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The Role of Behavioral Biases in High-Frequency Trading: Evidence from Stock Markets

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Abstract. With the widespread application of algorithmic trading and artificial intelligence in financial markets, high-frequency trading (HFT) has become an integral component of modern securities markets. Although HFT is characterized by high speed and automation, the trading strategies and algorithmic designs underlying these systems remain significantly influenced by human behavioral biases. Drawing on the behavioral finance framework, this paper provides a systematic review of recent domestic and international empirical studies on behavioral biases in high-frequency trading. The analysis focuses on the manifestations and transmission mechanisms of overconfidence, herding behavior, and the disposition effect in high-frequency traders' decision-making processes. The literature review indicates that these biases may amplify short-term market volatility, weaken price discovery efficiency, and intensify systemic risk during periods of extreme market conditions. Finally, this paper discusses directions for future research, including the incorporation of behavioral characteristics into algorithm design and the improvement of market regulation and risk management from a behavioral perspective.

Keywords: Behavioral Bias, Overconfidence, Herding, Disposition Effect, High-Frequency Trading

1. Introduction

HFT has become one of the most prominent forms of algorithmic trading in modern financial markets. By leveraging high-speed communication networks, co-location services, and automated decision-making systems, HFT firms are able to submit, modify, and cancel a large number of orders within extremely short time intervals. Existing studies suggest that the growth of HFT has contributed to enhanced market liquidity, narrower bid–ask spreads, and faster price discovery in equity markets [1]. At the same time, growing concerns have been raised regarding market stability, particularly during periods of stress, when rapid trading activity and large-scale order cancellations may amplify short-term volatility and systemic risk [2].

Traditional financial theory is grounded in the assumption that market participants are rational and that asset prices fully and effectively reflect available information. However, research in behavioral finance has consistently documented systematic deviations from rational decision-making. Behavioral biases such as overconfidence, herding behavior, and the disposition effect have been shown to influence trading behavior and market outcomes across different financial settings.

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An important and still unresolved question is whether these behavioral patterns remain relevant in HFT environments, which are characterized by a high degree of automation, data-driven strategies, and limited direct human intervention.

This paper seeks to address this gap by providing a systematic review of recent empirical studies that examine the role of behavioral biases in HFT within stock markets. Focusing on overconfidence, herding, and the disposition effect, the study synthesizes evidence on how these biases manifest in high-frequency contexts and the mechanisms through which they affect market liquidity, volatility, and price efficiency. By comparing findings across different market structures and types of market participants, this review aims to clarify the role of behavioral biases in HFT and to offer insights for future research, algorithm design, and the development of regulatory policies.

2. Theoretical framework and research background

2.1. Characteristics and market role of HFT

HFT refers to a subset of algorithmic trading strategies characterized by extremely low latency, high-speed data processing, and automated order execution. HFT strategies typically involve very short holding periods, frequent order submissions and cancellations, and the exploitation of small and transient price discrepancies. Technological advantages such as co-location services, direct market access, and advanced hardware infrastructure allow high-frequency traders to react to market information within milliseconds [3].

From a market microstructure perspective, extensive research has examined the role of HFT in liquidity provision and price efficiency. Empirical evidence generally suggests that HFT activity is associated with narrower bid–ask spreads, increased depth at the best quotes, and faster incorporation of information into prices under normal market conditions [4]. However, these same features may also contribute to market fragility. During periods of heightened uncertainty or stress, rapid order cancellations and synchronized trading behavior can lead to sudden liquidity withdrawal and sharp price movements, raising concerns about volatility amplification and systemic risk.

2.2. Trading decision biases from a behavioral finance perspective

Behavioral finance challenges the traditional assumption of fully rational market participants by emphasizing the role of cognitive limitations, heuristics, and psychological biases in decision-making. A large body of literature documents that investors systematically deviate from optimal behavior due to factors such as overconfidence, social influence, and loss aversion. These behavioral biases have been shown to affect trading frequency, risk-taking behavior, and asset price dynamics across a wide range of financial markets [5].

Overconfidence refers to the tendency of traders to overestimate the precision of their information or their ability to predict market outcomes, often leading to excessive trading and aggressive order placement. Herding behavior arises when traders imitate the actions of others rather than relying solely on private information, which may generate price clustering and momentum effects. The disposition effect reflects investors' reluctance to realize losses while exhibiting a greater willingness to realize gains, resulting in asymmetric selling behavior. Although these biases were originally documented in retail and discretionary trading environments, subsequent research suggests that they may persist even as trading becomes increasingly automated [6].

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2.3. Transmission mechanisms of behavioral biases in HFT

Despite the highly automated nature of HFT, human behavioral biases can continue to influence market outcomes through several transmission mechanisms. First, trading algorithms are designed, calibrated, and periodically adjusted by human decision-makers. As a result, subjective beliefs and behavioral tendencies may be embedded in model assumptions, parameter choices, and strategy selection. Overconfidence, for example, may manifest in overly aggressive execution rules or insufficient risk constraints.

