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The Impact of Herding and Loss Aversion on Individual Investor Decision-Making

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ABSTRACT:

This thesis examines behavioral biases and their influence on individual investor decision-making. It focuses mainly on two biases, herding and loss aversion. The study uses traditional behavioral finance theories and prior empirical findings to analyse how these cognitive biases affect trading behavior, portfolio performance and market movements. Periods of heightened uncertainty and market stress are themain focus of the analysis, because during these times deviations from rational decision-making tend to intensify.

The literature reviewed indicates that herding and loss aversion are persistent and economically significant features of financial markets. Herding behavior is shown to be especially intense in times of informational uncertainty, leading to more synchronized trading decisions. Loss aversion on the other hand, can influence investors' responses to gains and losses, that may result in suboptimal trading decisions. While herding and loss aversion are often studied separately, the findings on this thesis propose that both biases become particularly relevant under similar market conditions. The existing literature provides limited direct evidence on whether these biases systematically reinforce one another. Overall, the study highlights the importance of behavioral finance in explaining investor behavior and market outcomes that differ from the traditional models.

KEYWORDS: Herding, Loss Aversion, Behavioral Finance, Decision-Making, Individual Investors

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Tiivistelmä:

Tässä tutkielmassa tarkastellaan käyttäytymiseen liittyvien vinoumien vaikutusta yksityissijoittajien päätöksentekoon, keskittyen erityisesti laumakäyttäytymiseen ja tappionkarttamiseen. Tutkimus perustuu vakiintuneisiin käyttäytymistaloustieteen teorioihin sekä aiempaan empiiriseen kirjallisuuteen, ja siinä analysoidaan, miten nämä vinoumat vaikuttavat kaupankäyntikäyttäytymiseen, salkun tuottoon ja markkinoiden liikkeisiin. Analyysi painottuu erityisesti epävarmuuden ja markkinastressin jaksoihin, jolloin poikkeamat rationaalisesta päätöksenteosta tyypillisesti voimistuvat.

Kirjallisuuskatsaus osoittaa, että laumakäyttäytyminen ja tappionkarttaminen ovat pysyviä ja taloudellisesti merkittäviä ilmiöitä rahoitusmarkkinoilla. Laumakäyttäytyminen on erityisen voimakasta tilanteissa, joissa informaatio on epävarmaa, mikä johtaa aiempaa synkronoidumpiin kaupankäyntipäätöksiin. Tappionkarttaminen puolestaan vaikuttaa sijoittajien reaktioihin voittoihin ja tappioihin ja johtaa usein epäoptimaalisiin päätöksiin. Vaikka näitä käyttäytymisvinoumia tarkastellaan kirjallisuudessa usein erillisinä ilmiöinä, tulokset viittaavat siihen, että ne korostuvat erityisesti samankaltaisissa markkinaolosuhteissa. Nykyinen kirjallisuus tarjoaa kuitenkin vain rajallisesti suoraa näyttöä siitä, vahvistavatko nämä vinoumat toisiaan systemaattisesti. Kokonaisuutena tutkielma korostaa käyttäytymistaloustieteen merkitystä sijoittajakäyttäytymisen ja sellaisten markkinailmiöiden selittämisessä, jotka poikkeavat perinteisten rahoitusteorioiden ennusteista.

Avainsanat: Laumakäyttäytyminen, Tappionkarttaminen, Käyttäytymistaloustiede, Sijoittajien päätöksenteko, Yksityissijoittajat

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1 Introduction

The field of behavioral finance challenges the traditional view that investors act fully rationally. In financial markets, investor decision-making is often affected by cognitive biases and emotions rather than rational analysis. These behaviors can impact market dynamics and volatility. Traditional financial theories and The Efficient Market Hypothesis struggle to fully explain market bubbles, crashes and financial crises, however behavioral finance offers a psychological view that can help us understand the reasoning behind these types of irrational market events.

Among the many cognitive biases studied in behavioral finance, herding and loss aversion receive considerable attention in the literature of individual investor decision-making. Herding in financial markets refers to investors mimicking each other by trading in the same way. Individual investors may herd due to irrational behavior, or they might think that other individuals may have better knowledge (Spyrou, 2013).

Loss aversion is a key part of prospect theory developed by Kahneman and Tversky (1979), and it is considered a core cognitive bias. Loss aversion helps to explain investor decision-making under risk. This concept proposes that investors experience losses more than equivalent gains. Investors who are loss averse are likely to hold on to losing stocks too long to avoid realizing the loss and sell winning stocks too early to lock in the gain.

These biases can result in poor investment decisions like chasing past returns, overreacting to market movements or holding on to losing stocks too long. Herding can strengthen market bubbles when many investors follow the trend and act in the same direction without their own analysis. Loss aversion may cause investors to overreact to short time market movements and miss potential opportunities. While behavioral finance is well studied there is relatively little research of these two biases together and how they affect individual investors decision-making.

In today's world loss aversion and herding are more important than ever due to social media and its ability to move information among investors. The influence these biases have on the decision-making process of individual investors may also cause financial instability and wider market inefficiencies. In 2021 the GameStop stock prices increased largely because of many investors bought it at the same time, and right after the stock price collapsed. That shows how coordinated investor behavior can lead to extreme price movements. The importance of herding and loss aversion highlights the need for more research on how these psychological biases affect decision-making from an individual investor's perspective.

1.1 Purpose of the thesis

The purpose of this thesis is to examine how herding and loss aversion affect decision-making among individual investors. While behavioral biases, such as herding and loss aversion have been studied widely, there is relatively little research on their combined impact on individual investors' decision-making. Generally, the studies on behavioral finance tend to examine behavioral biases on their own and they do not examine their interaction. Understanding how these biases might work together is important because imitating others and fearing losses can often go hand in hand in investors decision-making.

