Adv. Math. Fin. App., 2024, **9**(1), P. 291-303

Advances in Mathematical Finance & Applications
www.amfa.iau-arak.ac.ir
Print ISSN: 2538-5569
Online ISSN: 2645-4610
Doi: 10.22034/AMFA.2023.1963410.1773

Applied-Research Paper

Impact of Investors' Sentiments on Volatility of Stock Exchange Index in Tehran Stock Exchange

Roozbeh Balounejad Nouri[a*], Fatemeh Bagjavany[b], Masoumeh Amiri Hosseini[c]

[a] *Department of Economics, Economic Affairs Research Institute, Tehran, Iran*
b Department of Economics, University of Mazandaran
c. Department of Economics, University of Bu-Ali Sina

ARTICLE INFO
Article history:
Received 2022-07-16
Accepted 2023-01-22

Keywords:
Feeling and sentiments
Volatility
EMSI Index
GARCH
Tehran Stock Exchange

ABSTRACT

The stock market is one of the main components of the economy, and various factors cause fluctuations in it, one of which is the effect of investors' behaviour. Therefore, present study seeks to answer the question of whether the feelings and sentiments of investors might intensify the fluctuations in the Tehran Stock Exchange or not. To answer this question, at first, in order to quantify sentiments, as non-abstract variables, the Equity Market Sentiment Index (EMSI) was used that investors are classified in 5 categories of completely risk-averse, risk-averse, neutral-risk, risk-taking and completely risk-taking. Using GARCHi-in-Mean, results indicate that the sentiments of investors will result in greater fluctuations in the Tehran Stock Exchange. Hence, if fluctuation is considered an indicator of market risk, the excitement associated with an abnormal rise in volumes will increase that risk.

1 Introduction

Any country's financial market is one of the most crucial and can greatly affect other economic sectors. As one of the most important investment channels in the world, the stock market is an important part of financial markets. The stock market is characterized by several characteristics, one of which is that it has fluctuations. The reasons for modeling stock market fluctuations vary greatly. An increase in fluctuations may result in higher investment risks and maintenance costs, and, consequently, lower investment. On the other hand, in order to properly manage the risks associated with holding various assets, it is necessary to gather sufficient information regarding the potential increase or decrease in portfolio value. Investors need to be aware of how the current period fluctuation affects future fluctuation, in order to avoid potential losses that may result from future fluctuations [19]. Furthermore, the fluctuation of stock returns may harm the movement of the financial system and may negatively affect the performance & economic development through various channels such as consumer expenditures & investment [26]. Thus, fluctuations in the stock market price index have created a lot of emotional turmoil in the minds of capital activists, and in recent decades, researchers have studied investor behavior to discover the underlying reasons for how people make

* Corresponding author. Tel.: +98-936-170-9039; fax: +98-218-880-10613.
E-mail address: roozbeh_noury@yahoo.com

investment decisions [18]. According to traditional and classical models, such as the capital asset pricing model, investors are rational, so they all understand risk and return to the same extent [28,1]. While in the new theories of behavioral finance, a new paradigm has been formed based on which it is believed that people's tendencies and preferences towards profit and loss are different. For example, the pleasure a person gains from a certain amount of profit are less than the suffering he or she receives when that same amount of loss is incurred [35,15]. Thus, the assumption of rational investors may prove to be less realistic, and accordingly, human decisions may deviate from the standard economic assumptions. As a matter of fact, behavioral finance theories assume that investors behave irrationally rather than rationally. In a way that Shefrin and Statman's [27] Behavioral Portfolio Theory replaces the Markowitz mean-variance theory and models such as the Linter and Sharpe asset pricing model are replaced by the Statman behavioral asset pricing model [25].

The findings show that the individual characteristics of investors affect their perception of risk and their willingness to accept risk. Financial decisions have many complexities and are associated with risk and uncertainty. This is because sentiments and feelings may influence financial decisions [22]. Many recent asset price researches (such as [8,24]) have focused on the issue of investor sentiments, which is often far from assuming a rational attitude on the part of investors. Research has shown that changes in investor sentiment can cause price changes in assets and could even be an important factor in market pricing. Occasionally, changes in investor sentiment are a better explanation for short-term swings in asset prices than any other fundamental factor. As such, this study examines the role of sentiments in causing and accelerating stock market fluctuations according to modern behavioral financial theories.

The innovation of this research is that for the first time for Iran, the main question of the research has been answered in the framework of behavioral economics. According to this, the present article is comprised of five sections: The first introduces the key issue of the research. As part of the second section of the article, we will discuss the theoretical foundations of the study and review past studies, followed by a presentation of the research method in the third section. Fourth, we will discuss data analysis, while in the fifth part we will present summaries and recommendations.

