Proposing a model for assessing Herding behavior in the Iranian capital market using meta-heuristic algorithms

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ABSTRACT

The main purpose of this article is to provide a model for assessing the Herding behavior of investors in the Iranian capital market based on fundamental and non-fundamental factors using meta-heuristic algorithms, based on DNA and racial complement calculations. The statistical population of the present study includes all companies that have been active in the Tehran Stock Exchange during the period of 2009 to 2019, and 129 companies were selected as a statistical sample. Fundamental and non-fundamental factors were identified as factors affecting the Herding behavior of investors and after collecting data, meta-heuristic algorithms were used to predict the dependent variable. Also, the results obtained from the algorithms were compared with each other in terms of accuracy and speed of algorithm measurement. The results showed that the variables "investors 'emotional decision making", "momentum strategy", "stock price volatility", "return on investment", "investors' emotions", "economic news", "oil price", "dollar price", "gold price" and "economic growth" have a positive and direct effect on "Herding behaviors in the Iranian capital market" and the variables "risk of stock price falls" and "inflation rate" have a negative effect on "Herding behaviors in the Iranian capital market". Comparison of the results of meta-heuristic algorithms also shows that the prediction error according to MSE and MAPE criteria in the shrimp batch algorithm is less than that in the three humpback whale algorithms, the improved genetic algorithm and the simple genetic algorithm; The prediction error rate according to the RMSE criterion in the humpback whale algorithm is less than that in three shrimp batch movement algorithms, improved genetics and simple genetics. On the other hand, the execution time of a simple genetic algorithm is less than the other three algorithms. In general, it can be said that the shrimp batch movement algorithm and the humpback whale algorithm are better than the simple and improved genetic algorithm in predicting the Herding behavior of investors in the Iranian capital market and have higher accuracy. Comparing the execution time of shrimp batch movement and humpback whale algorithms showed that the shrimp batch movement algorithm has a higher speed than the humpback whale algorithm.

Keywords: investors' Herding behavior; Meta-heuristic algorithms; DNA calculations; Racial complement.

1. Introduction

One of the most challenging topics in the field of financial literature is understanding the process and how investors and participants in the capital market make decisions. In recent years, with the governance of behavioral financial paradigm and the standard financial theories being challenged, and due to their inability to explain the anomalies observed in the capital market, financial researches have entered a new intellectual age. In some, the assumptions of modern financial economics have been challenged. One of these assumptions is the rationality of investors, which has been seriously challenged. The phenomenon of Herding behavior is one of the well-known behavioral biases of investors in financial markets. Collective behavior or Herding behavior represents the correlation of investors' transactions and investment decisions by following the behavior of other investors or showing the same behavior as the investment behavior of the whole market and the reasons and factors of formation of Herding behavior of investors in financial markets can be classified from different aspects.

Although in the conducted researches, the existence or absence of Herding behavior in the capital markets has been repeatedly examined, the influential and aggravating factors of this phenomenon have been considered to a lesser extent in the Tehran Stock Exchange. There is a belief in Herding behavior in various fields of science such as psychology, sociology, economics and finance. In general, Herding behavior can be defined as the actions of a group of people imitating a representative. Abandoning individual thinking and following group behavior can have economic consequences for investors. Predicting and describing stock market fluctuations in recent decades has been the focus of attention of researchers, scholars, investors and relevant regulatory bodies. Over time, two conflicting views on the underlying mechanisms of behavior in the capital market have evolved. The first view, known as the efficient market hypothesis, was developed in the works by Sherpe (1964), Fama (1965), Jensen (1967), Fama (1970), and others. In this view, it is assumed that markets behave efficiently and investors behave rationally, that is, the stock price includes all the information available in the capital market. According to the amount of information in the market, markets can be divided into weak, semi-strong and fully efficient. The final conclusion that can be drawn from the efficient market hypothesis is that it is impossible for stock prices to fluctuate continuously in this market, although one may do so by chance at any given time. Gradually, evidence emerged that challenged the ideas of the efficient market hypothesis. On the other hand, these studies show that more changes in assets can explain than efficient asset pricing models (Leroy, Porter, 1981) and explain the existence of financial crises (Razf and Kinney, 1976; Kim, 1983). Researchers have developed other theories to find an explanation for these anomalies, thus a new branch of financial researches called behavioral finance was developed (Schiller, 2003).

Proponents of behavioral finance point out that there are certain barriers to market efficiency that need to be considered, for example:

restrictions on predicting investors' behavior factors, loss of future profits among investors (Hayek, List, 2005) , overconfidence of managers and investors (Daniel, Hirschlifer, Subramaniam, 1998), and portfolio diversification bias (Mawk, Salzider, 2015). The findings of researchers working in the field of behavioral finance have many important implications. These findings suggest that rational investors may not always be able to makeup past trading losses with new rational trades, hence, markets may deviate from an efficient market. In addition, in some cases, rational investors tend to trade before institutional traders, the possible consequences of such actions, lead to the formation of Herding market behavior (Delang, Schliffer, Summers, Waldman, 1990).

It can be said that the Herding behavior of securities analysts is the behavior that analysts show when forecasting the financial condition of public stock companies and when providing investment advice. This type of behavior can be divided into two categories based on the differences in the factors that cause the analyst Herding behavior (Jagdish 2010). The first category is created by many analysts from a similar analysis of available public information, such as the latest financial reports of companies accepted in the capital market, new financial market rules and regulations, industry standards approved by the government, and so on. Based on the fundamental analysis of this information, analysts make similar suggestions. The second category is when the analyst follows the reports of a well-known analyst due to his lack of ability in doing research ability and offering suggestions, which is the same as Herding behavior. Other factors such as the number of years of experience, number of securities and companies that the analyst study and the analyst's reputation can lead to further formation of this phenomenon. In the first case, the analyst uses the latest information available for his predictions and reviews, and in the second case, they use and follow only the predictions and decisions of others without using the available information. The main purpose of this study is to investigate the effect of fundamental and non-fundamental factors on the formation of Herding behavior in the Iranian capital market using meta-heuristic algorithms based on DNA calculations and racial complement. Accordingly, the main question about the existence or non-existence, why and how of the occurrence and manifestation of Herding behavior and its roots and causes in the financial markets, is a necessary and inevitable challenge. Considering the conditions of the Iranian capital market and being close to the hypothesis of the existence of the phenomenon of Herding behavior in the Iranian capital market, the issue can be expressed as follows; Is the Iranian capital market affected by the phenomenon of collective or Herding behavior? Are there the same results obtained about this phenomenon in the Iranian capital market, under different models and patterns of measuring behavioral phenomena? Are there any variables that play a decisive role in the occurrence of this behavioral phenomenon in the Iranian capital market? What distinguishes this study from other domestic and foreign studies is that some domestic researches, the formation of Herding behavior is studied in the form of a survey and a questionnaire. However, in this study, we examine Herding behavior through the financial data of companies listed on the stock exchange. Also, in addition to examining the factors influencing the formation of Herding behavior, this study provides a model for measuring Herding behavior based on fundamental and non-fundamental variables based on meta-heuristic algorithms. On the other hand, unlike foreign conducted researches, which examined the formation of Herding behavior using one or more limited samples (mainly using the trading data of all investors in one or more agencies) and naturally has little generalizability. In this study, we examine the financial data of companies listed on the Tehran Stock Exchange for a period of ten years. Finally, unlike most related studies conducted in developed countries involving investors' trading attitudes, in this study we examine the formation of Herding behavior in a developing country with the characteristics of collectivism.

