participation banking is compatible with the ethical banking model. Although the market share of these banks is still limited in terms of the size of funds under management by alternative banking models, their value proposition is quite remarkable and in line with the search for a different paradigm in finance.

Table 1.2: Sector Shares of Different Types of Banking

Shares	**Deposit (Conventional) Banking**	**Participation Banking**	**Development and Investment Banking**	**Total**
Total Assets in Sector	86.08%	8.10%	5.82%	100%
Collected Funds in Sector	90.71%	9.29%	0%	100%
Provided Funds in Sector	85.43%	7.30%	7.27%	100%

(Source: PBA)

According to Participation Banks Association (PBA) 2024 data, the total asset sector share of participation banks in Türkiye is approximately 8.10%; the sector share in funds collected is approximately 9.30% percent; and the sector share in provided funds is approximately 7.30% percent (Table 1.2). The participation banking sector is intended to be empowered through public and licensed digital banks. Graph 1.1 provides Islamic banking share in total banking assets for selected countries.



Graph 1.1: Islamic Banking Shares in Different Countries
(Source: IFSB, 2023)

The chart indicates the share of Islamic banks in different countries. The Gulf Cooperation Council (GCC), South-East Asia (SEA), and Middle East and South Asia (MESA) are the regions with the largest market share in Islamic banking (IFSB, 2023).

1.3.3. Participation Indices

The participation indices are the most important indices representing stock markets in the participation finance system. Similar to faith-based indices around the world, the Borsa Istanbul Participation Indices are based on the inclusion of listed companies in the index according to certain criteria. Borsa Istanbul calculate many indices following specific criteria. Table 1.3 shows participation indices.

Table 1.3: Participation Indices

Index Name	Index Code	First Value Date	First Value
Participation 100	XK100	10/01/2021	1,406.39
Participation 50	XK050	10/01/2021	1,406.39
Participation 30	XK030	10/01/2021	1,406.39
Participation Sustainability	XSRDK	10/01/2021	1,406.39
Participation Dividend	XKTMT	11/01/2022	3,951.33
Participation All Shares	XKTUM	10/01/2021	1,406.39

(Source: Borsa Istanbul)

Table 1.4 provides examples of fatih-based and ethical indices around the world.

Table 1.4: Examples of Faith-Based and Ethical Indices

Index Name	Index Code	Description
S&P 500 Catholic Values Index	SPXCVUP	The index eliminates companies engaged in activities that inconsistent with Catholic values.
STOXX Europe Christian Index	SXCHP	The index represents companies evaluated on their social, environmental, ethical, and economic criteria aligned with Christian values.
Jantzi Social Index	JSI	The index includes 50 Canadian companies that comply with set of ESG criteria.
Dow Jones Islamic Market World Index	DJIM	The index measures the performance of global equities that comply with Shari'ah investment principles.
FTSE4Good Index Series	FT4GDGLOB100	The index seeks to identify investable companies based on social responsibility and sustainability principles.

(Source: Created by author using index factsheets)

In parallel with global practices, participation indices are created by Borsa Istanbul following a set of faith-based and ethical rules. The steps are as follows:

- Stocks that are not traded in the BIST Stars Market, BIST Main Market or Sub-Market at the start of the index period are excluded. In other words the status of the market in which the companies are traded is taken into consideration.
- Companies are excluded if they are ethically questionable, negatively affect people and other living beings, have a negative impact on their mental and physical health, and are intensive in money trading and interest-bearing transactions.
- Shares with certain privileges, such as profit or liquidation rights or usufruct shares, are excluded. In addition, in the monitoring of financial ratios, companies' links to sectors rated as completely inappropriate in their interest-bearing assets and liabilities are limited to certain reference values to ensure compliance with the index (Borsa Istanbul, 2024).

The index construction method is in line with ethical, moral, and socially responsible investment approach in terms of participation finance system.

1.4. Conclusion

The integration of different disciplines, research projects and alternative approaches has changed modern finance thought and conventional financial systems. The issues evaluated in this study focus on the need to rethink modern and conventional financial systems. In addition, it is important to evaluate alternative approaches and practices in financial systems. In this context, we investigate postmodern finance approaches to seek a new paradigm in finance.

Even if the idea of radically changing a model or system is consistent and fascinating at its origin, alternative system proponents emphasize that this is not realistic. Serrats (2014) argued the following about the idea of radically changing a model or system: *"One of the greatest temptations for many is to radically change the model. Many unrealistic proposals propose to reform the model, separate real activity from financial activity, and submit all financial activities to play a minimal but essential role in our global society. I understand that it can be very tempting for many to take the situation to this point, but we must understand the importance of the financial services industry as the genuine architect of economic global development and undeniable global, leading actor."* The idea that finance and financial thinking need to be changed is discussed, including the

proposal for radical changes. In this respect, we think that alternative approaches should have two basic notions: *realism and feasibility*. In this way, it will be possible to integrate realistic (compatible with real-life practices) and feasible (possible to build on the system) approaches into the system.

Ethical, social, and responsible finance, good finance, humanitarian finance, Islamic finance, alternative finance, and participation finance system are considered to have powerful connections with each other and are compatible with the changing paradigm of finance. The aforementioned approaches, referred to as *postmodern* in this study, are symbiotically related. There are many remarkable studies on the ESG approach, ethical banking, impact investing, social finance, and green investment in the existing literature. Additionally, these topics are at the center of attention in the financial sector.

We think that the participation finance system and its components are unique and remarkable in the Turkish finance system. This system reflects the basic features of Islamic finance in terms of its principles and structures. However, when the structures within the system are analyzed, it is thought that the system can be considered a hybrid model (in terms of convergence to conventional systems). The legal status of the institutions and organizations within the system and the regulations to which they are subject constitute important evidence in this regard. For example, it is known that participation banks operate to function on the same legal status as other (conventional) banks based on local legislation. On the other hand, this system is based on the *principle of non-interest*, and advisory boards (Shariah boards) grant permission for the compatibility of financial transactions with the basic principles and set their own norms in terms of accounting and auditing standards in the system. Such evidence confirms the emphasis on hybrid features of the system.

A prominent factor in the evaluation of the participation finance system in terms of banking and capital markets is the set of ethical values. Based on these values, the aim is to conduct transactions that do not contradict the ethical and moral principles within the system itself in terms of providing funds and investments. The banking model specifies the areas of operations that are inappropriate for financing. On the capital market side, there are criteria for inclusion in the stock market indices. This shows that these practices

within the system are in line with approaches such as ethical banking, ethical investment, and socially responsible investment. Additionally, the compatibility of the participation finance system with Islamic finance principles suggests that the system has a unique and synthesized structure.

In addition to the banking model, the participation finance system includes various financing models, tools, and products. However, it is clear that the banking model has been widely analyzed in terms of the phases it has undergone in the historical process. The problems experienced by participation banks when they were defined as *private financial houses* have been frequently reported in the literature. The dominant perception of the role of banks in financial intermediation requires the integration of financial institutions within the participation finance system into the system as banks. Although this is historically important, it is an issue worthy of discussion. Examining the issue of trust in financial institutions, especially banks, in the context of the changing paradigm of finance can be explored as the subject of a different study. On the other hand, as Vigano (2021) states in his study, in terms of financial intermediation role, banks have the privilege of interacting directly with a broad and diverse customer base. This privilege imposes a responsibility on banks to conduct long-term relationships with their customer base based on the principles of trust, transparency, and ethical behavior.

In this study, we introduced research fields and practices that impact the paradigm to change as postmodern finance approaches, and analyzed their integration into the financial system. Additionally, a general review was conducted of the participation finance system, which has entered the literature as an alternative system for the necessity of rethinking finance, and the Turkish perspective of this approach. We think that the participation banking model, capital market (stock market and mutual funds), and other components within the participation finance system, which are institutionalized in line with the principles of Islamic finance, are compatible with ethical banking, ethical investment, socially responsible investments, and ESG components proposed by researchers, and have the characteristics of being a composite system.

ESSAY 2. PORTFOLIO CONSTRUCTION IN PARTICIPATION INDEX WITH POSTMODERN PORTFOLIO THEORY

2.1. Introduction

It is important for investors to manage the uncertainty and risks arising from market conditions. The common strategy is to minimize risk through diversification. Diversification is the main strategy for portfolio management and modern portfolio theory (MPT). Optimal allocation through diversification differs according to market conditions, investor preferences, and the risk-return trade-off. As a traditional approach, the mean-variance model is the core of the MPT for constructing optimal portfolios. In Harry Markowitz's (1970) fundamental approach, the foundation for modern finance, the measure of risk is variance, or standard deviation as it is commonly used. Portfolio risk depends on the correlation between the assets that compose the portfolio. Beta, the coefficient of systematic risk in the MPT, is accepted by investors as the sensitivity of a financial asset to market returns. The beta coefficient is included as a risk measure in the CAPM formula developed by William Sharpe and his contemporaries (Petzel, 2022, p. 48). The market premium for tolerating an asset's volatility relative to a benchmark, which is the return on a risk-free investment, is measured using CAPM (Chen, 2016, p. 9).

The standard deviation that the traditional risk measure of MPT represents volatility in the return series but does not reflect asymmetric risk. Nevertheless, the standard deviation is a powerful volatility measure for financial markets. In addition, the Sharpe ratio is still a useful indicator for portfolio management and includes standard deviation as a risk measure. On the other hand, downside risk measures, such as downside volatility and downside beta, are feasible for investors to capture negative returns. Estrada (2002, 2007) provides empirical evidence that downside risk metrics and the Downside Capital Asset Pricing Model (D-CAPM), as an alternative model, enable a more accurate representation of market pricing. Moreover, according to Estrada, the findings on downside risk measures are consistent with investors' loss aversion in behavioral finance literature. In another study, Yildiz and Erzurumlu (2018) proved the validity of downside risk metrics and D-CAPM in the Turkish stock market. The authors find that the PMPT is more acceptable than the MPT for explaining average stock returns in Borsa Istanbul.

To express the motivation for this research, a literature review is based on the PMPT is necessary and provided in the third title. In line with the findings of studies in the literature, the main function of this study is to construct portfolios using the PMPT framework and compare them with MPT portfolios, equally weighted portfolios, and the market index in terms of returns. In other words, this study aims to use the PMPT approach and tools for portfolio optimization. In this respect, Sortino, Sharpe, and Equally Weighted (EW) portfolios are created for 450 trading days (May 2022 to April 2024) and four periods using the Borsa Istanbul Participation 30s Index (XK030) daily stock returns.

The Borsa Istanbul Participation 30 Index is a thematic index (the Turkish Islamic Index), and stocks in the index are specified according to certain criteria and rules. The companies included in the index are reviewed in terms of the market segment, financial privileges in company shares against the interests of shareholders, and their fields of activity. Activities considered to have a negative impact on social benefits are excluded from the index, and further filters are carried out for companies with revenues, liabilities, and assets aligned with these fields. This is realized based on objective data from companies' financial statements. The expected percentage of revenues aligned with specified activities is 5 percent of the total revenues. Additionally, the ratio of interest-bearing assets and liabilities (debts) to average market value or total assets should not exceed 33 percent. Participation indices are composed of companies in accordance with a set of rules and criteria (Borsa Istanbul, 2024).

