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Herding behavior and market bubbles

A behavioral finance perspective

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ABSTRACT:
This thesis examines the relationship between herding behavior and market bubbles from a behavioral finance perspective. The paper discusses how different biases, social influence, and informational cascades affect investor decision-making, often leading them to mimic others rather than relying on their private information. This study aims to examine the situations where herding is the most common, such as periods of high uncertainty and volatility in the financial markets. At the core of the paper is the model of Cross-Sectional Absolute Deviation (CSAD), which is used to detect the presence of herding behavior in financial markets.

The goal is to understand how herding is currently empirically tested and explore if patterns of herding could be an early warning or indicator of specific circumstances that contribute to speculative market bubbles. The findings of this thesis suggest that herding has a significant role in increasing asset mispricing and market volatility. Therefore, it could contribute to the formation of financial instability, such as speculative market bubbles. This makes it important for investors and regulators to be aware of these risks, since there is a need for improved market transparency and investor education to reduce the likelihood of future bubbles forming.

KEYWORDS: Behavioural economics, extrapolation, investor communication, volatility, herding, decision making

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TIIVISTELMÄ:

Tässä tutkielmassa tarkastellaan sijoittajien laumakäyttäytymisen ja markkinakuplien välistä yhteyttä käyttäytymistaloustieteen ja rahoitusteorioiden näkökulmasta. Tutkielma keskittyy siihen, kuinka sosiaalinen vaikutus ja informaatioketjut voivat johtaa sijoittajia jäljittelemään toistensa käyttäytymistä, joka usein poikkeaa heidän omasta perustuvanlaatuisesta tiedostansa. Tavoitteena on analysoida tilanteita, joissa laumakäyttäytyminen on erityisen voimakasta rahoitusmarkkinoilla, kuten epävarmuuden ja suuren volatiliteetin aikana. Tutkielman keskiössä on Cross-Sectional Absolute Deviation (CSAD) -malli, jota käytetään laumakäyttäytymisen havaitsemiseen rahoitusmarkkinoilla.

Tutkimuksen tavoitteena on ymmärtää, miten laumakäyttäytymistä tällä hetkellä empiirisesti mitataan sekä tarkastella, voiko mallin avulla havaita varhaisessa vaiheessa olosuhteita, jotka edistävät spekulatiivisien markkinakuplien muodostumista. Tutkielman tulokset osoittavat, että laumakäyttäytymisellä on merkittävä vaikutus hinnoitteluvirheiden ja volatiliteetin voimakkuuteen, mikä voi kasvattaa epävakautta rahoitusmarkkinoilla. On tärkeää, että sijoittajat ja viranomaiset ovat tietoisia mahdollisista riskeistä, jotta markkinoiden avoimuutta ja sijoittajien koulutusta voidaan parantaa ja täten tulevien markkinakuplien muodostumisen todennäköisyyttä voidaan vähentää.

AVAINSANAT: Käyttäytymistaloustiede, ekstrapolointi, sijoittajaviestintä, volatiliteetti, laumakäyttäytyminen, päätöksenteko

Contents

Figures

Equations

1 Introduction

Financial markets are vulnerable to investors' behavior, as their decisions are often affected by emotions, social dynamics and psychological biases, rather than solely analytical reasoning. Many of historical episodes of market bubbles and past financial crises challenge the traditional view of finance and market efficiency. These kinds of events are, for example, the Dot-com bubble from the early 2000s, the Subprime crisis, which was followed by the global financial crisis of 2008, and more recently the GameStop phenomenon in 2021. They demonstrate that asset prices often diverge from their fundamental values, usually combined with investor sentiment, speculation and herding behavior. The deviations can lead to market bubbles and crashes, which could cause economic damages, job losses, and financial instability.

Traditional finance theories are struggling to recognise market inefficiencies that lead to investor irrationality and socially driven behavior. While market uncertainty receives a lot of attention from the public and is commonly linked to herding behavior as a cause of extreme market movements, empirical evidence often fails to explain herding as the leading factor (Spyrou, 2013). The difficulty with most of the current measures is that they fail to measure the wanted aspects of herding, which reduces the ability to explain the findings. The methods currently at use, fail to accurately measure herding due to limitations in the CAPM which will be explored in later sections.

The role of herding behavior in the formation of speculative market bubbles is an area in continuing need of active research. It is important to understand how the actions of individuals can develop into herding that pushes asset prices far from their fundamentals. Identifying the settings where herding appears and results in mispricing and market instability is important for improving theoretical models and for informing regulatory policies aimed at preventing future bubbles and crashes. Understanding which psychological biases contribute to herding can help illustrate how social and emotional influences mislead market participants away from so-called rational decision-making.

1.1 Purpose of the thesis

The purpose of the thesis is to examine herding behavior in financial markets and its possible affects on the formation of speculative market bubbles. Behavioral finance studies often prefer herding as a popular explanation for market fluctuations and deviations from efficiency (Stavroyiannis & Babalos, 2020). Herding behavior can be described investors following the actions of others instead of their own beliefs and given private information (Banerjee, 1992; Spyrou, 2013). Models by Christie and Huang (1995) and Chang et al. (2000) provide one of the most used methodologies that detect herding behavior, as they provide a foundation for most of the research conducted in the reviewed literature.

One of the main motivations for this thesis comes from the inconclusive research results that appear in related literature. The results highlight the lack of consensus regarding the precise ways in where herding behavior influences market volatility, especially during periods of uncertainty. The unclear results may be seen as a limitation of existing herding-related research, but they also highlight the complexity of investor behavior and the need for more targeted empirical approaches. Despite the increasing literature on behavioral finance and herding, there is still limited empirical research on how investor psychology and social dynamics contribute to the formation market bubbles. Therefore, this thesis seeks to answer how social influence, cognitive biases, and market conditions drive herding behavior and strengthen speculative bubbles in financial markets.

