Modeling the effects of Tehran Stock Exchange investors' sentiment on stock price within a heterogeneous agent model

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Submit: 12/08/2022 Accept: 29/11/2022

ABSTRACT

The purpose of this article is to investigate the effects of investors' sentiments on stock prices and its modeling in the framework of the heterogeneous agent model. In this regard, by using simulation, stock prices are calculated at the time of investors' sentiments, and the results are compared with stock prices in the real market to determine how much the simulated market matches the real market. The current research is descriptive in terms of purpose and content analysis has been used to evaluate the simulation results. Therefore, first, the point of crash of the stock market was determined in the framework of theoretical discussions. Then, the input variables including positive sentiments, negative sentiments and herd behavior were entered into the model and the price simulation process was done for each of the biases during the market crash. Considering the heterogeneous agents in the market and the dynamics of investors' behavior, Monte Carlo simulation was used and coding was done in MATLAB.

By comparing simulated prices with real market prices at the time of investors' sentiments, the model's ability to estimate real market prices was investigated. The research results show that the heterogeneous factor model can predict the effects of investors' emotions when the stock market falls. Especially when negative emotions appear in the market, the presented model provides the best estimate compared to the real market.

Keywords:

heterogeneous agent model; simulation; Investors' sentiment; Herd behavior

1. Introduction

Classical financial economics theories are based on the efficient market hypothesis, the complete rationality of factors in the use of information, and decisions based on maximizing expected utility. These assumptions play an important role in determining the price of assets in classical economics (Rakik et al،2014)

The efficiency of the stock market is one of the main pillars of financial theories and is said to be a situation in which the price of securities is equal to its intrinsic value, assuming that the expectations of rational investors are properly formed based on available information. In this market, investors react quickly to new news and information, and all new information is quickly reflected in prices, leaving no one with the opportunity to make unusual profits based on this information. In fact, stock prices are commensurate with the fundamental variables of the economy, and one cannot find a stock that is unrealistically priced. But from a practical point of view, in recent decades, phenomena based on market inefficiency have been observed in various stock exchanges around the world. Phenomena such as sharp fluctuations in prices, bubbles and stock market collapse indicate market inefficiency and lack of proportionality between prices and fundamental variables, which are known as financial market anomalies (Gol Arzi and Ziachi, 2014). Explaining these anomalies, the researchers said that some financial phenomena could be better explained by using models in which some actors in the economy are not completely rational.

By observing different features in price dynamics in financial markets that did not agree with the predictions of market theory, a new chapter in research and studies on financial management was opened and models based on human behavior gradually entered this field. The Iranian stock market has always been faced with severe fluctuations and market managers are trying to make the market more efficient and reduce these fluctuations. The main purpose of this study is to design a simulation model based on the Iranian capital market factor with a focus on the behaviors and sentiment of investors to answer these questions and help market managers in making decisions.

One of the proven topics in psychology is the influence of people's emotions on the decision-making process and their judgment about future events. In such a way that when people have positive emotions, they make optimistic choices and when they have negative emotions, they make pessimistic choices. Market sentiment reflects the attitude of investors towards the projected prices in the market. Because investors reflect their emotions in the capital market, it is expected that investors' emotions can influence their behavior (Vieira and Pereira, 2014).

So far, various researches have been done on modeling investors' decision-making scenarios based on emotions, the main purpose of which has been to identify the behavior of agents (fundamentalists and chartists) as accurately as possible, followed by predicting asset prices based on their behavior. Fundamentalists are the agents who believe that the price of an asset returns to its underlying price in the long run and make decisions based on Fundamental information. Chartists, on the other hand, are agents who make decisions based on asset pricing trends without regard to Fundamental information.

Therefore, according to the dynamic nature of agents' decision-making, the methods that have more ability to express more accurately the different decision-making scenarios of agents based on feeling, will be considered more than methods the Tehran Stock Exchange has always faced severe fluctuations and market managers are looking for making the market more efficient and reducing these fluctuations, especially when behavioral patterns are formed in the stock market. Among these, there is research that has been done in the heterogeneous agent model. In this regard, the current research tries to design a agent-based simulation model in Iran's stock market, focusing on investors' behaviors and sentiment, in order to answer these questions and help market managers in making decisions. The present research examines the impact of investors' sentiment on the price dynamics of Tehran Stock Exchange transactions in companies admitted to the Tehran Stock Exchange.

In this research, the behavioral indicators of the agents are used to provide a dynamic model according to the decisions of fundamentalists and chartists regarding the prediction of asset prices, so that the model is able to predict price fluctuations and convergent and divergent movements of asset prices under the influence of market sentiment parameters. and change the strategy of a group of traders.

The purpose of this article is to model the sentiment of investors in the Tehran Stock Exchange in the framework of heterogeneous agent models. To estimate.In the continuation of the article, the theoretical and experimental foundations of the research are stated and with the help of it, the research method is developed. In the next section, the research findings are presented and finally, the research conclusions and discussion are stated.

2.Theoretical Foundations

The present study is formed by connecting the findings of researchers in the field of financial behavior and investor sentiment with research in the field of heterogeneous agent models. In fact, modeling and simulating prices at the time of investor sentiment is based on research conducted in these two areas.

