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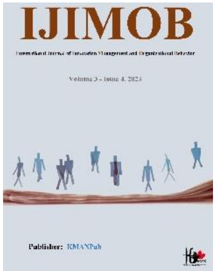

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Agent-Based Simulation in the Financial Management of Stock Portfolios

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ABSTRACT

Objective: Considering the inconsistency of behavioral factors in investors' decision-making, the primary challenge for shareholders is the selection of a stock portfolio in a way that maximizes returns. The Iranian stock market is always faced with significant volatility, which is a critical factor in shareholders' decision-making in stock selection. Awareness of the impacts and prediction of stock price trends before selecting a portfolio helps shareholders reduce losses or increase returns. The main goal of this research is to create a stock portfolio aligned with the Iranian stock market in a way that can simulate various scenarios.
Methodology: The selection of a stock portfolio is an area where agent-based modeling tools can significantly assist investors. This research focuses on the capabilities of agent-based modeling, where investors, dealing with securities including 20 symbols from various industries, have been modeled.
Findings: Factors in this artificial market behave in each transaction period according to trading strategies and learning outcomes, leading to buying or selling actions. For model validation, the output of this market has been approved by experts, professors, and managers in the capital market domain, confirming its credibility.
Conclusion: Despite the variable behaviors of factors, it is possible to form a stock portfolio for each group that leads to the relative satisfaction of shareholders.
Keywords: *Stock market, stock portfolio, research in behavioral operations, simulation, agent-based modeling*

1 Introduction

Earnings per share is one of the very important financial statistics that attracts the attention of investors and financial analysts. Earnings per share indicate the profit allocated to each ordinary share and are often used for evaluating profitability and the risk associated with earnings as well as judging the stock price. In many countries around the world, the importance of this figure is such that it is considered one of the fundamental criteria affecting stock price determination and is widely used in stock valuation models (Joshi & Bedau, 1998). Investment is one of the important factors for development in this century. Investment requires planning. Planning provides the opportunity for appropriate utilization of available opportunities. To increase the effectiveness of planning, it is necessary to improve the ability for accurate and continuous forecasting.

Optimization for determining the stock portfolio has been of great interest to researchers. The most important issue in portfolio optimization is minimizing investment risk and achieving the expected return, or conversely, maximizing the expected return while reducing risk. Different approaches measure different risks, examples of various risk measures include: return variance, CVaR (Conditional Value at Risk), and the Sortino ratio (Li & Teo, 2021; Ponta et al., 2018). Another challenge in portfolio optimization is index tracking, which involves tracking the performance of a financial index. There are various methods for measuring tracking performance, and thus, different (and sometimes incomparable) models exist for this purpose.

Simulation models for complex systems are generally more accurate than mathematical models. On the other hand, if mathematical analysis is applied, it provides the actual value of the model parameter, whereas simulation analysis offers a statistical estimate of the parameter (Bak et al., 1997). The issue is so complex that solving it manually is very time-consuming; therefore, solving this problem automatically with the help of computers has attracted the interest and attention of many researchers around the world. Computer simulation is one of the best solutions for optimizing real-world problems.

The integration of simulation and planning in stock portfolios can lead to time savings, resource conservation, risk reduction, and increased returns and profitability, which in today's competitive world, paying attention to every detail regarding stocks to reduce risk and increase returns is considered a competitive advantage. These factors have collectively led to significant research in this field. In the study by Li et al. (2021), titled "Portfolio optimization in real financial markets with both uncertainty and randomness," the financial market is described as a complex system filled with unknowns and uncertainties. It is well recognized that uncertainty and randomness are the two main types of uncertainties. Therefore, the complexity of real financial markets may result in various types of security returns. When there is sufficient historical data, they are usually considered as random variables. In the case of a lack of data, they can be considered as uncertain variables (Li & Teo, 2021). However, uncertainty and randomness often coexist. In this article, we consider a portfolio optimization problem in real financial markets with both uncertainty and randomness. Initially, skewness for three types of uncertain random variables is derived. Then, in an uncertain random environment, considering different risk priorities, a mean-variance-skewness model for the portfolio optimization problem is proposed. Furthermore, a normalization method is used to eliminate the impact of investment returns and risks of different units. Finally, numerical simulations are conducted to demonstrate the realism and applicability of the proposed model. An artificial stock market based on the information by Ponta et al. (2018) consists of stocks and a population of homogeneous agents. In the market, agents trade risky assets for cash. Alongside the liquidity and stocks owned by each agent, the sentiments of each agent are specified, and agents share their sentiments through network interactions (Ponta et al., 2018). A market maker determines the pricing process of each stock through the intersection of the supply and demand curve. The stock price alone indicates the clustering of volatility and the fat-tailed distribution of returns when the pricing process shows both static and dynamic realities. Static agents are considered as a source of cross-correlation of returns of different stocks.