The first section introduces the PMPT framework and provides a theoretical background compared to the MPT. Furthermore, it addresses PMPT measures and tools. The literature review is followed by an explanation of the data used in the study and the applied optimization methods. The final section presents the findings and results.

2.2. Postmodern Portfolio Theory Framework

The fundamental measures of the MPT, which have mathematical foundations in Markowitz's mean-variance model, have certain limitations. One such limitation is the use of standard deviation as a risk measure based on the symmetricity of the return distribution. According to Rom and Ferguson (2001), an MPT's risk measure does not reflect an investor's perception of risk. In fact, they emphasize that investors do not accept

movements above the target return -known as upside volatility- as a risk. Rather, they consider that risk to be the possibility of positive returns (Riddles, 2001, p. 93). According to Harlow (1991), it is meaningful to use downside risk metrics because these indicators are consistent with investors' perceptions of risk. Founded in 1987 by Frank A. Sortino and introduced by Rom and Ferguson (1994) under the title "*Comes of Age*" the general framework of PMPT focuses on downside risk. As an asymmetric measure of risk, downside volatility is related to below-expected or target returns (Figure 2.1). In the PMPT, downside risk is divided into two components: the probability of loss and the magnitude of the probability (Chhatwani, 2019, p.3).

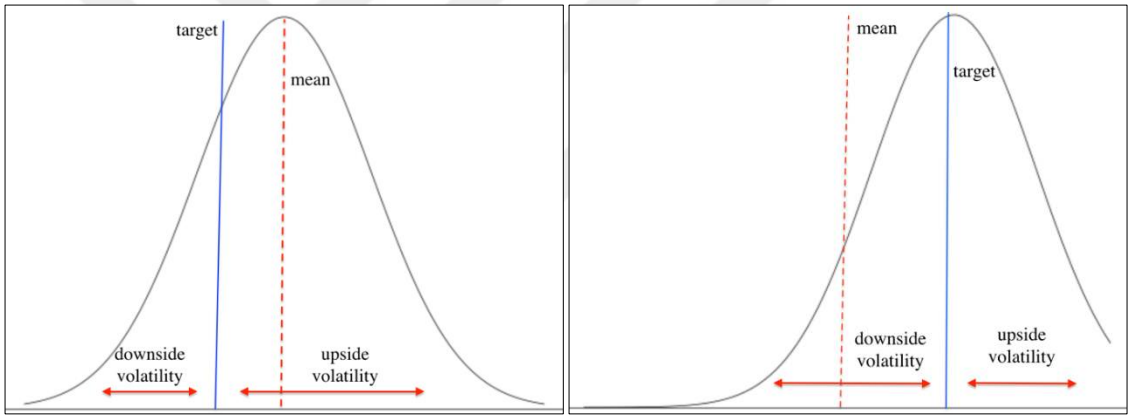


Figure 2.1a: Symmetric distribution

Figure 2.1b: Skewed distribution

Figure 2.1: Downside Volatility in Case of Symmetric and Skewed Distribution
(Source: Rigamonti, 2020)

The reason for using the standard deviation as a measure of risk in MPT is the assumption of a symmetric distribution. Under the assumption shown in Figure 2.1a, the risk is reduced by minimizing the deviations from the mean. However, in real life, return series are not symmetrically distributed, and risk cannot be measured fairly by minimizing the deviation (Figure 2.1b). In other words, if returns have a skewed distribution, minimizing the total risk is not equivalent to minimizing the downside risk. Moreover, investors may take a different position than the average return (Swisher & Kasten, 2005).

The PMPT's heuristic approach is suited to estimating the downside volatility that investors consider risky. In the following, the tools of the PMPT are explained.

2.2.1. Downside Risk and Sortino Ratio

The calculation of the downside deviation (σ_d) or standard deviation of negative returns is the most widely used method for determining the downside risk. Downside deviation is a percentage measure calculated by dividing the square root of the sum of squares of returns below the target by the number of periods. The formula is as follows:

$$\sigma_d = \sqrt{\frac{\sum_{i=1}^{n} (\min(0, r_i - r_t))^2}{n-1}} \tag{1}$$

where r_i denotes the return of stock and r_t denotes target return or minimum acceptable return (MAR). r_i can be computed using equation 7.

As shown in equations 2 and 3, unlike the traditional Sharpe ratio formulation, the Sortino ratio, which is calculated using PMPT's risk measure (σ_d), focuses on the difference between the portfolio return and the MAR (Sortino & Van der Meer, 1991; Sortino & Price, 1994).

$$sharpe = \frac{r_i - r_f}{\sigma} \tag{2}$$

where r_f denotes the risk-free rate and σ denotes standard deviation.

$$sortino = \frac{r_i - r_t}{\sigma_d} \tag{3}$$

Sharpe and Sortino ratios are used to compare portfolio performance in terms of the risk-return trade-off. However, as stated by Chen (2016), the downside deviation in the denominator of the Sortino ratio, which is the main risk measure of PMPT, is *"the natural starting point for pursuit of a single risk measure reflecting both volatility and skewness."*

2.2.2. Downside Beta and D-CAPM

Downside beta (β_d) is a downside measure of systematic risk. The downside beta, a coefficient that measures the sensitivity of stocks to the market when the market shows

a downside trend, differs from traditional beta. The standard beta is mathematically calculated as the covariance between stock returns and market returns divided by the variance of market returns. Beta is the slope coefficient of the regression equation (slope of the regression line). There are different approaches in the literature regarding the calculation of downside beta. In this study, the formula given by Charoenwong and Ng (2013), based on the approach of Bawa and Linderberg (1977), was preferred. In equation 4, the numerator represents the covariance of stock returns and negative returns of market portfolio. The denominator shows the square of the negative returns of the market portfolios. It measures the co-movement of stock and market returns during market downturns.

$$\beta_d = \frac{\mathrm{E}[(r_i - r_f)\min(r_m - r_f, 0)]}{\mathrm{E}[\min(r_m - r_f, 0)]^2} \tag{4}$$

where r_m denotes market return.

In the conventional CAPM, beta is a measure of systematic risk. In terms of the PMPT, the use of downside beta in the conventional CAPM formula transforms to a special form called D-CAPM (Equation 5). The notation r_m-r_f on the right side of the equation shows excess return and r_f shows the risk-free rate.

$$\mathrm{E}(r_i) = r_f + \beta_d(r_m - r_f) \tag{5}$$

Empirical evidence of the superiority of the D-CAPM over the CAPM does not imply invalidity of the traditional form. It is stated that the implementation of the PMPT and the existence of an alternative model, D-CAPM, is necessary. It is known that asset returns do not follow a normal distribution and return series are often skewed (Abbas et al., 2011, p. 194).

2.2.3. Volatility Skewness

In PMPT, volatility skewness ratio (s_v) is obtained by dividing the upside variance of the distribution of the return series by the downside variance (Equation 6). The upside and downside variance were calculated based on the arithmetic mean (r_i).

$$s_v = \frac{\frac{1}{n-1}\sum_{i=1}^{n}\max(0, r_i - t)^2}{\frac{1}{n-1}\sum_{i=1}^{n}\min(0, r_i - t)^2} \quad (6)$$

where t donates the target return.

The ratio of 1.00 indicates a symmetric distribution, values greater than 1.00 indicate positive skewness, and values less than 1.00 indicate negative skewness. Rom and Ferguson (2001) stated in their study, *"one might expect that bull markets produce positive skewness and bear markets negative skewness."*

Table 2.1: Volatility Skewness Ratios

Index	Upside variance	Downside variance	Skewness ratio
XU100	0.000195156	0.000215292	0.90647
XK030	0.000200175	0.000214790	0.93196

We evaluated the volatility skewness ratios for the Borsa Istanbul 100 Index (XU100) and the Borsa Istanbul Participation 30 Index (XK030) over 500 trading days. The indices were negatively skewed (Table 2.1), meaning that the downside volatility of the series is higher than the upside volatility.

2.3. Literature Review

We evaluate relevant literature in two groups. The first group includes empirical research testing the PMPT in different markets. These studies examined the ability of PMPT measures to explain stock returns.

Artavanis et al. (2010) tested the explanatory power of PMPT risk measures such as semi-deviation and downside beta on mean returns in the London Stock Exchange (LSE) and Paris Stock Exchange (Euronext Paris). Researchers who estimated cross-sectional linear sample regression and cross-sectional bivariate regression for two periods obtained different results in the stock markets they examined. According to the findings, downside risk measures are found to be more effective for stocks. In contrast, there is no difference between downside beta and conventional beta for portfolios.

In their study on emerging markets, Mamoghli and Daboussi (2010) found that a capital asset pricing model in the downside framework better explains asset valuation. In addition, the authors proposed new performance measures based on downside risk. Tahir et al. (2013) reported that the D-CAPM is a convenient model explaining risk-return trade-off in an empirical analysis for the Karachi Stock Exchange (KSE).

El-Masry and El-Mosallamy (2016) analyzed the performance of 21 mutual funds in Saudi Arabia and emphasized that the D-CAPM is a more applicable measure for emerging markets than conventional CAPM. In addition, the authors revealed that Islamic mutual funds outperformed conventional funds and market portfolio. Similar findings are obtained by Rasool et al. (2018) for Bangladesh, India, Pakistan and Sri Lanka. While the results of Raza's (2018) study were not consistent with the others, the author states that both conventional CAPM and D-CAPM can be used in asset valuation in volatile and emerging markets where returns are not normally distributed.

Yildiz and Erzurumlu (2018) tested the explanatory power of downside risk metrics for stock returns in Borsa Istanbul with local and global one-factor models using panel data analysis. The results show that D-CAPM provides more explanatory power than the traditional CAPM in Borsa Istanbul. In other words, authors reported that downside risk metrics are considerable for emerging markets. Venkataraman (2021) examined the D-CAPM in Nifty 50 and S&P BSE Sensex. The results show that no evidence disproves D-CAPM validity. In general, the results of the studies show applicable PMPT measures for investing and risk management in different markets.

In the second group, we examine studies on portfolio selection, asset allocation, and optimization based on the downside risk metrics and PMPT.

Geambaşu et al. (2013) using the data from 40 companies in the Bucharest Stock Exchange, emphasize that PMPT increases the investor's ability to manage risk under different market conditions. It is stated that the risk measurement of MPT based on mean return is inefficient, especially during financial crisis periods. Garcia et al. (2019) proposed a portfolio selection model that enables investors to simultaneously evaluate average stock returns, downside risk, and ESG criteria. The researchers used the Sortino ratio to determine the optimal portfolio. As a result of the application based on the

proposed model, it was observed that those designated *socially responsible portfolios* outperformed the benchmark. Jankova (2019) analyzed the risk-return results of two portfolios based on MPT and PMPT in an application for the Prague Stock Exchange. The author concluded that portfolios constructed with the PMPT provide lower risk and more diversification. Bayat and Yiğiter (2022) constructed a portfolio in Borsa Istanbul 100 Index using MPT and downside metrics. The findings indicated that the alternative portfolio has a reduced risk compared to the MPT portfolio.