This thesis investigates herding and loss aversion and their effect on individual investors decision-making separately and together. Herding is when investors trade in the same direction by imitating each other's actions (Spyrou, 2013). Investors who have the tendency of herding are following masses and they also rely on public information rather than their own analysis (Caparrelli et al., 2004). Traditional finance theories often claim that individuals act rationally and base their decisions on all available information. Behavioral finance theories suggest that this is not the case always. This motivates the thesis's first hypothesis:

H1: Individual investors tend to imitate the trading behavior of others suggesting the existence of herding.

Secondly, loss aversion influences how investors respond to gains and losses by making potential losses feel more significant than equivalent gains. This thesis examines if this type of behavior affects investors' portfolio performance. Odean (1998) shows that investors often sell winning assets too early and hold on to the losers for too long. This type of behavior illustratates how loss aversion shapes investor behavior. Shefrin and Statman (1985) describe this behavior through the disposition effect, where investors realize gains quickly to experience pride but avoid realizing losses because of regret aversion. Barberis and Xiong (2009) further suggest that this behavior is linked to investors becoming risk-seeking after losses and risk-averse after gains. That is why, the second hypothesis is:

H2: Investors that are loss-averse tend to hold on losing assets too long and sell winning assets too early, which weakens their portfolio performance

The aim of this study is to examine how these behavioral biases interact together and whether they reinforce one another. For example, an investor who is both loss averse and prone to herding may follow others into an overvalued asset because of fear of missing out (FOMO). Then they hold on to the asset even as the prices decline to avoid realizing the loss. This leads to the third and final hypothesis:

H3: The combined presence of herding and loss aversion leads to more noticeable irrational investment behavior more than either bias alone.

A more complete view of investor behavior could be achieved by understanding how these biases interact. This thesis aims to offer a deeper understanding of their combined effect on individual investor decision-making, since behavioral biases are usually studied individually.

1.2 Structure of the study

This thesis is divided in five chapters. The first chapter consists of introduction, purpose of the study and hypotheses shape the motivation and contribution of this study. The second chapter presents the theoretical background, starting with traditional finance theories such as the Efficient Market Hypothesis, after that the second chapter moves on to behavioral finance theories. This chapter explains the main concepts including prospect theory and loss aversion, information cascades and herding theory and the disposition effect. The third chapter reviews the existing literature about herding and loss aversion and their impact on individual investors decision-making. The fourth chapter discusses the limitations of the study and has some practical implications. And the last chapter presents the conclusions, summarizing the key findings. Reference list is included after the last chapter.

2 Theoretical background

Investor rationality, market efficiency and the Capital Asset Pricing Model (CAPM) are key concepts of traditional finance theories. Yet still, these models have difficulties while explaining real-world investor behaviors like excessive trading (Subrahmanyam, 2007). Behavioral finance offers a different perspective. It recognizes the influence that systematic biases and heuristics have on investors. These factors are important for understanding market inefficiencies such as anomalies, bubbles and irrational trading patterns that traditional finance models cannot fully explain (Hirshleifer, 2001). Recognizing the limits of traditional finance and the contribution provided by behavioral finance provides a solid theoretical background for analyzing investor decision-making in the literature review part.

2.1 Traditional finance theories

Rationality and using all available information to make optimal decisions are heavily supported by traditional finance theories. This perspective views markets efficient environments where asset valuations incorporate all applicable information. Mathematical models are used to explain and predict financial behavior in traditional finance theories (Baker & Ricciardi, 2014).

Classical decision theory views decision-making as a rational process where humans are selfish, and they judge all possible outcomes before selecting the most beneficial option. Decision-makers try to choose the option that gives them the highest expected benefit and then they maximize their excepted utility (Baker & Ricciardi, 2014). Although this model gives a framework for rational decision-making, investors often must make decisions under risk and uncertainty. Classical decision theory offers a foundation for understanding traditional finance and the basic assumptions many of these theories have. The next section examines one of the most influential frameworks of traditional finance, the Efficient Market Hypothesis (EMH).

2.1.1 Efficient Market Hypothesis

In traditional finance the Efficient Market Hypothesis (EMH) is a central concept (Fama, 1970). In this model investors are assumed to be rational, and asset valuations incorporate all available information. According to Fama (1970), market is considered efficient when prices adjust quickly to new information, ensuring that higher returns are reachable only by accepting greater risk. In efficient market hypothesis, efficiency comes in three forms, the weak, the semi-strong and the strong form (Fama, 1970).

Fama (1970) suggests that under weak-form efficiency, historical data including prior price movements and trading activity is already embedded in the present market price. This implies that past prices do not help predict future movements since all relevant information from past market activity has already been included into the prices. Thus, it is impossible for individuals to earn irregular profits using trading strategies based on past trends. Prices then follow a “random walk”, where future price movements are independent of past performance. Malkiel (2003) notes that if markets entirely include all past data into prices, then future price movements will be unpredictable because prices only depend on new information.

Now if company earnings reports, economic indicators, dividend announcements and news releases are incorporated as well as past trading data it represents the semi-strong form of efficiency. Semi-strong efficiency is achieved when all data available to the public has been integrated into security prices (Fama, 1970). Now the prices adjust immediately to new information (Fama, 1970).

The strong form of market efficiency incorporates all public and private information fully into market prices (Fama, 1970). With that being said, if an investor has non-public or insider information the investor still cannot consistently earn superior returns. The strong form of efficiency assumes that no one has privileged access to information that would allow them to outperform the market. However, Malkiel (2003) finds that insiders can sometimes achieve abnormal profits by trading on non-public information and that the strong form of efficiency does not always hold in real-world situations. Despite some arguments, the Efficient Market Hypothesis continues to be a foundation of traditional finance and is still used for understanding market behavior.

