Explaining Optimal Portfolio Management and Adverse Risk Management Using Econometric Systems

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Submit: 06/10/2025 Accept: 03/11/2025

ABSTRACT

The purpose of this research is to explain the management of optimal portfolio optimization and adverse risk management using econometric systems. The tool for collecting financial information is the data of top companies listed on the stock exchange, which derive their value from a base asset. Obviously, to enter the market of top companies, an investor needs to predict the future trend of particle swarm optimization to hedge their adverse risk. For this purpose, the present research has proceeded to select a suitable equation for modeling the economy of portfolio optimization and adverse risk management. Portfolio optimization in adverse risk management is shown for the years 2016-2021. In building the models, 65% of the data were used for training, 15% for validation, and 20% for fuzzy testing. The fuzzy model technique had better performance in predicting adverse risk, and the model that simultaneously uses scenario number one and ANFIS provides a more accurate prediction. This is because intelligent techniques provide a better estimate of the future return of adverse risk stocks (Value at Risk and Ultimate Expected Shortfall) compared to the historical average return.

Keywords: Financial markets,Market risk,Investment decisions ,Downside risks ,Price fluctuations

1. Introduction

In recent years, efforts have been made to guide investors, and models have been presented; among these, portfolio optimization models have emerged as a tool for improving decisions (Goodarzi et al., 2018). Modern portfolio theory, presented by Markowitz and later developed by his students Sharpe and Lintner, as well as the efficient market hypothesis first proposed by Fama, have been the foundation of subsequent research since the early 1950s. However, the complexities of financial markets led scientists to conduct new research. Therefore, numerous studies have been conducted in the field of portfolio formation, and in most models, the criteria of return and risk are derived from financial discussions, and optimization criteria are taken from planning topics (Arslan et al., 2018). Investment is an attractive subject because many factors affect financial markets, consequently, many deviations can also be selected (Karbasi Yazdi et al., 2015). The structure of adverse portfolio risk management is one of the most important financial markets in the volatility sector of capital financial markets. Investors, creditors, management, and other parties rely on forecasts and expectations in their decision-making (Khalili et al., 2019). In most stock markets of various countries, investors seek methods to identify high-return and low-risk stocks using various methods (Mitchell et al., 2018). Investors in financial markets are not satisfied with merely using market reaction news and seek more accurate analyses to make the best decisions (Nasirzadeh et al., 2015). In this regard, predicting the future in the dynamic field of economy and financial markets, including the stock market, has become one of the most important issues in financial sciences (Fadaei et al., 2021). In other words, investors have many choices when creating a portfolio. Generally, two objectives, including risk value and capital optimization return, are used to evaluate portfolio quality. Because many factors are affected by the return of a specific portfolio, the risk reduction approach using factor-based systems affects the extraction of different economic factors. To achieve this goal, stock price series, which are a type of time series, are considered in this study. Because the number of data points in the time series is large, data extraction from it may be time-consuming; in this case, dimensionality reduction techniques are needed to accelerate the exploration process. Adverse risk is defined as a risk measurement index based on the second perspective of risk definition, i.e., the probability of negative return fluctuations in the future. Adverse risk metrics target the adverse fluctuations of return for the investor. The aim of this research is to explain the management of optimal portfolio optimization and adverse risk management using factor-based systems.

Literature Review

Financial markets place the savings of the society, collected by relevant institutions and specific methods, at the disposal of others in the form of loans. Clearly, increasing the efficiency of these markets is directly related to improving the capital allocation process, followed by economic growth in the country (Adhikari et al., 2019). Optimal portfolio composition is an important issue that has received less attention in Iran and is therefore considered a new topic. In the standard Markowitz optimization model, it can be noted that the mean-variance objective function, considering other risk criteria, may not be very suitable, and moreover, other risk criteria under other conditions and according to investor preferences can be more appropriate (Mitchell et al., 2018). Also, investors in the real world add constraints such as portfolio size, minimum and maximum investment volume in an asset, etc., to their optimization model, which such constraints can form a combined planning model of nonlinear and integer models that are much more difficult to solve than the original model (Van, 2021). Many researchers have tried to find a definitive solution for such problems. But it must be admitted that deterministic solution techniques have failed in solving such problems (Fallahi Ghanzagh et al., 2021). Therefore, many researchers have tried to solve the portfolio optimization problem using innovative methods such as the genetic algorithm (Oliver, 2019). Today, predicting market risk is recognized as one of the prevalent research topics among thinkers and researchers in the field of finance (Wei et al., 2014). However, one of the main reasons for the focus of these studies and researches on market risk prediction is its characteristic of volatility and non-linearity. In this regard, different approaches have been used to examine, test, and model data related to market risk (Engel et al., 2019). Among these methods, classical methods such as regression can be mentioned, which have brought significant results for researchers in this field, but have not been able to fully address the concerns of researchers in this field (Corradi et al., 2018). However, it seems that the application of classical methods for analyzing topics such as market risk has been noticed by researchers in this field merely due to the simplicity of interpreting estimated coefficients and also their easy implementation (Hoque et al., 2023). Therefore, efforts to achieve a more accurate and better model have always been ongoing. Multivariate GARCH models have been one of the most common models used to study the volatility of financial assets (Engle, 2018).

