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Designing a Model for Analyzing Financial Behavioral Change in Stock Market Actors in Response to Macroeconomic Variables: A Study with Agent-Based Simulation Approach

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Abstract

The dynamics of the capital market is recognized as a key factor in the economic growth of countries. The reactions of stock market participants to changes in macroeconomic variables can have both positive and negative effects on the market. Identifying existing threats and transforming them into opportunities is of particular importance. Given the complexities of financial market structures and human behaviors, designing a simulation model to manage these complexities appears to be essential. This research focuses on the development of a model for the financial analysis of the country's stock market. After examining the market structure and price microstructures, broader characteristics have been predicted using a qualitative and inductive approach, resulting in a conceptual model design. The analysis and comparison of artificial markets, along with a comparative study and the use of a mixed-method approach to integrate human behaviors with quantitative and qualitative research techniques, constitute the next steps of this research. Ultimately, simulation technology has been utilized as a third method in scientific research approaches. The research is considered descriptive and practical in its objectives. For simulation purposes, the effective factors and their interactions have been identified and implemented as programming objects in NetLogo. The model validation has been conducted based on the proposed methods of Ronald Rust and William Rand, and sensitivity analysis has been performed according to Borgonov's systematic approach. The findings indicate the impact of macroeconomic variables on the decisions of portfolio managers and investment funds concerning the growth of the overall stock index.

Keywords

Agent-BasedSimulation,Stock Exchange,Macroeconomic Variables, Behavioral Finance

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2.Introduction

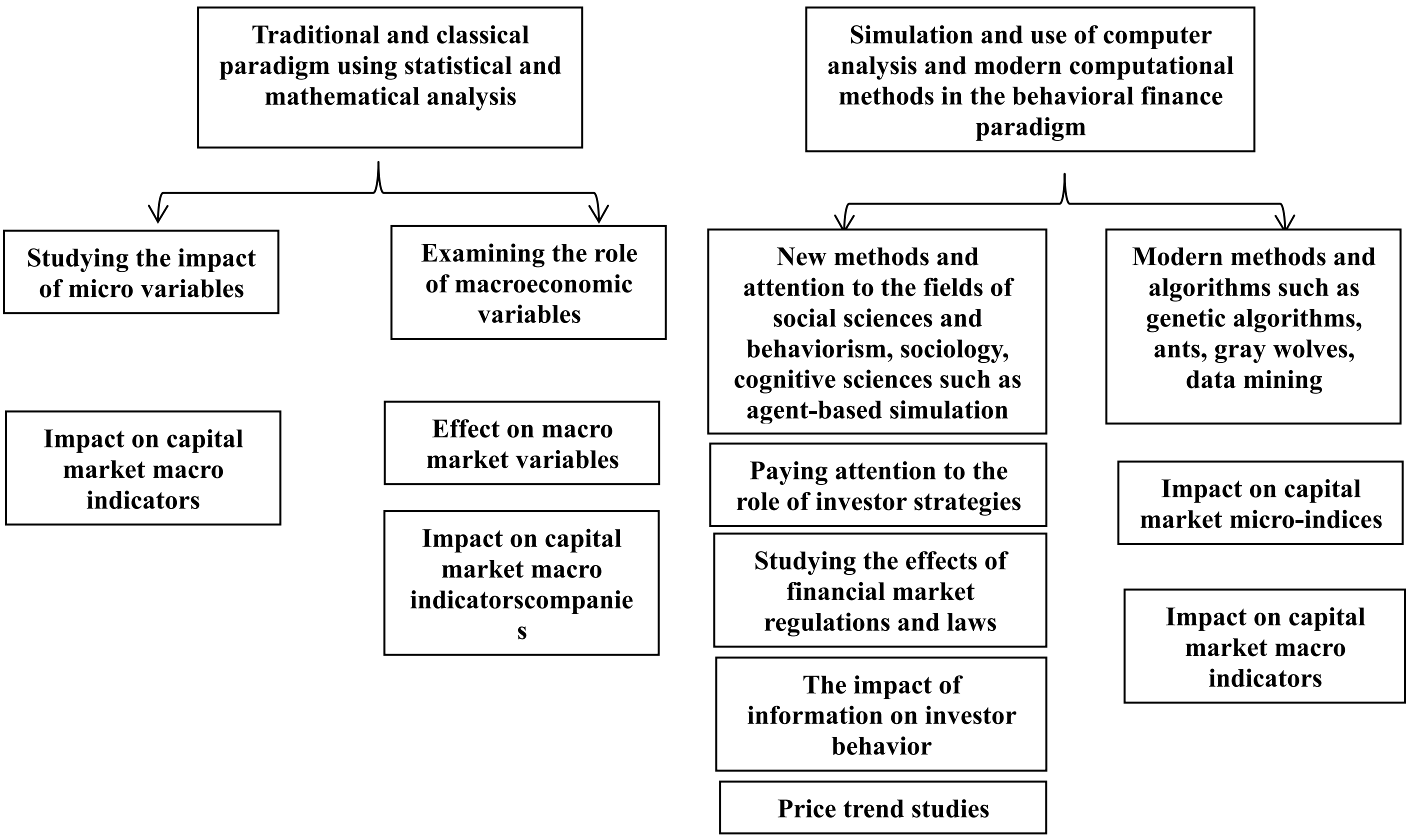
Due to the influence of market behaviors on the country's economy through their capability to channel investor capital and alter investor behaviors and decisions, which can result in economic dynamism or lack thereof (leading investors to exit the market if they fail to achieve the expected utility, or, conversely, encouraging their continued participation and even increased capital inflow) the level of investor awareness regarding the roles of all stock market actors and their accurate understanding of the impact of macroeconomic variables on these actors is highly significant. Considering the existing complexities and the inability to manipulate variables in the real world to study their effects, having tools that allow for predicting the implications of changes in macroeconomic variables on the behavior of market participants, thereby minimizing the complexities arising from collective human behavior, seems critical for preventing a repetition of recent negative developments in the stock market. Additionally, the inefficacy of traditional paradigms used in securities pricing paradigms based on the rational human assumption, such as the Efficient Market Hypothesis alongside the formation of price bubbles or the incomplete reflection of information in prices, has led to investor dissatisfaction. This was the beginning of the emergence of a new paradigm called "behavioral finance." In reality, linear models can no longer adequately analyze financial phenomena; they can only reproduce the main macro-level features of the market and cannot replicate the emerging characteristics of markets. Thus, modeling systems with minimal cost and effort, and without distorting events, is the best method available to address this issue. Some of these models have examined fundamental behavioral traits of actors or stock market processes. These models show that a small set of simple assumptions can explain a series of manipulated empirical facts that reflect the market as a whole. This capability is seen as a developed platform in which actors interact with a spectrum of behaviors (Muchnik et al., 2006). John McMillan, an economist who used game theory to examine many markets, believed: "A market operates well only if it is well-designed." The design of the market (regulations and rules) determines whether a market will operate well or poorly. McMillan also concluded that "the economy is a highly complex system," and we know that the economy is at least as complex as systems studied by physicists and biologists. Melanie Mitchell, a computer scientist, also believes that "economies are complex systems comprising simple microscopic components individuals and the buying and selling of goods and collective behavior is the complex and unpredictable behavior of markets (e.g., stock price volatility)." Financial markets are also extraordinarily complex systems in which the simple aggregation of micro-processes (actor behaviors) does not sufficiently explain macro phenomena (price formation). Slight rule changes, even seemingly trivial ones, can sometimes lead to major, unpredictable side effects. Designing a well-functioning financial market is vital for developing and maintaining an advanced economy; however, this is not easy, because small and seemingly insignificant rule changes can generate large, unforeseen consequences, making predictions more difficult and complexity more pronounced. A simulation using an agent-based model can directly address such complex systems where micro-processes and macro phenomena interact and provide a clear explanation. Many effective agent-based models analyzing human behavior have already been developed; further artificial market models will continue to aid in designing financial markets and can be well-utilized to further develop advanced economies (Mizuta, 2021). Concepts of behavior, decision-making, and interaction are relevant for modeling many types of systems. An agent is a broad concept with diverse applications. Agents are often used to represent individuals or groups of people. The relationships among agents represent processes of social interaction (Gilbert & Troitzsch, 2005). The development of agent-based modeling tools, access to micro-data from transactions and agent interactions, as well as computational advances, have enabled an increasing number of agent-based system applications across various domains and disciplines (Macal & North, 2014). Capitalizing on the capabilities, features, advantages, and potential of agent-based modeling and simulation part of which has been discussed aimed at contributing to stability in the country's stock market (which in recent years has suffered serious damage from unforeseen collective behaviors by stock market participants) has motivated us to develop a stock market model for the country through the present research, employing agent-based simulation.

