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# Designing the optimal investment model based on the parameters of predicting stock returns and the risk factors of disruptive traders

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**Abstract**

Noise traders cause severe fluctuations and deviation of asset values from their intrinsic value; thus, this article designs an optimal investment model based on the parameters of predicting stock returns and noise trader risk factors. This is an applied post-event paper. In this article, first, the stock returns predicting parameters are obtained followed by the noise traders' risk factors obtained through behavioural error or the beta difference in transactions, according to the combined regression model or models, which are the results of the risk factors. Then, noise traders and stock return predictor variables were designed and tested using econometric software, including Eviews9 software and Matlab algorithmic models. The statistical population of this research includes all companies admitted to the Tehran Stock Exchange, whose shares were traded until March 19, 2020. Also, in this research, PCA, GSADF, and logit methods were used to determine the impact of noise traders in determining the incidence of the bubble used in the Tehran Stock Exchange. The research findings show that noise traders have a positive and significant effect on the occurrence of a bubble, and an increase of one unit of optimistic sentiments and optimistic sentiments with a break in the stock market increases the probability of a bubble occurrence.

Keywords: optimal investment, stock returns, risk factors noise trader
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## 1 Introduction

The Efficient Market Hypothesis is addressed by every capital market for its special effect on every analysis and transaction. The Efficient Market Hypothesis has been proposed and emphasized as the main foundation of the conventional financial economy. By definition, an efficient market is one in which prices always fully reflect available information. Evaluating market efficiency as a measure of the capital market's ability to achieve its goals has always been important, and the evolution of its methods has had a tremendous impact on the development and deepening of financial economics. Market efficiency is classified into three categories: informational efficiency, operational efficiency,