2.1. Market sentiment

Market sentiment is an atmosphere of market boom or bust. When the market is booming, investors want to buy even higher than the real value. In this case, investors tend to accept more risk, which indicates confidence in the market and economic conditions. In this case, they expect the market to continue and predict that prices will rise again (Kim et al., 2014). In capital markets, there is a set of information from social emotions along with logical information. How much he can overcome his social emotions and listen to the call of logic shows how successful he is in investing in reason.

The ratio of the number of days with an upward trend in stock prices to the number of days with a downward trend in stock prices is related to market power in the period of imbalance in sales. When the sentiment for an investment is positive, there is a greater tendency to buy stocks at a higher price, and in these cases, there is a so-called buying queue in the stock market for trading stocks, which means that most stocks are priced higher. They are approaching. This creates a rise in stock prices that reflects positive emotions. Also, the unwillingness to buy or hold a share in the investor's portfolio will create a sales queue for that share and as a result of this increase in supply, will reduce the share price. In other words, when negative emotions occur for an investment, it will lower stock prices (Brown and Cliff, 2004).

In general, it can be said that behavioral finance is a combination of classical and financial economics with psychology and decision making that seeks to explain and explain the unusual phenomena observed in the field of finance. From Rakik's point of view, classical financial economics theories are based on the efficient market hypothesis, the complete rationality of factors in the use of information, and decisions based on maximizing the expected utility. These assumptions play an important role in determining the factors of asset price, risk attitude and financial management in classical economics (Rakik, 2014)

Behavioral finance can be seen as a response to the infinitely unrealistic assumptions of the efficient market hypothesis. Just like heterogeneous agent models, behavioral finance is based on finite rationality and states that some phenomena observed in the financial world can be better explained by using models with factors that are not entirely logical. Behavioral finance applies psychology to financial issues and examines the effects of these behaviors on financial markets by examining investor behavior. This area has emerged in recent decades in response to the shortcomings of modern financial theory in explaining the behaviors observed in investors and financial markets.

2.2. Heterogeneous agent models

The main idea of heterogeneous agent models is to leave the "rationality" of agents, in other words, agents have limited rationality in decision-making (Simon, 1955).
Nonlinear agent\model methods are able to produce economic models that are very accurate in estimating the real world. Factor-based modeling has been used in many economic environments. But financial markets due to the nature of price dynamics, heterogeneity of factors and different investment behaviors of agents, more attention has been paid (Lux, 2010).

There are many different approaches to modeling heterogeneous factors, all of which are similar in nature. This paper is based on one of the influential heterogeneous factor models introduced by Brooke and Homes in 1998. This approach is seen as the basis for modeling heterogeneous factors in the field of financial markets (Baronick and Kokaka, 2013).

According to researchers, there is a close relationship between the heterogeneous agent model and behavioral finance (Grimaldi, 2005). The heterogeneous agent model Brooke and Homes has two main parts, including traders and the market. The set of traders in the market, each chooses one of the trading strategies for investing. These strategies are very simple and show different types of participants in real markets. In Brooke and Homes heterogeneous agent model, like other heterogeneous models, two types of Fundamental trading strategies are considered, which include Fundamental and technical strategies.

Fundamental analysts believe that prices are determined only by economic variables and in accordance with the efficient market hypothesis (Fama, 1970). In their view, even if a short-term deviation occurs, we expect prices to return to their fundamental value. Technical analysts, on the other hand, believe that futures prices can be predicted using simple trading rules.

Accordingly, if market prices are higher than fundamental stock prices, fundamental analysts expect stock prices to decline in the future while technical analysts expect stock prices to rise. In other words, traders act with a fundamental strategy of a market stabilizing force, while traders with a technical strategy act as a market destabilizer. In different approaches of heterogeneous agent model, different types of these two types of strategies are used.

As mentioned, one of the most important approaches to the heterogeneous agent model was proposed by Brooke Wohms in 1998 and developed in 2006. In Brooke and Homes model, the transfer of factors between different groups is done for the base of the polynomial logit model. The limited rationality of factors plays a big role in the evolutionary choice of expectations. One of the most important advantages of Brooke and Homes model is Real data is more relevant in financial markets. Also, in this model, the weight given to a strategy is based on its past performance, but in other models, it is the size of the group that influences the choice of factors (Chiarla, 2003).