Second, many high-frequency strategies incorporate learning algorithms and adaptive feedback mechanisms that respond to short-term performance signals. Under certain market conditions, these systems may reinforce behavior patterns by amplifying herding or trend-following behavior. Finally, interactions among multiple high-frequency traders operating similar strategies can generate collective dynamics, such as trade clustering and rapid liquidity shifts, which magnify the market-level impact of individual biases [7].

Taken together, these transmission mechanisms provide a theoretical foundation for understanding how behavioral biases may persist and propagate within HFT environments, even in the presence of advanced technology and automation.

3. Overconfidence bias: manifestations and market impact

3.1. Characteristics and measurement of overconfidence in HFT

Overconfidence bias refers to the tendency of traders to overestimate the precision of their information or their ability to predict market movements. In traditional trading environments, overconfidence has been linked to excessive trading volume, underestimation of risk, and suboptimal portfolio performance. In HFT contexts, overconfidence is less directly observable through specific behavioral proxies [8].

Empirical studies commonly measure overconfidence in HFT by examining indicators such as abnormal trading intensity, aggressive order placement, and rapid strategy turnover following short-term success. At the firm or strategy level, repeated profitability in narrow time windows may reinforce traders' confidence in algorithmic models, even when performance is largely driven by favorable market conditions rather than superior information. Such reinforcement mechanisms can lead to persistent deviations from optimal execution behavior.

3.2. Effects on quote aggressiveness and order cancellation

One important channel through which overconfidence affects HFT behavior is quote aggressiveness. Overconfident traders are more likely to submit marketable limit orders or to quote closer to the best bid or ask, reflecting an inflated belief in the expected profitability of rapid execution. While aggressive quoting may enhance short-term liquidity provision, it simultaneously increases exposure to adverse selection and execution risk.

Overconfidence has also been associated with elevated order cancellation rates. High-frequency traders who overestimate the reliability of their signals may frequently revise or withdraw orders when market conditions evolve differently than anticipated. Although frequent cancellations are a defining feature of HFT, excessive cancellation activity can contribute to fleeting liquidity and reduced market resilience, particularly during periods of heightened uncertainty [9].

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3.3. Empirical evidence on profitability, liquidity, and volatility

Empirical findings on the market impact of overconfidence in HFT remain mixed. Some studies find that moderate levels of aggressive trading behavior can improve liquidity provision and reduce transaction costs under normal market conditions. However, excessive overconfidence is frequently linked to declining profitability over time, as increased trading costs and adverse selection outweigh short-term gains [10].

At the market level, overconfident HFT behavior has been associated with increased intraday volatility and sharper price fluctuations. These effects tend to intensify during periods of market stress, when rapid strategy adjustments and synchronized responses can amplify price movements. Overall, the literature suggests that while overconfidence may temporarily enhance trading performance or liquidity, it poses risks to market stability when embedded within HFT systems at scale [11].

4. Herding and the disposition effect: micro-level mechanisms

4.1. Herding behavior and short-term price clustering

Herding behavior refers to the tendency of traders to imitate the actions of others rather than relying exclusively on private information. In HFT environments, herding may arise from algorithmic synchronization, shared data feeds, and similar strategy designs. When multiple high-frequency traders respond to identical signals or market events within extremely short time intervals, their trading actions can become highly correlated, even in the absence of explicit coordination [12].

Empirical research shows that herding in HFT is often associated with short-term price clustering and momentum effects. Rapid order submissions in the same direction can temporarily push prices away from fundamental values, particularly in less liquid securities or during periods of elevated market uncertainty. While such behavior may contribute to faster information incorporation under certain conditions, excessive herding can reduce informational diversity and increase the likelihood of abrupt price reversals, thereby weakening market stability.

4.2. Evolution of the disposition effect in HFT

The disposition effect describes investors' tendency to sell winning positions too early while holding on to losing positions for extended periods. Traditionally, this behavior bias has been attributed to loss aversion and mental accounting in discretionary trading environments. In HFT, the manifestation of the disposition effect differs due to short holding periods and automated execution mechanisms; yet behavioral asymmetries remain observable [13].

Studies suggest that algorithmic strategies may implicitly reflect disposition-like behavior through asymmetric order adjustments and position management rules. For example, some algorithms are designed to quickly realize small gains while delaying the unwinding of losing positions in anticipation of short-term price corrections. These patterns indicate that behavioral preferences and biases can be embedded in algorithmic decision rules, even when direct human intervention is limited and trading is largely automated.

4.3. Trade clustering, volatility amplification, and tail risk

When herding behavior and disposition effects interact within HFT systems, their combined influence may amplify market volatility and tail risk. Herding-induced trade clustering can intensify

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order flow imbalances, while disposition-driven asymmetries may delay corrective price adjustments. Together, these mechanisms can contribute to sudden liquidity shortages and sharp intraday price fluctuations [14].

