IFA
Iranian Journal of Finance
Print ISSN 2676-6337
Online ISSN 2676-6345

Portfolio Optimization with Systemic Risk Approach

Mohammad Azad

Ph.D. Candidate in Financial Management, Department of Financial Management, Bank and Insurance, Central Tehran Branch, Islamic Azad University, Tehran, Iran. (Email: azad-muhammad@hotmail.com)

Mirfeiz Fallah Shams*

*Corresponding Author, Associate Prof., Department of Financial Management, Bank and Insurance, Central Tehran Branch, Islamic Azad University, Tehran, Iran. (Email: mir.fallahshams@iauctb.ac.ir)

Ali Rahmani

Prof., Department of Accounting, Faculty of Social Sciences and Economics, Alzahra University, Tehran, Iran. (Email: rahmani@alzahra.ac.ir)

Teymour Mohammadi

Prof., Department of Theoretical Economics, Faculty of Economics, Allameh Tabataba'i University, Tehran, Iran. (Email: atmahmadi@gmail.com)

Iranian Journal of Finance, 2025, Vol. 9, No.1, pp. 32-61.
Publisher: Iran Finance Association
doi: https://doi.org/ 10.30699/ijf.2024.446203.1461
Article Type: Original Article

Received: March 02, 2024
Received in revised form: September 15, 2024
Accepted: October 28, 2024
Published online: January 01, 2025

Abstract

Portfolio optimization has always been the main concern of investors. What differentiates different optimization models from each other is the risk measure. The main contribution of this paper is to provide a portfolio optimization model that considers systemic risk so that it can help investors make optimal investment decisions as a general model. For this purpose, two models are presented. In the first model, systemic and systematic risk were considered simultaneously, and in the second model, only systemic risk was considered. In the two mentioned models, delta conditional value at risk (ΔCoVaR) and the Markowitz model are used respectively to measure systemic risk and a benchmark model. Also, the criteria used to compare the performance of the reviewed models include the ratio of reward-to-risk, along with the Sortino ratio and the Omega ratio. The problem of optimization and examination of the results was carried out on a selected sample, 38 companies listed in the Tehran Stock Exchange (TSE) from 2013 to 2023. The results of empirical analysis of out-of-sample data (during a period of 1198 days) show that based on all three mentioned criteria, the first proposed model shows the best performance among the three models. In addition, the performance of the second model is ranked second. In short, it can be said that considering systemic risk in portfolio optimization leads to better performance than the Markowitz model.

Keywords: Delta Conditional Value at Risk (ΔCoVaR), Sharpe Ratio, Modern Portfolio Theory (MPT), Post-Modern Portfolio Theory (PMPT), Efficient Frontier.

Introduction

Selecting the optimal portfolio is one of the most important concerns that has always occupied the minds of investors, especially capital market participants. What distinguishes different portfolio optimization models from each other is the risk measure. Launching the modern portfolio theory (MPT) is considered a big step in the field of investment. In this theory, a logical relationship between the distribution of return rate and investment risk was established. The type of risk in question is systematic risk and its main measures are standard deviation and variance. However, in post-modern portfolio theory (PMPT), the type of risk included is systematic risk but with downside risk metrics.

As opposed to a firm's individual risk of failure, which can be contained without harming the entire financial system, systemic risk is the risk of collapse of the entire financial system or market. The financial crisis of 2007-

2009 clearly revealed the importance and necessity of a better understanding of systemic risk for the financial industry, policymakers, and market participants. Since the financial crisis, numerous attempts have been made to identify and measure the systemic risk of financial institutions (see, for example, Adrian and Brunnermeier (2011), Brownlees and Engle (2012), Acharya et al. (2017)). In this respect, the following question arises: How can a given systemic risk measure be used to construct portfolios that perform relatively well when systemic risk materializes?

In this paper, we develop a framework for the optimal portfolio choice based on exogenously given systemic risk measures.

Research shows that the possible effects of systemic risk, even with a small probability of occurrence, can significantly reduce the benefits of diversification and portfolio formation. Prevention of damages caused by the existence of correlation and complexity of communication networks between companies requires the identification of systemic risk and its inclusion in the selection of assets in the investment portfolio. "You know something is happening here, but you do not know what it is.". This Bob Dylan's phrase summarizes the promise of financial indicators discussed in the post-2008 financial crisis (Civitarese, 2016).

Failure to consider systemic risk in decisions can cause losses due to the bankruptcy of a capitalized company that has been damaged only because of the connection and interdependence in the market and as a result of the failure of a company or a group of companies. Moreover, it is possible that the vulnerable company, directly or indirectly, is not exposed to the failure factor created for other companies. In order to eliminate this effect as much as possible, by determining the appropriate measure for systemic risk and minimizing mutual effects, an investment portfolio can be formed that minimizes the vulnerability and risk of the portfolio. There has yet to be a consensus regarding the concept of financial stability and systemic risk. The materialization of systemic risk during the recent global financial crisis demonstrated that the financial safety net and financial institutions significantly underestimated it. Systemic risk is much more than just the composition of individual types of risks affecting financial institutions. While credit risk, liquidity risk, operational risk, etc., can be directly attributed to a given institution, systemic risk can only be attributed indirectly (Smaga, 2014).

The capital market of Iran, especially the companies listed in the Tehran Stock Exchange, is not exempted from these conditions due to its financial relations, ownership, and operational intertwining.

The present research from the theoretical aspect, through a special study on how to consider this aspect of risk, in addition to the general classification of the pioneers of the matter (separation of risk into two main systematic and unsystematic groups), the problem of portfolio optimization (especially in the formation stock portfolio), will contribute to the existing knowledge and literature related to choosing the optimal portfolio. However, can the consideration of systemic risk in portfolio optimization always lead to better performance results than the Markowitz model?

After the introduction, the literature of the research has been reviewed. Then, the methodology of the research and the method of data analysis will be discussed. Also, the operational definition of the variables, the scope of the research, and the objective function of solving the optimization problem are presented in each of the models. Then, the main question and hypothesis of the research, which shows the purpose of the research, is stated. In the end, research findings, discussion, and conclusions are presented.

Why ΔCoVaR?

Systemic risk measurement and evaluation is a difficult and complex process, and it is important to monitor and identify places that could lead to systemic risk. Analysis showed that from 2009–to January 2018, not only did the quantity of research in the systemic risk measurement area increase but new methods were also used to measure systemic risk. The most common systemic risk measurements are the Delta conditional value-at-risk (ΔCoVaR) and the conditional value-at-risk (Dič et al., 2018). In this study, they analyzed 95 publications to determine the methods used to measure systemic risk. A meta-analysis of scientific articles performed based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method and using a network approach presents the main interconnection of the methods used to measure systemic risk.

Figure 1 shows that the most common systemic risk measurements are the Delta conditional value-at-risk (ΔCoVaR) and the conditional value-at-risk (CoVaR) methods. Another widely used method to assess systemic risk is the Marginal Expected Shortfall (MES). It is worth mentioning that more than a fifth of the articles included in our study used the CoVaR method and about one-third the ΔCoVaR systemic risk measurement method. The MES method has also been used in more than a fifth of all analyzed articles. So, in the present article, the ΔCoVaR systemic risk measurement method is used.