The present study is based on the initial framework of Brooke and Homes model (1998) and its subsequent modifications in (2006). Brooke & Homes's heterogeneous agent model framework is a financial market adaptive belief system (ABS) whose evolutionary choices and heterogeneous expectations are its most important features. In the initial pricing model, there was a risky asset and a risk-free asset that dynamically represented the level of wealth. Presented

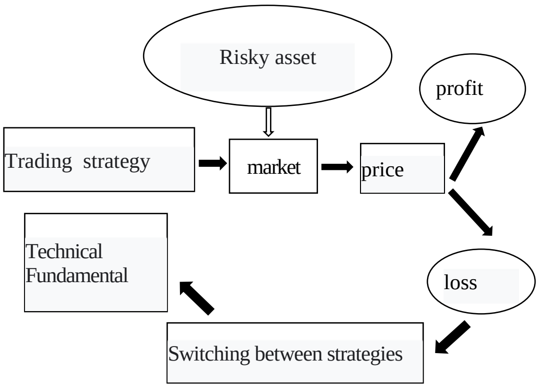

Figure1- Brook and Homes heterogeneous agent model structure

Source: (Kukacka& Barunik,2013)

In this model, people enter the market with different strategies and invest in a variety of risky and non-risk assets. As a result of investing people with different strategies in the market, the price of securities is discovered. Investors change the strategy to choose the best strategy with higher returns according to the discovered price and the profit and losses resulting from it, and this cycle continues.

3. research background

Using the factor-based computational economics approach, Marwat et al. Simulated a model that explains the continuous deviation of market prices from its base prices using interactions between heterogeneous factors in the market. They argue that among the literature of heterogeneous factor-based models, models based on the interactions between fundamentalists and charters are particularly important because one of the factors that can play an important role in explaining stock market fluctuations is investors' sentiment about Future changes in stock prices of companies (Marwat et al., 2016).

In their research paper, Rakik sought to explain behavioral stock price fluctuations. He simulated the artificial stock market, which includes both risky and non-risky assets, which include two groups of fundamental and non-fundamental factors. Non-fundamental factors are in fact a group of traders who have one of the anchors of anchorage, loss avoidance and imitation. By presenting a mathematical model of how the expectations of each group of agents are formed and the possibility of learning agents using artificial neural networks, he showed the stock market price fluctuations despite behavioral biases and stated that there are factors with beliefs and preferences. Heterogeneity is more useful for explaining financial market price dynamics (Rocky et al., 1397).

Simulated stock market models are designed to study investor behavior and how they affect market behavior, price discovery mechanisms, and the reproduction of real-time financial time series such as stock fluctuations. Based on the research results, the factor-based modeling approach has increased the accuracy and efficiency of studies related to financial markets (Vakilifard et al., 2014).

In a study using a heterogeneous pricing model, Homes et al. Examined how expectations are formed in a controlled laboratory environment. In this study, investors or traders used a standard pricing model to predict stock prices. The controlled environment showed that real prices differed significantly from core values (Homes et al., 2003). In 2009, wacha presented a simple form of market sentiment in the context of the heterogeneous agent model in order to develop the Brook and Homes model, showing the effects of different changes in sentiment on stock prices (Basujik, 2007). In a 2005 paper, Baker suggested several approaches to modeling sentiment and overconfidence. Baker and Warger discuss the sentiment index in 2007. In fact, they introduce a method for measuring investor emotion (Baker, 2007).

Lieberman (2005) states that factor-based technologies are suitable for testing behavioral theories. In various studies, different behavioral biases have been investigated in the context of heterogeneous agent models. Market sentiment refers to pessimistic or optimistic exaggerated beliefs and aspirations about future market development and stock cash flows. It also addresses investment risks that are not fully justified by available information. Market sentiment seems to be the strongest driver for the stock market. In early 1936, Keynes examined the role of sentiment as a major determinant of investment decisions, especially in times of market downturn (De jong & Zwinkel, 2010).

Di Grimaldi examined market sentiment in 2007 in the context of the heterogeneous agent model, and in 2003 Chiarla emphasized herd behavior. One of the most important studies conducted in 2013 was the article of Coca-Cola and Baronick. Have dealt with traders with heterogeneous expectations. In this study, behavioral biases were included in a pricing model that has breakdown points to directly examine their effect. That is, the model dynamically evaluates price changes around the stock market crash point.

The results of Kokaka and Baronick research showed that behavioral biases can be well modeled through the framework of heterogeneous agent models and through the development of initial models.

This paper tries to study and model the effects of investors' sentiment on stock price dynamics with the help of Brooke and Homes's factor-based computational model and the developments made in it.

4- Research method

The present study is applied in terms of research results and descriptive in terms of purpose. Content analysis method was used to evaluate the simulation results.

Our statistical population has been Tehran Stock Exchange companies so that there is no trading interruption during the crisis. Based on this, using the official website of Tehran Stock Exchange and performing calculations, we have obtained the daily stock market price and the Fundamental stock price of companies 40 working days before and 40 working days after the stock market crash point.

4.1. Research model

The general concept of factor-based models can be deduced from the term Herbert Simon's finite rationality; finite rationality means that agents can only use a limited amount of information (Simon Herbert, 1996). In other words, they cannot consider options and make decisions indefinitely, and this is in stark contrast to the assumptions of traditional paradigms, such as neoclassical economics, according to which decision makers use unlimited information to make decisions. They have unlimited.

In Brooke and Homes model, the transfer of factors between different groups is done for the log of the polynomial logit model. The limited rationality of factors plays a major role in the evolutionary choice of expectations. One of the most important advantages of Brooke and Homes model is that Brooke and Homes adaptive belief system is more compatible with real data in financial markets. Also, in this model, the weight given to a strategy is based on its past performance, but in other models, it is the size of the group that influences the choice of factors (Chiarla et al., 2014).