We can present different studies based on PMPT tools in the second group. Huang (2008) used the mean-semivariance model for fuzzy simulation based on a genetic algorithm. In a study introducing PMPT models such as tracking error minimization, mean absolute deviation minimization, and shortfall probability models, Galloppo (2010) reported that the resampling method in PMPT models improved portfolio performance. Todoni (2015) proposed a new method called multipliers method and applied it in the emerging markets such as Romania, Hungary, Czech Republic, Bulgaria, and Poland. Todoni (2015) used the Sortino ratio and the multiplier method to analyze the risk-adjusted return performance of the markets. Nassar and Ephrem (2020) concluded that asset allocation based on Sortino ratio is highly efficient in different market conditions. May and Yeing (2022) developed stock selection strategy based on Sortino. They found that the performance of these portfolios outperforms others.

In general, the performance of PMPT models is better than that of MPT in emerging markets. Additionally, researchers have focused on finding evidence in emerging markets. In this respect, we believe this study contributes to the relevant literature. Our opinion is that the application of the PMPT to the Borsa Istanbul Participation Index will be important in terms of empirical literature.

2.4. Data and Methodology

This study used daily stock return data, calculated using closing prices from the period of November 15, 2021, to March 1, 2024. Closing price data were collected from Refinitiv Eikon Datastream. Daily returns were calculated using equation 7. The research sample consisted of 52 companies on the Borsa Istanbul Participation 30 Index (XK030). Four periods were included in the research considering the index review periods (See

Table A.1). The stock weights in the portfolio for each period were calculated based on the previous review period. For example, the weights from the October 2022 to April 2023 index period were calculated using return data from May 2022 to September 2022. In other words, the previous period was considered *ex-ante*. This calculation was based on Sharpe ratio optimization in accordance with the MPT approach and Sortino ratio optimization in accordance with the PMPT. Then, the daily portfolio returns for the period were calculated using the weights. This relevant period is considered *ex-post*. Following this method, daily portfolio returns were calculated for 450 trading days between May 6, 2022, and March 1, 2024.

$$r_i = \frac{p_t}{p_{t-1}} - 1 \tag{7}$$

where p_t denotes closing price at time t.

In summary, we optimized the Sharpe and Sortino portfolios. In addition, we included the EW (equally weighted) portfolio and XK030 returns as a benchmark index in the analysis for comparison. All computations were conducted using MS Excel and MS Excel Solver.

2.4.1. Sharpe Ratio Optimization

We conducted Sharpe ratio optimization by following a calculation method in accordance with the MPT. We used the weights calculated as a result of Sharpe ratio optimization using ex-ante data to construct a portfolio in the ex-post period. The objective function and constraints of the model are as follows.

$$maximize \left(\frac{\mathrm{E}(r_p) - r_f}{\sigma_p} \right) \tag{8}$$

$$r_p = \sum_{i=1}^{n} \mathrm{E}(r_i) w_i \tag{9}$$

$$subject\ to \sum_{i=1}^{n} w_i = 1 \tag{10}$$

$$0.001 \leq w_i \leq 0.1, \forall i \tag{11}$$

In Sharpe ratio optimization, expected returns $E(r_i)$ were calculated based on the standard CAPM formula. w denotes stock weight in portfolio. Türkiye 2-year bond yield (TR2YT=XX) was used as the risk-free rate. Constraints were added to the optimization model to follow the weighting methodology appropriate for the index and prevent concentration.

2.4.2. Sortino Ratio Optimization

We conducted Sortino ratio optimization by following a calculation method in accordance with the PMPT tools. In the ex-post period we built a portfolio using the weights determined through Sortino ratio optimization with ex-ante data. The objective function and constraints of the model are as follows.

$$maximize \left(\frac{E(r_p) - r_t}{\sigma_{p_d}} \right) \tag{12}$$

$$r_p = \sum_{i=1}^{n} E(r_i) w_i \tag{13}$$

$$subject\ to \sum_{i=1}^{n} w_i = 1 \tag{14}$$

$$0.001 \leq w_i \leq 0.1, \forall i \tag{15}$$

In the Sortino ratio optimization, the expected returns $E(r_i)$ were computed using D-CAPM (Equation 5). σ_{pd} denotes as downside deviation of portfolio. The target return was 1% over Türkiye 2-year bond yield (TR2YT=XX). To simulate index weighting, constraints were added to the model, as in the Sharpe ratio optimization.

2.4.3. Portfolio Construction

Portfolio returns for 450 trading days were calculated using the weights obtained after the Sharpe and Sortino optimization process steps. In addition, the daily returns of equally weighted portfolios (EW) and daily returns of the Participation 30 Index (XK030) were calculated. The stock weights in the Sharpe and Sortino portfolios were updated for each period.

$$r_p = \sum_{i=1}^{n} r_i w_i \tag{16}$$

The actual return of the portfolios was calculated by multiplying the daily realized return of each stock (r_i) by its weight (w_i) in the portfolio (Equation 16). Next, the return graphs of Sharpe, Sortino, Equal-Weighted Portfolio, and Benchmark Index (XK030) were created and compared based on the calculated daily portfolio returns.

$$HI = \sum_{i=1}^{n} w_i^2 \tag{17}$$

$$NHI = \frac{HI - 1/n}{1 - 1/n} \tag{18}$$

where n denotes number of stocks.

Normalized Herfindahl Index (NHI) is a coefficient that measures the concentration within portfolio and is a normalized form of the HI index. It ranged from 0 to 1. A coefficient close to 0 indicates a fair distribution, whereas a value close to 1 implies a high concentration. n denotes the number of periods (Busse et al., 2006, p. 6).

2.5. Findings and Results

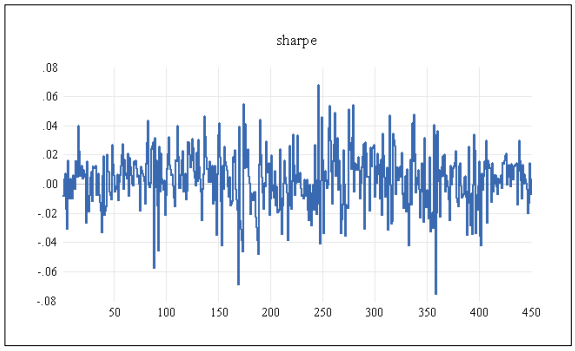
The stock weights and concentration coefficients of the Sharpe and Sortino portfolios are given in Table 2.2 according to the outputs of the optimization models solved under the specified objective function and constraints.

Using the weights, daily portfolio returns were calculated daily for 101 portfolio returns for the period 05/06/2022 to 09/30/2022, 138 portfolio returns for the period 10/04/2022 to 04/28/2023, 103 portfolio returns for the period 05/03/2023 to 09/29/2023, and 108 portfolio returns for the period 10/03/2023 to 03/01/2024. Equally weighted portfolio returns were calculated for specified data ranges. Sharpe, Sortino, and EW return series were created for 450 trading days. The Borsa Istanbul Participation 30 Index (XK030) 450-day returns were used as benchmarks. Below we provide the analyses, graphs, and estimates of the research findings. We provide 450-day return graphs for the four portfolios in Graph 2.1.

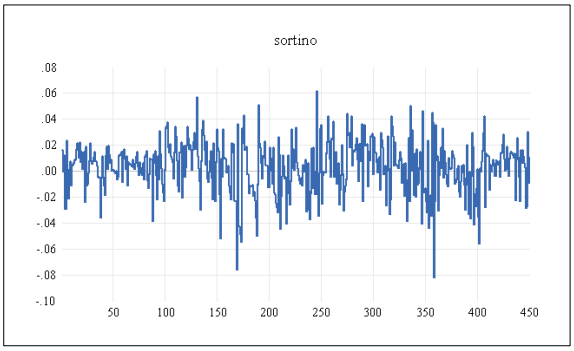
Table 2.2: Stock Weights in Portfolios

	Period I (Estimation Data Range: 11/16/2021 – 04/29/2022)		Period II (Estimation Data Range: 04/05/2022 – 09/30/2022)		Period III (Estimation Data Range: 11/01/2022 – 04/28/2023)		Period IV (Estimation Data Range: 05/03/2023 – 09/29/2023)	
Stocks	**Sharpe**	**Sortino**	**Sharpe**	**Sortino**	**Sharpe**	**Sortino**	**Sharpe**	**Sortino**
1	4.44%	10.0%	4.48%	7.06%	0.10%	10.0%	2.13%	0.10%
2	1.50%	10.0%	3.50%	10.0%	3.96%	10.0%	0.77%	0.10%
3	1.07%	6.64%	0.10%	0.10%	1.16%	0.10%	0.10%	10.0%
4	10.0%	0.10%	9.83%	3.23%	1.98%	10.0%	0.10%	10.0%
5	0.81%	0.10%	1.33%	0.10%	5.78%	10.0%	7.63%	0.10%
6	2.13%	10.0%	1.84%	10.0%	0.61%	10.0%	10.0%	10.0%
7	8.58%	0.10%	10.0%	0.10%	1.81%	0.10%	0.26%	0.10%
8	0.84%	0.10%	0.10%	8.40%	9.17%	10.0%	2.35%	0.10%
9	7.02%	4.73%	2.62%	10.0%	4.04%	0.10%	2.56%	2.96%
10	0.10%	10.0%	1.27%	2.39%	2.14%	0.35%	6.22%	0.10%
11	1.35%	10.0%	10.0%	0.10%	0.10%	0.10%	2.87%	0.10%
12	9.90%	0.10%	1.49%	0.10%	0.10%	2.27%	4.48%	9.84%
13	0.52%	10.0%	4.66%	3.30%	10.0%	0.10%	2.39%	0.10%
14	0.10%	7.80%	1.87%	0.10%	0.10%	0.10%	1.00%	9.94%
15	6.75%	0.15%	2.01%	3.92%	4.23%	9.46%	3.38%	0.10%
16	1.18%	10.0%	4.98%	0.10%	2.96%	0.10%	0.49%	0.10%
17	2.03%	0.10%	2.26%	10.0%	2.89%	0.10%	2.81%	10.0%
18	1.32%	7.57%	1.57%	0.10%	2.29%	1.78%	0.32%	0.10%
19	8.38%	1.06%	1.00%	0.10%	3.12%	0.10%	3.05%	0.10%
20	2.34%	0.10%	0.10%	10.0%	4.13%	0.10%	4.75%	3.43%
21	4.88%	0.10%	2.53%	5.16%	3.06%	0.10%	7.06%	4.01%
22	0.10%	0.46%	0.77%	5.50%	5.41%	0.10%	0.47%	9.06%
23	0.10%	0.10%	5.74%	0.10%	9.59%	0.10%	8.14%	0.10%
24	8.53%	0.10%	10.0%	0.10%	0.10%	0.10%	1.61%	2.80%
25	10.0%	0.10%	0.10%	0.10%	0.10%	6.20%	2.29%	0.10%
26	2.89%	0.10%	0.10%	0.15%	1.47%	0.10%	0.33%	0.10%
27	0.20%	0.10%	10.0%	0.32%	8.96%	1.74%	10.0%	3.15%
28	1.72%	0.10%	3.72%	0.10%	9.25%	6.61%	10.0%	10.0%
29	1.11%	0.10%	0.67%	0.10%	1.29%	10.0%	1.46%	0.10%
30	0.10%	0.10%	1.37%	9.18%	0.10%	0.10%	0.97%	3.21%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
NHI*	0.037	0.057	0.034	0.049	0.031	0.057	0.030	0.053