Theoretical foundations of the research, research background, hypotheses, methodology, and research findings are presented.

2. Theoretical foundations and research background

In recent years, with the dominance of the financial behavior paradigm and the standard financial theories being challenged and due to their inability to explain the anomalies observed in the capital market, financial researches have entered a new intellectual age, and in some of them, modern financial economic assumptions have been challenged. One of these assumptions is the assumption of rationality of investors, which has been seriously challenged and several studies have been devoted to this issue. Until the end of the twentieth century, neoclassical financial theories were the dominant paradigm of financial markets. Rationality of human was the basic premise of these theories, an issue that has been challenged in recent decades, mainly with the introduction of psychology into economics and finance, and behavioral finance has gradually become the dominant discourse among financial theorists.

2.1. Theoretical Foundations

Herding behavior is the most common phenomenon known in financial markets in the context of psychology. This phenomenon can cause irrational behaviors by investors. A number of investors may come to this conclusion through fundamental and technical analysis that a certain stock is priced lower than its real value and it makes sense to buy that stock, but they refuse to buy that stock and act like other investors, and even perfectly reasonable people can suffer from this phenomenon. (Saeedi and Farhanian, 2015). Thorstin Veblen (1899) was the first economist to study the Herding behavior of investors in the form of sudden changes in consumer behavior, such as temporary styles and desires of consumers. . Keynes believes that people ignore their personal ideas and beliefs because they fear that their decisions will be considered unconventional, thus they act according to the Herding behavior. Banerjee (1992) believes that each person pays more attention to other people's decisions than his own, when making decisions.

He considers this method of decision-making to be a logical one, because previous people may have more information. While this method of decision making can be logical, it can ultimately lead to market inefficiencies. Bikhchandani et al. (1992) consider the informational cascades as the source of the formation of Herding behavior. Froot et al. (1992) conducted a study knew the use of shared information resources as a reason for the collective behavior of investors in the capital market, and believe that this phenomenon can indicate information transparency in the market or market efficiency. Kim and Nofsinger (2008) identified investors' behavior in a study entitled Behavioral Finance in Asia. The results of this study show that Asia is an interesting place to study behavioral finance due to its different levels of capitalism. Individual investor in Asia is often seen as an exclusive exchange broker. Asians suffer more from cognitive biases than Western cultures and are more inclined to behave according to the groups. This collectivist society has led to overconfidence and is a cognitive bias. Zhou and Lai (2009) provide evidence of Herding behavior based on information asymmetry in Hong Kong. Chiang and Zheng (2010) conducted a comprehensive study on institutional investors with a sample of 18 advanced and emerging economies around the world. Researchers see no evidence of Herding behavior in US and Latin American markets. Researchers say Asian markets exhibit a certain amount of Herding behavior at both high and low levels. Khan et al. (2011) show that the rate of Herding behavior decreases during turmoil. Examining the effects of events is not limited to the period of financial turmoil. Bashir (2013) examined the effect of behavioral biases on investment decisions. In this study, respondents' gender was considered as a dependent variable and behavioral biases, delusion of power, overconfidence and lack of discrepancy were considered as independent variables.

The results of his research showed that there is not much difference between male and female investors in the degree of behavioral bias. Garg and Jindal (2014) found no evidence of Herding behavior in the Indian stock market during 2000-2012. While Puohakwale and Mandal (2014) claim that Herding behavior has been identified in this country (India). Galariotis et al. (2015) distinguish between the various basic mechanisms of this phenomenon and divide Herding behavior into logical (intentional) and irrational (unintentional) parts. Researchers regularly find no evidence of this type of behavior in the United States and the United Kingdom. Hedesstrom et al. (2015) also show that performance-based rewards lead to higher levels of Herding behavior. Zheng et al. (2015) find significant Herding buying behavior among Chinese institutional investors, which is reinforced in times of turnmoil. Research on institutional investors in the market has been more extensive and in some cases contradictory. Choi (2016) investigates the formation of Herding behavior among online and offline investors in the Korean capital market and concludes that the reason for the Herding behavior formation can be due to the exchange of information between market activists. Guvercin, (2016) looks at the markets of Egypt and Saudi Arabia and finds that Herding behavior exists only in Egypt, while the market in Saudi Arabia does not show such behavior. In their study, Wang et al. (2017) examined whether the demand for underwriting of the initial public offering of stock affects the Herding behavior of investors in Taiwan. In this regard, they state that the initial public offering of shares in Taiwan mainly consists of the initial fixed price and the public offering of shares, which only allows individual investors to participate in trading. They believe that the disclosure of underwriting application information on the Taiwan Stock Exchange takes place after individual investors request the highest underwriting rate; this, in turn, makes formation of Herding behavior of investors in Taiwan possible. One of the most important factors influencing Herding behavior, which has been researched, is the effect of periods of financial turmoil on the formation of Herding behavior, which is believed to be accompanied by more uncertainty.

But in some financial markets, the evidence contradicts this theory. For example, Chiang and Zheng (2010) show signs of Herding behavior in the country, where the crisis has arisen, and claim that major crises have negative external consequences that lead to Herding behavior in financial markets and they usually do not show it (like in the US). Galariotis et al. (2015) support the hypothesis that Herding behavior is seen during the crisis in the United States and during the Asian crisis of 1997-1998 in the United Kingdom. At the same time, a number of articles (for example

Khan et al., 2011) show that the rate of Herding behavior decreases during turmoil. Examining the effects of events is not limited to periods of financial turmoil.