Empirical evidence links high levels of synchronized trading activity to volatility spikes and fat-tailed return distributions, particularly during periods of market stress. Such dynamics have raised concerns about the role of HFT in transmitting and amplifying systemic risk. The literature suggests that understanding these behavioral mechanisms is essential for evaluating the broader implications of algorithmic trading on market stability and for designing effective regulatory and risk management frameworks [15].

5. Conclusion

This paper provides a systematic review of recent empirical research on the role of behavioral biases in HFT within stock markets. Drawing on the behavioral finance framework, the review focuses on three prominent biases—overconfidence, herding behavior, and the disposition effect—and examines how they manifest in highly automated and data-driven trading environments. The reviewed evidence suggests that, despite the increasing sophistication of trading algorithms, behavioral biases remain relevant and continue to influence trading behavior and market outcomes.

Overall, the literature indicates that behavioral biases influence market stability and price discovery through multiple channels. Overconfidence among high-frequency traders is associated with aggressive quoting strategies, elevated order cancellation activity, and increased intraday volatility, particularly during periods of market stress. Herding behavior contributes to short-term price clustering and momentum effects, which may temporarily enhance liquidity but also increase the risk of abrupt price reversals. The disposition effect, although modified by short holding periods and automated execution, persists through asymmetric position adjustments and may delay corrective price movements. When these biases interact within HFT systems, their combined effects can amplify volatility and tail risk, raising concerns about systemic stability in modern financial markets.

The findings offer important implications for algorithm design and risk management. Incorporating behavioral awareness into algorithmic trading models may help mitigate excessive risk-taking and reduce destabilizing feedback effects. From a regulatory perspective, improved monitoring of synchronized trading activity and order cancellation behavior could enhance early detection of market fragility.

Several limitations should be acknowledged. The empirical identification of behavioral biases in HFT remains challenging due to data constraints, proprietary algorithms, and heterogeneity across markets. In addition, many studies rely on indirect behavioral proxies, which may limit causal interpretation. Future research would benefit from richer datasets, improved identification strategies, and closer integration of behavioral finance with artificial intelligence. In particular, the development of explainable and behavior-aware trading algorithms represents a promising direction for enhancing market resilience and informing effective regulatory policy.

References

[1] Brogaard, J., Hagströmer, B., Nordén, L., et al. (2014) High-frequency trading and price discovery. Rev Financ Stud, 27(8): 2267–2306.
[2] Kirilenko, A., Kyle, A.S., Samadi, M., et al. (2017) The flash crash: The impact of high-frequency trading in an electronic market. J Finance, 72(3): 967–998.
[3] Menkveld, A.J. (2013) High frequency trading and the new market makers. J Financ Mark, 16(4): 712–740.

DOI: 10.54254/2754-1169/2026.LD31434

[4] Biais, B., Foucault, T., Moinas, S. (2015) Equilibrium fast trading. J Financ Econ, 116(2): 292–313.
[5] Barberis, N., Thaler, R. (2003) A survey of behavioral finance. In: Constantinides G, Harris M, Stulz R, editors. Handbook of the Economics of Finance, 1: 1053–1128.
[6] Daniel, K., Hirshleifer, D., Subrahmanyam, A. (2001) Overconfidence, arbitrage, and equilibrium asset pricing. J Finance, 56(3): 921–965.
[7] Broussard, J.P. (2013) Human bias in algorithmic trading. SSRN Electron J.
[8] Ben-David I., Graham J.R., Harvey C.R. (2013) Managerial miscalibration. Q J Econ, 128(4): 1547–1584.
[9] Manahov V. (2021) High-frequency trading order cancellations and market quality: Is stricter regulation the answer? Int J Financ Econ, 26(4): 5385–5407.
[10] Fu, , S.M. (2024) Does algorithmic trading induce herding? Int J Financ Econ, 25(3): 356–373.
[11] Eaton, G.W., Green, T.C., Roseman, B.S., et al. (2021) Zero-commission individual investors, high-frequency traders, and stock market quality. High Frequency Traders, and Stock Market Quality., 141(2): 514–546.
[12] Hendershott, T., Jones, C.M., Menkveld, A.J. (2011) Does algorithmic trading improve liquidity? J Finance, 66(1): 1–33.
[13] Odean, T. (1998) Are investors reluctant to realize their losses? J Finance. 53(5): 1775–1798.
[14] Weber M, Camerer CF. (1998) The disposition effect in securities trading: An experimental analysis. J Finance. 53(5): 1775–1798.
[15] Cont, R., & Bouchaud, J. P. (2000) Herd behavior and aggregate fluctuations in financial markets. Macroeconomic dynamics, 4(2): 170-196. doi: 10.1017/S1365100500015029.