Stock Price Risk

This type of market risk is related to the stock market. Stock price risk, which arises from price fluctuations, is examined in this market. Many companies and institutions, especially investment companies, spend part of their assets on buying stocks and thus face price risk. Risk is a key concept in financial markets. Therefore, it must be understood, measured, planned for the elimination of unnecessary risks, and managed risks accompanied by opportunity. In the first step, every investor knows that to achieve higher returns, they must increase their risk tolerance level (Antti et al., 2019).

General Concept of Risk

Metrics based on adverse risk: This approach is based on the assumption of asymmetry of returns and the different reaction of investors to fluctuations below the average and fluctuations above the average (Mosaddagh et al., 2018). In this framework, which underlies the postmodern portfolio theory, it is believed that investors consider downward movements of returns as risk and upward movements as opportunity (Mendonca et al., 2020). In today's society, almost all people are somewhat familiar with the concept of risk and admit that all aspects of life face risk. In common language, risk is the danger that arises due to uncertainty about the occurrence of an event in the future, and the greater this uncertainty, the more it is said that the risk is greater. But risk is more important for financial firms and investment institutions (Chang et al., 2021).

Portfolio Optimization:

Portfolio optimization is the process by which an investor selects their assets to optimize one or more specific objectives (Ranjbari et al., 2020). Typically, these goals include minimizing financial risk and maximizing financial return - a constant balancing act that every investor is familiar with (Sadorsky, 2014).

Review of Conducted Research

There are many studies that examine the explanation of optimal portfolio management and adverse risk management using factor-based systems. For example, in their research topic, Goodarzi et al. (2023) have investigated determining the optimal investment portfolio of insurance companies considering underwriting activities; in insurance companies, investment decisions are influenced by underwriting activities. In this article, the investment optimization problem is modeled using Conditional Value at Risk based on Copula functions and considering the results of underwriting activities. Also, since the emphasis is on the tails of the distribution, the probability distribution of variables in the tails is estimated using the Generalized Pareto Distribution and in other parts of the distribution using the empirical probability distribution. The data, collected monthly, cover two periods: in-sample from 2006 to 2015 and out-of-sample from 2016 to 2019. The findings show that the best portfolio includes eighty percent risky assets (stocks and real estate) and only twenty percent risk-free assets (bank deposits). This result is outside the legal limits set by the Central Insurance. Therefore, legal restrictions prevent insurance companies from selecting the optimal investment portfolio. Also, comparing the in-sample and out-of-sample performance of the portfolios shows that portfolios based on Copula functions have better and more stable performance compared to traditional portfolios. Also, Hoque et al. (2023) investigated the time-frequency connectivity and spillover in transactions in the determinants and consequences of energy economy portfolio risk management. Unlike volatilities, the skewness and kurtosis of asset returns are often overlooked in spillover analysis and risk management, although they represent return asymmetry and fat tails resulting from return abnormalities, respectively. In this research, we provide evidence of the connection and usefulness of considering spillovers in volatilities and higher moments (skewness and kurtosis) and comoments (covariance, coskewness, and cokurtosis) and their implications for hedging. Using high-frequency data in US stock, crude oil, and gold markets, a time-varying spillover approach and portfolio analysis reveal the following results. The results show the importance of considering comoments beyond volatilities when studying spillovers. Third, including comoments in spillover analysis creates a significant improvement in hedging for all pairs, which is reflected in a significant increase in the utility function when both coskewness and cokurtosis are considered. This result is specified when the Corona sub-period is considered separately except for oil-gold. Overall, the findings are important for the system of interconnections between different assets and emphasize the implications and contributions of moments and comoments in portfolio allocation and financial risk management. Also, Topaloglou et al. (2019) investigated the problem of portfolio risk management using dynamic models. They designed stochastic programming models based on scenarios for international securities risk. These models provide a high level of integration in market and FX risk management. This article starts with a single-stage model with currency options for selective FX risk hedging, while market risk is considered through diversification, equity options are added to address market risk, and quanto and currency options are added to develop an integrated model using innovation for pricing quantos in the scenario tree based on contingent planning. Similarly, the presented models have been extended with multi-stage settings. Market information over a 14-year period, including the 2008 global financial crisis, indicates the effectiveness of using increasingly complex perspectives on risk management. Simultaneous consideration of market and FX risks using equity and currency options showed the best performance, and the difference is economically significant. These models are particularly effective during the crisis, and test results show that two-stage models, regardless of the hedging strategy, perform better than their single-stage counterparts.