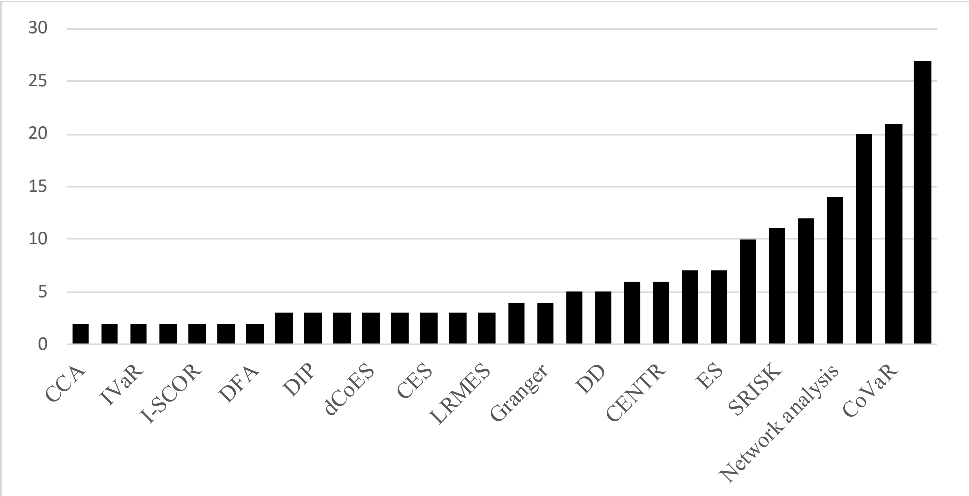

Figure 1. Frequency of methods used to measure systemic risk in analyzed publications

Literature Review

Restrictions related to investors' rational behavior and their pure interest just in maximization of economic utility were put under question by behavioral finance that reflects the investors' trend to obtain emotional comfort prior to optimal financial efficiency. The prospect theory (Kahneman, Tversky, 1979) presents a new face for the investor.

The investor is not just rational as the previous financial literature assumes he should be, but he is also a human person with emotions and preconceptions. The humanized investor is a person with different reactions to losses and gains resulting from his investment, depending on the individual assumption of risks (Şova et al., 2018). Financial behavior presents the investor as a person who is reluctant to lose but not to gain over the minimum expected return. Previously, it was considered that an investor was interested in investing in a portfolio with a return that did not vary much from the average. The research of the investor reactions shows that he is, in fact, interested in obtaining a minimum desired return; any result below the minimum desired return is considered a loss, while gains higher than the expected level of return do not constitute a concern, (but contrary, they are considered as premium for the courage of investing), the "good surprise" (Şova et al., 2018).

The risk in the post-modern portfolio theory is considered as the possibility of return rates being situated beneath the minimum expected return; investors are preoccupied mostly with limiting this kind of variation from their investment.

The post-modern portfolio theory has a wider application than the MPT and includes the expectation of investors related to a minimum desired return rate as a benchmark rather than the average return rate (Şova et al., 2018). A summary of the main characteristics of the two investment theories is presented in Table 1 (Heybati & Mousavi, 2009, & Markowitz, 1952).

Table 1. Characteristics of Modern Portfolio Theory vs Post-Modern Portfolio Theory

Description	Modern Portfolio Theory (MPT)	Post Modern Portfolio Theory (PMPT)
Risk Measure	Standard Deviation, Variance	Downside risk, Semi Variance, Semi Standard Deviation
Assumption of Probability Distribution	Normal Distribution	non- Normal Distribution
Skewness	Not Calculating Skewness	Calculating Skewness
The Value of Low and High Volatilities	Both of Low and High Volatilities	High Volatilities Valuable and Low Volatilities of not- Valuable
Interpretation of Risk	Risk as deviation from the average return	Risk as Deviation From the Average of the Specific Target
Performance Measure	$Sharp\ ratio = \frac{r - r_f}{\sigma}$	$Sortino\ Ratio = \frac{r - d}{Downside\ Risk}$
r, rate of return, σ, the standard deviation of r, d, target return, r_f, risk-free ate, and Downside Risk, the risk of the actual return being below the expected return.		

Various reasons recommend the use of the expected return-variance of return rule, both as a hypothesis to explain well-established investment behavior and as a maxim to guide one's own action. The rule serves better; we will see, as an explanation of, and guide to, "investment" as distinguished from "speculative" behavior. The concepts "yield" and "risk" appear frequently in financial writings. Usually, if the term "yield" were replaced by "expected yield" or "expected return" and "risk" by "variance of return," little change of apparent meaning would result. Variance is a well-known measure of dispersion about the expected. If instead of variance, the investor was concerned with standard error,$\boldsymbol{\sigma} = \sqrt{\boldsymbol{V}}$, or with the coefficient of dispersion, $\boldsymbol{\sigma}/\boldsymbol{E}$, his choice would still lie in the set of efficient portfolios (Markowitz, 1952).

Although modern portfolio theory remained a significant benchmark in portfolio theory, the post-modern portfolio theory moves the financial theory and practice a step forward, considering investor expectations. Both theories are used within financial research but also outside this area; researchers and business people extend their application to other economic domains (such as real estate, energy portfolios, and other investments except stocks) with interesting results and ways of applying the methods of quantifying risk (Nateghi et al., 2016, & Şova et al., 2018).

Since the beginning of the present financial crisis, many researchers and portfolio managers have revived the question regarding the MPT realism relative to market conditions. Although modern portfolio theory was preferred and used for decades before the financial crisis in 2008, the theory was blamed for failing in those moments. Investors and researchers have started to look for alternative theories that measure risk (Şova et al., 2018). Systemic risk studies in Iran, like global research, have a short-term background. Especially in the field of portfolio optimization with a systemic risk approach, there has been no investigation in the country. Therefore, the contribution of the present research is important from this point of view.

Biglova et al. study the problem of portfolio selection in the presence of systemic risk. They propose measures of risk and return that determine systemic risk and provide a methodology for creating realistic return scenarios. This method first includes the analysis of the experimental behavior of several countries' stock indices, which suggests a basis for future scenarios. Then, they examine the profitability of several strategies based on the predicted return trend. In the following, in particular, the selected methods of optimal future wealth obtained by optimizing the portfolio through the ratio between risk and return on the simulated data are compared with the retrospective performance resulting from the application. Selected portfolio strategies are compared. They state that Markowitz's portfolio selection approach does not consider systemic risk because the proposal is to diversify the portfolio among the assets that offer the lowest variance and the highest average and have a greater mutual relationship with each other, and therefore The problem can increase the systemic risk (Biglova et al., 2015).

Lin et al. propose a new method to form an optimal portfolio that specifically takes systemic events into account. In maximizing the Sharpe ratio, investors adjust the conditions according to a systemic event, and this last case (systemic event) is actually interpreted as the condition of low market performance. They solve the problem of allocating weights in the portfolio analytically and numerically, respectively, under the conditions of no borrowing sales restrictions and when borrowing selling restrictions are applied. This method is operationalized to obtain portfolio allocation in a multivariate dynamic environment using dynamic conditional correlation and copula models (Lin et al., 2020).

Capponi et al. assume that the investor in question seeks to create a balance between the final risk and the expected growth of an investment. They measure marginal risk through the portfolio's expected losses subject to a systemic event: financial market losses exactly equal to, or at least equal to, its conditional value at risk, and portfolio losses the investor above the value level is exposed to conditional risk. They provide a closed solution for the investment problem and divide it into a part similar to Markowitz's mean-variance portfolio theory and an adjustment part for systemic risk. Thus, they show that the confidence levels of the mentioned metrics control the relative sensitivity of the investor's target performance to portfolio-market correlation and portfolio variance, respectively. Their empirical analysis shows that investors get higher risk-adjusted returns during the period of market recession compared to known portfolio criteria. Portfolios that perform best in adverse market conditions are less diversified and focus on a small number of stocks that have a weak correlation with the market (Capponi & Rubtsov, 2021). In another work, in their modeling approach, they used two risk criteria, including value at risk and conditional value at risk. Their model investor maximizes the expected returns of the portfolio under the condition that the systemic risk index is at (or at most at) the level of the value at risk and the returns of the stock portfolio are lower than their level. Under some assumptions, the optimal investment strategy is achieved in a closed form. The proposed method works in balancing the importance of portfolio variance and the correlation of stock portfolios with the flexible system risk index. This model was applied in the Canadian stock market, and it showed relatively good performance during the recession (Capponi et al., 2018).

In mean-variance portfolio optimization, factor models can accelerate computation, reduce input requirements, facilitate understanding, and allow easy adjustment to changing conditions more effectively than full covariance matrix estimation. Varmaz et al. develop a factor model-based portfolio optimization approach that takes into account aspects of the environment, social responsibility, and corporate governance (ESG). Investments in assets related to ESG have recently grown, attracting interest from both academic research and investment fund practice. Various literature strands in this area address the theoretical and empirical relation among return, risk, and ESG.