The null hypothesis for this study is based on traditional financial theories. According to the models in traditional finance the dispersion of stock returns should follow a normal distribution. Therefore, the null hypothesis of this paper is:

H0: Herding behavior has no significant affect in financial markets and does not contribute to the formation of speculative market bubbles.

While acknowledging that various factors affect asset price fluctuations and market inefficiencies, this brings up the thesis's first hypothesis:

H1: Herding behavior exists and has a significant affect on financial markets.

Secondly, if herding behavior exists in financial markets and is indeed a continuous factor there, this thesis will further explore how this kind of behavior affects financial markets, in asset pricing, volatility, and therefore potentially contributes to the formation of market bubbles. This leads to the second hypothesis:

H2: Herding behavior contributes to the formation of speculative market bubbles.

The goal is to combine existing literature and empirical results for a better understanding herding behavior in financial markets. This thesis particularly focuses on investors in general and their behavior, because most of the models this study uses aren't able to recognise which market participant causes the herding. By combining existing theoretical findings and literature, this paper aims to clarify how and when herding behavior influences asset prices and the formation of speculative market bubbles. The practical implications of this study are relevant for individual investors and other market participants, offering insights into the psychological factors that affect their decision-making. This thesis aims to support more informed and wise investment decisions, by increasing awareness of these behavioral biases, improving their future investment performance.

The scope of this paper is limited purposely to only on measures detecting herding and the factors behind investor behavior. Understanding how market bubbles are formed and measured is important, but to narrow the field of research, the subject must be excluded. However, it might be possible to state that the current methods to detect market bubbles work better than existing methods to measure herding. This being the reason why the focus is more on the current methodologies that try to catch herding.

1.2 Structure of the thesis

This study is divided in four chapters, and the structure of the thesis is organized as follows. The first chapter including the introduction, offers the motives and the contribution of this study. Chapter two provides the theoretical background, which outlines the key theories of both traditional and behavioral finance, with a particular focus on individual investor behavior and two of the most used methods for measuring herding. Chapter three presents the literature review, where related research is examined from psychological, empirical and regulatory perspectives, as it explores the connection between herding and market bubbles. Finally, chapter four summarizes the main findings and discusses future research directions.

2 Theoretical background

Traditional finance theories are based on the assumption that markets are efficient, and investors behave rationally. Regardless, financial crises have repeatedly shown that markets are prone to inefficacies. Behavioral finance, being a more recent aspect of finance, challenges the traditional financial theories, such as the efficient market hypothesis (EMH). According to Baker and Ricciardi (2014) traditional finance theories are normative and behavioral finance theories are more descriptive. Normative theories show how investors should make decisions. On the contrary, descriptive approach tries to explain why investors make the decision (Baker & Ricciardi, 2014). This chapter discusses the contrasts between the traditional theories and behavioral finance, setting a theoretical background for the analysis of herding behavior and market bubbles in the literature review.

2.1 Traditional finance theories

Traditional finance theories have dominated financial economics for most of the history of finance. These theories emphasize market efficiency, rational decision-making and the assumption that asset prices reflect all available information. Baker and Ricciardi (2014) note that decision-making requires individuals to review possible choices under uncertainty. They highlight that the classical approach of financial theories takes a normative view in decision-making. This means that classical decision theory assumes humans as rational decision makers who are selfish and optimise under constraints, trying to reach the best and the most optimal decision. Baker and Ricciardi (2014) state expected utility theory (EUT) is to show how choices are made, as it determines rational choices under uncertainty. Baker and Ricciardi (2014) point out there are different definitions of what it means to be rational. The conceptual rational differs from the rational observed.

Baker and Ricciardi (2014) indicate that the trade-off between risk and return is a key factor in investment choices. It should be noted that the trade-off has a pivotal role in modern financial theories such as portfolio theory, efficient market hypothesis (EMH), security market line (SML) and capital asset pricing model (CAPM). Even though all four of these theories and EUT are important in traditional finance, the focus of this literature review is on measuring herding rather than assessing the rationality of investor decision-making. Thus, EUT, SML and portfolio theory are excluded from this thesis. Out of traditional finance theories, this paper focuses more on efficient market hypothesis (EMH) and capital asset pricing model (CAPM), since both have an impact on the development of behavioral finance theories that will be discussed later in the theoretical framework as well.

2.1.1 Efficient market hypothesis

The efficient market hypothesis (EMH), developed by Fama (1970) is a widely used financial theory that assumes that markets are informationally efficient, where prices reflect information that is publicly available. The theory assumes that investors are fully rational. Fama (1970) divides the model's tests into three categories: weak form, semi-strong-form and strong-form. The weak form of EMH states that stock prices reflect all past trading information, including trading volumes and past prices which reflect past returns. The semi-strong-form suggests that prices reflect information that is publicly available, which includes earnings reports, news and past prices. The strong-form indicates that prices reflect all information public and private, including inside information. According to Fama (1970), investment strategies that outperform the market shouldn't exist and neither delayed reactions nor information asymmetry could be used for gaining abnormal returns.

This discussion of the efficient market hypothesis provides a foundation for introducing behavioral finance. It was developed in response to the limitations of traditional finance theories that assume fully efficient markets. A various body of research attempts to explain the failure of the EMH by appealing to psychological factors that influence human behavior (Stavroyiannis & Babalos, 2020). Recognising that efficient market theory has no primacy in determining asset prices, it's possible to understand market fluctuations by looking more at other factors (Shiller, 2014). While efficient market hypothesis may work theoretically, real-life market interactions, bubbles, crashes, and past financial crises have shown that mispricing and deviations affect the validity of the EMH. Hence, information asymmetries, behavioral biases and market irrationality can push prices far from fundamental values.

2.1.2 Capital asset pricing model

Capital asset pricing model (CAPM) is a simple model for estimating expected returns, but the model has limitations because of market inefficacies. CAPM doesn't have a specific singular developer, but the model has been formed from works of Sharpe (1964), Litner (1965) and Mossin (1966). The portfolio theory by Markowitz (1952) has also played a central role on the fundamental development of the CAPM. CAPM describes the relationship between systematic risk and expected return for assets. The model's key idea is that investors should be compensated for the risk they take and for the time value of money.