2 Literature Review

2.1 Behavioral Economy

Studies of asset pricing in the past have emphasized fundamental and specific features of the firm, as well as economic factors, and have considered changes in asset prices in response to these factors. However, some researchers have recently turned to investor psychology to explain asset price behavior. Before, it was believed that investor sentiments did not affect stock prices; alternatively, different sentiments neutralize each other without affecting market prices. Financial theories traditionally address this issue by assuming individual and market rationality within capital asset pricing models and the efficient market hypothesis. As a result of changeable, uncertain, complex and ambiguous circumstances, one has to speculate about the future results and this challenges the assumption that economic humans are rational, fully informed, and well informed. In these environments, the investor is limited in terms of both time and cognitive resources. Limited capacity to process information leads to mistakes in decision making. Study of this issue has mainly focused on the triangle of behavioral financial studies, which covers decision making, bias, and sentiments [11].

2.2 Investors' Sentiments and Volatility of Stock Exchange

Human characteristics such as sentiments affect decision making at individual and collective levels [24]. There has been a study investigating the impact of individual and market sentiment on incorrect market pricing and predictability. Working in this area is in turbulent stages, with a variety of perspectives [5]. The definition of emotion in financial research sources is ambiguous and unstable without any definite definition

[36]. A variety of definitions, including the investor's general attitude toward financial markets [28], the formation of a belief that leads to less and more overreactions to stock returns [5], the tendency to speculate about future cash flows based on investor optimism / pessimism about the financial markets [16], the market expectation toward a norm [23] or even investor belief in the fundamental value of assets [31], have emerged to define sentiments. If good news is released about a stock, its price rises, and if bad news is released, the stock price drops. While the market adjusts to its unusual reactions, it eventually returns a stock that is worth more or less what it is worth based on its intrinsic value. This price return is done by arbitrageurs (rational traders) [3]. According to traditional theories that are based on rational behavior, irrational investors (disruptors) always lose money in transactions and eventually disappear from the market [7]. Similar conditions exist in the field of stock market fluctuations [17]. According to traditional theories, stock market fluctuations are due to changes in the underlying factors of the stock, however, the increase in fluctuations that have occurred in recent years due to increased trading volume that has changed investor sentiment is not consistent with this logic. This means that market participants may overreact to the release of new information and news and that the so-called hyperactivity occurs when investors place more weight on new information in their decisions than on previously published stock information. It results in investors making extreme reactions to new information. Consequently, stock prices deviate from their intrinsic value when there is a meta-reaction in the market.

As a result, it seems that the factors affecting stock market fluctuations are beyond the fundamental factors and should be modeled with theories other than traditional theories that assume the rational behavior of investors. To explain these irregularities from the perspective of financial behavior, researchers have argued that stock market fluctuations are determined by the behavior of noise traders and rational investors. Disruptive traders are more likely to overreact or underreact to market news, so their price fluctuations do not result in a significant reduction of stock risk, despite diversified portfolios [28]. It is important to note that the existence and continued presence of these types of traders on the financial markets can have a significant impact and impose a systematic risk on the markets, especially on the emerging and inefficient ones [34]. As a result, behavioral finance theories are based on two main assumptions: first, that investors make decisions based on their emotional inclinations rather than rational considerations. Secondly, investors will not be too busy returning prices to their base prices since arbitrage is a risky and expensive emotional experience. Modern behavioral finance believes that arbitrage is limited [4].

As mentioned, sentiments can affect the stock market, including trading volume, through noise traders. The relationship between stock market fluctuations and the sentiments of noise traders in valuable studies was first investigated in studies by Black, Campbell and Kale, Shleifer and colleagues [28]. It has been shown that emotional changes, along with an increase in emotional transactions, lead to abnormal returns and fluctuations in returns [9,12,35]. Noise investor sentiment, according to their findings, causes double fluctuations in the financial markets. It leads to an incorrect pricing of financial assets during periods of high sentiment. A situation such as this may because long-term fluctuations in the financial market as irrational traders avoid short-term sales. These findings are consistent with Liu's finding that, according to his study, as liquidity increases on the US stock market, the sentiment index rises, and as a result, noise traders' trading volume increases, disrupting the correct pricing process. Meanwhile, rational traders have entered the market to take advantage of these sentiments and imbalances. Unlike the direction of buying and selling by traders, the behavior of rational traders is disruptive and emotional, and this leads to an increase in the volume of transactions and, consequently, the volume of market liquidity. It is true that he argues this conclusion is valid when there are no restrictions on arbitrage and the unusual returns are in line with the level of riskiness of the noise traders to induce them to participate in the transaction. Obviously, it has been shown in many studies that even rational traders demand more speculation in emotional market conditions [6,14,11]. There is research that shows that when the portfolio of noise investors is associated with low (high) specific risk, the noise investors will demand only high (low) risks. It was found that on certain levels of specific risk, small traders who have low emotional exposure have lower expected returns than micro-investors with high emotional inclinations; in other words, equity risk and stock returns are influenced by micro-investors' emotional tendencies. Asghari et al [2] assessed the impact of investors' emotional inclinations and behavioral sentiments on the degree of liquidity in the stock market. For this purpose, a model of Dabata and colleagues [6] was used and data from 14 countries were analyzed to determine the impact of sentiments and behavioral tendencies of investors on the liquidity of the stock market. Experimental results of the present study suggest that investor sentiment in the study countries has a positive effect on stock market trading volume, increasing the trading volume and stock market liquidity. In their study, Hu and colleagues [13] formed their sentiments index using 5 sentiment-related variables, and studied the relationship between sentiment, market return, and market volatility using the VAR-MS model. According to the analysis of orthogonal impulsive reactions, investors' feelings have a significant impact on stock market returns and fluctuations, and this effect is greater in ascending stock markets than in descending stocks, and they generally argued that the impact of investor sentiment on the stock market was asymmetric. Hence, the effect of investor sentiment on the stock market is different in different stock market regimes.