3.Literature Review

To achieve the research objectives and gain a comprehensive understanding of how the market is organized, its structure, microstructures, and the mechanisms of price formation, as well as to study the realities of the capital market, predict broader characteristics, conduct analyses, compare artificial markets through comparative studies, and employ a hybrid method to combine human behaviors with quantitative and qualitative research techniques thus enhancing the quality level of the simulation a thorough literature review was conducted in various areas within capital market research. These are categorized as follows:

3-1.Studies and Research conducted in the Capital Market

(Figure-1)

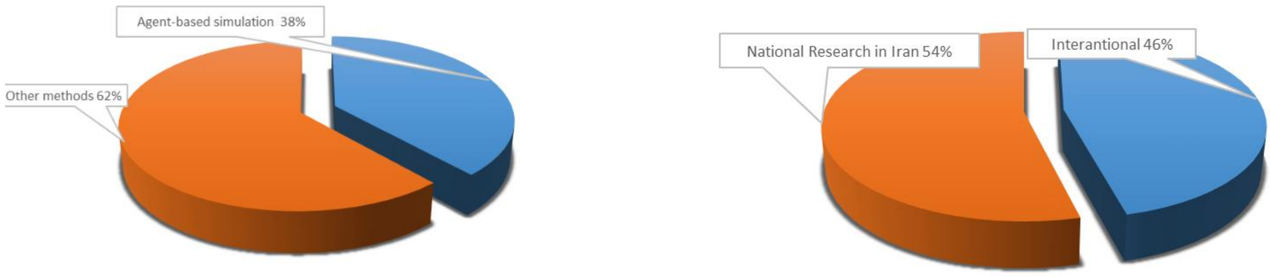


Classification chart of research conducted in the field of capital markets

3-2.Categorizing research conducted based on paradigm as well as geographical area

Of the total 65 studies collected and reviewed, 25 (38%) used the agent-based modeling and simulation approach, and another 40 (62%) used other methods. Also, 35 of these studies were selected from foreign research and 30 from domestic research, as shown in the relative chart below.

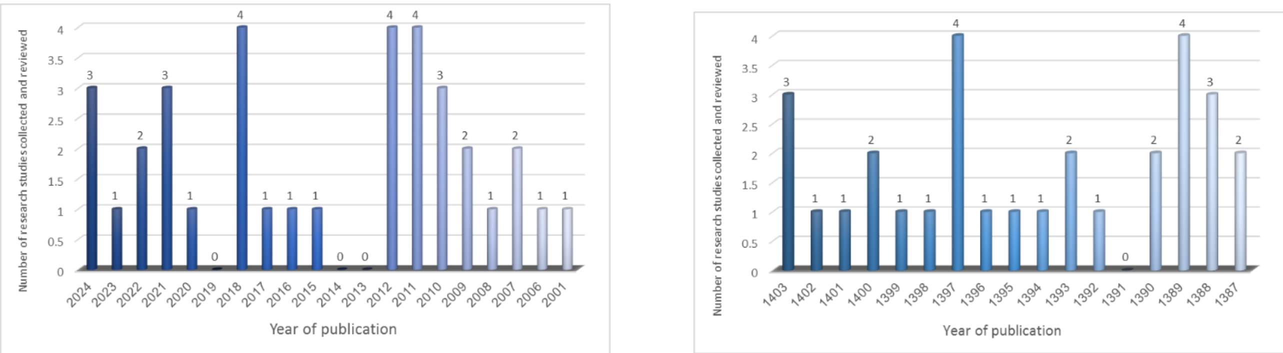
(Figure-2)



Classification chart of research conducted in the field of capital markets

The following are time distribution charts of research conducted in different years, separated into domestic and foreign research:

(Figure-3)



time distribution charts of research conducted in different years

3-3.A Review of the Research Background

3-3-1.Interantional Research

3-3-1-1. Research conducted using agent-based simulation

- **Kang Zhao et al. (2024):** By implementing agent-based models to generate data in artificial markets, they concluded that the price-formation process arises from interactions among momentum traders, fundamental traders, and noise traders. However, their study neglected the role of other capital market participants.
- **Takanobu Mizuta et al. (2022):** Built a model called an artificial market and introduced technical analysis strategy agents, adding an optimized parameter to an existing model. They examined whether the inability of investors to accurately estimate market impacts in their optimizations leads to instability. They concluded that the investment strategy parameter never converged to a specific value but continued to change. This outcome suggests that financial markets embody a natural uniformity principle and illustrate the difficulty of forming an equation-based model explaining the time evolution of prices.
- **Mizuta Takanoba (2022):** In another study the same year, he introduced recent articles on artificial market research regarding financial rules and

regulations. However, he focused solely on one set of environmental parameters (laws and regulations) and neglected the roles of other actors or other variables affecting market trends.

- **Ben Hammada & Amblard (2021):** In an article, they built an agent-based model to study informational cascades in financial markets. Their proposed model reduced the unrealistic assumptions of earlier analytical models, specifically trader homogeneity and universal access to all past decisions. They concluded that policies aimed at reducing uncertainty among investors can prevent informational cascades.
- **Takanobu Mizuta (2021):** In a study on designing a financial market using agent-based simulation, he stated that designing a well-functioning financial market is crucial for developing or preserving an economy, but minor rule changes can lead to major, unintended consequences; however, an agent-based computational simulation can straightforwardly address these complexities by clarifying how micro-processes interact with macro phenomena.
- **Fouad Ben Abdelaziz & Fatma Mrad (2021):** They investigated the information game in an artificial financial market, implementing an agent-based model to simulate complex stock markets. Previous simulation models have focused on the buying and selling of assets. Their research advanced beyond prior agent-based simulations in capital market modeling but did not address the process of information exchange.
- **Yang et al. (2020):** Explored how a minimum tick size impacts market quality using an agent-based artificial stock market. Their results showed that hybrid, step-by-step systems can improve market quality in ways a uniform system cannot. This was the first theoretical study analyzing tick-size systems, yet it ignored the role of other market actors.
- **Ponta et al. (2018):** Introduced an artificial stock market based on share information and populations of heterogeneous agents. These agents buy and sell risky assets for cash transactions. Liquidity and owned shares for each agent are represented alongside the agent's sentiment. Agents share their sentiment through network interactions. The stock pricing process is based on supply and demand charts managed by a professional market operator. They showed that share prices are a good indicator for volatility clustering and wide return distributions.
- **Alegria et al. (2018):** Developed a stock market model where the share of investor participation depends on the fundamental value of the market and the market's attractiveness. In this market, share prices are adjusted proportionally to excess demand, which directly connects to several economic and environmental factors. Participants can switch between different strategies. Their results showed that investor participation and adaptation to experimental and empirical evidence can lead to market dynamism and boom.

3-3-1-2. Research conducted in classical paradigms

- **Arshad Bhatti & Mahmoud Hanif (2018):** Investigated short- and long-term causal relationships between some macroeconomic variables such as the industrial production index, money supply, oil price, consumer price index, foreign investment portfolio, and exchange rate and the stock market return in Pakistan.
- **Talal Al-Sulaimani et al. (2016):** Examined the features of a calibrated network structure in an agent-based model for a simulated financial market. Their findings showed significant

differences in emergent market behavior from the perspective of returns and price levels, even though the market value approached the scaled financial market. Their research suggested the distribution of wealth deviates less heterogeneously than a real market. While the study was more comprehensive than many earlier agent-based models, it still addressed only external factors, ignoring firms' internal variables.

- **Ali Omar Ahmed et al. (2015):** Studied and analyzed the role of macroeconomic variables in stock returns. Their findings clearly indicated a relationship between stock returns and macroeconomic variables both short-term and long-term.
- **Daniel Sungyoon et al. (2024):** Using conventional stochastic differential equations, they found that in recessionary periods, herding behavior in the stock market is stronger than in boom periods. They also overlooked the impact of macroeconomic variables and other market actors in their research.
- **Asif Khan et al. (2024):** Combining quantitative and qualitative methods (regression, Likert scales, and factor analysis), they concluded that investor biases significantly influence investor behavior, and behavioral shifts can either stimulate or dampen market activity. However, they paid no attention to the impact of human behaviors, or psychological and sociological factors.

3-3-2.National Research in Iran

3-3-2-1. Research conducted using agent-based simulation

- **Mehrzad Ebrahimi (2019 [1398 SH]):** Used data-mining algorithms to identify important and influential variables on the long-term relationship of the overall stock index. The results showed that the trade balance, inflation rate, and GDP were deemed essential by 80% of weighting algorithms. Among these, GDP was assigned the highest weighting (over 90%). While this perspective offers a new horizon for investors and policymakers, the study did not consider behavioral parameters, social factors, or other actors, creating a theoretical gap.
- **Adel Azar et al. (2018 [1397 SH]):** Aimed to resolve regulators' concerns about the unknown effects of new strategies given heterogeneity, bounded rationality, and behavioral factors in shareholder decisions, they used agent-based simulation to model shareholder behaviors in the Iranian stock market. Their results showed that in the short term, due to immaturity, the Iranian stock market experiences extreme volatility with mechanisms like price fluctuation limits in place, but in the long run, these controls become more effective. However, they merely modeled investor behavior and regulatory rules, ignoring other market actors, which can lead to inaccuracies in approximating and forecasting the stock market's trajectory.
- **Abbasi Sir et al. (2022 [1401 SH]):** Through modeling with agent-based simulation, concluded that among shareholders, 48% are emotional (type one) and 52% are short-term traders (type two), but they also did not consider the role of all market actors or macroeconomic variables.

