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RESEARCH PAPER

Exchange Rates, Gold Coin Prices, and Herding in the Stock Market

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Abstract
This study investigated the occurrence of herding in the Iranian stock market and the effects of gold prices and currency exchange rates on this phenomenon. For this purpose, the rate at which herding occurs in the Tehran Stock Exchange was calculated and analyzed, after which stock price data were classified based on gold prices and currency exchange rates. Herding under different exchange rates and gold price returns was also examined. Results showed that herding in the stock market was significant at the 1% level during sharp changes in gold and currency prices.
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Introduction

Most people think or act irrationally under the influence of others around them because individuals do not live in a vacuum and may not necessarily realize that others are behaving illogically. We may therefore attach a certain merit to the decisions and actions of others and conduct ourselves in accordance with this supposed merit. In these situations, decisions and behaviors become very similar to the point where people appear to be imitating one another (Tuominen, 2017). Emulation of this type is called “herd behavior” or “herding.”

Herd behavior can stem from sensible causes, which are explained through rational herding models. The first type of such a representation is the information-based model, which maintains that rational herding occurs when people have access to information that is unavailable to others (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1992). The second type is the information acquisition model, which holds that the identicality of investment decisions lies in access to similar information (Froot et al., 1992; Hrachleifer et al., 1994). The third type of rational models is grounded in representative theory and posits that the inability of investors to evaluate the decisions of investment managers drives them to imitate how others conduct themselves (Scharfstein and Stein, 1990; Trueman, 1994). The fourth type attributes the occurrence of herding to similarities in the risk preference characteristics of investors (Gompers and Metrick, 2001), and the last kind of rational models argue that herd behavior is caused by fads (Friedman, 1984) and feedback trading (Barberis and Shleifer, 2003).

Despite the long history of herd behavior analysis in the economic literature and the existence of numerous theories about this conduct, measuring it remains a challenging task (Raafat et al., 2009). Herding measurement models are generally classified into four

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representations, namely, ownership, state-space, return dispersion, and computational models. State-space and return dispersion models measure herd behavior on the basis of price divergence from rational values, whereas ownership and computational models identify and ascertain herding without relying on financial models. Ownership models measure herd behavior among investors, whereas computational models are employed to examine herding on the grounds of prices. Yet, the existence of these models has not eliminated the difficulty with which herding is measured given their ineffectiveness in capturing the phenomenon (Spyrou, 2013; Bohl et al., 2017). Compounding this problem is the minimal attention paid to alternative markets; buyers and sellers tend to migrate when a crisis is anticipated or occurs in financial markets (Baur and McDermott, 2010), thereby causing herd behavior. Another important issue for consideration is the correlation among the trends in alternative contexts (Hillier et al., 2006; Baur and Lucey, 2010).

To address the above-mentioned deficiencies, the current research used the models of Bikhchandani et al. (1992), Sharma (2004), and Aydogdu (2016) as basis in measuring herding and evaluating its relationship with exchange rates and gold coin prices in the Tehran Stock Exchange. Specifically, we investigated herd behavior in the capital market in Iran by classifying stock price data into 10 groups on the basis of changes in currency exchange rates and gold prices. The results showed significant herding (1% level) with intensifying changes in the aforementioned rates and prices. The phenomenon was also positive and significant both when prices increased and decreased. These findings led to the conclusion that the Iranian stock market generally behaves in line with forecasts drawn using the efficient market hypothesis.

Literature Review

Theoretical Foundations

The scope of research on herd behavior is not limited to financial markets but encompasses a wide range of economic and social psychological issues, as well as other topics that include market bubbles, financial speculation, political choices, and consumer preferences. These matters are typically illuminated using two broad categories of approaches, namely, those grounded in thought/behavior transmission mechanisms and connection patterns (Raafat et al., 2009).

The connection pattern approach is based on the argument that herding may be caused by the way people communicate and organize, not the manner by which they perceive the world. Each human is considered an atom with simple and specific properties, whose ways of interaction with others cause and shape herd behavior. Connection pattern models emphasize physical laws, distance, and speed rather than the emotional state of individuals. In contrast, methods anchored in thought/behavior transmission mechanisms explain the rational and emotional causes of herd behavior by focusing on the human mind. In general, there are two rational drivers of an individual’s decision to abandon personal judgment and merely gravitate toward the tendencies of the majority; these drivers are information pressure and reputation (peer pressure). Under the assumption of rationality and incomplete information, individuals might mimic the behaviors of others despite their own private motivations and the value of the information that they hold. Non-subjective theories attribute herding to the involuntary propagation of emotions. Examples include the spread of happiness during a party and the conduct of sports fans. This phenomenon, in an acute form, is called mass hysteria, which can manifest as people erroneously thinking of themselves as sick or in social configurations, such as riots and marches.

In economics, several basic theories are used to justify the rationality of herd behavior.

Two of these perspectives are discount rate theory and rational bubble theory, which postulate that the difference between personal analysis and eventual action derives from the expected rate of return and the arrival of new information. Discount rate theory assumes that the excess volatility of financial markets is caused by variations in discounted dividend rates (Campbell & Shiller, 1988). Rational bubble theory, however, attributes the divergence of prices from their intrinsic value to the arrival of unexpected information (Harras and Sornette, 2011). Shiller (2007), one of the most prominent critics of classical financial theory, illustrated that price volatility is greater than the variance between profit and its intrinsic value—a finding that contradicts the claims of discount rate theory. This same argument negates the validity of rational bubble theory and its ascription of price fluctuations to new information. The shortcomings of classical theories have thus invited challenge and stimulated the development of financial behavioral perspectives. With these newly formulated theories, real events are explained on the basis of human reactions, which may be incorrect or irrational.

Sharma (2004) groups rational models of herding into five categories. The first is information-based. Banerjee (1992), and Bikhchandani et al. (1992), Welch (2000) explain that investors observe others' trades believing they could gain useful information, and it may result in disregarding their own information. Ultimately, an informational cascade occurs, where every investor merely imitates others' transactions. As such cascades are grounded in limited information, they make markets fragile and unstable.

