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-

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based, and the Generalized Behavioral Asset Pricing Model [11]. Barberis, Sheifer, and Vishny introduced the trust-based model, emphasizing two investor beliefs regarding company value fluctuations and profit trends [12]. Daniel, Hirshleifer, and Subharmayan's model suggests investors overreact to significant information and underreact to new, contrasting information [13]. Barberis, Nicholas, Huang, and Santos presented a preference-based model, focusing on shifting risk attitudes and probability misperception [14–16]. Szyszka's Generalized Behavioral Asset Pricing Model emphasizes asset pricing prediction [11].

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].

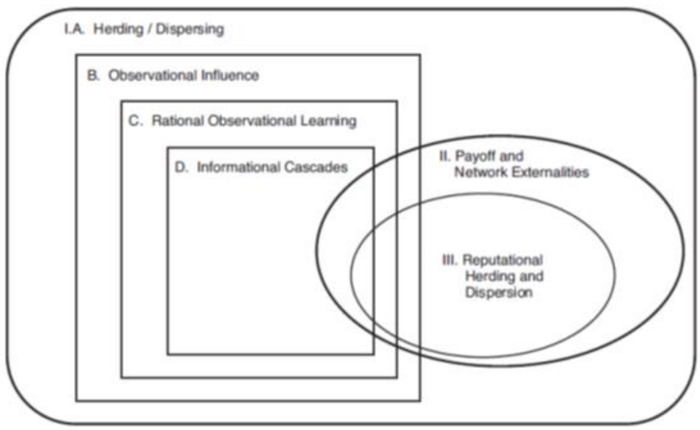

Figure 1. Hirshleifer and Teoh's taxonomy

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

No	Researcher	Year	Citation	Country	Article Type	Research
1	K.A. FROOT, D.S. SCHARFSTEIN, J.C. STEIN	1992	526	USA	empirical	Proofing the investors' herding behavior in the capital market
2	D. HIRSHLEIFER, A. SUBRAHMANYAM, S. TITMAN	1994	332	USA	conceptual	Mathematical model of herding behavior
3	M. SPIEGEL, A. SUBRAHMANYAM	1995	50	USA	conceptual	Mathematical model of herding behavior
4	William G. Christie and Roger D. Huang	1995	1467	USA	conceptual	Using dispersion to predict the occurrence of herding behavior bias in emerging market.
4	Andrea Devenow, Ivo Welch	1996	587	USA	literary	Herding research literature
5	E.C. Chang, J.W. Cheng, A. Khorana	2000	524	Emerging Market	empirical	Comparison of herding behavior in emerging markets using the CSAD model.
6	V.M. Eguiluz, M.G. Zimmermann	2000	245	Spanyol	conceptual	Mathematical model of herding behavior
7	SUSHIL BIKHCHANDANI, SUNIL SHARMA	2000	1495	USA	literary	Herding research literature
8	D. Hirshleifer, S. Hong Teoh	2003	403	USA	literary	Herding research literature
9	Yi-Tsung Lee, Yu-Jane Liu, Richard Roll, and Avanidhar Subrahmanyam	2004	220	Taiwan	empirical	Herding behavior of different types of investors.
10	S. Alfarano, T. Lux, F. Wagner	2005	202	Germany	conceptual	Mathematical model of herding behavior
11	D. Sornette, W.-X. Zhou	2006	67	USA	empirical	Memory affects herding.
12	J. Henker, T. Henker, A. Mitsios	2006	56	Australia	empirical	Herding behavior on intraday transactions in the capital market.
13	C. Goodfellow, M.T. Bohl, B. Gebka	2009	55	Polandia	empirical	Herding behavior of different types of investors.
14	S. Alfarano, M. MilakoviÄ‡	2009	61	Germany	conceptual	Mathematical model of herding behavior
15	Z.-Q. Jiang, W.-X. Zhou, D. Sornette, R. Woodard, K. Bastiaensen, P. Cauwels	2010	135	China	conceptual	Combining several theories and models (one of which is herding behavior bias) to predict the occurrence of bubbles.
16	I. Venezia, A. Nashikkar, Z. Shapira	2011	72	Israel	empirical	Herding behavior of different types of investors.
17	A. Dasgupta, A. Prat, M. Verardo	2011	73	USA	empirical	Combining several theories and models (one of which is herding behavior bias) to predict the occurrence of bubbles

18 N. Blasco, P. Corredor, S. Ferreruela 2012 74 Spanish empirical Proofing the investors' herding behavior in the capital market

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

19 L. Bursztyn, F. Ederer, B. Ferman, N. Yuchtman 2014 177 USA empirical Social learning and social utility affect herding behavior.

20 C.-H. Chang, S.-J. Lin 2015 60 Taiwan empirical Culture influences herding behavior.

21 S. Kumar, N. Goyal 2015 75 International literary Herding research literature

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.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2}{N-1}}$$

$R_{i,t}$ 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, sidelining 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).

$$CSSD_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + u_t$$

D_t^U and D_t^L are dummies variable 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 β^U and β^L have a consistently negative relationship. The coefficients β^U and β^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).

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{m,t}|}{N}$$

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

$$CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + u_t$$

$r_{m,t}$ 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 β_3 indicates herding, while a positive value β_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 herd-ing, where investors mimic others due to perceived better information elsewhere. This can cause price imbalances and even asset price bubbles. Herding involves individu-als 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 usingdata and statistical tools. Key methods include the Cross Sectional Standard Devia-tion (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 herd-ing in the market.

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