Their portfolio optimization approach is flexible enough to take these literature strands into account and does not require large-scale covariance matrix estimation. An extension of their approach even allows investors to discriminate empirically among the literature strands. A case study demonstrates the application of our portfolio optimization approach (Varmaz et al., 2022).

Ahmadi et al. aims to investigate portfolio optimization under various market risk conditions using copula dependence and extreme value approaches. According to the modern portfolio theory, diversifying investments in assets that are less correlated with one another allows investors to assume less risk. In many models, asset returns are assumed to follow a normal distribution. Consequently, the linear correlation coefficient explains the dependence between financial assets, and the Markowitz mean-variance optimization model is used to calculate efficient asset portfolios. In this regard, monthly data-driven information on the top 30 companies from 2011 to 2021 was the subject of consideration. In addition, extreme value theory was utilized to model the asset return distribution. Using Gumbel's copula model, the dependence structure of returns has been analyzed. Distribution tails were modeled utilizing extreme value theory. If the weights of the investment portfolio are allocated according to Gumbel's copula model, a risk of 2.8% should be considered to obtain a return of 3.2%, according to the obtained results (Ahmadi et al., 2023).

Portfolio optimization is the process of distributing a specific amount of wealth across various available assets, with the aim of achieving the highest possible returns while simultaneously mitigating investment risks. While numerous studies have investigated portfolio optimization across various domains, there needs to be more literature regarding its application, specifically within the automotive industry as one of the largest manufacturing sectors in the global economy. Since the economic activity of this industry has a coherent pattern with that of the global economy, the automotive industry is very sensitive to the booms and busts of business cycles. Due to the volatile global economic environment and significant inter-industry implications, providing an appropriate approach to investing in this sector is essential. Thus, this paper aims to address this need by proposing a suitable investment methodology in the aforementioned sector. In this study, an extended Conditional Drawdown at Risk (CDaR) model with cardinality and threshold constraints for portfolio optimization problems is proposed, which is highly beneficial in practical portfolio management. The feature of this risk management technique is that it admits the formulation of a portfolio optimization model as a linear programming problem. The CDaR risk functions family also enables a risk manager to control the worst $(1 - \alpha) \times 100\%$ drawdowns. In order to demonstrate the effectiveness of the proposed model, a real-world empirical case study from the annual financial statements of automotive companies and their suppliers in the Tehran Stock Exchange (TSE) database is utilized. The empirical results of this study may appeal to investors and risk managers for advanced portfolio management (Ghanbari et al., 2023).

Conditional Portfolio Optimization is a portfolio optimization technique that adapts to market regimes via machine learning. Traditional portfolio optimization methods take summary statistics of historical constituent returns as input and produce a portfolio that was optimal in the past but may not be optimal going forward. Machine learning can condition the optimization of a large number of market features and propose a portfolio that is optimal under the current market regime. Applications on portfolios in vastly different markets suggest that Conditional Portfolio Optimization (CPO) can outperform traditional optimization methods under varying market regimes (Chan et al., 2023).

Cajas presents two approaches that allow us to diversify portfolios based on the graphical representation of the relationships among assets. The information obtained from graphs like the minimum spanning tree (MST) or the triangulated maximally filtered graph (TMPG) to diversify portfolio based on the influence of assets in the graph (centrality) and the asset's neighborhood are used. These formulations are simple and versatile because they consist of additional constraints that we can add to traditional convex portfolio optimization problems. They run some examples that show how classic convex models and graph clustering-based asset allocation models do not incorporate information about the centrality and connections among assets in the optimization process, while the addition of constraints on a centrality measure or in the asset's neighborhood allows us to diversify our portfolio selecting assets in the periphery of the graph or assets that are not directly connected in the graph respectively (Cajas, 2023).

Another work by Cajas presents the portfolio optimization model of Brownian distance variance or distance variance. The Brownian distance covariance or distance covariance is a function that quantifies how similar the two variables are. It has the advantage that it considers linear and nonlinear relationships. The distance variance is the special case of distance covariance when both variables are the same. First, they show several ways to calculate the sample distance variance. Then, they pose a quadratic portfolio model that allows us to optimize the distance variance. This formulation allows us to use distance variance in several portfolio optimization problems, like maximizing the risk-adjusted return ratio, risk constraints, or risk parity. Finally, they run some examples that show how different portfolios optimize variance and distance variance (Cajas, 2023).

Rey proves that when regular intra-period portfolio rebalancing strategies are applied, the one-period portfolio optimization problem already has a unique solution without a need for specification of utility or risk trade-offs. This portfolio is a linear combination of the minimum variance portfolio and the mean-variance optimal portfolio (Rey, 2023).

Portfolio optimization has a mixed reputation among investment managers, with some being so skeptical that they believe it is almost useless due to the inherent parameter uncertainty. It is undeniable that portfolio optimization problems are sensitive to parameter estimates, especially the expected returns, which are arguably also the hardest parameters to estimate. However, most practitioners still attempt to build mean-risk optimal portfolios, albeit in implicit ways. Resampled optimization is a popular mathematical heuristic that tackles the parameter uncertainty issue. It computes optimal portfolios using sampled parameter estimates and calculates a simple average of the portfolio exposures across samples. The unsatisfactory aspect of the resampled approach is that there needs to be a mathematical justification for using the average of portfolio exposures; it just works well in practice. Kristensen et al. provide perspectives for understanding the resampling approach by analyzing the portfolio exposure estimation process from a bias-variance trade-off. They show that the traditional resampled optimization corresponds to a naive version of stacked generalization. Finally, they introduce a stacked generalization approach that can be used to handle both parameter uncertainty and combine optimization methods in full generality. They coin the new method of Exposure Stacking (Kristensen et al., 2024).

Lorimer et al. use a numerical methods algorithm based on gradient descent to optimize investment portfolios of global indices using raw and forecasted risk measures at differing frequencies. The results permit a comparison of how the characteristics of risk measures other than the variance and standard deviation impact portfolio performance. Asymmetric risk measures result in superior portfolio returns, while risk measures incorporating unsquared deviations outperform those incorporating squared deviations. Risk measures forecasted using the exponentially weighted moving average (EWMA) methodology do not yield significant increases in portfolio returns. Semi-absolute deviation, mean absolute deviation, and downside semi-deviation perform favorably in producing higher returns (Lorimer et al., 2024).

Research Methodology

Portfolio selection is one of the most common issues faced by different investors with varying levels of capital, and yet one of the most complex in the financial world (Qu & Suganthan, 2011). The issue of portfolio selection is a model of balancing risk and return. This involves a set of securities that attempt to determine the proportion of investment in each in order to minimize investment risk and maximize return on investment (Karimi et al., 2007). However, high returns are usually high risk (Deng et al., 2012). Investors typically hold several securities in an investment portfolio (Chang et al., 2000). In 1952, Harry Markowitz used mathematical programming and variance to evaluate portfolio, mean and return, and portfolio selection by optimizing two conflicting criteria of risk and return (Markowitz, 1952).

The first model, optimization with simultaneous consideration of systematic and systemic risk

In this method, the optimization problem is solved by using the Markowitz optimization model and applying a new constraint in order to control the systemic risk. As a result, in addition to the systematic risk that is considered based on the standard deviation of the portfolio, by applying the above limit, the weight of each company in the portfolio is calculated according to the systematic risk. It is expected that the stock portfolio considered in this model will be less diverse than the Markowitz model in terms of diversity in the selection of companies. In this research, the measure of delta conditional value at risk is considered a measure of systemic risk. Therefore, the limit of systemic risk in the Markowitz model is based on the mentioned criterion. The application of this restriction in the Markowitz optimization model is as follows:

$$\min_{w} \sigma_p^2 = w^T \Sigma\, w \qquad (1)$$

$$s.t.\; w^T \mu \geq \bar{\mu}_p$$

$$w^T \Delta CoVaR_{sys} \leq q_{|\Delta CoVaR|}$$

$$w^T 1 = 1$$

$$w \geq 0$$

In which $\boldsymbol{\Delta CoVaR_{sys}}$, delta conditional value at risk of the system, and q the first-order quartile of the positive values of delta conditional value at risk. In fact, in the system limit, it is expected that according to the obtained optimal weights, the amount of delta conditional value at risk is less than 0.25 of the values of delta conditional value at risk obtained for each company. This method performed better than considering the mean or other quartiles for delta conditional value at risk.