The second group of rational models is information-acquisition models. According to Froot, Scharfstein, and Stein (1992), herding appears because investors access similar sources of information. Hirshleifer et al. (1994) contend that herding occurs because investors use similar stocks or sources of information for decision-making. Unlike most information-acquisition models, they assume some that investors receive private information earlier, which prompts them to concentrate on similar stocks, and their concentration triggers herd behavior. In information-acquisition models, investors imitate each other because they have similar information.

The third group of rational herding models is principal–agent models as developed by Scharfstein and Stein (1990) and Trueman (1994). When a principal hesitate an agent's ability to choose stocks, the agent is encouraged to imitate the decisions of others, generating herding. They suggest herding originates in the uncertainty principals, who direct agents to imitate others.

The fourth group of models argues that investors share preferences or aversions to products of certain risk, size, or other characteristics, and it only seems they imitate each other (Gompers and Metrick, 2001). The fifth group attributes herding to fads (Dreman, 1979; Shiller et al., 1984) or feedback from past trends. According to that, capital may shift toward high-return stocks and lift prices from intrinsic values (Sharma, 2004). In these models participants have common characteristics and imitate each other.

Measurement of Herd Behavior

Although herd behavior has been the subject of numerous theoretical debates, many challenges continue to deter the empirical measurement of this phenomenon in financial markets. According to Welch (2000), herding occurs very frequently in financial markets, but even this prevalence does little to ease identification and measurement through financial models. Additionally, modeling results are often divergent and sometimes contradictory (Spiro, 2013). This section reviews the methods available for measuring herd behavior.

Existing approaches to ascertaining investor sentiment can be divided into qualitative and quantitative methods. Qualitative methods include survey-based techniques, which involve administering surveys to market participants to determine their views (Zhou, 2018). These approaches typically obtain findings that are difficult to generalize given their grounding in specific data (Hirshleifer and Hong Teoh, 2003). Quantitative methods can be classified into four groups, namely, ownership, state-space, return dispersion, and computational models, which are described in the following subsections.

Ownership Models

Early and subsequent studies on the identification of herd behavior (e.g., Lakonishok et al., 1992; Sias, 2004) focused on asset holding and measured herding using changes in investor assets as reference. Lakonishok et al. (1992) use investors' simultaneous demand to measure herding (LSV model):

$$H(i) = \left|\frac{B(i)}{B(i)+S(i)} - p(t)\right| - AF(i) \tag{1}$$

In Equation (1) $H(i)$ represent herding. $B(i)$ and $S(i)$ denote the number of money managers who have bought and sold stock i during the target period. p(t) is the mean of the proportion of number of buyers relative to number of active managers, and AF(i) is an adjustment factor which is equal to $\left|\frac{B(i)}{B(i)+S(i)} - p(t)\right|$.

Lakonishok et al. (1992) explored the phenomenon on the basis of the simultaneous demand of investors for assets, whereas Sias (2004) adopted the autocorrelation of institutional demand for a particular stock as his explanatory grounding. These measures are useful in advanced markets, where seasonal ownership information is readily available in very short time frames, but they are rarely employed because in many cases, the required investor information is simply unavailable (Demirer and Zhang, 2018). These models also inadequately gauge herd behavior in the overall market (Lee, 2017).

State-space Models

A state-space model was developed by Hwang and Salmon (2004) using the sectional distribution of asset sensitivity to fundamentals as

$$std_c(\beta_{imt}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\beta_{imt} - E_c(\beta_{imt}))} \tag{2}$$

β_{imt} is cross-sectional beta for asset i, which is calculated from an asset-pricing model. $E_c(\beta_{imt})$ and $std_c(\beta_{imt})$ are the expected value and its standard deviation, respectively. The idea is that when herding occurs, $std_c(\beta_{imt})$ differs from its biased value $std_c(\beta_{imt}^{b})$. The herding detection model is formulated as

$$\begin{aligned} &log\, std_c(\beta_{imt}^{b}) = \mu_m + h_{mt} + \nu_{mt} \\ &h_{mt} = \varphi_m h_{mt-1} + \eta_{mt} \end{aligned} \tag{3}$$

In Equation (3), $h_{mt} = 0$ indicates the absence of herd behavior, $0 < h_{mt} < 1$ its presence, and $h_{mt} = 1$ complete herding.

The model enabled the authors to discover that significant variations in herd behavior exist between the US and South Korean markets but that in both contexts, such conduct is sustained. Among different herding measurement instruments, state-space models allow the consideration of the time variability of beta components, but they have also been criticized in several respects. First, they assume that the drivers of herd behavior are autoregressive to simplify calculations. Second, these models involve an estimation of time-varying betas, but no consensus has been reached as to how this approximation is carried out. Third, significant variances in calculations frequently arise, thereby reducing discriminative power and causing the over-detection of herding (Xie et al., 2015). To eliminate these issues, Huang et al. (2018) modified the state-space design to establish a representation that entails the updating of standardized betas. The modification diminishes the interpretability of results but mitigates bias in estimates.

Return Dispersion Models

Return dispersion models identify herd behavior at the market level under the assumption of rational asset pricing. This type of model was used by Christie and Huang (1995), who used return information to pinpoint the tendency for imitation and were the first to introduce the cross-sectional standard deviation of stock returns as a measure of herding at the overall market level (i.e., the CH model). The researchers found that considerable return dispersions occur during sharp price changes, thus contradicting herd behavior. The CH model was expanded by Chang, Cheng, and Khorana (2000) using the cross-sectional absolute deviation to measure the dispersion of returns (i.e., the CCK model):

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right| \tag{4}$$

In Equation (4), N represent number of stocks, $R_{i,t}$ the return of stock i, and $R_{m,t}$ the market return during period t. Their idea is that the relation between market returns and CSAD should be nonlinear when herding occurs. Therefore, when herding occurs, β_1 in Equation (5) will be negative and significant.

$$CSSD_t = \alpha + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{5}$$

They argued that with the assumption of the capital asset pricing model as a representation of rational asset pricing, market return and cross-sectional absolute deviation exhibit a non-linear relationship when herd behavior occurs.