For example, Galariotis et al. (2015) examined the impact of important news announcements on the Herding behavior and found important evidence of this phenomenon for the United States these days. Finding relevant American news by Belgacem and Lahiani (2013) is present in France, Switzerland, Portugal, Greece and Germany. In addition, Belgacem and Lahiani (2013) noted that investors in Belgium, Finland, and Ireland behave Herdingively only in the American news, and domestic news does not lead to the formation of Herding behavior. Gaverlidis et al.

(2015) study the effects of institutional investors and the month of Ramadan in a sample of Muslim countries. Researchers conclude that in most sample countries, Herding behavior intensifies during the days of Ramadan. Demir et al. (2016) investigate the effect of military action on Herding behavior. Researchers find no little evidence that Herding behavior is driven by military intervention in Syria and Egypt. Apart from the above, it is a common and experimental way to escape foreign financial markets and investor uncertainty, and it is usually provided in that country by the market overall index or specific economic scales. According to the first factor, Chiang and Zheng (2010) state that US stock market developments tend to make a significant contribution to the formation of Herding behavior in non-US markets. In addition, Yang and Chen (2015) found that Herding behaviorist activities in China and Taiwan were negatively associated with investors' Herding behavior in the United States. Cakan and Balagyozyan (2016) apply fluctuations to sector analysis and find their impact only in the financial, service and technology sectors. In addition, oil price is considered as one of the potential factors in forming Herding behavior for companies that export resources. The relationship between price and Herding behavior has been tested by Balcilar et al. (2014) and Demir et al. (2016). The researchers found that oil price fluctuations were linked to the formation of Herding behavior in the United States and Qatar. Since the holding company trades a significant number of investors in the same direction, this phenomenon should be accompanied by an increase in liquidity. At the same time, the relationship between market and liquidity has not been extensively studied. To the best of researchers' knowledge, two studies have been devoted to examining the relationship between the market and market liquidity. Thirikwa (2015) reported that firms with capital face higher rates of Herding behavior in the small markets.

According to researchers, this may be a sign that investors are trying to get enough relevant information about these companies. To conclude, there is no global agreement on a complete list of factors associated with the formation of Herding behavior, although the empirical literature pays more attention to the impact of crises and uncertainty. However, the results of these studies are in some cases contradictory. In addition, current researches do not pay much attention to other potential factors related to Herding behavior, such as liquidity and the information environment. Moreover, as mentioned earlier, most of the articles in this field do not distinguish between intentional and unintentional Herding behavior. Geographically, the existing literature focuses mainly on identifying factors related to Herding behavior in the United States, the development of European markets, and emerging markets in Asia and the Middle East.

2.2. Research background

Wanidwaraan,padurgsakawasdi (2020)Return jumps increase in frequency and are considered to reflect the arrival of non-trivial information. We thus question the impact of return jumps on herd behavior in global equity markets. New herding detection models that incorporate return jumps overcome multi collinearity and sample-splitting problems found in prior studies. While the traditional model does not detect herd behavior in most cases, our augmented model incorporating return jumps detects more cases of herd behavior. We find the strongest effect on jump and negative return dates, supporting existing evidence of asymmetric herd behavior. In general, incorporating return jump dummy variables underlines the existence of herd behavior and an information cascade-argument helps explain this phenomenon well. Our results are robust to altering the identification of return jumps and the herd behavior model.

Zarmba et al. (2020) studied stock markets in 64 countries between 1973 and 2018 in a study entitled Herding Behavior and Earning, Market Size, and Stock Returns Section. In this study, the effect of market size and returns and stock price fluctuations and the trend of changes in financial markets on the formation of Herding behavior in ascending and descending periods has been studied. The results show that Herding behavior has existed in all markets at different times and the size of the stock market and the numerous investment portfolios in ascending periods lead to a reduction in Herding behavior. Esteliani et al. (2020) in a study examined the impact of monetary policy on the formation of Herding behavior at the international level. In this study, for the first time, the effect of expansionary and contractionary monetary policies of the US Federal Reserve and the European Union on the formation of Herding behavior in the stock market at the international level has been investigated. Findings show that central bank policies such as reducing bank deposit rates lead to liquidity movement towards the stock market. This increase in liquidity will lead to emotional behavior in investors and the formation of Herding behavior in the capital market. The US Federal Reserve also adopts conventional monetary policy, which justifies a significant percentage of the deviations of Herding behavior in the US stock market. While the adoption of expansionary policies by the European Central Bank leads to an increase in the formation of Herding behavior in the stock markets of Italy and Spain. Bonches et al. in a study entitled “Herding Behavior in Investment in Stock Exchange”, examined Herding behavior in the managers of international funds. Findings of this study show that managers of international funds tend to invest in shares of holding companies and invest in shares of companies with fundamental structure. This study also shows that Herding behaviors in the managers of investment funds are formed at the time of fluctuations in the stock market. This group of investment funds are looking for stocks that increase the fund's return and reduce the fund's investment risk. Jamshidi and Ghalibaf (2020) in a study entitled Analysis of transaction behavior of real and institutional investors of the stock exchange, from the perspective of behavioral biases and factors affecting it, examined the behavior of investors and the purpose of this study was to investigate the behavior of real and institutional investors in Tehran securities from different aspects. For this purpose, the status of their portfolio during the 5-year period from 2012 to 2016 has been reviewed and analyzed. The results show that the behavior of investors indicates some cognitive errors. Clearly, (along with the bias of tendency effect) both groups of investors tend to sell a stock the price of which has risen and hold a stock that has fallen in price, although this tendency is greater in real investors. Investors also view past stock returns as an indicator of future returns (representational bias), and their trading behavior (especially that of real investors) reflects their overconfidence. Also, in order to investigate the effect of investors 'characteristics on their cognitive errors, behavioral biases and transaction errors based on investors' characteristics (including frequency of transactions, account history and account value) were examined and analyzed. Jafari (2019) in a study examined the intensity and weakness of Herding behavior with a new method based on stock market value in Tehran Stock Exchange. The purpose of this study is to investigate the phenomenon of collective behavior or Herding behavior as a behavioral bias among investors. For this purpose, using the daily stock price information of 184 active companies listed on the Tehran Stock Exchange during the years 2013 to 2017, the existence of Herding behavior in the Tehran Stock Exchange has been investigated with a new approach, and the intensity and weakness of this behavior during the years of research and the effective observations in its occurrence were verified. For data analysis, based on time series data principles and using standard scoring techniques and points of impact have been used. Findings of the study, while confirming the existence of Herding behavior in all years of research, has shown the distribution of severity and weakness of this behavior on a daily basis along with effective observations and with the help of effective impact point recognition technique, time sections of strong collective behavior have been extracted. The results also show that Herding behavior occurs in descending trends occurs with more intensity than in ascending trends. Mirhashemi Nasab et al. (2019) in a study entitled “Providing a model to investigate the combined effects of risk-taking, individual and cultural characteristics on the occurrence of Herding behavior in investors in Tehran Stock Exchange” studied the individual and cultural characteristics of investors. The results of research show that, in order to determine the value of stocks, investors in Tehran Stock Exchange, in addition to quantitative methods, use judgments based on mental images, unscientific information, rumors, and blind follow-up from a small number of participants in the capital market, also known as collective, herd, and Herding behavior. The purpose of this study is to introduce a model to investigate the combination of factors affecting the occurrence of Herding behavior of investors in the Tehran Stock Exchange, based on the background of related studies in this field. This research is of mixed type which is applied in terms of purpose and is a survey from descriptive point of view. In this study, 190 investors have completed an online questionnaire as an available sample and hypothesis testing has been evaluated using SPSS22 and AMOS18 software in the framework of structural equation method and the research model has been drawn. The results show that the proposed model has a good fit to express the relationship between the factors affecting the occurrence of Herding behavior of investors and can specify the relationships and mediating effects between individual and cultural characteristics, risk-taking and Herding behavior in investors.

