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Herding behavior in the US stock markets

Does market capitalization matter?

Finance
Master's thesis in Finance
The School of Accounting and Finance

Vaasa 2022

UNIVERSITY OF VAASA
The School of Accounting and Finance
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Thesis: Herding behavior in the US stock markets
Degree: Master of Science in Economics and Business Administration
Subject: Accounting and Finance
Supervisor: John Kihn
Year: 2022
Pages: 89

ABSTRACT :

Herding behavior has been recognized as a significant factor and phenomenon in investors' decision-making process. Herding as a concept derives from animals and has analogously been adopted by economists to describe comparable human behavior in financial markets. This phenomenon applies to both individual and institutional investors, the difference being mostly in the causes and effects of the behavior.

This thesis aims to sufficiently review recent literature of the herding effect in financial markets and conduct an empirical study that measures the intensity of herding in different equity indices. The empirical testing of the thesis focuses on the S&P 500, S&P 400 MidCap and S&P 600 SmallCap. The goal is to evaluate if the size of market capitalization influences the volume of herding in markets. In addition, a similar comparison is conducted between a value stock index and a growth stock grouping. The paper also introduces the herding concept and reviews its various forms.

Particularly compared to more recent literature, the results are at least partially consistent with earlier research. The literature review shows that herding research results have experienced some transformation over time. More recent studies seem to yield more robust evidence of herding. This may be due to enhanced research methods. This study applies the CSAD-model that has received some criticism of its ability to detect herding.

Although, at standard statistical levels, and consistent with studies that use the CSAD measure of herding, the full sample testing results of this thesis find no evidence of herding. In contrast to full sample results, statistically significant evidence of herding behavior is found in more focused sample sets. For example, year by year and other data arrangements reveal significant evidence of the occurrence of herd behavior. This study also finds evidence of correlation between herding and volatility. The sample period as a single entity does not reliably show that investors consistently herd toward specific stock characteristics, rather it depends on market conditions. One observation from the results is that investors tend to herd toward large-cap stocks in times of high uncertainty. Tests on large capitalization growth stocks reveal that they have experienced significant herding in the last few years.

KEYWORDS: Behavioral finance, Herding behavior, Market efficiency, US stock market, S&P 500, S&P 400 MidCap, S&P 600 SmallCap, Market capitalization

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Abbreviations

BF	Behavioral Finance
CAPM	Capital Asset Pricing Model
CSAD	Cross Sectional Absolute Deviation
CSSD	Cross Sectional Standard Deviation
EMH	Efficient Market Hypothesis
FAANG	Facebook, Amazon, Apple, Netflix, Google
FTSE	Financial Times and Stock Exchange
GP	Growth portfolio
S&P	Standard and Poor’s
UK	United Kingdom
US	United States

1 Introduction

Generally, in the behavioral finance literature herding behavior describes the correlation in investment decisions that are a result of interactions between investors. The phenomenon has been studied extensively in an attempt to uncover where the urge to risk one's own money solely based on others' actions originates from. Bluntly stated, why would rational human beings act as "sheep", as Shiller (2015) describes them, when making investment decisions? Obviously, successful investing can significantly influence an individual's level of their autarky. When given the opportunity to gain relative individual prosperity, and assuming that equity markets can provide differential financial performance, would it not be logical to assume that people want to stand out and separate themselves from the "pack"?

The ability to answer these kinds of questions derive from the fundamental limitations we have as humans (Simon, 1986). Kahneman and Tversky (1979) have provided some outstanding explanations for the effects the human mind has on people's behavior in the economic field. Our desire to be perceived as capable as others, our need to be accepted as a part of the group and the aversion we demonstrate towards personal losses all hinder us from behaving with clinical callousness and logic in investment activities as well as in other areas of life.

1.1 Purpose and motivation for the study

This thesis aims to outline herding behavior in the context of stock markets. The purpose is to research herding in the United States (US) stock markets, focusing on three major indices: (1) S&P 500, (2) S&P 400 MidCap, and (3) S&P 600 SmallCap. The intention is to discover if herding occurs with alternating levels of intensity in the different indices. In other words, the primary intent of this thesis is to investigate if market capitalization influences herding propensities. This thesis will conduct an empirical study on all three indices and compare the results to see if, ceteris paribus, the degree of herding is significantly different when comparing one index to another. In addition, the study will similarly compare a basket of large-cap growth stocks to a basket of value stocks to determine if return chasing is more prevalent in one relative to the other. The thesis will also introduce and briefly assess the renowned models for detecting herd behavior in financial markets, and how they have been applied and modified by various researchers.

Herding behavior in financial markets can lead to significant mispricing of assets. To understand the fundamental differences in assumptions towards investment behavior, this thesis separates the opposing views to the categories of traditional or standard compared to behavioral finance. The traditional view is predominately based on three parts: (A) the standard efficient market hypothesis (EMH) as put forth by Fama (1970), (B) investor rationality (and the underlying assumptions of the notion), and (C) unlimited arbitrage. In contrast, behavioral finance is more focused on investor psychology and limits to arbitrage (Barberis & Thaler, 2003).

It has been suggested by academics and researchers that behavioral finance has emerged as a counterforce to various 'anomalies' in the financial markets (i.e., a phenomenon that cannot be explained by traditional theories and models). Several stock crashes and financial crises throughout history have escalated research towards the behavioral approach and, as a result, the influence of human psychology has been adopted and recognized as a significant factor in the investment decision making processes.

In recent history, the consensus seems to be that herding behavior is firmly connected to different kinds of crashes and crises. Christie and Huang (1995), among others, suggest that herding can also be used as an explanation for over-proportional volatility in stock markets and therefore stock returns. As mentioned, herding behavior can lead to price instability, and researchers have expressed concern for its tendency to inflate bubbles and cause severe chaos in markets over time (Spyrou, 2013).

This thesis is motivated by economists' interest in both market behavior and the psychology of individual decision making (De Bondt & Thaler, 1985). Behavioral finance is commonly considered to be a field within finance that often proposes psychology-based theories to explain financial market 'anomalies' (Qawi, 2010). Herd behavior, a derivative of zoology and psychology, is often cited as one of these explanations. The effects of herding in stock markets have been debated over time and the results of empirical research have also been considered inconclusive (Spyrou, 2013).

One popular measurement model for herding is the Cross-sectional absolute deviation model (CSAD) introduced by Chang, Cheng and Khorana (2000). The model is another motivation for this study, and it is used in the paper's empirical research. While the model is intended for measuring herding, it is difficult to categorically quantify why certain investment decisions are made. To absolutely identify that an investment decision is herding, one would have to interview the decision-maker and seek an honest admission of herding. That kind of scenario implausibly and minimally assumes both truthful answers for each investor involved and accessibility to all decision-makers, and as a result, given current methods, a highly improbable research outcome.

Research suggests (e.g., Schmitt & Westerhoff, 2017; Yamamoto, 2011) that herding behavior causes volatility clustering in stock markets. To simplify, where there is herding, there is volatility. This results in an argument that the CSAD-model essentially measures volatility, and it is assumed that herding behavior is the cause. In turn, this leaves causality up for interpretation. This important critical weakness regarding the model is discussed further in chapter 6, but it is mentioned at this point to underscore a common weakness of empirical research focused on herding in the financial markets, namely that current methods and/or techniques for measuring herding are neither ideal nor even directly measure herding itself. For example, CSAD may indeed be more a measure of volatility changes over time than a measure of herding, but it has at least become an accepted method for, at the minimum, tangentially measuring herding in the financial markets. In short, we can strive for a more ideal measure of herding behavior, but at this time the acceptance and popularity of CSAD gives confidence that it at least measures an approximate general level of investors herding behavior in the stock market analyzed in this thesis.

1.2 Research hypotheses

This thesis contributes to behavioral finance literature by trying to detect herding behavior in financial markets, and furthermore by measuring if market capitalization is a factor in guiding it. The specific and new contribution to financial literature is the latter, since we hope to demonstrate whether specific stock characteristics (i.e., market capitalization and growth) influence herds, and research of this viewpoint is rather scarce. The thesis focuses on three US stock indices, as well as somewhat more arbitrary growth and value baskets of stocks. The basic concepts and measurement models will be introduced, as will the data set and review period. The empirical results will be discussed mainly in chapters 7 and 8. The review of the literature strongly indicates that herding takes place in international markets, including the US, and notably shows that the herding phenomenon intensifies during extreme market movements.

The primary objective is to discover whether market capitalization matters for herding behavior, and to find out if there are differences between value and growth portfolios. First it is important to search for herding in each of the indices and portfolios. After establishing whether herding exists, as measured by CSAD, the study will seek differences between the indices/portfolios. Lastly, the study will review and summarize the results. To reach the objectives of the thesis, the following hypotheses are formed:

H0: Herd behavior does not occur in financial markets.

H1: Herding occurs and may create mispricing.

H2: Market capitalization affects the degree of herding.

H3: Herding is more intense in large-capitalization growth stocks compared to mid-/small-cap value stocks (i.e., size and/or value matters).

2 Theory

This chapter will attempt to create a theoretical outline that can support the analysis of herding behavior in stock markets. Standard finance theory will be introduced with the concentration on the efficient market hypothesis (EMH) and asset pricing models. The Random Walk Hypothesis (RWH) will also be presented. In addition, this chapter will discuss behavioral finance focusing mainly on full rationality of agents to frame reasons for irrational behavior in the context of investing. The purpose is to establish how herding opposes EMH, standard asset pricing models and their hypotheses.

2.1 Efficient Market Hypothesis and anomalies

In its commonly accepted form, the EMH was introduced by Eugene Fama (1970). The hypothesis and forms of efficiency are founded on theories about arbitrage and investor rationality. According to EMH, if markets are fully efficient, the market price always reliably reflects the intrinsic value of a security. This is enabled by the assumption that investors have consistently up-to-date information on the content and risk of each security (Fama, 1970; Shleifer, 2000).

The EMH also presumes that agents in financial markets are rational utility maximizers. Even if some irrational behavior occurs, the transactions are invalidated by opposing irrational decision-making. This notion is important to emphasize since, according to the theory, two types of irrational behavior result in rational behavior, which could also be argued to be relatively nonsensical.

Furthermore, according to EMH, if the effects of irrational investing reach markets, arbitrageurs eliminate their impact on prices (Shleifer, 2000). EMH can be described as a symmetric hypothesis, which impacts both positive and negative returns. As a result, in the framework of EMH, it is extremely difficult for an investor to gain excess returns if markets are efficient. Fama (1970) proposed that market efficiency would be divided into three separate levels: weak form, semi-strong form, and strong form. The information available to an investor increases when moving from weak to strong form.

In the *weak form of efficiency*, the relevant information available comprises of historical prices, trading volumes and returns which also are reflected in the market price. The risk-adjusted returns of an individual investor cannot exceed the market's returns since all decisions have based on historical data. It also eliminates technical analysis since according to Fama (1970), history does not tend to repeat itself with easily discovered return patterns (Fama, 1970). In this scenario, predicting stock prices is not productive because the price development can only follow an unpredictable *random walk* (Fama, 1965).

Regarding stock markets, the RWH suggests that changes in stock prices are similarly distributed and independent of each other. Therefore, past price trends cannot be used to predict future movement. According to the theory, stocks follow a random and unpredictable path, which makes methods of price prediction futile in the long term. As a result, the RWH believes that it is not possible to outperform the market without assuming additional risk (Fama, 1965).

Semi-strong efficiency occurs when market prices contain all present publicly available information along with the historical technical information. If the semi-strong form occurs, the information gathered from e.g., financial statements, profit forecasts and dividend policies are immediately reflected in the market price. Therefore, fundamental analysis is inefficient in pursuing excess returns (Fama, 1970).

In the *strong form of efficiency*, the quoted prices already contain all possible and relevant information. As a result, no investment strategy can be formed to "beat" the market since even private information is included in the market price. Only new information induces a change in market value and the movement is immediate and exact. Information asymmetry or delayed reactions in price do not exist, therefore neither can be utilized for gaining abnormal returns (Fama, 1970).

The EMH has been considered as the core of rational market theory. It has been utilized as the foundation for modeling stock market behavior since it creates a base for various analyses and seeks to rationalize the occurring mechanisms of stock markets. In the last few decades, however, researchers have begun to recognize that empirical evidence does not abide the principles of neoclassical finance theory and the EMH. After the 1970's, researchers have found several anomalies that do not comply with the dogmas of standard theory.