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and allocative efficiency. Lim and Brooks [18], in the definitions of efficiency, state that informational efficiency refers to the use of information in prices, and operational efficiency also refers to the cost of transactions in the capital market. Allocative efficiency also examines the efficiency of capital allocation to economic sectors with the highest capital productivity. Market efficiency has been examined in the whole stock market around the globe, accordingly, many studies have addressed this issue in recent years in Iran, considering the efficiency of the Iranian capital market to be weak. Weak market efficiency causes the emotional tendencies of investors and impacts the trading process and the price of securities. The behavioral finance point of view shows that some changes in the securities prices do not have any fundamental reason, but originate from the emotional tendency of investors, and play an important role in determining the prices. Iran's stock market has a favorable background for testing the theory of noise traders hypotheses because it is a developing and emerging market due to conditions, including a lack of efficiency in the market [27, 28] and making investment decisions collectively without considering fundamental variables [22]. Disruptions have always existed in financial markets. These disruptions, which are in the form of daily stock price fluctuations, are caused by factors such as the arrival of news or information, mass behavior, or the impact of fundamental factors. The occurrence of global financial crises shows that traditional financial theories are unable to explain the origin of some of these disruptions and provide a logical solution to overcome them. To investigate their behavior, financial market traders were classified into two groups: the first groups are Smart Money Traders or completely rational traders, and the second group of Noise Trader, whose investment decisions are often made based on word of mouth, and most importantly, imitating others [31]. Shleifer and Summers [33] consider the decisions of noise traders to be influenced by their systematic distortions, emotions, illusions, and desires. Based on the efficient market hypothesis, noise investors are marginal traders who are quickly eliminated by smart money traders as a result of the arbitrage process [29, 30]; it seems that many investors are less professional and do their transactions based on psychology or noise and wrong information that is not necessarily related to the fundamental values of the company and the real information of the market and economy. The presence of noise traders can potentially explain the presence of several irregularities observed in the market: feedback trading, price bubbles, and excessive volatility [1]. Any trader who trades without the necessary information is called a noise trader [32]. Noise traders are mainly prone to fads, overconfidence, and other behavioral biases, they engage in various trading behaviors such as trend-following. In contrast to this behavior, professional investors take advantage of the irrational misunderstandings of this group of traders and when the noise traders are frustrated, they buy stocks and vice versa with an inverted behavior [21]. Scientific research on noise traders started when Fischer Black [8] proposed the argument that noise traders contribute to market liquidity, and thus challenged the paradigm of removing noise traders as marginal traders by arbitrageurs. Following this research, De Long et al. [12] provided evidence of the impact of noise traders on stock returns, providing strong empirical evidence in support of Black's argument, and after that, contradictory discussions regarding noise traders were raised. Some researchers believe that the presence of noise traders is useful and necessary to increase market liquidity [8, 9]. While others believe that the presence of such a group in the financial market, especially in big numbers, causes problems such as faulty pricing in the market [26]. Opponents also believe that the presence of this category of traders increases the risk of securities transactions due to the difficulty of predicting their activities and decisions, and their continuous presence in big numbers affects trust in the financial markets [15] and may harm the smart money traders group disrupting market equilibrium relationships [26]. In practice, the line between arbitrageurs (smart money traders) and noise traders may seem unclear; nonetheless, since arbitrageurs play the role of moving prices towards fundamental values in the market, they can help make a clear distinction between these two groups of investors [33]. Financial markets, both as a place for traders and as a suitable place for investment, have always attracted the attention of capital owners; however, the question that is always raised for newcomers in this field is "How do the activists and professionals of these markets make decisions?" [3]. In the stock market, each share has its conditions. If the same index with default parameter is used for all stock types, the quality of response received for each stock will be different from another. This means, if an index with default parameters provides a good forecast for one stock, it may not provide a good answer for another stock. Therefore, it is necessary to optimize the parameters of technical analysis indicators for each share individually, because each share has its parameters [4]. Until today, many researchers have examined the factors affecting stock returns. The first stock return estimation model, The Capital Asset Pricing Model (CAPM) developed by William Sharpe defines systematic risk or its beta coefficient as the only factor that explains the difference in stock returns. Strong theoretical foundations and empirical evidence supporting this model, along with the fact that this financial theory is successful, made it the most famous asset pricing model among academics and professionals. With this simple tool, investors could evaluate their investment solutions by comparing the predicted returns of the model with actual achievements or by calculating the cost of capital based on the level of risk. The deviations and anomalies of the CAPM model were revealed from 1975 to 1990. According to the researchers, these anomalies were raised as a challenge to the validity of CAPM in the ability to describe the expected return by the systematic risk factor, and gradually the use of multi-factor models in explaining stock returns replaced the single-factor model of capital asset pricing. The arbitrage pricing model was introduced by Ross in the late 1970s, which had two advantages over the capital assets pricing model: firstly, there were fewer restrictions in its assumptions, and secondly, the model can be tested experimentally [24]. Kholdy and Sohrabian [16] compared the effects of noise traders and smart money investors on stock returns in the form of two groups of individual institutional investors in the American market. This research was conducted during the 1990s and 2000s, respectively, as prosperity and fluctuating period were examined. The results showed that the emotional tendencies of real investors (the measure of the risk of noise traders) can often affect the returns of the market shares when the prices in the market are on the upward trend and the borrowing sale has a high risk, while the sentiments of the institutional investors when the market is volatile and the risk of borrowing sales is low, can affect the stock returns in the market. Investors' emotional tendencies are a measure to measure the risk of noise traders. Also, different regression models can be used to calculate the risk of noise traders. Many pieces of evidence show the noise traders' significant effect on the stock market [37], so they may even get more profit than smart money investors (arbitrageurs) [15]. Based on an important assumption of behavioral theory, the transactions of these noise traders are not independent from each other and have a systematic correlation with each other, so their role and impact in the financial markets cannot be ignored and they cannot be considered insignificant part of the investment process in the financial markets. In Iran, despite the importance of this issue, no research has identified noise traders and quantified their risk [31]. Noise transactions prevent the information efficiency of the market and cause stock prices to deviate from their fundamental values, usually, a stock market bubble is formed when the intensity of the effect of such noise traders has increased. One of the critical factors that prevent rational traders from eliminating wrong pricing based on the demands of noise traders is their short time horizons [1]. Behavioral finance theory expresses two basic assumptions: the first assumption is that investors make decisions under the influence of their emotional tendencies. The second assumption is that arbitrage is risky and costly for emotional investors; Therefore, smart money investors or arbitrageurs are not aggressive in returning prices to the fundamental price. Modern behavioral finance believes that there are limits to arbitrage. The dynamic interaction between noise traders and smart money arbitrageurs shapes prices, and if a stock has more noise traders or fewer smart money traders, its price volatility is significant [39]. The importance of studying investors' reactions in the face of information and a disorder can be found well in the literature which requires the need for more general research in this field in our country [1]. Also, taking into account that the behavior of the stock market is chaotic and like many natural phenomena, it has a non-linear behavior, the design of non-linear models to predict the stock market has become very important [4]. Therefore, considering the uncertainty that governs the stock market and also considering the different tendencies and preferences of investors, finding a method to choose a suitable set of securities through which it is possible to overcome uncertainties and different preferences seems necessary [25]. Considering what has been mentioned so far and considering the important role of noise traders in the capital market, their small number causes market liquidity, and their big number causes risk and disrupts the market. Therefore, the purpose of this research is to design an optimal investment model based on the parameters of predicting stock returns and the risk factors of noise traders.