The structure of the capital asset pricing model goes as follows (Bodie et al., 2023):

$$E(r_i) = r_f + \beta_i\left[r_m - r_f\right] \tag{1}$$

where:

$E(r_i) =$ Expected return of an asset

$r_f =$ Risk-free interest rate

$\beta_i =$ Beta

$r_m =$ Market's expected return.

Equation 1. Capital asset pricing model

According to Bodie et al. (2023, p. 284), CAPM is a model that calculates expected returns on risky assets. The model is based on two sets of assumptions, one concerning individual behavior and the other related to market structure. Individual behavior forms from three assumptions: investors are rational and optimize mean-variance, their planning horizon is a single period and all of them use identical input lists (Bodie et al., 2023, p. 284). The market structure contains four assumptions: assets are publicly traded and held on public exchanges, investors can take short positions and lend or borrow at a risk-free rate, there are no taxes, and there are no trading costs (Bodie et al., 2023, p. 284).

While CAPM is widely used, it does not fully meet the requirements of empirical testing (Bodie et al., 2023, p. 283). The model's weaknesses come from its unrealistic assumptions that rarely occur in the financial markets. Baker and Ricciardi (2014) highlight that the discussed models cannot describe actual observed behavior. They suggest that normative models could fail because of the irrational acts of investors or because the models are based on incorrect assumptions. The premise used in the CAPM contradicts the existence of herding since it assumes that investors behave rationally. Understanding the formula behind CAPM provides insight to one the most used mathematical models used in measuring herding. These measures will be discussed next, as the focus shifts to behavioral finance theories.

2.2 Behavioral finance theories

Behavioral finance integrates psychological views into traditional financial theories, offering alternative explanations for market behavior that cannot be fully understood through traditional models alone. The concept of herding challenges the validity of traditional finance theories. According to Baker and Ricciardi (2014) behavioral finance uses the views from other sciences to help explain the decisions made by investors. Consequently, the theories aim to explain why investors make irrational decisions, and what is their contribution to market anomalies such as bubbles and crashes. The philosophical nature of anomalies is paradoxical, since they are recorded and do happen in financial markets, making them not anomalies. The word is either way used to describe abnormal events in markets.

This section introduces several central theories of behavioral finance. It discusses prospect theory, herding behavior, key psychological biases to understand their impact on financial markets, investor psychology and decision-making. CSSD and CSAD models are presented as the main quantitative methods used to measure herding in financial markets.

2.2.1 Prospect theory

One of the key theories in behavioral finance is the prospect theory by Kahneman and Tversky (1979). It explains how individuals evaluate gains and losses. Their research main objective was to develop an alternative for expected utility theory, which the authors criticize in their paper. Kahneman and Tversky (1979) find that likely outcomes are underweighted in comparison with outcomes that are certain. This leads to risk aversion in choices that contain certain losses, which is called as the certainty affect (Kahneman & Tversky, 1979).

Kahneman and Tversky (1979) present a decision weight function in their model, called the value function. The S-shaped function is steeper for losses than for gains and is commonly concave for gains and more convex for losses (Kahneman & Tversky, 1979). The value function depicts how individuals tend to see the equal values of gains and losses differently, weighting a greater sensitivity to the loss compared to the gain. Figure 1 gives insight on how the S-shaped function is illustrated in the model.

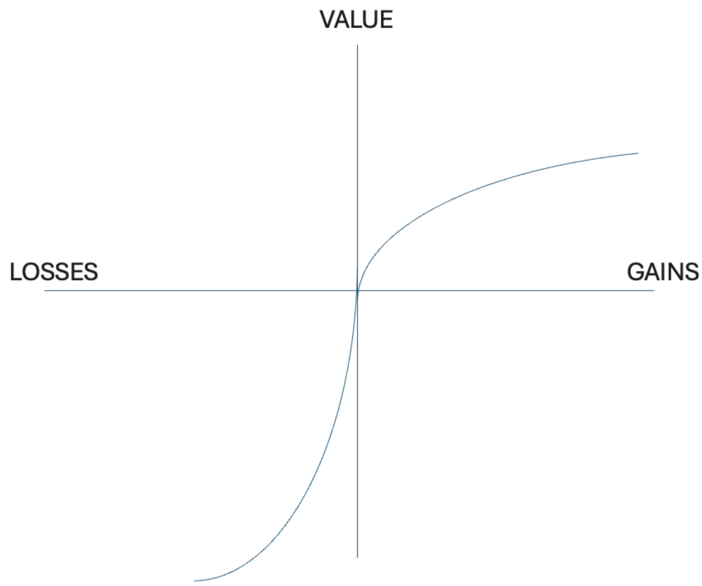

Figure 1. Value function

Barberis et al. (2021) argue that people weight outcomes by transformed probabilities rather than objective probabilities. This leads individuals to overweigh the possibility of outcomes in the tails of the distribution they are evaluating. Prospect theory is often combined with narrow framing, which is a phenomenon where individual separates their existing risks when evaluating a new one (Barberis et al., 2021).

Barberis et al. (2021) argue that, since investors are loss averse and evaluate assets in isolation to some extent, they require a higher average return on volatile assets and value assets that have volatile returns as unappealing. On the other hand, according to the prospect theory, investors tend to demand lower return from assets that have more positively skewed returns (Barberis et al., 2021), since investors overweight the tails of the distribution, placing greater focus on possible gains and losses. Additionally, the convexity of the utility function over losses and its concavity over gains, indicates that investors require higher average returns on assets in which they have already experienced prior gains (Barberis et al., 2021).

2.2.2 Herding and informational cascades

Traditional literature introducing herding behavior is conducted by Banerjee (1992) and Bikhchandani et al. (1992). Their work lays the foundation for understanding how individuals make their decisions based on the actions of others rather than their own private information, leading to herding in financial markets. This may lead to inefficient asset pricing, causing bubbles or crashes, as investors' decisions are not based on fundamentals.