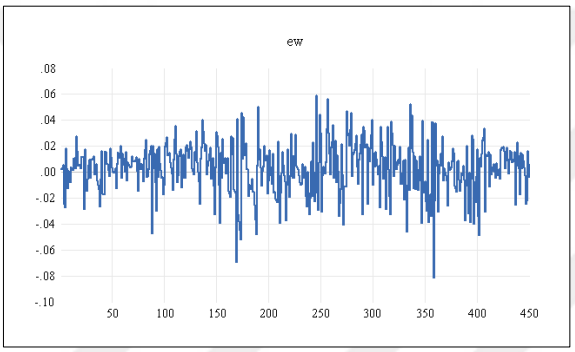
*Normalized Herfindahl Index



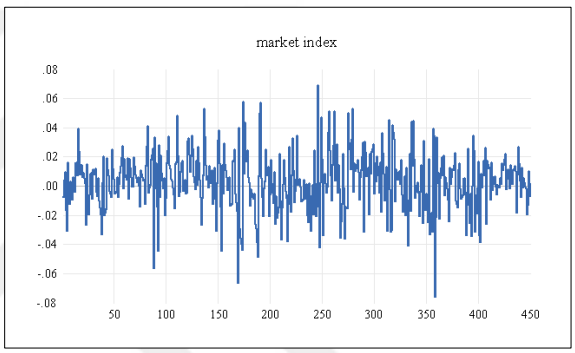
Graph 2.1a: Sharpe



Graph 2.1b: Sortino



Graph 2.1c: EW



Graph 2.1d: Market Index

Graph 2.1: Distribution Graphs of Portfolio Returns

Table 2.3 provides descriptive statistics of the 450-day portfolio returns.

Table 2.3: Descriptive Statistics of Portfolio Returns

	Sharpe	Sortino	EW	Market Index
Mean	0.003028	0.002969	0.002860	0.003040
Median	0.004519	0.005036	0.004267	0.004109
Max	0.067744	0.061911	0.058943	0.069182
Min	-0.075513	-0.081938	-0.081326	-0.076167
Std. Dev.	0.019897	0.020442	0.019693	0.020150
Skewness	-0.214489	-0.485867	-0.427928	-0.134271
Kurtosis	3.883362	3.902202	3.985350	3.877079
Jarque-Bera	18.08156	32.96689	31.93883	15.77590
Prob.	0.000118	0.000000	0.000000	0.000000
Observation	450	450	450	450

When the statistical features of the return series were analyzed, it was observed that the series did not follow a normal distribution. The distribution was skewed to the left. The market index had the highest mean value, and EW had the lowest mean value.

When the standard deviation values of the series were examined, the portfolio with the lowest value was the EW portfolio and the portfolio with the highest value was the Sortino portfolio. The correlation coefficients of the return series are presented in Table 2.4.

Table 2.4: Correlation Matrix of Portfolios

	Sharpe	**Sortino**	**EW**	**Market Index**
Sharpe	1.000	0.885	0.958	0.988
Sortino	0.885	1.000	0.944	0.887
EW	0.958	0.944	1.000	0.952
Market Index	0.988	0.887	0.952	1.000

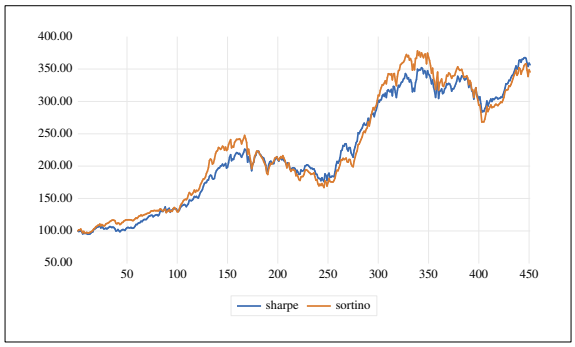
According to the correlation coefficients, there is a high correlation (0.99) between the Sharpe portfolio and market index returns and a relatively lower correlation (0.89) between the Sortino and Sharpe portfolios and between Sortino and the benchmark index. It can be stated that the Sharpe portfolio follows the market index. In other words, the Sharpe portfolio returns converge to the benchmark index. For a more detailed analysis, we provide a compound return graph for the portfolios in Graph 2.2.

Graph 2.2 shows the return trends for the four portfolios, starting with an investment simulation of 100 units (left axis) over 450 trading days. According to the graph, Sortino diverged significantly from the benchmark index and others in a positive (upward) direction in certain periods. This divergence is particularly evident in the 28-81, 131-172, 301-353, and 358-378 trading day intervals. In Graph 2.3 we present comparative performance of the portfolios.

Graph 2.2: Compound Return of Portfolios (450-day)

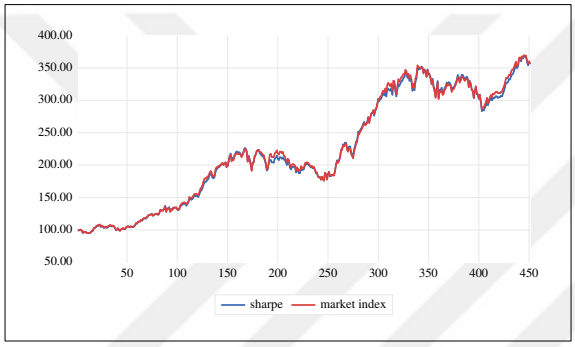
A review of graphs 2.3a and 2.3b demonstrates that the Sortino portfolio follows the Sharpe and market index in short periods when the market index is in an upward trend and then diverges positively for an average of 50 trading days. In relevant periods, the Sortino portfolio repeated a similar tendency in different ranges. The Sortino portfolio moves with the market portfolio for short periods, while markets exhibit a downward trend but then diverge in a negative direction from the market. During the downward market period, Sortino underperforms the market index.

Although Graph 2.3c shows that the Sharpe portfolio diverges positively (upward) and negatively (downward) from the market index in some periods, the two portfolios are close in terms of return performance. In other words, the Sharpe portfolio follows the market index by excluding exceptional circumstances. On the other hand, the graphs indicate that the EW portfolio underperforms the Sharpe, Sortino, and market portfolios.

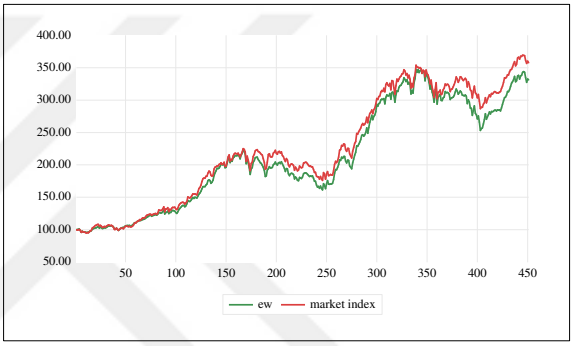


Graph 2.3a: Sharpe vs. Sortino

Graph 2.3b: Sortino vs. Market Index



Graph 2.3c: Sharpe vs. Market Index



Graph 2.3d: EW vs. Market Index

Graph 2.3: Comparative Graphs of Portfolios

In the examined period, the highest returns reached by portfolios were as follows: 367.76 units for the Sharpe portfolio on the 445th trading day, 378.10 units for the Sortino portfolio on the 338th trading day, 347.37 units for EW on the 338th trading day, 369.44 units for the market index on the 444th trading day. The Sortino portfolio reached its highest return on the 338th trading day, surpassing the Sharpe returns of 349.80 units, and the market return of 353.99 units on the same day. During this period, the Sortino portfolio achieved the maximum return (378.10). In other words, Sortino outperformed the market index in a specific range of time. The Sortino portfolio's total return exceeded the market index by 0.36%.

2.6. Conclusion

In this study, the Sharpe and Sortino portfolios were constructed in the Borsa Istanbul Participation 30 Index using MPT and PMPT measures. For this purpose, the Sharpe and Sortino ratios were calculated and optimized under the specified constraints. To construct a portfolio, we considered four index periods. In the calculation of stock weights, we used the GRG Nonlinear method based on maximizing Sharpe and Sortino ratios (See Table A.2). The period preceding the index period was considered ex-ante, and an ex-post analysis was conducted during the index period. After the weight calculation, the Sharpe and Sortino portfolios were constructed, and portfolio returns were obtained in the ex-post periods. In addition, we created an EW portfolio and used XK030 as a benchmark. As a result, we compute the returns of the four portfolios covering 450 trading days and four periods. The following comments were made regarding the findings and results:

- During the sample period, the Sortino portfolio outperformed the benchmark index when the market had an upward trend. In other words, the Sortino portfolio achieved higher returns in the bullish market regime while underperforming the market index in the bearish period (See Graph 2.3b).
- The Sharpe portfolio consistently follows the market index (See Graph 2.3c). This convergence could be adopted as an alternative strategy by investors to avoid losses during a market downturn.
- We observe that portfolios constructed by equally weighting each stock underperform the market index and other portfolios (See Graph 2.2 and 2.3). In this respect, it can be stated that dynamic portfolio management is important for investors.
- As shown in Table 2.2, the concentration in the Sortino portfolios is higher than that in Sharpe portfolios. It is possible to state that Sharpe portfolios are better diversified than Sortino. The concentration of stocks in the Sortino portfolio indicates the overweighting of specific stocks, which can have an impact on the overall performance of the portfolio.

- PMPT measures, such as downside risk, downside beta, D-CAPM, and the Sortino ratio, can be used as portfolio construction and weighting strategies. Additionally, this study proves that outperforming market returns can be obtained using alternative approaches.
- Investors can take positions according to different market conditions using an active investment strategy based on alternative strategies. However, the market timing and other analytical skills of investors are important.
- This study provides evidence that the PMPT approach to portfolio management is feasible and can be used in combination with other strategies. In future studies, researchers could work on different indices. In addition, they could compare the findings and results with those of our study.