Momentum strategies (Chan, Jegadeesh & Lakonishok, 1996), contrarian strategies (Bondt & Thaler, 1985) and diversification all violate the assumptions of rational utility maximizing and market prices reflecting the intrinsic value of an asset. These discoveries suggest that there are sociological and psychological factors that influence investors' behavior and therefore the market price.

Kahneman and Tversky (1979) present an alternative model to the hypothesis of expected utility. According to Prospect theory (Kahneman & Tversky, 1979), an agent's decision-making is based on the expected value of wins and losses instead of results. They also find that agents tend to overemphasize small probability events and underestimate high probability events. This goes against the normative view of rational behavior and provides more of a descriptive approach.

These separate findings suggest that investment behavior is not bounded by rationality and investors cannot be considered rational utility maximizers in a broad spectrum (Simon 1986). Even Fama and French (2015) find that all assets cannot be priced correctly. In the framework of the EMH, market prices consist of all available information, but it disregards observed human factors such as the capability to process information. Kahneman (2011) suggests that humans tend to use heuristic shortcuts to avoid complex processing. Simon (1986) argued later that humans' fundamental limitations in information processing is a cause for irrational behavior. These non-rational psychological phenomena are related to the herding effect, which is a phenomenon of its own.

2.2 Capital Asset Pricing and the Security Market Line

The Capital Asset Pricing Model (CAPM) is a model for calculating expected returns of stocks (Bodie, Kane & Marcus, 2014). CAPM does not have an unequivocal inventor, but it was formed in consequence by articles written by William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). The foundation of modern portfolio theory laid out by Harry Markowitz (1952) contributed heavily to the model's development. Effectively the model describes the trade-off between risk and return.

According to CAPM, the expected return is obtained by adding the markets' risk premium multiplied by beta to the risk-free interest rate. Beta represents the systematic risk related to an individual stock in comparison to the market. The asset pricing formula indicates the long-term expected return of an asset, i.e., the average return that investors demand from the security. Short- and medium-term returns can be affected by volatility, but the long-term returns should be analogous with the actual returns (Sharpe, 1964; Lintner, 1965; Mossin, 1966). The CAPM formula is as follows:

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

$E(r_i)$ is the expected return of a security, r_f is the risk-free interest rate, β_i is beta, i.e., the systematic risk related to a security and $E(r_m)$ is the expected return of the market (Bodie et al., 2014).

The relationship between beta and expected return can be viewed as a risk-reward equation. The Security Market Line (SML) portrays the relationship graphically, where the slope is the markets' risk premium. The figure effectively illustrates whether a security is underpriced, fairly priced, or overpriced. "Fairly priced" assets fall directly on the SML since their expected returns are commensurate with their risk (Sharpe, 1964; Bodie et al., 2014). In short, SML displays the expected rate of return of a security as a function of non-diversifiable systematic risk.

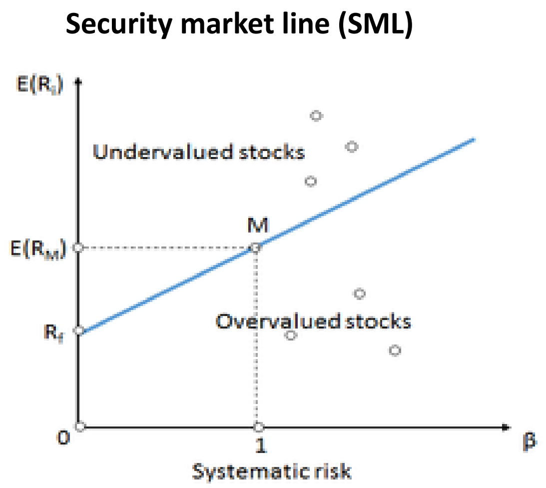

Figure 1: Security Market Line portrays the correlation between expected returns and systematic risk (Sharpe, 1964).

2.3 Behavioral Finance opposing efficient markets

The Capital Asset Pricing Model and EMH are foundational elements in standard finance theory. For them to be applicable, they require two assumptions to be true. Market prices reflect the intrinsic value of a security, and the majority of agents are rational utility maximizers (Fama, 1970; Schleifer, 2000). Standard asset pricing models predict that most investors buy and hold the market portfolio of stocks and its expected returns follow a linear pattern (Fama, 1970; Fama & French, 1992; Lakonishok, Shleifer & Vishny, 1992).

Contrary to their predictions, most investors follow strategies that involve active picking and trading of stocks. More frequent buying and selling decisions may move stock prices. Traditional asset pricing models are not able to predict stock prices at a consistent level (Lakonishok et al., 1992). Therefore, reasons for their failure must be explored outside of their core assumptions.

In its essence, *behavioral economics* studies the impact of social, psychological, cognitive, and emotional factors on economic decision-making (Thaler, 2005). This applies for individual investors as well for institutions. The line of study also explores the decision-makings consequences for the market and how resources are allocated (Kahneman & Tversky, 1979).

Behavioral finance can be perceived as a countermovement towards the linearity of asset pricing models which assume the truthfulness of the EMH and rational behavior (Hodnett, 2012). It studies the human elements as an explanatory factor of the difficulties in predicting market prices and provides an explanation to why standard finance theories project differing results from reality (Kahneman 2011; Kahneman & Tversky, 1979; Simon, 1986). As shown above, neoclassical theories effectively ignore this aspect in their modelling.

Behavioral finance is a research field closely related to behavioral economics. It seeks to provide cognitive and psychological explanations for various anomalies in financial markets. The standard theories of finance base their models on rational investors' behavior (Fama, 1970; Lintner, 1965; Mossin, 1966; Sharpe, 1964). In the framework of behavioral finance, contrary to assumptions of neoclassical theories, humans are not capable of fully rational decision-making. Behavioral Finance considers investors' rationality limited at best, while it acknowledges that there is effort towards rational behavior (De Bondt, Muradoglu, Shefrin & Staikouras, 2008). This means even though individuals can strive for rational decisions, humans' fundamental limitations hinder fully rational behavior (Simon, 1986).

Limits to arbitrage are reinforced by investor psychology. Barberis and Thaler (2003) consider these two areas as building blocks of behavioral finance. Limits to arbitrage indirectly cause irrational investment behavior. Barberis and Thaler (2002) argue that transaction costs limit the possibilities of utilizing and exploiting arbitrage opportunities. In addition, self-doubt of investors hinders them from taking advantage of every arbitrage opportunity. The assumptions of the EMH (Fama, 1970), where irrational behavior that reaches markets is nullified by arbitrageurs, can no longer be possible in the framework of behavioral finance. Limits to arbitrage may cause continuous mispricing of securities, which leads to inefficient markets.

The second building block, investor psychology, seeks to understand the reasons why investors behave how they do (Barberis & Thaler, 2005). This subchapter of behavioral finance pursues to measure and appraise different types of behavior to understand why they occur and secondly when they occur (Daniel, Hirshleifer & Subrahmanyam, 1998).

Daniel et al. (1998) suggest that information discovered from this line of research could be utilized in all market conditions. Analysts and investors generate information for investing through different means, such as analyzing financial statements, interviewing management, and following macroeconomic trends. The information processing can be executed with varying degrees of skill. If an investor or analyst overestimates their ability to process information, or the ability to correctly evaluate the significance of existing data, this will lead to underestimating forecast errors (Daniel et al., 1998). The theory is based on *overconfidence* (Debondt & Thaler, 1995) and *attribution bias* (Langer, 1975).

What can be established with these findings is that agents in financial markets may cause mispricing of assets and therefore inefficiency of markets with their behavior. Some irrational decisions are caused by the inability to assess information correctly when aiming toward rational behavior and some agents abandon the processing altogether due to their fundamental nature (Daniel et al., 1998; Kahneman, 2011; Kahneman & Tversky, 1979). The reasons for irrational decision-making may vary, but they lead to the same result regarding the efficiency of markets.

On more example of how investors' behavior can affect the marketplace are financial crises. According to the EMH and the CAPM, investors react only upon new information, and they also have the capability to evaluate the new information correctly (Fama, 1970;

Sharpe, 1964). The reaction then moves the market price to the new “correct” level. Humayun (2018), for example, suggests that there were few fundamental reasons for market prices to drop so severely in 2008. Reasons for the overreaction must be searched from the framework of behavioral finance.

De Bondt et al. (2008) suggest that financial crises may be ultimately caused by human behavior and standard financial theories have few to no explanations for those events occurring. They suggest investor psychology to be one of the prominent factors of spiraling economic situations. In an economic spiral, significant dumping of stock tends to lead to more selling and as consequence, the market price begins to slide. The latter sales are based solely on the first sales, that is, the herding effect. In this scenario, the market price no longer reflects the intrinsic value of a security and the assumptions of the EMH have been negated.

It is important to notice that irrational behavior and herding are not limited to inexperienced individual investors. Devenow and Welch (1996) find that even household investors and analysts for influential institutions have made decisions and recommendations based on the actions of others. Suboptimal decision-making cannot be segregated to a certain “class” of investors.

To summarize, behavioral finance recognizes the human aspect in market movements and asset pricing. It has been established in the field of psychology and economics that humans are prone to irrational psychological biases, for example anchoring, mental accounting and loss aversion are a few of them not presented in this chapter. These forms of irrational behavior, along with herding, have been suggested to provide explanations for several market anomalies, which oppose the discussed standard theory. The next chapter will assess different types of herding behavior.

3 Herding behavior

The following chapter will further enlighten the meaning of herding and present customary forms of herding behavior. The first part of the chapter will seek to establish herding as a concept and as a phenomenon. The second part will discuss different forms of herding and the basis for the division, as well as point out some inconsistencies among the concepts. It may also give some insight on if crowds herd more towards growth stocks versus value stocks or vice versa. The purpose is to further enable interpretation of the research results.

3.1 Herding

It is important to understand that herding is not an act which only occurs on stock markets and investors are the only agents participating in it. Conversely, herding is an addition to zoology, an extensively debated and comparatively well researched subject in psychology, sociology, and neurology (Spyrou, 2013). The initial act of herding refers to animals, hence the addition to zoology. In the original meaning, herding is animals assembling to form a group in order to follow each other (Spyrou, 2013). This phenomenon can be effortlessly applied to humans as well, a topical example could be trend setting through social media accounts of famous individuals.

When discussing economics and stock markets specifically, herding as a term means the event where agents imitate each other and/or base their decisions upon actions of others (Spyrou, 2013). It can be described as investors ignoring their initial evaluations and trading by following the trend in the previous trade (Avery & Zemsky, 1998), excessive agreement in analyst predictions (De Bondt & Forbes, 1999), mutual imitation (Welch, 2000), a group of investors following each other into (out of) the same securities (Sias, 2004) among other homogeneous definitions.

The above descriptions can be challenging to explain or measure. The characterization of herding differs in research and literature. To add on the above descriptions, Bikhchandani and Sharma (2000) define it as the correlation between individual investors' causal investment behavior. Banerjee (1992) describes it as everyone doing what everyone else is doing, even when the available information suggests doing something different.

As can be seen, the descriptions shift and differ but in general they describe the same phenomenon, and practically characterize the same type of behavior. For example, the definition provided by Avery and Zemsky (1998) leads to investors wandering aimlessly and eventually following market trends without purpose. Shiller's (2015) description is even more ominous since investors are essentially described as sheep who follow a herd with little consciousness of their own.

The reasons behind this behavior may be diverse, however. This thesis has already demonstrated some of the psychological factors that may lead to irrational behavior, meaning that herding can simply originate from social and psychological conventions. It can also be the simultaneous reaction to new fundamental data or market participants inferring information from the actions of previous participants (Spyrou, 2013). The latter description illustrates that herding may derive from rational behavior, thus leading to efficient outcomes. The basis of herding is acting solely upon the actions of others, whereas the latter is a rational reaction coinciding with other rational reactions. As can be seen, herding may result, at least in theory, in efficiency, although it is debatable if the description is herding at all, but rather investors drawing similar conclusions simultaneously. Conversely, some economists suggest that herding can lead to prices destabilizing and cause bubbles in financial markets (Spyrou, 2013).