In Brooke and Homes model, the fundamental price of a risk asset is determined by fundamental factors with the following formula:

$$p_t^* = \sum_{k=1}^{\infty} \frac{E_t[y_t + k]}{(1+r)^k}. \qquad (1)$$

In this formula, the base price is actually obtained by calculating the present value of cash flows. Brooke and Homes suggested that for a more accurate analysis, it is better to work on deviations from the fundamental price. Thus $x_t = p_t - p_t^*$where Pt is the current price of the risk asset (stock) and Pt * is its fundamental price.

4.1.1. Heterogeneous beliefs:

In the Brook Homes agent model, the basis for valuing a risky asset consists of two parts. The first part is based on fundamental calculations and the second part, evaluation is based on the effects of psychological factors on different strategies of investors.

$$E_{h.t}(P_{t+1} + y_{t+1}) = E_t(P_{t+1}^* + y_{t+1}) + f_h(x_{t-1}. \dots . x_{t-L}) \quad h \,\&\, t \; for \; all \quad (2)$$

in fact, heterogeneous beliefs of investors cause stock market prices to deviate from the fundamental price, and this is one of the most important steps in modeling the heterogeneous agent. The part related to (f_h) is the valuation of risky assets according to the effects of psychological factors of different strategies (Homes, 2008). The following important relation can be reached by mathematical calculations and simplification of formula (2).

$$Rx_t = \sum_{h=1}^{H} n_{h.t} E_{h.t}[X_{t+1}]$$
$$= \sum_{h=1}^{H} n_{h,t} f_h(X_{t-1}. \dots . X_{t-L})$$
$$\equiv \sum_{h=1}^{H} n_{h,t} f_{h,t} \qquad (3)$$

In formula (3), $n_{h,\ t}$ refers to the part of the shareholders that have a strategy of h

$$\sum_{h=1}^{H} n_{h.t} = 1 \qquad (4)$$

In formula (3) to calculate n_h, t and determine how many traders have a strategy h must first calculate the performance of each strategy and based on that the weight of traders in each of the beliefs or strategies will be determined. Now we come to the part where we talk about the middle ground. Performance size is actually the realization of profit for strategy h at time t and is defined as follows:

$$\pi_{h.t} = (x_t - Rx_{t-1})\frac{f_{h.t-1} - Rx_{t-1}}{a\sigma^2} \qquad (5)$$

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$$U_{h.t} = \pi_{h.t} + \eta U_{h.t-1} \qquad (6)$$

$$U_{h.t-1} = (x_{t-1} - Rx_{t-2})\frac{f_{h.t-2} - Rx_{t-2}}{a\sigma^2} \qquad (7)$$

Therefore, calculating the performance size of a strategy can be different depending on the memory or without considering the memory (= 0 η). Also, to calculate the weight or fraction of shareholders who use the strategy h at time t, use the following formula Becomes.

$$n_{h,t} = \frac{\exp(\beta U_{h.t-1})}{\sum \exp(\beta \cup \mathrm{h.t} - 1)} \qquad (8)$$

In Equation (8), the beta coefficient is the uncertainty in the choice of traders. The higher the uncertainty, the smaller the beta if ∞ + = β, then all traders homogeneously choose the best strategy with the highest performance size. If β is then traders are confused in choosing a strategy and have no motivation to adapt to one of the strategies. So they randomly select one of the strategies and follow one of the available traders. A higher yield size by a strategy calculated using Equations (6) and (7) will cause that strategy to be chosen by traders in the near future. (Baronick and Kokaka, 2013). For positive betas, traders act on the basis of limited rationality and the actual appropriateness of each strategy.

In Brooke and Homes model, for the dynamics of the model, the number of beliefs or strategies governing the market (h) can be changed according to the prevailing market conditions, so that in the initial model, a small number of strategies were introduced to simplify (Homes, 2008). All beliefs or strategies (h) have the following simple linear form.

$$f_{h,t} = g_h x_{t-1} + b_h \qquad (9)$$

Using formula (9), the updated structure of beliefs in the framework of Brooke and Homes model can be seen in Table (2).

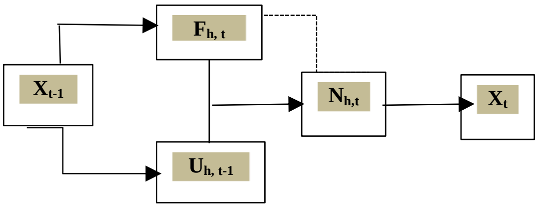


Figure 2 - The process of simulating today's stock price (X_t) with the help of price in the past days
Source: (Kukacka& Barunik,2013)

The above structure actually shows the process of estimating today's price (xt) using the stock price of the previous day (Xt-1), according to Brooke and Homes model. Therefore, the following figure briefly shows how the Brooke and Homes model works. Model 4 defines the type of trader with different strategies (h) in the market (a, b, c, d).