Despite the Efficient Market Hypothesis being a widely accepted baseline for price reflection, it still has some flaws several empirical studies have pointed out. While information is reflected in prices, psychological and social factors also play an important role Shiller (2003). These studies show that individuals do not always act rationally and that emotions, group behavior and biases can play a significant role in shaping bubbles and crashes. Behavioral finance emerged to provide an explanation for the deviations from rationality that traditional finance theories could not fully address.

2.2 Behavioral finance theories

Behavioral finance uses insights from other sciences, like psychology, sociology and other social sciences that study human behavior to address the limitations of traditional finance theories in explaining the decision-making process of individuals (Baker & Ricciardi, 2014). Unlike traditional finance theories, behavioral finance theories do not rely on the same assumptions that individuals act rationally and that markets are always efficient. Instead, behavioral finance recognizes the fact that investors´ decision-making is frequently influenced by cognitive biases and emotions (Shiller, 2003). Behavioral finance looks to explain market phenomena such as bubbles and crashes that classical finance theories, such as the Efficient Market Hypothesis or Capital Asset Pricing Model cannot fully explain.

The following sections introduce core theories of behavioral finance including the Prospect Theory and loss aversion, information cascades and herding theory, and the disposition effect. Together these theories offer important understanding of the psychological and behavioral factors that influence individual investors´ decision-making.

Behavioral finance has become more important than ever because modern markets show investor behavior and patterns of volatility that cannot be fully explained by classical theories alone.

2.2.1 Prospect theory and loss aversion

Prospect theory developed by Kahneman and Tversky (1979), is one of the key theories in behavioral finance. This theory explains how individuals evaluate potential gains and losses under conditions of uncertainty. Kahneman and Tversky (1979) provided a critical assessment of the expected utility theory and proposed a different model for decision-making under risk. Kahneman and Tversky (1979) discovered that individuals tend to overweight certain outcomes relative to probable ones. This means that individuals prefer guaranteed results over uncertain ones even if the expected value is higher in the uncertain option.

Kahneman and Tversky (1979) propose a value function that illustrates how individuals perceive gains and losses. The function is S-shaped and asymmetric, concave over gains and convex over losses. The curve is steepest at the reference point, meaning that individuals value losses more than equivalent gains. Figure 1 gives insight on what is the negative emotional impact when dealing with losses versus the positive emotional impact when perceiving gains, forming the foundation of loss aversion (Kahneman & Tversky, 1979).

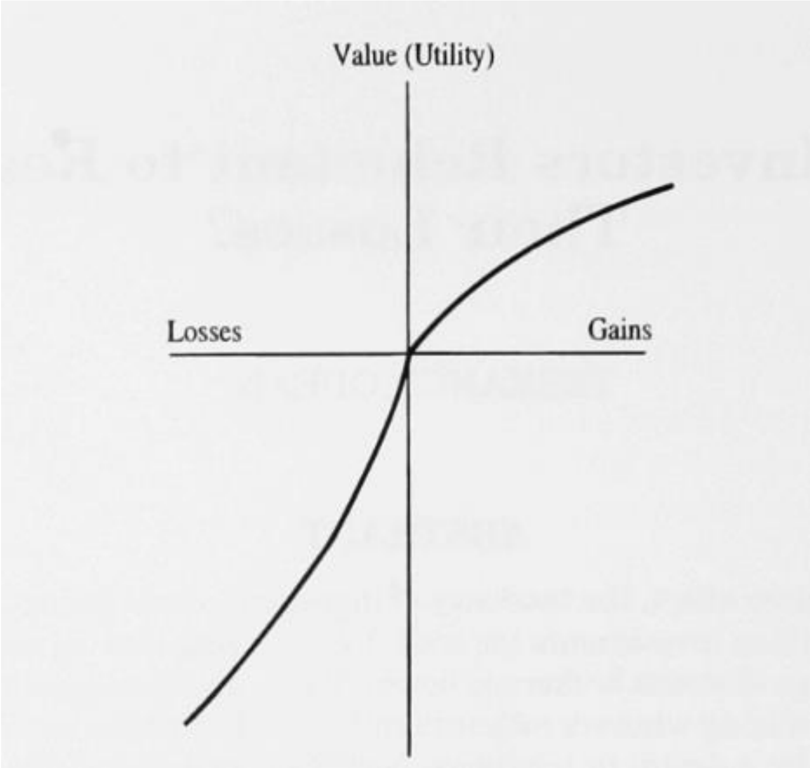

Figure 1. Value function (Odean, 1998, p. 1776)

Loss aversion is one of the key concepts in prospect theory and it refers to the tendency to experience losses more than equivalent gains. According to Kahneman and Tversky (1979), investors assess outcomes based on deviations from a reference point, not absolute values. Losing 1000$ often feels more significant than gaining 1000$, which makes this bias highly influential for decision-making and leads investors to behave more cautiously towards potential losses.

The idea that loss aversion causes individuals to keep on to losing stocks too long to avoid realizing the losses is supported by Barberis et al. (2001). Thaler (1985) also points out that investors may sell winning assets too early to secure the gains, even though they could get more profit by keeping the asset longer. This behavior is known as the disposition effect, where investors value gains and losses differently.

Kahneman and Tversky (1979) suggest that people avoid risk when they expect gains but seek risk when they face possible losses. This implies that an investor who is experiencing a loss may take on extra risk to recover it rather than accept the loss. As a result, loss aversion may lead to excessive trading and delayed selling of declining assets.