Stock prices usually experience more volatility than what could be expected based on fundamentals and conditions of the market (Lux, 1995). The unexpected volatility raises questions about market efficiency and the phenomenon has usually been explained as a causal effect of herding (Christie & Huang, 1995). Herd behavior is often assumed, predominantly by the press, to be widespread among institutional and individual investors. Herding is often cited as one of the main reasons for periods of extreme volatility and market instability, and furthermore, for bubbles and financial crises (Spyrou, 2013).

After a financial crisis there is often an increased interest in herd behavior. The consensus is that economists and researchers believe that market-wide herding occurs in financial markets, and at least Devenow and Welch (1996) concur with that sentiment. In addition to the press and general public (Spyrou, 2013), some scholars believe that widespread herding may contribute to financial crises (Chari & Kehoe, 2004).

While the concept of herding seems rather straightforward, measuring its scale and narrowing its effects is a multifaceted problem. Even the evidence suggesting that it is a widespread form of behavior is inconclusive (Spyrou, 2013). Welch (2000) points out that herding in financial markets is often presumed to be prevalent, while extensive empirical evidence is surprisingly sparse. Secondly, the theoretical models proposed to explain herd behavior can be divided in two main classes regarding their core assumptions: models that assume rational or near rational agents and models that assume non-rational behavior (Spyrou, 2013).

In addition to differing measurement models, the varying results from different viewpoints present a problem. For example, Chang et al. (2000) find no evidence of herding in stock markets of US and Hong Kong but find robust signs of herding in the emerging markets of Taiwan and South Korea. Zheng, Li and Zhu (2015) suggest that investor herding is stronger on actively traded stocks and the effect is more powerful if investors are inexperienced and have less information. On the other hand, institutions are more likely to herd in seemingly undervalued stocks since they assume to be better informed than individual investors (Bailey, Cai, Cheung & Wang, 2009).

It is important to note that the approaches and results of research conducted on herding differ almost as similarly as the definitions of it. When discussing some of the pioneers of this specific research field, the theoretical models developed by Scharfstein and Stein (1990), Bikhchandani, Hirshleifer and Welch (1992) and Devenow and Welch (1996) must be mentioned. In addition, notable research includes studies made by Christie and Huang (1995) and Chang et al. (2000) among others. These models and findings have in part laid the foundation for methods of measurement and the behavioral approach for the modern concept of herding in financial markets. The differing results of some of these studies will be discussed further in chapter 4. Next, we discuss the standard forms of herd behavior.

3.2 Different forms of herding

When making investment decisions, investors typically analyze the fundamental data of a company and make investment decisions based on the information drawn from the data. This describes rational behavior in financial markets. This is in accordance with standard finance theory and empirical evidence suggests that this type of behavior is quite common among investors. Whether the interpretations are correct or coherent, at least a portion of investors effort towards rational behavior. When this happens simultaneously and leads to similar decisions, it could easily be construed as herding. Bikhchandani and Sharma (2000) call this spurious herding or unintentional herding.

The below figure illustrates the division of herding. The most common distinction comes from Bikhchandani and Sharma (2000), which has been applied as a basis for various research. Other distinctions exist, but the content remains similar. Choi and Skiba (2015) for example, divide herding to reputational herding, characteristic herding, and fads. In any case, the consensus of researchers and economists is that herding should primarily be divided to spurious (Bikhchandani & Sharma, 2000) and intentional, and moreover to rational and irrational.

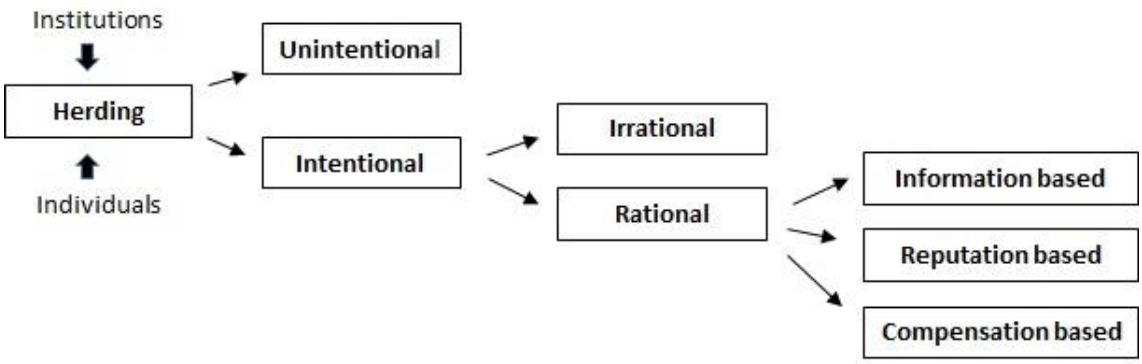

Figure 2: Division of herding (Bikhchandani & Sharma 2000).

Figure 2 displays the division of herding behavior. As the figure illustrates, herding is seen to be exercised by two separate agents in financial markets, individuals, and institutions. Also noteworthy is that unintentional herding a.k.a. spurious herding has no subdivisions. Intentional herding is, however, divided further into subcategories of rational and irrational behavior. Distinguishing intentional and unintentional herding from one another can be difficult in reality (Bikhchandani & Sharma, 2000).

Intentional and irrational herding derives from the psychology of an investor. Spyrou (2013) describes it as investors making irrational decisions because of ulterior pressure caused by social circles and stigmas. Shiller (2015) states that irrational herders tend to make surprising and sudden decisions of poor quality, which are based on insufficient information. Irrational investors are prone to making decisions based on market consensus, and Choi and Skiba (2015) suggest that the concept applies to both individuals and institutions. Uncertainty in the market and a scarcity of information added to humane psychological shortcomings can lead even experienced investors to falter (Spyrou 2013).

A subdivision not shown in the figure is intentional but not fully rational herding. It would be placed in between rational and irrational herding in the illustration. In this type of behavior, investors trade stocks according to their historical performance. Bikhchandani and Sharma (2000) suggest that it can be seen as a momentum strategy of sort. In this subdivision, investors rationally seek to mimic the historical profits of others but irrationally conduct the behavior because there is no evidence to suggest that past performance is a valid indication of the present or future. The tactic can however develop into rational herding depending on the results. According to Bikhchandani and Sharma (2000), the strategy can be considered rational if it turns out to be profitable.

Another subdivision of intentional herding is rational herding. As shown in the illustration, it can be divided further into three categories where herding is based on either information, reputation, or compensation. Information-based herders have a firm belief that other investors have better insight and knowledge of market conditions and thereby deliberately follow their decisions. The scarcity of knowledge deriving from the investors' belief of their inability to process information causes them to follow the example of others (Bikhchandani & Sharma, 2000).

Reputation- and compensation-based herding are more interconnected since their common denominator is employment (Bikhchandani & Sharma, 2000). An investor's reputation can be damaged if he or she makes even a few erroneous investment decisions. This may not be significant for an individual investor, but more so for stock analysts for example. Reputation-based herding can be a safety net for employment because, as Spyrou (2013) points out, making unprofitable investment decisions along with the herd is far less damaging than decisions against the common consensus that result in loss-making. Spyrou (2013) continues that the latter can cause analysts to suffer from significant distrust from investors hoping for accurate predictions, while the impact is much less significant if the recommendations originally coincided with the general opinion.

Compensational herding occurs when an employee's salary is tied to performance. Making decisions that deviate from the market consensus can be seen as unnecessary risk-taking and may ultimately lead to unemployment. Following the consensus can conversely serve as an insurance for the employee. (Bikhchandani & Sharma, 2000.) The logic is that the expectation is to perform at least on par with competitors but especially not inferior (Spyrou, 2013). One could argue that *loss aversion* (Kahneman & Tversky, 1979) induces herding in this scenario (Spyrou, 2013).

The definitions and different forms of herding behavior are important for understanding the concept. The different forms provide multiple explanations for why herding formations occur, and why investors may abandon fundamental information and follow the crowd. The many types of so-called rational herding are interesting, since the essence of behavioral finance and, in extension, herding is that humans do not behave rationally. It can be argued that although compensation- and reputation-based herding are better for keeping employment, it does not make the implied behavior rational, but rather another reason for participating in wide-spread groupthink. On the other hand, if information-based herding occurs, it implies that information is not distributed evenly, which then contradicts the assumptions of the EMH. These observations of inconsistencies and contradictions suggest that although the definitions are useful, the theories of herding are not complete.

4 Literature review

This section will go over and compile some of the most notable empirical studies on herding in financial markets. The research results of these studies should provide a decent indication of the intensity and distribution of herd behavior regarding investment activities. The focus of the thesis is on the US stock market and market capitalization and the presented articles have similarities in their framework. The chapter will go through earlier evidence along with more recent articles. This should demonstrate whether the results have experienced transformation over time. An extensive overview of the applied methodology in each study will not be presented, the emphasis will be on the results and conclusions gathered from the research.

4.1 Early evidence

One of the most notable earlier studies focusing on herding is conducted by the previously mentioned Christie and Huang (1995). They focus on the US stock market in a period from 1925 to 1988. Christie and Huang (1995) hypothesize that the deviation between returns of individual stocks and the market index should decrease and definitely not increase when herd behavior is occurring in the marketplace. Their empirical results are inconclusive and not consistent with the supposition of herding being detectable in volatile conditions.

Christie and Huang (1995) apply the CSSD-model for measuring and justify it by explaining that dispersion quantifies the average proximity of individual returns to the mean and therefore it indicates herd behavior when individual returns follow the returns of the portfolio. Contrary to their hypothesis, they find that dispersions between returns increase significantly during market stress or considerable price movements, implying that individual returns do not cluster around the index during volatile periods (Christie and Huang, 1995). Their research also discovers that the actual dispersion between returns is similar to the dispersion predicted by rational asset pricing models. Christie and

Huang (1995) conclude that their evidence suggests that herding is close to an insignificant factor in ascertaining stock returns during market stress.

Chang et al. (2000) employ the nonlinear CSAD-model in order to detect herding. They examine herding from 1963 to 1997 in various international markets with the intention to discover if the development stage of the market has an impact on the results. The chosen stock markets are the US, Hong Kong, Japan, South Korea, and Taiwan. As does the research conducted by Christie and Huang (1995), the measurement period is relatively long and can be considered to provide a sufficient overview. Consistent with the findings of Christie and Huang (1995), Chang et al. (2000) find no considerable evidence from the proposedly developed markets of the US and Hong Kong. In these markets, equity return dispersions continue to increase linearly during periods of extreme price movements. The study finds partial evidence of herding in Japan (Chang et al., 2000).

However, in the emerging markets of South Korea and Taiwan, the evidence of herding is relatively significant. Chang et al. (2000) find a considerable non-linear relation between equity return dispersions and the underlying price movement in markets. In other words, the return dispersion either increases at a decreasing rate or diminishes with an increase in the absolute value of market returns. Chang et al. (2000) also find that the rate of increase in return dispersions as a function of the aggregate market return is higher when the market is ascending than when it is declining. This discovery applies to all the five markets that were examined (Chang et al., 2000).

Other notable findings by Chang et al. (2000) are that where the evidence supporting the existence of herd behavior is most pronounced, systematic risk accounts for a comparatively large portion of the overall risk. Chang et al. (2000) suggest that this is consistent with the perception that the relative scarcity of accurate and immediately available firm-specific information in emerging markets may cause investors to concentrate more on macroeconomic information. Therefore, announcements concerning the macroeconomic state may have a relatively significant impact on market prices compared to fundamental information regarding a specific company.

Furthermore, results of the market capitalization-based portfolio tests indicate that the amount of herding is not driven by small or large-capitalization stocks in the markets of South Korea and Taiwan. In addition, the results for both emerging markets remain relatively robust in varying sub-period tests that were designed to capture movement in investment behavior associated with the liberalization of these economies (Chang et al., 2000).

In conclusion, the results from the US stock market gathered by Chang et al. (2000) are consistent with the findings of Christie and Huang (1995). In addition, Chang et al. (2000) find minimal evidence of herding in Hong Kong and Japan. In the emerging markets of South Korea and Taiwan the results are dramatically different. With their empirical specification, they can test equity return dispersions during both extreme up and down price movements and find that the dispersion decreases in both situations. Chang et al. (2000) suggest that this can be at least partially attributed to the incomplete information disclosure of the emerging markets.