ESSAY 3. VOLATILITY FORECASTING IN PARTICIPATION AND CONVENTIONAL INDICES

3.1. Introduction

Volatility refers to unexpected or inexpressible fluctuations in financial asset prices. Typically, in financial markets, volatility concerned with the spread of asset returns (Poon, 2005; Kayalidere, 2013). Volatility is a measure by which financial market participants are closely monitored. As input, it plays an important role in investment decisions and portfolio management. In this respect, volatility modeling is an attractive area of study for researchers. The main motivation for study in this area is to estimate and forecast volatility. Although many volatility forecasting models exist, GARCH family models are widely used because of their advantages. According to empirical findings, GARCH models that successfully capture dynamic changes in a series can model unexpected shocks to the series, accurately reflect the asymmetry and leverage effect in volatility, and have high forecasting capabilities (Pilbeam & Langeland, 2015). For this study, we used the GARCH, TGARCH, EGARCH, APARCH, and EGARCH-M models to estimate and forecast index volatility.

In this study, we model and forecast the volatility of the Borsa Istanbul Participation 30 (XK030), Borsa Istanbul Participation 50 (XK050), Borsa Istanbul 30 (XU030), and Borsa Istanbul 100 (XU100) indices using GARCH models. XK030 and XK050 are participation indices calculated by Borsa Istanbul and formed according to specific rules. These indices are called "*Islamic Index*" generally, and they serve as an alternative for financial markets and are of interest to different segments in the Turkish finance system. XU030 and XU100 are conventional indices, and XU100 is called *"market index."*

The main motivation of this research was to estimate volatility in related indices using GARCH-family models and to examine the volatility forecasting performance of these models. The secondary objective was examining the volatility features (characteristics) of the indices according to the estimated parameters. This study is important in two respects. First, it contributes to the expansion of literature on participation indices, particularly the participation finance system. Second, the realized

volatility is calculated using 5-minute data so that it is consistent with the measure of accurate volatility defined in the literature.

3.2. Literature Review

There are several empirical studies in the literature on modeling and forecasting volatility in financial time series. As Kashyap (2023) states, researchers commonly use GARCH models for volatility estimation and forecasting. In addition, they compared the forecasting performances of the models using statistical error measures. There are studies such as those by Kuen and Hoong (1992) and Yu (2002) using MA, EWMA to forecasting the volatility of financial time series, however, GARCH-type models have become preferred for volatility modelling. Researchers have reported their estimation and forecasting results obtained from GARCH models with different parameters and hybrid models trained with neural networks. Examples of these studies include Bildirici and Ersin (2009), Ou and Wang (2010), Hajizadeh et al. (2011), Kristjanpoller and Minutolo (2015), and Katsiampa (2017). More recently, machine learning-based models have been using volatility forecasting. Examples of such include Rahimikia and Poon (2020), Christensen et al. (2023), and Zhang (2024s). Here, we examine the findings and results of several studies including GARCH family models which we consider important for our study in this section.

Abdalla and Winker (2012) conducted parameter estimation using GARCH-type models and analyzed the volatility of the index series in the Sudan (KSE) and Egypt (CASE) stock markets. Using the daily price data of the indices, the researchers examined the main features, such as volatility persistence, asymmetric effect, and risk-return trade-off. A similar study was conducted by Sharma and Vipul (2015) on 21 indices, which contrary to common findings, concluded that the standard GARCH model produces better forecasting results than asymmetric models. Bora and Adhikary (2021) reported that the EGARCH model was optimal for forecasting the asymmetric effect in their study on the Indian Stock Market (NSE). The same results were observed in the study by Naik and Padhi (2014). Nilsson (2017) compared the EWMA and GARCH models and reported that the best model for volatility estimates is APARCH on the Swedish Stock Market.

In a recent study, Petkov et al. (2024) estimated SOFIX volatility between 2000 and 2024 using five different GARCH models in modeling. It has been reported that the optimal estimate results are obtained from the ARMA (1,1)-CGARCH (1,1) model with the *Student's t* distribution. Khan et al. (2023) analyzed the period from 2016-2021 in three distinct periods: pre-pandemic, post-pandemic, and all periods. The researchers used GARCH models to estimated the volatility of selected financial instruments and reported that EGARCH was the optimal model for volatility estimates in the pre-pandemic period. Ahmed et al. (2016) estimated volatilities of Islamic and conventional indices selected from Karachi Stock Exchange (KSE) and Dow Jones indices. The results showed that the APARCH model outperformed conventional indices, while the EGARCH and standard GARCH model better estimated volatility in Islamic indices.

We consider it important to review the results of empirical studies that use intraday data. Liu et al. (2021) reported that high-frequency data were more useful in volatility modeling and improved out-of-sample forecasting performance. Chai et al. (2023) proposed a semiparametric volatility model and emphasized that forecast accuracy can be enhanced with high-frequency data. Herrera et al. (2018) used RiskMetrics and GARCH models to estimate and forecast the volatility of crude oil return series. The researchers tested the out-of-sample forecasting performance of the models using performance metrics, such as MSE and QLIKE, for short, medium, and long periods. The results of the study showed that the EGARCH model produced successful predictions for the medium term, and the *Student's t* distribution was optimal. In a similar study, Hattori (2020) applied GARCH models to a Bitcoin return series. The researcher estimated the parameters using daily return data and calculated realized volatility using intraday 5-minute return data. The results of Hattori's study emphasize the superiority of the EGARCH and APARCH models for volatility forecasting.

Other remarkable studies in literature that employ intraday data include those by Hansen and Lunde (2011), Kayalidere (2013), Phan et al. (2016), and Frömmel and Kadioglu (2023). The consensus in the literature is that volatility estimates and forecasts are more accurate with intraday data. Lyocsa et al. (2021) provide empirical evidence to the contrary, arguing that volatility forecasting with high-frequency data outperforms in

short periods. This study aligns with the relevant literature and uses daily and intraday returns data.

3.3. GARCH Models

Volatility is related to variance fluctuation rather than returns. Therefore, nonlinear time series models are preferred for estimation of the volatility of financial assets. The most widely used models are GARCH-type models. In this regard, we use GARCH (Bollerslev, 1986), TGARCH (Zakoian, 1994), EGARCH (Nelson, 1991), APARCH (Ding et al., 1993), and EGARCH-M (Engle et al., 1987)[2] models in this study. The general specification for the conditional variance equations is as follows (Bolgün & Akçay, 2009; Poon, 2005):

$$\text{GARCH (1,1):}\quad \sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{19}$$

The variance estimated in the GARCH model is defined as the conditional variance and is denoted by σ_t^2. ω is the constant term. α (reaction parameter) indicates the effect of unexpected change in return on volatility, β (continuous parameter) indicates how the change in the previous volatility affects the volatility in the following period. $\alpha + \beta$ denotes the persistence of volatility.

$$\text{TGARCH (1,1):}\quad \sigma_t^2 = \omega + \alpha u_{t-1}^2 + \gamma N_{t-1} u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{20}$$

TGARCH is an asymmetric model. According to the model's specification, positive and negative shocks are assumed to have different effects on volatility. If $u_{t-1}^2 < 0$, N_{t-1} is equal to 1. If $u_{t-1}^2 \geq 0$, N_{t-1} is equal to 0. $\gamma > 0$ indicates that negative shocks increase volatility more than positive shocks. ω, α, and β denote the constant term, ARCH and GARCH parameter, respectively.

$$\text{EGARCH (1,1):}\ \log\left(\sigma_t^2\right) = \omega + \beta \log\left(\sigma_{t-1}^2\right) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{21}$$

[2] Here, we cited GARCH-M model as a reference. We integrated the conditional standard deviation of returns as an independent variable to the mean equation.

The EGARCH model uses the logarithm of the variance. ω, α, and β denote the constant term, ARCH and GARCH parameter, respectively. $y \neq 0$ indicates that positive and negative shocks have different effects on volatility. If y is negative, negative shocks increase volatility more than positive shocks.

$$\text{APARCH (1,1): } \sigma_t^{\delta} = \omega + \alpha(|u_{t-1}| - \gamma u_{t-1})^{\delta} + \beta\sigma_{t-1}^{\delta} \tag{22}$$

In addition to the classical GARCH model, this model includes the asymmetry parameter (y) and power parameter (δ). The power parameter makes it possible to model different volatility levels. ω, α, and β denote the constant term, ARCH and GARCH parameter, respectively. If $y > 0$, negative shocks (bad news) increase volatility more than positive shocks (good news).

3.4. Data, Methodology and Findings

Volatility estimation and forecasting were conducted using GARCH family models for the four indices in Borsa Istanbul (BIST). The XK030, XK050, XU030, and XU100 indices were included in the scope of this research. The 809-day logarithmic returns of the indices on January 4, 2021, and March 29, 2024, were used to estimate the model parameters. Logarithmic returns were calculated from the closing price data (Equation 23). For the forecasting period, returns were calculated from intraday 5-minute price data from April 1, 2024, to June 28, 2024. There were 5577 intraday observations. The square of intraday returns is used as a measure of volatility, which is consistent with Andersen and Bollerslev (1988). (Equation 24). After the calculation, a 57-day realized volatility (σ_t^2) series was obtained. Thus, the forecasting ability of the models for realized volatility is analyzed using regression analysis (Equation 25). All data were collected from the Refinitiv Eikon DataStream. The analyses and computations were conducted using EViews 12 Student Lite edition and MS Excel.

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{23}$$

where p_t denotes as closing price at the time t. ln indicates logarithm function.

$$\sigma_t^2 = \sum_{i=1}^{n} r_i^2 \tag{24}$$

where r denotes as intraday returns.

$$\sigma_t^2 = \vartheta + \tau\hat{\sigma}_t^2 + \varepsilon_t \quad (25)$$

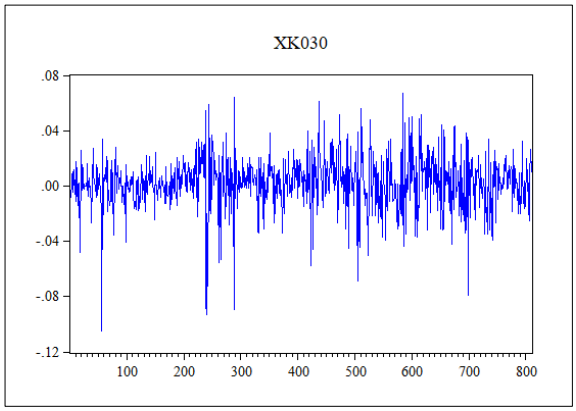
where σ_t^2 denotes as realized volatility series. $\hat{\sigma}_t^2$ indicates forecasting series.

The descriptive statistics of the indices for the estimation period are presented in Table 3.1. First, the stationarity test (ADF) was applied to logarithmic returns (Table 3.2). To ensure the adequacy and reliability of the volatility forecasting models, suitable autoregressive (AR) and moving average (MA) mean equations are determined (Table 3.3). The autocorrelation and ARCH effects in the residuals of the mean equation were tested for different lag levels. Accordingly, autoregressive conditional variance modeling was performed using the GARCH family of models. In this study, GARCH, TGARCH, EGARCH, APARCH, and EGARCH-M models were estimated for volatility forecasting.