3-3-2-2. Research conducted in classical paradigms

- **Reisi et al. (2024 [1403 SH]):** Using structural equation modeling with LISREL, they found that personality traits and their components (neuroticism, extraversion, openness, conscientiousness, and agreeableness) have a direct and significant relationship with investors' behavioral biases, but they did not address the role of all market actors and macroeconomic variables.

- **Biat et al. (2024 [1403 SH]):** Utilizing a causal correlation method, they concluded that managerial overconfidence in decision-making has a direct and significant relationship with divergence in investor behavior, but they also ignored the impact of other market actors on investor behavior.
- **Sotudeh et al. (2024 [1403 SH]):** Using Friedman's test to measure risk, introduced 31 indicators and 8 components relating to behavioral decision-making patterns among investors; however, they did not examine the impact of human behavior, psychological and sociological factors.
- **Tehrani et al. (2024 [1403 SH]):** Using a mixed-frequency data approach, concluded that oil prices, liquidity, and the exchange rate have a positive and significant effect on the stock market, but they overlooked the role of all market actors and other macro variables, constituting a gap in their research.
- **Hadipour et al. (2021 [1400 SH]):** Employed conditional volatility methods to study factors affecting the instability index in the basic metals sector of the Tehran Stock Exchange. Their findings showed that political disputes and international issues cause fluctuations in the industry, which is also influenced by fluctuations in parallel markets such as oil, gold, and foreign exchange. Their research gap was not examining internal variables and focusing solely on macroeconomic, political, and environmental factors, overlooking human and social behavioral issues.
- **Valizadeh et al. (2021 [1400 SH]):** Proposed a model to predict factors influencing stock price crash risk in the Tehran Stock Exchange. By reviewing the literature on stock price crash risk, they selected 12 experts from among capital market specialists. They then extracted factors influencing stock price crash risk using appropriate tools, documents, and interviews, employing structural equation modeling for final analysis. Their research found that certain factors influencing the risk of stock price crashes can be predicted. However, they adopted a static approach merely identifying influential factors and did not dynamically predict how the stock market might behave if micro or macro environmental variables changed, which is the gap in their study.
- **Hosein Fakhari & Mehrab Nasiri (2020 [1399 SH]):** Studied the effect of corporate performance and the risk of future stock price crashes among companies listed on the Tehran Stock Exchange, using multiple regression with panel data. Their results showed that one could predict future stock price crashes by considering a company's performance, guiding decisions about holding, buying, or selling its shares. The gap here is solely focusing on internal variables while ignoring macroeconomic and environmental variables, as well as other market actors, as well as human and social behavioral factors.
- **Botshekan & Mohseni (2018 [1397 SH]):** Investigated the conditional dynamic correlation and volatility spillover from oil prices to stock index returns using multivariate GARCH models. Their results showed short-term conditional correlations and spillover effects of oil prices on the stock index. However, employing classic statistical and mathematical approaches without focusing on behavioral or macroeconomic variables, or other market actors, is the main limitation.
- **Shirazian et al. (2018 [1397 SH]):** Studied volatility clustering in financial markets with agent-based simulation. The time series of asset returns indicate volatility clustering, meaning significant price changes tend

to cluster, and these clusters persist for a period of time. By applying econometric models, they attributed such phenomena to various factors like newly arrived market information and participant behaviors. The result underscores a relationship between significant upward or downward market volatility and threshold-based participant behavior, linking investment inertia to volatility. Because they adopted a post-event approach, focusing on observed price changes rather than predicting or preventing group behaviors that could harm the stock market, they did not help forecast or prevent detrimental collective actions.

- **Sara Qaikhlo & Mahmudi Pati (2017 [1396 SH]):** Showed that, from the perspective of managers and capital market experts, inflation volatility is the most significant macroeconomic variable affecting the overall stock index. They concluded that brokers and representatives could prevent performance risks in the stock market by determining suitable performance metrics.
- **Rahnemaie Rudposhti & Shirazian (2014 [1393 SH]):** Used agent-based simulation to classify investors into two groups random and momentum investors and concluded that the Tehran Stock Exchange is a favorable environment for momentum investors due to its inefficiency and nascent stage compared to advanced global markets. They found that the threshold for momentum investors' reaction was about three times the volatility created by random investors. While more influential than purely classical or behavioral finance studies, they only examined momentum investors' strategies and thus cannot provide a global perspective or predict other strategies' outcomes in the stock market.
- **Vakili-Fard et al. (2014 [1393 SH]):** Cited complexities in investor behavior, regulatory constraints, the retrospective nature of data, data confidentiality, and limited access to personal accounts and financial information as reasons for introducing a new approach in financial studies using artificial intelligence and simulations in designing and developing artificial financial markets.

3-4.Theoretical Gap in Previous Research and Innovations of This Study

Prior research in the stock market generally focuses on market trends, volatility, and pricing. Most of these studies do not provide accurate predictions to end-users, mainly due to complexity from collective human behavior, which is unpredictable using purely mathematical and statistical models. Additionally, reasons such as retrospective data, heterogeneity, bounded rationality, strict data-sharing rules, and insufficient investor information may limit their applicability. Even in studies employing agent-based simulations, most only focus on investors, ignoring other market participants or external changes like macroeconomic factors. In summary, previous research falls into three paradigms:

1. Classical paradigm using statistical and mathematical models
2. Behavioral finance paradigm
3. Paradigm utilizing agent-based modeling and simulation

Compared to these three paradigms, this study is innovative for the following reasons:

1. For the first time, it investigates not only investors but also other stakeholders in the stock market. Prior studies overlooked these other stock market players.
2. For the first time, it uses agent-based simulation to assess the influence of macroeconomic variables on the stock market's trajectory.
3. It enables monitoring and identifying the optimum level of influence exerted

by certain players such as market makers, portfolio managers, and investment funds.

4. It makes it possible not only to discover the positive or negative influence of different investor personality types but also to determine the ideal weighted combination of these personality types.
5. It explores, for the first time, the effects of macroeconomic variables on the behavior of participants other than investors.

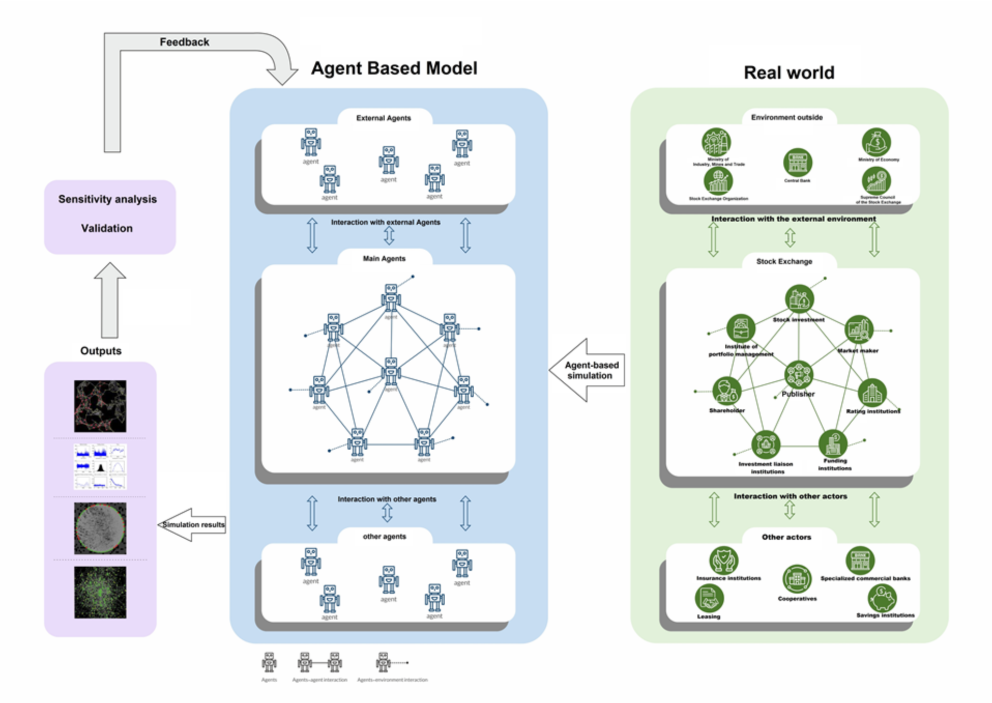
4.Research Method

To create an artificial market that operates realistically and whose predictions align with real conditions, it is vital to include the roles of all existing market actors. Therefore, the first step is to gain a deep understanding of the structure and organization of the market, which this research has examined. Next, to predict market participants' behavior, we must properly understand microstructures and the mechanisms of price formation, which the present study has addressed. Thus, with a qualitative, inductive approach through observation, examination, and in-depth analysis of the capital market realities we predicted broader features and presented a conceptual model.