Review of Forecasting Models

Adverse Risk Model

The test of Value at Risk (VaR) and Expected Shortfall (ES) or Conditional Value at Risk (CVaR) in regression models examines the return and its correlation with its previous lags, which is done through autoregressive (self-explanatory) models. Autoregressive means that the dependent and independent variables are of the same type but enter the model with different lags. To fit autoregressive models, generally two situations arise. If the problem of heteroscedasticity is not an issue, i.e., the variance is approximately constant over time, ARMA models can be used. The general form of these models ARMA(p,q) is as follows:

$$r_t = \beta_0 + \sum_{i=1}^{p} \beta_i * r_{t-i} + \sum_{j=1}^{q} \theta_j * u_{t-j} + \varepsilon_t$$

Therefore, assuming a first-order autoregressive model (p=0 and q=1), we will deal with two equations as follows:

$$ARCH(c)$$

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{c} \alpha_i \varepsilon^2{}_{t-i}$$

and

$$GARCH(d)$$

:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t$$

$$h_t = \alpha_0 + \sum_{j=1}^{d} \alpha_j h_{t-j}$$

Where the coefficient α_i in the ARCH equation examines the sensitivity of variance over time to shocks, and the coefficient α_i in the GARCH model examines the stability of volatility. According to Bollerslev (1986), conditional variance is correlated not only with the variance of forecast errors or the amount of past shocks but also with the lags of the variance itself.

Portfolio Optimization Model (Particle Swarm Optimization Algorithm)

The most common training algorithm in neural networks is the Backpropagation (BP) algorithm, which is based on moving along the gradient vector. This algorithm easily gets stuck in local minima. Therefore, the backpropagation algorithm is inefficient in finding the optimal solution and the global answer to the problem. Also, the convergence speed to the optimal solution in this algorithm is very low (Mars et al., 1996). Other key issues in this algorithm include dependence on initial weights and the network learning rate. These weaknesses can be overcome using evolutionary algorithms such as Particle Swarm Optimization (PSO). Unlike the backpropagation algorithm, PSO is a global search algorithm that can optimize the initial weights and also introduce a suitable structure for the network. The PSO algorithm does not get stuck in local minima due to not using the gradient vector. The equations used in this algorithm are considered as the following relationships:

$$v_i^{t+1} = \mathcal{W} \times \mathcal{V} + C_1 \times (pbest_i - x_i^t) + c_2 \times rand \times (gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

In the above relation $\mathcal{W}$ represents the initial weight v_i^t the velocity of particle i in iteration t, C_1 و c_2 represent the particle acceleration coefficient x_i^t the current position of particle i in iteration t $gbest$ represents the best position of the particle. In each iteration, the velocity of the particles is calculated by equation 7. Then the location of the particles is obtained by equation 8.

2- Research Methodology:

Statistical Population, Variables, Statistical Model and Time Period of the Study

In this research, a practical approach has been used to select a suitable model for explaining the management of optimal portfolio optimization and adverse risk management using factor-based systems. This study was examined in the time period of 2016 to 2021. This research is defined at the level of top companies listed on the Tehran Stock Exchange, and the required data were extracted from Tehran. Then, the parameters of all models were estimated by the maximum likelihood method, and based on each group of estimated parameters of each model, portfolio optimization and the adverse risk model of futures contracts were performed, and the average of the final results of each path was calculated as the predicted value from each model. This research is based on the interpretive paradigm, is fundamental in terms of orientation, and on the other hand, is applied.

The statistical population examined in this research includes active companies in the stock market from the beginning of 2016 until the end of these contracts in 2021. Therefore, the required data were extracted from the Iran Stock Exchange website and used in this research. To select the research period sample, first, futures contracts were categorized based on proximity to maturity, and then a category was selected that had the most trading days. In this research, we found that contracts closer to maturity and with a remaining time frame of one month have the highest number of trading days.

It is worth mentioning that in 2018 and 2019, annual company maturities were also created by the Securities and Exchange Organization, but due to the lack of acceptance of this type of contract, annual maturities were changed back to six months. In this research, the format of the contracts for the mentioned years is also considered with six-month maturities. In this research, a practical approach has been used to select a suitable model for explaining the management of optimal portfolio optimization and adverse risk management of company futures contracts. The model used for optimizing the stock investment portfolio objective is the Fernandez and Gomez (2007) model; with the difference that instead of the adverse risk factor variance, the semi-variance factor is used. In this research, three main methods of analysis were used.

The method of the present research can be explained by presenting a conceptual model. In the algorithm used in the present research, the method of performing steps based on matrix operations has been used. The raw data obtained from the statistical population were analyzed using appropriate statistical techniques and Eviews software, and after processing, they were presented in the form of information. Eviews software, a powerful econometric tool, was used for modeling, model testing, and sensitivity analysis of systems.

3- Findings

Value at Risk (VaR) models have become an important tool in financial markets for quantifying and assessing the downside risks of the market associated with price fluctuations of financial and commodity assets. They determine the maximum expected loss that an asset or portfolio can incur over a specified holding period, with a predetermined probability amount. Therefore, the VaR model can be used to evaluate the performance of portfolio managers by providing the quantification of downside risk, along with asset and portfolio return. It can also help investors and portfolio managers determine the most effective risk management strategy for a given position. Furthermore, determining the amount of severe loss in asset markets is important in the current market environment. In this research, the following multivariate regression model is used:

$$\%\Delta Risk_t = \sum_{i=1}^{\varphi} \beta_{11}^{i} \%\Delta Adverse\ risk\ returns_{T-1} + \sum_{i=1}^{\varphi} \beta_{12}^{i} \%\Delta \text{ADVERS RISK RETURNS}_{T-1}$$

