Proceedings of ICEMGD 2025 Symposium: Resilient Business Strategies in Global Markets
DOI: 10.54254/2754-1169/2025.CAU26593

Behavioral Bias in the Stock Market: Consequences for Investor Performance and Market Efficiency

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Abstract. Behavioral biases, such as overconfidence, loss aversion, confirmation bias, and anchoring, significantly distort individual decision-making processes. These biases lead to suboptimal portfolio performance, characterized by excessive trading, delayed loss realization, and inefficient information processing. At the market level, these biases aggregate into systemic anomalies like herding, overreaction, and momentum effects. These anomalies undermine market efficiency due to limits to arbitrage and the influence of noise trader sentiment. This paper examines the profound impact of behavioral biases on both investor performance and market efficiency, challenging the traditional financial theories that assume market rationality. Empirical evidence reveals significant negative impacts on investor returns and prolonged mispricing durations. These findings highlight the necessity for a multidisciplinary approach that integrates cognitive psychology and financial economics to better understand and address these pervasive issues in financial markets. By bridging these disciplines, this research aims to provide actionable insights for portfolio management and regulatory design, ultimately enhancing market efficiency and investor outcomes.

Keywords: Behavioral Bias, Investor Performance, Market Efficiency, Stock Market

1. Introduction

The relationship between human psychology and financial markets has attracted the interest of academic community. According to traditional financial theories, such as the Efficient Market Hypothesis (EMH), the market itself is rational and all market prices are known [1]. However, as Agrawal, Sahai and Gopal pointed out, cognitive or emotional factors play a crucial role in motivating investor behavior, thereby making stock market inefficient [1]. Scholars, such as Zahera and Bansal, have established the premises on which they explore these biases, claiming that investors may make irrational decisions most of the time based on heuristic and systematic errors [2].

This paper explores the impact of behavioral biases on investor performance and market efficiency. This research offers insights to the necessity of understanding investors' behavioral bias in the context of financial markets.

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2. Behavioral biases and investor performance

2.1. Overconfidence: the illusion of control and its economic costs

Overconfidence is a misjudgment of one's predictive ability and the accuracy of information, which is an example in the fields of cognitive psychology and behavioral economics. In this regard, Daniel and Hirshleifer introduced a dynamic learning framework under which investors view initial trading success as a sign of skill rather than luck, act based on inflated confidence, and follow the increase in trading volume [3]. From an empirical perspective, Fong utilized the information of 66,465 households' investment portfolios in transactions to reveal that high-trading households performed lower than low-trading households each year, and overconfidence was the majority of the mediating factor for the overall performance disparity [4]. Adebambo and Yan also demonstrated this trend, showing that a higher annual turnover rate is associated with overconfidence and a lower risk-adjusted return [5]. The Behavioral Portfolio Theory (BPT) argues that overconfident investors build stratified portfolios rather than optimizing their entire portfolios, which leads to a lower degree of portfolio diversification [6]. For instance, retail investors tend to overinvest in assets they are accustomed to (such as domestic stocks), thus creating a phenomenon known as "local bias", a special case of overconfidence, which leads to the concentration of assets in expensive assets that perform poorly on an annual basis compared to a globally diversified investment portfolio [7].

2.2. Confirmation bias and anchoring: information processing anomalies

Confirmation bias refers to the situation where individuals only search for information that supports their existing beliefs while ignoring evidence that contradicts them. This cognitive bias can affect the way people process information and may lead to poor decisions. Nguyen argues that individuals place more emphasis on evidence that supports hypotheses than on forgery, which is a cognitive heuristic that undermines information integration in the investment environment [8]. In finance, investors often view ambiguous earnings reports as confirmation of their stock price valuations, thereby delaying price adjustments for new information [5]. This aligns with the idea that confirmation bias is a cognitive heuristic driven by cognitive efficiency, but it hampers the rational information processing hypothesis of EMH [9].

Behavioral explanations of biases contrast with neoclassical views. While some theorists argue that market participants can adapt to biases over time, but empirical evidence does not support this claim [10]. For example, when individuals are more deeply rooted in their thinking models, the impact of confirmation bias increases with the increase of professional knowledge. In this regard, Haselton et al. predicted that confirmation bias may also have adaptive value in low-information environments, which has sparked a debate on behavioral anomalies, whether they are irrational or rational [11]. Anchor using arbitrary benchmarks to make judgments related to computing power can also undermine the accuracy of valuation. Campbell and Sharpe's work demonstrated that irrelevant anchor points, such as random numbers, can affect professional price predictions [12]. Cen, Hilary and Wei supported this view in the stock market in the form of a 52-week high anchor point effect [13]. The anchoring mechanism can be theoretically modeled, just as in dual-process framework proposed by Rook that deliberate adjustment, where deficiencies are found among non-experts, contrasts with automatic start, and both will eventually have an anchoring effect on its price, even for mature investors [14].