2 Methods and Materials

This research is an optimization problem based on agent-based simulation technique, and it will be conducted with the objective of determining the best stocks in the stock portfolio. This research is descriptive/modeling based on simulation, in terms of goal it is applied, and the scope of the research includes companies accepted and tradable in the stock exchange and OTC markets. In terms of data collection method, data has been collected from websites and information published by the Securities and Exchange Organization. In a simulation project, the ultimate use of input data is to construct the simulation model. This process involves collecting input data, analyzing input data, and using these analyzed input data in the simulation model. Input data may come from data recorded in documents or through collection from the real world by timing methods. Analysis includes specifying the theoretical functions that provide the input data, and these distribution functions are used in simulation.

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In the broadest division, the research method has been considered as library and field, both of which have been used in the current research. That is, the researcher has used library resources and scientific articles, information available on the CODAL website, financial data from the Securities and Exchange information database, and also the use of modern software, studying books, articles, and collecting necessary information.

One of the most fundamental and important parts of research is the method of collecting information and processing it. Which collection method the researcher decides to use for their research depends on the nature of the research, the type of required information, and the possibilities and limitations of the research. All information used in this research has been collected from financial data available in the Securities and Exchange information database.

The statistical population used for conducting the mentioned research consists of 52 industries and approximately 1,543 accepted symbols on which daily transactions are carried out in the securities market. This research considers 20 symbols (companies) selected from among the industries. Information related to the daily price of shares and the daily index from October 1, 2008, to October 26, 2021, has been considered. The necessary information has been obtained from the financial data available in the securities exchange database and the CODAL website. The probabilistic distributions commonly used in simulation include the negative exponential, normal, and Poisson distributions, as well as the gamma, Weibull, Erlang, and beta distributions. The negative exponential density function is considered as a hypothetical probability distribution. We have used the Easy fit software to identify the distribution functions of each symbol's data. The data have been analyzed in this manner, and the distribution functions for the return and risk of each of the symbols listed in Table 1 have been extracted. In this research, 20 symbols have been examined, which introduce probability distribution functions such as gamma, beta, Johnson, etc. Then, using the distribution functions related to the risk and return of each share, we have proceeded to generate random numbers for risk and return.

According to experts, consultants, and supervising professors, 20 symbols from various industries have been selected from among the tradable symbols in the securities exchange.

3 Findings and Results

A. Designing an Agent-based Capital Market Model

The model design proceeds in four stages (conceptual modeling, mathematical modeling, model implementation, and scenario development). The first step of conceptual modeling involved interviews with shareholders and experts and studying research literature to form the preliminary framework of the agent-based model.

B. Conceptual Model

After developing the conceptual model and identifying the agents and the environment, the second step, namely agent-based simulation or mathematical modeling, begins. In this phase, the characteristics of the agents as well as the interactive rules among agents are precisely identified and defined.

C. Modeling Assumptions

In the modeling process, considering the conditions of the capital market like any simulation method, a number of assumptions are made. Agents in this model are divided into two categories: professional and novice. Agents are randomly professional or novice. In this model, it is assumed that the heterogeneity of agents stems from risk aversion, risk-taking, and normal behavior. Each agent randomly possesses one of these heterogeneities.

D. Model Components

The mathematical model components, based on the conceptual model, are divided into variables and modules, which we briefly describe.

E. Variables

a) Agent Variables: The current model allows for any pattern selection for agents so that all agents can be professional, all risk-taking, or all normal, and the choice exists for novice agents as well, even allowing for a proportional selection of professional and novice agents. Also, each group can randomly have characteristics of risk-taking, risk aversion, or normal behavior.