Wang et al. [33] conduct a global study of investor sentiment across 40 international stock markets to examine the impact of investor sentiment on stock returns via both direct and indirect channels and how the impact varies across bull and bear market regimes. Results confirm a conditional impact of investor sentiment on stock returns via both channels: In bull regimes, optimistic (pessimistic) shifts in investor sentiment would increase (decrease) stock returns, while in bear regimes, optimistic (pessimistic) shifts would decrease (increase) stock returns. Sogn et al. [29] construct an investor sentiment indicator (SsPCA) to predict stock volatility in the Chinese stock market by applying the scaled principal component analysis (sPCA). Their results indicate that SsPCA is a robust volatility predictor from various aspects and performs better compared with existing sentiment indicators. Shen et al. [26] proposes a Chinese investor sentiment index based on the Long Short-Term Memory (LSTM) deep learning method, and investigates the effect of investor sentiment on new energy stock returns as well as value at risks (VaR) behavior before and during COVID-19. Their empirical results show that investor sentiment has significant effects on stock returns and VaR of both new and traditional energy companies but the effects are stronger in the new energy industry. The effects of investor sentiment have increased during COVID-19, and investors pay more attention on risks than returns during COVID-19.

3 Methodology

Since the present study was intended to examine the contagiousness of investors' sentiments as it relates to fluctuations on the Tehran Stock Exchange, it was considered to be a correlational study. The time domain of the research also includes the daily time period of March 25, 2009 to March 17, 2021 including 2908 observations and its spatial domain was allocated to the Tehran Stock Exchange. Data for measuring the sentiment index were extracted from financial reports of all listed companies listed on the Tehran Stock Exchange. From the official website of the Tehran Stock Exchange, data on the price of the stock exchange (TEPIX) were gathered. In this regard, before introducing the research model, it is necessary to present how to quantify the feelings and sentiments of the investor as follows.

3.1 Manner of Calculation of the Equity Market Sentiment Index (EMSI)

An Equity Market Sentiment Index was used in this study to measure investors' sentiments. In the first step, the daily returns of each of the securities in the index are calculated. A sampling of the five-day standard deviation of returns for each day of the period is also conducted (with the aim of estimating historical fluctuations). The fluctuations and calculations of the Spearman rank correlation coefficient are multiplied by the daily return rank for each firm and the rank of the historical fluctuations of the return for each firm, and the result is multiplied by 100 times. This index has been expanded by Bandopadhyaya and Jones [5] by modifying the model presented by Prsavd and has been used in several studies[1]:

$$EMSI \quad = \frac{\sum(R_{i,t}-\bar{R}_{i,t})(R_{,v}-\bar{R}_v)}{\left[\sum(R_{i,t}-\bar{R}_r)^2 \sum(R_{i,v}-\bar{R}_v)^2\right]^{1/2}} \times 100 \quad , \quad -100 \leq EMSI \leq +100 \tag{1}$$

In which:

R_{it}= Rate of daily return of the stock of Company i in t daily

R_{iv}= Rate of historical volatility of Company i in t daily

$\bar{R}_r$ =Mean rate of the daily return of the stock of portfolio companies

$\bar{R}_v$=Mean rate of historical volatility of the stock of portfolio companies

The mean standard deviation of stock returns from five months ago is used as a means to estimate historical volatility similar to Jones [14] research and by modifying Prsavd's model. Jones and Bandopadhyaya [5] studies also used the index to assess the correlation between the EMSI index and the stock market return index. EMSI values are typically classified into five categories. For values between -10 to +10, the market is considered risk-neutral, for values between -10 to -30 it is considered relatively risk-averse, and for values below -30 it is considered completely risk-averse. Similarly, if the EMSI is between +10 and +30 [6], the market is considered relatively risky, and if the index is above +30, it is considered completely risky.

3.2 Generalized conditional heterogeneous variance model in mean[2]

Consider the stock return (r_t), that is, the percent change in stock value over t time, as a random variable. In this case, the return series consists of two components: the predictable component ($E(r_t|\Phi_{t-1})$) (and the unpredictable component (ε_t)

$$r_t = E(r_t|\Phi_{t-1}) + \varepsilon_t \tag{2}$$

Where E is the conditional mean operator and Φ_{t-1} is the set of information available in t time.