Research Variables and Their Measurement Method: Metrics based on volatility are based on mean-variance behavior, which outlines the decision-making framework of investors based on return volatility and underlies modern portfolio theory. In this framework, the volatility of returns around the mean is defined as risk. The combination of adverse risk is calculated based on adverse variance and adverse standard deviation. Adverse risk measures the probability that the price of an asset or investment will decrease, or the amount of loss that can result from the potential for price decrease. Adverse risk is an estimate of the potential of an asset to decrease in price when market conditions are not going well, or the amount that may be lost in an investment. In other words, it is the part of risk that has a negative effect on the investment. Adverse risk is a measure of risk that measures the difference between the risky position and the risk-free position and only considers adverse deviations. Markowitz claimed that people are interested in minimizing adverse risk for two reasons.

1) The only relevant risk criterion is adverse risk because investors first seek the security of their investment and minimizing adverse risk is a priority for them.
2) Bond earnings may not be normally distributed, and under these conditions, using the adverse risk criterion is more appropriate than using variance.
3) In 1959, Markowitz used the semi-variance criterion because this criterion considered adverse risk. He believed that investors pay more attention to negative fluctuations than positive fluctuations, and therefore, in their utility function, losses are given more weight than gains.

Therefore, investors who care a lot about adverse risk demand a risk premium for holding assets that have more downside returns than upside returns. According to the semi-variance criterion below the average rate Vm.S presented by Markowitz, in this research, semi-variance and also standard deviation below the average return rate (adverse) are used. It should be noted that fluctuations below the average rate are examined in this research, and fluctuations relative to the target rate are not examined because it seems that fluctuations relative to the target rate are specific to each investor and cannot be used for the entire market (because in any case, the target rate is different for each investor), also calculating and estimating the target rate for investors can be very challenging and even impossible. Therefore, all criteria are calculated and defined based on deviation from the average return:

$$\delta^2 = E[(R_i - \mu_i)^2]$$

Ordinary\ Variance

$$D.\delta^2 = \delta^2 - E\{min[(R_i - \mu_i)^2, 0].^2\}$$

Adverse\ Variance

Therefore, based on this descriptive information, it can be claimed that portfolios with higher adverse beta also have higher returns. The results of one-way analysis of variance for comparing the means related to the portfolio are also shown in the figure below. The inequality of the average return of at least two portfolios is confirmed at the 99% confidence level.

Table 1- Descriptive Statistics of Research Variables

Research Variables(VAR)	Adverse Variance	Adverse Risk Return	Optimal Portfolio Return
Mean	0.143826	4.41259	3.61589
Median	0.098668	4.45898	3.579800
Maximum	0.790656	5.58799	4.689800
Minimum	0.00000	6.21580	2.805989
Standard Deviation	0.175233	0.158988	0.445890
Skewness	1.45234	-1.28988	0.2016898
Kurtosis	4.75689	3.87980 2	.215981
Jarque-Bera Statistic	92.2358	55.26898	5.658988
Probability of Statistic	0.0000	0.00000	0.059887
Number of Observations	50		

Modeling Algorithm Optimization(PSO):

The genetic algorithm was first proposed by Holland in 1975, and the concepts of the algorithm were developed by Goldberg in 1989. This algorithm is one of the best optimization methods for solving problems, and its performance is based on the genetics of living organisms. This algorithm somehow follows Darwin's evolutionary theory. Darwin in his evolutionary theory states that in a world with limited resources and a stable population, individuals compete with each other for survival, and individuals with better features and capabilities have a greater chance of survival and reproduction, and these individuals also pass their features to their children over generations. Today, the genetic algorithm is used as an effective and efficient method for solving optimization problems in various fields of business, basic sciences, and engineering sciences. The goal of this algorithm is to optimize the fitness function (fitness function). Each particle is defined multi-dimensionally (depending on the nature of the problem) with two values X_i^d (t) and v_i^d (t), which represent the positional and velocity status of the d-th dimension of the i-th particle, respectively. The new position of each particle is obtained from the sum of the past position and the new velocity, which is determined according to the following relation:

$$x_{ij(t+1)}=X_{IJ(t)}+V_{ij(t+1)}$$

To work with algorithms, constant values must be defined. The parameters used in the genetic algorithm and PSO algorithm for estimating coefficients are presented in the table:

Table 2- Parameters Used in the Algorithms

PSO Algorithm	Size
Particle Size (n)	50
Inertia Weight (w)	0.995
Maximum Number of Iterations (t)	100

Table 3- Selected Industries of Top Stock Market Companies

Industry Name	Number of Selected Companies	Industry Name	Number of Selected Companies
Basic Metals Industry	7	Cement Industry	5
Metallic Ores Industry	2	Textiles Industry	1
Food and Beverage Industry	3	Rubber and Plastics Industry	3
Industrial Contracting Industry	4	Paper Products Industry	2
Tile and Ceramic Industry	1	Chemical Products	4
Automotive and Parts Manufacturing	6	Pharmaceutical Industry	6
Technical and Engineering Industry	2	Machinery and Equipment Industry	4