A certain amount of money is considered for each agent in the model, with which agents proceed to buy and sell symbols, and if they run out of money, they exit the process based on their characteristics.

b) Investment Decision Variables: The designed model allows for investment, buying, and selling in 20 symbols. In this model, 20 symbols from various industries have been selected, and the possibility of investing in the mentioned symbols exists. The rate of return for symbols varies between [-5, +5] and the level of risk between [-1, +1], allowing the user to determine the return and risk based on the characteristics of the agents.

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c) Market Mechanism Variables: Considering the discrete simulation system model, each trading day in the market is considered a trading period. In each trading period, the price of symbols can only fluctuate by 5 percent, within a positive and negative 5 percent range, and the level of risk can fluctuate by 1 percent, within a positive and negative 1 percent range.

F. Modules

The model's modules are the operational programs that are sequentially executed for agents to trade in a random environment. These modules include: a module for creating agents randomly as novice or professional, a module for stock selection from among 20 symbols, a module for determining agents randomly as risk-averse, risk-taking, or normal, and a module for generating random numbers for return and risk.

G- Model Implementation

Given that the simulation program was carried out using NetLogo software, this software provides the capability to monitor the behavior of market agents over a period and report each run. Before executing the model, the user performs a set of configurations for better implementation of the model according to the programming done. After coding and initial settings, companies, the percentage of novice and professional agents, the percentage of agents with characteristics of risk-taking, normal, and risk-averse, the market transaction mechanism (expected return and risk level), and the mechanism for learning and interactions among agents were established.

After executing the model, a remaining total of 920 agents was obtained, and some agents exited the buying and selling process. Subtracting the determined number of agents from the remaining ones yielded the number of agents that exited. Consequently, the number of shares purchased by agents amounted to 7,990 from among the specified 20 symbols. Moreover, the profit or loss resulting from the buying and selling transactions was 186,715.

Table 1

Agent Characteristics

Number	Number of Shares	Profit/Loss
1	291	0
2	751	751
3	642	57,780
4	99	0
5	224	1,344
6	660	17,820
7	130	0
8	237	0
9	627	(31,350)
10	291	6,693
11	380	98,800
12	454	40,860
13	2	(34)
14	497	(8,449)
15	383	3,830
16	25	9,000
17	398	1,990
18	642	(38,520)
19	602	0
20	655	26,200
Total	7,990	186,715

Table 1 specifies the number of shares purchased by novice agents who are risk-takers, the profit or loss per share, and ultimately the total profit is specified.

H- Model Validation and Designing Different Scenarios

Model validation and designing different scenarios typically confirm the validity of agent-based market models by checking the model's ability to reproduce a set of empirical facts (such as clustering, absence of autocorrelation, levels of kurtosis and skewness, etc.).

The challenge of validating agent-based models relates to the intrinsic complexity of these types of models where non-linearity of interactions, heterogeneity, stochastic dynamics, micro-level interactions among agents, and macro and micro feedback loops are usually present. This has led to intense

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discussions about how to validate agent-based models and different levels of validation have been proposed: 1- Replicative validity (model outputs are compared with data now obtained from the real-world system), 2- Predictive validity (the model has the ability to generate system behavior before it occurs in the real system), 3- Structural validity (the model not only reproduces the real system's behavior but also accurately reflects the way the real system operates to produce this behavior).

For model validation, after preparing the final version, the output characteristics of the simulated model are compared with real data from the Tehran Stock Exchange and reviewed by experts, professors, and stock exchange managers to confirm the model's validity and, subsequently, the simulation scenario outputs become referenceable.

The model's output was shared with experts, professors, and managers in the stock and capital market domain, whose verification confirmed the accuracy of the model's output and the model's validity.

This research aimed to examine investor behaviors in the market through designing an agent-based stock portfolio model and evaluating different scenarios to assist in making strategic decisions. In this research, 20 symbols were used to analyze agent behaviors, initially gathering historical data on the symbols from 1999 to 2021 and calculating each symbol's risk and return. The return on investment in ordinary shares, for a specific period, is obtained based on the initial and final price of the period and the benefits from ownership. The benefits of ownership are allocated to the shareholder in periods when the company has held its assembly, and in periods without an assembly, the benefits of ownership are zero. After calculating the risk and beta of each symbol, the distribution function of the risk and return of the symbols was obtained. Using the NetLogo simulation software, modeling was carried out, and this model was executed separately in two categories: professional, novice, and with characteristics of risk-taking, risk-averse, and normal, in 6 stages according to the Table 2.

