Herding Behavior and Investor Investment Decisions in Capital Market

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Abstract. The paradigm of conventional financial science assumes that market participants are rational in explaining financial markets. Sadly, it was later discovered that the aggregate capital market, the average rate of return, and the behavior of traders did not conform to these assumptions. Herding is a behavioral bias that can influence individual and institutional investors' investment decisions. The fear of getting a loss on an investment will encourage human instincts to follow the information conveyed by the news or other investors, even though this step is not necessarily correct. This study consists of a literature review. Researchers compiled credible articles that explored the impact of herding tendency on investors' investment decisions. The journal is then classified as empirical, conceptual, and literary. In the first part, this paper discusses the effect of herding behavior and the factors causing herding behavior in the financial market. Then this paper continued to discuss research related to herding behavior from early 1990. As a closing, researcher explain study discusses how to identify the occurrence of herding behavior in the financial market.

Keywords: herding, investor, financial behavior

1 Introduction

Behavioral finance emerged as a response to the traditional financial science paradigm, which assumed market actors were rational. However, discrepancies in market behavior and average returns highlighted the need for a new approach [1]. Behavioral finance, formally developing since 1980, suggests that not all market actors are rational [1]. Early research by De Bondt and Thaler [2] found that individuals often overreact to dramatic events, affecting stock prices in line with the overreaction hypothesis. While market efficiency was once attributed to arbitrage, its limitations have been recognized, allowing for price errors [3,4]. Kahneman and Tversky introduced cognitive psychology's influence, developing the prospect theory model of irrational behavior [5,6]. Current research in behavioral finance focuses on individual investors' behavior, with significant contributions from Barber and Odean [7–9].

Investor sentiment in the capital market arises from irrational behavior and is linked to confidence in future cash flow and risk, often without fundamental analysis [10]. Three primary behavioral models determine asset prices: trust-based, preference-

Herding behavior, a behavioral bias, can lead investors to make similar stock choices based on general information [17,18]. This behavior can result in market bubbles and increased volatility [19]. Individual investors are more susceptible to herding, often influenced by large groups or past experiences [17,20,21]. Herding is a natural human tendency, seen in both consumption and investment. It can lead to asset bubbles and market collapses due to the fear of loss and the desire to conform [19,22]. This research categorizes journals discussing herding behavior's impact on investment decisions, aiming to map its influence on the capital market and investor behavior.

2 Herding Behavior Bias

"Herding" describes the tendency of investors to make similar investment choices based on both private and public information [19]. This behavior often arises because investors believe others possess superior information [23,24]. For instance, advice from a TV show can sway investment decisions [23]. Venezia et al. [25] and others argue that herding stems from information imbalances and the human desire for social validation [26–28]. Roider and Voskort's experiment demonstrated that investors, when aware of others' choices, tend to mimic those decisions [27]. Notably, both amateur and professional investors, including analysts, exhibit herding behavior [25,26]. Analysts, in particular, adjust their forecasts to align with the majority to safeguard their reputations [26–28]. Economists link herding to price imbalances and the onset of market bubbles, supported by its correlation with stock price volatility [25,26,28].

3 The Formation of Herding Bias

Hirshleifer and Teoh [29] describe herding behavior as the imitation arising from individual interactions. Such behavior is influenced by verbal communication, observed actions, and their outcomes. Five primary reasons for imitation include: Payoff externalities, where group activities prompt others to join, like using a specific social media platform; Sanctions for deviations, where rules or punishments enforce conformity; Social interactions leading to shared preferences; Direct communication, where advice influences imitation; Observations of others' actions affecting one's choices [29].

Figure 1 showcases the influence levels causing convergent or divergent behavior [29]. Two hierarchies, one based on observation (A, B, C, D) and the other on
interaction outcomes (I, II, III), dictate decisions to conform or resist. The observation hierarchy ranges from general observations, where imitation isn't guaranteed, to informational cascades, where observed actions strongly influence imitation [29]. The interaction outcome hierarchy spans from broad herding/dispersion behaviors to reputational herding, where maintaining a good image is paramount [29].

In summary, herding behavior has various influencing factors, from the desire to fit in to preserving one's reputation [30,31]. The most encompassing category is herding/dispersing, while informational cascades are more restrictive [30].

![Figure 1. Hirshleifer and Teoh's taxonomy](image)

**4 METHOD**

**Investor Herding Behavior Bias in the Capital Market**

Table 1 summarizes the evolution of herding research, primarily sourced from reputable, frequently-cited journals. Research on herding bias emerged in the early 1990s, with articles categorized as empirical, conceptual, or literary [17]. Empirical articles focus on observational and experimental case studies, conceptual ones on model or theory development, and literary articles review specific topics.