2.2.2 Disposition effect

The disposition effect means that investors often sell stocks that have gone up too soon and keep stocks that have lost value for too long. According to Shefrin and Statman (1985) the disposition effect can be explained with several behavioral factors, such as prospect theory, regret aversion, mental accounting and low self-control. Investors compare prices to the reference point, usually to purchase price rather than evaluating outcomes in terms of total wealth. Therefore, realizing the loss is psychologically painful for the investor because it signals as a mistake and causes regret. Due to that investors tend to retain losing positions in a hope for breaking even and sell winners too early to lock in the gain and experience pride.

Empirical evidence from Odean (1998) shows a clear pattern where traders capitalize on profits far more frequently than they accept losses. The study shows that disposition effect is widespread and systematic pattern in real trading behavior. This type of selling behavior can be harmful for portfolio returns, because holding on to losers for too long prevents investors to invest in better assets and selling winners too early limits potential gains. Dhar and Zhu (2006), find that the disposition effect is stronger among individuals who have smaller portfolios, lower incomes and shorter investment experience, suggesting that investors who are financially more sophisticated may be more resistant for this type of behavior. The disposition effect highlights how investors´ make emotionally motivated decisions driven by loss aversion. The fear of losses can also lead investors to follow others instead of relying on their own analysis. This behavior is known as herding, which highlights the influence of social forces on investor decision-making.

2.2.3 Information cascades and herding theory

Bikhchandani et al. (1992) define an informational cascade as a situation where a person ignores their own findings to follow the visible actions of those who moved before them. Bikhchandani et al. (1992) argue that informational cascades can be used to explain the fragility of mass behaviors and the localized conformity of behavior. Because investors can only follow what others do and not the fundamental information behind those actions, the decisions of early movers strongly influence those who follow. Banerjee (1992) finds that when individuals rely on the actions of others to guide their decisions, subsequent decisions become less informative for later decision-makers. Bikhchandani et al. (1992) highlight that once a cascade has formed, individuals resume to follow the established pattern even if their own information points to a different direction, because diverting from the crowd appears riskier. These mechanisms of information cascades form the foundation of herding behavior in financial markets.

Market herding describes a phenomenon in which many investors decide to trade in a similar way during a specific timeframe (Nofsinger & Sias, 1999). Investors then are prone to copy others rather than basing their decisions on their own. Nofsinger and Sias (1999) argue that herd behavior may help to explain different types of market phenomena, such as momentum, excess volatility and reversals in stock prices. Banerjee (1992) introduces a model of herding where individuals make decisions one after another, and each individual can see what the earlier participants answered, but not why they answered that way. Because of this, individuals assume that others may have private information. If the first participants choose the same option, later individuals may start copying them, even if their own information would suggest otherwise.

Herding challenges the traditional models that assume that investors act rationally and rely on their own information and analysis. There are many reasons on why herd behavior may occur. Investors may just be irrational and follow others due to psychological and social conventions, or investors may adjust their behavior when new fundamental information becomes available (Spyrou, 2013).

Together, these theoretical frameworks highlight that herding is not driven by a single factor but arises from a blend of psychological, informational and social mechanisms. Often individual investors have limited information and lack of confidence in their own analysis and that is why the pressure of following others may be particularly strong. Understanding why and how herd behavior occurs is important because it can destabilize prices and result in speculative bubbles in financial markets (Spyrou, 2013).

2.2.4 Measures of herding

Empirical research on herding behavior in financial markets remains relatively limited, partly because of challenges with measuring collective investor behavior. Few mathematical models have been presented to detect herding, however these methods have important limitations. Many models are designed to detect herding only under specific market conditions, such as periods of extreme price movements, and may not fully account for asymmetric investor responses. A common empirical approach is to examine the variation of individual stock returns relative to the market return. If investors make decisions independently, return dispersion should reflect differences in firm-specific information. However, when herding occurs, individuals are more probable to align their decisions with the general market opinion which causes returns to align more closely with the market return

This section focuses on two studies that examine herding under varying market environments. The first study is from Christie and Huang (1995), their approach is based on the cross-sectional standard deviation of returns (CSSD). The CSSD measures how individual stock returns deviate from the market return at a given point in time. A low CSSD value indicates that investors are squashing their own private information and following the market consensus (Christie & Huang, 1995)

The CSSD model is defined as follows (Christie & Huang, 1995):

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

where:

$R_{i,t}$ = Observed return of share i at time t

$R_{m,t}$ = Cross-sectional average return for market portfolio at time t

N = Number of assets in the sample

Equation 1. Cross-sectional standard deviation

Christie and Huang (1995) suggests that herding is more likely to occur during periods of extreme market movements and heightened stress. During these conditions, investors may ignore their own analysis and follow the general market opinion. By following the market, individual stock returns tend to have smaller deviations from the market return, resulting in lower than average dispersion during these periods (Christie & Huang, 1995).

Chang et al. (2000) propose a new model to address the limitations of the CSSD approach. The Cross-Sectional Absolute Deviation (CSAD) detects herding based on equity return behavior. The authors use a non-linear regression specification to examine the relation between the level of equity return dispersions and the overall market return (Chang et al., 2000).

The CSAD measure is defined as follows (Chang et al., 2000):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \left|R_{i,t} - R_{m,t}\right| \tag{2}$$

where:

$R_{i,t}$ = Observed return of asset i at time t

$R_{m,t}$ = Market return at time t

N = Number of assets in the sample

Equation 2. Cross-sectional absolute deviation

Chang et al. (2000) argue that the CSAD measure does not directly measure herding. Herding behavior is identified through the link between return variability and the market return (Chang et al., 2000). Under rational asset pricing models equity return dispersions is expected to increase linearly with the market return. Herding in unstable market environments may cause the normally linear relationship between dispersion and the market return to fail, resulting in a non-linear trend in either direction (Chang et al., 2000).