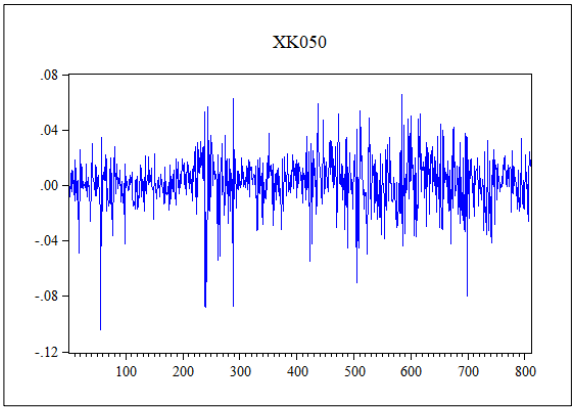
Table 3.1: Descriptive Statistics

Estimation Period (01/04/2021 – 03/29/2024)				
	XK030	**XK050**	**XU030**	**XU100**
Mean	0.002194	0.002180	0.002222	0.002254
Median	0.003048	0.002931	0.002164	0.002761
Maximum	0.066894	0.065889	0.080433	0.075718
Minimum	-0.104589	-0.104294	-0.104760	-0.103068
Std. Dev.	0.019284	0.018932	0.019705	0.018767
Skewness	-0.705099	-0.735594	-0.609272	-0.780083
Kurtosis	6.681969	6.718602	6.630241	6.963847
Jarque-Bera	524.0148	539.0769	494.2822	611.6782
Prob.	0.0000	0.0000	0.0000	0.0000
Observation	809	809	809	809

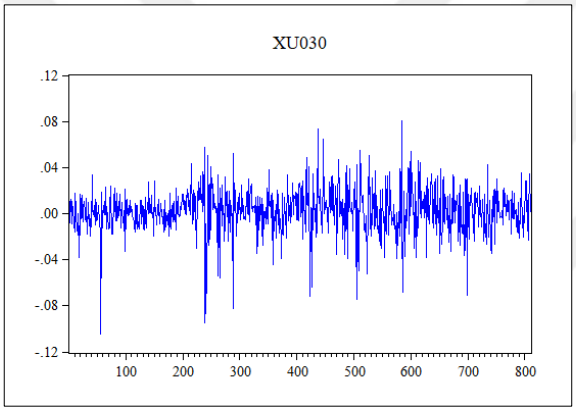
According to the statistical features of the return series of the indices, the mean returns in the estimation period are positive. Additionally, the return series exhibits a left-skewed distribution and does not follow a normal distribution, as expected. The return distributions of the indices are shown in Graph 3.1.



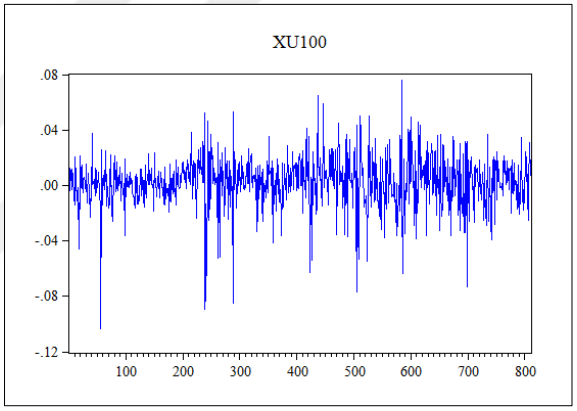
Graph 3.1a: XK030



Graph 3.1b: XK050



Graph 3.1c: XU030



Graph 3.1d: XU100

Graph 3.1: Return Distribution of Indices (809-day)

It can be observed in the ADF unit root test results in Table 3.2, that the index return series provides the stationarity requirement for modeling volatility. Test findings show that return series are stationary and do not include a unit root.

Table 3.2: Unit Root Test Results

Augmented Dickey-Fuller (ADF)		
Index	**t-Statistic**	**Prob.**
XK030	-27.98382	0.0000*
XK050	-28.09791	0.0000*
XU030	-28.93461	0.0000*
XU100	-28.74098	0.0000*
Note: Test critical values are -3.438218 for 1%; -2.864902 for 5%; and -2.568615 for 10%.		
*Probability values indicate the rejection of the null hypothesis at the 1% significance level.		

The logarithmic returns of the four indices were tested up to two lags, and the mean equation including suitable AR and MA terms was selected according to the Log Likelihood, Akaike Information Criteria (AIC), and R-squared (Table 3.3). The mean equation of the indices was determined as ARMA (1,1).

Table 3.3: Statistics of Mean Equation

Index	ARMA(p,q)*	AIC Value	Log Likelihood	R-Squared
XK030	ARMA(1,1)	-5.052169	2047.602	Positive
XK050	ARMA(1,1)	-5.089444	2062.680	Positive
XU030	ARMA(1,1)	-5.011765	2031.259	Positive
XU100	ARMA(1,1)	-5.108758	2070.493	Positive

*The coefficients of mean equation are statistically significant.

The autocorrelation problem in the variance of the residuals in the mean equation, in other words, autoregressive conditional heteroskedasticity, was examined using the ARCH-LM test for three, five, and ten lags. The results are shown in Table 3.4. An ARCH effect in the residuals of the mean equation selected for the indices was observed; therefore, ARCH-type modeling could be conducted.

Table 3.4: Examination of ARCH Effect in Mean Equations

	XK030	XK050	XU030	XU100
Number of Lags: 3				
F-statistic	19.93141	19.18010	13.62166	13.00045
Prob. F(3,802)	0.0000*	0.0000*	0.0000*	0.0000*
Number of Lags: 5				
F-statistic	12.06419	11.60662	8.256661	7.805079
Prob. F(5,798)	0.0000*	0.0000*	0.0000*	0.0000*
Number of Lags: 10				
F-statistic	6.060143	5.827750	4.635464	4.103966
Prob. F(10,788)	0.0000*	0.0000*	0.0000*	0.0000*

* Probability values indicate the rejection of the null hypothesis at the 1% significance level.

Table 3.5 shows the parameter estimates of GARCH-type models for XK030. The Log Likelihood and AIC values indicate, it is seen that the optimal model was EGARCH-M. The GARCH(1,1) model parameter estimates are statistically significant. The sum of

α and β parameters is less than 1.00, indicating that volatility is predictable (0.84003). Approximately 54% of the change in volatility may cause conditional variance of the series in the previous period, while approximately 30% may cause past volatility shocks or unexpected returns. The long-run mean variance is 0.04% and volatility is 2.10%. The half-life volatility in the series was calculated as 3.97 days (See Table 3.13).

The TGARCH(1,1) model parameter estimates are at the 1% significance level, except for α parameter. In addition, γ indicates that there is an asymmetric effect. The coefficient is both positive and statistically significant. Negative and positive shocks had different effects on volatility. In other words, negative shocks have a greater impact on volatility than positive shocks. It is observed that negative shocks elicited a reaction on volatility up to the sum of α and γ (0.4991).

The EGARCH(1,1) model parameter coefficients are statistically significant. The asymmetry term (γ) is negative, indicating that volatility is more affected by negative shocks (reactions up to α-γ). According to negative γ parameter, it can be stated that there is leverage effect for XK030. The results are consistent with the TGARCH model.

The APARCH(1,1) parameter coefficients are statistically significant except for the parameter ω. The asymmetry term (γ) is positive and consistent with other asymmetric model estimates. The power parameter reflects the power of asymmetric effect in the model (δ=0.789775).

In the EGARCH-M(1,1) model, we examined the rationality of the risk-return trade-off for XK030. The conditional standard deviation of the return is defined as an independent variable in the conditional mean equation. The estimates reveal that the coefficient is positive and significant at the 5% level. This indicates the rationality of the risk-return trade-off.

Table 3.5: Parameter Estimates of GARCH Models for XK030

Models	ω	α	β	γ	δ	LL	AIC
GARCH(1,1)	7.07E-05 (0.0007)	0.300540 (0.0001)	0.539497 (0.0000)	-	-	2135.920	-5.269604
TGARCH(1,1)	5.71E-05 (0.0002)	0.098565 (0.0570)	0.599101 (0.0000)	0.400539 (0.0025)	-	2149.494	-5.300727
EGARCH(1,1)	-1.279423 (0.0001)	0.291892 (0.0000)	0.868132 (0.0000)	-0.191344 (0.0000)	-	2152.363	-5.307829
APARCH (1,1)	0.005009 (0.3382)	0.176945 (0.0000)	0.760953 (0.0000)	0.742679 (0.0000)	0.789775 (0.0014)	2155.098	-5.312125
EGARCH-M (1,1)*	-1.348436 (0.0000)	0.298781 (0.0000)	0.859783 (0.0000)	-0.171122 (0.0001)	-	2155.545	-5.313231

* Coefficient estimate of $\sqrt{\sigma^2_n}$ term in mean equation: 0.451298 (Prob. 0.0161)

Note: Estimation results are given by testing the student's t distribution for TGARCH, EGARCH, APARCH and EGARCH-M. GARCH model estimates are based on the GED distribution.

The ARCH-LM (Lagrange Multiplier) test results are presented in Table 3.6. According to test results, the models eliminated the heteroskedasticity problem in residuals. The lag lengths were determined as three, five, and ten.

Table 3.6: ARCH-LM Test Results of GARCH Models for XK030

	GARCH(1,1)	**TGARCH(1,1)**	**EGARCH(1,1)**	**APARCH(1,1)**	**EGARCH-M(1,1)**
Number of Lags: 3					
F-statistic	0.226736	0.312942	0.835540	1.262706	0.195268
Prob. F(3,801)	0.8778*	0.8160*	0.4745*	0.2860*	0.8996*
Number of Lags: 5					
F-statistic	0.202857	0.271195	0.531053	0.786359	0.141321
Prob. F(5,797)	0.9613*	0.9289*	0.7529*	0.5596*	0.9825*
Number of Lags: 10					
F-statistic	0.393174	0.381809	0.444961	0.558837	0.285505
Prob. F(10,787)	0.9499*	0.9548*	0.9242*	0.8479*	0.9844*

* Probability values indicate the not rejection of the null hypothesis.

Table 3.7 shows the parameter estimates of the GARCH-type models for XK050. Regarding the Log Likelihood and AIC values, the optimal model was APARCH. The GARCH(1,1) model parameter estimates are statistically significant. The sum of α and β parameters is less than 1.00, implying that volatility is predictable (0.891889). It is observed that approximately 56% of the change in volatility can be explained by the previous period's conditional variance of series, while approximately 34% can be

explained by past volatility shocks or unexpected returns. The long-run mean variance is 0.06% and the volatility is 2.38%. The half-life volatility in the series was calculated as 6.05 days (see Table 3.13).

The TGARCH(1,1) model parameter estimates are statistically significant at 1% level, except for the α parameter. Furthermore, γ indicates the presence of asymmetric effect. Negative and positive shocks have distinct effects on volatility. Negative shocks have a greater impact on volatility than positive shocks. Negative shocks caused a reaction in volatility equal to the sum of α and γ (0.5187).