In the unpredictable section (ε_t), the impact of shocks and news is expressed as follows:

$$\varepsilon_t = z_t\sigma_t \qquad \varepsilon_t \sim iid(0,1) \tag{3}$$

Where z_1 is a random variable distributed with zero mean and unit variance. The ε_t conditional variance is also equal to σ_t^2 and the variable over time is positive and measurable based on the set of information available at the t time (Φ_{t-1}). Engel introduced the ARCH (q) model for calculating conditional variance and introduced it as a function of values with ε_t values as follows:

[1] For further study, please refer to:
- Tuyon, A and etc, (2016), "The Roles of Investor Sentiment in Malaysian Stock Market", Asian Academy of Management Journal of Accounting and Finance, Vol 12, pp.43-75.
- Lin, Sh and Jun Lu, (2020), "Did Institutional Investors' Behavior Affect U.S.-China Equity Market Sentiment? Evidence from the U.S.-China Trade Turbulence", Mathematics, Vol 8(6), Availble at: https://doi.org/10.3390/math8060952
[2] Garch in mean

$$\sigma_t^2 = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}, a) \tag{4}$$

Where q is the order of ARCH and α is the vector of unknown parameters. In its simplest form, Engel (1982) considered conditional variance as a linear function of the shock squares of previous periods as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \tag{5}$$

If $\alpha_1, \alpha_2, \ldots, \alpha_n$ values are equal to zero, the estimated variance will be equal to w and constant. Also, the required condition for positive variance is that:

$$w > 0 \ , \quad a_i \geq 0 \quad (i = 1,2,\dots,q) \tag{6}$$

A subsequent experimental study has shown that high q intervals are required in order to accurately characterize the ARCH (q) pattern. Boleslaw , one of the first students studying the parasite, proposed the generalized conditional heterogeneous variance model (GARCH) as a solution to this problem. The specification of GARCH (p, q) is as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta \sigma_{t-j}^2 \tag{7}$$

In other words, GARCH model is constituted of 3 parts: (w) stationary component, fluctuations of the previous periods ($\sum_{i=1}^{q} a_i \varepsilon_{t-i}^2$) and the predicted variance of the previous periods ($\sum_{j=1}^{p} \beta \sigma_{t-j}^2$).

As mentioned, when introducing the ARCH model, Engel chose the assumption of normal shock distribution. However, due to the special properties of the efficiency series, Boleslaw proposed the t distribution density function with a degree of freedom $v > 2$ as follows:

$$D(z_t \ ; v) = \frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{\pi(v-2)}} \left(1 + \frac{z_t^2}{v-2}\right)^{-\frac{v+1}{2}} \tag{8}$$

Where Γ (.) is a gamma function[3]. For v> 4, the distribution t is symmetrically distributed around zero and has a conditional elongation equal to $3(v-2)(v-4)^{-1}$, which is greater than the height of the normal distribution (i.e., 3).[4] The maximum likelihood method is generally used to estimate ARCH models. Assuming a uniform distribution of z_t and the probability density function $D(z_t; v)$, the likelihood logarithm function $\{z_t(\theta)\}$ for an example with T is:

$$L_T(\{y_t\}; \theta) = \sum_{t=1}^{T} \left[[ln(D[(z(\theta); v])] - \frac{1}{2} ln\left(\sigma_t^2(\theta)\right) \right] \tag{9}$$

Where θ represents the vector of parameters that must be estimated for the conditional mean, conditional variance, and probability density function. By maximizing the above relation, the estimator vector of the

[3] The Gamma function is $\Gamma(v) = \int_0^\infty e^{-x} x^{v-1} dx$

[4] It should be noted that with the degree of freedom tends towards infinity, the distribution of t tends towards the standard normal distribution.

maximum likelihood (θ.) is estimated. Maximum likelihood is estimated as follows when assuming a normal distribution for GARCH model (p, q):

$$L_T(\{y_t\};\theta) = -\frac{1}{2}\left[Tln(2\pi) + \sum_{i=1}^{T} z_t^2 + \sum_{t=1}^{T} ln\Big(ln(\sigma_t^2)\Big)\right] \tag{10}$$

To determine the appropriate intervals for p and q, Akaike, Schwartz, and likelihood logarithms are used. In particular, the appropriate model minimizes Akaike and Schwartz values while maximizing likelihood logarithms.

The variable is classified as an exogenous variable in the equation of variance (Equation 3-6) if it is the purpose of the study to estimate output fluctuations caused by an exogenous variable. Thus, the effect of this variable on efficiency fluctuations is measured. The present study takes the EMSI variable as a measure of sentiment in capital markets, and if the index coefficient is positive and significant, the ratio of the research hypothesis can be interpreted properly. Therefore, the final model of the research is presented as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta \sigma_{t-j}^2 + \gamma EMSI_i \tag{11}$$