Return dispersion models have been employed in a wide range of studies (e.g., Chiang and Zheng, 2010; Demirer et al., 2014; Galariotis et al., 2015; Economou et al., 2018), but these initiatives derived disparate results regarding the presence or absence of herd behavior. This discrepancy is attributed to the measures used to assess herding behavior and the focus of exploration on market behavior (Lee, 2017). The similarities between herd behavior measures and market sentiment measures highlight the necessity of intensified attention to herd behavior detection (Zhou, 2018). Note that unlike ownership-based measures, tests anchored in divergence (variation) are susceptible to bias as they are grounded in divergence from theoretical pricing models. Thus, herding factors can be altered by model specification errors and then mistakenly be attributed to herd behavior.

Computational Models

Another group of methods used to understand herd behavior consists of artificial stock market models, which are computational in nature. These methods involve using soft computing techniques, such as artificial neural networks, to represent and simulate the general mechanism underlying herd behavior. A representative example is Kononovicius and Gontis's

(2013) agent-based model for capital markets, which the authors developed by modeling three groups of agents engaged in herding and creating a system of stochastic equations. The researchers demonstrated that under certain conditions, the agent-based model can clarify complex statistical characteristics.

Computational models, including those featuring artificial intelligence, can also be used to overcome two other important issues in the analysis of herd behavior—the large size and tremendous complexity of financial models and the multitude of variables affecting herd behavior. Krichene and El-Aroui (2018) developed an artificial stock market model to simulate information asymmetry and herd behavior in markets with different maturity levels. In the model, each agent engages in trading according to its wealth and behavior as well as available information. The researchers combined agent behavior modeling with social network simulation to reproduce transaction mechanisms and different degrees of information asymmetry and herd behavior. One of their most important results is that the greater the assumed information asymmetry and herd behavior in the market, the closer the similarity between the characteristics of an artificial stock market and real underdeveloped markets. The shortcomings of the model, however, are its disregard of certain characteristics of immature markets, such as poor liquidity, and its limited generalizability owing to its assumption of a stable economic situation in the short term.

Empirical Studies

Herd behavior has been the subject of many empirical studies in various fields of science. In what follows, we review investigations that are most relevant to the economics and finance domains. Most of these explorations can be classified into two groups. The first consists of studies that examined herding among specific entities or instruments, such as financial analysts, institutional investors, and pension or investment funds (Graham, 1999; Wermers, 1999; Welch, 2000; Clement and Tse, 2005). The second group of studies looked into herd behavior at the macro level and how it affects the market (Litimi, 2017). Herd behavior has also been extensively scrutinized from a geographical perspective, but this phenomenon has been more frequently reported in emerging markets—a trend attributed to higher information asymmetry and lower maturity in the latter (Chang et al., 2000). A case in point is the study of Yao et al. (2014) on herding in the Chinese stock market. The authors found evidence of herding occurrence in the B-market and strong herd behavior at the industry level. The results also indicated that the behavior manifests more strongly in large and small firms as well as under high growth shares. Chung and Kim (2017) studied the effects of herd behavior on extreme stock returns and uncovered that stocks for which more (less) herding is reflected were subjected to the greatest price drop (rise) during a crisis. In other words, herd behavior increases return volatility.

Yahyazadehfar et al. (2009) analyzed investors' behavior in Tehran Stock Exchange. The findings showed that political factors, psychological factors, economic factors and internal factors are the most important factors that affect the stocks trading in Tehran Stock Exchange, respectively. Thus economic factors might not explain investors' behavior. Mamipour and Sepahi (2015) tested the formation of bubbles as in the Tehran Stock Exchange. They found that the presence of amateur investors increases the probability of bubble formation as a behavioral phenomenon.

Overall, the existing literature can be evaluated as offering no comprehensive theoretical model of herd behavior, and only a few empirical studies have been devoted to the relationship between herding in the stock market and alternative markets. Furthermore, numerous studies modify the measurement models, but their statistical modifications are not totally successful (Bohl et al., 2017; Van Campenhout and Verhestraeten, 2010). Therefore the present research attempted to address this gap through a price-type herding model, which was used in the analysis of the association between the occurrence of herd behavior and changes in currency exchange rates and gold prices as alternatives to the stock market.

Methodology

The main purpose of the research is to capture price herding in different markets. Therefore four groups of price-based herding models are used to capture herding. The first group is state-space models; the second is the cross-sectional absolute deviation model; the third group is cross-sectional square deviation; and the forth group is price-herding-model.

Based on Bikhchandani et al. (1992), when herding occurs the number of buys (sell) is more than normal. Therefore supply and demand law, derives prices to rises (reduces) at the same time. In other word herding could change the prices similarly. Raafat et al. (2009) reviewed such herding models as pattern-based approaches to herding behavior.

Aydogdu (2016) formulated a mathematical model that represents the group behavior of birds sitting on wires. In this model, which was formulated in a one-dimensional space, the position vector of birds is time dependent and, given the interaction among birds, is a mapping from a one-dimensional real space to an N-dimensional real space. Assuming that the position of bird i∈ {1,2, ... N} is $x_i(t)$, the model is defined as

$$y_i = \sum_{i\in M(i)} \left(\left|x_j - x_i\right|^{m_a-1} - \xi^{m_a-m_r} \left|x_j - x_i\right|^{m_r-1} \right) \left(x_j - x_i\right) \qquad \forall i \in 1,2,\dots N \quad (6)$$

which is equivalent to the following equations:

$$y_i = f_i(x) \qquad \forall i \in 1,2,\dots N \quad (7)$$

$$f_i(x) = \sum_{i\in M(i)} \left(\left|x_j - x_i\right|^{m_a} \frac{(x_j - x_i)}{|x_j - x_i|} - \xi^{m_a-m_r} \sum_{i\in M(i)} \left|x_j - x_i\right|^{m_a} \frac{|x_j - x_i|}{(x_j - x_i)} \right) \quad (8)$$

where $M(i)$ denotes the neighborhood of bird i and encompasses the group of birds that affect this bird; $m_a > 0$ and $m_r < 0$ are the exponents that determine the attraction and repulsion forces of the group (attraction for mating, food search, and predator avoidance and repulsion to prevent excessive crowding); and $\xi > 0$ represents the desired distance between two birds and compares the relative strength of repulsion and absorption forces. Aydogdu (2016) emphasized that the above-mentioned equation depends only on the relative distance between pairs of birds and not on their absolute position in space.