Banerjee (1992) provides a model of herding, where the agents discard their own beliefs and follow others despite knowing if the previous person is correct. According to Banerjee (1992) this leads to a situation where everyone chooses the same option, as it appears to be what others believe is optimal, rather than choosing what would be optimal based on their own information. Banerjee's (1992) model first and foremost shows that rational individuals may end up following and mimicking others regardless if it contradicts with their own private information, which results in a cascade of identical decisions.

Bikhchandani et al. (1992) introduces the concept of informational cascades, which is a specific mechanism where herding can emerge. The framework of Bikhchandani et al. (1992) illustrates how fashion leaders choose a specific action, which may lead individuals to rationally choose to ignore their information and follow the crowd. This creates an environment that is fragile in decision-making. The cascade can be triggered by limited original information and is extremely sensitive to small shocks (Bikhchandani et al., 1992).

Both models by Banerjee (1992) and Bikhchandani et al. (1992) challenge the traditional view of rational and independent investors in efficient market hypothesis. Their findings underline how the timing of decisions and social learning could lead to group behavior that isn't strictly informationally efficient or optimal. In the context of financial markets, these dynamics are relevant when examining sudden falloffs or market manias. Together

Banerjee (1992) and Bikhchandani et al. (1992) provide the theoretical background for a large part of the literature in behavioral finance and herding, as they highlight how investor rationality may still lead to non-optimal outcomes through informational dispersion.

2.2.3 CSSD and CSAD models

Empirical research covering herding behavior is quite limited. There are a few mathematical models that can detect herding, but there are limitations, as they detect only extreme herding or won't consider asymmetric investor behavior. In this section the focus is on two studies that propose that herding may appear during times when market volatility is high. These periods, such as speculative market bubbles, are more common when there is increased uncertainty in the market, whilst investors may become more prone to mimicking others. This connection between market movements and investor behavior is relevant to the hypothesis of this paper.

By analysing how investor behavior changes during market volatility, the studies by Christie and Huang (1995) and Chang et al. (2000) provide empirical findings that herding exist and it may act as a driver for extreme market movements. Research by Christie and Huang (1995) is introduced first, which is then followed by research conducted by Chang et al. (2000). The two methodologies are similar, but their results and conclusion may differ (Chang et al., 2000). Both studies investigate herding behavior empirically under different market conditions.

Christie and Huang (1995) presented first empirical study that detects herding among investment behavior of market participants. The model uses cross-sectional standard deviation of returns (CSSD) to measure how individual assets return deviates from the average market return on a specific day. A low output value given by the CSSD model implies a strong appearance of herding (Christie & Huang, 1995).

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

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

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 companies in the portfolio, the sample size.

Equation 2. Cross-sectional standard deviation

Christie and Huang (1995) argue that herding toward the market consensus is most common when there are extreme market movements as well during periods of market stress. Since herding can be described as investors willingness to ignore their own knowledge to follow the market consensus, especially during unusual market movements, Christie and Huang (1995) assume that the dispersion between individual stocks and the market index returns should be significantly lower than average during extreme market movements.

Chang et al. (2000) developed a model in the context of Christie and Huang's (1995) CSSD methodology, as Chang et al. (2000) extend the approach to cross-sectional absolute deviation of returns (CSAD) as the measure of dispersion.

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

$$CSAD_t = \frac{1}{N}\Sigma_{i=t}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{3}$$

where:

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

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

N = Number of companies in the portfolio, the sample size.

Equation 3. Cross-sectional absolute deviation

Chang et al. (2000) find that CSAD itself isn't a measure of herding, therefore they use the relationship between $CSAD_t$ and $R_{m,t}$ to discover herd behavior. The original equation by Chang et al. (2000) has less variables, as Tan et al. (2008) have adjusted the equation by adding a term that allows the model to detect herding even further.

The relationship is expressed in the following form (Chang et al., 2000; Tan et al., 2008):

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t \qquad (4)$$

where:

$\alpha =$ The constant term

$R_{m,t} =$ The normal term, market portfolio's return at time t

$\left|R_{m,t}\right| =$ The absolute term, cross-sectional market index returns at time t

$R_{m,t}^2 =$ The non-linear term

$\varepsilon_t =$ The error term

$\gamma_1, \gamma_2, \gamma_3 =$ The coefficients

$CSAD_t =$ The average AVD_t, as the absolute value of each stock's deviation.

Equation 4. Measure of herding

Both models by Christie and Huang (1995) and Chang et al. (2000) offer measures for identifying herding behavior in financial markets, as they calculate the dispersion of individual asset returns around average market returns. Despite the methodological differences that CSSD and CSAD have, they provide empirical frameworks to test the presence of herding, as proposed in the first hypothesis. The models are biased to find no herding, since they are based on the CAPM. Furthermore, the models are made to detect anti-herding rather than herding, making the premises for measuring not ideal. However, the models do not explain the underlying psychological factors that affect collective behavior. To address this, the following section discusses key cognitive biases that affect herding behavior and investor irrationality, from a behavioral finance perspective.

2.2.4 Key psychological biases in finance

Investor behavior is often affected by psychological biases that differ from expected rational decision-making. In this thesis, the focus is on overconfidence and confirmation bias. These mechanisms help explain why herding behavior happens, while complementing the theoretical models discussed above. In financial markets, the biases can distort investors' perceptions of fundamentals, reduce independent thinking and strengthen herd behavior, especially when the narratives align with the already existing sentiment.

Overconfidence refers to individuals' tendency to overestimate their knowledge, abilities and prospects (Barber & Odean, 2001). According to Barber and Odean (2001) greater overconfidence leads to excessive trading and lower expected returns. They also find that men trade more frequently than women, which according to Barber and Odean (2001) is consistent with psychological literature, where men are documented with greater overconfidence. Daniel et al. (1998) propose that market over- and underreactions are consequences of investor's overconfidence about their own private information and distorted self-attribution. They also argue that overconfident investors tend to overweight signals that confirm their beliefs. This tendency is also known as confirmation bias.