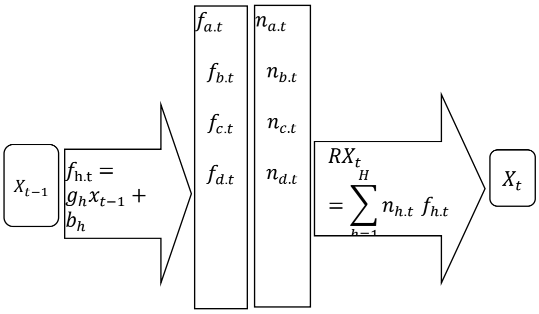


Figure3- The process of updating prices according to the beliefs of investors in the previous day
Source: (Kukacka& Barunik,2013)

Figure (2) shows well how the model works. In fact, having the price the day before (x_{t-1}) and entering the effect of psychological factors (g_h and b_h) on it, the price is estimated on the current day (x_t).
Suppose we are at time t-1. At time t-1 we have an x_{t-1} calculated from the difference between the market price and the base price($x_{t-1}=p_{t-1}-p_t^*$).Now we define the function f_h, t which is equal to

$$f_{h,t} = g_h x_{t-1} + b_h \qquad (8)$$

In this equation, g_h and b_h are in fact the psychological parameters of the trader h, which affects xt-1 and its output is $f_{h,t}$. Given the size of the function calculated at time t-1, we can obtain $n_{h,t}$. $n_{h,t}$ is actually the weight of each idea to the total investors. In other words, $n_{h,t}$ means what part of the total investors choose strategy h to invest in time t. $n_{h,t}$ is equal to the weight of each strategy. Now using the formula

$$RX_t = \sum_{h=1}^{H} n_{h.t}\, f_{h.t} \qquad (9)$$

We can calculate the value of Xt. Therefore, we were able to calculate the value of Xt based on Xt_{-1} and the influence of psychological factors on it based on different strategies, and this cycle will continue to produce new X_t in the coming days. In fact, we want to use this model to estimate stock prices at times when the market is in crisis and behavioral disorders are formed. Each behavioral pattern has its own psychological factors (g_h and b_h). Using simulations, the effects of each behavioral pattern on stock prices around the break-even point are estimated. The estimated prices for each model are then compared to the actual market prices to see if the model has been able to estimate the actual market prices. In fact, at a time when an effective event (the collapse of the Tehran Stock Exchange in 1399), the market is in crisis and behavioral biases appear. The estimated prices are then compared with actual market prices to examine the model's ability to estimate prices in the event of behavioral disturbances and investors' emotions. In this study, total market investors are divided into four groups, each group of investors, have their own strategy and beliefs for investing.

4.2. Data analysis method

Our statistical population has been Tehran Stock Exchange companies. Based on this, using the official website of Tehran Stock Exchange, we have obtained the daily stock market price and the Fundamental stock price of companies 40 working days before and 40 working days after the event. We also used the Novin Rahavard software to prepare the stock index and other required statistical information. According to the subject literature and theoretical framework, behavioral biases of negative emotions, positive emotions and herd behavior entered the simulation process.

In order to be able to compare the simulated data with the real market data, it is necessary to calculate the descriptive table of data before and after the stock market crash point. Therefore, for before and after the event, we prepared the mean, variance, Kurtusis and skewness, as well as the jarck test, and determined the changes after the event compared to before it.

According to the operational implementation process of Brooke and Homes model and the initial settings for the implementation of each of the behavioral patterns, coding was done to perform the simulation in the software. In order to achieve a more appropriate response for each of the behavioral patterns of this simulation, it is performed 100 times.

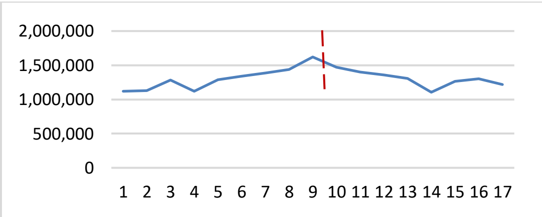
5. Research findings

Findings of research are presented in two sections: Descriptive statistics and Inferential statistics:

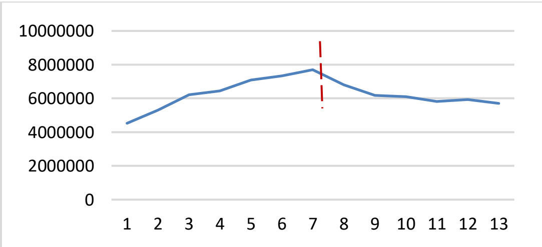
5.1. Descriptive findings

5.1.1. Changes around the stock market crash point

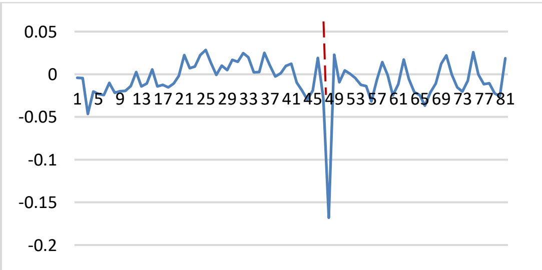
The fall of the stock market in December 1399 can be called one of the crises that have occurred in recent years in the Tehran Stock Exchange. Therefore, the decline of the stock market in this period was considered as the time period for conducting research. In various studies, to consider a downtrend as a market crash point, criteria have been considered, including Salasinus et al., Three criteria to call a downtrend a stock market crash point. Continuous and significant decline of the index, continuous and significant decrease in trading volume and finally a significant decrease in market value (Rakik, 2014). Had a stock market crash. The following diagrams (1) to (3) show the changes in the stock market statistics around the event.