The starting point for Chiang and Zheng (2010) is very similar to Chang et al. (2000). They examine herd behavior in a global setting with the CSAD-model. Their research covers a period from 1988 to 2009 in 18 different countries and therefore stock markets, locating in the United States, Asia, and Latin America (Chiang and Zheng, 2010). The equation applied for this study is comparable to the one applied by Chang et al. (2000).

Chiang and Zheng (2010) find significant evidence of herding in all the proposedly advanced, i.e., developed markets apart from the US. This includes stock markets in Australia, France, Germany, Hong Kong, Japan, and the United Kingdom. They also find considerable evidence of herd behavior in the Asian markets located in China, South Korea, Taiwan, Indonesia, Malaysia, Singapore, and Thailand. Alongside with the US stock market, Chiang and Zheng (2010) do not find evidence of herding in the Latin American markets (Chiang and Zheng, 2010).

The authors find that in the advanced markets where herding occurs, the phenomena is present in both up and down markets (Chiang and Zheng, 2010). This includes the Asian markets where herding is found to be prevalent. Contrary to the assumptions of Christie and Huang (1995), herding is found to be similarly intensive in both market conditions and furthermore, the herding asymmetry is more profound in Asia during rising markets. Interestingly, Chiang and Zheng (2010) also find considerable evidence of herding in the Hong Kong stock market, which opposes the evidence reported by Chang et al. (2000).

Ironically, while Chiang and Zheng (2010) discover minimal evidence of herding in the US stock market, the market is found to have a significant impact on the herding volume of advanced and especially Asian markets. They can demonstrate it with consistently positive coefficients of the domestic CSAD-model, suggesting a dominant influence of the return dispersions in the US over other international markets. Chiang and Zheng (2010) propose that this could be explained by modern global information processing. Investors in Asian markets tend to follow global news and form their investment strategies based on those of the institutional investors residing on Wall Street. Wall Street is considered as a center for disseminating and processing global information regarding investment activities. If investors in international markets have confidence in the outlook of Wall Street and form a consensus about investment decisions, it results in a herding formation. Chiang and Zheng (2010) point out that this can be considered rational behavior if the cost of information gathering supersedes the investment decision. The explanation is similar for the herding activities in advanced markets, although less intensive as in the Asian markets (Chiang and Zheng, 2010).

Regarding the US, the lack of herding activities may be attributed to the existence of strongly various and diverse opinions offered by venture capital conglomerates, leading financial firms, and the media. Chang and Zheng (2010) also suggest that this landscape may generate differing beliefs, resulting in heterogeneous investors who make investments based solely on their own information, reducing the probability of herding formations (Chiang and Zheng, 2010).

Chiang and Zheng (2010) find indications of herding in the US and Latin American markets only during extremely downward market movements, meaning that herding is detectable during some crisis periods. Conversely to the advanced and Asian markets, no evidence is otherwise found in the Latin American markets, which Chiang and Zheng (2010) also attribute at least partially to global information processing. Herding around the US stock market is less prevalent in Latin America where investment decisions are rather based on domestic information (Chiang and Zheng, 2010).

Another observation by Chiang and Zheng (2010) is the contagion patterns of herding in crisis situations. If herding occurs in the country wherefrom the crisis originates, the behavior spreads cross borders to neighbor countries. Excluding the Latin American and US stock markets, Chiang and Zheng (2010) report considerable evidence of herding in the target countries. They find that most investors herd with the US stock market in addition to their domestic markets. The evidence gathered from the US stock market by Chiang and Zheng (2010) are consistent with the findings of Christie and Huang (1995) and Chang et al. (2000). The results are partially consistent regarding the Asian markets with Chang et al. (2000), however the evidence found from Hong Kong and Japan offer an opposing view.

4.2 More recent evidence

4.2.1 Research on individual herding

Galariotis, Rong and Spyrou (2015) study leading stocks in the US and UK markets to test for herding towards the market consensus. Galariotis et al. (2015) examine a period from

1989 to 2011 by utilizing the daily price data from the S&P 100 and FTSE 100, which are subsets of the S&P 500 and FTSE 350 respectively. Galariotis et al. (2015) adopt the CSAD-model to detect herding activity, similarly to Chang et al. (2000) and Chiang and Zheng (2010). Their paper is one of the first studies to test for herding when important fundamental macroeconomic information is released, conversely to previous studies which tend to test solely for up- and down-market days (Galariotis et al., 2015).

The research party finds statistically significant evidence of herding in both countries during specific time periods and discover that the drivers of herding behavior are variable. Galariotis et al. (2015) report evidence of herding towards the consensus in US stock prices during periods when important domestic macroeconomic information is released, and that the formation persists irrespective of the investment style, e.g., value vs growth and small vs large. The discovery opposes the findings of Christie and Huang (1995), Chang et al. (2000) and Chiang and Zheng (2010).

Since previous studies have indicated that herding is more probable during extreme market movements, Galariotis et al. (2015) isolate significant periods of volatility, such as the Asian crisis, the Dotcom bubble and the Subprime crisis. The party detects herding driven by fundamental information during the Asian and the Russian crisis in the US market for value, small and big capitalization investment styles. For the UK market, fundamental herding is discovered during the Dotcom bubble burst for all investment styles (Galariotis et al., 2015). The research paper also points out, that the herding activities seem to be *spurious* (Bikhchandani & Sharma, 2000).

Herding driven by non-fundamental information is found during the Subprime crises in the US market. Non-fundamental herding is not detected in the UK market. Galariotis et al. (2015) suggest that the intensity and proximity of financial turmoil in the US in 2008 may have affected investor behavior. The authors estimate that *availability heuristic* (Kahneman, 2011), where people may evaluate an event’s probability by the ease with which relevant occurrences and information are recalled to mind, influenced investment behavior during the Subprime crisis (Galariotis et al., 2015).

Galariotis et al. (2015) conclude that full sample testing results in no significant evidence of herding. This includes both countries. The findings are consistent with the results of Chang et al. (2000) among others. Similar to Chiang and Zheng (2010), Galariotis et al. (2015) report evidence of the spill-over effect of the US market. During the Asian crisis and the Dotcom bubble, Galariotis et al. (2015) find that herding spill-over effects took place from the US to the UK. This coincides at least partially with the results of Chang et al. (2000) among others.

Bohl, Branger and Trede (2017) challenge the herding measure implemented by Chang et al. (2000). They argue that the coefficient of the market return is positive under the null hypothesis of no herding and opposes the supposition of over-proportional movement in the level of return dispersions. Bohl et al. (2017) approach their research from a relatively different angle compared to the previously mentioned studies, since they effort to oppose the hypothesis of the CSAD-model applied by Chang et al. (2000). Bohl et al. (2017) argue that the CSAD-model provides valid statistical inference only under conditions of identically zero idiosyncratic components. Bohl et al. (2017) argue for a stronger case for herding than the previous studies show and demonstrate how the assumptions of the CSAD-equation can be biased against finding statistically significant evidence of herding and towards finding evidence for anti-herding, where the increase of return dispersions are exaggerated.

Bohl et al. (2017) test their modified model in the American S&P 500 and the European EuroStoxx50 in a five-year sample period from 2008 to 2013. In their model, the coefficient y_2 is positive under the null hypothesis of no herding. Bohl et al. (2017) find significantly negative estimates of the coefficient, which results in the rejection of the null hypothesis in both markets. Tests based on the modified null hypothesis on the S&P 500 yield opposing results to the findings of Chang et al. (2000). As to EuroStoxx50, statistical evidence is reported to support the hypothesis of herding taking place, which is consistent with the research results gathered by Chiang and Zheng (2010). The article concludes that although it does not provide a framework to analyze the economic causes, it strongly supports the economic reasons behind herding behavior and lobbies for herding to be taken seriously (Bohl et al., 2017).

In conclusion, the results go through a rather significant transformation from the early evidence towards the more recent literature. Chiang and Zheng (2010) find some indications of herding in the US stock market and suggest that it takes place only in extremely downward market movements. This is already a shift from the earlier evidence gathered by Christie and Huang (1995) and Chang et al. (2000). Galariotis et al. (2015) report statistically significant evidence of intense herding in the US market during several downward market movements. They also find evidence of herding in ascending markets, which they partially attribute to releases of domestic macroeconomic information.

Galariotis et al. (2015) continue their research by testing separately for herding driven by fundamental and non-fundamental information. Fundamental herding is detected in both the US and UK markets, which opposes the inference gathered from the early evidence that herding is more likely to appear only in developing markets. Bohl et al. (2017) coincide at least partially with Galariotis et al. (2015) and consider the herding effect to be even stronger than previous studies have demonstrated. Also noteworthy is that Chiang and Zheng (2010) and Galariotis et al. (2015) concur on the spill-over effect of the US stock market.

4.2.2 Research on institutional herding

Studies conducted on herding are often separated by research directed towards individual and institutional herding. Choi and Skiba (2015) examine herding behavior of institutional investors in international markets. They find significant evidence of widespread herding in 41 of their sample of 86 countries in a period from 1999 to 2010. Diverging from the previously presented studies, Choi and Skiba (2015) utilize the holdings data of international institutional investors to compute their herding measures, contrary to applying the market return data.

Choi and Skiba (2015) explore the relation between institutional investors' herding behavior and the extent of information asymmetry in the 41 target countries where widespread herding is found to be prevalent. Interestingly, Choi and Skiba (2015) find evidence that institutional investors herd more in markets that are characterized by low degrees of information asymmetry. Choi and Skiba (2015) suggest that the results may indicate that institutional herding is driven by correlated signals from fundamental information. They also show that stock prices adjust faster in markets with high levels of information transparency (Choi and Skiba, 2015).

The 41 target countries consist of advanced, emerging and in between markets from all over the world. Countries included are the United States, Finland, Germany, Hong Kong, Thailand, Australia, Nigeria, and Argentina for example. Choi and Skiba (2015) find statistically significant herding propensities in all the target countries that also have a considerable presence of institutional investors. Additionally, Choi and Skiba (2015) suggest that the level of information asymmetry is inversely related to herding propensities. They find minimal evidence of informational cascades causing herding, and rather propose that herding takes place when investors interpret information similarly and make resembling decisions from the underlying facts, effectively describing the form of *spurious* (Bikchandani and Sharma, 2000) herding. Rather surprisingly, Choi and Skiba (2015) find herding to have a stabilizing effect on prices, which opposes the view of several previous studies.

Deng, Hung and Qiao (2018) apply a relatively similar approach as Choi and Skiba (2015) differing in that they investigate if mutual fund herding behavior has an impact on stock price crashes. The authors combine a dataset of accounting data and stock return data to discover institutional herding and assess its effects on price crashes. The research covers a sample period from 1989 to 2013. Deng et al. (2018) report evidence showing that mutual fund herding is associated with a weak information environment and a low quality of information disclosing. The finding is not consistent with the results of Choi and Skiba (2015).

In addition to detecting herding in the marketplace, Deng et al. (2018) are also able to demonstrate some of the effects it has on stock prices. Staying in the framework of institutional herding, Deng et al. (2018) find that mutual fund herding may deteriorate corporate disclosure quality. They also note that institutions that perceive to be less informed compared to others tend to actively herd in mutual funds. Lastly, Deng et al. (2018) find a robust predictive relationship between mutual fund herding and stock price crashes and discover this to be the most intense in buy-herding rather than sell-herding. Deng et al. (2018) conclude that a strong mutual fund buy-herding signal can act as an alert for holding investors.

The last piece of literature discussed in this thesis is the study conducted by Jiang and Verardo (2018). First, they seek to show that mutual funds and other institutional investors tend to herd in their investment decisions and secondly, assess the relation between herding and skill with the underlying presumption that herding exists. Jiang and Verardo (2018) deploy a sample consisting of all actively managed US equity funds and their returns in a period from 1990 to 2009. To conduct their measurements, Jiang and Verardo (2018) utilize a modified model that can function in the basis for their study, similar to Deng et al. (2018).

Jiang and Verardo (2018) report significant evidence of herding among institutional investors. The study also shows that herding behavior strongly and negatively predicts the cross section of mutual fund returns. The discoveries of herding among institutional investors are consistent with the results provided by Choi and Skiba (2015) and Deng et al.

(2018). While the previous studies model herding from the angle of information asymmetry, Jiang and Verardo (2018) do not take a stand on this matter and rather attribute the volume of herding to the experience and skill level of fund managers. The authors suggest that differences in skill drive the performance gap of herding and anti-herding funds. Lastly, an interesting note from the study is that Jiang and Verardo (2018) find anti-herding funds to consistently outperform their herding peers, reporting an over 2% difference in yearly returns.