Together the CSSD and CSAD models provide complementary frameworks to detect herding behavior in financial markets and form the basis for empirical literature that is reviewed in the following chapter.

3 Literature review

This chapter explores behavioral biases in financial decision-making, specifically focusing on herding and loss aversion among individual investors. The chapter aims to examine how these psychological factors influence investment behavior and contribute to deviations from rational decision-making. Key theoretical frameworks including herding, loss aversion, prospect theory, the disposition effect and informational cascades are reviewed in this chapter. By combining theoretical foundations and empirical findings, it offers a broad overview of the psychological mechanisms that shape investor behavior. Special attention is paid to how these biases influence portfolio performance, trading decisions and overall market dynamics. Finally, the chapter also examines whether there is interaction between herding and loss aversion and if there is, do they reinforce each other.

3.1 Herding in financial markets

Banerjee (1992) defines herding as a situation in which individuals disregard their own analysis and follow the behavior of others in decision-making. Galariotis et al. (2015) suggests that market participant may herd for different reasons. For example, investors may form expectations by observing the decisions of others or by reacting to newly released fundamental information, analysts might herd to protect their reputation, and institutional investors may herd to protect their remuneration (Spyrou, 2013; Galariotis et al., 2015). Bikhchandani et al. (1992) argue that herding may arise through informational cascades where people follow previous actions even though their own information would suggest a different decision would be more rational.

There are different opinions among economists about the influence herding has in the market. Other scholars argue that herding could result in efficient outcomes, while some economists believe that it can also destabilize prices and lead to bubbles in financial markets (Spyrou, 2013). Mavruk (2022) finds that herding does not help investors to outperform the market or non-herding investors. When a large number of investors follow the same trend, stock prices may deviate from their fundamental values, increasing the likelihood of mispricing and market volatility (Chiang & Zheng, 2010). Galariotis et al. (2015) show that herding is a recurring factor and often appears during financial crises, when uncertainty and fear increase investors' reliance on others. Similarly, Chiang and Zheng (2010) detect stronger herding behavior in periods of high volatility, supporting the idea that investors are more likely to follow the crowd when conditions are unstable. Using data from both emerging and developed stock markets, Chiang and Zheng (2010) provide empirical evidence that herding occurs across different market environments, although its intensity varies depending on the market conditions.

Spyrou (2013) reviews empirical studies of herding across a variety of markets and time periods and finds that herding behavior can be observed many different settings, especially during unstable periods. Herding appears to be a recurring and systematic feature in financial markets (Galariotis et al., 2015; Chiang & Zheng, 2010). The following section therefore focuses on the empirical methods and findings used to measure and identify herding in financial markets.

3.1.1 Empirical evidence of herding

Empirical studies measure herding behavior in financial markets by using two main methodological approaches. Spyrou (2013) explains that one group of studies relies on micro-level or proprietary data to examine whether particular types of investors, such as individuals or institutions tend to herd in their trading behavior. The second group of studies complise price and market activity data to examine whether investors as a whole move towards the market opinion (Spyrou, 2013).

Within these approaches, several methods have been developed to detect herding empirically. For studies based on micro data, commonly used measures are presented by Lakonishok et al. (1992) and Sias (2004), who examine if specific investor groups systematically buy or sell the same stocks at the same time (Spyrou, 2013). Christie and

Huang (1995) introduced the Cross-Sectional Standard Deviation (CSSD), and Chang et al. (2000) introduced the Cross-Sectional Absolute Deviation (CSAD), these are the most influential empirical measures for market-wide analyses. These measures examine whether individual stock returns cluster more closely around the market return during periods of market stress, which illuminate as evidence of herding. Christie and Huang (1995) argue that if investors disregard their private information and follow the market consensus, return dispersions should decrease in unstable market conditions. Chang et al. (2000) build on this approach and show that return co-movements can follow nonlinear patterns consistent with herding, especially during large market swings.

Empirical studies applying these measures provide significant but mixed evidence of herding across international markets. Choi (2016) uses the herding measure proposed by Lakonishok et al. (1992) and finds that offline investors tend to herd more than online investors. Chiang and Zheng (2010) find evidence of herding in both developed and emerging markets using the CSAD measure, especially during financial crises. Similarly, Galariotis et al. (2015) find that uncertainty increases investors' tendency to follow the crowd. Galariotis et al. (2015) however find that not all crises are the same and they find evidence of herding during the Subprime crisis due to non-fundamental information in the US, suggesting that proximity and intensity of the financial turmoil might affect investor behavior.

Hwang and Salmon (2004) provide a different approach to measure herding by focusing on changes in the cross-sectional dispersion of factor sensitives rather than on return dispersions. Their measure examines whether investors' betas converge toward a common value overtime, which would signal that investors are adjusting their portfolios in a similar way and therefore herding. Hwang and Salmon (2004) applied their approach to the South Korean and US stock markets and found out that herding toward the market exhibits strong and persistent patterns that are not fully accounted for by market conditions such as return volatility or average returns. They also point out that macroeconomic factors do not explain the herd behavior.

Hasan et al. (2023) examine herding from a systemic-risk perspective in global stock markets. Their approach measures herding by conditioning return co-movements on different levels of systemic risk. By analyzing how return dispersion behaves across varying systemic risk states. By investigating herding in different market conditions Hasan et al. (2023) finds evidence that herding is almost invincible during periods of low or medium systemic risk but becomes significant when systemic risk is high. This means that market stress plays a huge role in amplifying herding behavior. Hasan et al. (2023) find that during China's market crash, volatile market conditions drove both intentional and spurious herding. During the Covid-19 pandemic, herding was primarily associated with non-fundamental factors. These results indicate that herding intensifies in extreme periods and is strongly linked to elevated systemic risk (Hasan et al., 2023).