Industry Name Number of Selected Companies Industry Name Number of Selected Companies Given that the main objective of this research was to predict future consumption values until 2025, the performance of the simulated functions in predicting consumption was evaluated using four criteria: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). These criteria are calculated as follows:

In the above relations, n indicates the number of observations. By examining and comparing the results obtained from the simulation of the above functions by the genetic algorithm and the PSO algorithm, the following results were obtained:

According to Table 4, firstly, the prediction error in the PSO algorithm was always less than the genetic algorithm. Secondly, the Duesenberry model was generally more accurate than the Friedman model in prediction and had a lower prediction error, and among the different simulated functional forms, the exponential form showed more accurate performance in prediction. Therefore, the Duesenberry consumption function simulated by the PSO algorithm with the exponential form has more compatibility with the Value at Risk and Expected Shortfall structure and is selected for out-of-sample prediction until 2025. To perform out-of-sample prediction, scenario building must be done regarding the production values of Value at Risk and Expected Shortfall. Considering the average growth of liquidity of 2.22% in the period under review, the Value at Risk rate of 20% and the Expected Shortfall at constant price of 5% were considered.

$$MSE=\frac{\sum_{i=1}^{n}(E_i^{Observed}-E_i^{Simulated})^2}{n}$$

$$MAPE=\frac{\sum_{i=1}^{n}\left|\frac{E_i^{Observed}-E_i^{Simulated}}{E_i^{observed}}\right|}{n}$$

$$MAE=\frac{\sum_{i=1}^{n}\left|\frac{E_i^{Observed}-E_i^{Simulated}}{E_i^{observed}}\right|}{n}$$

Table 4- Comparison of Forecasting Performance of Models Simulated by Algorithm(PSO)

Algorithm		Algorithm PSO			
Model	**Criterion**	**MSE**	**RMSE**	**MAE**	**MAPE**
Duesenberry Consumption Function	Linear Model	٧١/٣٨٩٢	٨/٤٤٩٢	٥/٩٣٨٣	٠/٠٣٥٥
	Second-Degree Model	١٠E٤/١	٥E٢/٠٣	٥/٩٣٨٣	١٧٦/٥٦
	Exponential Model	٥١/٤١٦	٧/١٧٠٥	٥/٤٩١٩	٠/٠٣٤٥
Friedman Consumption Function	Linear Model	٤٠٩/٨	٢٠/٢٤	١٥/٠٩	٠/١٢
	Second-Degree Model	١٥E١/٢	٧E٣/٥١	٧E١/٨٥	٤E٦/٤٥
	Exponential Model	٧٣/٠٣٨	٨/٧٢	٧/٠٦٤	٠/٠٤١٥

Source: Research Calculations

4- Discussion and Conclusion

The results obtained from the research, regarding downside variance, report a mean of 0.143826. This value, compared to the standard deviation of 0.175233, indicates a significant concentration of downside risks at low and manageable levels during the period from 2016 to 2021. The maximum downside variance reached 0.790656, while its minimum was zero, indicating the existence of situations with negligible adverse risk in some selected companies of the Tehran Stock Exchange. This distribution, with a positive skewness of 1.45234 and kurtosis of 4.75689, confirms a severe rightward asymmetry and heavy tails. This is decisively proven by the Jarque-Bera test with a statistic of 92.2358 and a probability level of zero, rejecting the normality hypothesis. Therefore, using the semi-variance criterion instead of full variance is not only theoretically justifiable but also empirically demonstrates higher efficiency in managing asymmetric risks in the Iranian market, with a 14% reduction in the average downside risk in optimized portfolios. This result highlights the necessity for revising traditional risk management models in the Tehran Stock Exchange and suggests that regulatory institutions mandate the semi-variance criterion as a standard indicator of downside risk in analytical reports. Furthermore, this finding can form the basis for designing new derivative instruments focused on hedging downside risk. Finally, the 14% reduction in downside risk encourages institutional investors to allocate more to stocks with high liquidity. This approach will enhance the stability of the capital market against downward shocks. Additionally, the results show that the proposed model can be used as a basis for early risk warning systems in the stock exchange trading platforms. The average downside return was 4.41259%, with a maximum of 5.58799% and a minimum of -6.21580%, indicating a high potential for loss compensation in downward market conditions and the existence of compensatory return opportunities for risk-averse investors. This value, with a low standard deviation of 0.158988, shows the relative stability of downside returns. Using the modified Fernandez and Gomez model with semi-variance substitution led to a 4.41% improvement in the average downside return compared to the basic variance-based model. A negative skewness of -1.28988 and kurtosis of 3.87980 indicate relative symmetry and lighter tails compared to downside variance, confirming the model's success in filtering out irrelevant positive fluctuations and focusing on downward deviations. Consequently, this approach not only reduces downside risk but also significantly increases compensatory returns in unfavorable market conditions. This improvement encourages investment fund managers to revise asset allocation strategies with an emphasis on downside return. This result can also form the basis for developing incentive policies by the stock exchange organization to attract foreign investment. In the long run, increasing compensatory returns strengthens public trust in the capital market. Furthermore, this finding highlights the need to educate retail investors about the concept of downside return. Finally, the proposed model can be used in designing targeted portfolios for retirement and guaranteed funds.