3. Research hypotheses

Dong and Lin (2016) stated that non-fundamental factors (factors other than financial data) are the main reason for the formation of Herding behavior in financial markets in Vietnam. In a study, Philip et al. (2015) examines four developed European markets, including France, the United Kingdom, Germany, and Italy. Their findings confirm the existence of Herding investors' behavior in the financial markets of developed countries. Lack of transparency in the presentation of financial data and information asymmetry encourage investors to make decisions by tracking the actions of other investors. These results cannot be used by investors in making decision due to the weakness and lack of quality of information. Recent evidence supports the formation of Herding behavior in financial markets (Balkilar, Demir, Hamoudeh, 2013; Balkilar et al., 2014; Goni et al., 2017). Numerous evidences of the formation of Herding behavior in financial markets may be related to the lack of distinction between Herding behavior due to basic and unessential information. If investors show their Herding behavior toward the middle of the market through one type of information, while they release another type of information through it, these effects may lead to no Herding behavior if summarized. Therefore, it is important to distinguish between Herding behavior as a result of fundamental information or non-fundamental factors. Research background shows that the effects of institutional investors in emerging and developing markets are greater than those in developed cases. In this case, investors are expected to exhibit Herding behavior, mainly by non-fundamental factors, in less developed markets due to low information transparency, they are encouraged to reply less on general knowledge and rely more on Herding behavior. (Balkilar, Demir, Hamoudeh, 2013; Bechler et al., 2014; Dong and Lin, 2016; Jenny et al., 2017). Therefore, in this study, we distinguish between Herding behaviors caused by fundamental and non-fundamental information and we expect that Herding behavior in the Iranian financial market occur by non-fundamental factors due to a clearer information space that forces investors to infer information from the decisions of other investors.

Hypothesis 1) There is a significant relationship between "investor decision-making attitude" and Herding behaviors in the Iranian capital market.

Hypothesis 2) There is a significant relationship between "adopting momentum strategy" and Herding behaviors in the Iranian capital market

Hypothesis 3) There is a significant relationship between "rate of return on capital" and Herding behaviors in the Iranian capital market.

Hypothesis 4) There is a significant relationship between "price fluctuations" and Herding behaviors in the Iranian capital market.

Hypothesis 5) Momentum strategy leads to the formation of Herding behavior in the Iranian capital market.

Hypothesis 6) There is a significant relationship between "falling stock prices" and Herding behaviors in the Iranian capital market.

Hypothesis 7) There is a significant relationship between "exchange rate" and Herding behaviors in the Iranian capital market.

Hypothesis 8) There is a significant relationship between the "global price of gold" and Herding behaviors in the Iranian capital market.

Hypothesis 9) There is a significant relationship between "economic news publication" and Herding behaviors in the Iranian capital market.

Hypothesis 10) There is a significant relationship between the "global oil price" and Herding behaviors in the Iranian capital market.

4. Methodology

This research is an applied research from the perspective of classification based on purpose. On the other hand, the present research is descriptive-correlational in terms of classification of research in terms of method. The implementation of descriptive method can only help to better understand the existing conditions or help the decision-making process and predict future conditions. Also, this research is a correlation study. In this research, the relationship between variables is analyzed based on the purpose of the research.

4.1. Statistical population of the research

All companies that have been active in the Tehran Stock Exchange during the period of 2009 to 2019 and have the following conditions, have been selected as a statistical sample of this study. In order for the information to be comparable, the end of the companies' fiscal year must end on March 20. The companies have not changed the fiscal period in the period (10 years) under consideration. Data related to selected variables in this study are available. Their shares have been traded in the market. Based on the above restrictions, 129 companies have been selected.

4.2. Research variables

In this section, the comprehensive method used by researchers in this article to identify Herding behavior in the Iranian financial market is discussed. In this study, we use the method proposed by Chang et al. (2000) to calculate Herding behavior. It focuses on the study of the relationship between market returns and the dispersion of individual asset returns and its corrections by Gallariotis et al. (2015) and Deng anad Lin (2016). In the present study, Herding behavior in the capital market is a dependent variable. Chang et al. (2000) model was used to measure Herding behavior. According to this model, when the deviation of companies stock returns from market returns decreases, the signs of Herding behavior become apparent. In this model, in order to show the existence of Herding behavior in the capital market, the second power factor of market return is used. If this coefficient is negative, it indicates the existence of Herding behavior in the capital market. Also, the linear relationship between the absolute value of market returns and the cross-sectional deviation of returns indicates the existence of a balance relationship between risk and return in the capital asset pricing model (CAPM).

$$1) CASD_t = \beta_0 + \beta_1 |R_{mt}| + \beta_2 R_{mt}^2 + \varepsilon_t$$

$CASD_t$: Cross-sectional deviation of daily stock returns of companies from market returns and $|R_m|$: absolute value of market returns, R_m^2: second power of market returns. The following equation is used to calculate the return deviation:

$$2) CASD_t = \frac{1}{N}\sum_{1}^{N} |R_{it} - R_{mt}|$$

Share return (market return) is also calculated from the difference between the final price (total market index) of period t and the final price (total market index) of period t-1 divided by the final price (total market index) of period t-1. Arms index was used to measure investors' emotions. The Arms index is based on market data (Blasco et al. 2012; Wang et al. 2006).