4 Data analysis

First, the index of investors' emotions and feelings is calculated according to the method introduced in Section 3-1. The market sentiment index represents investors' general attitude toward a particular security or market. This feeling represents the sentiment of the market or the psychology of the population, which can be measured through the price movement of the securities traded in that market. Generally, rising prices reflect bullish sentiment, while declining prices reflect negative sentiment. This index generally fluctuates between -100 to +100 and are typically classified into five categories. For values between -10 to +10, the market is considered risk-neutral, for values between -10 to -30 it is considered relatively risk-averse, and for values below -30 it is considered completely risk-averse. Similarly, if the numerical value of the index is between +10 and +30, the market is considered relatively risky, and if the index is greater than +30, it is considered completely risky. Based on the data shown in Figure 4-1, we can see how the sentiment index has changed over time. The results show that out of 2908 days studied, in 355 days the value of the index was greater than +30 and it can be said that in 12% of the market sample volume it was in a completely risky situation while in 400 days of the sample volume (equivalent to 13.7% of the sample volume days) the market was in a state of complete risk-averse. Furthermore, in 842 research days, the emotion index ranged from -10 to +10, thus indicating a risk-neutral market in 29% of observations. In the following table you will find a summary of investor sentiment during the reviewing period:

Table 1: Descriptive Status of the Sentiments through the Reviewing Period:

EMSI Index	EMSI>+30	+10<EMSI<+30	-10<EMSI<+10	-30<EMSI<-10	EMSI-<30
Number of Days	355	610	842	701	400
Sample Volume Percent	12/2%	20/9%	29%	24/2%	13/7%
Result	Completely Risky	Risky	Risk-neutral	Risk-averse	Completely Risk-averse

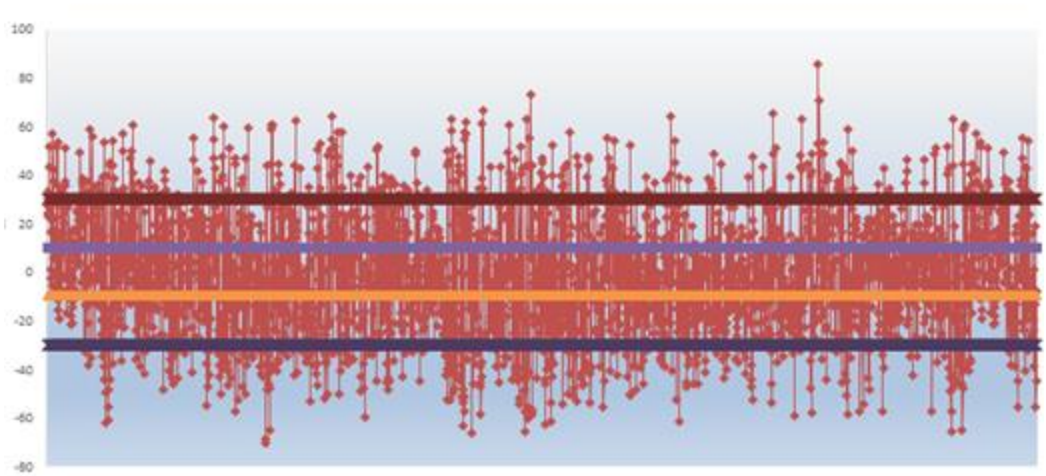

Diagram 1: Diagram for the Sentiment Index through the Reviewing Period

4.2 Descriptive Statistics

In this research, the differential logarithm of the total price index has been used to calculate the return of the price index of Tehran Stock Exchange.

$$r_t = ln\left(\frac{TEPIX_t}{TEPIX_{t-1}}\right) * 100 \tag{12}$$

Table 4-2 shows that the stock exchange price index's mean return was 0.17%, with a skew of 0.46 and a strain of 9.13, higher than the strain of a standard distribution. As a result, it is much more likely to be associated with the final values of the efficiency series than the normal distribution. In other words, markets are more likely to experience sudden and sharp increases or decreases. Jarque-Bera statistic also shows rejection of the hypothesis that efficiency series are normally distributed. The increase of the skewness of return series suggests that market participants think negative returns are more likely. Relatively similar conditions apply to the emotion index series.

Table 2: Descriptive Statistics

	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Statistic
R	0.17	0.06	1.06	0.46	9.13	4670
EMSI	-1.15	-1.85	25.4	0.11	2.6	21.9

Source: Research Achievements

Similarly, based on the diagram of the price return series in Tehran Stock Exchange and considering the Q Lejang- Bera statistic, it is evident that there is a correlation in the return's series. In addition, the existence of autocorrelation in the series of return squares is also confirmed for all interruptions, which the value of Q^2 statistic confirms the existence of arch effects. This finding is not far off the mark and can be discerned from the performance series table.

The ARCH-LM test is also performed to test the presence of the fifth order of ARCH by fitting the squares of the ARMA curves to a fixed value and the q interrupt of the squares of the residuals. To test the null hypothesis that there are no Arch effects, the following statistic is calculated up to the q interval in the residuals:

$$e_t^2 = \beta\left(\sum_{s=1}^{q} \beta_s e_{t-s}^2\right) + V_t \tag{13}$$

Where e_t is the remainder of the ARMA process. The Lagrangian coefficient (LM) test statistic was introduced by Engel which has a chi-square distribution with degree of freedom q (χ_q^2). The results of the Arch test for the efficiency series are as demonstrated in Table 3.