In conclusion, the recent literature on institutional herding is in consensus of the existence of herding in stock markets. Each one of the reviewed studies report significant evidence of herding in markets where institutional investing is prevalent. Choi and Skiba (2015) suggest that information asymmetry is correlated with herding propensities and find that investors tend to herd more in markets of low-level information asymmetry, i.e., advanced markets. Deng et al. (2018) oppose the findings and report institutional herding to be more intense in markets of high levels of information asymmetry. Jiang and Verardo (2018) attribute institutional herding on the skill level of fund managers. It is noteworthy that although the studies differ on the reasons behind institutional herding, they all report evidence of its significant effect on institutional investment activities.

The most important literature concerning this thesis is from Chang et al. (2000), Chiang and Zheng, (2010), and Galariotis et al. (2015). The first two research groups are the first to apply and modify the CSAD-model, which this paper utilizes. The latter conducts tests on market capitalization-based portfolios, as do Chang et al. (2000), which is relevant considering the topic of this paper. It is interesting to see how specific tests correlate with the above literature, as we move forward toward the empirical study. A final observation from the literature is how some of the writers describe the discovered herding as rational. Some of the problems of this description are mentioned in chapter 3.

5 Data and descriptive statistics

5.1 Data

The data for this thesis is collected from the Thomson Reuters DataStream. The study uses data from the US stock market and specifically from three different equity indices. All closing prices are in local currency (US dollar) and the sample period is from January 2005 to February 2022. To measure the effect of market capitalization as a driver of herding, the study conducts tests on the S&P 500, S&P 400 MidCap, and S&P 600 SmallCap. To find differences in herding propensities between value and growth stocks, one arbitrary growth portfolio is formed. All stocks in the large-cap growth portfolio are also included in the S&P 500.

The S&P 500 index consists of 500 leading publicly traded companies in the United States. It is a market-capitalization-weighted index and can be considered one of the best gauges of prominent US equities' performance. It is not an exact list of the top 500 US companies by market cap since there are other criteria involved, but close enough to represent the large market capitalization stocks for this study.

The S&P 400 MidCap index is comprised of 400 companies that broadly represent companies with midrange market capitalizations between 3.1 billion and 13.1 billion US dollars. The index is published by Standard & Poor's and can similarly be used as a gauge for market performance. The S&P 400 serves as the midcap market capitalization index for the study.

The S&P 600 SmallCap index tracks a broad set of 600 small companies that meet specific liquidity requirements. Market capitalizations range between 850 million and 3.6 billion US dollars. Logically, the S&P 600 SmallCap index represents small-cap stocks for the study.

To evaluate herding propensities in stocks with different market capitalizations, all current stocks in the different indices are included in the study. The contents of the indices have changed over time, meaning some stocks have been removed from the indices and some have been added during the sample period. To mitigate these changes, it has been decided to proceed as follows: stocks that have not been in the indices since the beginning of the review period, are given the average value of the market portfolio i.e., the days that have no record of returns are given the average daily market return.

The total number of stocks included in the market capitalization study is 1500, which derives from the content of each index. The total number of observations is 4466 for each index. The daily return is calculated for each stock and index by using the daily closing prices. The daily return is calculated by using the logarithmic return which is the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

Where R_t is the daily change (i.e., daily return) in the stock price or market index, P_t is the stock price at time t, P_{t-1} is the corresponding value day prior and ln is natural logarithm.

5.1.1 Sample period

The sample period is from the beginning of 2005 to early 2022. The period is interesting, since it contains several major crises, including the 2008 financial crisis and the 2020 Covid-19 related bear market among others. The period has also seen historical amounts of quantitative easing (QE) by the Federal Reserve, which has put downward pressure on interest rates and induced a massive amount of cheap loans for institutions and corporations which has led to excessive stock repurchases (Al-Jassar & Moosa, 2019).

Poutachidou and Papadamou (2021) argue that excessive returns over the last two decades can at least partially be explained by QE. Lower interest rates have led investors to seek returns outside of bonds, thus generating more capital allocation toward the stock market. This has led to a scenario where massive amounts of capital inflow into index funds, exchange traded funds and direct stock purchases among others has lifted the aggregate market. When stock markets and indices have saturated, investors have looked to even riskier growth stocks in search of returns. This has generated remarkable price increases in large-cap growth stocks and has caused growth stocks to outperform value stocks.

All the above has been a tailwind for the stock market. The last two decades can be described as not normal, since the level of expansionary monetary policy has been historic (Al-Jassar & Moosa, 2019; Poutachidou & Papadamou, 2021). Normally, value stocks tend to outperform growth stocks over time and especially when adjusted for risk (Fama & French, 1998). This has not been the case during the sample period, especially in the last decade. It is interesting to see how the uncharacteristic conditions of the review period affect the indicators of herding behavior.

5.1.2 Sample period index returns

Approximately 17 years of data should be sufficient for evaluating if herding behavior is more prevalent in one index or another. The 17-year period shows a variety of market movements, including a relatively long bull market as well as two major crises. 2008 saw a major bear market when the 2008 Financial crisis caused a severe and rapid downtrend in stocks, as did spring 2020 when stock prices plummeted following the increased news coverage and threat of lockdowns caused by the Covid-19 virus. The sample period also includes the European sovereign debt crises in 2010 and the stock market selloff of 2018. However, despite the multiple bear markets, all three indices demonstrate a significant upward trend.

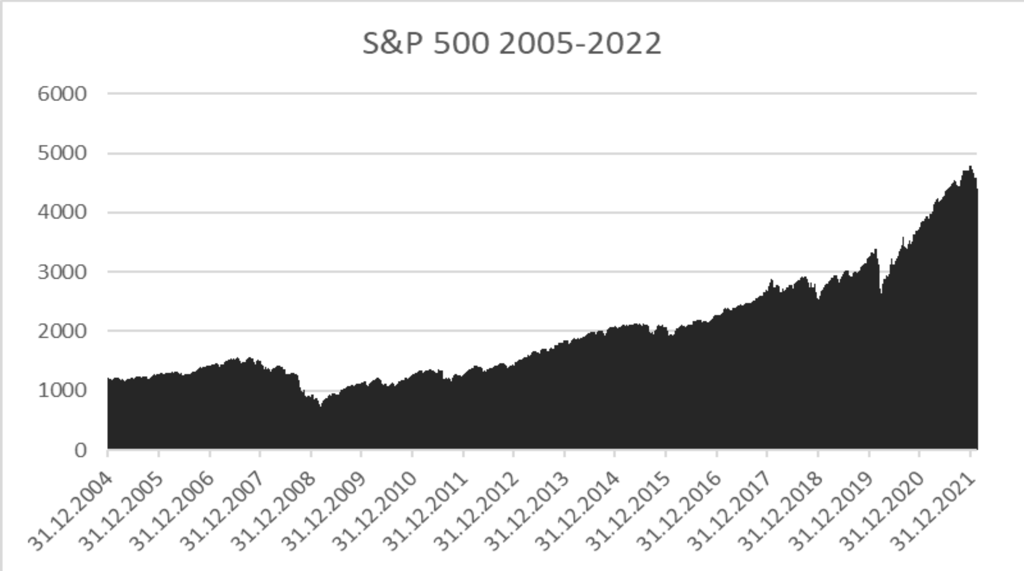

Figure 3: S&P 500 Index value 2005-2022

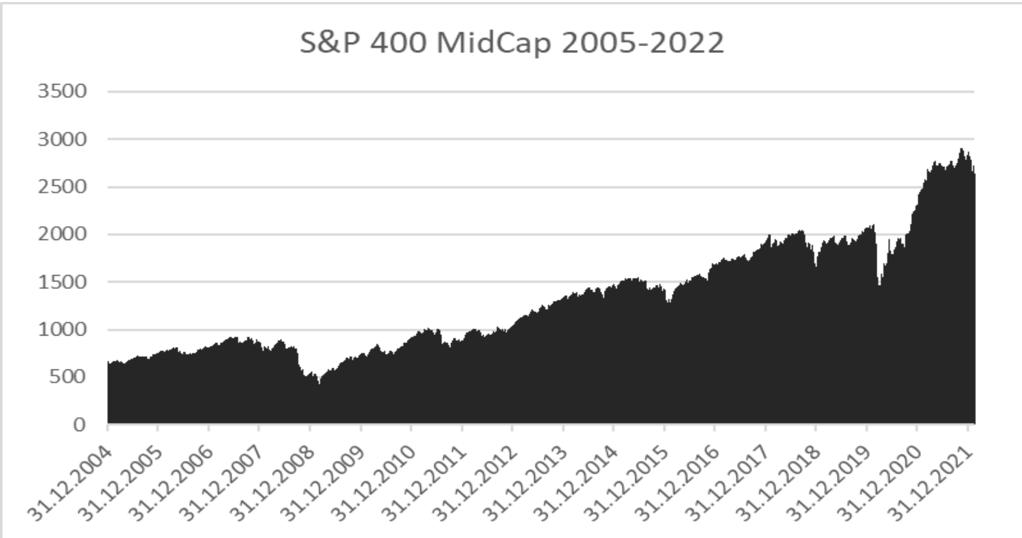

Figure 4: S&P 400 Index value 2005-2022

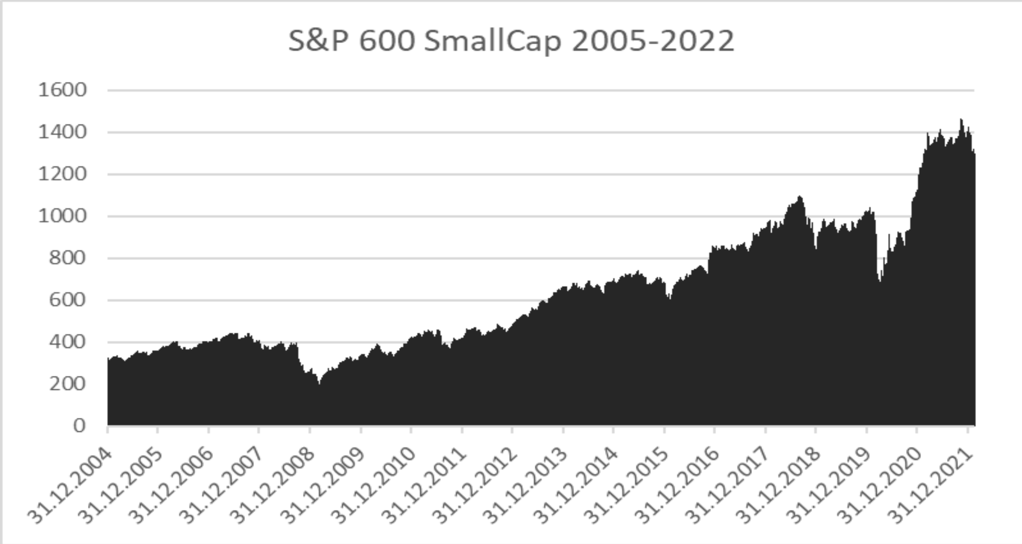

Figure 5: S&P 600 Index value 2005-2022

All three indices have a relatively similar upward trend during the sample period. Some interesting observations include the steadily increasing trend from 2008 to 2020 in all three indices. From a historical perspective a relatively stable 12-year bull market is rather rare. Interestingly, during this 12-year bull run there is a rapid downtrend present around the end of 2015 in both the S&P 400 and S&P 600 which seems to be absent from the S&P 500. Also, the rate of recovery after the spring 2020 selloff is remarkable, possibly aided by the Federal Reserve's quantitative easing programs. Lastly, a notable difference between the S&P 500 and the other two is that the S&P 500 has ascended all the way to the end of the sample period from the 2020 selloff, while the other indices saw a rapid increase in value after 2020 but have somewhat steadied for the last year.

5.1.3 The growth portfolio

The growth portfolio constructed for this paper consists of six stocks, which are Facebook, Amazon, Apple, Netflix, Google (Alphabet) and Tesla. The first five stocks are also known as FAANG-stocks. They are similar in that they are growth technology companies with large market capitalizations. Tesla is added to the portfolio since it has similar characteristics and has also been very popular among investors particularly in recent years.