In the third stage, having mastered the real market's structure and performance, we analyzed and compared artificial markets. This provides a comprehensive overview of prior research in this field. Next, by designing a specialized model for Iran's stock exchange and evaluating its validity, we simulated the behavior of market participants using agent-based modeling. This method serves as the third approach to scientific research and effectively covers previous gaps. The simulated model focuses on all stakeholders in the capital market. Through defining diverse scenarios, it can evaluate agent behavior and answer specific research questions. Furthermore, owing to the flexibility of agent-based modeling, this research can accurately analyze and forecast these agents' behaviors. The study is therefore descriptive in terms of objectives and applied in nature. It describes a combined methodology in which agent-based models are integrated with quantitative and qualitative research methods. This mixed-method approach collects, integrates, and analyzes quantitative and qualitative data to achieve deeper insights (Creswell, 2003).

After this stage, the performance of each agent in the model is programmed as an object and the interaction between the choices and behaviors of each of these objects is considered in the form of a general program. As a result, the requirement to use object-oriented programming arises. The structure and algorithm of the model are carried out through pseudocode and simulated by the NetLogo software. This simulation process for studying the problem includes both building the model and its analytical use. By building the model, whether at the time of its construction or afterwards, we can understand the structure and behavior of the real system and predict its behavior under different conditions. After that, we will be able to test different scenarios designed with different combinations of actors and different types of investors to improve the performance of the system. This is achieved by repeating experiments and generating new experiments and using special features of agent-based simulation such as the autonomy* of agents and the independence of traders. For this purpose, in this research, by assigning factors to the internal actors of the stock exchange (namely: issuer, investor, market makers, portfolio managers, capital institutions, rating agencies) and selecting macroeconomic variables (seven main variables: dollar rate, OPEC crude oil price, inflation rate, one-year deposit bank interest rate, money volume, liquidity growth, trade balance) as input variables and the total stock exchange index as the output variable of the research, (the model of which is presented in Figure 12), coding and simulation have been performed in NetLogo.

(Figure-4)



Final conceptual model of the research

5.Model Assumptions

1. The data collected in this study is based on information published on the websites of the Central Bank at cbi.ir, the Stock Exchange Organization at tsetmc.com and tse.ir, and the Statistical Center of Iran at amar.org.ir for the database simulation of the fifteen-year period from 1386 to 1401 AH, which in the modeling process was simulated for the fifteen-year period after, i.e. from 1402 to 1416 AH. It is worth noting that the aforementioned data is available live from the mentioned addresses.

(Figure-5)

Sliders for simulation timeframes and the forecast period

2. we can predict typical behaviors for each market participant during bullish, bearish, and stable market conditions. These forecasts are summarized in the table below. Depending on the market's condition (bullish, bearish, or stable), buying or selling is executed based on the assigned role of each internal market actor, and its impact on the overall market index is observed.

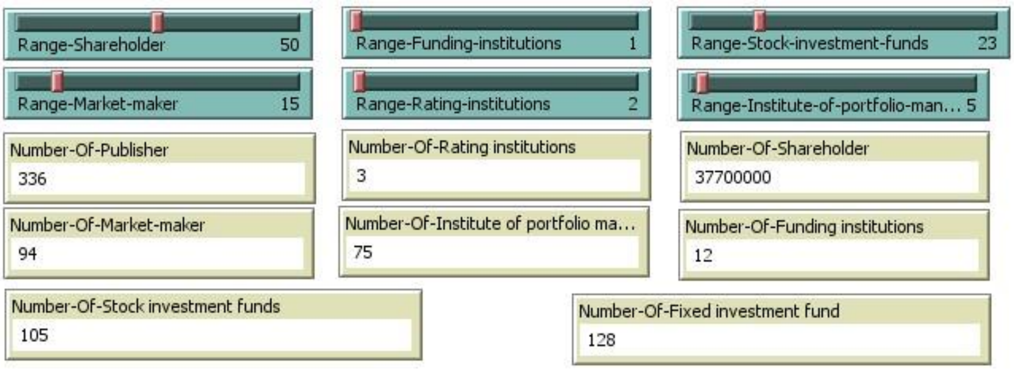
Table 1

Agent	Market uptrend	Market Downtrend	Stability in the market
Publisher	Irrelevant tasks and verbs	Irrelevant tasks and verbs	Irrelevant tasks and verbs
Investor	Shopping	Sale	Capital preservation
Marketers	Sale	Shopping	Equilibrium buying and selling
Basket makers	Sale	Shopping	Equilibrium buying and selling
Capital funding institutions	Increased activity	Decreased activity	Maintaining the process
Rating agencies	Increase in average scores	Decrease in average grades	Maintaining the process
Equity investment funds	Shopping	Sale	Equilibrium buying and selling

Typical behaviors of active stock market participants under various market trends

3. The number of agents in the model matches the actual count as of the last trading day of the market on March 19, 2023 (28 Esfand 1401 SH). To determine the weighted ratio or “penetration rate” of these agents, sliders were implemented in NetLogo, and sensitivity analysis was performed.

(Figure-6)



Data inputs in NetLogo

4. Given that over the past 15 years, macroeconomic variables and the overall stock index have shown consistent upward trends, we introduced a random model alongside the data-based simulation to explore other possible scenarios. Both scenarios were simulated, their results extracted, and sensitivity analyses performed. This approach allows us not only to reflect historical trends but also to predict potential market behavior under different conditions.

(Figure-7)

Enabling random vs. data-based simulation

5. In this study, the capital market ecosystem’s participants are divided into external and internal agents. We disregarded external agents such as the Central Bank, Ministry of Economic Affairs and Finance, Ministry of Industry, Mines, and Trade, the High Council of the Stock Exchange, and the Securities and Exchange Organization despite their direct impact on the stock market, because this impact can be tracked via indicators like the overall market index, which is treated as the output variable. The internal market agents include issuers, investors, market makers, portfolio managers, investment banks, and rating agencies. Meanwhile, the exchange rate, OPEC crude oil price, inflation rate, one-year bank deposit rate, money supply, monetary growth, and trade balance were set as eight input variables in the model.
6. The collected data used as the NetLogo database for the simulation are shown in the following table:

Table 2

Index / Year(SH)	۱۸ carat gold rate	OPEC oil price	US dollar rate	Interest rate	Inflation rate	Balance of payments	Liquidity growth	Liquidity	TEPIX
1386	175,100	99	8,956	16	18.4	15,246	27.7	1,640,293	9,249
1387	219,800	39	9,717	17.25	25.4	8,229	15.9	1,901,366	7,967
1388	268,500	81	9,834	14.5	10.8	7,268-	23.9	2,355,890	12,537
1389	358,700	111	10,364	14	12.4	947-	25.2	2,948,870	23,295
1390	775,000	123	12,260	12.5	21.5	21,436	20.1	3,522,200	25,906
1391	1,332,000	106	18,440	23	30.5	12,213	30	4,607,000	38,041
1392	970,730	104	25,102	24	34.7	13,175	38.8	5,947,750	79,015
1393	964,050	49	33,380	22	15.6	8,561	22.3	7,823,800	62,532
1394	1,034,700	36	34,250	18	11.9	2,233	30	10,172,800	80,219
1395	1,153,640	49	37,480	15	9	7,666-	23.2	12,533,900	77,230
1396	1,533,410	63	48,990	15	9.6	8,140-	22.1	15,299,800	96,290
1397	4,298,700	67	128,940	15	31.2	9,880	23.1	18,828,000	178,659
1398	6,026,000	27	149,030	15	41.2	671	31.3	24,721,000	512,900
1399	10,855,000	67	239,630	14	36.4	2,641-	40.6	34,750,000	1,307,657
1400	12,291,000	105	262,300	14	40.2	895	39.7	48,320,000	1,367,250
1401	26,406,000	74	538,000	20.5	46.5	6,489-	30	62,820,000	1,960,457
Unit of measurement	Rial	Dollar	Rial	Percentage	Percentage	Million Dollar	Percentage	Billion Rial	Percentage

Fifteen years data used in NetLogo as the simulation database

6.Mathematical Model

To calculate the overall index, the current value of the market during the period under study is divided by the market’s base-year value and multiplied by 100, yielding the price and cash return index:

$$TEDPIX_t = \frac{\sum_{i=1}^{n} p_{it} \times q_{it}}{RD_t}$$

$$RD_{t+1} = \frac{\sum_{i=1}^{n} p_{it} \times q_{it} - \sum_{i=1}^{n} DPS_{it+1}}{\sum_{i=1}^{n} p_{it} \times q_{it}} \times RD_t + \frac{RD_t}{D_t} + (D_{t+1} - D_t)$$