## 2 Literature review

Qalibaf Asal et al. [13] conducted a research with the title of "Designing a model for forecasting long-term stock returns with non-parametric simulation of debt bond returns", to predict excess stock returns based on data based on debt bonds and other economic and capital market variables in Iran. The results of the model implementation showed that in all three steps of identifying the variables influencing the rate of return of securities, structuring the model for predicting the rate of return of debt securities and determining the factors influencing the prediction of the excess rate of return of stocks, the implementation of different models based on the non-parametric approach outperforms the parametric approach. Nadi Qomi and Seif [24] conducted a research titled "Bubble analysis on stock returns". This research presented a pricing model in bubble conditions and investigated the influencing factors on stock returns using the completed Famau-Fritch model. For this purpose, the investigated sample includes 81 active companies in the Tehran Stock Exchange from 2008 to 2012, which were selected by screening method. The results of this research reveal that out of 5 market factors, company size, book value to price, momentum and bubble, only 2 factors, momentum and bubble, affect abnormal returns. Saranj et al. [31] conducted a research titled "Identifying trading behaviors and risk of noise traders in the Iranian stock market". In this research, for the first time, multi-viewer symbols have been used to compile a new behavioral index. This new indicator is used to identify noise traders, and it can be used to achieve a more accurate beta than the market beta. Also, using the capital asset pricing model and asset pricing behavioral model in the six-year period of 1395-1390 for 96 companies, they showed that the Iranian stock market has a significant behavioral error. In addition, the results of using the information-adjusted noise model showed that noise traders are active in the Iranian stock market 100% of the time and cause its inefficiency. The biggest type of inefficiency in this market is overreaction in 46.67% of the time, followed by incorrect pricing and underreaction in 45.63% and 71.7% of the time, respectively. The findings of this research help to understand the prevailing atmosphere in the market and the new behavioral index (BIX) can be used as an indicator of the tendencies of Iranian investors. Yu et al. [38] conducted a research titled "Stock price prediction based on the LLE-BP neural network model. In this research, a local linear embedding algorithm (LLE) was chosen to reduce the dimensions of factors affecting the stock market. Data after dimension reduction was used as new input variable of Back Propagation (BP) neural network to realize stock price prediction. Prediction results were compared with BP neural network model, PCA-BP model and traditional ARIMA model (3,1,1). The results showed that the LLE-BP neural network model has a higher prediction accuracy in stock price prediction and is an effective and practical method for stock price prediction. Wang et al. [35] conducted a research titled "Forecasting Stock Price Volatility: New Evidence from GARCH-MIDAS Model". In this research, a combination of asymmetry and the effects of extreme fluctuations have been introduced to create superior elasticity of the GARCH-MIDAS model for modeling and forecasting stock fluctuations. The results clearly confirmed that extreme shocks have a significant effect on stock volatility and volatility is more affected by asymmetry than the effect of extreme volatility in the long and short term. Out-of-sample results with several strong reviews showed that the proposed models of this research can outperform in predicting fluctuations. Moreover, the improvement in predictive ability is stronger for the short-term volatility component than introducing asymmetry and extreme volatility effects. Harve et al. [14] investigated noise traders and smart money in a research. Traditional financial theories hold that attracting the attention of smart money investors offsets the impact of noise traders on asset prices. This paper uses online search data to examine the impact of noise traders and smart investors on stock returns and stock volatility. For example, this research used 87 French companies from 2008 to 2018 and showed that only the attention of noise traders can affect stock returns. The attention of noise traders increases volatility by creating additional risk that is priced into the market. In contrast, the attention of smart investors reduces volatility because their presence increases stock prices by reducing uncertainty.

## 3 Research question

What is the optimal investment model based on the parameters of predicting stock returns and the risk factors of noise traders in Iran's capital market?

## 4 Research method

Research methods refer to the methods of designing research studies and data analysis procedures. It is not possible to achieve the goals of the research unless the research process is carried out with the correct methodology. In general, the research method can be defined as a set of reliable and systematic rules, tools and ways that are used to investigate facts, discover unknowns and reach solutions to problems. This section addresses the research method and reviews the related materials, considering that, the researcher seeks to design an optimal investment model based on the parameters of predicting stock returns and the risk factors of noise traders. In other words, this research results after the completion of the work can be used immediately in the target society and improve the existing situation, so this research is considered as an applied research based on its purpose, because its results can be used in the stock exchange organization. In this research, we first obtain the predictor parameters of stock returns, and then the risk factors of noise traders are obtained through behavioral error or beta difference in transactions. After that, according to the combined regression model or models, which is designed from the risk factors of noise traders and predictor variables of stock returns, it is examined and tested using econometric software such as Eviews9 software, and if needed, the algorithmic models will also used. The statistical population of this research includes all companies admitted to the Tehran Stock Exchange, whose shares were traded until March 19, 2020. In this article, the content validity was used to check the validity of the questionnaire. Thus, experienced professors and advisor were consultated and surveyed and they approved the question items and dimensions.

**The research variables include:**

**Independent variables include:**

**A. Noise and emotional transactions variable;** Noise and emotional traders make decisions under the influence of market emotions and sentiments; therefore, emotional indexing is used to explain the behavior of this type of traders. Emotional indices or indicators show the feelings of a group of traders and indicate how optimistic or pessimistic they are about the current and future market situation [34] . In this research, an emotional composite index consisting of the combination of several variables and an emotional index has been extracted using the principal component analysis method. In this research, first, seven variables were selected based on the frequency of use in different researches, limitations of data access and consultation with experts, which are explained below:

1. The monthly volume of small transactions to the total volume of stock market transactions: the possibility that small and inexperienced investors are exposed to emotions is more than institutional investors. Barber, Odean and Zhu [6] by researching transaction data at the micro level, find that retail investors buy and sell shares in unison, which is compatible with systematic sentiments.
2. The monthly volume of online transactions to the total volume of stock market transactions: when the feeling of optimism and excitement in the market is high, the volume of online transactions will increase, and on the contrary, when the excitement is reduced and the feeling of pessimism is common, the volume of online transactions will decrease. This measure has been added to the total variables after consulting experts.
3. The monthly ratio of active trading codes to all market trading codes: in this research, instead of new trading codes, which has been used in various researches [36], the data related to the number of trading codes was considered active. Active codes mean codes that have made at least 4 transactions per month (one transaction per week). This ratio indicates that the number of active codes will increase with the increase in the emotions and excitement of traders in the market. This ratio has been chosen as a replacement for the new codes after polling experts and based on the conditions of the Iranian stock market.
4. The average yield of the first week of initial public offerings: Baker and Wurgler [5] have called this index a good variable to show the emotional tendency of investors. In Iran, due to the limitation of the fluctuation range, experts considered the return of the first five days (the first working week), instead of the first day's return.
5. The ratio of the monthly value of issuing units of investment funds in stocks to its cancellation value: Brown and Cliff [10] suggested that investors' transfers between risky growth stock funds and risk-free fixed income funds can be adopted as a measure of emotional orientation of the investor. According to the experts' opinion, considering that the inflow and outflow of fixed income funds in Iran, in addition to emotions, is strongly influenced by the monetary and credit policies of the central bank in determining the bank interest rate, therefore, only the inflow and outflow of cash flows to investment in shares was considered.
6. The ratio of shares in the portfolio of investment funds: this ratio indicates that when emotions and excitement are high in the market and there is an atmosphere of optimism in the market, fund managers (both fixed income funds and shares) and portfolios are more inclined to keep stocks (according to the quorum and regulatory limits) in their portfolio.
7. The monthly volume of stock transactions by funds and portfolio management companies to the total volume of market transactions: Here, too, the volume of equity transactions (specifically funds and portfolio management companies) is considered as an indicator to show the emotional tendencies of this category. Finally, based on the specific value (percentage variance of the first component) and factor load values (coefficients) of the variables in the first component of PCA, only three variables remained in the final index, two of which: "monthly volume of retail transactions to the total volume of stock market transactions (vs)" and "Monthly volume of online transactions to the total volume of stock market transactions (vo)" relate to small and real traders and a variable "monthly volume of stock transactions by funds and portfolio management companies to the total volume of market transactions (vf)" relate to institutional and legal traders.

**B. Control variables;** The control variables of this research are: inflation, Brent oil price, gold price (the price of Bahar Azadi coin of the old design), liquidity and exchange rate (dollar parity rate). These variables have been used to remove the effect of the basic factors in the occurrence of sentiments in extracting the composite index of sentimental orientation, and the turbulence and uncertainty of these variables have been used in the final logit model. The monthly data of inflation, liquidity, dollar parity rate and the price of Bahar Azadi coin were extracted from the website of the Central Bank of the Islamic Republic of Iran and the economic graph magazine and the monthly data of the price of Brent oil were extracted from the US Energy Information Administration.

**Dependent variable**

In this article, the dependent variable is a two-valued variable with two optional modes of zero and one, where zero indicates the absence of a noise and one indicates the occurrence of health.

The index of "reliability coefficient" is used to measure reliability, and it usually varies between zero and one. A reliability coefficient of zero indicates lack of reliability and a reliability coefficient of one indicates complete reliability. Reliability is the ability of a measuring instrument to maintain its stability over time. The most important method for rating scales is the " Lee Coronbach " method or the attitude meter, which was studied and presented by three researchers named Coronbach, Rajaratnam, and Gillers, but it is only known by the name of Coronbach, and in it, in addition to the fact that an index is obtained to confirm the sizes obtained from groups and individuals, the generalizability of this size is determined to other sizes as well [40]. In this paper, the reliability of the questionnaire was calculated by Cronbach's alpha method in SPSS.

In the first stage, the researcher faced a vague, unfamiliar and uncertain situation called the design of the optimal investment model based on the parameters of predicting stock returns and the risk factors of noise traders. In the next step, he searched so that he can guess the factors that have potentially led to the issue or obtain assumptions about it. In the third stage, the researcher formulated research questions or hypotheses. In the fourth stage, observations were made, and at the end of the work, according to the information obtained from their analysis, the questions were rejected or confirmed. Therefore, the research steps are as follows:

1. Obtaining parameters predicting stock returns
2. Identifying the risk factors of noise traders
3. Examining the effect and relationship of risk factors on parameters
4. Presenting the regression model and testing it
5. Presentation of the optimal and final model

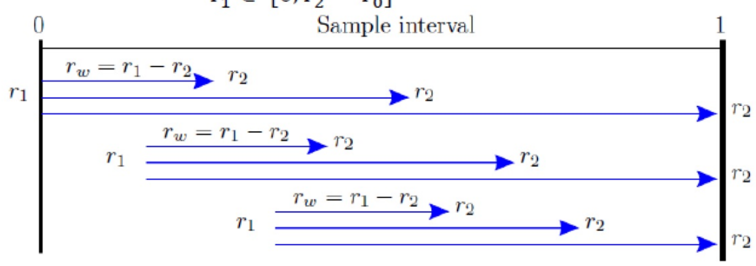
Analysis of research data includes several steps. In the first step, an emotional composite variable and index is extracted to explain the behavior of noise and emotional traders, which is similar to many researches conducted in this field [5, 11, 19, 20]. Also, principal component analysis method was used. In this method, the variables in a correlated multistate space are summarized into a set of uncorrelated components, each of which is a linear combination of the original variables. The obtained uncorrelated components are called basic components, which are obtained from the eigenvectors of the covariance matrix or the correlation matrix of the main variables [23]. The regression of the measured variables on the current variables provides weights called factor loadings; in other words, it is a structural factor that is defined by its factor load [17].