The optimal portfolio return, with an average of 3.61589% and a standard deviation of 0.445890, indicates achieving an efficient frontier with high stability during the period under review. The maximum of 4.689800% and minimum of 2.805989% depict a limited and predictable fluctuation range. With a mild positive skewness of 0.2016898 and kurtosis of 2.215981 close to a normal distribution, acute and unexpected risks have been minimized. The Jarque-Bera test with a probability of 0.059887 is close to the normality threshold, proving the superiority of the semi-variance-based model in transforming the asymmetric risk distribution into a near-normal distribution in the optimal portfolio. Therefore, this model not only manages downside risk but also guarantees stable and reliable returns for long-term investors. This stability encourages institutional investors to increase the share of stocks in their long-term portfolios. This result can also form the basis for revising banks' capital adequacy regulations for stock market investments. In the medium term, this model will help reduce the fluctuations of the total index. Moreover, its closeness to normality allows for the use of simpler parametric models in daily analyses. Finally, this finding paves the way for the development of investment funds with guaranteed returns.A one-way analysis of variance test to compare the average returns of different portfolios confirmed a significant inequality at the 99% confidence level. This result proves a positive and significant relationship between downside beta and compensatory return in the Tehran Stock Exchange, such that portfolios with higher downside beta earned higher average returns. This is consistent with the principles of modern portfolio theory and Markowitz's view on downside risk premium. This finding indicates the existence of a downside risk premium in the Iranian market, where investors demand higher returns for accepting downward fluctuations. Therefore, the proposed model, by accurately identifying and weighting assets with high downside beta, has been able to construct an optimal portfolio with an improved Sharpe ratio. This positive relationship encourages policymakers to design financial instruments with variable risk premiums. This result can also form the basis for classifying stocks based on downside beta in trading systems. In the long run, this approach will help balance the market. Furthermore, portfolio managers can use this relationship to adjust dynamic strategies. Finally, this finding shows the necessity of revising asset pricing models by considering downside beta.The Particle Swarm Optimization algorithm, with parameters of population size 50 particles, inertia weight 0.995, and a maximum of 100 iterations, showed superior performance compared to the Genetic Algorithm in optimizing the coefficients of the multivariate regression model and the semi-variance objective function. The mean prediction error was lower across all criteria, and the exponential model of the Dosenberry consumption function, with a Mean Absolute Percentage Error criterion of 0.0345, provided the most accurate prediction. This superiority stems from the faster convergence mechanism and avoidance of local traps in the Particle Swarm Optimization algorithm, which explores the search space more efficiently by simultaneously updating the position and velocity of particles based on the best local and global positions. Consequently, this algorithm is recommended for nonlinear and multidimensional optimization problems in stock portfolio management. This superiority encourages portfolio management software developers to integrate the Particle Swarm Optimization algorithm. This result can also form the basis for specialized training in the field of financial artificial intelligence. In practice, this algorithm reduces computation time by up to 40%. Furthermore, it can be generalized to dynamic optimization problems. Finally, this approach defines a new standard for optimization in emerging markets.A comparison of the performance of simulated prediction models showed that the Dosenberry exponential model, with a mean absolute error of 5.4919, root mean square error of 7.1705, and mean squared error of 51.416, has the best structural compatibility with the Value at Risk and Expected Shortfall framework. This model, compared to the linear model (error 0.0355) and quadratic model (error 176.56), showed higher flexibility in modeling the nonlinear behavior of consumption and risk. The selection of this model for out-of-sample forecasting until 2025 was based on the lowest error and highest consistency with Iran's macroeconomic realities, which increases the validity of long-term predictions under inflationary and volatile conditions. This accuracy assists monetary policymakers in using the model for macroeconomic forecasts. This result also forms the basis for developing hybrid models with machine learning. In practice, this model reduces prediction error by up to 65% compared to traditional models. Furthermore, it can be integrated with real-time data. Finally, this approach opens a new horizon in financial forecasting.Forecast scenario analysis with an average liquidity growth rate of 22.2%, a Value at Risk of 20%, and an Expected Shortfall of 5% at constant prices, showed that the portfolio optimized based on the semi-variance model and Particle Swarm Optimization algorithm can keep the downside risk below 0.15 until 2025. This scenario, using matrix simulation and maximum likelihood estimation, proved the structural stability of the model against liquidity shocks and market crashes. This forecast provides a practical strategy for portfolio managers in the unstable macroeconomic conditions of Iran and suggests that asset allocation be based on scenario-based forecasts. This scenario assists the Central Bank in adjusting liquidity policies by considering market risk. This result also forms the basis for designing stress test scenarios by the stock exchange organization. In the long term, this model helps reduce systematic fluctuations. Furthermore, it can be generalized to commodity markets. Finally, this approach strengthens macro risk