Assuming that each of these market players makes random trades in order to prevent their capital from decreasing or to earn more profit, the trade will be executed if their sell order is the lowest available bid price in the market or their buy order is the highest available bid price. The equation for this process can be seen as follows:

$$S_i = P_{(t)} \times [1 - (RND - Riski) \times y]$$

Given the assumptions made, the following decision-making function can be proposed for actors in the agent-based simulation. This function is formed under the influence of macroeconomic variables and their decisions regarding the total stock market index. For this purpose, it is assumed that each of the actors in the simulation has access to information such as OPEC oil prices, dollar prices, gold prices, inflation rates, liquidity volume, money supply, liquidity growth, and balance of payments. It is also assumed that the actors representing investors have two types: risk-averse and risk-taking. The decision-making function is defined as follows:

$$D = f(R.I.X.C.T)$$

$$f(R.I.X.C.T) = \alpha \times R + \beta \times I + \gamma \times X + \delta \times C + \eta \times T + \varepsilon$$

Table 3

Row	Variable	Introduction within the framework of theoretical foundations
1	RDt	The cash return of companies at time t paid by the issuer to shareholders
2	P_{it}	Represents the stock price of company i at time t
3	q_{it}	Number of shares of company i at time t
4	Si	Selling limit, at time t
5	P	Stock price at time t
6	Riski	Indicates the trader's level of risk aversion
7	D	The decision made by the agent (investor, market maker, portfolio manager, fund, etc.)
8	R	It refers to a set of macroeconomic variables such as OPEC oil prices, dollar rates, inflation rates, gold prices, liquidity volume, and money supply.
9	I	It represents past capital market information.
10	X	Represents the agent's decisions, which include a combination of buying, selling, or not trading.
11	C	Refers to the overall stock market index
12	T	The type of investment determines the agent, who can be risk-averse or risk-taking.
13	α، β، γ، δ و η	Coefficients that express the weighting of different variables in the decision are the factor.
14	ε	Unpredictable fluctuations or errors
15	RND	It is a number between zero and one with a uniform distribution and indicates that the higher the degree of risk aversion in a random actor, the greater the likelihood that she will offer attractive rates.

nomenclature table defining variables and their theoretical foundations

7.Exponential Moving Average (EMA) Algorithm

The EMA algorithm, inspired by how elites trade on the stock market, tackles optimization problems. By carefully observing how experts trade in the stock market, this heuristic algorithm took shape. It features two search operators and two attractor operators converging toward the elite trader, enabling the most effective generation and organization of random numbers (Ghorbani & Babaei, 2015 [1394 SH]). To compute the EMA indicator, the simple moving average (SMA) is first calculated over the target period and variable by summing closing values across that period and dividing by the number of periods. Then, a smoothing factor is introduced for the exponential moving average. If the moving-average period is n and the smoothing factor is x , the smoothing factor is computed as:

$$X = \frac{2}{n} + 1$$

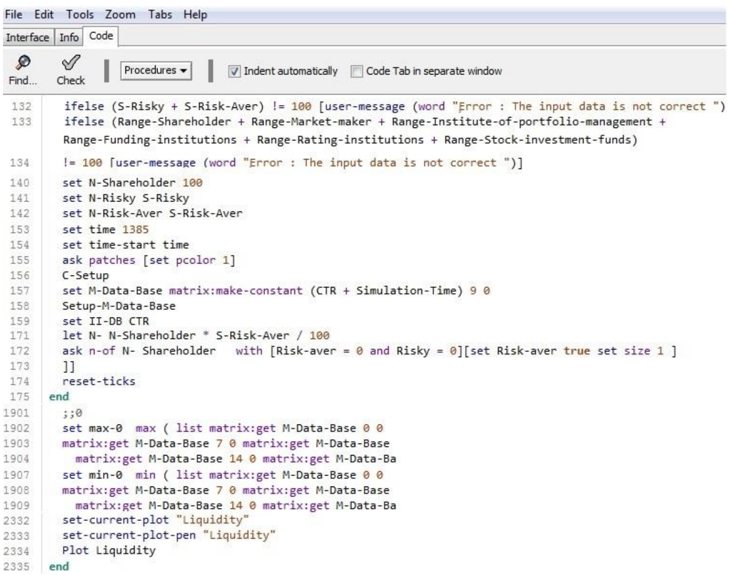
After determining xxx, the EMA for each period depends on the value of the previous period (A), the current period's closing price (P), and the smoothing factor x:

$$\text{EMA} = (P \times X) + \big(A \times (1 - X)\big)$$

8.Initial Model Implementation in Software

The simulation was carried out using NetLogo version 6.3.0. Considering the features of agents and their interactions such as probable decisions by actors, actual market mechanisms, and interrelationships 2,335 lines of code were written. The software's capabilities were used to observe and monitor agent behaviors throughout the trading process. Based on these interactions, the agents learn, and the user can run the modules, activating the artificial market for participants to act and enabling forecasts. The agents, whose behaviors are coded according to variable tables and role definitions, aim to avoid capital losses and maximize benefits. They conduct trades according to changes in the input variables and their market roles, affecting the overall stock index. This effect is displayed graphically and numerically in the forecasted overall index output. Conditional If-Else commands, along with Matrix-Set, Matrix-Get, and Ask calls, were employed to facilitate interaction among agents. In the following, random examples of codes from different lines have been captured and displayed with the aim of showing the use of the mentioned functions and rules and commands:

(Figure-8)

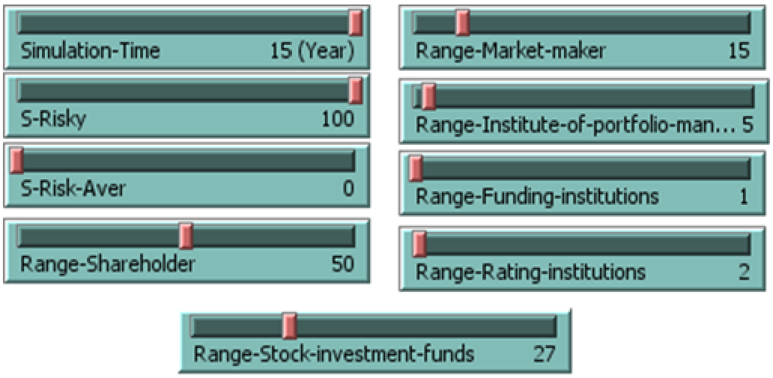


Examples of programming and code written to implement the model in NetLogo.

8-1.Pre-Processing (Setup)

In this phase, pressing the **Setup** button sets the environment for agent interactions. Initially, the simulator or researcher can view and adjust various input variables (sliders). After pressing **Setup**, different agent behaviors are initialized, and time steps (Ticks) and environmental patches (Patch) are configured.

(Figure-9)