Humayun (2018) uses the Cross-Sectional Absolute Deviation (CSAD) and augmented CSAD models to study herding among investors in the US stock market during the financial crisis of 2008. Humayun (2018) distinguishes between herding driven by fundamental and non-fundamental information and finds that commercial banks and investment banks primarily herd in response to fundamental factors, indicating that herding is spurious rather than intentional. Spurious herding intensifies when market volatility increases, suggesting that investors are more likely to follow the market consensus during extreme market conditions. On the other hand, Humayun (2018) finds evidence of herding based on non-fundamental information in low volatility regimes, but mainly on savings and loan institutions and investment banks in high volatility regime.

Choi and Skiba (2015) examine institutional herding in international equity markets by using extensive holdings data across 41 countries. Choi and Skiba (2015) find that herding among institutional investors is widespread but primarily reflects fundamental information rather than irrational crowd behavior. Choi and Skiba (2015) also state that herding appears price stabilizing rather than irrational behavior. Unlike some other studies on this subject, Choi and Skiba (2015) find no evidence for informational cascades, but rather for investigative herding.

Clements et al. (2017) examine herding in the US stock market by analyzing return dispersion among the 30 Dow Jones Industrial Average constituents. Clements et al. (2017) use a time-varying Granger causality framework to examine whether extreme market returns predict cross-sectional return convergence, which would mean that there is movement towards the market consensus. Clements et al. (2017) find episodic evidence of herding, showing that investors tend to herd primarily during periods of pronounced market stress. During extreme market conditions, such as the US debt-ceiling crisis, Chinese stock market crash and European debt crisis, Clements et al. (2017) find clear evidence of herding

Overall, Empirical findings suggest that herding is a recurrent feature of financial markets, especially during periods of heightened volatility, uncertainty or systemic stress (Chiang & Zheng, 2010; Hasan et al., 2023; Clements et al.,2017). Regardless of the model, the evidence generally shows that during periods of turbulent market conditions, investors tend to align their trading behavior closely with the broader market. However, herding is not always irrational. In some cases, it reflects investors reacting to fundamental information (Choi & Skiba, 2015). Overall, the literature suggests that herding can influence market stability, price dynamics and return co-movement. This chapter reviewed studies on herding at the market level. The following section focuses more on the behavioral and psychological mechanisms that lead individual investors to imitate others.

3.1.2 Information cascades and social learning

The idea that investors often observe the actions of others before making their own decisions is highly supported by the literature on herding. Banerjee (1992) shows that sequential decision-making creates a setting where investors treat earlier market actions as signals of superior information. The emerging crowd behavior may begin to dominate individual beliefs when new participants observe previous trades, causing later decisions to reveal less private information to the market (Banerjee, 1992). An informational cascade can develop when public actions dominate private signals. In these situations investors rationally follow the decisions of others despite having conflicting personal information (Bikhchandani et al., 1992). Once conformity takes hold, individual investors signals cease to influence decisions, making future choices driven more by prior actions than by fundamentals. After a cascade forms, later decisions stop adding meaningful private information and imitation continues even when market fundamentals no longer support the consensus. (Bikhchandani et al., 1992; Banerjee, 1992).

Because information spreads rapidly through markets, social learning can lead investors to overweight publicly observable actions while at the same time disregarding their own private assessments. Hirshleifer and Teoh (2003) observe that when investors struggle to assess the validity of market signals independently, they put greater weight on the actions of others. The authors also note that information cascades are fragile because they are not built on the fundamental strength of private information but on the assumption that earlier market participants have superior knowledge. Hirshleifer and Teoh (2003) argue that because information cascades are built on imitation rather than private analysis or information, even slightest contradictory news can trigger rapid unwinding. The authors suggest that when the informational foundation behind the cascade collapses, investors collectively reverse course and it can cause sharp and abrupt market adjustments.

Individual investors typically have less informational access and weaker analytical resources than institutional groups, so these cascade dynamics are very relevant for them. When market conditions become turbulent individual investors tend to rely on the actions of others (Chiang & Zheng, 2010; Galariotis et al., 2015). Having summarized how cascades emerge and outwind, the next chapter examines why individual investors tend to follow the crowd more than institutions.

3.1.3 Individual investors and herding behavior

Individual investors have the tendency to herd for various reasons, but the reason why they tend to herd more often than other market participants is simply because they operate with limited information and fewer analytical resources. Bikhchandani and Sharma (2000) note that individuals may assume that other investors have superior information if they start acting differently and because of that they might abandon their own investment decisions and start following the crowd. Individual investors are often uncertain about their own information, leading them to imitate others because they might view others' actions as informative signals about market conditions (Devenow & Welch, 1996). This behavior tends to appear more often during volatile or uncertain times, when investors are more likely to follow market trends than rely on their own analysis (Chiang & Zheng, 2010).

Herd behavior among individual investors may result from various social and psychological influences. Bikhchandani and Sharma (2000) argue that individuals frequently prefer conformity, aligning their decisions with the majority even when the choices lack fundamental support. Shiller (2003) observes that social channels spread popular narratives, shaping investor sentiment and fueling collective enthusiasm in financial markets. Lux (1995) demonstrates that interactions among investors can generate self-reinforcing patterns of buying or selling, as individuals imitate each other and intensify emerging market trends. Herding can also emerge even in simplified environments, implying that sequential decision-making alone may prompt individuals to coordinate their actions with others (Cipriani & Guarino, 2009). Collectively, these findings suggest that individual investors are highly vulnerable to social influence, because the urge to follow others can quickly replace independent judgment and private information.