In the second step, EGARCH conditional variance heteroscedasticity model is used for modeling and extracting fluctuations (noise) of control variables. The reason for using this model is that the time series fluctuation of the aforementioned variables may not show the same response to positive and negative shocks, and to analyze the behavior of the fluctuations, it is necessary to use an asymmetric model. The conditional variances of the EGARCH(p,q) model are calculated as follows:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_j \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=1}^{P} \alpha_j \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + V_t \tag{4.1}$$

In the third step, the Generalized Sup Augmented Dickey-Fuller (GSADF) test was used for the health field and to identify the factors affecting the health field. To perform this test, rtadf plugin is used in Eviews software. The main feature of this test is that it provides the possibility of considering non-linear dynamics and structural failure at the same time as factors affecting health in time series. As seen in diagram 1, in this test, the starting point ($r_2$) is allowed to be variable in the range $(0, r_2 - r_0)$ of GSADF. Statistics are defined as:

$$\mathrm{GSADF}(\mathrm{r_0}) = \sup_{\substack{\mathrm{r_2} \in [\mathrm{r_0}, 1] \\ \mathrm{r_1} \in [0, \mathrm{r_2} - \mathrm{r_0}]}} \{\mathrm{ADF}_{\mathrm{r_1}}^{\mathrm{r_2}}\}$$




(4.2)

In the last step, the logit regression model has been used for the impact of the role of noise traders in the field of health.

$$\log\left[\frac{P_i}{(1 - P_i)}\right] = Z = \alpha + \sum_{i=1}^{k} b_i X_i \tag{4.3}$$

In this research, the dependent variable (z) is health probability logarithm, the independent variables (Xi) also include control variables and emotional variables. Similar to the normal distribution function, the probability that $y_i = 1$ is equal to

$$P(Y_l = 1|X_l'') = G(X_l''\beta) = \frac{|1}{1+e^{-x_i'\beta}} = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}} \tag{4.4}$$

The probability that $y_i = 0$ is equal to:

$$P(Y_i = 0|X_i) = 1 - P(Y_i = 1|X_i) = \frac{1}{1+e^{x_i'\beta}} \tag{4.5}$$

In this research, primary data and indicators will be analyzed using regression models and using Eviews9 software. Also, regression models obtained from the research and Eviews9 software were used in final analysis. Therefore, tests appropriate to the research and data will be used in research. Also, if the regression models were not effective for designing the optimal investment model, meta-innovative algorithms such as artificial intelligence and neural networks were used in the related software environment such as Matlab or GAMS.

## 5 Research findings

Default assumptions are considered in the optimization of the stock portfolio, the most important of which is the normality of the distribution function of the formed portfolio. In this test, the hypotheses $H_0$ and $H_1$ are stated as follows and the results of the Kolmogorov-Smirnov test have been calculated using daily returns at the 95% confidence level, Table 1 shows the results.

Table 1: Kolmogorov Smirnov test

| Variable | Kolmogorov Smirnov Z-statistic | Significance | Result |
|---|---|---|---|
| Daily return | 1.091 | 0.464 | Distribution is normal |

According to Table 1 and Kolmogorov Smirnov's Z-statistic, since the significance level for the daily stock return is greater than 0.05, the $H_0$ hypothesis is confirmed, so with 95% confidence, we can say that the distribution function of the stock portfolio returns has a normal distribution.

**Feedback test (validity check of calculated risk)**

Table 2 presents the results of feedback test and risk calculation of stock portfolios in the studied period. In this test, the hypotheses $H_0$ and $H_1$ are as follows:

$H_0$= risk ($\beta$) calculated using daily returns is correct.

$H_1$= Risk ($\beta$) calculated using daily returns is not correct.

Table 2: Feedback test results

| Feedback test result | The variance calculated for e | Stock Portfolio number |
|---|---|---|
| $H_0$ hypothesis is confirmed | 0.93816 | 1 |
| $H_0$ hypothesis is confirmed | 0.98199 | 2 |
| $H_0$ hypothesis is confirmed | 0.9713 | 3 |
| $H_0$ hypothesis is confirmed | 0.95729 | 4 |
| $H_0$ hypothesis is confirmed | 1.02434 | 5 |
| $H_0$ hypothesis is confirmed | 1.06512 | 6 |
| $H_0$ hypothesis is confirmed | 1.08054 | 7 |

According to Table 2, the variance values for each stock portfolio have been calculated and if these variances have a value smaller than 2, it can be confidently claimed that the $H_0$ hypothesis is confirmed, which can be seen in the calculations performed in all 7 stock portfolios, the hypothesis $H_0$ is confirmed, that is, the risk calculated using daily returns is correct and they are stable over time (The tests are valid).

**Check the convergence of the algorithm**

Convergence means that all points move around the same point and reach close solutions with repeated executions of the algorithm. In this research, algorithms based on ant theory and gray theory are used to optimize the stock portfolio, here our algorithm is single-stage and is processed by Matlab software. Subsequently, the results of the convergence check are presented in Figure 1 and it shows full density in a path and around specific points, and no significant dispersion is observed, which is established as a result of the convergence of the algorithm.