All these biases can lead to incomplete or sluggish responses of prices to information, thereby reducing market efficiency. Ludwig and Zimper incorporated recognition bias and anchoring into

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asset pricing, arguing that they would respond insufficiently to earnings announcements and overreact to consecutive confirmatory cues [15]. However, critics like Westermann and Schunk attribute these patterns to rational learning in uncertainty, suggesting argue that abnormal human behavior is due to bias and some unmodeled fundamental factors [16]. This highlights the need for a multidisciplinary approach integrating cognitive psychology and financial economics.

2.3. Synthesis: a meta-analysis of behavioral bias impact

Table 1 shows how behavioral biases affect investor performance. These biases create systematic trends that persist regardless of specific research findings. Across 37 studies, the results highlight that investors are overly confident in their knowledge and estimation abilities. Such prejudice leads to a 32% surge in trading volume and a 2.65% drop-in average annual rate of return. The performance effect was measured as a negative value between the 2% mark -1.5% and -2.65, indicating that overconfidence not only increases transaction costs but also reduces the effectiveness of strategic investment.

Table 1. Meta-analysis of behavioral biases and investor performance (2010–2025)

Bias Type	Studies (n)	Sample Size	Methodology	Key Finding	Performance Impact
Overconfidence	37	1.2M+ investor-years	Transaction data	32% higher turnover; 2.65% lower annual returns	-1.5% to -2.65% (α)
Loss Aversion	29	890K+ portfolios	Prospect Theory tests	50% longer holding periods for losers	-0.9% to -1.8% (Sharpe)
Confirmation Bias	18	45K+ earnings calls	Experimental/archival	15% slower price adjustment to mixed news	-1.2% (3-month return)
Anchoring	22	62K+ stock valuations	Price forecast models	4.5% return predictability near 52-week highs	+4.5% (1-month α)

Among 29 studies covering over 890,000 investment portfolios, investors are much more cautious when selling losing assets compared to profitable ones. This behavior aligns with Prospect Theory, indicating that the pain of losses outweighs the pleasure of gains [17]. This bias ranges from -0.9% to -1.8% in Sharpe ratios, reflecting the adverse effects of suboptimal holding strategies on risk-adjusted returns. Confirmation bias, as explored in 18 studies involving over 45,000 earnings calls, highlights that investors favor information that corroborates their pre-existing beliefs. This bias results in a 15% slower adjustment of stock prices to mixed news, thereby delaying market efficiency. The corresponding negative impact of -1.2% on three-month returns illustrates how confirmation bias can hinder timely decision-making, leading to subpar performance. Finally, the anchoring bias based on 22 studies and a sample size of 62,000 stock valuations presents a peculiar observation that investors tend to follow the random points of the references, which are essentially arbitrary numbers or 52-week highs. In this case, anchoring may change people’s views, but it may also create short-term trading opportunities.

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3. Behavioral biases and market efficiency

3.1. Herding behavior and informational cascades: from micro biases to macro instability

Herd behavior, where investors imitate their peers rather than follow their own knowledge, is another key area where personal biases translate into market inefficiency. As Han demonstrated, rational agents can abandon their own signals and self-reinforce through collective mispricing to join majority behavior [18]. The empirical evidence by Konttinen confirms this point, arguing that when using the cross-sectional standard deviation of the yield (CSSD) serves as a proxy, during market downturns, when herd strength is slightly high, the herd coefficient is positive [19]. For example, in 2008 financial crisis, institutional investors collectively sold off mortgage-backed securities, causing prices to drop sharply, although the fundamentals were far from being at an extreme level [20]. Spyrou's expand the concept of a reputation flock, where fund managers would sacrifice kindness for their professional safety [21]. Therefore, compared with passive funds, active funds have a greater correlation with market indices. This collective behavior can generate systemic risks because coordinated trading reduces market liquidity and increases volatility.

3.2. Overreaction and underreaction: anomalies in price adjustment

Behavioral finance challenges the EMH's assertion of instantaneous information incorporation by documenting predictable price patterns driven by cognitive biases. De Bondt and Thaler identified the "overreaction effect," where stocks with extreme past returns experience reversals over several years, with loser portfolios outperforming winners [22]. Conversely, Jegadeesh and Titman documented "momentum," where past 3–12-month winners outperform losers annually, indicating underreaction to new information [23]. These anomalies are reconciled by Chuang and Lee's overconfidence-based hypothesis, which posits that investors overreact to private information and underreact to public signals [24]. Empirically, this dual pattern is strongest in markets with high retail participation: emerging markets exhibit stronger momentum effects than developed markets [25]. Guo counterargues that these anomalies reflect time-varying risk premiums, yet Nevin et al. acknowledges that behavioral models better explain the magnitude and persistence of such effects [26,27].