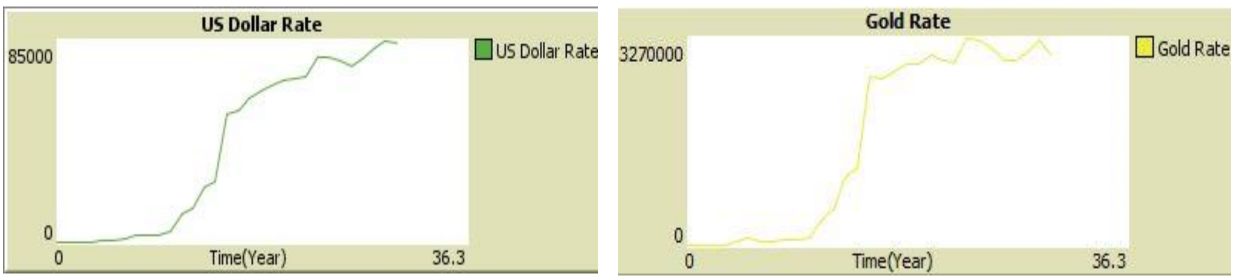


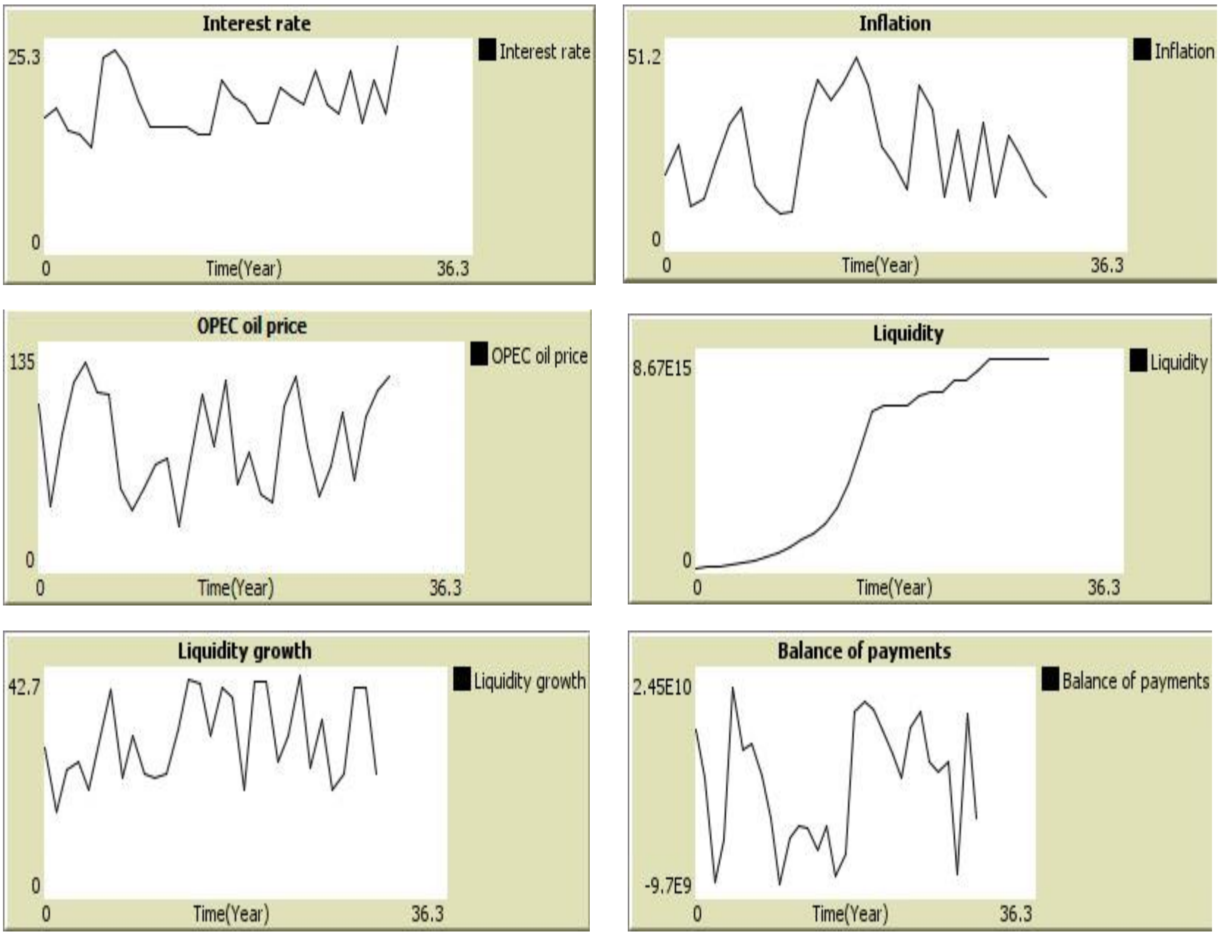
Sliders for setting simulation timeframes

8-2.Post-Processing

In the post-processing stage, after execution, which is actually the last stage of model execution, by executing the Go key, the impact of factors and variables is measured and calculated, and this is realized sequentially based on the target setting. This means that by executing the model, the software uses the moving average algorithm to discover data patterns of the past fifteen years of input variables, i.e. macroeconomic variables, to calculate the future trend of the variables. After that, the defined factors, i.e. stock market players (investors and non-investor players such as market makers, portfolio managers and others), make decisions and trade autonomously by looking at the generated numbers. The results of their trades are visible in the control index and in the next steps, sensitivity analysis is performed.

(Figure-10)





Sample charts for USD exchange rate, gold price, interest rate, inflation, OPEC oil price, liquidity, liquidity growth, balance of payments, and final output monitor for the overall stock index

(Figure-11)

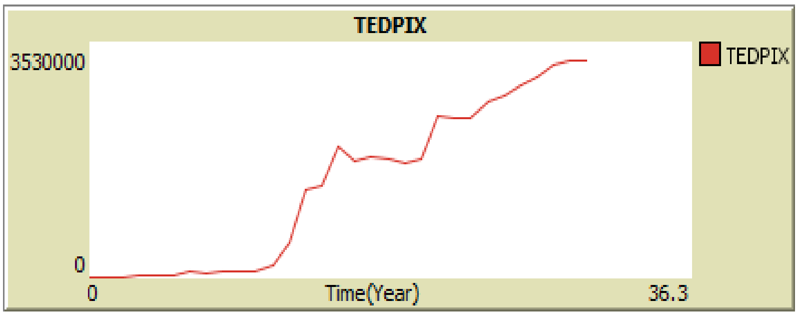
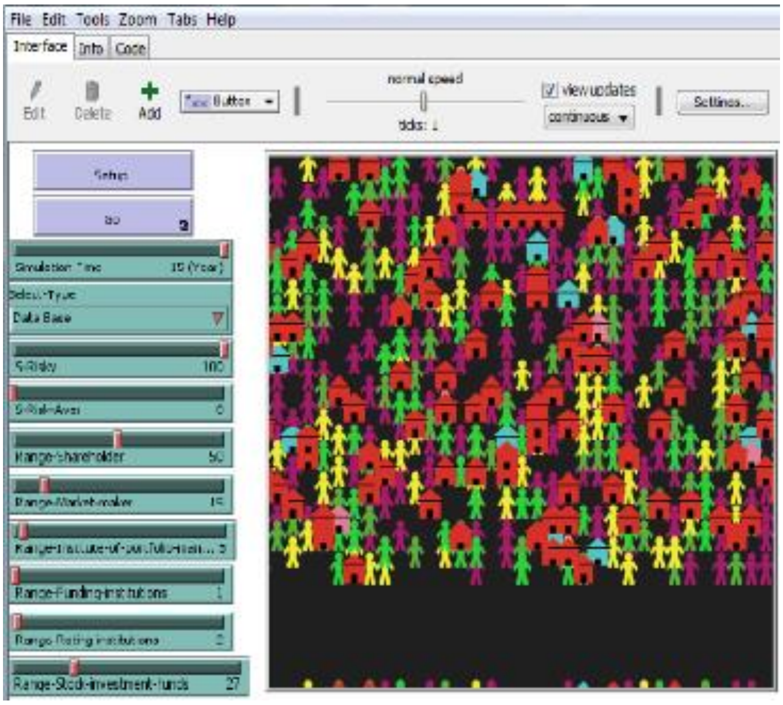


Image of the monitor or plot of the model output variable in NetLogo during the post-processing stage

8-3.Virtual Experiment

To uncover system dynamics, a virtual experiment is necessary. First, the potentially most influential parameters or variables are identified (Otomo et al., 2011). Next, their value ranges are defined in the model via sliders (Azar et al., 2017 [1396 SH]).

(Figure-12)



NetLogo interface after running the model

9.Model Validation and Verification

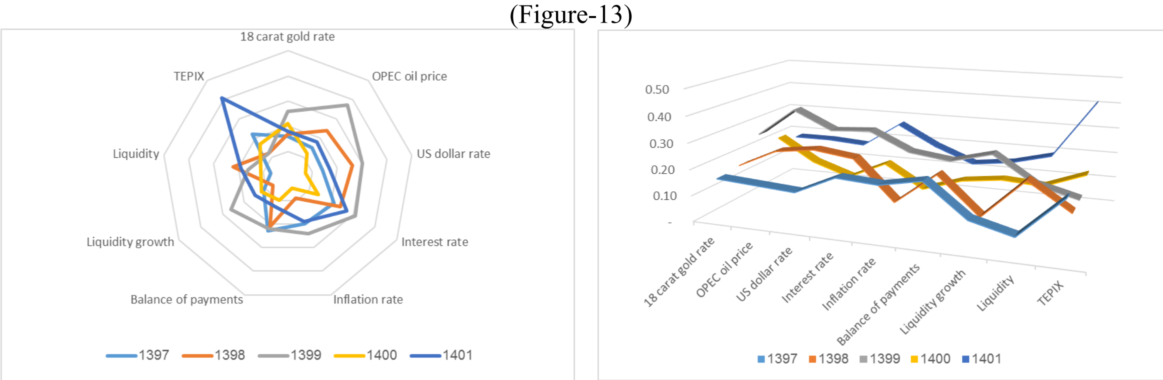
In 2011, William Rand and Ronald Rust proposed a framework and method for verifying agent-based models, citing studies by North & Macal (2007) and Gilbert (2008). Verification checks how closely the implemented model matches the conceptual model. Their model has three key verification steps: documentation, program testing, and test cases. In our design, all three stages have been completed. For documentation, the first step explaining the model's design serves as conceptual model documentation, and the code is documented. For program testing, a combination of code solutions, unit testing, and debugging ensured that the code behaves as expected. The code comprises main procedures tested individually with fixed input values. After verifying that each procedure worked, they were gradually combined and re-verified. This reduces model complexity and facilitates verification. Finally, several random test scenarios were chosen to ensure the model did not show abnormal behavior. Notably, NetLogo facilitates this process by issuing error messages upon encountering invalid inputs. Given the strictly upward historical trend of macro variables and the overall stock index in our 15-year dataset, we also tested random data inputs. We validated and confirmed our approach across strictly upward or downward scenarios.