The second model, optimization only in terms of systemic risk

In this model, it is assumed that it is desirable for the investor to form a portfolio that performs well in the conditions of the overall market recession. Systemic risk is included directly in the portfolio optimization model to protect a certain portfolio against market stagnation. Simply put, it estimates the expected loss of a portfolio in a low-return environment when the market is in distress (the market is exactly at its value-at-risk level). Therefore, the problem of portfolio selection can be stated as follows (Capponi & Rubtsov, 2021):

$$\min_{w} CoES = \cdots \quad (2)$$

$$s.t.\ w^T\mu = \bar{\mu}_p$$

$$w^T 1 = 1$$

$$w \geq 0$$

In fact, we find a portfolio that reaches the expected return $\bar{\boldsymbol{\mu}}_{\boldsymbol{p}}$ in normal times and also performs well when the market is at the level of value at risk and the portfolio loss is higher than the conditional value at risk.

Considering that the t distribution (t) with v degrees of freedom (return length) was used for the returns (according to default tests and skewness and skewness values), the optimization problem is presented as follows:

$$\min_{w} CoES = -w^T\hat{\mu} + \lambda\sqrt{w^T\hat{\Sigma}w}$$

$$s.t.\ w^T\mu = \bar{\mu}_p \quad (3)$$

$$w^T 1 = 1$$

$$w \geq 0$$

In which $\hat{\mu}=\mu+\sqrt{(\nu-2)/\nu}\ T_\nu^{-1}(1-\alpha')\sigma/\sigma_m$, $\lambda=F(\alpha,\alpha',\nu)/(1-\alpha')$., $\hat{\Sigma}=\Sigma-(\sigma\sigma^T)/(\sigma_m^2)$

$$F(\alpha, \alpha', \nu) = \sqrt{\frac{(\nu - 2)\left(\nu + (T_\nu^{-1}(1 - \alpha'))^2\right)}{\nu(\nu + 1)}} t_{\nu+1,1} T_\nu^{-1}(1 - \alpha)\left(\frac{\left(\nu + 1 + (T_\nu^{-1}(1 - \alpha))^2\right)}{\nu}\right)$$

α' Confidence level of the system, α confidence level of the portfolio, σ^2 variance of returns, and σ_m covariance of returns of companies with the market. The confidence level of the system and portfolio should be considered higher than 0.5 (Capponi & Rubtsov, 2021).

The third model, Markowitz

Markowitz introduced and developed the concept of diversification in the stock portfolio. He suggested that investors take risk and return together and select the amount of capital allocation between different investment opportunities based on the interaction between the two (Fabozzi et al., 1997). He generally showed how diversification in the capital portfolio reduces the risk for the investor. Investors can obtain an efficient stock portfolio for a certain return by minimizing portfolio risk. To obtain and select the optimal portfolio in the Markowitz method, which is the minimum variance for a certain level of return, we have the following planning model:

$$\min_{w} \sigma_p^2 = w^T \Sigma w$$

$$s.t.\ w^T \mu = \bar{\mu}_p \qquad (4)$$

$$w^T 1 = 1$$

$$w \geq 0$$

Where Σ the covariance matrix, μ the return of each company, $\bar{\mu}_p$ is the unconditional expected return of the stock portfolio. The weights obtained by this model for determining the stock portfolio are without considering the systemic risk, so the variety in-stock selection is greater in this model.

In the following, the variables used in the investigation are briefly introduced:

1. The return of each company is calculated based on the natural logarithm of the closing price as follows:

In such a way that P_t represents the (adjusted) daily price of each company.

$$r_t = Ln(P_t/P_{(t-1)}) \quad (5)$$

2. Company weight: the ratio of the market value of each company to the total market value of the sample companies (system market value)

3. System return: This is obtained based on the weighted average of the returns of the companies in the system.

4. Delta Conditional Value at Risk (systemic risk measure)

During the financial crisis of 2007-2009, worldwide taxpayers had to bail out many financial institutions. Governments are now trying to understand why the regulation failed, why capital requirements were not enough, and how a guaranty fund should be built to face the next crisis. An important element is missing in the above assessment of risk: it is the dependency between the individual institution and the economy or the financial system. In this regard, Adrian and Brunnermeier (2010) defined the CoVaR measure. The idea is to compare the Value-at-Risk (VaR) of the system under "normal conditions" and the VaR of the system conditional on the fact that a given institution is under stress (Bernard et al., 2012).

In order to calculate the mentioned measure, the value at risk, the conditional variance, and the variable beta over time have also been calculated, which will be briefly described first. To calculate the value at risk, you can use the following equation or the GARCH model:

$$VaR_{\alpha} = \mu + \sigma F^{(-1)}(\alpha) \quad (6)$$

Where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, respectively, mean and conditional variance are obtained from the GARCH model and $\boldsymbol{F^{-1}(\alpha)}$ inverse function of return distribution at the $\boldsymbol{\alpha}$ **point**.

The variable beta over time for my company $\boldsymbol{i}$ is obtained as follows:

$$\boldsymbol{\beta_{it} = \frac{\sigma_{it}\rho_{it}}{\sigma_{mt}}} \quad \textbf{(7)}$$

Which is obtained according to the conditional variance-covariance matrix obtained from the DCC model.

The measure of delta conditional value at risk (ΔCoVaR) was proposed by Adrien and Brunnermeier in 2011 and is based on value-at-risk. This measure represents the value exposed to the risk of the system, with the condition that the company in question is exposed to the risk of crisis. In the context of measuring systemic risk, ΔCoVaR means the difference between the maximum expected loss of the system in case of criticality of the company $\boldsymbol{i}$ and the maximum expected loss of the system in case of normal conditions of the company $\boldsymbol{i}$. The contribution of the systemic risk of a specific company to the risk of a specific system is determined using a measure that is equal to:

$$\Delta\mathbf{CoVaR_{it}} = \frac{\sigma_{mt}\rho_{it}}{\sigma_{it}}[\mathbf{VaR_{it}}(\alpha) - \mathbf{VaR_{it}}(\mathbf{0.5})] \quad \textbf{(8)}$$

Which $\boldsymbol{VaR_{it}}(\mathbf{0.5})$ will be equal to zero for symmetric distributions (Benoit et al., 2012).

5. GARCH models

The fluctuation change of financial time series over time is known as a phenomenon. In the early 1960s, Mandelbrot observed that there are certain patterns in the changes in the volatility of financial time series in such a way that often large changes follow large changes, and small changes follow small changes. Following this study, much research was done on this feature of financial time series, and the results indicated that the fluctuations occur more often in some periods and less frequently in other periods. Auto regression models conditional on variance heterogeneity (ARCH) and generalized auto regression conditional on variance heterogeneity (GARCH) were designed to deal with this set of data. The arch model was proposed and presented by Engel in 1982. Bullerself generalized the arch model in 1986 under the name GARCH. This model is also the weighted average of the squared residuals of the previous periods, but it has weights that continuously decrease but never become zero. In addition, the statement of this model is low-cost and the estimation of its parameters is relatively simple. According to the work of Brownless and Engel (2012) regarding the behavior of returns, a multivariate GARCH process is considered as follows (Brownlees & Engle, 2012):

$$r_t = H_t^{1/2} v_t \quad (9)$$

Where $\boldsymbol{r_t} = (\boldsymbol{r_{mt}}.\boldsymbol{r_{it}})$ represents the return of the market and my company $\boldsymbol{i}$, respectively. The matrix $\boldsymbol{H_t}$ is the conditional variance-covariance matrix that can be displayed as follows:

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\sigma_{it}\rho_{it} \\ \sigma_{mt}\sigma_{it}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \quad (10)$$

Moreover, in that $\boldsymbol{\sigma_{it}}$ and $\boldsymbol{\sigma_{mt}}$ represent conditional standard deviations and $\boldsymbol{\rho_{it}}$conditional correlations. There are no special assumptions about the bivariate distribution of standardized innovations ($\boldsymbol{v_t}$). The only assumption here is related to $\boldsymbol{\rho_{it}}$ and it is assumed that this expression completely covers the dependence between the company's return and the market.