Rabin and Schrag (1999) develop a model to detect confirmatory bias. The model discovers that confirmation bias leads individuals to become overconfident in their beliefs, even when they are incorrect (Rabin & Schrag, 1999). Their framework shows that confirmation bias can continue despite the availability of large amounts of information, and investors can have incorrect conclusions with high confidence. According to Bodie et al. (2023, p. 384), if investors receive positive information about the stock markets future performance, they will confirm their existing beliefs and push prices even further, because they interpret the signals too optimistically.

3 Literature review

One fundamental question regarding the research and existing theories in financial markets, is what contributes to price fluctuations of speculative assets (Shiller, 2014). Simultaneously, they suggest there is an acceptance that financial markets are essentially guided by psychology, but this agreement isn't congruent between the parties. This contradiction between efficient market supporters and those who believe in behavioral finance has led to disagreements over whether herding behavior or market bubbles actually exist (Shiller, 2014; Barberis et al., 2018; Stavroyiannis & Babalos, 2020).

The detection of herding behavior depends heavily on the testing procedure, the testing period and the financial market being analysed (Stavroyiannis & Babalos, 2020). Therefore, the empirical results may vary regarding whether herding can be detected in the market and to of what significance. In the context of CSAD model, the stock returns are explained by the CAPM, which is why significant deviations that differ from the model's predictions may indicate herding behavior (Stavroyiannis & Babalos, 2020). The CSAD model assumes that stock dispersion, like non-linear increases or decreases, are a signal of market-wide herding. The opposite is expected by rational asset pricing models. As noted, because rational asset pricing models, for example CAPM, are not able to capture market reality as it is, it's difficult to assume that the CAPM's reverse reaction would be evidence of market-wide herding.

According to Galariotis et al. (2015) there are two main trends in the empirical literature related to herding, as one focuses on institutional investors herding and another that analyses aggregated data from market and explores herding towards the market consensus. This thesis focuses more on the latter, as it directly relates to the central research question and the second hypothesis of whether herding behavior contributes to the formation of market bubbles.

This chapter analyses recent empirical findings to explore whether there is a connection between herding behavior and market bubbles, and how existing literature characterizes herding as a potential amplifier of mispricing. Additionally, this section studies what psychological and environmental factors affect investor decision-making under different market conditions.

3.1 Herding in financial markets

Spyrou (2013) suggests that different market participants may herd differently and the factors behind herding behavior could vary. Galariotis et al. (2015) indicate that herding behavior is driven by multiple factors, although they refer herding as market participants changing behavior towards the consensus and trading in the same direction. Investors may behave irrationally and herd because of social or psychological interactions, analyst could herd to protect their reputation, institutional investors may do so for compensation-related reasons and some investors may simply herd in response to appearance of fundamental information (Spyrou, 2013; Galariotis et al., 2015).

Spyrou (2013) points out that economists suggest herding behavior could contribute to price instability and therefore result in bubble-like periods in financial markets. Barberis et al. (2018) define financial market bubbles as a situation where the price of an asset rises exponentially during a short period of time and reaches value which is far above the asset's future cash flows. The price increases are usually involved with high trading volumes and extensive speculation (Barberis et al. 2018). Financial crises and past market bubbles often reveal herding as a recurring factor, which existing literature also suggests (Spyrou, 2013; Galariotis et al., 2015; Humayun, 2018).

However, the main empirical methods CSSD and CSAD, have limitations that won't allow economists completely to understand the herding process (Spyrou, 2013). According to Spyrou (2013) there are restrictions with the existing measures of herding, which could partially explain the unclear empirical evidence. The current empirical tests measure herding indirectly and require strong assumptions, while they leave out specifics such as investor status. It is fair to assume that one of the main limitations for herding related research is the lack of appropriate methods. Next, the current empirical evidence on herding is discussed, as well as the market conditions where it is strongest, and the financial instability it may cause.

3.1.1 Empirical evidence of herding

The empirical evidence that detects herding often relies on the works of Christie and Huang (1995) and Chang et al. (2000), as they are widely used in academic studies examining return dispersions as a substitute for herding behavior under different market conditions and asset classes. As discussed in the theoretical background section, the model by Chang et al. (2000) measures herding as statistically significant deviation from the prediction of asset pricing model. Stavroyiannis and Babalos (2020) highlight that if investors disregard their individual information and therefore herd, the dispersion of returns will deviate from the expected linear response to the market. Much of the existing literature reviewed in this thesis uses the CSAD model, often with adjustments, as different authors incorporate additional variables to detect herding in their altered versions. These are for example models by Galariotis et al. (2015), Humayun (2018) and Stavroyiannis and Babalos (2020). It's important to interpret the empirical results with caution, as mentioned earlier, the testing measures of CSSD or CSAD don't capture herding as intended.

Galariotis et al. (2015) find a connection with investor behavior and macroeconomic news. Their findings reveal statistically significant evidence of herding behavior towards the market consensus on days when there are important macroeconomic announcements made in the US, which reflects in stock price movements. Galariotis et al. (2015) find that in the US, herding is a result of both fundamental and non-fundamental factors, documenting differences between crises. Their results show that during the Russian and the Asian crises, herding was primarily a response to fundamental information, whereas during the Subprime crisis, it was mostly triggered by non-fundamental information. In contrast, investors from the UK herd primarily in response to fundamental information, only during specific event such as the Dot-com bubble burst (Galariotis et al., 2015).

Results from Humayun (2018) are equal to the findings of Galariotis et al. (2015), as they examine the reactions to fundamental and non-fundamental information. Humayun (2018) finds herding in their model, especially among investment banks and commercial banks during periods of financial stress and heightened volatility, implying that specific herding is spurious. Humayun (2018) detects that investors herd in response non-fundamental information even when the volatility is low. These results are observed in all financial institutions, as the author suggest that the spillover affects of herding are limited when investors encounter non-fundamental information (Humayun, 2018).