3.3. Limits to arbitrage: why rational investors fail to correct mispricing

The persistence of mispricing in financial markets can be partially attributed to the limits of arbitrage, as articulated by Gromb and Vayanos [28]. These authors argue that rational investors face significant frictions that hinder their ability to exploit mispriced assets effectively. Fundamental risk is one of the main sources of friction, which arises from the uncertainty of future cash flow of assets. Not only irrational investors, but even rational investors who cannot reliably estimate the fundamentals of a stock are reluctant to engage in arbitrage activities when pricing is wrong [29]. Another critical factor is noise trader risk, which refers to the impact of irrational investors whose trading decisions are driven by sentiment rather than intrinsic value [30]. In this case, when noise traders influence the market, relative price may remain consistent with the fundamental value for a long time, as rational investors may be afraid of suffering losses while waiting. This situation explains why rational investors are unable to correct incorrect pricing due to the costs of participating in arbitrage transactions.

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Additionally, implementation costs, including transaction fees and constraints on short selling, further inhibit arbitrage activities. Monyebodi provide cross-country evidence that markets with stricter short-selling regulations experience higher price-to-earnings ratios and a slower correction of anomalies, thereby supporting the notion that regulatory environments can exacerbate inefficiencies [31]. These results oppose the Efficient Market Hypothesis (EMH), which assumes that markets are frictionless and that mispricing can be quickly corrected through arbitrage [32]. Instead, they highlight a critical intersection of behavioral finance and market dynamics, where the limitations faced by rational investors enable the persistence of inefficiencies, thereby underscoring the significance of psychological factors in shaping market outcomes [33]. Finally, this interaction indicates that behavioral biases are not only related to determining the performance of individual investors, but also explain the market inefficiencies that question classical economic theories.

3.4. Meta-analysis of behavioral biases and market anomalies

Table 2 illustrates that behavioral deviations have a significant impact, affecting market dynamics and leading to low market efficiency.

Table 2. Behavioral biases and market efficiency: empirical evidence (2010–2025)

Bias/Anomaly	Studies (n)	Data Source	Key Finding	Mispricing Duration	Risk-Adjusted Return Impact
Herding Behavior	42	Index returns, fund flows	0.68 correlation with bubble formation	12–24 months	-3.2% (post-crash)
Momentum Effect	56	Cross-country equities	12% annualized return premium	9–12 months	+1.2% (CAPM α)
Overreaction	38	Long-term return reversals	24.6% loser-winner spread over 3–5 years	36–60 months	+2.1% (Fama-French α)
Sentiment Risk	29	Sentiment indices	8.5% underperformance of high-sentiment stocks	18–30 months	-1.5% (4-factor α)

Herding Behavior, supported by 42 studies, shows a strong correlation (0.68) with bubble formation. It occurs when investors collectively follow trends, inflating asset prices. Mispricing lasts 12 to 24 months, with a post-crash return impact of -3.2%, causing significant losses. The Momentum Effect, analyzed across 56 studies, reveals an annualized return premium of 12% for assets exhibiting momentum characteristics, lasting 9 to 12 months. The positive risk-adjusted return (+1.2% CAPM α) highlights inefficiencies in price adjustments, as investors chase winners and sell losers, perpetuating trends. Overreaction, found in 38 studies, shows a significant 24.6% spread between losing and winning stocks over a 3 to 5-year horizon. Mispricing lasts 36 to 60 months, with a risk-adjusted return impact of +2.1% (Fama-French α). Investors often overestimate the impact of news, causing price deviations that eventually correct. Sentiment Risk, covered in 29 studies, shows an 8.5% underperformance of high-sentiment stocks over an 18 to 30-month period. The negative risk-adjusted return impact of -1.5% (4-factor α) indicates that stocks driven by excessive optimism tend to revert to fundamental values, highlighting the detrimental effects of sentiment on market efficiency.

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4. Conclusion

This paper explores the impact of behavioral biases on investor performance and market efficiency, challenging the rationality assumptions of traditional financial theories. Through a synthesis of empirical evidence and theoretical frameworks, it demonstrates that cognitive biases, including overconfidence, loss aversion, confirmation bias, and anchoring, systematically distort individual decision-making, leading to suboptimal portfolio performance characterized by excessive turnover, delayed loss realization, and inefficient information processing. At market level, these biases aggregate into systemic anomalies such as herding, overreaction, and momentum effects, which persist due to limits to arbitrage and noise trader sentiment, undermining the Efficient Market Hypothesis. The findings show that behavioral biases impose measurable performance penalties, while also creating predictable return patterns that contradict market efficiency.

Although this paper has achieved certain research results, for limitations, this research relies on Western-centric data and literature, with limited cross-cultural validation of bias intensity and impact. Future studies could address this by incorporating emerging market datasets and exploring how cultural heuristics moderate behavioral effects. Methodologically, longitudinal analyses tracking bias evolution amid technological disruption (e.g., algorithmic trading, robo-advisors) would enhance understanding of dynamic market behavior. Additionally, integrating neurofinancial insights to measure physiological correlates of biases could provide deeper mechanistic explanations, bridging psychological and financial frameworks. Such advancements would further validate behavioral finance as a cornerstone of modern investment theory, offering actionable implications for portfolio management and regulatory design.

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