Froot et al. [31] identified herding behavior in capital markets, noting that short-horizon speculator investors are more prone to herding than long-horizon investors. This finding was supported by Blasco [32], who linked herding to market volatility. However, on the intraday market, herding behavior was not detected [33]. Chang et al. [34] found varying herding behavior across international markets, with significant herding in South Korea and Taiwan, minimal in Japan, and none in the US and Hong Kong. Other factors influencing herding include memory [35], investor type [21,25,36], social learning [37], and culture [38], with herding also being a predictor of income [39].
Conceptually, Hirshleifer et al. [40] introduced a model exploring trader behavior based on advance information, aligning with herding strategies. Spiegel et al. [41] proposed a framework analyzing the dynamic effects of stress on risk, revealing institutional trading patterns indicative of herding. Various mathematical models to detect herding in capital markets have also been suggested [34,42–45].

Table 1. Research on Herding Behavior Bias in the Capital Market

<table>
<thead>
<tr>
<th>No</th>
<th>Researcher</th>
<th>Year</th>
<th>Citation</th>
<th>Country</th>
<th>Article Type</th>
<th>Research</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>K.A. FROOT, D.S. SCHARFSTEIN, J.C. STEIN</td>
<td>1992</td>
<td>526</td>
<td>USA</td>
<td>empirical</td>
<td>Proofing the investors' herding behavior in the capital market</td>
</tr>
<tr>
<td>2</td>
<td>D. HIRSHLEIFER, A. SUBRAHMANYAM, S. TITMAN</td>
<td>1994</td>
<td>332</td>
<td>USA</td>
<td>conceptual</td>
<td>Mathematical model of herding behavior</td>
</tr>
<tr>
<td>3</td>
<td>M. SPIEGEL, A. SUBRAHMANYAM</td>
<td>1995</td>
<td>50</td>
<td>USA</td>
<td>conceptual</td>
<td>Mathematical model of herding behavior</td>
</tr>
<tr>
<td>4</td>
<td>William G. Christie and Roger D. Huang</td>
<td>1995</td>
<td>1467</td>
<td>USA</td>
<td>conceptual</td>
<td>Using dispersion to predict the occurrence of herding behavior bias in emerging market.</td>
</tr>
<tr>
<td>5</td>
<td>Andrea Devenow, Ivo Welch</td>
<td>1996</td>
<td>587</td>
<td>USA</td>
<td>literary</td>
<td>Herding research literature</td>
</tr>
<tr>
<td>7</td>
<td>V.M. Egiluz, M.G. Zimmermann</td>
<td>2000</td>
<td>245</td>
<td>Spain</td>
<td>conceptual</td>
<td>Mathematical model of herding behavior</td>
</tr>
<tr>
<td>8</td>
<td>SUSHIL BIKHCHANDANI, SUNIL SHARMA</td>
<td>2000</td>
<td>1495</td>
<td>USA</td>
<td>literary</td>
<td>Herding research literature</td>
</tr>
<tr>
<td>9</td>
<td>Yi-Tsung Lee, Yu-Jane Liu, Richard Roll, and Avanidhar Subrahmanyam</td>
<td>2004</td>
<td>220</td>
<td>Taiwan</td>
<td>empirical</td>
<td>Herding behavior of different types of investors.</td>
</tr>
<tr>
<td>10</td>
<td>S. Alfarano, T. Lux, F. Wagner</td>
<td>2005</td>
<td>202</td>
<td>Germany</td>
<td>conceptual</td>
<td>Mathematical model of herding behavior</td>
</tr>
<tr>
<td>12</td>
<td>J. Henker, T. Henker, A. Mitsios</td>
<td>2006</td>
<td>56</td>
<td>Australia</td>
<td>empirical</td>
<td>Herding behavior on intraday transactions in the capital market.</td>
</tr>
<tr>
<td>13</td>
<td>C. Goodfellow, M.T. Bohl, B. Gebka</td>
<td>2009</td>
<td>55</td>
<td>Poland</td>
<td>empirical</td>
<td>Herding behavior of different types of investors.</td>
</tr>
<tr>
<td>14</td>
<td>S. Alfarano, M. Milaković</td>
<td>2009</td>
<td>61</td>
<td>Germany</td>
<td>conceptual</td>
<td>Mathematical model of herding behavior</td>
</tr>
<tr>
<td>15</td>
<td>Z.-Q. Jiang, W.-X. Zhou, D. Sornette, R. Woodard, K. Bastiaensen, P. Cauwels</td>
<td>2010</td>
<td>135</td>
<td>China</td>
<td>conceptual</td>
<td>Combining several theories and models (one of which is herding behavior bias) to predict the occurrence of bubbles.</td>
</tr>
<tr>
<td>16</td>
<td>I. Venezia, A. Nashshkar, Z. Shapira</td>
<td>2011</td>
<td>72</td>
<td>Israel</td>
<td>empirical</td>
<td>Herding behavior of different types of investors.</td>
</tr>
<tr>
<td>17</td>
<td>A. Dasgupta, A. Prat, M. Verardo</td>
<td>2011</td>
<td>73</td>
<td>USA</td>
<td>empirical</td>
<td>Combining several theories and models (one of which is herding behavior bias) to predict the occurrence of bubbles.</td>
</tr>
</tbody>
</table>
Eguiluz et al. [45] developed a stochastic model using information dissemination to detect herding in capital markets. Alfarano et al. [43] introduced an agent-based model predicting trader interactions in the German market, revealing a herding tendency from trader interactions. They later presented a probability model linking behavioral heterogeneity to herding, emphasizing the role of agent interactions [43]. Jiang et al. [22] integrated various theories and the LPPL model to identify economic bubbles. Devenow and Welch [18] consolidated research on herding in financial markets, highlighting its origins in payoff externalities, principal-agent issues, and information cascades. Hirshleifer and Hong [29] provided a comprehensive review of herding, introducing a taxonomy to explain its occurrence in capital markets and its impact on investor gains and losses. Kumar and Goyal [17] analyzed 117 articles over 33 years to understand investor behavioral biases.