To evaluate whether herding is more intense in large growth stocks compared to small/midcap value stocks, the empirical study will produce a side-by-side comparison between the growth basket and the S&P 600 SmallCap index. S&P 600 represents the small/midcap value stock basket in this study. As mentioned, growth stocks have outperformed value stocks in recent years, while the opposite tends to be true in normal times (Fama & French, 1998). It is interesting to explore if herding has been prevalent in the growth portfolio.

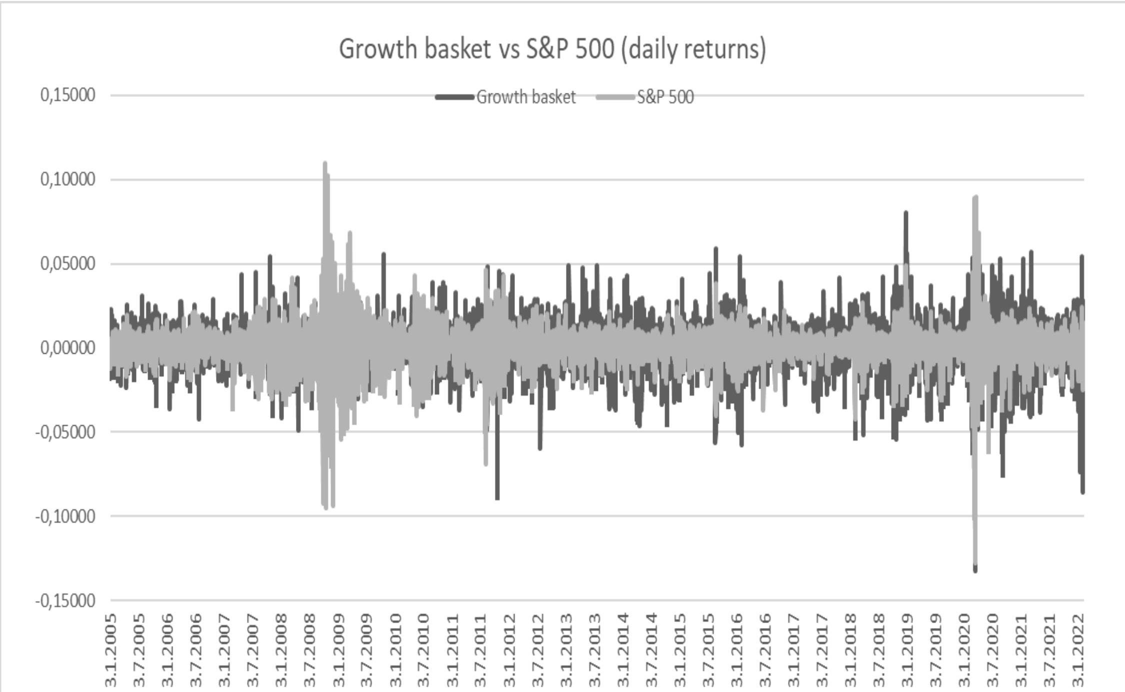

Figure 6: Daily movement of Growth portfolio and S&P 500 2005-2022

The figure shows a line chart of the daily returns of the growth basket and S&P 500. The growth basket shows to be more volatile than the index which is to be expected. After the 2008 financial crisis, the daily returns to either direction have been larger relatively consistently.

5.2 Descriptive statistics

Table 1 presents descriptive statistics for the daily CSAD, and index returns for all three indices. There are 4466 observations for all indices, meaning 4466 days of trading per index. The table shows the mean, median and standard deviation among others to support the empirical study in chapter 7. The table shows first the market return and second the CSAD values per index.

Table 1.

Descriptive statistics

Index	S&P 500		S&P 400		S&P 600	
	Rm	*CSAD*	*Rm*	*CSAD*	*Rm*	*CSAD*
Mean	0,029	1,049	0,031	1,225	0,031	1,461
Median	0,044	0,932	0,057	1,091	0,034	1,317
Maximum	10,957	6,184	10,173	8,144	8,624	10,445
Minimum	-12,765	0,00006	-14,803	0	-14,282	0
Standard deviation	1,207	0,559	1,376	0,64	1,504	0,736
Kurtosis	14,736	14,255	12,446	16,961	8,750	19,017
Skewness	-0,572	2,784	-0,792	2,910	-0,614	2,977
No. of observations	4466	4466	4466	4466	4466	4466

Descriptive statistics of daily index returns (Rm) and daily cross-sectional absolute deviations (CSAD) for the S&P 500, S&P 400 (MidCap) and S&P 600 SmallCap).
Sample period 31.12.2004 - 14.2.2022.

The descriptive statistics show that the values of $CSAD_t$ and $R_{m,t}$ are similar for all three indices, although incrementally higher for S&P 400 and S&P 600. The mean values for $CSAD$ are significantly higher than for R_m in all three indices. The maximum values for S&P 500 and S&P 400 are relatively similar whereas the S&P 600 is the only index where the maximum value for R_m is smaller than the $CSAD$ value. The minimum values are similar across the indices. The markets have experienced severe volatility over time since the maximum values are all close to 10% and the minimum values are over 10% for all indices.

The standard deviations for $CSAD$ values range from 0,559 to 0,736 and from 1,207 to 1,504 for the R_m values. Standard deviations are relatively close to each other across all three stock indices. Kurtosis is similar for both values in the S&P 500 and S&P 400 but shows 8,750 for the R_m value and 19,017 for the $CSAD$ value in the S&P 600. Skewness behaves similarly for all three indices, the significant difference being that skewness is negative in R_m values. Kurtosis and skewness both describe distribution, and the values suggest that returns are not normally distributed. It will be interesting to see how the relatively small, yet significant differences affect the results of the study.

Table 2.

Descriptive statistics

Growth portfolio

	Rp	CSAD
Mean	0,097	1,294
Median	0,096	1,125
Maximum	7,980	9,274
Minimum	13,230	0
Standard Deviation	1,510	0,849
Kurtosis	4,628	8,005
Skewness	-0,480	2,052
No. of observations	4466	4466

Descriptive statistics of daily growth portfolio returns (Rp) and daily cross-sectional absolute deviations (CSAD) for the portfolio.
Sample period 31.12.2004 - 14.2.2022

Descriptive statistics for the growth portfolio are presented in table 2. The values and differences are relatively consistent with the values between index returns and their corresponding $CSAD$ values. However, mean, and median values for the portfolio are significantly higher compared to the index values. Kurtosis and skewness suggest that returns are not normally distributed, although kurtosis is significantly smaller compared to index values.

The growth portfolio consists of FAANG stocks and Tesla. According to data from Thomson Reuters, the 2021 year-end market capitalization for these six stocks was 23,5% of the aggregate market value of the S&P 500. This means that the growth portfolio makes up almost a quarter of the entire market value of the S&P 500 and thus has a strong influence in determining the movement of the index. The growth of the market share of these six companies is an interesting development and is motivation for this study to further explore if herding is a factor.

6 Methodology

This study examines herding in the US stock market. The purpose of this chapter is to present and briefly decrypt the measurement models that have been applied in research. The CSAD-model will also be used to conduct this study on the relationship between herding and market capitalization. The applied methods are developed by Christie and Huang (1995), Chang et al. (2000) and Chiang and Zheng (2010). The measurement models are mostly constructed after Lakonishok et al. (1992).

It is important to note that although the models have detected herding in various instances, they cannot specifically measure the impact on market efficiency or asset pricing. The purpose of their use is to attempt to discover herding at all. Also noteworthy is that these are not the only models for uncovering herding, but they have been utilized in the most notable studies and specifically in the research that was discussed in chapter 4.

The intention is to investigate whether there is herding overall and more specifically to determine if herding occurs differently in stocks with different market capitalizations. The study will also examine if crowds herd more toward growth stocks or value stocks. Return chasing is an established phenomenon (Lakonishok et al. 1992) and this study will contribute to herding research by investigating if the characteristics of stocks affects crowds' decision making. The empirical study corresponds to the hypotheses presented in chapter 1.

6.1 CSSD-model

Research conducted by Christie and Huang (1995) and Chang et al. (2000) attempt to discover if market-wide herding exists. Both parties propose that investors may herd during periods of high market volatility. Christie and Huang (1995) suggest that in instances where herding occurs, returns of individual stocks and the market index would aggregate, i.e., the herding effect should result in moderate differences between their returns.

The method Christie and Huang (1995) apply to measure the dispersion between returns is the cross-sectional standard deviation model (CSSD). It is a measurement model which is utilized to measure the differences between stock returns when markets are turbulent. The dispersion increases when the returns of individual stocks and the market index diverge and vice versa.

The reasoning for the model is that irrational investors' behavior should drive share prices away from their intrinsic values, particularly under economically stressful times (Christie & Huang, 1995). This should cause the deviation between stock returns to diminish as investors abandon fundamental data-analysis and follow the market performance (Christie & Huang, 1995). In economically stable times and decreasing amounts of herding, individual stock returns should follow a *random walk* and thus show a greater dispersion from the market index. The model has received some criticism for its ability to detect herding only in certain market conditions and its sensitivity to outliers (Chiang & Zheng, 2010).

$$CSSD_t = \sqrt{\frac{\sum_{i=t}^{N}(R_{i,t}-R_{m,t})^2}{(N-1)}} \tag{3}$$

Where $R_{i,t}$ is the observed return of share i at time t, $R_{m,t}$ is the cross-sectional average return for the market portfolio at time t and N is the sample size, i.e. the number of firms in the portfolio. Christie and Huang (1995) suggest that individuals are most likely to herd toward the market consensus during periods of extreme market movement and perform testing by using the following regression:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{4}$$

Where $D_t^L = 1$ if the market return on day t lies in the extreme lower tail of the return distribution and (= 0) if otherwise. $D_t^U = 1$ if the market return on day t lies in the extreme upper tail of the return distribution and (= 0) if otherwise. The α coefficient denotes the average dispersion of the sample excluding the regions covered by the two dummy variables that are designed to capture differences in investor behavior in extreme up or down versus stable markets. Christie & Huang (1995) suggest that negative estimates of β_1 and β_2 would be consistent with the presence of herding. They use one or five percent of the observations in the upper and lower tail of the market return distribution to define days of extreme price movement (Christie & Huang, 1995).

Earlier research results have indicated that individuals are more likely to follow the market movement and herd during periods of extreme volatility. The dispersion between returns of individual stocks and the market index should be decreasing with the CSSD-model. Standard asset pricing models usually assume that dispersion strengthens under extreme market conditions.

6.2 CSAD-model

Chang et al. (2000) and Chiang and Zheng (2010) apply a different measurement model. Cross-sectional absolute deviation (CSAD) is less rigid but demands more linearity between returns of the market and individual stocks. Chang et al. (2000) apply the CSAD-model to measure the deviation of returns as the measure of dispersion. They write that if market participants tend to follow aggregate market behavior and abandon their own analysis during extreme market movements, the linear relation between dispersion and market return will no longer hold. Instead, the relation should become increasingly or decreasingly non-linear (Chang et al., 2000; Chiang & Zheng, 2010).

$$CSAD_t = \frac{1}{N}\sum_{i=t}^{N}|R_{i,t} - R_{m,t}| \tag{5}$$

Where $R_{i,t}$ is the return of the share at time t, $R_{m,t}$ is the market portfolio at time t and N is the sample size, i.e. the number of companies in the portfolio.

Chang et al. (2000) apply the CSAD-model to measure dispersions. They argue that the amount of dispersion does not sufficiently reveal if herding is taking place. Chang et al. (2000) develop an empirical methodology to detect the presence of herd behavior, with the underlying assumption that the relation between dispersion and market return becomes non-linear. Chiang and Zheng (2010) apply a similar method and propose that herding is most widespread and intensive when the absolute deviation between returns decreases or increases at a slowing speed. To conduct a test for herding activity, Chang et al. (2000) run the following empirical specification:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{6}$$

Where α is the constant term, $R_{m,t}$ is the normal term, the market index return at time t, whereas $\left|R_{m,t}\right|$ is the absolute term of the cross-sectional market index return at time t, $R_{m,t}^2$ is the non-linear term and ϵ_t is the error term. $CSAD_t$ is the average AVD_t which is the absolute value of the deviation of each stock and γ_1, γ_2 and γ_3 are coefficients. (Chang et al., 2000).