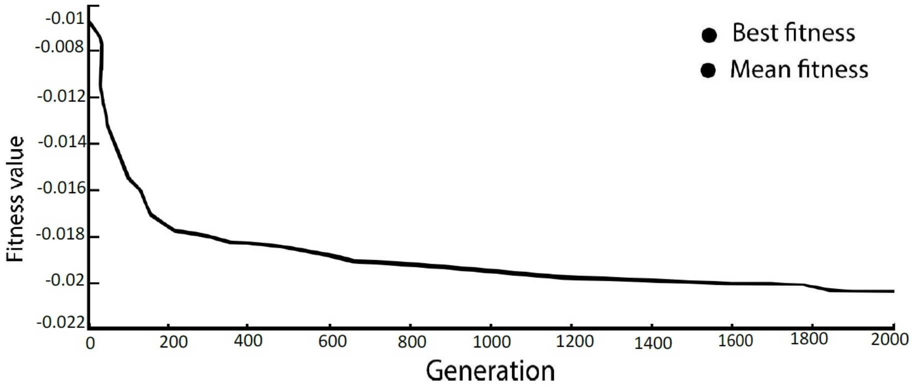



Figure 1: Check algorithm convergence

**Check the stability of algorithm answers**

Another important test about the algorithm is to check the stability of the algorithm, i.e. whether a unique and identical optimal solution has been obtained by repeating the algorithm. For this purpose, a stock portfolio with 15 shares with return and risk criteria is considered, the results are presented in Table 3. In each execution, the algorithms have been repeated a thousand times and each time there is a series of errors, and if the errors are close to each other in each series, it means that there is convergence. The results indicate an insignificant difference between the answers obtained from the repeated algorithm. Thus, the variance of the algorithm's answers in 20 repetitions is close to zero (0.0000051975).

In this article, the principal component analysis method was used to extract a composite index of emotional orientation, and the first common component was considered as the indicator. The eigenvalue was the criteria for determining the first common component (the first component percentage of variance) and the factor load values (coefficients) of the variables in the first component. In this study, based on these criteria, but in the end, three variables remained in the first common component. It is noted that sometimes the sentimental tendency and excitement may be caused by the change of some fundamental factors [5]. So, to purify excitements and remove the effects of fundamental factors, after seasonal adjustment and removing the effects on each of ARIMA of the seasonal calendar of each of the time series, the time series model of extracted excitements variables was implemented (Table 3) and the noise and residual component of each model was used as an index of pure excitemental tendency in PCA.

Table 3: Estimation of ARIMA model for each of the excitemental orientation variables

| **ARIMA model for the logarithm of the ratio of the volume of online transactions to the total volume of transactions (VO)** | | | | |
|---|---|---|---|---|
| Variable probability | Statistics t | standard deviation | Coefficient | Variable |
| 0.0034 | −3.033 | 0.6639 | 02.0142 | C |
| 0.000 | 42.301 | 0.0234 | 0.9886 | AR(1) |
| 0.000 | −4.4314 | 0.1095 | −0.4854 | MA(1) |
| 0.000 | 5.7380 | 0.0087 | 0.0499 | SIGMASQ |
| **ARIMA model for the logarithm of the ratio of the volume of online transactions to the total volume of transactions (VS)** | | | | |
| 0.000 | −5.1990 | 0.1549 | 0.8053 | C |
| 0.000 | 18.0766 | 0.0620 | 0.9348 | AR(1) |

Table 4 shows the percentage of total variance explained by the common components extracted in the PCA model for these three variables. Table also indicates the eigenvalue of the first common component (PCA1) as the desired composite index is 71.37%, which means that the extracted composite index will explain 71.37% of the total variance and is a desirable value.

Also, in the formula below, the amount of influence of each variable in the estimation of the first common component

| | | | | |
|---|---|---|---|---|
| 0.0001 | −4.2620 | 0.1417 | −0.6039 | MA(1) |
| 0.000 | 6.9252 | 0.0061 | 0.0423 | SIGMASQ |
| **ARIMA model for the monthly volume of stock transactions by funds and portfolio management companies to the total volume of market transactions** | | | | |
| 0.000 | −35.248 | 0.118 | −4.161 | C |
| 0.000 | 7.779 | 0.077 | 0.597 | AR(1) |
| 0.000 | 6.47 | 0.023 | 0.146 | SIGMASQ |

Table 4: The percentage of total variance

| **Component** | **Elementary eigen vector** | | | **Characteristics of the selected composite index (first common component)** | | |
|---|---|---|---|---|---|---|
| 1 | Total | Percentage of variance | Cumulative percentage of variance | Total | Percentage of variance | Cumulative percentage of variance |
| 2 | 2.141 | 71.366 | 71.366 | 2.1141 | 71.366 | 71.366 |
| 3 | 0.708 | 23.610 | 94.976 | | | |
| 4 | 0.151 | 5.024 | 100.00 | | | |

is presented in the form of the score coefficients of the elements (factor load), which are all higher than 6.