Steps To Ensure Rigor In Validation:
1. Documentation Conceptual design and the implemented model should be documented.
2. Programmatic Testing Testing of the code of the model.
Unit Testing: Each unit of functional code is separately tested.
Code Walkthroughs: The code is examined in a group setting.
Debugging Walkthroughs: Execution of the code is stepped through.
Formal Testing: Proof of verification using formal logic.
3. Test Cases and Scenarios: Without using data,model functions are examined to see if they
operate according to the conceptual model.
Corner Cases: Extreme values are examined to make sure the model operates as
expected.
Sampled Cases: A subset of parameter inputs are examined to discover any aberrant behavior.

Specific Scenarios : Specific inputs for which the outputs are already known.
Relative Value Testing: Examining the relationship between inputs and outputs (Rand & Rust,2011).

Also, based on the model of Yumoto et al. published in 2011, which proposed two internal and external stages for validating factor-based models, the results of the simulation were compared with the experimental (real world) results. For this purpose, considering the collection of fifteen years of data on variables for the simulation database, the data of the first ten years in the experimental phase was considered as the database, and the simulation results of the next five years were compared with the actual data of the final five years, and the average of the means obtained from the simulation and the experimental evidence had a deviation of less than 0.2 percent. The results are shown in Table and Figure 13.

(Figure-13)



Graphs of validation results

Table 4

Index	18 carat gold rate	OPEC oil price	US dollar rate	Interest rate	Inflation rate	Balance of payments	Liquidity growth	Liquidity	TEPIX
1397	0.84	0.85	0.86	0.79	0.80	0.77	0.89	0.93	0.78
1398	0.83	0.76	0.74	0.76	0.91	0.79	0.93	0.78	0.88
1399	0.74	0.63	0.70	0.69	0.76	0.78	0.74	0.84	0.88
1400	0.79	0.88	0.93	0.86	0.95	0.90	0.88	0.89	0.83
1401	0.82	0.82	0.83	0.73	0.81	0.87	0.85	0.81	0.59

Table of deviations from reality in validation

Table 5

Results	Index	18 carat gold rate	OPEC oil price	US dollar rate	Interest rate	Inflation rate	Balance of payments	Liquidity growth	Liquidity	TEPIX
Real results	1397	4,298,700	67.0	128,940	15.0	31.2	9,880	23.1	18,828,000	178,659
Simulation results	1397	4,262,591	66.4	127,831	14.9	31.0	9,804	22.9	18,652,900	177,265
Real results	1398	6,026,000	27.0	149,030	15.0	41.2	671	31.3	24,721,000	512,900
Simulation results	1398	5,975,984	26.8	147,927	14.9	40.8	666	31.0	24,528,176	508,386
Real results	1399	10,855,000	67.0	239,630	14.0	36.4	(2,641)	40.6	34,750,000	1,307,657
Simulation results	1399	10,774,673	66.6	237,953	13.9	36.1	(2,620)	40.3	34,458,100	1,296,150
Real results	1400	12,291,000	105.0	262,300	14.0	40.2	895	39.7	48,320,000	1,367,250
Simulation results	1400	12,193,901	104.1	259,861	13.9	39.8	887	39.4	47,889,952	1,355,902
Real results	1401	26,406,000	74.0	538,000	20.5	46.5	(6,489)	30.0	62,820,000	1,960,457
Simulation results	1401	26,189,471	73.4	533,535	20.4	46.1	(6,433)	29.7	62,311,158	1,948,890

Table of validation results

10.Sensitivity Analysis

In 2022, Borgonovo et al. proposed a systematic framework for sensitivity analysis in agent-based models to address criticisms of their validity. Their approach identifies a target for analysis among four common aims: (1) Are the results robust? (2) Which elements have the greatest impact on outcomes? (3) How do these elements interact to shape outcomes? (4) Which direction do results move in when elements change? Their method has six steps:

1. Select the output of interest
2. Define the analysis goal and prioritize
3. Choose the elements
4. Choose or design a method
5. Assign values
6. Visualize results

For this study, data were drawn from two sources: a database ("data-based" approach) and random inputs. We controlled changes in the input variables and examined their impact on the output variable, displaying the results in tables and charts for both approaches. We considered three separate scenarios, running each model scenario 100 times, recording the average outcome. After about 100 runs, the results stabilized, and no major changes were observed. In each scenario, we adjusted the relevant variable by 10% increments from 10% to 100%. Combining the two input approaches and three scenarios (for each scenario, 100 runs at each 10% level) yielded a total of 6,600 runs.

11.Findings

11-1.Sensitivity Analysis of Model Agents (Active Stock Market Players)

Recognizing the vital roles of market makers, portfolio managers, investment funds, investment banks, and rating agencies in the capital market, we designated these as key agents in our model. To evaluate how each agent impacts stock market activity, we introduced individual sliders controlling the weight of each agent, then performed sensitivity analysis. During this process, we kept other agent weights constant while incrementally increasing the selected agent's weight by 10% (reducing each of the other agents by a combined 2% each time, so the total always sums to 100%). Each stage ran 100 simulations. We stored these outputs in spreadsheets (like Table 3, which shows a zero-percent presence of market makers as an example). Next, each set of 100 runs was summarized and the averages computed. Then, the resulting matrices for 15 years were compared, and we charted each scenario. Finally, to explore the long-term trend (the 15-year span), the average values for each scenario were plotted. Overall, 1,100 runs were executed for this section.

Table 6

100 executions with the slider set to zero means assuming zero percent presence or absence of the market							
year	The First execution	The second execution	The third execution	…	The ninety-nine execution	Execution of hundreds	Average
1402	1,960,457	1,973,200	1,951,635	…	1,903,604	1,910,465	1,833,011
1403	2,163,364	2,001,627	1,951,635	…	1,950,655	2,024,172	1,901,333
…	…	…	…	…	…	…	…
1415	2,819,137	3,009,301	3,198,486	…	2,646,617	3,031,847	2,917,241
1416	2,819,137	3,056,352	3,341,599	…	2,655,439	3,053,412	3,009,187

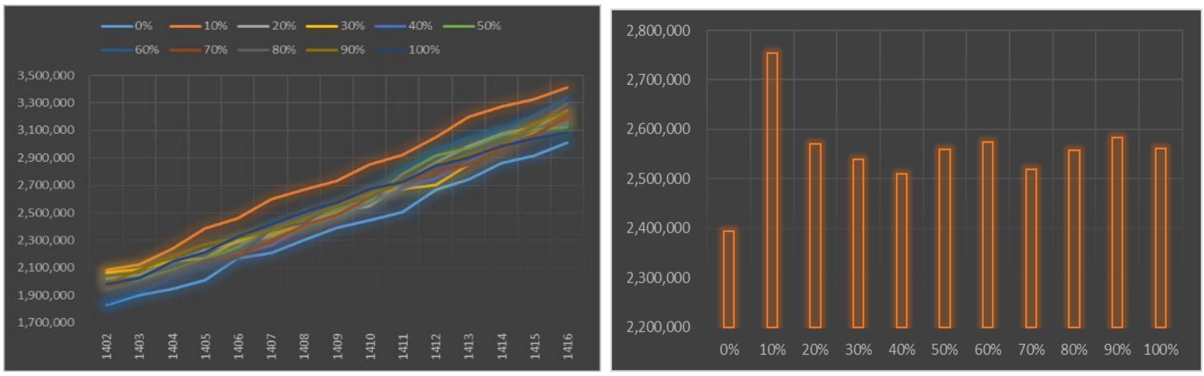
Sample output for 0% market maker presence

Table 7

year	0%	10%	…	20%	90%	100%
1402	1,833,011	2,082,610	…	2,018,786	1,983,688	1,981,924
1403	1,901,333	2,124,270	…	2,050,741	2,085,730	2,024,564
1404	1,943,776	2,237,780	…	2,137,491	2,181,695	2,141,309
1405	2,008,570	2,386,187	…	2,225,810	2,270,013	2,212,572
1406	2,166,386	2,459,312	…	2,287,466	2,314,418	2,328,043
1407	2,207,164	2,598,504	…	2,325,891	2,378,721	2,414,695
1408	2,299,795	2,667,905	…	2,429,305	2,454,884	2,503,406
1409	2,391,643	2,733,286	…	2,508,508	2,555,554	2,572,806
1410	2,446,144	2,851,992	…	2,549,677	2,643,578	2,672,691
1411	2,504,173	2,923,352	…	2,717,885	2,717,880	2,720,722
1412	2,668,263	3,049,410	…	2,864,723	2,853,739	2,842,173
1413	2,742,369	3,197,326	…	2,987,643	2,922,061	2,900,398
1414	2,863,525	3,273,294	…	3,076,550	2,988,521	2,985,776
1415	2,917,241	3,325,050	…	3,122,033	3,149,866	3,037,630
1416	3,009,187	3,409,349	…	3,240,542	3,238,283	3,084,681
سال	0%	10%	…	20%	90%	100%
avrage	2,393,505	2,754,642	…	2,569,537	2,582,575	2,561,559