Herding Bias of Investor in Crowdfunding Market

Technology has made it easier for investors to explore more ways to invest. It helps people communicate better and meet directly, reducing the need for middlemen in finance. Now, we have crowdfunding sites that support peer-to-peer lending and equity crowdfunding. Some studies have noticed "herding" behavior, where investors follow trends, in peer-to-peer lending [46–48] and equity crowdfunding [49,50]. New digital currencies, called cryptocurrencies, are also popular among investors. This "herding" trend is seen in cryptocurrency investments too [51,52].

Indicators of Herding Behavior Bias in the Capital Market

Capital market returns help identify herding behavior biases. To spot this, researchers look for dispersion patterns in the market. By analyzing this data statistically, dispersion can be detected. Christie and Huang [44] developed the Cross-Sectional Standard Deviation (CSSD) algorithm for this purpose. They suggest that herding biases intensify during market downturns. The CSSD, represented by Formula (1), determines the presence of herding behavior.

\[
\text{CSSD}_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2}{N-1}}
\]

\(R_{i,t}\) is the rate of return on shares of a company \(i\) at time \(t\), and \(R_{m,t}\) is the cross-sectional average rate of return on \(N\) returns in the aggregate market at time \(t\). \(N\) is the number of companies in the capital market.
When the market moves significantly, herding bias is indicated by low dispersion values. This is because investors tend to follow the general market consensus, sideling their own beliefs. Yet, a rise in dispersion doesn't always point to herding, as it might be linked to the rational asset pricing model, which guides investors based on varied market return beliefs. To differentiate between herding and this model, Christie and Huang [44] introduced the CSSD regression model, represented by Formula (2).

\[
\text{CSSD}_{(m,t)} = \alpha + \beta^U D_t^U + \beta^L D_t^L + u_t
\]

\(D_t^U\) and \(D_t^L\) are dummy variables whose value is equal to 1 if the rate of return on the market on day \(t\) is extreme, both upper tail and lower tail [52]. The herding phenomenon is considered to occur when the coefficients \(\beta^U\) and \(\beta^L\) have a consistently negative relationship. The coefficients \(\beta^U\) and \(\beta^L\), which have a consistently positive relationship, refer to the asset pricing model predictions.

Chang et al. [34] enhanced Christie and Huang's [44] method by presenting the Cross-Sectional Absolute Deviation (CSAD) algorithm. They emphasized its importance especially during tough market conditions. Typically, the CAPM has a straightforward link with CSAD and market returns. However, during stressed market situations, a herding bias appears due to a non-linear connection between CAPM and CSAD [53], as depicted in formula (3).

\[
\text{CSAD}_{(m,t)} = \left( \sum_{i=1}^{N} |r_{(i,t)} - r_{(m,t)}| \right) / N
\]

Meanwhile, the CSAD regression model, related to the market rate of return, is shown in formula (4).

\[
\text{CSAD}_{(m,t)} = \alpha + \beta_1 r_{(m,t)} + \beta_2 |r_{(m,t)}| + \beta_3 r_{(m,t)}^2 + u_t
\]

\(r_{(m,t)}\) represents the market rate of return at time \(t\). Unlike the Christie and Huang [44] model, Chang et al. [34] show that the rational asset pricing model can predict a linear relationship between CSAD and market returns. A negative coefficient \(\beta_3\) indicates herding, while a positive value \(\beta_3\) indicates a rational asset pricing model [52].
5 CONCLUSION

Behavioral finance suggests that not all market participants act rationally, leading to investor sentiment in the capital market. One outcome of this irrationality is herding, where investors mimic others due to perceived better information elsewhere. This can cause price imbalances and even asset price bubbles. Herding involves individuals influencing others through words, actions, or observed outcomes.

Research on herding in the capital market started in the early 1990s with works like Froot et al. [31], showing investors’ susceptibility to herding. Later studies by Hirshleifer et al. [40], Spiegel et al. [41], and Christy and Huang [44] used statistics to predict herding occurrences. With technological advancements, new investment areas like crowdfunding and cryptocurrencies have also been studied for herding behavior.

To identify herding bias, researchers look for dispersion in the capital market using data and statistical tools. Key methods include the Cross Sectional Standard Deviation (CSSD) by Christie and Huang [44] and the Cross-Sectional Absolute Deviation (CSAD) by Chang et al. [34]. These tools help determine the main indicators of herding in the market.

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