graph 1- Tehran Stock Exchange index trend in 40 days before and after the fall of 1399
Source: Research Findings



graph 2- Changes in the stock market value 40 days before and after the fall of 1399
Source: Research Findings



graph3- Changes in the daily return of the stock market 40 days before and after the fall of 1399
Source: Research Findings

As can be seen from the charts above, the proposed indicators have experienced a significant decline simultaneously. Figure 3 also shows the changes in daily returns around the market crash point, which clearly show fluctuations and scatter of returns in the 40 days after the event compared to before, which is in line with expectations.

5.1.2. Statistical indicators of sample prices before and after events

Changes in statistical indicators in the real market before and after the event can be seen in the following table using the criteria of mean, variance, skewness and elongation.

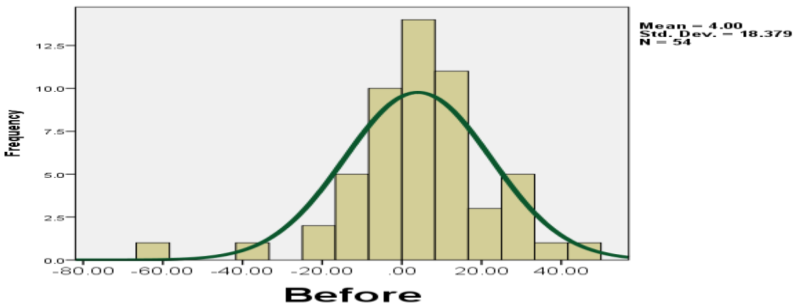
At first glance, with the help of the Jark test, it is observed that the data at the event section do not have a normal distribution. Table (4) shows a significant transfer of mean, variance, elongation and skewness before and after the event. Three of the four cases of descriptive statistics calculated increased. These findings are not only statistically interesting but also economically debatable. Let's start with the average statistic, where the average price difference in the 40 days after the event has sharply decreased compared to the 40 days before the event. From an economic point of view, the decrease in the average is understandable due to the increase in supply at the event due to the expression of emotions and sentiment in investors. Comparison of Table (4) with Figure (3) shows the daily return. At the event, although the average has decreased overall, but on some days, a positive return has been created in the market. This could be due to the activity of speculators, and it may also have peaked in the process of time with the excitement of falling prices, and there is no room for further decline. So prices naturally rise.

Regarding the second descriptive statistic, the variance of Table (4) shows that the variance has increased significantly after the stock market crash point, which is understandable given the increased risk and unpredictability of the factors at the time of the event. In the case of skewness, it is clear that negative skewness has increased. In other words, the data to the left show a greater inclination, which seems reasonable given the decrease in average prices. Decreased that this could indicate more data scatter and is in line with the increase in variance at this point.

Table 1 - Statistical indicators of sample prices before and after the event

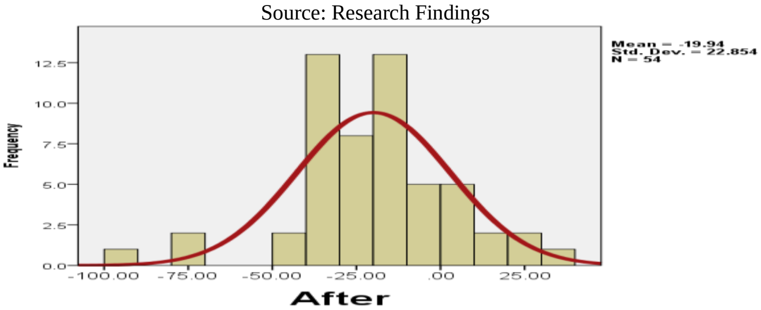
Statistics	JarqueBera test	Average	Variance	Skewness	Kurtusis	Min	Max
40 days before the event	0.0275	4.003	337.793	-0.866	2.822	-63.714	43.06
40 days after the event	0.0284	-19.936	522.304	-0.377	1.752	-93.111	31.33

Source: Research Findings



Graph4 - Density distribution probability of price difference in 40 days before the December 2016 event

Source: Research Findings



Graph5-Density distribution of the probability of price difference in 40 days after the December 2016 event

Source: Research Findings

The results of the Jark test show that the data do not have a normal distribution in times of crisis and the null hypothesis is rejected at 99% confidence level. The Kramer test also shows that the data before and after the event do not have the same distribution, in other words, by rejecting the null hypothesis, it is shown that the data distribution is not the same.

5.2. Implementation of research model

5.2.1. Initial simulation settings

Brook and Homes agent model and initial settings in this model are used to perform simulations in the event section. To simulate market behavior, they divided the entire market traders into several groups, each with the same heterogeneous strategy or belief. In Brooke and Homes' initial model, the strategy was selected based on the size of the bias and trend parameters in Formula (8). The risk-free rate of return (R) is assumed to be 1.17.