Sample output of the average role of market makers in the sensitivity analysis

(Figure-14)



Sample chart of sensitivity analysis for market makers' average values

11-1-1.Discussion and Conclusion

Given the trend of macroeconomic variable changes, how these stock market actors are influenced by macro variables, and the market's importance for economic vitality, an agent-based simulation model of the Tehran Stock Exchange has been designed. By defining agents that mirror these actors and forecasting their behavioral changes along with controlling other simulated agents we can provide valuable information for decision-makers and policymakers to adopt optimal strategies. This approach can replace statistical, mathematical, or classical analyses that fail to factor in social, psychological, human, and behavioral elements. It is also important to acknowledge that a lack of comprehensive analysis (e.g., focusing solely on one dimension of participant behavior or ignoring the interactions among actors) is a serious flaw in some prior artificial market research. Such gaps often lead to discrepancies between simulated outcomes and real-world behavior. In our research, by examining all market actors, accounting for their sensitivity to macroeconomic variables, and modeling their interactions, we address this flaw. The key results from the sensitivity analysis are summarized below:

11-1-2.Results from the Sensitivity Analysis of Market Makers

1. Without market makers, the index's growth is at its lowest.
2. The highest index growth occurs when the slider is set at 10%, which implies market makers are performing their duties correctly, injecting liquidity during downturns, and steering the market toward greater dynamism.
3. As market makers' influence grows (from 10% to 90%), overall market index growth declines, suggesting that if they overstep their duties and intervene excessively, they not only lose their catalytic efficacy but also harm public trust, reducing the market's dynamism. At a hypothetical 100% weight, an exception emerges because, in practice, no opposing forces remain in the simulation, so a single-sided flow of buy and sell orders from market makers artificially boosts growth.

The results of this section clearly show how the behavior of market makers can add to the complexity of collective behavior and influence the rational behavior of actors by instilling unhelpful motives in them. In other words, by interfering excessively, market makers can divert market flows from their logical routine and, while preserving their own interests, cause serious damage to the small capital of collective investors. Therefore, increasing controls and monitoring the performance of market makers in the capital market is of great importance, and recommendations in this regard have been made in the practical suggestions section.

11-1-3.International Studies Supporting These Findings:

- **Faisal Sultan Qadri et al. (2018):** Showed a relationship between market makers' behavior and overall stock returns in Pakistan's stock index.
- **Zhi Xiang & Xing Zhu (2018):** Investigated dynamic connections between market makers and overall stock returns in emerging Asian markets, arriving at similar conclusions.

11-2.Results from the Sensitivity Analysis of Portfolio Managers

1. If portfolio managers are absent, the index's mean remains very low.
2. As portfolio managers increasingly direct idle capital into the stock market, enabling specialized trades, the overall index gradually rises. Up to a 30% share for portfolio managers, the index reaches its highest average.
3. Beyond 30%, the index mean dips until the share of portfolio managers hits 70%, where the index experiences a minimal rise, indicating an overly conservative approach to risk.
4. From 70% to a full (100%) market share by portfolio managers, a relative rebound occurs. While a purely portfolio-managed market may not reach maximum growth, it can maintain moderate, stable growth while avoiding the losses caused by panic and volatile behavior.

Similarly, the results of this section also indicate the importance of the presence of actors other than investors in the market, and neglecting their presence and activity can seriously challenge market behavioral analyses and lead to unpredictable behaviors from the masses of investors. As a result, monitoring and controlling the behavior of portfolio managers has a special place, and practical recommendations are provided in the practical suggestions section.

11-2-1.International Studies Supporting These Findings:

- **Zhang (2020):** Analyzed portfolio manager transactions' impact on China's stock market.
- **Wong (2009):** Studied the relationship between portfolio managers and the overall market index in international futures markets, reporting similar outcomes.

11-3.Results from the Sensitivity Analysis of Investment Funds

1. Setting the slider for equity investment funds to zero yields the lowest growth for the overall index, mainly because of the absence of these funds' relatively large liquidity and because risk-averse investors who trust such funds may leave the market.
2. The highest index growth rate appears between 10% and 20%.
3. From 20% to 100%, the presence of funds largely sustains market growth, with no major deviation from the mean, reflecting a balanced approach to portfolio management.

Given the alignment of this fund with the capital of retail investors, it is essential for executive policy-making institutions to support these funds, for example, the National Development Fund's support for them, the allocation of low-interest loans, etc. It is obvious that in these circumstances, when a fund enjoys government support, the possibility of monitoring and controlling it increases, meaning that they can be used as policy-making arms in critical situations to control behavioral complexities by requiring the purchase, sale, or holding of shares.

11-4.Sensitivity Analysis of Investment Banks and Rating Agencies

Based on expert opinions regarding the penetration rate of each internal market actor and the results of sensitivity analysis on six distinct agents, and considering that investment banks (1%) and rating agencies (3%) have low overall impact, we anticipated negligible significance from slider changes. Preliminary one-step tests confirmed this. To avoid overly lengthy text, we do not present their detailed sensitivity analyses. Instead, in line with step three (elements) of Borgonovo's methodology, we only included them among the six agents to be consistent but did not elaborate on the results.

12.Scientific and Practical Recommendations

Drawing on the discussion of theoretical gaps in prior research and the results of this study along with the innovative features of our model we offer the following scientific and practical suggestions:

1. **Market Makers:** Given the sensitivity analysis results highlighting their major role, comprehensive tools should be implemented to manage their behavior throughout their entire life cycle (from licensure to operation and eventual exit). This includes accurate selection processes, robust behavioral monitoring, effective regulatory oversight, and balanced controls to maintain their optimal level of participation. After the licensing stage, their activities must be reviewed and controlled using various methods and tools, and inherently restrictions are imposed on them so that policymakers can have more control when necessary, for example, imposing a limit on their trading ceiling of up to 10 percent, preventing them from trading in short-term time frames, and requiring them to hold shares over time to prevent their arbitrage behavior in the volume ranges of 10 to 30 percent, and the like.
2. **Portfolio Managers:** Similar to the suggestions for market makers, comparable oversight and selection mechanisms should apply to portfolio managers, given their role's demonstrated importance in supporting the overall stock index. And restrictions on the number of their transactions, the volume of transactions, the time intervals between transactions of a stock code, the volume of cash inflows and outflows in specific downward and upward trends, and vice versa, this means requiring them to buy and sell during times of market downturn.
3. **Investment Funds (Equity Funds):** Our findings indicate their role in guiding overall market trends. Beyond the suggestions in point one, adopting flexible regulatory protocols at key intervals to manage the trading weight of equity funds and, by extension, scattered small investments can help stabilize the market.
4. **Further Variables:** The artificial market model can be expanded to include additional macroeconomic or even non-economic variables (provided they are quantifiable) to study their effect on the overall stock index and manage potential risks during transformations or crises.
5. **Investor Behavior:** With the model's current capabilities and historical data on various investor behaviors (trained vs. untrained, fundamental vs. technical, momentum vs. random), one can propose new incentives or controls to encourage constructive behavior and enhance market dynamism.
6. **Other Actors:** Using this model, policymakers can identify disruptive behaviors by any actor that might favor individual gains at the expense of small investors, taking preventive measures against them.
7. **Parallel Markets:** By adapting this research foundation agent-based

systems, complexity, and access to data analysts and policymakers can model parallel markets like foreign exchange, gold, or real estate, thereby gaining broader insights to boost overall economic dynamism.

8. **Alternative Stock Indices:** While this study uses the overall stock index as its output variable, other significant metrics such as the equal-weight index can also be investigated with this model.

13.Glossary:

Autonomy: The agent performs its actions based on its perceptions and internal knowledge. If it acts only on its internal knowledge, it lacks autonomy (Jude Kay, 2006).

Multi-agent systems: Systems consisting of a group of agents that potentially interact with each other, which are defined by a specific infrastructure of communication and interaction protocols and include agents that are autonomous and distributed or cooperative (Weiss, 2000).

Agent: In computer science, a software agent or a software agent is a computer program that acts as an agent for the user or other programs. (Franklin and Grosser, 1996).

Microstructure: The analysis and study of the process in which demand and volume of transactions are derived from investor demand in the form of explicit transaction rules. (Mohajari et al., 2024)

Agent-based simulation: An approach to modeling systems consisting of individual, independent, and interacting “agents.” Agent-based modeling provides ways to more easily model individual behaviors and how those behaviors affect others, and offers methods that were not previously available (McCall and North, 2014). Agent-based simulation is most commonly used to model individual decision-making and social and organizational behavior (Banabeau, 2001).

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