The Arms index is calculated as follows:

$$3)\ ARMZ_t = \frac{Adv_t/Dec_t}{Advvol_t/Decvol_t}$$

The Arms index is obtained by dividing the two ratios. In the first ratio, the number of companies that their prices have increased in a t-period is divided by the number of companies that their prices have decreased in the same t-period (ie Adv_t/Dec_t). In the second ratio, the volume of traded stocks the price of which has increased is divided by the volume of traded stocks the price of which has decreased (ie $Advvol_t/Decvol_t$). Finally, the two ratios are divided by each other. The Arms index can be more or less than one. In order to measure the size of t-period of the company's of the market value of the stock traded and the number of shares of the company, the following equation is used:

$$4)\ Size\ Firm_t = In(\frac{1}{n}\sum_{1}^{n} Pri_t * NS_t)$$

Pri: Final stock price, NS: Number of shares issued by the company, n: Number of companies traded in a period t and after calculating the size of the company in period t and obtaining its mean, the companies are divided into two small and large size. The statistical model is also defined as follows:

5) $R_{it} = \alpha_0 + \alpha_1 HM_{it} + \epsilon_{it}$

$\mathrm{R_{it}}$: stock returns, $\mathrm{HM_{it}}$: Herding behavior of institutional investors, ϵ_{it}: estimation error, α_0: y-intercept, α_1: regression line slope estimator

And as mentioned earlier, in this study, meta-heuristic algorithms have been used to investigate the effect of independent and control variables on the dependent variable. In fact, the purpose of implementing this algorithm is to predict the Herding behavior of investors in the Iranian capital market based on the above variables. It should be noted that the proposed structure of this algorithm is designed to solve the problem under study as a combination of complementary approach and DNA calculations. Accordingly, the conceptual model of research is a view of the research model (researcher-made) and is as follows:

6) $Y_{it} = \alpha_0 + \beta_1 Xn_{it} + \beta_2 Con_{it} + \varepsilon_{it}$

Y_{it}: dependent variable and Xn_{it}: independent variable, Con_{it}: control variable, α and β: model coefficients, ε: model error, i: company, t: time period

3.4. Method of data analysis

In order to investigate the effect and assess the Herding behavior of investors in the Iranian capital market based on fundamental and non-fundamental factors using meta-heuristic algorithms and based on DNA and racial complement calculations, the data of this study have been fitted using four models of meta-heuristic algorithms. Finally, the degree of accuracy and speed of each algorithm is compared with other algorithms and optimal algorithms are introduced.

4.3.1. Meta-heuristic algorithms

Meta-heuristic algorithms are a type of random algorithms that are used to find the optimal answer. Optimization methods and algorithms are divided into two categories:

exact algorithms and approximate algorithms. Exact algorithms are able to find the optimal answer accurately, but they are not efficient enough in the case of hard optimization problems, and their execution time increases exponentially according to the dimensions of the problems. Approximate algorithms are able to find good (near-optimal) answers in a short time for difficult optimization problems. Approximate algorithms are also divided into three categories of heuristic, meta-heuristic and hyper-heuristic algorithms. The two main problems with heuristic algorithms are that they get stuck at optimal local points and converge prematurely. Meta-heuristic algorithms have been proposed to solve the problems of heuristic algorithms. In fact, meta-heuristic algorithms are one of the types of approximate optimization algorithms that have solutions for exiting local optimal points and can be used in a wide range of problems. Various classes of this type of algorithm have been developed in recent decades, all of which are subsets of meta-heuristic algorithms.

4.3.1.1. Genetic Algorithm

Genetic algorithm is a computer science search technique for finding approximate solutions to optimize models, mathematics, and search problems. Genetic algorithm is a special type of evolutionary algorithm that uses evolutionary biology techniques such as inheritance, mutation biology, and Darwin's principles of choice to find the optimal formula for predicting or matching the pattern. Genetic algorithms are often a good choice for regression-based prediction techniques. Genetic algorithm modeling is a programming technique that uses genetic evolution as a problem-solving model. The problem to be solved has inputs that is converted into solutions during a modeled process of genetic evolution, then the solutions are evaluated as candidates by the fitness function, and the algorithm terminates if the exit condition is met. In general, it is an iteration-based algorithm in which most of its parts are selected as random processes, and these algorithms consist of the parts of the function of fitting, display, selection and change. Genetic algorithm as an optimization computational algorithm, by effectively considering the set of response space points in each computational iteration, effectively searches for different areas of the response space. In genetic algorithms, a set of design variables is encoded by strings of fixed length or variable, which are called chromosomes or individuals in biological systems. Each string or chromosome indicates a response point in the search space. The structure of strings, that is, the set of parameters displayed by a particular chromosome, is called the genotype and the amount of its decoding is called the phenotype. Inheritance algorithms are iterative processes; each iterative step is called a generation and the sets of responses in each generation is called population. Genetic algorithms perform the main search in the response space. These algorithms begin by seeding that is responsible for creating a set of primary search points called "initial populations" and are selected selectively or randomly. Because genetic algorithms use statistical methods to guide search operations to the optimal point, in a process that depends on natural selection, the existing population is selected in proportion to the fitness of its individuals for the next generation. Then genetic operators, including selection, crossover (recombination), mutation, and other possible applied operators and a new population are created. After that, a new population replaces the previous population and this cycle continues.

4.3.1.1. Improved genetic algorithm

The structure of this algorithm is exactly like the simple genetic algorithm, the only difference with the simple algorithm is the use of kinship coefficient concepts in parental selection.

4.3.2. Humpback Whale Algorithm

One of the largest mammals in the world is the whale. Among the 7 whales in the world, the humpback whale is the most famous. An adult humpback whale is about the size of a school bus. The favorite preys of whales are krill and groups of small fish. The most interesting thing about humpback whales is their special hunting method. This exploratory behavior is known as the bubble-net feeding method. Humpback whales prefer to hunt a group of krill or small fish near the surface of the water. It has been observed that this exploration and hunting is done by creating index bubbles along a circle or paths. The humpback whale algorithm is one of the nature-inspired and population-based optimization algorithms that can be used in various fields. The steps of the algorithm are done in three stages or three phases, which are: siege hunting, exploitation phase, method of attacking the bubble-net of the exploration phase, hunting search

4.3.3. Shrimp batch algorithm

This algorithm is simulated based on the response to the biological needs and environmental operations of the shrimp batch. This algorithm was presented in 2012 by Gandami and Alavi. This algorithm belongs to the category of crowded intelligence algorithms and examines the Herding movement of shrimp to find food. The fitness function of each shrimp is unique and is considered as the distance of the shrimp from the food and the population of the shrimp. As mentioned, the algorithm is based on the movements of shrimp towards food