$SENTi = 0.916EVO + 0.929EVS + 0.661EV$

In the second step, the conditional mean equation of each of time series was estimated after confidence about the stationarity of time series of inflation, Brent oil price, gold price (the price of the Bahar Azadi coin of the old design), liquidity and exchange rate to estimate the EGARCH model from the aforementioned variables. The suitable model for the time series of each of the variables is estimated using the Box - Jenkins Analysis method and based on the correlation diagram of the residuals of the models and the minimum Akaike information criterion (AIC) and Schwarzbein (SBC) so that the EGARCH model is run on the residue of each model, after achieving the optimal model. Table 5 shows the conditional variance equations of inflation, exchange rate, gold price, oil price and liquidity, respectively. The correlation diagram related to the squared residuals obtained from the estimation of the ARMA model for each of the variables has been used to select the most suitable model for the conditional variance equation. Also, the results of the ARCH homogeneity variance test on the residual of EGARCH models show the absence of ARCH effect in the residual of the models.

Table 5: Estimation results of turbulence model of control variables

| | | | | | |
|---|---|---|---|---|---|
| **Oil prices** | **Coefficient** | **4.4689** | **0.1564** | **0.7854** | **0.9857** |
| | standard deviation | 0.1965 | 0.0344 | 0.0252 | 0.0045 |
| **Conditional variance equation of oil price** | Coefficient | $\beta_0$ | $\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$ | $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ | $\mathrm{Log}(\sigma_t^2-1)$ |
| | Coefficient | -3.2349 | -0.5565 | -1.2478 | 0.3669 |
| | standard deviation | 0.6272 | 0.2619 | 0.1849 | 0.1369 |
| **Conditional average liquidity equation** | Variable | $\alpha_0$ | @Trend | AR(1) | MA(1) |
| | Coefficient | 14.8489 | 0.0211 | 0.8659 | -0.1547 |
| | standard deviation | 0.0020 | 0.0018 | 0.0246 | 0.0467 |
| **Liquidity Conditional Variance Equation** | Variable | $\beta_0$ | $\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$ | $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ | $\mathrm{Log}(\sigma_t^2-1)$ |
| | Coefficient | -2.1625 | -0.5875 | -0.6317 | 0.7380 |
| | standard deviation | 0.9412 | 0.3325 | 0.1832 | 0.1078 |

In the next step, the GSADF test was used to measure the components of the bubble occurrence in the Tehran Stock Exchange, the results of which are given below:

The above table shows the t statistic is greater than the critical values at all levels of significance, so the existence of explosive behavior at all levels of significance is confirmed. The confirmation of this explosive behavior is strong evidence of the influence of noise traders on the area of bubble occurrence.

| | **Variable** | **$\alpha_0$** | **AR(1)** | **AR(2)** | **MA(1)** |
|---|---|---|---|---|---|
| **Conditional average inflation equatio** | Coefficient | 6.8607 | 1.7721 | -0.7738 | -0.4163 |
| | standard deviation | 0.2090 | 0.000 | 0.000 | 0.0773 |
| **Conditional variance equation of inflation** | Variable | $\beta_0$ | $\left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert$ | $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ | $\mathrm{Log}(\sigma_t^2 -1)$ |
| | Coefficient | -1.6616 | -0.4984 | 0.5732 | 0.8066 |
| | standard deviation | 0.6896 | 0.1959 | 0.1449 | 0.0637 |
| **Conditional average exchange rate equation** | Variable | $\alpha_0$ | AR(1) | MA(1) | |
| | Coefficient | 10.8077 | 0.98050 | 0.3716 | |
| | standard deviation | 0.4332 | 0.0056 | 0.1472 | |
| **Conditional variance equation of exchange rate** | Variable | $\beta_0$ | $\left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert$ | $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ | $\mathrm{Log}(\sigma_t^2 -1)$ |
| | Coefficient | -1.9439 | 0.7229 | 0.2802 | 0.7841 |
| | standard deviation | 0.4043 | 0.3617 | 0.1799 | 0.0577 |
| **Conditional average equation of gold price** | Variable | $\alpha_0$ | @Trend | AR(1) | MA(1) |
| | Coefficient | 8.5088 | 0.0124 | 0.9670 | 0.2302 |
| | standard deviation | 0.0679 | 0.0018 | 0.0251 | 0.1004 |
| **Conditional variance equation of gold price** | Variable | $\beta_0$ | $\left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert$ | $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ | $\mathrm{Log}(\sigma_t^2 -1)$ |
| | Coefficient | 0.0351 | -0.3412 | 0.1953 | 0.9643 |
| | standard deviation | 0.1101 | 0.1172 | 0.1043 | 0.000 |
| **Conditional mean equation** | Variable | $\alpha_0$ | AR(1) | AR(2) | MA(1) |

| **Test GSADF** | | | | |
|---|---|---|---|---|
| **Critical Value at Level.10** | **Critical Value at Level.5** | **Critical Value at Level.1** | **t-statistic** | **Variable** |
| 0.847036 | 1.089921 | 1.606306 | 3.689538 | Health components |