The results from Galariotis et al. (2015) suggest that the causes of herding behavior are dependent on specific period and country. These results go together with the findings from Chang et al. (2000), Clements et al. (2017) and Stavroyiannis and Babalos (2020), where they detect no herding or anti-herding when the full sample period and stocks are being used, but do find herding when the sample size and variables are narrowed down.

Stavroyiannis and Babalos (2020) also report mixed evidence on herding behavior, as they document herding behavior in the eurozone on two different periods, first from the beginning of sample period until 2009 and the second from the beginning until 2012. However, Stavroyiannis and Babalos (2020) find that when regression parameters are allowed to vary over time, as suggested by the stochastic volatility model, the results are changed, showing signs of anti-herding behavior across the full sample.

On the other hand, Clements et al. (2017) find clear evidence of herding as they use different empirical framework, called Markov-switching framework, that allows time-varying regime shifts in investor behavior. Results from Clements et al. (2017) reveal that herding appears in short-lived episodes, especially during periods of market stress. They identify herding during periods that line up with the subprime crisis, the European debt crisis, the US debt-ceiling crisis and the Chinese stock market crash. The findings show that herding has an essential role during market distress (Clements et al., 2017).

Pochea et al. (2017) measure herding in CEE capital markets, using quantile regression analysis. According to them, the analysis offers more detailed image of conditional distribution returns on CSAD. The findings detect herding behavior on all CEE markets, excluding Poland and Romania. The quantile regression analysis gives an overview of the relation between dispersion measure and the descriptive variables (Pochea et al., 2017). According to the authors the estimators are generated by minimizing the weighted sum of errors given a set of quantile values, which is a suitable estimation approach when extreme values are present.

Choi and Skiba (2015) study institutional herding by using holdings data. They find that herding is widespread in international markets. Choi and Skiba (2015) document herd behavior in 41 countries, where the presence of institutional investors is significant. The results suggest that herding has a price stabilizing affect rather than resulting in irrational behavior. This contradicts previous findings from herding-related literature, where it is suggested that herding could cause asset mispricing. Choi and Skiba (2015) indicate that herding is probably based on fundamental information, which is also found by Galariotis et al. (2015). Choi and Skiba (2015) refer herding as a mechanism that incorporates fundamental information into asset prices.

Deng et al. (2018) examine if mutual fund herding have affects on corporate announcements and if it results in stock price crashes. They adopt a similar approach to that used in the Choi and Skiba's (2015) model, finding that the herding reduces the quality of corporate disclosure. The authors detect strong predictive correlation between asset price crashes and institutional herding, as they combine datasets from stock returns and accounting. They discover the relationship to be more concentrated in buy-herding rather than sell-herding. The findings from Deng et al. (2018) are opposite to the results from Choi and Skiba (2015), even though they both find institutional herding in their models. Deng et al. (2018) reason that a strong buy-signal from mutual fund herding can serve as a warning to holding investors, which could affect asset prices.

All the literature discussed above, detect herding to some extent in their models. The measurements and empirical results may differ from each other. Some of them leave a research gap to investigate what is the underlying reason for herd behavior. The literature acknowledges that it is common sense, that herding happens in all markets all the time. However, if bad methods are used, where the results are based on false set of assumptions like CAPM, CSSD and CSAD, poor results should not come as a surprise. Next, one of the possible reasons for herding behavior is discussed as the focus moves on extrapolative expectations.

3.1.2 Herding and extrapolative expectations

Thoma (2013) finds that bubbles are more common when the tendency to herd is greater. Other studies show that herding behavior and phenomenon that are bubble-like can be the result of psychological incentives or consequence of irrational investors (Galariotis et al., 2015). Barberis et al. (2018) argue that extrapolation is at the core of the conventional historical narrative of bubbles. Extrapolation can be seen as investors basing the formation of expected returns on past returns (Barberis et al, 2018). Meaning investors tend to buy assets that have gone up in prices, expecting that the prices will keep going up.

The evidence from Barberis et al. (2018), Han et al. (2022), Schaal and Taschereau-Dumouchel (2023) and He et al. (2024) suggests that investors often extrapolate recent trends into the future, which could lead to coordinated behavior like herding. Thoma (2013) uses simulation-based analysis and discovers that even small increases in the tendency to herd could lead to a notable increase in the frequency of market bubbles. Thoma (2013) finds that increasing the herding parameter from 0.05 to 0.15 increases the appearance of bubbles from 1.35 to 12.71 occurrences per 250 years in the simulations. This suggests that financial markets may become more volatile with even small changes in the investor behavior.

Evidence from He et al. (2024) suggests that both corporate managers and individual investors are prone to extrapolating stock returns and economic fundamentals, often becoming overoptimistic following positive news and being pessimistic after negative ones. This is also documented by Barberis et al. (2018), once the news of positive cash flows comes, they push prices up, leading extrapolators to increase their demand on stocks for the following periods, pushing prices far above their fundamentals. The same phenomenon is also found in the model of Han et al. (2022), where volatile assets are discussed more in social networks, increasing the demand in these specific shares and thus pushes their prices even higher. Extrapolative expectations are a behavioral mechanism, where herding behavior can boost market bubbles, as investors overreact to short-term trends in financial markets.

Schaal and Taschereau-Dumouchel (2023) show how rational herding combined with extrapolative expectations, could lead to economic booms and busts, even when there isn’t an exogenous shock. In their model investors receive overly optimistic signals, leading to increased investments, which therefore can be misinterpreted as strong fundamentals. This leads to an extrapolative process, where past success is projected into the future until the economy reaches a peak. According to Schaal and Taschereau-Dumouchel (2023), when the peak is reached, it is followed by a crash once the agents realize their mistakes.