4.4. Chromosomes Display

In order to meet the information needs of each of the problem variables, it is necessary to determine the status of each of these needs accurately and clearly. Accordingly, based on modeling, it is necessary to determine the weight of each of the effective factors on the Herding behavior of investors. As it is clear, all the effective factors identified should be weighed, then their performance in the degree of predicting the Herding behavior should be investigated. As the weight matrix of the effective factors show. A one-dimensional matrix should be defined as follows. The number of rows of this matrix is equal to one and the number of columns is equal to the number of effective factors identified. Therefore, each of the cells in this array can be considered as a numerical expression, which, if it has a value, it will indicate the weight of the factor in the desired factor. Also, this array should be examined in the next steps so that it can be expected to respond to the final variable, which is Herding behavior. In other words, the effective weights in these values must be able to correctly determine the Herding behavior. Accordingly, the shape of this matrix is as follows:

Factor 1	Factor 2	factor 3	factor 4	...	Factor n-2	Factor n-1	Factor n

Figure 1. display of the information array of assigning weights to factors

As you can see, this is a two-dimensional matrix (one row and a number of columns) that when added to the population of chromosomes, another dimension must be added, and in fact the considered array is a three-dimensional array of equal size with the number of chromosomes. The cell values of a chromosome are numbers between -1 and 1, and the initial population of the algorithm is generated randomly.

4.5. Fitness function

The fitness function is used to evaluate each chromosome. In order to evaluate the prediction performance, three known criteria for evaluating the prediction performance have been used. These three criteria are: 1- Mean squared error between actual values and predicted values, 2- Squared mean of squared error and 3- Mean absolute value of error percentage. These three criteria are calculated by the following equations, respectively.

$$7)\ MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{E}_{\mathrm{i}}^{\mathrm{actual}} - \mathrm{E}_{\mathrm{i}}^{\mathrm{predicted}}\right)^2$$

$$8)\ RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{E}_{\mathrm{i}}^{\mathrm{actual}} - \mathrm{E}_{\mathrm{i}}^{\mathrm{predicted}}\right)^2}$$

$$9)\ MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{E}_{\mathrm{i}}^{\mathrm{actual}} - \mathrm{E}_{\mathrm{i}}^{\mathrm{predicted}}}{\mathrm{E}_{\mathrm{i}}^{\mathrm{actual}}}\right|$$

In the above relationships, n is the number of observations. In the present paper, the sum of the weight of these three criteria is used, and the lower the sum, the higher the fitness of the answer or the chromosome. Therefore, it can be said that the fitness function is the inverse of the total weight of the three criteria above.

4.6. VNS algorithm

It should be noted that each neighborhood search operator in the structure above is represented by the term NSS, and the four operators used in the VNS structure are the same local search operators described in the previous section. In fact, each of the answers selected to apply the mutation operator contains a specific value for the coefficients of the Herding behavior components of investors, and as a result, each answer results in a specific value of the Herding behavior variable. Now this structure is applied to each of the answers and tries to find a neighbor of the answer that has a better prediction of the value of the dependent variable.

Local Search Operator 1: The operation of this operator is that the indices of the two cells of the answer matrix are randomly generated and the values in these cells are swapped together.

Local Search Operator 2: The operation of this operator is such that the indices of two cells of the answer matrix are randomly generated and the values of the cells between the two cells are inverted.

Local Search Operator 3: The operation of this operator is that the indices of 4 cells from the answer matrix are generated randomly and the values in these 4 cells are exchanged in pairs.

Local Search Operator 4: The operation of this operator is such that the values of the answer matrix are completely inverted.

4.7. Crossover operator

The crossover operator is applied to two answers and two children will be generated. The crossover operator designed in this paper works as follows. This operator is a single point crossover operator. That is, an index is selected from the numbers of the random answer cells and each of the input answers (parent) of this operator is divided into two parts. New answers (child) are then created from the following input (parent) answers:

Section 1 first child = Section 1 parent 1
Section 2 first child = Section 2 second parent
Section 1 second child = Section 1 second parent
Section 1 second child = Section 2 first parent

In this article, the roulette wheel method has been used to select parents. After selecting the parents with the mentioned method, which is in line with the selection of the answers with the superior race, the kinship coefficient of the selected parents is calculated. If the kinship coefficient of the population exceeds the threshold, among the unselected answers, a higher quality answer will replace one of the parents. This process will continue until two parents are selected with a kinship coefficient below the threshold.

4.7.1. Calculation of kinship coefficient

As mentioned, to measure and predict the Herding behavior of investors in the Iranian capital market, meta-heuristic algorithms based on DNA calculations and racial complement will be used. In this study, to improve the genetic algorithm, a new method called without GA Arisen has been used in which the kinship coefficient criterion is used to quantify the similarity of the members of the population and by using the idea of breeding methods, the genetic algorithm crossover operator has been modified so that the population is distributed in the problem space and reduces the probability of producing repetitive and optimal local solutions. To calculate the kinship coefficient, two methods of percentage similarity of genes and genealogy tree have been used: In the first method, the percentage of total similarity of answer matrices with each other is calculated and in the second method, the kinship matrix is used, which is a square matrix and the number of rows and columns is equal to the total number of answers, and at the end of each iteration, the genetic algorithm is updated.

4.7.2. Kinship Matrix

The kinship matrix is a two-dimensional matrix with identical and symmetrical dimensions and its number of rows and columns is equal to the size of the population. In cells of the original diameter of this matrix, the number is 1. In other cells of the matrix, the number is 0, if the answers are not related to each other (not produced from the same parent) and is equal to 0.5, if in the previous iteration of the algorithm, they were generated from the same parent. This matrix at the end of each iteration of the genetic algorithm is updated based on the same iteration information and becomes ready for use in the next iteration.

5. Statistical findings of the research

5.1. Descriptive findings

In order to study the general characteristics of variables and their detailed analysis, it is necessary to be familiar with descriptive statistics related to variables. Figure (1) shows the descriptive statistics of the data related to the variables used in the research. Descriptive statistics are related to 129 sample companies during a period of 10 years (2009 to 2019).