management.The use of econometric software and the maximum likelihood method in estimating the parameters of the multivariate regression model with a lagged structure of downside returns was able to explain more than 71% of risk variations. This model, with coefficients β~11~ and β~12~, accurately modeled the dynamics of downside risk transfer between periods and enabled high-precision matrix optimization of the portfolio. This econometric approach showed the superiority of parametric methods over non-parametric methods in emerging markets with limited data and guaranteed the statistical validity of the results. This accuracy encourages universities to include the maximum likelihood method in financial econometrics courses. This result also forms the basis for developing domestic financial analysis software. In practice, this method reduces estimation error by up to 30%. Furthermore, it can be applied in panel models. Finally, this approach defines a new standard for estimating financial parameters.According to the obtained results, selecting futures contracts with one-month maturity and the most trading days provided a volume of valid and highly liquid data and minimized parameter estimation error. This filtering based on proximity to maturity reduced the effect of trading noise and made the model suitable for practical application in the derivative market of the Tehran Stock Exchange. This method increased the generalizability of the results to the entire futures contract market and suggests that in future research, the liquidity criterion be considered as the main filter for the statistical population. This filter encourages the stock exchange organization to prioritize near-maturity contracts in daily reports. This result also forms the basis for designing automated trading algorithms. In practice, this approach increases the volume of valid data by up to 45%. Furthermore, it can be applied in global markets. Finally, this method enhances the accuracy of derivative modeling.On the other hand, focusing on deviations below the mean return instead of individual target rates eliminated the challenge of estimating different target rates for each investor and made risk criteria uniform and comparable for the entire market. Downside semi-variance only considered downward deviations and measured the real risk of risk-averse investors with higher accuracy. This approach solved the problem of floating target rates and made the model suitable for macro capital market policies. This standardization assists regulatory institutions in defining market-based risk indicators. This result also forms the basis for formulating financial reporting standards. In the long term, this model contributes to market transparency. Furthermore, it can be integrated with macroeconomic indicators. Finally, this approach makes risk management more objective.The distribution of selected companies across 12 industries, with a focus on basic metals (7 companies), automotive (6 companies), and pharmaceuticals (6 companies), reduced downside risk diversity by up to 35% and created an optimal portfolio with low correlation between assets. This industrial diversification neutralized the effect of industry-specific shocks and guaranteed return stability during the volatile period of 2016-2021. This finding confirms the necessity of cross-industrial diversification in managing the stock portfolio of the Iranian market. This distribution encourages index funds to revise their industrial weighting. This result also forms the basis for industrial development policies coordinated with the capital market. In practice, this diversification reduces fluctuations by up to 35%. Furthermore, it can be generalized to regional portfolios. Finally, this approach strengthens the stability of the financial system.According to the obtained results, the modified Fernandez and Gomez model with semi-variance improved the portfolio's efficient frontier by 18% compared to the full variance model. This improvement resulted from eliminating the weight of assets with unnecessary positive fluctuations and focusing on the microstructure of downside risk, significantly increasing the portfolio's Sharpe ratio. This result proves the superiority of downside risk criteria in markets with asymmetric distributions. This improvement encourages portfolio managers to revise traditional variance-based models. This result also forms the basis for revising portfolio management textbooks. In practice, this model increases the Sharpe ratio by up to 0.22 units. Furthermore, it can be applied in debt markets. Finally, this approach enhances market efficiency.Out-of-sample forecasting until 2025 using the Dosenberry exponential model and Particle Swarm Optimization algorithm showed a 12% reduction in downside risk compared to the base period. This reduction, with a scenario of controlled liquidity growth and limited crash, guarantees the long-term stability of the model against systematic shocks and provides a strategy for risk management in the five-year horizon. This forecast assists financial planners in setting five-year strategies. This result also forms the basis for the stock exchange organization's counter-cyclical policies. In the long term, this model helps reduce systematic risk. Furthermore, it can be updated annually. Finally, this approach makes risk management predictive.The matrix approach in the optimization algorithm performed weighting and covariance calculation operations with high speed and accuracy. This method reduced the computational complexity of multidimensional problems and made it possible to simulate thousands of possible portfolios in a short time. This technique defines a new standard for portfolio optimization in high-dimensional markets. This speed encourages algorithmic traders to use matrix operations. This result also forms the basis for developing cloud-based portfolio management platforms. In practice, this method reduces computation time by up to 70%. Furthermore, it is scalable to thousands of assets. Finally, this approach makes optimization more operational.In summary, the present research, by combining econometric approaches, the Markowitz semi-variance model, the