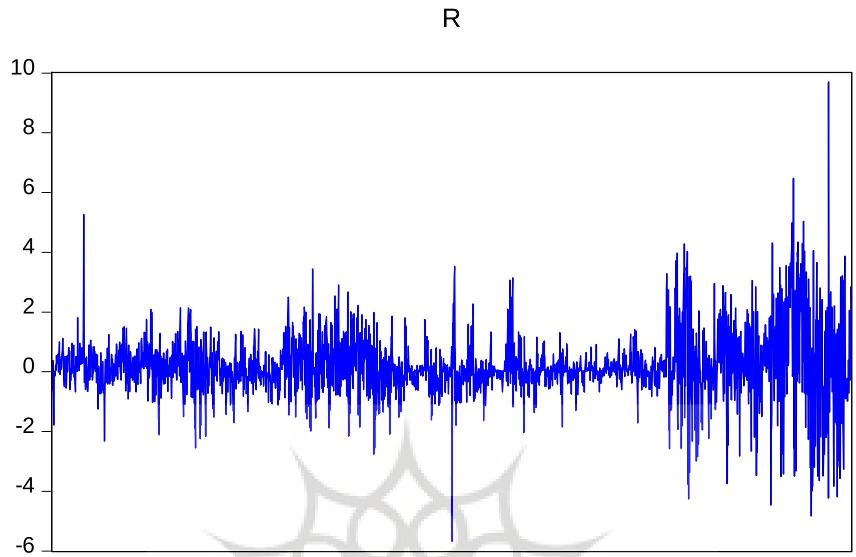

Diagram 2: Diagram for Return through the Reviewing Period

Table 3: Results of ARCH-LM Test

Result	Probability Level	F Statistic
Confirmation of the Presence of Variance Heterogeneity	0.00	216.95

Source: Research Achievements

To estimate the GARCH model correctly, the choice of a suitable conditional mean equation is determined by the correlation diagram, as well as by Akaike and Schwarz criteria. Based on the above criteria, the efficiency series is based on the ARMA model (3,3). Table 4 presents the generalized conditional heterogeneous variance model with the purpose of modeling the fluctuation of performance and its effect on sentiments by considering the sentiment index variable.

Table 4: Estimation of the Model of GARCH-in-Mean

Mean Equation						
C	Ar(1)	Ar(2)	Ar(3)	Ma(1)	Ma(2)	Ma(3)
0.003	-0.121	0.772	0.191	0.522	-0.677	-0.379
[0.90]	[0.61]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]
Variance Equation						
ω	α	β	$EMSI$			
0.016	0.155	0.832	0.0006			
[0.00]	[0.00]	[0.00]	[0.00]			
Diagnostic Tests						
Akaike	Schwarz	Log Likelihood	$Q(10)$	$Q(15)$	$Q(20)$	Arch lm
2.160	2.180	-3126	0.018 [0.13]	-0.008 [0.21]	-0.005 [0.52]	

Diagnostic tests show the appropriate specification of the estimated model. According to the correlation diagram of the standardized residual series and its squares, there is no serial autocorrelation in the residuals of the yield and squared series, as shown by the Ljung-box statistic for intervals of 11-15-20. Arch tests show that arch effects are not evident on the remains. Having established the proper specification of the model through the diagnostic tests, the research results can now be interpreted. Except for ar(1), the coefficients of the conditional mean equation are significant at the high level. By analyzing the ARMA model, it is evident that the hypothesis of information efficiency in a mild form is rejected in the Tehran Stock Exchange. The price of a new period can be predicted from the price of the previous period, based on the research findings. In other words, new information does not impact prices immediately in each period. Lack of information efficiency can be due to lack of symmetry and transparency of information, slow information flow, youth and emergence of the stock market, lack of sufficient skills of shareholders in analyzing fluctuations and news, and lack of professional market factors.
Using the mean equation, Arch's estimated coefficient is statistically significant. The coefficient represents the information and news of the previous period. In other words, the information and news from a past period can have a positive effect on the fluctuations in a current period. Moreover, beta coefficient estimates show that fluctuations from the past period inexorably affect fluctuations from the present period. The sum of α and β coefficients is also smaller than a unit, which indicates the stability of the model. Furthermore, this index of investor sentiment has a positive and significant impact on the fluctuations in Tehran Stock Exchange. Accordingly, the fluctuation of Iran's stock market will also rise due to the increased excitement from investors. Accordingly, contrary to traditional theories that the stock market fluctuations are due to changes in fundamentals, functional fluctuations other than fundamentals include an abnormal increase in trading volume through overreactions to investors' feelings and sentiments. This means that market participants may overreact to the release of new information and news and that the so-called hyperactivity occurs when investors place more weight on new information in their decisions than on previously published stock information. It results in investors making extreme reactions to new information and consequently, the stock price deviates from its intrinsic value. Thus, it is highly likely that most of the market risk-averse people will be removed from the market in this case (which accounts for 81% of the sample size in the present study). This, in turn, can lead to increased volatility.