The EGARCH(1,1) model parameter coefficients are statistically significant. The asymmetry term (γ) is negative, this meaning that volatility was more affected by negative shocks (reaction up to α-γ). Furthermore, we observe the existence of leverage effect for XK050 according to negative γ parameter. The results were consistent with the TGARCH model.

The APARCH(1,1) parameter coefficients are statistically significant, except for parameter ω. The asymmetry term (γ) is positive, and consistent with other asymmetric model estimates. The power parameter reflects power of asymmetric effect in the model (δ=0.634017). In addition, the leverage effect was strong in XK050 according to APARCH parameter estimates (γ=0.813426).

In the EGARCH-M(1,1) model, the rationality of the risk-return trade-off for XK050 was examined. The estimates reveal that the coefficient is positive and significant at the 5% level. This indicates the rationality of the risk-return trade-off.

Table 3.7: Parameter Estimates of GARCH Models for XK050

Models	ω	α	β	γ	δ	LL	AIC
GARCH(1,1)	6.10E-05 (0.0006)	0.335382 (0.0001)	0.556507 (0.0000)	-	-	2159.537	-5.328061
TGARCH(1,1)	5.43E-05 (0.0001)	0.098686 (0.0623)	0.594542 (0.0000)	0.420111 (0.0020)	-	2167.516	-5.345336
EGARCH(1,1)	-1.261914 (0.0001)	0.288581 (0.0000)	0.870960 (0.0000)	-0.196399 (0.0000)	-	2170.767	-5.353385
APARCH (1,1)	0.008469 (0.2930)	0.163405 (0.0000)	0.781632 (0.0000)	0.813426 (0.0000)	0.634017 (0.0041)	2175.118	-5.361678
EGARCH-M (1,1)*	-1.345008 (0.0000)	0.294598 (0.0000)	0.860975 (0.0001)	-0.177469 (0.0001)		2173.945	-5.358775

* Coefficient estimate of $\sqrt{\sigma^2_n}$ term in mean equation: 0.443111 (Prob. 0.0195)

Note: Estimation results are given by testing the student's t distribution for all models.

Table 3.8 shows the ARCH-LM (Lagrange Multiplier) test results. According to statistics, the models eliminated the heteroskedasticity problem in the residuals. The lag lengths were determined as three, five, and ten.

Table 3.8: ARCH-LM Test Results of GARCH Models for XK050

	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	APARCH(1,1)	EGARCH-M(1,1)
Number of Lags: 3					
F-statistic	0.216174	0.378412	0.800651	1.315613	0.169370
Prob. F(3,801)	0.6421*	0.7686*	0.4937*	0.2681*	0.9171*
Number of Lags: 5					
F-statistic	0.271204	0.315031	0.516689	0.803919	0.122139
Prob. F(5,797)	0.9289*	0.9041*	0.7638*	0.5470*	0.9875*
Number of Lags: 10					
F-statistic	0.442369	0.392375	0.442828	0.558972	0.269921
Prob. F(10,787)	0.9257*	0.9503*	0.9254*	0.8478*	0.9875*

* Probability values indicate the not rejection of the null hypothesis.

Table 3.9 shows the parameter estimates of GARCH models for XU030. Regarding the Log Likelihood and AIC values, the optimal model was APARCH. In the GARCH(1,1) model, α and β parameter estimates were significant at the 1% level. The sum of α and β parameters is less than 1.00, indicating that volatility is predictable (0.969292). The persistence of volatility is higher than that of other indices. It is observed that approximately 90% of the change in volatility could be explained by the previous period's conditional variance of series, while approximately 7% could be explained by

past volatility shocks or unexpected returns. The long-run mean variance is 0.04% and the volatility is 2.04%. The half-life volatility in the series was calculated as 22.2 days (See Table 3.13).

In the TGARCH(1,1) model, γ indicates the presence of an asymmetric effect (γ > 0.). This evidence is supported by EGARCH model results. The EGARCH(1,1) model parameter coefficients are statistically significant. Negative shocks caused a reaction in volatility up to α-γ (0.407056). Furthermore, γ is negative, this means that volatility is more affected by negative shocks. There is a leverage effect in XU030.

APARCH(1,1) parameter coefficients are statistically significant except for parameter ω. The asymmetry term (γ) is positive and consistent with EGARCH model estimates. The power parameter (δ) is higher than other indices, reflecting power of asymmetric effect in the model (δ=0.842251).

In the EGARCH-M(1,1) model, the rationality of the risk-return trade-off for XU030 was examined. The conditional standard deviation of the return is defined as an independent variable in the conditional mean equation. The estimates show that the coefficient was positive, but not statistically significant. This implies that the risk-return trade-off is theoretically rational.

Table 3.9: Parameter Estimates of GARCH Models for XU030

Models	ω	α	β	γ	δ	LL	AIC
GARCH(1,1)	1.28E-05 (0.0222)	0.069974 (0.0007)	0.899318 (0.0000)	-	-	2103.871	-5.190276
TGARCH(1,1)	6.30E-05 (0.0026)	0.085492 (0.0310)	0.659162 (0.0000)	0.218404 (0.0171)	-	2107.405	-5.196546
EGARCH(1,1)	-1.360030 (0.0018)	0.288215 (0.0000)	0.855610 (0.0000)	-0.118841 (0.0024)	-	2109.353	-5.201370
APARCH (1,1)	0.004828 (0.4402)	0.165957 (0.0000)	0.746112 (0.0000)	0.474423 (0.0004)	0.842251 (0.0063)	2110.410	-5.201510
EGARCH-M (1,1)*	-1.415896 (0.0011)	0.304794 (0.0000)	0.851032 (0.0000)	-0.075010 (0.0235)	-	2103.392	-5.184139

* Coefficient estimate of $\sqrt{\sigma^2_n}$ term in mean equation: 0.199447 (Prob. 0.1757)

Note: Estimation results are given by testing the student's t distribution for GARCH, TGARCH, EGARCH, APARCH. EGARCH-M model estimates are based on the GED distribution.

The ARCH-LM (Lagrange Multiplier) test results are presented in Table 3.10. According to test results, the models eliminate the heteroskedasticity problem in residuals. The lag lengths were determined as three, five, and ten.

Table 3.10: ARCH-LM Test Results of GARCH Models for XU030

	GARCH(1,1)	**TGARCH(1,1)**	**EGARCH(1,1)**	**APARCH(1,1)**	**EGARCH-M(1,1)**
Number of Lags: 3					
F-statistic	0.420367	0.166244	0.487666	1.005045	0.113053
Prob. F(3,801)	0.7384*	0.9191*	0.6909*	0.3899*	0.9525*
Number of Lags: 5					
F-statistic	0.312168	0.106104	0.303832	0.630168	0.089559
Prob. F(5,797)	0.9058*	0.9909*	0.9107*	0.6768*	0.9939*
Number of Lags: 10					
F-statistic	0.391616	0.394668	0.419056	0.571546	0.392632
Prob. F(10,787)	0.9506*	0.9493*	0.9378*	0.8379*	0.9502*

* Probability values indicate the not rejection of the null hypothesis.

Table 3.11 shows the parameter estimates of GARCH models for XU100. Regarding the Log Likelihood and AIC values, the optimal model is APARCH. The GARCH(1,1) model parameter estimates were statistically significant. The sum of α and β parameters is less than 1.00, indicating that volatility is predictable (0.871929). It can be stated that approximately 68% of the change in volatility may cause conditional variance of the series in the previous period, while approximately 19% may cause past volatility shocks or unexpected returns. The long-run mean variance is 0.04% and the volatility is 2.03%. The half-life volatility in the series was calculated as 5.05 days (see Table 3.13).

The TGARCH(1,1) model parameter estimates are 1% significance level except for α parameter. There is an asymmetric effect in XU100 ($\gamma > 0$). Negative shocks have a greater impact on volatility than positive shocks. The EGARCH(1,1) model parameter coefficients are statistically significant. A negative asymmetry term (γ) indicates that there is a leverage effect in the XU100. The results are consistent with the TGARCH model.

APARCH(1,1) parameter coefficients are statistically significant except for parameter ω. The asymmetry term (γ) is positive, and consistent with other asymmetric model estimates. The power parameter reflects power of asymmetric effect in the model (δ=0.733301).

In the EGARCH-M(1,1) model, the rationality of the risk-return trade-off for XU030 was examined. The conditional standard deviation of the return is defined as an independent variable in the conditional mean equation. The estimates show that the coefficient is positive, but not statistically significant. This implies that the risk-return trade-off is theoretically rational.

Table 3.11: Parameter Estimates of GARCH Models for XU100

Models	ω	α	β	γ	δ	LL	AIC
GARCH(1,1)	5.27E-05 (0.0067)	0.194739 (0.0008)	0.677190 (0.0000)	-	-	2152.243	-5.310008
TGARCH(1,1)	6.72E-05 (0.0003)	0.046701 (0.2634)	0.609046 (0.0000)	0.403013 (0.0038)	-	2164.396	-5.337615
EGARCH(1,1)	-1.662255 (0.0007)	0.302957 (0.0001)	0.820777 (0.0000)	-0.142719 (0.0014)	-	2159.400	-5.325249
APARCH (1,1)	0.006350 (0.3067)	0.146184 (0.0000)	0.788055 (0.0000)	0.951958 (0.0000)	0.733301 (0.0012)	2174.029	-5.358982
EGARCH-M (1,1)*	-1.786857 (0.0002)	0.299216 (0.0003)	0.806561 (0.0000)	-0.150754 (0.0003)	-	2160.491	-5.325473

* Coefficient estimate of $\sqrt{\sigma^2_n}$ term in mean equation: 0.324308 (Prob. 0.0981)

Note: Estimation results are given by testing the student's t distribution for GARCH, TGARCH, EGARCH, APARCH. EGARCH-M model estimates are based on the GED distribution.

Table 3.12 shows the ARCH-LM (Lagrange Multiplier) test results. Accordingly, the models eliminate the heteroskedasticity problem in the residuals. The lag lengths were determined as three, five, and ten. Additionally, Ljung-box test statistics are presented Table A.3 (See Appendices).

Table 3.12: ARCH-LM Test Results of GARCH Models for XU100

	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	APARCH(1,1)	EGARCH-M(1,1)
Number of Lags: 3					
F-statistic	0.099473	0.104594	0.297271	1.134312	0.089564
Prob. F(3,801)	0.9603*	0.9574*	0.8274*	0.3343*	0.9658*
Number of Lags: 5					
F-statistic	0.158402	0.130747	0.200257	0.719240	0.091484
Prob. F(5,794)	0.9775*	0.9854*	0.9624*	0.6091*	0.9936*
Number of Lags: 10					
F-statistic	0.388630	0.274732	0.269640	0.483511	0.239014
Prob. F(10,784)	0.9519*	0.9866*	0.9875*	0.9013*	0.9923*

* Indicates the not rejection of the null hypotheses.