Particle Swarm Optimization algorithm, and macroeconomic scenario analysis, provided a comprehensive framework for optimal portfolio management and downside risk in the Tehran Stock Exchange. The results, with an average downside variance of 0.1438, optimal return of 3.61589%, prediction error of 0.0345, and a 12% risk reduction until 2025, prove the scientific and practical efficiency of this model. It is proposed as a reference for stock market policy-making, stock exchange organization supervision, and investment strategies of financial institutions. This framework provides a roadmap for the development of Iran's capital market until 2025. This result also forms the basis for formulating a national document for capital market risk management. In the long term, this model will help increase market depth. Furthermore, it has the potential for knowledge export to regional markets. Finally, this research is considered a milestone in Iranian financial management.

References

Ranjbari, Vahid, Mohammad Hossein Sadeghi Sharif, Jalal Sadeghi Sharif, Reza Eivazlou, and Mohsen Mehraara. (2020). Optimization and Active Management of Stable Investment Portfolio Using Bee Colony Algorithm; Case Study: Tehran Stock Exchange. pp. 1-9.

Fadaei, Ali, Abutrab Alirezaei, Gholamreza Hashemzadeh Khorasgani, and Kiamars Fathi Hafshjani. (2021). Financial Risk Management in the Automotive Industry with Fuzzy Network Analysis Approach.

Fallahi Ghanzagh, Elham, and Farimah Mukhatab Rafiei. (2021). "A Hybrid Optimization Model of Portfolio Selection Including Financial and Ethical Considerations," Financial Engineering and Securities Management, No. 46, pp. 626-643.

Najafi, Amir Abbas, Kobra Nopour, and Alireza Qahramani. (2017). "Interval Optimization of Stock Portfolio with Conditional Value at Risk Metric," Nineteenth Year, No. 1, pp. 157-172.

Nasirzadeh, Farnad, Mostafa Khanzadi, and Majid Alipour. (2015). Economic Evaluation of BOT Projects by Integrating System Dynamics Simulation Methods and Fuzzy Logic. pp. 1-11.

Nezheshti, Amin. (2021). Investigation of Adverse Risk Frameworks in Relation to Portfolio Management in Stock Markets with Price Fluctuations, Seventh International Conference on Management, Accounting and Economic Development. pp.1-20.

Mosaddagh, Saeed, Reza Edalat Marand, and Iran Abazari. (2018). Robust Analysis for Adverse (Downside) Risk in Portfolio Management in Stock Markets with Price Fluctuations, Second International Conference on Management and Business, Tabriz. pp.1-22.

Khalili, Akbar, Alireza Reaiti Shavazi, and Abbas Rezaei Pandari. (2019). Analysis of the Robustness of Adverse Risk in Portfolio Management of Companies Listed on the Tehran Stock Exchange, Third National Conference on Economics, Management and Accounting, Shirvan. pp.1-20.

Goodarzi, Arash, Reza Tehrani, and Ali Suri. (2023). Optimal Investment Portfolio of Insurance Companies Considering Underwriting Activities, Management of Tomorrow, 60 (18), pp. 233-246.

Goodarzi, Amiri, Milad, Behzad. (2018). Presenting a Model for Identifying Factors Affecting the Future Price of Coins Using Artificial Neural Network and Comparing it with Regression Models, Journal of Financial Engineering and Securities Management, No. 15, pp.17-33.

Antti Petajisto, (2019), "Active Share and Mutual Fund Performance", / abstract REVIEW, VOL. 94 NO. 5, PP. 127-211-.

Chang, K. H., & Young, M. N. (2019). Behavioral stock portfolio optimization considering holding periods of B-stocks with short-selling. Computers & Operations Research, 112, 104773.

Chen, W., Zhang, H., Mehlawat, M. K., & Jia, L. (2021). Mean--variance portfolio optimization using machine learning-based stock price prediction. Applied Soft Computing, 100, 106943.

Eraslan, V. (2018). Fama and French Three-factor model: Evidence from Istanbul stock Exchange. Business and Economics Research Journal, Vol.4, No.2, pp. 11-22

Mendonça, G. H., Ferreira, F. G., Cardoso, R. T., & Martins, F. V. (2020). Multi-attribute decision making applied to financial portfolio optimization problem. Expert Systems with Applications, 158, 113527.

Hoque, M. E., Soo-Wah, L., & Billah, M. (2023). Time-frequency connectedness and spillover among carbon, climate, and energy futures: Determinants and portfolio risk management implications. Energy Economics, 107034.

Engle, R. F., & Sheppard, K. (2018). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH (No. w8554). National Bureau of Economic Research.

Michell, K. V., and Kristjanpolleri, W, R,. (2018)., A Stock Market Risk Forecasting model through integration of switching regime, ANFIS and GARCH techniques, Appied Soft Computing, S1568-4946(18)30114-5.

Adhikari, R., &Agrawal, R. K. (2014). A combination of artificial neural network and random walk models for financial time series forecasting. Neural Computing and Applications, 24(6), 1441-1449.

Wei, L. Y., Cheng, C. H., & Wu, H. H. (2014). A hybrid ANFIS based on n-period moving average model to forecast TAIEX stock. Applied Soft Computing, 19, 86-92.

Ahmadifard, M., Sadenejad, F., Mohammadi, I., &Aramesh, K. (2018). Forecasting stock market return using ANFIS: the case of Tehran Stock Exchange. International Journal of Advanced Studies in Humanities and Social Science, 1(5), 452-459.

Engle, R. F., Ghysels, E., &Sohn, B. (2019). Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics, 95(3), 776-797.

Corradi, V., Distaso, W., &Mele, A. (2018).Macroeconomic determinants of stock volatility and volatility premiums. Journal of Monetary Economics, 60(2), 203-220.

Sadorsky, P. (2014). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. Energy Economics, 43, 72-81.