5 Conclusion

Using financial-behavioral models, the study aimed to determine the effect of sentiments on fluctuations at the Tehran Stock Exchange. In recent years, investor sentiment has become a subject of much research relating to asset pricing. Numerous studies have documented that investor sentiment changes can impact asset prices and may, in fact, be a significant factor in the process of market pricing. In some cases, changes in investor sentiment can explain short-term movements in asset prices better than any other fundamental factor. Previously, it was thought that there was little connection between investor sentiment and stock prices; So different sentiments cancel each other out and have no effect on market prices. If, on the other hand, there is enough consensus among investors, their opinions will not be compensated, but rather become a fundamental part of the pricing process. This study quantified the sentiment variable by using the Equity Market Sentiment Index (EMSI). This index generally fluctuates between -100 to +100 and are typically classified into five categories. For values between -10 to +10, the market is considered risk-neutral, for values between -10 to -30 it is considered relatively risk-averse, and for values below -30 it is considered completely risk-averse. As well, the generalized conditional heterogeneity variance model was used in this study to model the fluctuations, and the data related to the price index for a period of March 25, 2009 to March 17, 2021 including 2908 observations were extracted from the official website of Tehran Stock Exchange. It turns out that investors' feelings and sentiments have contributed to an increase in volatility at the Tehran Stock Exchange. Hence, if fluctuation is considered an indicator of market risk, the excitement associated with an abnormal rise in volumes will increase that risk. The results are similar to Sreen and Nail [30] and Rupande et al. [25] show that the effect of investors' emotional feelings can explain more about the effective market performance, so it is recommended to pay more attention to the emotional tendencies of investors, as a result of the changes in the market and the dynamics of the market. Also, investors' analysts should take into account the effects of inflation, both negative and positive, of gross domestic product, and positive and negative, on the sentiments of market investors.

Conflict of interest: The authors have no relevant financial or non-financial interests to disclose.

References

[1] Antonides, G., Van Der Sar, N. L., Individual expectations, risk perception and preferences in relation to investment decision making, *Journal of Economic Psychology*, 1990; 11(2): 227-245. doi: 10.1016/0167-4870(90)90005-T

[2] Asghari, E., Abbasian Fereydouni, M. M., Nasl Mousavi, S. H., The Effect of Investors' Emotional Tendencies on the Degree of Liquidity of the Stock Marke, *Journal of Accounting Advances*, 2020; 12: 1-27. doi: 10.22099/jaa.2020.35769.1966

[3] Ataabadi, A, A., Hamidi, M., Over-Reaction to Earning Adjustment Based on Event Study Approach: Evidence from Tehran Stock Exchange, *Journal of Financial Management Perspective*, 2017; 7(17): 31-48. doi: 10.52547/jfmp.10.29.89

[4] Asadi, Gh., Morshedi, F., Investing the Effect of Investor Sentiments on the Stock Price Crash Risk in Tehran Stock Exchanges, *Journal of Financial Management Perspective*, 2019; 9(25): 9-30. doi: 10.52547/jfmp.9.25.9

[5] Bandopadhyaya, A., Jones, A.L., Measuring Investor Sentiment in Equity Markets, *Working Paper, University of Massachusetts Boston,* 2005.

[6] Devault, L., Sias, R., Starks, L., Sentiment metrics and investor demand. *Journal of Finance*, 2019; 74(2): 985–1024. doi: 10.1111/jofi.12754

[7] Friedman, M., The case for flexible exchange rates, *Essays on Positive Economics, University of Chicago Press*, Chicago, IL,1953.

[8] Gao, Y., Zhao, C., Sun, B., Effects of investor sentiment on stock volatility: new evidences from multi-source data in China’s green stock markets, *Financ Innov*, 2022; 8(77): 1-23. doi: 10.1186/s40854-022-00381-2

[9] Ghonghadze, J., Lux, T., Bringing an elementary agent-based model to the data: Estimation via GMM and an application to forecasting of asset price volatility, *Journal of Empirical Finance*, 2016; 37(1): 1–19. doi: 10.1016/j.jempfin.2016.02.002

[10] Gong, X., Zhang, W., Wang, J., Wang, Ch., Investor sentiment and stock volatility: New evidence, *International Review of Financial Analysis,* 2022; 80:1-18. doi: 10.1016/j.irfa.2022.102028

[11] Hsieh, T.U., Lee I., Huai, T., Idiosyncratic Risk, Stock Returns and Investor Sentiment, *Asian Economic and Financial Review*, 2018; 8(7): 853- 869. doi: 10.18488/journal.aefr.2018.87.914.924

[12] Hessary, Y. K., Hadzikadic, M., Role of behavioral heterogeneity in aggregate financial market behavior: An agent-based approach, *Procardia Computer Science*, 2017; 108(1): 978–987. doi:10.1016/j.