In financial crises, the assumption of conditional constant correlation causes risk to be underestimated, and under normal conditions, risk overestimation leads to losses. Various theoretical and practical research have been conducted in the field of conditional correlation dynamics, and various models, such as the DCC model, have been proposed. In 2002, Engel did not take into account the assumption of constant conditional correlations and presented the model of dynamic conditional correlations. In this model, the correlation matrix is allowed to change over time. This model is widely and easily used for supplementary calculations.

Results

The sample population in the present study is the companies listed in the Tehran Stock Exchange. The information related to the price, the market value of the companies, and the total index have been extracted and collected from the Bourse View website. The sample used for the empirical analysis of the portfolio optimization model was determined based on the following conditions from among the companies listed in the Tehran Stock Exchange by screening sampling or systematic exclusion:

1. Considering that the time period investigated in the research is the ten-year period ending at the end of March 2023, in order to access the information of the selected companies in the entire mentioned period, the first condition applied was that the selected company during the ten-year period year (from the beginning of 2013 to the end of 2023) to be listed in the market. By applying this condition, 272 companies were selected among the companies listed in the market.

2. In order to check the price information of the selected companies more accurately and to minimize the missing data, the second condition for the selection of the sample is the minimum number of trading days of the shares. At this stage, companies are selected whose minimum number of trading days is more than 80% of the total trading days in each year of the period under review. By applying this condition among the 272 filtered companies resulting from the application of the first condition, 42 companies were selected as the

research sample.

3. Finally, considering that the data of 4 companies were identified as outliers, the selected sample was determined to include 38 companies.

In order to gain more knowledge about the studied variables, a summary of the descriptive statistics of the research variables has been calculated. Descriptive statistics include the minimum, maximum, mean, standard deviation, etc. of each variable. All the variables used in this research are evaluated on a quantitative scale and observations in the form of time series, daily logarithmic return percentage for 38 companies, and the total index for the ten-year period from the beginning of 2013 to the end of March 2023. For the purpose of analysis, the data are divided into two categories: in-sample (first 5 years) and out-sample (second 5 years). Descriptive statistics related to the daily returns of the sample companies are given in Table 2. Shapiro-Wilk tests, generalized Dickey-Fuller unit root, and Arch effect were used to check the normality, significance, and heterogeneity of variance among the data before entering the modeling. According to the results of Table 2, according to the value of the Shapiro-Wilk test statistic for companies and the significant value, which are all less than 0.05, the assumption of normality of the data related to each company is rejected. This problem has been rejected according to the values of skewness and kurtosis listed in Table 2 of descriptive statistics. Therefore, in this research, the t-student distribution was used for modeling. In order to check the significance assumption of the return of the companies, the generalized Dickey-Fuller unit root test has been used, which, according to the statistic value for each company and the significance value less than or equal to 0.05, the significance assumption is accepted among the data of the companies.

In the end, according to the ARCH effects test, the assumption of heterogeneity of variance is accepted according to its statistical value for each company and a significance value less than or equal to 0.05 among the companies' data (except for a few companies). Therefore, in this research, GARCH models are used to analyze the data.

Table 2. Descriptive statistics related to the percentage of daily return of sample companies

symbol	Minimum	Maximum	Mean	Standard dev	Skewness	Kurtosis
Betrance	-0.0982	0.1778	0.00161	0.0267	0.47306	1.59807
Sefars	-0.0854	0.1121	0.00178	0.02781	0.21568	-0.27846
Fesorb	-0.1426	0.1753	0.00154	0.03017	0.07115	0.22992
Dejaber	-0.1787	0.2623	0.00188	0.02627	0.42914	5.1204
Dekosar	-0.4801	0.1501	0.00169	0.03061	-1.5169	25.23943
Vaghadir	-0.0819	0.1797	0.00174	0.02252	0.5047	2.73267
Vasakht	-0.205	0.2237	0.00148	0.03182	0.10526	2.53368
Valbor	-0.1079	0.089	0.00165	0.02538	0.15632	0.43717
Vasanat	-0.0748	0.2553	0.00172	0.0247	0.72582	5.02831
Sepaha	-0.2622	0.0903	0.00149	0.02805	-0.19598	2.86019
Seshomal	-0.2728	0.372	0.00166	0.02922	0.66707	13.54845
Khebahman	-0.0957	0.1922	0.00192	0.02775	0.45264	1.44536
Vaniki	-2.718	2.7263	0.00189	0.08234	0.08346	989.1095
Sekerma	-0.3612	0.4193	0.00196	0.02858	0.78426	30.22335
Derazak	-0.127	0.2819	0.0017	0.02672	0.61249	5.67152
Keroy	-0.1038	0.1628	0.00159	0.02845	0.24129	0.41653
Segharb	-0.1369	0.2754	0.00147	0.02894	0.4143	3.57741
Khemohareke	-0.6448	0.7171	0.00178	0.04031	2.65003	95.92611
Vatoosa	-0.1292	0.1865	0.00169	0.02717	0.2831	1.03329
Vasepah	-0.4023	0.4531	0.00182	0.0253	0.79621	68.3726
Fasmin	-0.1152	0.1401	0.00183	0.02687	0.17272	0.25069
Vatooshe	-0.1026	0.2579	0.00185	0.02645	0.4903	3.86946
Pardis	-0.1328	0.1251	0.00179	0.02412	0.22494	0.97085
Setran	-0.1174	0.2108	0.00158	0.02836	0.56596	2.2206
Desobha	-0.1953	0.2616	0.00206	0.02624	0.83121	8.7912
Ranfor	-0.1222	0.1666	0.00138	0.02177	0.36889	2.82674
Vanaft	-0.0844	0.1985	0.00156	0.0276	0.37439	0.80336
Vabooali	-0.1693	0.1357	0.00173	0.02643	0.12658	0.98824
Kheshargh	-0.216	0.3197	0.00179	0.0318	0.48387	5.08057
Semaskan	-0.2272	0.1399	0.00109	0.02743	0.04879	2.47691
Vasna	-0.0965	0.1047	0.00135	0.02743	0.18926	0.07817
Vabahman	-0.1587	0.2825	0.00156	0.02751	0.87136	7.35711
Valsapa	-0.0942	0.1238	0.00118	0.02698	0.1792	0.03268
Seshahed	-0.1756	0.1052	0.00137	0.02701	0.0061	1.09068
Shiraz	-0.1641	0.1689	0.00154	0.02517	0.39052	2.67918
Khegostar	-0.1391	0.7339	0.00192	0.03503	3.86802	78.29883
Fameli	-0.115	0.1722	0.00177	0.02377	0.66685	3.21903
Parsian	-0.1518	0.1426	0.00135	0.02616	0.21738	0.94519
TSE	-0.0567	0.0484	0.00164	0.01178	0.23183	2.53009