To define a topological neighborhood without loss of generality, we assumed that the members of the bird group are indexed, such that if i > j, then $x_i > x_j$. Accordingly, the neighborhood is defined as follows:

$$M(i) = \{ k \in \{1,2,..N\} \mid |i - k| < d \} \quad (9)$$

In this model, the solution of the equation $f(x) = 0$ is indicated as the equilibrium state. Aydogdu (2016) confirmed that the model always has a solution, and he showed that the larger the assumed neighborhood, the greater the distance between neighbors.

The core logic of Aydogdu's (2016) model is similar to that of other herding measurement models given that they often measure the sameness of behaviors. For instance, in the LSV model (Lacanisch et al., 1992) and the models of Nofsinger and Sias (1999) and Wermers (1999), herd behavior is attributed to a group of institutional investors who make the same transactions at the same time. In the dispersion-based models of Christie and Huang (1995) and Chang et al. (2000), herding takes place when changes are more uniform than the level predicted by rational pricing models. The intuitive understanding of herd behavior in nature is also consistent with the notion of relative repetition (the imitation of close individuals) (Welch, 2000; Lee, 2017). Correspondingly, we followed the approaches of Aydogdu (2016), Bikhchandani et al. (1998), Sharma (2004), and Lee (2017) in using the following metric of herding:

$$Price\ Herding\ Rate_{i,j} = HR_{i,j} = 1 - \frac{|r_i - r_j|}{\max(r_i\ r_j)} \tag{10}$$

where r_i is the price return of financial product i, r_j denotes the price return of financial product *j*, and $HR_{i,j}$ represents the price herding between them.

$HR_{i,j}$ measures how similar (repetitive) the changes of prices are. Higher values for $HR_{i,j}$ indicate stronger herding. For example, $HR_{i,j}$ will be 100% (maximum) in case of a 10% increase in prices of both stocks *i* and j. However, if the price of stock *i* rises 10% and stock *j* falls 10%, $HR_{i,j}$ will be −100% (minimum).

Using pattern-based approach, it is tried to capture herding in a step and leave evaluating reasons, effects and other issues about herding in another steps. Therefore we drop the subject of reasons for herding here and try to measure herding among prices. Using the same logic Lakonishok et al. (1992), Hwang and Salmon (2004), Lee (2017) also differentiate between detecting herding and studying the features of herding such as the reasons and effects of herding. Therefore our measure is focused on detecting Herding behavior.

The financial products considered in this study are stocks, gold coins (Bahar Azadi gold coins), and exchange rate (US dollar). Equation (10) measures the similarity in changes between two financial products. The higher the $HR_{i,j}$, the stronger the herd behavior. The individual herding rate in relation to one product is obtained using

$$HR_i = \frac{1}{n} \sum_{j=1}^{n} HR_{i,j} \tag{11}$$

where *n* is the number of sample products. The higher the HR_i, the greater the increase in prices in other markets. Because price data is generally expressed in the form of time series, the following equation is used for the dynamic computation of price herding:

$$HR_{i,j,t} = 1 - \frac{|r_{i,t} - r_{j,t}|}{\max(r_{i,t},\ r_{j,t})} \tag{12}$$

in which $HR_{i,j,t}$ stands for the rate of herding between financial markets *i* and *j* at time *t*. If the prices of products are expressed in time series form, the herding between the two financial instruments ($HR_{i,j}$; i.e., the herd behavior between financial instruments *i* and *j*) is calculated through averaging via Equation (13).

$$HR_{i,j} = \frac{1}{T} \sum_{t=1}^{T} HR_{i,j,t} \tag{13}$$

where *t* is the time of each data point (relevant day), and T pertains to the total period covered by the data. Considering the large number of financial instruments in stock markets, we adhered to Sharma's (2004) method and calculated the herding between the stock market and alternative markets through averaging.

Data Collection and Analysis

The first null hypothesis verified in this work is that the herding rate obtained from the sample is equal to the herding resulting from random price movements[1]. Given that the distribution function of the herding metric is unavailable, the Monte Carlo method was used to test the research hypotheses. The Monte Carlo method involves estimating the statistical distribution of parameters by performing extensive random sampling and determining critical values on the basis of the desired confidence level.

The second null hypothesis tested in this study is related to the occurrence of herding during sharp price changes. The intensification of herd behavior during sharp price increases and decreases has been the subject of much research. It is also possible to inquire into changes in herding rates along with variations in the rates at which prices change (returns). Accordingly, price data were categorized into 20 classes in terms of rate of return, after which the value of the herding rate in each class was separately calculated, and the significance of herding in each class was examined. Significance was also analyzed using the Monte Carlo method.

Testing a hypothesis often necessitates knowing the mean, standard deviation, and distribution of a research variable. In cases wherein these parameters are unavailable, the Monte Carlo approach can be used to verify suppositions. The method involves random sampling with a large number of statistical distributions to estimate a research parameter and determine critical values on the basis of the target confidence level. The distribution of price returns is also considered. As indicated in the geometric Brownian motion model, stock returns can be assumed to be independent and normally distributed in fixed time frames (daily or longer) (Dmouj, 2006). We therefore assumed that price returns were normally distributed over the investigated period, calculated the mean and standard deviation of the returns for each stock with the aforementioned assumption as grounding, and then obtained numerous random samples of normal returns using the available parameters. In Monte Carlo computation, a typical approach is to regard 1,000 iterations as acceptable and 10,000 iterations as sufficient. In this study, then, simulations were performed in 10,000 iterations. For a select number of stocks, the simulations were performed in 100,000 iterations to determine whether the iteration number exerts a significant effect on the results. A diagram of the convergence between the mean and variance of the proposed measure in 100,000 iterations is provided in Appendix 1. Ultimately, these simulations provide estimates of the mean, standard deviation, and critical values of testing, thereby allowing the validation of different hypotheses about herd behavior.