Inflation rate	Economic growth	Oil price logarithm	Gold price ىlogarithm mm	Dollar price logarithm	Momentum strategy	Stock price fluctuations	Type of investment return	Momentum strategy	Investors'emotional decision	Herding behavior	
1290	1290	1290	1290	1290	1290	1290	1290	1290	1290	1290	Number of observations
0.182	0.017	4.247	7.389	9.952	0.196	0.232	0.267	0.091	0.069	0.116	Mean
0.140	0.043	4.274	7.118	10.185	0.467	0.527	0.198	0.109	0.158	0.094	Median
0.347	0.229	4.584	9.722	10.645	2.777	4.002	4.334	0.937	0.874	0.839	Max
0.090	0.329-	3.774	6.973	9.193	1.423-	2.570-	0.000	0.931-	0.819-	0.789-	Min
0.089	0.136	0.294	0.786	0.539	0.726	0.659	0.290	0.291	0.397	0.149	SD
0.631	1.273-	0.274-	2.563	0.260-	0.373-	0.424-	4.282	0.214-	0.255-	0.319	Skewness
1.852	4.863	1.509	7.777	1.364	1.836	3.124	41.104	3.756	1.883	7.349	Kurtosis
15.655	53.505	13.552	26.399	15.837	10.279	39.549	81.984	40.698	80.994	10.387	Jarque-Bera test
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Jarque-Bera significance level

The main central indicator is the mean, which indicates the equilibrium point and center of gravity of the distribution, and is a good indicator of data centrality. For example, the mean value for the inflation rate is equal to (0.18), which indicates that most of the data is focused around this point. In other words, during the years under review, Iran has been involved with an inflation rate equivalent to 18%. In general, dispersion parameters are a criterion for determining the degree of dispersion from each other or the degree of dispersion relative to the mean. One of the most important scattering parameters is the standard deviation. The value of this parameter in general descriptive statistics is 0.786 for the gold price and 0.089 for the inflation rate, which shows that these two variables have the highest and lowest standard deviations, respectively. Skewness is a measure of the symmetry or asymmetry of the distribution function. For a perfectly symmetric distribution the skewness is zero and for an asymmetric distribution with skewness towards higher values the skewness is positive and for an asymmetric distribution with skewness towards smaller values the skewness value is negative. In general, if the skewness of the variable is in the range of +0.5 and -0.5; this variable is close to the normal distribution. Among the research variables, most of the variables are in this range and are close to the normal distribution. Kurtosis indicates the height of a distribution. In general, if the kurtosis of a variable is equal to 3, this variable will be close to the normal distribution. Among the research variables, only the stock price fluctuation variable is approximately 3 in terms of kurtosis. Therefore, it is concluded that there are no variables among the variables of the present study that are in the range of normal distribution at the same time in terms of skewness and kurtosis. This case has been confirmed by Jarque-Bera test that the significance level of Jarque-Bera for all variables is less than 5%, so the research variables have no normal distribution. According to the central limit theorem, if the number of observations is more than 30 observations (which in the present example is more than a thousand observations), there is no need for the variables to be normal. To run the meta-heuristic algorithm, the required parameters are set as follows:

- Mutation rate was considered equal to 0.2 and crossover rate equal to 0.8.
- The population size was equal to 500 and the number of iterations of the algorithm was equal to 1500.
- The number of iteration in the variable neighborhood search procedure (VNS) is equal to 15.

Table (2) Prediction results of meta-heuristic algorithms

Momentum strategy	**Stock price fluctuations**	**Investment return rate**	**Momentum strategy (MIS)**	**Risk of falling stock prices**	**Investors' emotions**	**Economic news**	**Oil**	**Gold**	**Dollar**	**Inflation (INF) rate**	**GDP**	**Dependent variable**
0.009	0.014	0.01	0.027	-0.001	0.006	0.005	0.008	0.004	0.003	-0.018	0.005	Improved genetic algorithm
0.007	0.038	0.048	0.041	-0.008	0.005	0.007	0.027	0.039	0.021	-0.027	0.034	Simple genetic algorithm
0.006	0.011	0.008	0.016	0.001-	0.002	0.003	0.006	0.004	0.004	0.013-	0.002	Whale Algorithm
0.004	0.008	0.006	0.009	0.0007-	0.002	0.003	0.004	0.003	0.002	0.01-	0.003	Shrimp batch algorithm

5.2. Testing the research hypotheses

As can be seen in Table (2), according to the results of the improved genetic algorithm, the variable coefficient of "investors' emotions" is 0.006; The variable coefficient of "momentum strategy" is equal to 0.009, the coefficient of "stock price fluctuation" is equal to 0.014, the coefficient of "return on investment rate" is equal to 0.01, the coefficient of "adopting momentum strategy" is equal to 0.027, the coefficient of "economic news" is equal to 0.005, the "oil price" coefficient is 0.008, the "gold price" coefficient is 0.004, the "dollar price" coefficient is 0.003 and the GDP variable coefficient is 0.005. In other words, the mentioned variables, according to the prediction by the improved genetic algorithm, have a direct impact on the Herding behavior of investors in the Iranian capital market. Also, according to the prediction results by the proposed algorithm, the coefficients of the variables "risk of falling stock prices" and "inflation rate" are -0.18 and -0.001, respectively, and these variables have an indirect effect on Herding behavior and their increase reduces the dependent variable. On the other hand, in Table (2) it can be seen that according to the simple genetic algorithm, the coefficient of the variable "investors' emotions" is equal to 0.005; the coefficient of "momentum strategy" is equal to 0.007, the coefficient of "stock price fluctuation" is equal to 0.038, the coefficient of the variable "capital return rate" is equal to 0.048, the coefficient of "adopting momentum strategy" is equal to 0.041, the coefficient of the variable "economic news" is equal to 0.007, the "oil price" coefficient is 0.027, the "gold price" coefficient is 0.039, the "dollar price" coefficient is 0.021 and the GDP variable coefficient is 0.034. In other words, the variables of these variables have a direct effect on the Herding behavior of investors in the Iranian capital market. Also as predicted by a simple genetic algorithm, the variables "stock price falling risk" and "inflation rate" have an indirect effect on Herding behavior and their increase reduces the dependent variable. According to the results of the whale algorithm, the coefficient of the variable "investors' emotions" equals 0.002; the coefficient of "momentum strategy" is equal to 0.006, the coefficient of the variable "stock price fluctuation" is equal to 0.011, the coefficient of "return on investment rate" is equal to 0.008, the coefficient of "adopting momentum strategy" is equal to 0.016, the coefficient of the variable "economic news" is equal to 0.003, the "oil price" coefficient is 0.006, the "gold price" coefficient is 0.004, the "dollar price" coefficient is 0.004 and the GDP variable coefficient is 0.002. In other words, the mentioned variables, according to the prediction by the whale algorithm, have a direct impact on the Herding behavior of investors in the Iranian capital market, and the increase of these variables increases the Herding behavior of investors in the capital market. On the other hand, the results of the whale algorithm showed that the variables "risk of falling stock prices" and "inflation rate" have an inverse effect on the Herding behavior of investors and increasing these variables reduces the Herding behavior of investors. The shrimp batch meta-heuristic algorithm is shown in Table (4-10), in explaining the dependent variable (Herding behavior of investors) the coefficient of the variable "investors' emotions" is 0.002; the coefficient of "momentum strategy" is equal to 0.004, the coefficient of "stock price fluctuation" is equal to 0.008, the coefficient of "return on investment rate" is equal to 0.006, the coefficient of "adopting momentum strategy" is equal to 0.009, the coefficient of "economic news" is equal to 0.003, the "oil price" coefficient is 0.004, the "gold price" coefficient is 0.003, the "dollar price" coefficient is 0.002 and the GDP variable coefficient is 0.003. According to these results, the mentioned variables, according to the shrimp batch algorithm, have a direct impact on the Herding behavior of investors in the Iranian capital market, and increasing these variables increases the Herding behavior of investors in the capital market. On the other hand, the results of the shrimp batch algorithm showed that the variables "stock price falling risk" with a coefficient of -0.0007 and "inflation rate" with a coefficient of -0.01 have an inverse effect on the Herding behavior of investors and increasing these variables reduces the Herding behavior of investors.