Table 3. Results of preliminary tests (before modelling to check basic assumptions)

symbol	ARCH effect test		Dickey-Fuller generalized test		Shapiro-Wilk test	
	statistic	Significance value	statistic	Significance value	statistic	Significance value
Betrance	<0.01	137.35184	<0.01	-11.92084	<0.01	0.97484
Sefars	<0.01	214.00839	<0.01	-11.50401	<0.01	0.99075
Fesorb	<0.01	85.96330	<0.01	-11.76702	<0.01	0.98619
Dejaber	0.0857	19.11852	<0.01	-11.47378	<0.01	0.96265
Dekosar	0.9961	2.91912	<0.01	-12.11793	<0.01	0.93030
Vaghadir	<0.01	258.94403	<0.01	-11.74467	<0.01	0.96592
Vasakht	<0.01	56.97033	<0.01	-11.60954	<0.01	0.97518
Valbor	<0.01	400.44054	<0.01	-11.81414	<0.01	0.98467
Vasanat	<0.01	63.71069	<0.01	-11.52095	<0.01	0.96684
Sepaha	0.0124	25.54288	<0.01	-12.04019	<0.01	0.97675
Seshomal	0.5355	10.92292	<0.01	-12.10103	<0.01	0.93860
Khebahman	<0.01	215.02991	<0.01	-11.66491	<0.01	0.97803
Vaniki	<0.01	1105.2788	<0.01	-12.81224	<0.01	0.15932
Sekerma	0.9999	1.36987	<0.01	-12.20804	<0.01	0.89233
Derazak	0.0362	22.12222	<0.01	-12.94171	<0.01	0.95565
Keroy	<0.01	99.03339	<0.01	-12.31378	<0.01	0.99009
Segharb	0.2885	14.19372	<0.01	-12.13327	<0.01	0.97726
Khemohareke	<0.01	712.20690	<0.01	-11.51803	<0.01	0.73974
Vatoosa	<0.01	109.92097	<0.01	-11.40167	<0.01	0.98680
Vasepah	<0.01	847.64347	<0.01	-12.01575	<0.01	0.82944
Fasmin	<0.01	101.78830	<0.01	-12.04810	<0.01	0.98994
Vatooshe	<0.01	36.16156	<0.01	-12.31772	<0.01	0.97674
Pardis	<0.01	235.00452	<0.01	-11.84153	<0.01	0.98124
Setran	<0.01	95.95429	<0.01	-10.95027	<0.01	0.97122
Desobha	<0.01	40.93968	<0.01	-12.04932	<0.01	0.93862
Ranfor	<0.01	124.81640	<0.01	-12.94123	<0.01	0.95920
Vanaft	<0.01	123.18565	<0.01	-11.26861	<0.01	0.98443
Vabooali	<0.01	138.24726	<0.01	-12.54628	<0.01	0.98521
Keshargh	0.9939	3.20445	<0.01	-11.12075	<0.01	0.96516
Semaskan	<0.01	114.26155	<0.01	-12.29278	<0.01	0.97864
Vasna	<0.01	200.39066	<0.01	-11.68603	<0.01	0.99184
Vabahman	<0.01	285.91588	<0.01	-12.11555	<0.01	0.94762
Valsapa	<0.01	230.98392	<0.01	-12.11677	<0.01	0.99196
Seshahed	<0.01	181.52264	<0.01	-10.14839	<0.01	0.98525
Shiraz	<0.01	236.09730	<0.01	-12.24367	<0.01	0.96963
Khegostar	1	0.21650	<0.01	-11.15839	<0.01	0.85847
Fameli	<0.01	97.71918	<0.01	-11.08183	<0.01	0.95769
Parsian	<0.01	130.79289	<0.01	-11.80304	<0.01	0.98377
TSE	<0.01	606.06700	<0.01	-9.10473	<0.01	0.93289

Next, the optimal portfolio weights (with the highest Sharpe) of each of the examined methods for 38 companies are presented in Table 3.

Table 4. Optimal weights according to the three methods, along with the systemic risk criterion values

symbol	ΔCoVaR	The first model	The second model	The third model
Betrance	-0.00137	0.075	0	0.062
Sefars	-0.00135	0.008	0.013	0.006
Fesorb	-0.00221	0.008	0.017	0.004
Dejaber	-0.00192	0.05	0.003	0.034
Dekosar	-0.00333	0.001	0.001	0.011
Vaghadir	-0.01265	0	0.046	0.057
Vasakht	-0.00232	0	0	0
Valbor	-0.0029	0	0.009	0.003
Vasanat	-0.00231	0.011	0.01	0.011
Sepaha	-0.00283	0	0.032	0
Seshomal	-0.00086	0.047	0.007	0.018
Khebahman	-0.0021	0.008	0	0
Vaniki	-0.00181	0.062	0	0.055
Sekerma	-0.00318	0.018	0.017	0.021
Derazak	-0.00247	0.066	0.062	0.059
Keroy	-0.00307	0	0.037	0
Segharb	-0.00411	0	0.016	0
Khemohareke	-0.00208	0	0.018	0
Vatoosa	-0.0003	0.06	0.023	0.031
Vasepah	-0.0034	0.011	0.049	0.046
Fasmin	-0.00312	0.011	0.056	0.019
Vatooshe	-0.00438	0.001	0.046	0.014
Pardis	-0.00259	0.04	0.068	0.041
Setran	-0.00045	0.043	0	0.024
Desobha	-0.002	0.048	0.05	0.033
Ranfor	-0.00382	0.084	0.11	0.122
Vanaft	-0.00192	0.001	0.019	0
Vabooali	-0.00122	0.05	0.044	0.03
Kheshargh	-0.00252	0.004	0.004	0.003
Semaskan	-0.00362	0.024	0.016	0.037
Vasna	-0.00449	0	0	0
Vabahman	-0.00052	0.085	0	0.054
Valsapa	-0.00535	0	0.017	0.006
Seshahed	-0.00111	0.045	0.071	0.032
Shiraz	-0.00177	0.052	0.047	0.049
Khegostar	-0.00086	0.052	0.013	0.036
Fameli	-0.01445	0	0.033	0.04
Parsian	-0.003	0.036	0.045	0.044
Sum of Weights	-	1.00	1.00	1.00

In the following, three portfolio optimization models, including the first model (with simultaneous consideration of systematic and systemic risk), the second model (only with consideration of systemic risk), and the third model (Markowitz, only with consideration of systematic risk), are briefly presented. It has been considered. Then, the optimization problem is solved in all three ways.

According to Table 4, the weights obtained in the third model (Markowitz), not considering systemic risk, do not show an effective relationship with the value of the systemic risk measure (delta conditional value at risk, ΔCoVaR). This is despite the fact that in the first (Markowitz with systemic risk limit) and second (in terms of systemic risk) models, the obtained weights were based on the values of the systemic risk measure, as can be seen in the mentioned table more weight is assigned to companies with lower systemic risk. The results of the selected optimal portfolio with an expected return of 0.001, based on these three models, are presented in the table below.

Table 5. The results of the selected optimal portfolio according to the optimal weights

Optimization methods	Sharpe Ratio
The first model (Markowitz with systemic risk limit)	0.150
The second model (only in terms of systemic risk)	0.178
The third model (Markowitz)	0.162

Based on the Sharpe ratio calculated for the optimal portfolio, the second model that only includes systemic risk shows the highest performance.

Also, based on the Sharpe ratio, the efficient frontier of each model based on the results of the second 5-year period (a 5-year out-of-sample period from 2018 to 2023 for 1198 working days), calculated as a rolling window has been extracted and presented in Figures 1 to 3.

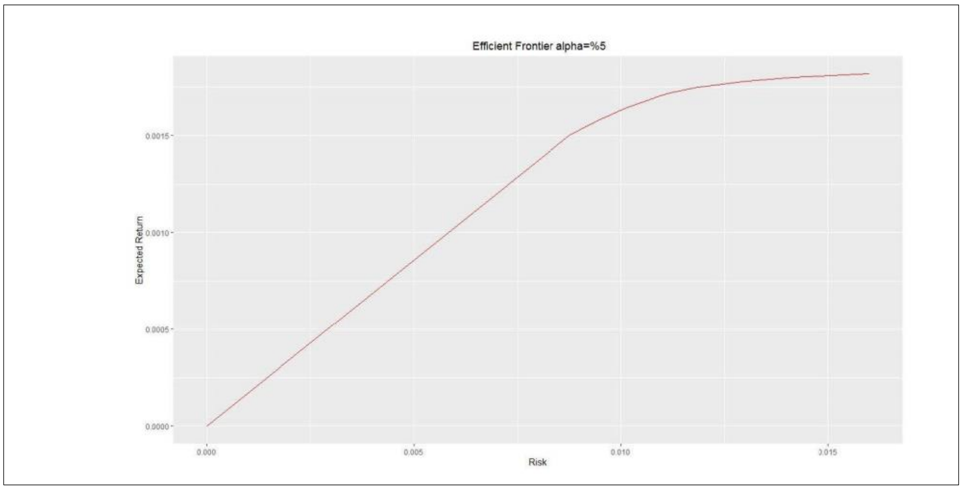

Figure 1. The efficient frontier of the first model (Markowitz with systemic risk limit)