Statistical Population and Sample

The statistical sample treated in this work comprised stock data from companies listed in the Tehran Stock Exchange, US dollar price data (free market rates), and gold price data covering the period 2015 to 2019. For complete comparability, companies that exited the market before the last day of data collection (companies from which no data could be obtained on the last day) were filtered out. Because stock price data should be consistent with gold price and US dollar price data, the days during which the stock market was closed, even as gold and US dollar markets were not (and vice versa), were removed from the dataset so that all days included in the sample reflect all three types of data. A total of 1,000 data points were collected from each company, and enterprises with fewer than this volume were excluded

1. In most simulations of empirical tests, the herding rate obtained under the assumption of random price movement is 0; empirically, therefore, the absence of herding can be considered roughly equivalent to the randomness of price changes.

from the analysis. The number of data points was set at 1,000 because aiming for more data points would sharply reduce the number of companies qualified for the examination.

The next data filter was the number of days during which a company's stock symbol was suspended. Companies whose symbols were suspended for more than 100 working days during the examined period were excluded to avoid the false detection of herding. This number was selected because using stricter requirements in this regard would considerably lower the number of stocks eligible for inclusion in the sample. These adjustments left us with a final sample of 392 financial products. The period covered by the data began at 29/07/2015 and ended at 28/09/2019. The end date was selected on the basis of the latest data available at the time of data collection, and the start date was obtained after applying the first filter (1,000 data points). These data were collected from the database of the Tehran Stock Exchange Technology Management Company and the software TSECLIENT. The gold and US dollar price data were acquired using the Rahavard-Novin software.

The descriptive statistics of the collected data are provided in Table 1. The sample consisted of data on 392 stocks for a period of 1,000 days, yielding 390,000 stock days. The maximum daily returns of gold and US dollar prices in the sample were 18.6% and 22.12%, respectively, but the stock price data contained records with returns as high as 440%. Nevertheless, the mean daily return of stock price was 0.17% (with a standard deviation of 3.56%), which is similar to the mean daily returns of gold (0.15%) and US dollar (0.17%) prices. Figure 1 also shows the returns of gold, US dollar, and Tehran stock market between 2015-07-29 and 2019-09-28.

Table 1. Descriptive Statistics of the Data

	Number of days	Mean	Standard deviation	Median	Minimum	Maximum
Stock price	1,000	13,604	89,108	3,293	210	1,140,000
US Dollar price	1,000	64,471	39,805	39,140	33,030	186,680
Gold price	1,000	21,176,857	14,248,200	12,232,750	8,715,000	54,150,000
Stock return	999	0.17%	3.33%	0.00%	-94.12%	440.00%
US dollar return	999	0.15%	2.14%	0.03%	-20.27%	18.60%
Gold coin return	999	0.17%	2.14%	0.09%	-15.57%	22.12%

Source: Research finding.

Analysis of Herd Behavior in the Stock Market

The first null hypothesis pertains to the absence of herd behavior in the stock market and is equivalent to the absence of a significant difference between the herding rate induced by stock returns and that observed from random data (Sharma, 2004). Table 2 shows the estimation results of state-space and CSAD models of herding.

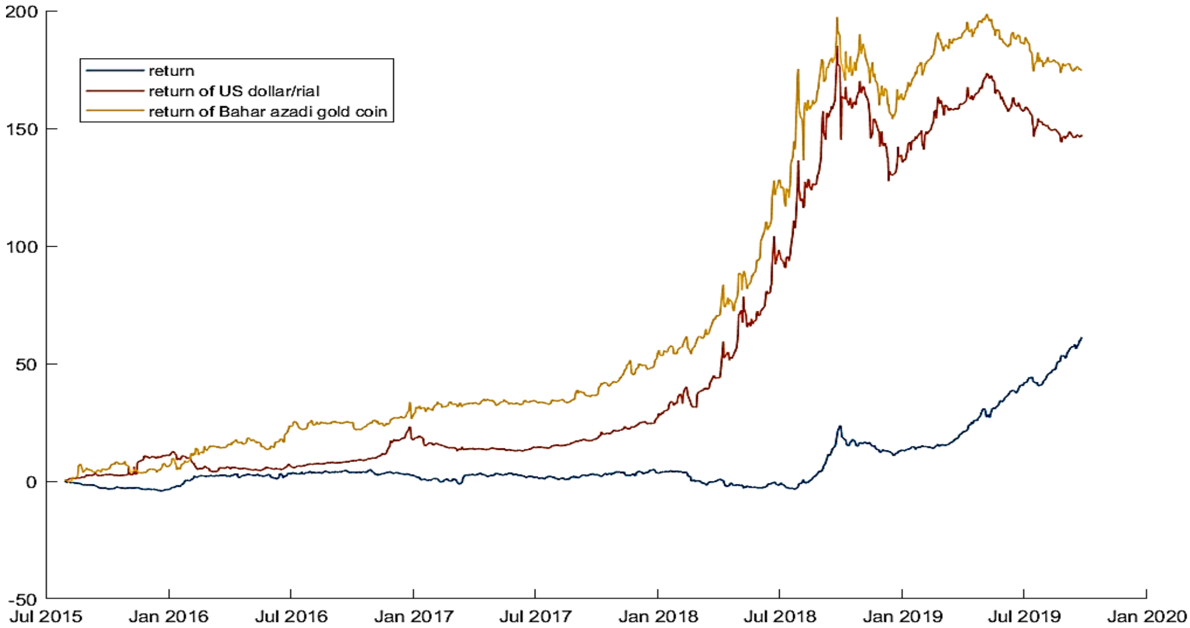

Figure 1. Returns of Gold, US dollar, and Tehran Stock Market
Source: Research finding.

Table 2. Estimates of Herding Based on Return Dispersion and State-space Models

	variable	Coefficient	Standard deviation	t statistics	Significance level
State-Space model (Equation 3)	μ_m	-0.192	0.160	-4..217	0.000
	φ_m	0.752	0.35	43.783	0.000
	$\sigma^2{}_{mv}$	0.000	0.000	1.552	0.067
	$\sigma^2{}_{mt}$	0.000	0.000	2.975	0.000
CSAD model (Equation 5)	α	0.021	0.001	16.761	0.000
	$\lvert R_{m,t}\rvert$	0.526	0.072	3.247	0.000
	$R^2_{m,t}$	-2.127	1.882	-0.751	0.254

Source: Research finding.