All variables in the specification are computed daily. Chang et al. (2000) write that if market participants do indeed herd around the consensus of all market constituents during extreme price swings, it would result in a non-linear relation between $CSAD_t$ and the average market return. They continue, that the non-linearity would be captured by a negative and statistically significant γ_3 coefficient. Chang et al. (2000) test the significance of the estimated coefficients and the corresponding t-statistics at significance levels of one and five percent.

An important note from the empirical specifications of Christie and Huang (1995) and Chang et al. (2000) is that they apply ex post data in their models, as does this study.

Both argue that lower levels of deviation in returns should indicate herding behavior but does not alone establish its existence. Chang et al. (2000) focus on investigating the relationship between $CSAD_t$ and $R_{m,t}$ to detect herd behavior. They argue that the method applied by Christie and Huang (1995) is more susceptible to positive coefficients, which may cause differences in the results of herding research.

In short, investor herding should occur as a negative CSAD value, or the value should at least increase at less-than-proportional rate compared to the market return. To imply a consistent herding effect, the γ_3 coefficient should be a negative and statistically significant value of R^2 (Chang et al. 2000).

To assess if herding occurs differently among stocks with different characteristics i.e., different market capitalizations, the test will be conducted in various settings. The review period (2005-2022) will first be tested as an entity with different data sets, and secondly split into 1-year sub-periods. These sub-periods include the market movements from the last 17 years in the US equity markets. The regression for market-wide herding is repeated for the sub-periods to assess whether herding occurs consistently throughout the sample period.

Previous research has found evidence that herding behavior often differs between various market sentiments. Investors tend to herd inconsistently between positive (bull) market sentiments and negative (bear) market sentiments (Chiang and Zheng, 2010; Galariotis et al., 2015). The 1-year sub-periods yield more specified market conditions than the entire review period. Significant bear markets occur in 2008, 2010, 2018 and 2020 for example, and the 1-year periods may reveal more robust herding behavior in different market sentiments.

This thesis aims to discover if market capitalization is a factor in driving herd behavior. The study aims to test for herding under various market conditions for all three stock indices. Therefor the 1-year sub-periods are useful for detecting inconsistencies among the indices. The paper will also test for herding in rising and falling markets, which is the third section of the empirical study. To test more specifically for herding under different market conditions, equation 7 is presented.

$$CSAD_t = \alpha + \gamma_1(1-D)R_{m,t} + \gamma_2(D)\left|R_{m,t}\right| + \gamma_3(1-D)R_{m,t}^2 + \gamma_4(D)R_{m,t}^2 + \varepsilon_t \qquad (7)$$

Equation 7 is important for this study because it tests for occurrence of herding behavior between rising and falling market days. The equation contains dummy variables (D) to distinguish between rising and falling markets. If the return of the index is negative, the dummy variable is one ($D = 1$) and if the index return is positive the dummy variable is zero ($D = 0$). As in equation 5, the negative and statistically significant coefficient γ_3 implies the occurrence of herd behavior. In this equation (7) the coefficient γ_3 describes rising market days. Correspondingly, the added coefficient γ_4 constitutes the occurrence of herd behavior in falling markets in the case it results as negative and statistically significant.

In summary, the empirical study will first test for herding for all three indices and growth portfolio throughout the review period. Secondly, full sample testing for all four portfolios is conducted with weekly, monthly, quarterly, and yearly data. Thirdly, the review period will be divided into 1-year sub-periods to capture herd behavior under different market conditions and sentiments. Lastly, equation 7 will be applied for all three indices to detect if herding is more prevalent between rising and falling markets. The growth portfolio is approached in a similar method. The goal is to first establish the existence of herd behavior and secondly to discover inconsistencies among the indices. Comparing results should allow for either the acceptance or rejection of hypotheses 2 and 3.

6.2.1 CSAD-model and volatility

As mentioned in chapter 1, the CSAD-model is a popular measurement to capture herding behavior among researchers (Chang et al., 2000; Chiang & Zheng, 2010; Galariotis et al., 2015). Multiple differentiations are generally made among various research papers but the core of the CSAD based research remains homogeneous, which is to measure a non-linear relationship between return dispersion and the market return. In herding research, the deviations are explained by investors following each other in and out of stocks, generating volatility since large quantities of similar buy or sell orders are placed in a very short time frame. This type of investor behavior opposes efficient market theory since rational investors should base investment decisions on fundamental information.

With a combination of information including news, academic research, investment stories, and logic, it can almost certainly be asserted that herding behavior exists in financial markets. Herding has been introduced as one explanation to phenomena that cannot be explained by efficient market theory, and while the reasoning is logical considering human behavior, the quantification of it is not necessarily straightforward. While CSAD is a popular measurement tool, it is not without criticism.

Bohl et al. (2017) for example argue that the CSAD-model is biased against finding evidence of herding and towards anti-herding, which would support EMH. Chiang and Zheng (2010) find significantly more evidence of herding than Chang et al. (2000) even while using the same measurement model. The inconsistencies can naturally be explained by different samples and conditions, but it is ambiguous if it explains the entirety of the differences. One explanation could be that CSAD essentially measures volatility, and it depends on changes in volatility, and the researchers' interpretation on of how much of it derives from herding.

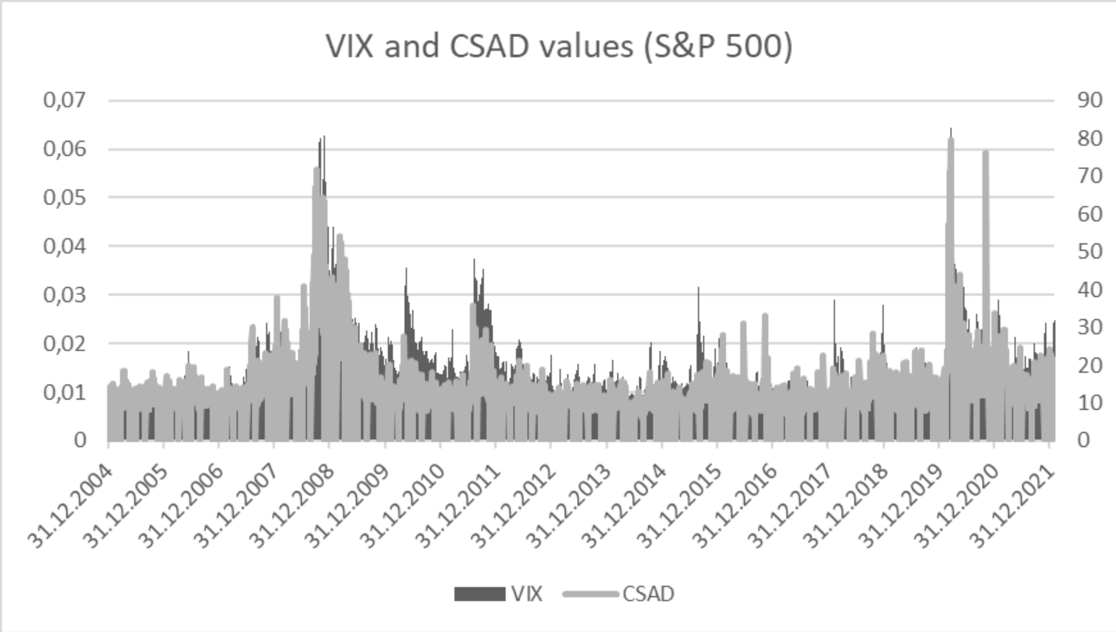

Figure 7: Correlation of VIX and CSAD (S&P 500)

Figure 7 presents the correlation between the Volatility Index (VIX) and the daily CSAD values of the S&P 500. The sample period of the chart is from the beginning of 2005 to early 2022. The VIX is a calculation designed to produce a measure of constant, 30-day expected volatility of the US stock market. The calculation is derived from real-time prices of S&P 500 call and put options, and it is one of the most recognized measures of volatility. The sample period correlation between VIX and CSAD is 0,72.

The high correlation is significant and enhances the argument that herding captured by the CSAD-model is more an indication of high volatility. This is supported by the literature review since it is common to find evidence of herding under extreme market conditions. Chang et al. (2000), Chiang and Zheng (2010) and Galariotis et al. (2015) apply the CSAD-model and find evidence of herding in relatively similar conditions. Specified and isolated periods produce evidence of herding, while full sample testing results in no evidence of herd behavior. Since this study applies the CSAD-model, it is interesting to discover if the results are consistent with previous research.

The next chapter will present the results of the study. The indices and growth portfolio are all measured with the CSAD-model under different conditions. The purpose is to determine if investors tend to herd toward stocks with certain characteristics with the focus on market capitalization and growth versus value. Corresponding to the presented criticism of the CSAD-model, the results are also discussed from the viewpoint of changing volatility.

7 Results

This chapter covers all the empirical results of the study. The results are presented in tables, which display them as clearly as possible. The tables are reviewed on a per table basis, with the intention of going over notable results and discussing how they correspond with the hypotheses. This paper tests for herding behavior in different conditions and samples. The results will show tables in two forms, one with a side-by-side display of measurements from the S&P 500, S&P 400, and S&P 600, and one with a similar presentation of the growth portfolio and the S&P 600, which represents the small/midcap value stocks. The growth portfolio is marked GP in the displayed tables. The first form of tables is meant to enable the evaluation of market capitalization as a factor in herding behavior, and the second form demonstrates differences between large-cap growth stocks and smaller value stocks.

7.1 Full sample testing

The first tables of the chapter show the regression results of full sample testing. Equations 5 and 6 are applied for daily data from the entire sample period, which is from 2005 to early 2022. The 17-year period is tested as a single entity, with all data points included in the regression. Full sample testing is conducted on both table forms, i.e., market capitalization (three indices), and growth versus value (growth portfolio and S&P 600). As mentioned in chapter 6, a negative and statistically significant γ_3 coefficient is a strong indicator of herding behavior.

7.1.1 Market capitalization

Table 3.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Daily data)

	α		γ_1		γ_2		γ_3		Adj. R^2
S&P 500	0,0074	***	0,0066		0,406	***	0,250		0,508
	(85,688)		(1,346)		(36,034)		(1,385)		
S&P 400	0,008	***	0,011	***	0,469	***	0,163		0,615
	(88,266)		(2,519)		(45,465)		(1,067)		
S&P 600	0,009	***	0,013	***	0,459	***	1,147	***	0,632
	(91,218)		(2,974)		(40,837)		(6,672)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 3 shows the results of full sample testing for the entire sample period. The stars after the measured values demonstrate statistical significance. Absence of stars indicates no statistical significance. The corresponding t-statistic for each value is displayed in parentheses below the coefficient values.

The results show that coefficient γ_3 is statistically significant only for the S&P 600. However, none of the index-measurements result in a negative γ_3 coefficient and thus full sample testing demonstrates no evidence of herding behavior, and the null hypothesis is accepted. The results are consistent with previous studies, where full sample testing with the CSAD-model consistently results in no evidence of herd behavior. Christie and Huang (1995) and Chiang and Zheng (2010) study the US stock market and find no evidence of herding with full sample testing. Chang et al. (2000) examine numerous developed markets and find no evidence of herding with all data points.

7.1.2 Growth versus value

Table 4.

Analysis of herding behavior in US stock markets									
Sample period 1.1.2005-14.2.2022 (Daily data)									
	α		γ_1		γ_2		γ_3		Adj. R^2
GP	0,011	***	-0,006		0,381	***	-0,471		0,159
	(59,061)		(-0,681)		(16,938)		(-1,307)		
S&P 600	0,009	***	0,013	***	0,459	***	1,147	***	0,632
	(91,218)		(2,974)		(40,837)		(6,672)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 4 shows the results of full sample testing for the growth portfolio (GP) and the S&P 600 SmallCap Index. The indicator of herding behavior is a negative γ_3 coefficient. The coefficient is negative for the growth portfolio but is not statistically significant. Interestingly, the examined coefficient is negative only for the growth portfolio. The results for S&P 600 are naturally identical to table 3 but are repeated in table 4 for the purpose of clarity. Full sample testing for the growth portfolio results in no statistically significant evidence of herding behavior and thus null hypothesis is accepted.

7.2 Weekly, monthly, quarterly, and yearly data testing

This subchapter will go over results from weekly, monthly, quarterly, and yearly data point testing. The data points cover the entire sample period. Full sample testing produces enormous volume for the regression and cutting a significant amount of data should eliminate some the noise that occurs in daily data testing. It is interesting to examine how the results differentiate with using only part of the data, although spread evenly over the full sample period.