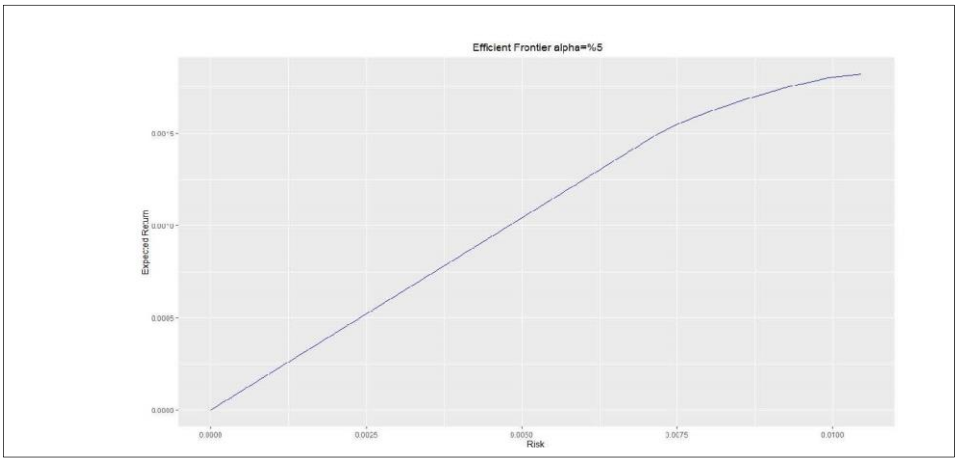

Figure 2. The efficient frontier of the second model (only in terms of systemic risk)

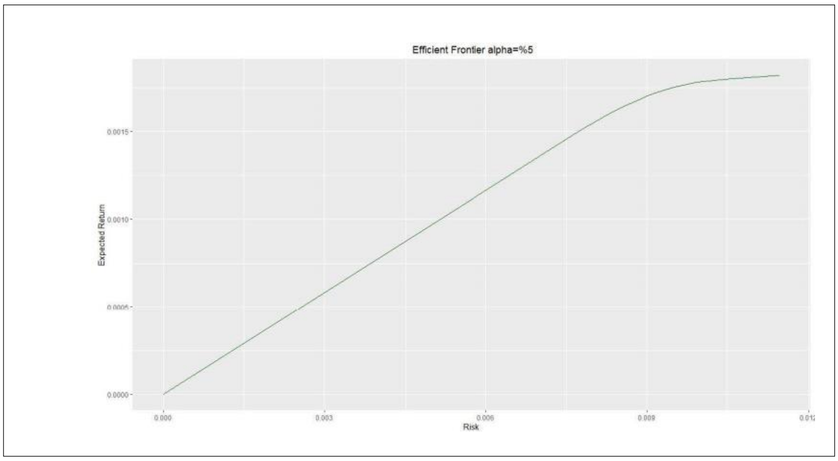

Figure 3. The efficiency frontier of the third model (Markowitz)

As stated, for the purpose of final experimental evaluation, a 5-year out-of-sample period from 2018 to 2023 for 1198 working days has been considered. The result of optimized portfolio return for the period of 1198 days is presented in Table 6.

Table 6. The results of the out-of-sample evaluation for 1198 days

description	the first model	the second model	The third model
Total Return	1355%	1319%	1021%

During the mentioned period and based on the risk measure of each model, the return to risk ratio is also presented in Table 7. In this section, the risk was calculated based on the risk criteria used in each model.

In addition, under the conditions of non-normal distribution of stock returns, especially in emerging markets such as the Tehran Stock Exchange, portfolio performance evaluation indices based on post-modern portfolio theory, including the Sortino ratio and the Omega ratio, have been used. Performance evaluation ratios of post-modern portfolio theory can provide a better insight into the performance of the investigated models, considering how to calculate and consider adverse risk on the one hand and emphasizing all elements of return distribution on the other hand.

Based on all three criteria, the first model, which considers systematic and systemic risk at the same time, shows a better performance compared to the other two models.

Table 7. The return to risk ratio of models in the out-of-sample review

description	the first model	the second model	The third model
Return to risk ratio	0.044947	0.044674	0.0175
Sortino Ratio	0.13501	0.13101	0.10983
Omega Ratio (Ω)	1.2698	1.2556	1.2378

The Kruskal-Wallis test was performed in order to check the significance of the difference between the average return of the three models. The results of the test are presented in Table 8.

Table 8. Kruskal-Wallis test on the returns of three models

The significant value	degree of freedom	statistics
0.915	2	0.17759

According to Table 8, the significance value is equal to 0.915, which is higher than the value of 0.05. As a result, the null hypothesis of the test that there is no significant difference in the return values obtained from the three models used in the research is confirmed. The return trend of the three models is presented in Figure 4.

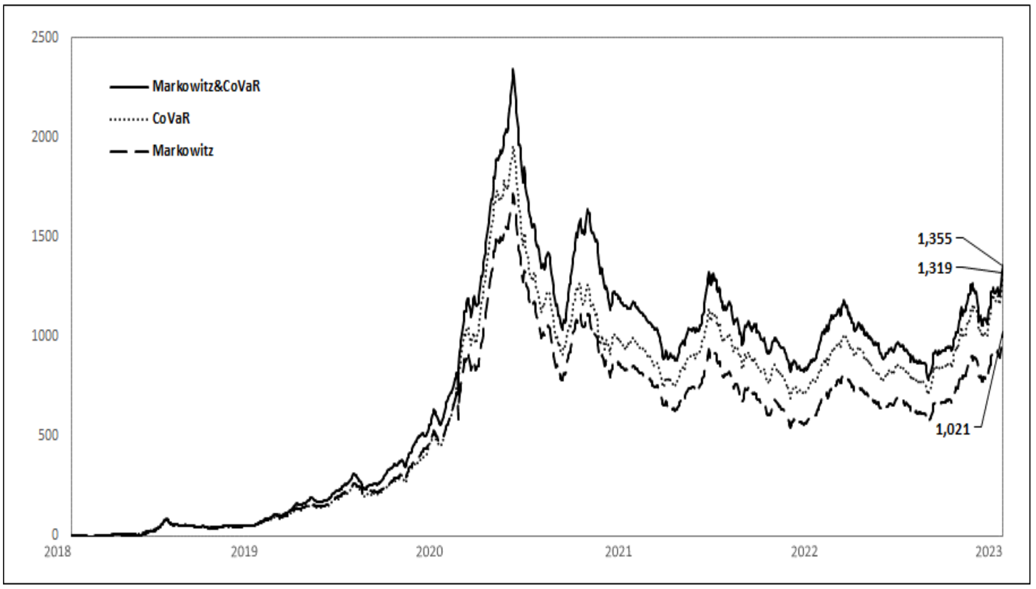

Figure 4. Performance comparison of three models (during the period of 1198 days out of sample in %)

Conclusion

As the father of portfolio management, Markowitz summarized the efforts of financial pioneers in balancing investment risk and returns and presented it as a modern portfolio theory (MPT). With this view that risk is an undesirable factor and should be reduced, he formulated the optimal portfolio model from the point of view of a rational human being. Markowitz showed that the standard deviation of the rate of return is a suitable measure for the risk of the portfolio of securities under a set of logical assumptions and explained a method for calculating the risk of the portfolio of securities. The distinguishing feature of other presented models is the risk measure used in the optimization problem. As the most important theory after Markowitz, it was the proposal of Post-modern portfolio theory (PMPT) that replaced the downside risk measure. After that, the value at risk of the portfolio is a basis for solving the problem.

The main contribution of this research is to provide a model to consider systemic risk in portfolio optimization. For this purpose, two models were examined. The first model presented, which is actually the main contribution of this research in helping the development of financial literature and investment management, is based on the simultaneous consideration of systematic and systemic risk in solving the portfolio optimization problem. In this model, systemic risk was added as a new limit to the model proposed by Markowitz in order to include systemic risk in solving the problem. In the second model, the optimization problem was solved only in terms of systemic risk and by solving the objective function of minimizing the portfolio systemic risk measure.