3.5. Results

Table 3.13 shows the volatility estimation results for the indices. The results indicate that the persistence effect in volatility is highest in XU030 and lowest in XK030. The half-life volatility is 22.2 days for XU030, which is quite high compared with the other indices. On the other hand, it is remarkable that the long-term average volatility of the index is 2.04%. An asymmetric effect was observed for all indices. In other words, negative market conditions (i.e., negative information or news) have a greater impact on volatility. Asymmetric models are optimal volatility estimation models for all the indices. The risk-return tradeoff is statistically significant in the participation indices, and the risk-reward relationship is rational. On the contrary, the risk-reward relationship in conventional indices is rational but statistically insignificant.

Table 3.13: Summary Details of GARCH Models Based on Indices

	$\alpha + \beta$	HV	Avg. volatility (%)	Optimal Model*	Asymmetric Effect	Risk-Return Trade-off
XK030	0.840030	3.97	2.10	EGARCH-M	✓	✓
XK050	0.891889	6.05	2.38	APARCH	✓	✓
XU030	0.969292	22.2	2.04	APARCH	✓	✓t
XU100	0.871929	5.05	2.03	APARCH	✓	✓t

*Based on Log Likelihood and AIC values.

(t) The coefficient is statistically insignificant, it is theoretically acceptable.

The forecasting performance of GARCH models depends on their accuracy of predicting realized volatility (See Graph A.1). The R^2 values of the regression equations in which the estimated variance series are analyzed as explanatory variables and the realized volatility as the dependent variable are given in Table 3.14. High R^2 coefficients indicate the success of the models in accurately forecasting the realized volatility.

Table 3.14: R-Squared Coefficients of Volatility Forecasting

Indices	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	APARCH(1,1)	EGARCH-M(1,1)
XK030	0.0009	0.0776	**0.1795**	0.1573	0.1149
XK050	0.0007	0.0445	**0.1164**	0.1053	0.0690
XU030	0.0000	0.0741	**0.1052**	0.0779	0.0680
XU100	0.0053	0.0981	**0.1302**	0.1001	0.1025

Note: These values are the estimates obtained from 20 regression solution.

According to Table 3.14, it can be stated that the most successful model for volatility forecasting is EGARCH. The R^2 coefficient indicates that the APARCH and EGARCH-M models are appropriate for forecasting. In addition, XK030 volatility is more predictable than the other indices.

3.6. Conclusion

In this study, we conducted volatility modeling and examined the forecasting performance of GARCH family models. We analyzed the parameter estimation results and examined the forecasting performance of the models using regression equations. These results are consistent with Hattori's (2020) findings. In addition, the findings of our study support the best model selection of Hajizadeh et al. (2012). According to the results of our research, we emphasize that asymmetric models, especially EGARCH, are still relevant for volatility forecasting. In addition, the results reveal that participation and conventional indices have a different volatility structure and Participation 30 Index is more predictable than other indices.

GENERAL CONCLUSION

The integration of different disciplines, research projects, ideas, and alternative approaches into the existing system has changed the structure of conventional finance. The dominant perspective in finance focuses only on profit and shareholder value. Recent studies have changed their focus from the mainstream perspective of the current regime and have adopted a multidimensional approach to finance.

The first essay explored alternative approaches and practices that are changing the direction of finance. This section assesses the multidimensional structure of the emerging finance paradigm, which refers to ethics, sustainability, and social responsibility under the title of ethical, social, and responsible finance. Here, the umbrella concept of postmodern finance thought is preferred, and under this title, the concepts and practices of good finance, humanitarian finance, Islamic finance, alternative finance, and the participation finance system are introduced. When the principles and fundamental components of the participation finance system are analyzed, it becomes apparent that the perspective provided by current approaches that have changed the direction of finance aligns with the principles of participation finance. It has been observed that the key concepts used by alternative approaches that have changed the paradigm of finance are ethics and morality, sustainability, governance performance, socially responsible investment, the humane dimension of finance, fair and transparent social contracts, democratization of finance, and innovative financial services and technologies.

Participation indices and ethical investment funds (participation funds), capital market instruments of the participation finance system, reveal the ethics-embedded nature of finance. In particular, it can be stated that participation indices represent a rather powerful alternative in Borsa Istanbul (Istanbul Stock Exchange) where conventional indices are dominant. Participation indices follow a monitoring methodology that includes a set of certain rules and does not include their portfolio companies whose activities are not consistent with the set of rules. The index criteria are largely based on the principle of interest-free. The second essay provides a return performance analysis of portfolios constructed using optimization techniques. Portfolios consist of stocks in Borsa Istanbul Participation 30 Index, with the stocks in the portfolio having been revised according to

monitoring periods. To calculate the stock weights, Sharpe ratio optimization, consistent with Modern Portfolio Theory and Sortino ratio optimization, in line with Postmodern Portfolio Theory, are used. These findings were encouraging. It was observed that the portfolios constructed using the companies in the participation index, which is a thematic index, can be preferred as an alternative investment strategy according to market conditions.

Considering the basic principles of the participation finance system and the purpose of calculating participation indices, it is expected that movements of the indices in the market will be more stable and predictable. It is known that the underperformance of conventional indices, especially during crisis periods, has increased the popularity of Islamic indices. Asutay et al. (2022) provide empirical evidence for this. In this respect, it is important to reveal the volatility characteristics of participation and conventional indices. In this context, the third essay presents volatility modeling and forecasting for four indices: two participation and two conventional indices. Using GARCH family models, model parameters are estimated, and the volatility structures of the indices are analyzed. In addition, the ability of the models to explain realized volatility in the out-of-sample period is examined according to the estimated R^2 coefficients. The results reveal important findings in favor of the Participation 30 Index in terms of volatility estimation and forecasting. Moreover, the risk-return trade-off in participation indices is statistically significant and rational. The results also demonstrate the strength of the EGARCH model.

This thesis investigates the participation finance system in terms of conceptual and stock market applications,and provides empirical evidence from stock markets. Future studies could analyze different components or instruments of the system in greater depth or improve the applications of this study.

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Appendices

Table A.1: Stocks in Participation 30 Index

Index Period I (May-September 2022)	Index Period II (October 2022-April 2023)	Index Period III (May -September 2023)	Index Period IV (October 2023-April 2024)*
AKSA	AKSA	AHGAZ	AKSA
AKSEN	AKSEN	AKSA	AKSEN
ARDYZ	ALBRK	AKSEN	ALBRK
ASELS	ASELS	ALBRK	ASGYO
BASGZ	BASGZ	ASELS	ASELS
BERA	BERA	ASTOR	BIMAS
BIMAS	BIMAS	BERA	CWENE
BIOEN	CIMSA	BIMAS	DOAS
CCOLA	DOAS	CIMSA	ENJSA
DOAS	EGEEN	DOAS	EREGL
EGEEN	EREGL	EGEEN	GESAN
EREGL	GOZDE	ENJSA	GUBRF
GENIL	GUBRF	EREGL	ISMDR
GOZDE	ISDMR	GESAN	KLSER
GUBRF	JANTS	GUBRF	KRDMD
ISDMR	KRDMD	ISDMR	KARSN
JANTS	KONTR	KRDMD	KONTR
KORDS	KORDS	KONTR	MAVI
KRDMD	MAVI	KORDS	ODAS
OTKAR	ODAS	ODAS	OYAKC
PGSUS	OTKAR	OYAKC	PGSUS
PRKAB	OYAKC	PGSUS	PENTA
PSGYO	PGSUS	SASA	SASA
SASA	SASA	SNGYO	SMRTG
THYAO	SNGYO	SMRTG	TKFEN
TKFEN	TUPRS	TKFEN	TUKAS
TRGYO	THYAO	TUPRS	TUPRS
TRILC	TTRAK	THYAO	THYAO
TTRAK	VESBE	TTRAK	VESTL
VESBE	YYLGD	VESBE	YEOTK

*Portfolio returns were calculated until 03/01/2024.

Table A.2: Computation Results of Optimization Parameters

Period	CAPM	D-CAPM	σ	σ_d	R_f	R_t	Sharpe	Sortino
1	0.34%	0.33%	2.40%	1.54%	0.0805%	0.0813%	0.11	0.16
2	0.27%	0.28%	1.54%	0.85%	0.0683%	0.0690%	0.13	0.25
3	0.12%	0.13%	2.15%	1.34%	0.0377%	0.0396%	0.04	0.07
4	0.63%	0.70%	2.29%	1.07%	0.0580%	0.0586%	0.25	0.60

*CAPM and D-CAPM represent expected returns.

**σ is the standard deviation of daily portfolio returns in ex-ante period, σ_d is the downside deviation of daily portfolio returns from the target return in ex-ante period.

***R_f is the daily risk-free rate, R_t is a daily target return.

Table A.3: Ljung-Box Test Statistics

	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	APARCH(1,1)	EGARCH-M(1,1)
XK030					
Number of Lags: 3					
Q-stat	0.6590	0.3849	0.5236	1.5376	2.2224
Prob.	0.417*	0.535*	0.469*	0.215*	0.136*
Number of Lags: 5					
Q-stat	2.6225	1.9775	1.4661	2.2402	2.7242
Prob.	0.454*	0.577*	0.690*	0.524*	0.436*
Number of Lags: 10					
Q-stat	4.2292	5.2935	5.4183	6.9815	8.6312
Prob.	0.836*	0.726*	0.712*	0.539*	0.374*
XK050					
Number of Lags: 3					
Q-stat	0.4104	0.3455	0.6407	2.1142	2.8633
Prob.	0.522*	0.557*	0.423*	0.146*	0.091*
Number of Lags: 5					
Q-stat	1.5006	1.5969	1.3221	2.5018	3.1860
Prob.	0.682*	0.660*	0.724*	0.475*	0.364*
Number of Lags: 10					
Q-stat	3.1581	4.2938	4.6153	6.8686	8.3867
Prob.	0.924*	0.830*	0.798*	0.551*	0.397*
XU030					
Number of Lags: 3					
Q-stat	1.3198	1.5702	1.9707	1.6914	2.3996
Prob.	0.251*	0.210*	0.160*	0.193*	0.121*
Number of Lags: 5					
Q-stat	6.2042	7.0218	6.8143	6.0213	7.9814
Prob.	0.102*	0.071*	0.078*	0.111*	0.046*
Number of Lags: 10					
Q-stat	6.5472	7.7449	7.4478	6.5872	8.2772
Prob.	0.586*	0.459*	0.489*	0.582*	0.407*
XU100					
Number of Lags: 3					
Q-stat	2.1343	0.7931	2.2935	3.4652	1.7908
Prob.	0.144*	0.373*	0.130*	0.063*	0.181*
Number of Lags: 5					
Q-stat	7.4460	2.0776	3.3474	4.9802	3.0703
Prob.	0.059*	0.556*	0.341*	0.173*	0.381*
Number of Lags: 10					
Q-stat	7.7322	6.1233	7.6127	8.7775	6.8817
Prob.	0.460*	0.633*	0.472*	0.361*	0.549*

* Probability values indicate the rejection of the null hypothesis.

Graph A.1: Realized Volatility of Indices