Fear of missing out (FOMO) is another factor that can cause herd behavior among individual investors. Investors may feel pressured to participate in the same trend when they see others earning profit to avoid being left behind. Retail participants are often drawn to securities that distinguish themselves through media highlights, significant daily price swings, or unusual surges in market activity (Barber & Odean, 2008). Attention-driven buying behavior makes individual investors very open to following market trends that have already gained momentum. Individual investors who want to earn higher profits may feel like they are missing out on possible opportunities if they do not take immediate actions. That can lead investors to biased decision-making and to be ignoring facts when acting out of this fear (Gupta & Shirvastava, 2022). Rapid and trend-driven decisions caused by fear of missing out instead of careful and independent evaluations contribute to herd behavior among individual investors. Fernandez et al. (2011) point out that herding behavior is difficult to predict because many factors may influence it.

3.2 Loss aversion and the disposition effect

Several studies use actual trading data to document how individual investors respond to gains and losses, the evidence on the disposition effect is extensive. By analyzing trading records for 10,000 accounts, Odean (1998) examines the disposition effect and finds that individual investors often sell winners too early and hold losers too long. However, in December when tax-motivated selling appears this pattern disappears. Odean (1998) finds no evidence that this type of behavior is primarily motivated by a desire to rebalance portfolios. Although this behavior is statistically significant, the findings suggest that it is harmful to portfolios because returns can decrease, especially for taxable accounts (Odean, 1998). The idea that loss aversion and the disposition effect are consistent features of individual investor behavior with important implications for portfolio performance are strongly supported by the evidence.

Trading behavior and investor characteristics differ systematically among investors, and as a result, the disposition effect is not always the same for every investor. By analyzing trading records of a major discount brokerage house Dhar and Zhu (2006) find differences in the disposition bias across investors. Their findings indicates that individuals who work in nonprofessional occupation and have lower incomes have the highest disposition effect. The investors with higher wealth and more expert occupations have a lower disposition effect (Dhar & Zhu, 2006). Dhar and Zhu (2006) observe that investors who trade more often appear to be less influenced by the disposition bias. The findings indicate that investor characteristics and trading behavior play a significant role in influencing the strength of the disposition effect.

Empirical evidence of loss aversion further shows that it influences individual investors' risk-taking behavior following gains and losses. In their study, Massa and Simonov (2005) analyze a dataset covering investors' total wealth and portfolio holdings and examine how changes in wealth can affect investment decisions. They find that prior gains increase investor risk taking, and previous losses reduce investor risk taking. Massa and Simonov (2005) suggest that investors are not evaluating losses solely at the level of individual securities but respond to changes in total wealth. The idea that loss aversion shapes individual investors' portfolio risk decisions in a systematic manner, influencing how risk exposure evolves following prior gains and losses is strongly supported by Massa and Simonov (2005).

Empirical support for loss aversion is further provided by Benartzi and Thaler (1995). They present the idea of myopic loss aversion to explain investors' reluctance to hold risky assets when investment outcomes are evaluated regularly. Benartzi and Thaler (1995) suggest that individuals are loss averse and assess their portfolios often, because of that the psychological impact of short-term losses increases. Using simulations calibrated with parameters from prospect theory, the authors demonstrate that frequent evaluation of equity returns exposes investors to a high probability of short-term losses that can make stock investments unattractive to loss-averse individuals (Benartzi & Thaler, 1995). Overall, Benartzi and Thaler (1995) find that loss aversion and short evaluation periods may help to explain the reduced willingness to bear equity risk.

Many studies indicate on loss aversion indicate that it can persist over time and influence individual investors' decision-making even when the outcomes are not optimal. Barberis and Xiong (2009) analyze investor preferences characterized by reference dependence and loss aversion and show that these preferences can influence how investors evaluate their gains and losses relative to a reference point. Their analysis shows that loss-averse preferences can imply deviations from optimal portfolio choices because investors place greater weight on losses than on gains (Barberis & Xiong, 2009). These ideas explain why investors remain loss-averse even when it leads to worse portfolio outcomes.

Several studies show that investors respond differently to gains and losses. That can lead to suboptimal trading patterns and portfolio choices that can reduce investment performance over time (Odean, 1998; Dhar & Zhu, 2006; Massa & Simonov, 2005). findings also suggests that loss-averse preferences influence investors' willingness to bear risk and hold equities, particularly when investment outcomes are evaluated frequently (Benartzi & Thaler, 1995). Individual investors decision-making that may lead to inefficient outcomes is shaped by loss aversion.

3.3 Interaction between herding and loss aversion

Herding and loss aversion are often studied individually. However, many studies suggest that different behavioral mechanisms may interact in shaping investor decision-making under uncertainty (Devenow & Welch, 1996; Hirshleifer, 2001). Loss aversion shapes how individual investors evaluate potential losses relative to a reference point, which leads to asymmetric reactions to gains and losses (Kahneman & Tversky, 1979; Barberis et al., 2001). Herding on the other hand, refers to the tendency of investors copying others, often because of informational uncertainty or reputational concerns (Banerjee, 1992; Bikhchandani et al., 1992).

Research on loss aversion shows that investors' sensitivity to losses can influence their trading behavior and their willingness to take risks in uncertain environments. Studies based on prospect theory further indicate that loss-averse preferences may affect portfolio choices and asset prices by changing investors' risk tolerance after gains and losses (Barberis et al., 2001). In the herding literature, uncertainty and limited private information are often linked to a greater reliance on social signals, which leads to more coordinated behavior among investors (Banerjee, 1992; Bikhchandani et al., 1992).