The results of CSAD model show that the coefficient of $R^2_{m,t}$ is not negative and significant, so the evidence of herding is not significant based on CSAD model. However, the estimation results of the state-space model represents that the coefficient of $R^2_{m,t}$ is significant, that is, the evidence of herding is significant. Although the evidence is significant, the extent of herd behavior is still unclear. Furthermore, the results of the state space model suffer from over estimation problem (Xie et al., 2015). The shortcomings of this models leads to use new herding models such as price herding.

To test no-herding hypothesis based on price Herding, first the mean value of the individual herding rate ($\overline{HR_{\iota,J}}$) is determined, which shows how much herding a company has experienced with other companies in the sample. We then performed the Monte Carlo simulation described in the previous section to calculate critical values. The critical values obtained for different levels are presented in Table 3.

Table 3. Critical Values in Relation to Herd Behavior

Critical value >10% (%)	Critical value <10% (%)	Critical value >5% (%)	Critical value <5% (%)	Critical value >1% (%)	Critical value <1% (%)
2.608	-2.605	3.121	-3.110	4.118	-4.114

Source: Research finding.

These results showed that 58.77% of all possible herding relationships among the sample were significant at the 1% level. The detailed findings regarding herding rate at the overall market level are presented in Table 4. As shown in the first row of the table, the mean individual herding rate was positive and equaled 3.87, which means that a +100% increase (decrease) in the price of one stock in the sample translated to an increase (decrease) in the stock price of other companies by an average of 3.87%. Given the critical values provided in Table 3 at the 1% error level, the mean herding rate at the overall market level did not significantly differ from 0. The same can be said for the situation at the 5% error level. However, the highest herding rate (6.97%) significantly varied from 0 at all error levels. These findings suggested that herding is significant in special cases.

Table 4. Estimates Herding Rates in the Stock Market

	Sample size	Mean (%)	Standard deviation (%)	Median (%)	Minimum (%)	Maximum (%)
Individual herding rate HR_i	392	3.870	1.603	4.129	-2.069	6.974
Cross-company herding rate $HR_{i,j}$	76636	3.870	3.068	3.486	-12.484	42.367

Source: Research finding.

Given the statistical significance of the highest herding rate but not the herding rate at the overall market level, a question arises as to the conditions wherein herding is significant. To shed light on this matter, we inquired into the herding rates obtained for each pair of companies ($HR_{i,j}$) (second row, Table 4). The mean cross-company herding rate (pairwise herding rate) was almost the same as the individual herding rate (first row). Among these results, the lowest value is –12.48, which was significant at the 1%, 5%, and 10% levels. The highest cross-company herding rate was 42.37. These results provide little evidence of significant herd behavior at the overall market level. At the overall level, therefore, the Tehran Stock Exchange behaves in line with forecasts derived using the efficient market hypothesis.

Herd Behavior and Price Returns

One of the important topics tackled in the literature on herd behavior is the relationship of this phenomenon with price returns. Previously published findings suggest that a sharp increase or decrease in prices leads to significant herding. To validate this claim, the sample was divided into 10 classes on the basis of daily price returns, and the herding rate of each class was separately calculated. As with the procedure described earlier, the critical values related to each class were obtained using the Monte Carlo method. Table 5 and Figure 2 demonstrate that herding was more or less symmetric. Analogously, as the absolute value of stock return increased, the herding rate initially decreased but then eventually rose. As shown in the middle rows of Table 5, the days characterized by little price change induced minimal herding. In the sixth class, for example, the mean herding rate was almost 0, meaning that small stock price variations could not have stimulated other prices and caused herding behavior. With an elevation in the return value, however, the mean herding rate turned in a positive direction and ultimately increased to 14%. This finding indicated that a rise in the price of one stock tends to augment the price of other stocks. Additionally, the higher the price increase, the greater the intensification of price imitation behavior. This relationship holds for the limit state of price increases, which corresponds to intensified herding. A similar trend can be observed with respect to price decreases.

Table 5. Estimates of Herding Rates on the Basis of Price Returns

	Class specification (%)		**Frequency**	**Mean herding rate**	**Standard deviation**	**Critical value <1%**	**Critical value >1%**	**Critical value <5%**	**Critical value >5%**
Class 1	-94.12	-2.91	35586	8.08	18.6	-4.18	4.17	-3.17	3.16
Class 2	-2.91	-1.34	35596	4.28	12.16	-2.31	2.32	-1.66	1.66
Class 3	-1.34	-0.53	35602	4.22	8.12	-2.78	2.78	-1.99	1.99
Class 4	-0.53	-0.12	35602	3.9	4.78	-3.6	3.62	-2.64	2.64
Class 5	-0.12	0	21145	2.36*	2.25	-3.87	3.88	-2.88	2.89
Class 6	0	0.06	85708	-0.18*	0.66	-4.2	4.22	-3.19	3.19
Class 7	0.06	0.63	35608	-2.37*	5.06	-3.92	3.9	-2.91	2.92
Class 8	0.63	1.88	35602	0.83*	10.41	-3.19	3.19	-2.29	2.3
Class 9	1.88	4.12	35581	7.81	15.89	-2.4	2.4	-1.71	1.71
Class 10	4.12	440	35578	14.18	18.02	-4.17	4.18	-3.17	3.18

Source: Research finding.

Note: The mean price herding rate was calculated using Equation (12), which is $HR_{i,j} = \frac{1}{T}\sum_{t=1}^{T} HR_{i,j,t}$.

*****The critical values indicated that the herding rates (classes 5–7) were not significant at the 1% level.

The herding rates obtained in different classes are plotted in Figure 2. As prices decreased, herd behavior increased. Increasing returns also intensified herding in the Tehran stock market. The herding rates derived in the fifth to eighth classes were non-significant. In the other classes, where most of the price changes occurred, the herding rates were significant at the 1% and 5% levels.