While much of the literature suggests that increased uncertainty amplifies herding behavior (Thoma, 2013; Galariotis et al., 2015; Clements et al., 2017; Humayun, 2018), recent research from Andrei et al. (2023) highlights that economic uncertainty plays a major role influencing investors’ focus on fundamental information, such as firm-specific data. The findings of Andrei et al. (2023) show that investors process earnings announcements more in depth when uncertainty in financial markets is high. Results by He et al.

(2024) suggest that macroeconomic views have a stronger influence on firms that are more risky, unprofitable and smaller.

The findings from Andrei et al. (2023) are in contrast with behavioral finance interpretations, where uncertainty often leads to noise trading, panic-driven behavior and mispricing. Taken together, these perspectives suggest that the affect of uncertainty on investor behavior is shaped by the broader information environment and the market participants involved. This highlights the importance in understanding how investors process information and how their attention may be influenced. Therefore, the focus moves on to the psychological and behavioral factors behind herding behavior. Particular attention will be in cognitive biases and emotional factors that can affect individual decision-making.

3.2 Psychological and behavioral drivers

Understanding the psychological and behavioral factors behind herding behavior is essential for explaining why investors often deviate from conceptual rational decision-making. Research in psychology suggests that memory is associative, which means that individuals are more likely to recall past information that is comparable to new information (Enke et al., 2024). Clean empirical evidence on memory's role in financial decision making is limited, even though the theoretical interest in memory has increased (Enke et al., 2024). Shiller (2014) argues that speculative bubble is a consequence of social psychology interacting with imperfect information channels and the influence of news media. The purpose of this section is to explore the psychological factors behind herding, and to examine how the literature discusses the impact of social media and environmental factors in investor behavior.

3.2.1 Social and informational cascades

Pedersen (2022) suggests that investors may learn via social networks, which can lead them to deviate from fundamental views for extended periods. According to them this disagreement is variable over time and can be predicted based on the structure of the social network. Pedersen (2022) argues that the dispute has potential to increase market volatility and contribute to the formation of speculative bubbles. This is also shown by Kim et al. (2023), who indicate that the behavior of individual investors can be affected by social media influence, and therefore, lead to informed irrationality in trading in the stock market. Han et al. (2022) present similar findings in their theoretical model, where they study how investment strategies are transmitted in social networks, and how distortions in the information transfer process affect decision-making and economic outcomes.

The study by Kim et al. (2023) shows that information through social media is perceived as more valuable. It can make individual investors think that they are more informed of market fluctuations and stock's price development, even if the information obtained is neither accurate nor new. Spyrou (2013) explains that when entering the market at a later stage, it may be optimal for investors to ignore their own private information and instead follow the trading behavior of earlier investors, if those investors have had access to better or more timely information. However, this assumption can reduce independent decision-making and encourage herding behavior, because more participants begin to rely on observed actions rather than doing their own analyses. According to Spyrou (2013) informational cascades can influence rational individuals, leading to the formation of bubbles.

The findings of Spyrou (2013), Pedersen (2022) and Kim et al. (2023) agree with theories in behavioral finance, especially with information cascades. In this context, social media increases the illusion of informed decision making, which leads investors to mimic other investors, assuming they are better informed. This interaction increases the possibility of herding behavior, asset mispricing and potential bubbles, as participants on the market rely more on the popularity of information rather than its validity.

3.2.2 Behavioral biases in financial decision-making

In the Pedersen (2022) model, the views of naive investors are based on the rational and fanatic views in the long run. Hence, the prices are dependent on these views and their relative influence on the market. The social dynamics may push asset prices far above their fundamental values, causing bubbles, or pull them below their fundamentals, leading to anti-bubbles (Pedersen, 2022). This is also illustrated in the model of Mendel and Shleifer (2012), where uninformed but allegedly rational investors chase noise as it were informative, moving prices far from their fundamental values and amplifying market shocks.

According to Enke et al. (2024), since memory is associative, it means that investors may reconstruct past information in a biased way, as they unconsciously retrieve past information that is similar to current news. This tendency aligns with the concept of confirmation bias, where individuals tend to favour information that supports their existing expectations or beliefs. As a result, the way investors process and internalize information can indirectly lead to behavior that resembles an overreaction to news (Enke et al., 2024). Together, these cognitive processes can appear overly optimistic or pessimistic narratives in financial markets, which can make investors more prone to herding or trend-following behavior.

3.3 Policy and market implications of herding

Since herding behavior can contribute to the formation and eventual collapse of market bubbles, it is important to recognise the role that regulators and policymakers have in promoting market stability and in limiting systematic risks. When investors abandon their own judgement and follow the crowd and herd, asset prices can deviate from their fundamental values. This can increase the possibilities of market mispricing and greater volatility. These affects create challenges for the market efficiency as well to financial stability. As a result, policymakers face two tasks, one to improve the transparency and spreading of information, while exploring regulatory measures to moderate excessive speculative behavior. This section examines few examples from past speculative market bubbles and then the possible policy implications. The focus is on how regulation can be used to manage the risks associated with investor decision-making in financial markets.

3.3.1 Financial instability and bubbles

Periods of financial instability are often accompanied by phases of extreme optimism. Schaal and Taschereau-Dumouchel (2023) argue that the Dot-com bubble happened because of herding behavior, where investors first overreacted to relatively positive information about IT technologies. Schaal and Taschereau-Dumouchel (2023) state that the economy entered a false-positive state, in which over-optimism fuelled an investment boom that was eventually followed by collapse as more detailed information emerged and investor sentiment turned pessimistic. This illustrates how endogenous mechanisms, driven by herding behavior, can create boom-bust cycles in financial markets, even when there is the absence of fundamental shocks.

Pedersen (2022) offers an example of the GameStop saga, which can be seen as a textbook case of bubble formation, which is caused by interactions in social networks and herding. According to Pedersen (2022) the GameStop phenomenon had multiple of the elements they include in the model. First, an investment strategy spreads in social networks and fanatical views become more dominant over time. Then the contagious investment idea results in impacting prices, starting a bubble (Pedersen, 2022). Prices begin to rise even further, when momentum investors ride the bubble while some investors bet against it, resulting in rising volatility and trading volumes (Pedersen, 2022). The Pedersen (2022) model and what happened with GameStop, has similar findings that

Mendel and Shleifer (2012), Han et al. (2022) and Kim et al. (2023) have, where information through social networks starts affecting investment strategies, resulting in price fluctuations and the formation of market bubbles.