Table (3) shows the comparison results of these four meta-heuristic algorithms based on comparative indicators.

As can be seen in the table above, the prediction error according to the MSE and MAPE criteria in the shrimp batch algorithm is less than the three whale algorithms, improved genetics and simple genetics; the prediction error rate according to the RMSE criterion in the whale algorithm is less than the three algorithms of shrimp batch, improved genetics and simple genetics. On the other hand, the execution time of a simple genetic algorithm is less than the other three algorithms. In general, it can be said that the shrimp batch and whale algorithms for predicting the Herding behavior of investors in the Iranian capital market are better than the simple and improved genetic algorithm and have higher accuracy. It can also be said that the shrimp batch algorithm has a higher speed than the whale algorithm.

Table (3)- Comparison of performance of meta-heuristic algorithms

execution time	MAPE	RMSE	MSE	results
0.0353	7.4	7.6	8.3	Improved genetic algorithm
0.0054	11.7	9.8	12.6	Simple genetic algorithm
0.0141	5.5	6.2	7.03	Whale Algorithm
0.0112	5.5	6.4	6.7	Shrimp batch algorithm

5.3. Conclusions and Suggestions

One of the most challenging topics in the field of financial literature is understanding the process and how investors and participants in the capital market make decisions. In recent years, with the dominance of the financial behavior paradigm and the challenge of standard financial theories due to their inability to explain the anomalies observed in the capital market, financial researches have entered a new intellectual age; in some of these researches modern financial economic assumptions have been challenged. One of these assumptions is the rationality of investors, which has been seriously challenged. The phenomenon of Herding behavior is one of the well-known behavioral biases of investors in financial markets. Collective behavior or Herding behavior represents the correlation of investors' transactions and investment decisions by following the behavior of other investors or showing the same behavior as the investment behavior of the whole market and the reasons and factors of formation of Herding behavior of investors in financial markets can be classified from different aspects. Although the existence or absence of Herding behavior in the capital markets has been repeatedly examined in conducted researches, the influential and aggravating factors of this phenomenon have been considered to a lesser extent in the Tehran Stock Exchange. There is a belief in Herding behavior in various fields of science such as psychology, sociology, economics and finance. In general, Herding behavior can be defined as the actions of a group of people imitating a representative. Abandoning individual thinking and following group behavior can have economic consequences for investors. The results of the present study showed that in the Iranian capital market (Tehran Stock Exchange) there is Herding behavior among investors and this is consistent with the results of the study by Esteliani Et al. (2020) and Wang et al. (2019) and Dong & Lin (2016) who stated that non-fundamental factors (factors other than financial data) and fundamental factors (financial data) are the main causes of the formation of Herding behavior in financial markets. It is also consistent with the results of the research by Philip et al. (2011), which confirms the existence of Herding behavior of investors in the financial markets of developed countries. The present study also confirms that changes in fundamental accounting variables lead to the formation of Herding behavior in the Iranian capital market, which is consistent with the findings of research by Zarmba et al. (2020) Wang et al. (2019) and Shirazian (2019).

5.3.1. Proposed Model

Based on the solution of the defined models for measuring behavioral behavior in the period under study, the values of fundamental and non-fundamental factors, which are different in values and conditions, are summarized in Table 5-1.

Economic news publication	Global gold price	Exchange rate	Stock price fall	Momentum strategy	Stock price fluctuations	Investment return rate	Momentum strategy	Investor's decision making attitude
x9	x8	x7	x6	x5	x4	x3	x2	x1
						Inflation rate	GDP growth	Global oil price
x18	x17	x16	x15	x14	x13	x12	x11	x10

Proposed model for measuring Herding behavior using fundamental and non-fundamental variables and by using meta-heuristic algorithms

$$\begin{aligned} HB_{it} \;&= \beta_0 + \beta_1 X1_{it} + \beta_2 X2_{it} + \beta_3 X3_{it} + \beta_4 X4_{it} \\ &\quad + \beta_5 X5_{it} - \beta_6 X6_{it} + \beta_7 X7_{it} \\ &\quad + \beta_8 X8_{it} + \beta_9 X9_{it} + \beta_{10} X10_{it} \\ &\quad + \beta_{11} X11_{it} - \beta_{12} X12_{it} + \varepsilon_{it} \end{aligned}$$

Reviewing the background and literature of behavioral finance and capital market psychology and increased stock market penetration rate among individuals in society and deepened capital market in terms of liquidity inflow, it is expected that Herding behavior be formed in the Iranian capital market at any time. Investors in the Iranian capital market are recommended to look at investing in the stock market as a long-term investment and become fully acquainted with the concepts of fundamental and technical analysis and the psychology of traders and capital market behaviors. Increasing the financial intelligence and literacy of investors will lead to a reduction in Herding behavior in the capital market in the long run. Therefore, it is suggested to the Tehran Stock Exchange to reduce the Herding behavior of investors by enacting laws and regulations to support shareholders. Adopting laws that lead to greater transparency of financial information and further reduction of information asymmetry. It is suggested to the Tehran Stock Exchange Organization and the auditing organization that the requirements of financial reporting and disclosure be formulated in such a way that it be impossible to manipulate and guide the decisions of investors. Finally, analysts, investors and capital market activists are suggested to identify and consider the factors influencing the formation of Herding behavior (such as initial public offering, increase in corporate capital, etc.). Researchers are also recommended to examine the impact of non-fundamental factors (such as changes in commodity rates, government support for the stock market, changes in global oil prices) in their researches as well as the impact of economic and political news on the formation of Herding behavior in the capital market in the Iranian capital market using other meta-heuristic algorithms.

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