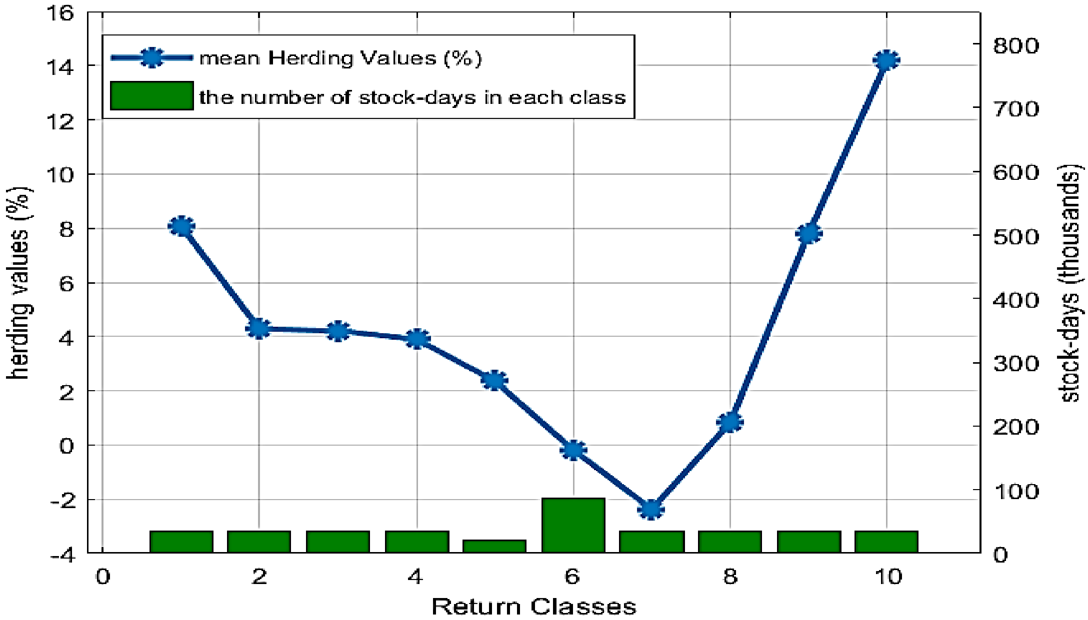

Figure 2. Mean of Herding Rates versus Stock Returns
Source: Research finding.

Herd Behavior and Currency Exchange Rates

Dornbusch and Fischer (1980) delved into the link between exchange rates and stock returns, arguing that an increase in the former elevates stock prices given improvements to the competitive advantage of domestic products. According to Chao et al. (2016), the relationship between stock markets and exchange rates depends on whether a country is a developing or developed economy. In their view, the capital inflow and outflow of companies rests on the condition of the global capital market. When such a market is in recession, for instance, capital flows to developed countries, and their emerging counterparts experience a positive correlation between stock markets and exchange rates. Najafzadeh et al. (2016) analyzed the effect of Exchange Rate on the Stock Exchange Return. Their findings showed that exchange rate volatility have a positive and significant effect on stock exchange return in Iran.

These patterns have motivated different views on the impact of exchange rates on stock markets. Nevertheless, these differences do not discount the correlation between exchange rates and stock prices uncovered in previous studies.

Theoretical evidence supports the relationship between stock markets and currency exchange rates, so we probed into the connection of herding in stock markets to exchange rates. For this purpose, we divided the price data into 10 classes on the grounds of the exchange rate (the price of a US dollar in Rial). We then calculated and analyzed the herding rate of each class, as described in the previous section.

Table 6. Estimates of Herding Rates on the Basis of US Dollar

	Class specification (%)		Frequency	Mean herding rate	Standard deviation	Critical value <1%	Critical value >1%	Critical value <5%	Critical value >5%
Class 1	-20.27	-1.1	100	6.3	0.19	-4.15	4.15	-3.14	3.13
Class 2	-1.1	-0.38	100	5.05	0.13	-3.21	3.2	-2.31	2.3
Class 3	-0.38	-0.13	100	3.19*	0.1	-3.3	3.32	-2.4	2.4
Class 4	-0.13	-0.03	100	2.29*	0.09	-3.64	3.64	-2.67	2.67

Class 5	-0.03	0.03	99	3.39*	0.1	-4.18	4.18	-3.19	3.19
Class 6	0.03	0.11	100	4.58	0.11	-3.52	3.53	-2.56	2.56
Class 7	0.11	0.25	100	3.14	0.08	-2.41	2.42	-1.72	1.72
Class 8	0.25	0.53	100	2.58	0.11	-2.27	2.29	-1.62	1.62
Class 9	0.53	1.52	100	5.78	0.14	-2.94	2.94	-2.12	2.11
Class 10	1.52	18.6	99	7.55	0.16	-4.05	4.05	-3.04	3.04

Source: Research finding.
Note: The mean price herding rate was calculated using Equation (12), which is $HR_{i,j} = \frac{1}{T}\sum_{t=1}^{T} HR_{i,j,t}$.
* The critical values indicated that these herding rates (classes 3–5) were not significant at the 1% level.

Table 6 illustrates that the herding rates in the third and fifth classes were non-significant. The sixth and eighth classes reflected no significant difference between the herding rates and the values captured using the random data at the 1% level (critical values). However, the herding rates obtained in the top and bottom classes were significant, pointing to substantial herding during dramatic changes in exchange rates. The results showed that no matter the market go up or done, if it moves fast (when notable changes occur), the chance for occurring herding could be more. Therefore, foreign currency market of US dollar might be affected by herding behavior, if large price movements occur.