Also, the criteria used to compare and evaluate the performance of each of the reviewed models include the ratio of reward to risk, along with two portfolio performance evaluation criteria based on post-modern portfolio theory. The results of the empirical analysis of the out-of-sample data show that based on all three mentioned criteria, the proposed model shows better performance than the two other models. In this way, the presented models will increase the practical aspect of the optimization problem.

For future works, the following suggestions are presented:

- Examining portfolio optimization models with other systemic risk measures
- Providing appropriate criteria to evaluate portfolio performance according to different risk criteria
- Providing an optimization model with two objective functions for both types of systematic and systemic risk.

As mentioned in the final suggestions of this section, in order to simultaneously consider systematic and systemic risk in solving the optimization problem, a two-function model can be used for each of the mentioned types of risk. Although this model may provide more accurate results, it will bring more complexity. Meanwhile, from a practical point of view, the presented model is only enough to add a new limit to the Markowitz model to curb the systemic risk in the selection of the portfolio composition and solve the optimization problem using the same original Markowitz method. Therefore, this model helps asset managers to consider systemic risk despite systematic risk simply.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest concerning the research, authorship and, or publication of this article.

Funding

The authors received no financial support for the research, authorship and, or publication of this article.

References

Acharya, V.V., Pedersen L.H., P., Th., Richardson, M., (2017), Measuring Systemic Risk, *The Review of Financial Studies,* 30 (1), 2–47, doi: https://doi.org/10.1093/rfs/hhw088

Adrian, T., Brunnermeier, M.K., (2011), CoVaR, *Federal Reserve Bank of New York Staff Reports*, doi: https://ssrn.com/abstract=3561153

Ahmadi, J., Ghodrati Ghezaani, H., Madanchi Zaj, M., Jabbari, H., Farzinfar, A., (2023). Portfolio Optimization under Varying Market Risk Conditions: Copula Dependence and Marginal Value Approaches. *Advances in Mathematical Finance and Applications*, 9(1), 321-335.

Benoit, S., Colletaz, G., Hurlin, Ch., Pérignon, Ch., (2012), A Theoretical and Empirical Comparison of Systemic Risk Measures.1-42, doi: halshs-00746272v1

Bernard, C., Brechmann, E., and Czado, C., (2012). Statistical Assessments of Systemic Risk Measures, 1-19. doi: https://ssrn.com/abstract=2056619.

Biglova, A., Ortobelli, S., and Fabozzi, F., (2015). Portfolio Selection in the Presence of Systemic Risk, *Journal of Asset Management*, 15(5), 285-299.

Biglova, A., Ortobelli, S., Rachev, S., Stoyanov, S., (2004). Different Approaches to Risk Estimation in Portfolio Theory, *Journal of Portfolio Management*, 31(1), 103-112.

Brownlees, Ch., and Engle R., (2012), Volatility, Correlation and Tails for Systemic Risk Measurement, *Available at SSRN*, doi: http://ssrn.com/abstract=1611229.

Cajas, D., (2023). A Graph Theory Approach to Portfolio Optimization, *SSRN*: https://ssrn.com/abstract=4602019.

Cajas, D., (2023). Portfolio Optimization of Brownian Distance Variance, *SSRN*: https://ssrn.com/abstract=4561293

Capponi, A., LaPlante, A., Rubtsov, A., (2018). Systemic Risk Measures and Portfolio Choice, *Global Risk Institute*, 1-29.

Capponi, A., Rubtsov, A., (2021). Systemic Risk Driven Portfolio Selection, *Available at SSRN*, 1-52. doi: https://ssrn.com/abstract=3394471.

Chan, E., Fan, H., Sawal, S., and Viville, Q., (2023). Conditional Portfolio Optimization: Using Machine Learning to Adapt Capital Allocations to Market Regimes, *SSRN*: https://ssrn.com/abstract=4383184.

Chang, T.J., Meade, N., Beasley, J.E., Sharaiha, Y.M., (2000). Heuristics for cardinality constrained portfolio optimization, *Computers & Operations Research*, 27(13), 1271–1302. doi:10.1016/S0305-0548(99)00074- X.

Civitarese, J., (2016), volatility and correlation-based systemic risk measures in the

US market, *Physica A*, 459, 55–67, http://www.elsevier.com/locate/physa.

Deng, G.F., Lin, W.T., Lo, C.C., (2012). Markowitz-based portfolio selection with cardinality constraints using improved particle swarm optimization, *Expert Systems with Applications*, 39(4), 4558-4566. doi:10.1016/j.eswa.2011.09.129.

Dič pinigaitienė, V., & Novickytė, L., (2018). Application of systemic risk measurement methods: A systematic review and meta-analysis using a network approach. Doi: 10.3934/QFE.2018.4.798

Fabozzi, F., Modigliani, F., Ferry, M., (1997). Translated by Abdullah Tabrizi, Fundamentals of Markets and Financial Institutions, *Pishbord Publishing*, (In Persian).

Ghanbari, H., Shabani, M., Mohammadi, E., (20230), Portfolio Optimization with Conditional Drawdown at Risk for the Automotive Industry. *Automotive Science and Engineering*, 4(13), 4236–4242.

Heybati, F., and Mousavi, S., (2009). Financial Theories. *Publications of the Research Institute of Economic Affairs*, Iran, p. 84–98, (In Persian).

Karimi, M., Ghalibaf e Asl, H., Mohammadi, Sh., (2007), Portfolio Optimization Using Value at Risk Model in Tehran Stock Exchange, *M.A. thesis*, Al-Zahra University, Tehran, Iran, (In Persian).

Kristensen, L., and Vorobets, A., (2024). Portfolio Optimization and Parameter *Uncertainty. SSRN: https://ssrn.com/abstract=4709317.*

Lin, W., and Olmo, J., and Taamouti, A., (2020). Portfolio Selection under Systemic Risk, *Available at SSRN*, doi https://ssrn.com/abstract=3561153.

Lleo, S., (2009). Risk Management: A Review, *Imperial College London, the research foundation of CFA Institute literature review*, 1–51.

Lorimer, D.A., Van Schalkwyk, C.H., Szczygielski, J.J., (2024). Portfolio optimization using alternative risk measures, *Finance Research Letters*, 67, 1-13.

Markowitz, H., (1952). Portfolio Selection, *the Journal of Finance*, 7(1), 77-91.

Nateghi Motlagh, S., Taqavi Moghadam, A., (2016). A review of modern and post-modern portfolio theories, *the second international conference on criticism and analysis of management in the third millennium*, 1-58, (In Persian).

Qu, B.Y., Suganthan. P.N., (2011). Constrained multi-objective optimization algorithm with an ensemble of constraint handling methods, *Engineering Optimization*, 43(4), 403–416. doi:10.1080/0305215X.2010.493937.

Raei, R., and Talangi, A. (2004). Advanced Investment Management. Iran, *The Organization for Researching and Composing University textbooks in the Humanities (SAMT)*, 429-456, (In Persian).

Rey, M., (2023). Rebalanced Portfolio Optimization. SSRN: https://ssrn.com/abstract=4526656.

Sheldon, G., and Maurer, M., (1998). Interbank Lending and Systemic Risk: An Empirical Analysis for Switzerland, *Swiss Journal of Economics and Statistics*, 134(2), 685–704.

Smaga, P., (2014), the Concept of Systemic Risk, *Systemic Risk Centre Special Paper, the London School of Economics and Political Science*, No 5, 1–29. doiDoi: https://ssrn.com/abstract=2477928.

Şova, R., Jianu, I., and Geambasu, L., (2018). Risk measurement in post-modern portfolio theory: Differences from modern portfolio theory, *The Bucharest Academy of Economic Studies,* 113-132. doiDoi: https://www.researchgate.net/publication/286072010.

Varmaz, A., Fieberg, Ch., and Poddig, Th., (2022), Portfolio Optimization for Sustainable Investments. *SSRN*: https://ssrn.com/abstract=3859616

Bibliographic information of this paper for citing:

Azad, Mohammad; Mirfeiz, Fallah Shams; Rahmani, Ali & Mohammadi, Teymour (2025). Portfolio Optimization with Systemic Risk Approach. *Iranian Journal of Finance*, 9(1), 32-61.