The type of strategy varies according to the risk-free rate of return (r) as well as the amount of bias and trend. If we consider the bias parameter as zero, if the trend parameter is greater than zero (g> 0) the trader has a trend-following strategy, if the trend parameter is less than zero (g <0) the trader has a trend-opposite strategy. If the trend parameter is zero (g = 0), the trader is bullish or bullish, and if both are zero, the trader is fundamental. Also, the latest strategy is actually traders who imitate one of the mentioned strategies.

Then, with the development of the initial model by Brooke and Homes and researchers such as (Vacha and Voserda, 2005), (Kokaka and Baronik, 2013), the random formation of beliefs and some behavioral patterns entered the model. The present study was based on the developed model of Brooke and Homes to simulate the market with the presence of fundamental traders and traders with behavioral biases of negative market emotions, positive market emotions and herd behavior, which is in fact an imitation strategy.

In the previous sections, it was stated that the adaptive belief system due to the large number of parameters in the model, and due to the difficulty of analyzing all parameters, and on the other hand due to the need to study the effects of changes in the main variables of the model, some variables in the above relations are considered constant with the initial values. Among these values, we can mention the return on risk-free assets, which is equivalent to 17%. As a result, we will have in all relations: R = 1 + r = 1.17

In this study, we used 4 types of traders (h = 4) or in other words, 4 types of strategies. Monte Carlo simulation was also used to investigate the effect of the proposed behavioral biases on the model output. In this method, we repeatedly randomly generated the main variables for each of the strategies or beliefs, and finally executed each of the strategies with the variables generated 100 times. To perform the simulation, first the following values were considered for the trend and bias and error parameters according to the researches (Homes,2006 and Boiswijik et al. 2007 and Chiarla et al., 2010). The trend parameter g_h with normal distribution N (0, 0.16), the bias parameter b_h with normal distribution N (0, 0.9), and the noise expression ϵ_t with uniform distribution U(-0.05, 0.05)

5.2.2. Simulation settings for each of the behavioral patterns

The initial adjustments made above based on the model in the event section generate data that is due to the occurrence of behavioral biases in general. But in order to produce data based on the characteristics of each behavioral pattern, it needs to be readjusted.

5.2.2.1. Settings for simulating negative market sentiment

In his 2009 paper, Waja presented a simple form of market sentiment in the context of a heterogeneous agent model, showing the effects of different changes in sentiment on stock prices. In modeling market sentiment, we use the transfer of the mean value. According to the generated coefficients of g_h and b_h in the process of simulating behavioral patterns, in order for the generated data to be formed with the effect of negative market sentiment, the mean shift for negative sentiment of the trend parameter in the range (-0.4 to -0.04) And is considered for the bias parameter in the range (-0.3 to -0.03) (Baronik and Kokaka, 2013)

5.2.2.2. Settings for simulating Positive market sentiment

In this research, market sentiment as the displacement of the mean is a function of the distribution of random values generated according to the initial settings in the simulation. Therefore, increasing the average means producing data with positive market emotions and decreasing the average means negative market sentiment. The mean shift for positive emotions is considered the trend parameter in the range (0.4 to 0.04) and for the bias parameter in the range (0.3 to 0.03).

5.2.2.3. Herd behavior simulation settings

In order to simulate and produce data affected by the bias, herd behavior is defined in accordance with Brooke and Homes model. Truth is an imitation pattern that chooses the best performance according to the performance of other patterns.

In each initial combination, one or more parameters are set. For example, when the simulation was performed. The output of each run is called a sample. Samples are created by gradually injecting information during the execution of the process. A complete sample contains 8000 views (including 40 days before the event, 40 days after the event in 100 runs). The results are obtained through statistical testing of samples after each run. Regarding beta and selection intensity, it can be said that due to the nonlinear structure of the model, estimating the beta value using real market data seems impossible.

As a result, the beta value remains a conceptual parameter. Higher beta values indicate that traders are more likely to switch between strategies based on their profitability. To cover a wide range of possible values for beta, in this study the interval (500-5) with a difference step of 55 based on research (Vacha and Sorda, 2002), (Chiarla et al., 2007) (Boiswijik et al., 2010) and (Kokaka and Baronick, 2013) have been used. In fact, the beta will be as follows:

β = 5-60-115-170-225-280-335-390-445-500

5.2.3. Simulation results

In this research, simulation was performed with 4 different patterns

These four patterns include a fundamental strategy, positive market sentiment, negative market sentiment, and herd behavior. The simulation results of these 4 modes are presented in Table (2). In fact, in each simulation, many features have been investigated

First: The parameters that have been studied in relation to the experimental data have been estimated. These parameters include mean shifts, variance, skewness, and data distortion before and after the stock market crash point. Second, we used the Kramer test to examine the equivalence of the observed distributions.