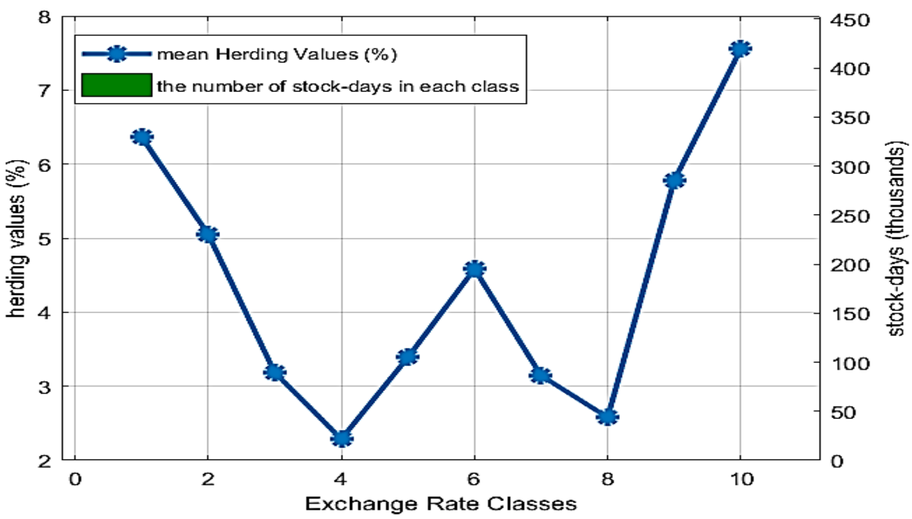

Figure 3. Mean of Herding Rates versus Exchange Rates
Source: Research finding.

Herd Behavior and Gold Prices

Baur and McDermott (2010) argued that gold is a good option for hedging against the risk of financial crises. At the onset of such catastrophes, therefore, investors may turn to the gold market. Similarly, Hillier et al. (2006) found evidence of a correlation between stock and gold markets, and Baur and Lucey's (2010) research on turbulence in financial markets underscored gold as a hedging tool that protects investors against turbulences. In line with these results, price changes in a gold market can spread to a stock market. If gold market effects spill over to a considerable number of stock market investors, herding may occur in stock markets. As dictated by this situation, the impact of gold price changes on herd behavior in the stock market was also examined in this work. The third null hypothesis is the absence of herd behavior during drastic gold price changes. As with the earlier procedures, the data were classified on the basis of gold price changes, and the herding rate of each class was calculated (Table 7).

Table 7. Estimates of Herding Rates on the basis of Gold Prices

	Class specification (%)		Frequency	Mean herding rate	Standard deviation	Critical value <1%	Critical value >1%	Critical value <5%	Critical value >5%
Class 1	-15.57	-1.33	100	7.05	18.18	-4.05	4.04	-3.05	3.04
Class 2	-1.33	-0.57	100	2.30*	11.54	-2.47	2.49	-1.79	1.79
Class 3	-0.57	-0.27	99	2.70	9.87	-2.3	2.3	-1.65	1.65
Class 4	-0.27	-0.08	100	3.75	9.18	-3.47	3.47	-2.5	2.51
Class 5	-0.08	0.09	100	3.63*	11.63	-4.19	4.19	-3.19	3.19
Class 6	0.09	0.28	101	1.91*	9.7	-3.52	3.52	-2.56	2.56
Class 7	0.28	0.54	100	6.04	11.71	-2.03	2.02	-1.46	1.46
Class 8	0.54	0.94	99	5.14	12.5	-1.59	1.59	-1.16	1.16
Class 9	0.94	1.9	100	5.54	14.37	-1.82	1.82	-1.32	1.32
Class 10	1.9	22.12	99	6.46	15.35	-4.07	4.07	-3.06	3.06

Source: Research finding.
Note: The mean price herding rate was calculated using Equation (12), which is $HR_{i,j} = \frac{1}{T}\sum_{t=1}^{T} HR_{i,j,t}$.
*****The critical values showed that these herding rates (classes 2, 5, and 6) were not significant at the 1% level.

Table 7 reflects that the herding rates in the second to fifth classes significantly differed from those in the other classes. The herding rate in the sixth class was non-significant, but those in the first class and bottom classes (seventh to tenth) were significant. The gold price returns in the seventh to tenth classes were higher than those in the other classes. These results indicated that herding in periods typified by drastic changes in gold prices is statistically significant. The results show that herding rates are less meaningful and they are less than herding rates in stock market and Exchange rate. This fact might roots in the massive global market of gold, which contains more different player with different information around the world.

Conclusion

We investigated the herding phenomenon in the stocks of 392 Iranian companies listed in the Tehran Stock Exchange as well as the currency exchange rates and gold prices in Iran from 2015 to 2019. First common herding models of CSAD and State-space have been used to capture herding. The evidence of herding was not significant based on CSAD model. Although herding was captured by State-space model, the overestimation problem of State-space models remains the problem of capturing herding unsolved. Then, price herding model was used to analyze herding. The findings showed that 58.77% of all possible herding relationships among the members of the sample were significant at the 1% level. The mean herding rate was 3.87%, which did not significantly differ from 0 at the 1% level, suggesting that herding at the overall market level was non-significant. Nonetheless, the results also implied that herding was significant in some situations, specifically under drastic changes in stock, gold, and currency prices. Hence, in the case of a sharp price increase in stock, currency, and gold markets, a dramatic increase in herding can be expected. These results are consistent with Bikhchandani et al. (1992) and Christie and Huang (1992), who asserted that individuals tend to make the same decisions that others make and that with the spreading of this kind of decision making, all individuals begin behaving similarly to one another.

Evidence of herding at the 1% error level indicated that this phenomenon can occur in both rising and declining markets, which means that the prediction of behavioral finance theory regarding the presence of herding in markets cannot be ruled out. However, the non-significance of herd behavior at the overall market points to the fact that herding does not affect the overall behavior of a market. It seems that nuclear negotiations and return of all United Nations sanctions on Iran affect the exchange rate in Iran and made herding rate more considerable during the research period. These findings are consistent with Lin (2012) and Cho et al. (2016). In the context of Iran, this means the country’s stock market generally behaves in correspondence with forecasts anchored in the efficient market hypothesis. In conclusion, although the behaviors of markets are consistent overall with the efficient market hypothesis, behavioral finance theories aver that such contexts do not always behave efficiently and may exhibit different tendencies in various situations. Put differently, markets may experience varying behavioral phenomena, including herding, on the path to efficiency.

Note that the data used in this study were daily records, but more than one day may pass before the signs of herding appear. Thus, testing the hypotheses under longer time frames may contribute to the expansion of the literature. The results of the present work can also be helpful in the identification of relationships between alternative markets and the formulation of investment strategies. The optimization of investment strategies based on the proposed model and the findings can be explored in future research.

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