### The impact role of noise traders in emergence of bubbles

Logit regression model has been used to measure the role of noise traders in the occurrence of bubbles. Considering that the bubble emergence is the result of optimistic feelings and sentiments in the market; therefore, at this stage, the extracted emotional orientation index is classified into two states: optimistic sentiments and pessimistic sentiments, based on the positive or negative sign of the monthly values of sentiments orientation. The index positive values indicate optimistic sentiments and negative values indicate pessimistic sentiments. Then the effect of sentiments and optimistic sentiments on the occurrence of the bubble is measured. Table 6 presents the results of logit regression estimation. The table shows the effect of uninterrupted and intermittent optimistic sentimental tendency on market health is positive and significant at the 1% probability level. Also, the effect of turbulence and fluctuation of liquidity and exchange rate on the occurrence of bubbles is positive and the effect fluctuation of gold price on the emergence of a negative bubble and all of them are significant at the 10% level; Therefore, with the increase in optimistic sentiments and excitement, as well as the increase in turbulence and fluctuations in liquidity and exchange rate, the probability of a bubble will increase. The probability of the LR statistic in the logit model indicates the probability or level of significance of the true exponential ratio and shows the significance of the logit clear regression. The probability of the LR statistic test equals to 0.0, which shows the overall significance of the logit regression at the confidence level of 1%.

Considering that the logit model is a logarithmic model, its coefficient cannot be interpreted directly; thus, the marginal effect or the final effect of variables is used. Final effects are used to measure the effect of each explanatory variable on the dependent variable of the model. The final effect of each variable is the amount of change in the predicted probabilities of the dependent variable of the model, i.e. the occurrence of a bubble, per unit change in that specific explanatory variable, in the case that the other variables are constant. Usually, the final effect of X on Y is

Table 6: Logit model results to identify the role of optimistic sentiments in bubble occurrence (It indicates significance at 1,5 and 10 percent probability levels)

| C Variable 1.609875 Coefficient | OPTNEW 1.678372 * | OPTNEW (-1) 1.955122 | LOG(GGLD) * -1.355959 | 1)LOG(GEXR (-1) *** 0.655747 | LOGIQ 0.861447 *** |
|---|---|---|---|---|---|
| 3.225446 SD | 0.610882 | 0.588420 | 0.418167 | 0.352970 | 0.450144 |
| 0.6177 Probability | 0.0060 | 0.0009 | 0.0012 | 0.0632 | 0.557 |
| McFadden s R2 | 0.32 | | | | |
| LR (correction rat io) | 27.05 | | | | |
| Probability (LR) statistic | 0.000 | | | | |

calculated for the average values of $x_i$'s.

$$\frac{dP(Y_i=1)}{dX_i} = g(\hat{\beta}1 + \hat{\beta}2\bar{X}2 + ... + \bar{\beta}k\bar{X}k)\hat{\beta}_i$$

Table 7 shows the results of the final effects of all variables on the possibility of creating a bubble. By estimating the final (marginal) effect, with an increase of one unit of optimistic sentiments in the market, the probability of a bubble will increase by 24%, and for one unit increase of optimistic sentiments with a break, the probability of health in the market will increase by 28%, which is a significant value. Also, with an increase of one unit of fluctuation in liquidity and exchange rate, the probability of bubble occurrence will increase by 12 and 10 percent, respectively. Also, the effect of gold price fluctuations is on non-occurrence of bubbles, and one unit increase in gold price reduces the probability of bubbles by 20%.

Table 7: The results of calculating the final effect of each of the independent variables

| Variable | Final effect |
|---|---|
| C | 0.000 |
| OPTNEW | 0.24 |
| OPTNEW(-1) | 0.28 |
| LOG(GGOL) | $-0.20$ |
| LOG(LIQ(-1)) | 0.12 |
| LOG(GEXR(-1)) | 0.10 |

## 6 Discussion and conclusion

This article examines the effect of noise traders on the occurrence of bubbles in the Tehran Stock Exchange with a quantitative method. In this research, to explain the behavior of noise traders, a sentimental composite index was extracted using the principal component analysis (PCA) method. In the next step, the existence of a bubble in the Tehran Stock Exchange was identified using the Generalized Sup Augmented Dickey-Fuller (GSADF). Finally, the effect of noise traders on the existence of a bubble in the Tehran Stock Exchange was measured through the logit model. The model, turbulence and uncertainty of a series of variables related to rival markets were added to the model as control variables. The results show that the effect of optimistic emotional tendency (OPTNEW) and its first break OPTNEW(-1) on the existence of a bubble in the stock market Tehran securities and it is significant at the probability level of 1%, which is consistent with the results of [7]. The final estimate (marginal) indicates that an increase of one unit increases optimistic sentiments and percentage, which is a significant amount. Also, with an increase of one unit of volatility in liquidity and exchange rate, the possibility of bubble in Tehran Stock Exchange will increase by 12 and 10 percent, respectively. Also, the effect of the gold price volatility is negative on the occurrence of a bubble, and one unit increase in the price of gold reduces the possibility of a bubble in the Tehran Stock Exchange by 20%.

## Research limitations

Knowing the limitations of the research plays an important role in the success of a research, and knowing these limitations makes the researcher better equipped to defend the research findings. Therefore, some limitations of the research are stated as follows:

- Inability to control other influencing variables on the dependent variable
- Lack of generalizability of research findings in other regions and organizations

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