In fact, we wanted to see if there was a statistically significant difference between the distribution of the samples. To confirm the results, we examined the distribution of four samples:

These four comparisons include comparing the total sample before the event (B) with the 20-day sample before the event (b), the 20-day sample before the event (b) with the 20-day sample after the event (a), the 20-day sample after the event (a) with the total sample after the event (A) and finally the total sample before the event (B) with the total sample after the event (A). As seen in Table (5). The two sets (B and A) as well as the two sets (b and a) do not have the same

distribution, the data generated in 20-day and 40-day periods before and after the event do not have the same distribution.

In the following, the normality of the output data distribution is determined using the Jark-Bra test. The parameters under columns B to A show the number of times that the output data of the model had a normal distribution, which according to the results seen in Table (2), most of the simulated performances for different behavioral patterns did not have a normal distribution.

Mean, variance, skewness and Kurtusis

parameters indicate the number of times that this parameter changes in the simulation according to its changes in real data. The parameters under columns B-b to A-B show the number of times that the data distribution of the two sets was the same. The parameters under columns B to A show the number of times that the model output data had a normal distribution.

On the main issue of the research and whether it is possible to model the patterns of behavior, especially the sentiment of investors, with the help of the heterogeneous factor model. It can be said that in Table (2) the simulation results of each behavioral pattern show that the heterogeneous agent model is well able to simulate and estimate the real market when investors' negative objects occur, while the model estimates the positive sentiment of investors. Also, herd behavior has not been very successful. The ability of the heterogeneous agent model to simulate the effects of each behavioral model using the four criteria of mean, variance, skewness and elongation is fully described.

Table (2) Simulation results for different behavioral patterns

JarqueBera test				Cramer test				Skewness	Kurtusis	Variance	Average	Sample
A	a	b	B	A-B	a-A	b-a	B-b					
35	25	89	70	85	100	90	100	21	49	4	55	Fundamental analysis
66	28	95	85	8	100	29	100	10	45	48	20	Herd behavior
32	24	89	69	12	100	18	100	28	36	15	3	Positive market sentiment
47	31	88	74	22	100	20	100	89	78	91	100	Negative market sentiment

Source: Research Findings

5.2.3.1 Herd behavior

The herd behavior pattern is based on the short-term profitability of investment strategies. This behavior is observed in some investors who seek short-term profitability using the strategy of other investors. In this model, one of the strategies is actually based on the behavior of the most successful trader. In other words, someone who has a herd behavior strategy decides based on the performance of other people the day before, and each person who performed better the day before acts as a criterion for deciding to buy a share. Brooke and Homes model introduces several

strategies and the last strategy imitates one of the other strategies according to their performance.
Based on the simulated results in the table, herd behavior has not been very successful in estimating the actual market. Matching the simulated table with the actual market based on the four criteria of mean, variance, skewness and elongation shows that only based on the criterion of variance, the simulated results have a relative agreement with the actual market data.

5.2.3.2. Negative sentiment

Based on the observations of the simulation table, the negative market sentiment strategy had the greatest effect on estimating market behavior. Especially in terms of the average criterion, the heterogeneous agent model has been able to estimate the negative market well by embedding the negative market sentiment and simulating it. This result may seem logical given the prevailing negative view of the stock market at the time of the event. Also, in terms of other statistical criteria (variance, skewness, elongation), the simulation process shows the best agreement with the real market when negative market sentiment occur.

5.2.3.3. Positive sentiment

the research results show that by including psychological factors of positive market emotions in the heterogeneous factor model, the model's ability to estimate the real market has been very low. This could be logical given the prevailing fears and concerns among shareholders in times of crisis.

6. Discussion and conclusion

In this research, we investigated the effects of investors' sentiment on stock prices. These sentiments were expressed as positive sentiment and negative sentiment in the framework of theoretical discussions and the background of the research. Until now, there have been various researches about investors' sentiments and its effects on stock prices. In this research, an attempt was made to investigate and model investors' sentiments in the Tehran Stock Exchange using the Brook and Holmes heterogeneous agent model.
Table (2) shows the output of the simulation, which helps us to answer the research

questions. In this table, the simulated data is based on four statistical indicators (mean, variance, skewness, Kurtusis), the ability of the model to repeat It shows the indicators related to the real data of the Tehran Stock Exchange.

The results of the research show that the behavioral pattern of investors' sentiment can be simulated in the framework of the heterogeneous agent model. Among the behavioral trends that have been investigated in this event according to the Brook and Holmes heterogeneous factor model, the modeling of negative market sentiment has performed best in estimating the real market.
The results of the research show that the traders who were exposed to the negative sentiment of the market, their simulation results had the best match, especially in terms of the average compared to the real market. In investors, their behavior and the effects that stock prices have on the real market are well explained. These results are consistent with the research conducted by Renik in 2013. In 2013, Kukaka highlighted the positive sentiments of the market in their research, which is not very consistent with the present research. This can be caused by the different conditions governing the markets during the crisis.
The results of the research can be used to predict stock prices at a time when we are facing the fall of the stock market and the emergence of behavioral phenomena, especially negative market sentiments. According to the developments made in the model, it is suggested to examine other behavioral patterns, especially with the presence of smart traders in the framework of the model. Also, in the research conducted so far, traders only invest in stocks as a risky asset, which can be expanded to other risky.

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