Table 2

Agent Characteristics

Characteristics	Professional	Novice	Risk-Taking	Risk-Averse	Normal
Agent	100%	---	100%	---	---
Agent	100%	---	---	100%	---
Agent	100%	---	---	---	100%
Agent	---	100%	100%	---	---
Agent	---	100%	---	100%	---
Agent	---	100%	---	---	100%

The model settings are carried out according to Table 2, and outputs are received separately from the model. After performing the mentioned settings, the model output is obtained according to Table 3.

Table 3

Number of Shares and Profit Earned per Agent

Agent Type	Characteristic	Number of Shares	Profit/Loss per Share	Remaining Agents	Agents Exited
Novice	Risk-Taking	7,990	186,715	920	80
	Risk-Averse	8,685	141,334	920	80
	Normal	6,152	224,685	887	113
Professional	Risk-Taking	9,003	400,741	921	79
	Risk-Averse	6,928	131,214	911	89
	Normal	7,102	249,621	911	89

Agents aim to maximize their profit in each stock transaction +5, and the difference among agents lies in the level of risk they accept. For risk-taking agents, the risk is set at 80%, for normal agents at 40%, and for risk-averse agents at 0%, and after executing the model, the output is obtained according to Table 3.

In conclusion, it was determined that:

A - Novice Agent: If characterized by risk aversion, the profit obtained is less than that of a risk-taking characteristic.

B - Novice Agent: If characterized by risk-taking, the profit obtained is less than that of a normal characteristic.

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Therefore, if the agents are novices, it is better for them to act normally in buying and selling shares to achieve the highest profit.

C - Professional Agent: If characterized by risk aversion, the profit obtained is less than that of a normal characteristic.

D - Professional Agent: If characterized by a normal attribute, the profit obtained is less than that of a risk-taking characteristic.

Therefore, if the agents are professionals, it is better for them to act as risk-takers in buying and selling shares to achieve the highest profit.

4 Discussion and Conclusion

The outcomes of this research offer significant insights into the behavior of investors, particularly highlighting the distinctions between novice and professional agents in the stock market. As indicated by the simulation results, the investment success of agents, whether novice or professional, largely depends on their risk-taking behavior and the inherent characteristics they exhibit towards risk.

For novice agents, those with a normal risk temperament were found to achieve higher profits compared to their risk-averse and risk-taking counterparts. This finding suggests that novice investors might benefit from a balanced approach to risk, avoiding extremes of risk aversion or risk-taking. This aligns with the notion that moderate risk-taking, accompanied by a well-informed strategy, can lead to optimal investment outcomes (Li & Teo, 2021). Novice investors often lack the experience and knowledge that professional investors might have, making a cautious yet open approach to risk-taking a prudent strategy.

Conversely, professional agents exhibited the highest profit margins when adopting risk-taking behaviors. This could be attributed to their experience and knowledge, which potentially allows them to navigate and exploit the market's volatility more effectively (Ponta et al., 2018). Professional investors' ability to tolerate higher levels of risk and their understanding of market dynamics likely contribute to their greater success when engaging in riskier investment strategies. This finding is consistent with the theory that informed risk-taking, grounded in experience and market understanding, can yield higher returns (Shatner et al., 2000).

The simulation-based approach utilized in this study, powered by NetLogo, enabled a nuanced exploration of investor behavior under varying conditions of risk and market dynamics. The agent-based model effectively demonstrated how different risk characteristics influence investment outcomes for both novice and professional investors. This methodological approach aligns with current trends in economic and financial research, where agent-based models are increasingly employed to capture the complexity of financial markets (Chwif et al., 2000; Krichene & El-Aroui, 2018; Robinson, 2001; Salt, 1993).

In conclusion, this research contributes to the understanding of investment behavior in the stock market, particularly emphasizing the importance of risk temperament in investment decision-making. The findings suggest that novice investors might achieve better outcomes by adopting a balanced risk temperament, whereas professional investors could benefit from leveraging their expertise to undertake informed risk-taking strategies. Future research could further explore the implications of these findings in more complex market scenarios and investigate additional variables that influence investment behavior and outcomes.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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