[13] Hu, J., Sui, Y., Ma, F., The Measurement Method of Investor Sentiment and Its Relationship with Stock Market, *Computational Intelligence and Neuroscience*, 2021; 24: 1-16. doi: 10.1155/2021/6672677

[14] Jang, J., Kang, J., Probability of price crashes, rational speculative bubbles, and the cross-section of stock returns, *Journal of Financial Economics*, 2018; 132(1): 222–247. doi: 10.1016/j.jfineco.2018.10.005

[15] Kahneman, D., Tversky, A., Prospect theory: An analysis of decision under risk, *Econometrica*, 1979; 47: 263-291. doi: 10.2307/1914185

[16] Khalil Moghadam, S., Mokhatab Rafiei, F., Rastegar, M. A., Aghayi Bejestan, H., Multiple portfolio optimization in Tehran Stock Exchange, *Advances in Mathematical Finance and Applications*, 2023; 8(1): 1-20. doi: 10.22034/amfa.2022.1930153.1592

[17] Kumari, J., Mahakud, J., Investor sentiment and stock market volatility: evidence from India, *J Asia Pac Bus*, 2016; 17(2): 173–202. doi: 10.1108/APJBA-11-2020-0405

[18] Li, J., Yu, L., Mei, X., Do social media constrain or promote company violations? *Account Finance*, 2022; 62(1): 31–70. doi: 10.1111/acfi.12780

[19] Li Gong, X., Liu, J., Xiong, X., Zhang, W., Research on stock volatility risk and investor sentiment contagion from the perspective of multi-layer dynamic network, *International Review of Financial Analysis*, 2022; 84: 1-15. doi: 10.1016/j.irfa.2022.102359

[20] Liu, S., Investor Sentiment and Stock Market Liquidity, *Journal of Behavioral Finance*, 2015; 16(1): 51–67. doi:10.1080/15427560.2015.1000334.

[21] Lin, Sh., Jun Lu., Did Institutional Investors' Behavior Affect U.S.-China Equity Market Sentiment? *Evidence from the U.S.-China Trade Turbulence*, Mathematics, 2020; 8(6): 1-17. doi: 10.3390/math8060952

[22] Nofsinger, J.R., The Psychology of Investing, *Pearson Prentice Hall, Upper Saddle River*, New Jersey, 2014.

[23] Noroozi, M., Foroghi, D., Karimi, F., Developing the Stock Pricing Model based on Bounded Rationality Theory, *Advances in Mathematical Finance and Applications*, 2023; 8(1): 1-20. doi: 10.22034/amfa.2022.1940035.1632

[24] P H, H., Rishad, A., An empirical examination of investor sentiment and stock market volatility: evidence from India, *Financ Innov*, 2022; 6(34): 1-22. doi: 10.1186/s40854-020-00198-x

[25] Rupande, L., Mogutu, H.T., Muzindutsi, F., Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange, *Economics & Finance*, 2019; 7(1): 1-17. doi: 10.1080/23322039.2019.1600233

[26] Shen, Y., Liu, Ch., Sun, X., Kun, G., Investor sentiment and the Chinese new energy stock market: A risk–return perspective, *International Review of Economics & Finance*, 2023; 84: 395-408. doi: 10.1016/j.iref.2022.11.035

[27] Shefrin, H., Statman, M., Behavioral Portfolio Theory, 2000; 35(2):127-151. Doi: 10.2307/2676187

[28] Shleifer, A., Summers, L.H., The Noise Trader Approach to Finance, *Journal of Economic Perspectives*, 1990; 4(2): 19-33.

[29] Song, Z., Gong, X., Zhang, Ch., Yu, CH., Investor sentiment based on scaled PCA method: A powerful predictor of realized volatility in the Chinese stock market, *International Review of Economics & Finance*, 2023; 83: 528-545. doi: 10.1016/j.iref.2022.10.007

[30] Sreen, N., Naik, S., Investor sentiment and stock return volatility: evidence from the Indian Stock Exchange, *Asia-Pacific Journal of Business Administration*, 2022; 14(4): 467-478. doi: 10.1108/APJBA-11-2020-0405

[31] Tripathi, S., Application of Mathematics in Financial Management, *Advances in Mathematical Finance and Applications*, 2019; 4(2): 1-14. doi: 10.22034/amfa.2019.583576.1169

[32] Tuyon, A., Zamari, A., Matahir, A., The Roles of Investor Sentiment in Malaysian Stock Market, *Asian Academy of Management Journal of Accounting and Finance*, 2016; 12: 43-75. doi: 10.21315/aamjaf2016.12.S1.3

[33] Wang, W., Su, Ch., Duxbury, D., The conditional impact of investor sentiment in global stock markets: A two-channel examination, Journal of Banking & Finance, 2022; 138: 1-24. doi: 10.1016/j.jbankfin.2022.106458

[34] Xu, X., Ramiah, V., Imad, M., Davidson, S., An application of the information-adjusted noise model to the Shenzhen stock market, *International Journal of Managerial Finance*, 2016; 12(1): 71-91. doi: 10.1108/IJMF-01-2015-0010

[35] Xiao, D., Wang, J., Niu, H., Volatility analysis of financial agent-based market dynamics from stochastic contact system, *Computational Economics*, 2016; 48(4): 607–625. doi: 10.1007/s10614-015-9539-y

[36] Yang, H., Xue, F., Analysis of stock market volatility: Adjusted VPIN with high-frequency data, *Int Rev Econ Financ*, 2021; 75:210–222. doi: 10.1016/j.iref.2021.04.003