Empirical evidence suppose that herding becomes stronger during times of market stress and uncertainty. During these times investors have difficulties to comprehend information and accurately assess the value of assets (Christie & Huang, 1995; Chang et al., 2000). Investors tend to trade similarly during these times, leading to more synchronized price movements and lower dispersion in returns (Christie & Huang, 1995).

At the same time, behavioral finance research indicates that periods of market stress are associated with greater sensitivity to downside risk, which increases the importance of loss-averse preferences in investment decisions. Evidence from studies on individual investors shows that loss aversion affects investors' willingness to bear risk and their reactions to poor outcomes, particularly after market declines (Shefrin & Statman, 1985; Odean, 1998). Periods of heightened uncertainty and market stress are the times when herding and loss aversion become influential. The literature often indicates that both biases occur and become stronger during these times.

Investors' uncertainty about stock prices and fear of losses may make them more sensitive to group behavior. Investors are more likely to observe the actions of others and base their decisions after others during these times. This type of behavior propose that herding and loss aversion are not only present under similar market conditions but may also reinforce each other in shaping investor decision-making during turbulent periods.

4 Discussion and limitations

This chapter points out the main implications of the behavioral finance literature reviewed earlier. It also outlines the most important limitations related to research on herding and loss aversion. Behavioral biases become more visible during periods of high uncertainty and market stress is the general conclusion these studies end up on. investors struggle to interpret information and assess fundamental values during these conditions. When uncertainty and turbulent conditions arise, herding can lead to more synchronized trading and loss aversion influences how investors react to negative outcomes and their willingness to accept risk. These behavioral patterns help explain why market outcomes often deviates from fully rational models, particularly during times of market turbulence.

Herding and loss aversion are widely studied but still have several weaknesses. Most studies examine these behavioral biases in isolation, which makes it hard to understand how different psychological biases interact and shape investor behavior. Measuring behavioral biases is challenging because most studies rely on indirect proxies, survey data, or specific market environments, which can limit the generalizability of their results. Empirical evidence that directly examines the combined effects of herding and loss aversion remains limited, making it difficult to draw strong conclusions about how these biases interact in real financial markets.

For investors, portfolio managers and financial research, the literature reviewed in this thesis have several practical implications. Individual investors should just be aware of herding and loss aversion during periods of heightened uncertainty and market stress and that could help them make better investment decisions. Recognizing these biases as risks highlights the importance of disciplined investment strategies and long-term planning that limit emotionally driven trading behavior (Almansour et al., 2023).

The evidence also has implications for institutional investors and portfolio managers. Increased market volatility and group behavior can be caused by these biases. During periods of market stress, herding can reduce the benefits of diversification and contribute to higher systemic risk. For this reason, risk management and portfolio construction may benefit from explicitly accounting for behavioral factors, which could help portfolios remain more resilient in turbulent market conditions.

The findings of this thesis point to several directions for future financial research. The limited evidence on how herding and loss aversion operate together shows the need of studying behavioral biases in combination rather than in isolation. Future research could build on this by integrating behavioral finance theory with investor-level data, offering deeper insight into how psychological biases interact and influence market outcomes.

5 Conclusion

This thesis explored how behavioral biases shape the decision-making of individual investor. The thesis focused on two biases, herding behavior and loss aversion. By integrating theoretical frameworks with empirical evidence from the behavioral finance literature, this study investigated the impact of these biases on trading behavior and market results, particularly in situations characterized by uncertainty and market pressure. In summary, the analysis provides insights into the reasons why investor behavior frequently diverges from the expectations set by completely rational financial models.

The existing literature supports the first hypothesis that investors are prone to mimic each other and disregard their own analysis. Early theoretical research shows that herding can arise when investors face informational uncertainty and observe the actions of others. That can lead them to disregard their own private information (Banerjee, 1992; Bikhchandani et al., 1992). Empirical studies reveal patterns that align with herding behavior, especially during times of market distress, when trading decisions become more synchronized and return dispersion declines (Christie & Huang, 1995; Chang et al., 2000). These findings suggest that herding forms a persistent and systematic aspect of investor behavior in uncertain market conditions.

The literature reviewed supports the second hypothesis, that loss aversion affects individual investors' trading behavior because investors hold on to losing assets too long and sell winning assets too early which affects their portfolio performance. According to prospect theory, investors evaluate outcomes relative to a reference point and place greater weight on losses than on gains, leading to asymmetric responses to market outcomes (Kahneman & Tversky, 1979; Barberis et al., 2001). Empirical evidence on the disposition effect provides support for this pattern. Investors tend to sell winning assets too early while holding losing assets for too long (Shefrin & Statman, 1985; Odean, 1998). Odean (1998) demonstrates that this behavior cannot be justified by rational portfolio rebalancing and that it impacts portfolio performance, as the assets that are sold tend to outperform those that are retained. These results suggest that loss aversion has significant economic implications for individual investors.

The third hypothesis proposes that herding and loss aversion jointly contribute to irrational investment behavior more than either bias alone is not supported by the literature reviewed. The limited evidence point out that they become more influential under increased uncertainty and market stress (Devenow & Welch, 1996; Shefrin & Statman, 1985; Odean, 1998). Review-based studies also note that multiple psychological mechanisms often operate at the same time in financial markets, especially during turbulent periods (Hirshleifer, 2001; Shiller, 2003). Because of no direct studies on these biases together the third hypothesis is not supported by the literature reviewed in this thesis.

Overall, the literature reviewed in this thesis points out the critical role of behavioral finance in explaining investor behavior and market outcomes. These behaviors and outcomes cannot be completely explained by traditional rational models. Herding and loss aversion offer important perspectives on observed trading patterns and performance effects, particularly during periods of market stress. Including these behavioral perspectives helps to develop a more comprehensive understanding of financial market dynamics and individual investor behavior.

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