3.3.2 Regulatory responses and policy tools

Fontanier (2025) analyses behavioral finance crises and offers guidelines for policies during these times. The findings highlight that known components of behavioral biases should be monitored because they can create losses during uncertainty. According to Fontanier (2025), individuals who display excessive pessimism during financial crises may over-borrow in good times, failing to acknowledge how their biases could shift over time. Since the interaction between financial factors is essential, the expected losses tend to be greater when excessive pessimism is combined with more severe financial crises (Fontanier, 2025). The consequences that over-borrowing and lending have, could be reduced through monetary policy, depending on the measures taken by central banks.

Fontanier (2025) finds two results that stand out in the model. The first one is that the probability of crises becomes higher as the over-optimism increases during good times. According to Fontanier (2025) this is due to an interaction with extrapolation of prices and different time periods, where over-optimism pushes up asset prices and makes the reversal steeper. Extrapolation is also discussed in the previous section, where Barberis et al. (2018), Schaal and Taschereau-Dumouchel (2023) and He et al. (2024) find that extrapolation and overreaction are at the centre of bubbles. These factors are the same reason why financial crises are more intense (Fontanier, 2025).

The second key finding from Fontanier (2025), is that the optimal policy response during a crisis becomes less aggressive. This occurs because macroprudential policy has positive second-round affect by reducing leverage, which in turn influences price expectations. As the economy transitions into a crisis period with higher net wealth, asset prices are better supported, which thereby reduces the extent of over-pessimism (Fontanier, 2025).

The findings suggest that proactive macroprudential measures strengthen financial resilience but at the same time temper behavioral biases during downturns.

Schaal and Taschereau-Dumouchel (2023) highlight that government policies may have a large impact on the magnitude and duration on market bubbles, likewise, affecting the timing and depth of the collapse. The model can predict the conditions where boom-bust cycles often emerge, as it calculates the frequency and timing of potential bubbles (Schaal & Taschereau-Dumouchel, 2023). Their framework can be used to analyse how stabilization or monetary policy interventions might affect the dynamics of herd-driven investment cycles. For instance, by adjusting interest rates or making financial information more transparent, policymakers could potentially reduce the link between investor optimism, capital allocation and overall market sentiment. The models developed by Schaal and Taschereau-Dumouchel (2023) and Fontanier (2025) offer valuable tools for understanding not only the endogenous formation of bubbles but also the policy tools available to lessen their macroeconomic consequences.

4 Conclusion

This study examines herding behavior in financial markets, and its contribution to the formation of market bubbles. The thesis's findings confirm that herding behavior is an existing phenomenon in the financial markets, that becomes more intense during periods of heightened market uncertainty. These results are in line with behavioral finance and descriptive theories, which suggest that investors often rely on the behavior of others, rather than making decisions based on individual analysis. The study supports the view that psychological biases affect market movements and asset pricing.

The first hypothesis that herding behavior appears on financial markets is supported by earlier empirical studies by many authors. Studies by Chang et al. (2000), Galariotis et al. (2015), Clements et al. (2017), among others, provide equal evidence of herding behavior under different market conditions. Based on the results discussed in the literature review, the first hypothesis can reasonably be considered true. Empirical studies constantly show that herding intensifies under specific market conditions, which are high volatility, economic uncertainty and during periods of macroeconomic announcements. The thesis's findings propose that herding is not a constant factor in market behavior, and it tends to appear more in times of stress or uncertainty.

One key insight from this thesis is that herding behavior and extrapolative expectations often expand one another. As shown in the models of Barberis et al. (2018), Schaal and Taschereau-Dumouchel (2023), He et al. (2024) and others, investors can overreact to recent trends and information. The reaction can have an impact on asset prices and the formation of bubbles. Moreover, the role of social networks and social media can increase this dynamic by spreading the publicly shared views and affecting observed trends (Shiller, 2014; Pedersen, 2022). Based on the functional measures reviewed, but also based on logic and reality, multiple factors, such as market uncertainty, volatility, extrapolative expectations, social networks, market interactions and investor behavior, all play a role in increasing herding behavior in financial markets. Even though both CSSD and CSAD are widely used methodologies in research on herding, this paper questions the models’ ability to detect herding. Most of the results with the models are unclear and they detect little to no herding, or anti-herding during sample periods where herding could be assumed. In addition, the relationship between herding and other variables are closely linked and possibly have a two-way relationship. Meaning that, herding can contribute to price fluctuations which increases uncertainty. Making herding not only a consequence of market stress factors but also a concept that feeds on itself.

What comes to the second hypothesis, which claims that herding behavior contributes to the formation of speculative market bubbles, the findings are partially supported by existing literature. Several studies report similar results. Clements et al. (2017) find a connection with herding behavior and periods of market distress and detect that herding appears in short periods that are in line with the history of financial crises and bubbles**.** However, it is still unclear whether herding contributes to the formation of market bubbles, or whether heightened uncertainty in financial markets causes investors to herd, creating a chicken and egg problem.

The research is quite limited by the fact that it is based on secondary data and there are only few published empirical models that can detect herding. Even though it is widely known fact that herding affects financial markets all the time, there is a need to specifically mention that the current empirical models are biased to find no herding. For future research directions, more work could be done to develop and test new methodologies for detecting herding behavior in real-time. Empirical studies across different markets could help clarifying the conditions where herding affects the most. Investigating which market participants cause the herding would open an avenue for future research.

Disclaimer: This thesis utilized OpenAI’s program ChatGPT, to help in refining the structure for the thesis and for giving suggestions for grammatical improvements. All research findings, analysis and written content are the result of the authors own critical thinking, and the final content of the thesis is on the full responsibility of the author.

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