7.2.1 Market capitalization

Table 5.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Weekly data)	α		γ_1	γ_2		γ_3		Adj. R^2
S&P 500	0,006	***	-0,002	0,510	***	-0,731	**	0,589
	(31,415)		(-0,179)	(20,395)		(-2,298)		
S&P 400	0,006	***	0,003	0,579	***	-1,097	***	0,669
	(31,887)		(0,322)	(25,954)		(-4,172)		
S&P 600	0,008	***	-0,009	0,603	***	-0,606	*	0,665
	(32,180)		(-0,869)	(24,065)		(-1,952)		
Sample period 1.1.2005-14.2.2022 (Monthly data)								
S&P 500	0,007	***	-0,017	0,375	***	0,407		0,517
	(16,566)		(-0,668)	(7,115)		(0,455)		
S&P 400	0,007	***	-0,003	0,428	***	0,555		0,664
	(17,543)		(-0,136)	(9,683)		(0,901)		
S&P 600	0,009	***	0,017	0,475	***	0,925		0,684
	(17,034)		(0,723)	(9,866)		(1,404)		
Sample period 1.1.2005-14.2.2022 (Quarterly data)								
S&P 500	0,004	***	0,002	0,802	***	-7,888	*	0,527
	(5,088)		(0,039)	(4,899)		(-1,693)		
S&P 400	0,004	***	-0,025	0,790	***	-6,514	**	0,620
	(5,406)		(-0,478)	(6,203)		(-2,183)		
S&P 600	0,005	***	0,012	0,756	***	-3,837	*	0,672
	(5,951)		(0,265)	(7,089)		(-1,886)		
Sample period 1.1.2005-14.2.2022 (Yearly data)								
S&P 500	0,003	*	0,157	0,611		-20,408		0,331
	(2,151)		(1,661)	(1,122)		(-0,613)		
S&P 400	0,007	***	-0,036	-0,294		34,745	***	0,898
	(11,099)		(-0,783)	(-1,739)		(4,537)		
S&P 600	0,011	***	-0,064	-0,378		36,146	***	0,867
	(11,156)		(-0,894)	(-1,607)		(3,721)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 5 shows the regression results with different datasets. The weekly data is tested by regressing one data point per week, monthly data with one data point per month and so forth throughout the full sample period. The data point for all sets is from the end of the period, i.e., from the end of the week, end of the month and so on.

The table shows interesting results. Tests with weekly data result in a negative γ_3 coefficient for all indices, indicating herding behavior. Moreover, the results are statistically significant, with S&P 500 showing significance at the 5% level, S&P 400 at the 1% level and S&P 600 at the 10% level. The statistically significant values demonstrate herding behavior, leading to the rejection of the null hypothesis with weekly data. Hypothesis 2, which is the assumption of market capitalization being a factor, remains inconclusive.

Use of monthly data results in no evidence of herding with positive γ_3 coefficients for all indices, while testing with quarterly data results in a negative coefficient for each index. Quarterly data yields statistically significant and increasingly negative γ_3 coefficients. Compared to weekly results, the coefficients are more negative which is an even stronger indicator of herd behavior according to the CSAD-model. The large- and small-cap indices are significant at the 10% level, while the mid-cap is significant at 5%. H1 is accepted with quarterly data. Yearly data results in statistical significance, but γ_3 is positive for the mid and small caps. S&P 500 shows a highly negative coefficient but is not statistically significant, thus leading to the acceptance of H0 with yearly data.

The difference in results is highly interesting, since weekly and quarterly data points are the sets that show statistically significant evidence of herding. The effect of noise trading and volume should be limited with the data arrangements. Compared to full sample testing, the results show significant evidence of herding behavior with two of the four alternative regressions. Only tests with monthly data do not capture a single negative γ_3 coefficient. The results are relatively consistent with previous research, since tests for specified conditions and periods more often result in evidence of herding, conversely to full sample testing.

7.2.2 Growth versus value

Table 6.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Weekly data)	α		γ_1		γ_2		γ_3		Adj. R^2
GP	0,009	***	0,009		0,445	***	-1,076	*	0,229
	(28,115)		(0,457)		(10,081)		(-1,914)		
S&P 600	0,008	***	-0,009		0,603	***	-0,606	*	0,665
	(32,180)		(-0,869)		(24,065)		(-1,952)		
Sample period 1.1.2005-14.2.2022 (Monthly data)									
GP	0,011	***	0,063		0,239	**	2,832	*	0,199
	(13,181)		(1,316)		(2,419)		(1,689)		
S&P 600	0,009	***	0,017		0,475	***	0,925		0,684
	(17,034)		(0,723)		(9,866)		(1,404)		
Sample period 1.1.2005-14.2.2022 (Quarterly data)									
GP	0,007	***	0,041		0,931	***	-17,518	*	0,107
	(4,414)		(0,367)		(2,784)		(-1,841)		
S&P 600	0,005	***	0,012		0,756	***	-3,837	*	0,672
	(5,951)		(0,265)		(7,089)		(-1,886)		
Sample period 1.1.2005-14.2.2022 (Yearly data)									
GP	0,006	**	0,258	*	0,674		-32,327		0,229
	(2,661)		(2,059)		(0,935)		(-0,733)		
S&P 600	0,011	***	-0,064		-0,378		36,146	***	0,867
	(11,156)		(-0,894)		(-1,607)		(3,721)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 6 shows results of regressions conducted on the growth portfolio. The growth portfolio results are relatively similar compared to the index measurements since tests with weekly and quarterly data result in negative and statistically significant γ_3 coefficients.

Yearly data testing results in a highly negative coefficient for the growth portfolio but lacks statistical significance. Monthly data yields positive coefficients and no indication of herd behavior.

The γ_3 coefficient is negative for the growth portfolio with weekly, quarterly, and yearly data, although the latter without statistical significance. In all cases, the coefficient is more negative compared to S&P 600 values, demonstrating stronger evidence of herding. Weekly and quarterly values are significant at the 10% level. The outcomes are noteworthy since cutting out volume from the regressions results in evidence of stronger herding toward the growth portfolio than small/midcap value stocks. H0 is rejected with weekly and quarterly data, and the results also allow for the acceptance of H3 due to the more negative coefficients.

7.3 Yearly period tests

Each year of the entire sample period is tested with daily data on a per year basis. This results in 18 years for both categories, i.e., market cap and growth versus value. Each year consists of approximately 260 observations (days when markets are open), excluding 2022 which consists of 30 days of data.

Dividing data to yearly periods allows for further examination of herding behavior in various conditions. The sample period covers 17 years and contains several bear and bull markets. The division shows how herding occurs in steadily rising markets as well as in severe downtrends. The data arrangement also yields the best opportunity to compare results to criticisms of the CSAD-model. According to figure 7, during the sample period volatility has been highest around 2006-2008, 2010-2011, and 2020-2021. The figure also shows volatility spikes around 2015 and 2018. The results are discussed more extensively from this viewpoint in the final chapter.

7.3.1 Market capitalization

Table 7.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Yearly periods)

	α		γ_1		γ_2		γ_3		Adj. R^2
2005									
S&P 500	0,006	***	-0,003		0,526	***	-9,617	*	0,472
	(30,167)		(-0,218)		(7,120)		(-1,860)		
S&P 400	0,006	***	-0,016		0,648	***	-9,661	***	0,687
	(29,516)		(-1,319)		(10,103)		(-2,598)		
S&P 600	0,007	***	-0,009		0,612	***	-4,206		0,742
	(31,617)		(-0,801)		(9,806)		(-1,401)		
2006									
S&P 500	0,007	***	0,011		0,461	***	-7,619	*	0,363
	(30,559)		(0,586)		(5,820)		(-1,605)		
S&P 400	0,006	***	0,001		0,546	***	-4,874	**	0,666
	(32,102)		(0,148)		(10,570)		(-2,123)		
S&P 600	0,008	***	-0,005		0,589	***	-4,271	*	0,700
	(32,465)		(-0,412)		(10,794)		(-1,968)		
2007									
S&P 500	0,007	***	-0,002		0,349	***	-0,756		0,435
	(25,366)		(-0,118)		(5,321)		(-0,298)		
S&P 400	0,007	***	-0,020		0,479	***	-1,461		0,447
	(18,800)		(-0,953)		(5,377)		(-0,404)		
S&P 600	0,008	***	0,005		0,635	***	-4,065	*	0,573
	(19,418)		(0,267)		(8,433)		(-1,665)		
2008									
S&P 500	0,010	***	0,021		0,534	***	-1,342	**	0,690
	(18,488)		(1,608)		(11,611)		(-2,406)		
S&P 400	0,011	***	0,025	**	0,563	***	-0,654		0,796
	(20,884)		(2,116)		(13,738)		(-1,319)		
S&P 600	0,011	***	0,038	***	0,648	***	-0,568		0,833
	(20,574)		(3,127)		(15,379)		(-1,055)		

2009								
S&P 500	0,010	***	0,004	0,490	***	-0,217		0,571
	(18,568)		(0,231)	(7,476)		(-0,158)		
S&P 400	0,011	***	0,001	0,445	***	1,393		0,679
	(20,003)		(0,092)	(7,417)		(1,232)		
S&P 600	0,013	***	-0,005	0,558	***	-0,091		0,726
	(21,932)		(-0,369)	(9,686)		(-0,089)		
2010								
S&P 500	0,007	***	0,001	0,345	***	-2,404	*	0,585
	(34,631)		(0,126)	(8,966)		(-1,953)		
S&P 400	0,007	***	-0,009	0,445	***	-2,746	***	0,727
	(34,521)		(-1,033)	(12,686)		(-2,810)		
S&P 600	0,009	***	-0,014	0,478	***	-2,493	**	0,751
	(35,477)		(-1,530)	(12,583)		(-2,542)		
2011								
S&P 500	0,007	***	0,004	0,286	***	0,360		0,663
	(30,422)		(0,463)	(9,092)		(0,509)		
S&P 400	0,007	***	0,003	0,373	***	-0,231		0,795
	(30,199)		(0,420)	(14,077)		(-0,486)		
S&P 600	0,009	***	0,004	0,380	***	0,337		0,832
	(32,899)		(0,620)	(13,936)		(0,725)		
2012								
S&P 500	0,007	***	0,008	0,301	***	-2,416		0,306
	(29,618)		(0,520)	(4,420)		(-0,696)		
S&P 400	0,007	***	0,004	0,453	***	-4,794	*	0,481
	(27,114)		(0,319)	(7,158)		(-1,763)		
S&P 600	0,008	***	-0,005	0,510	***	-5,751	*	0,505
	(28,352)		(-0,368)	(7,413)		(-1,950)		
2013								
S&P 500	0,006	***	-0,0003	0,340	***	-6,550	**	0,288
	(31,697)		(-0,020)	(6,013)		(-2,208)		
S&P 400	0,006	***	-0,006	0,368	***	-2,990		0,465
	(32,775)		(-0,470)	(7,073)		(-1,246)		
S&P 600	0,008	***	-0,012	0,410	***	-3,025		0,478
	(33,528)		(-0,824)	(7,221)		(-1,208)		

2014									
S&P 500	0,006	***	-0,023		0,325	***	-6,132	*	0,248
	(29,229)		(-1,386)		(4,971)		(-1,732)		
S&P 400	0,007	***	-0,018		0,454	***	-6,641	***	0,423
	(29,151)		(-1,115)		(8,275)		(-2,826)		
S&P 600	0,008	***	-0,006		0,389	***	-3,561		0,384
	(28,546)		(-0,451)		(5,930)		(-1,278)		
2015									
S&P 500	0,007	***	-0,004		0,232	***	-2,632		0,186
	(28,835)		(-0,316)		(4,684)		(-1,482)		
S&P 400	0,008	***	-0,015		0,358	***	-5,030	**	0,250
	(27,780)		(-0,849)		(5,900)		(-2,114)		
S&P 600	0,009	***	-0,011		0,455	***	-6,965	**	0,302
	(27,836)		(-0,615)		(6,423)		(-2,467)		
2016									
S&P 500	0,007	***	-0,061	**	0,292	***	0,105		0,249
	(23,671)		(-2,423)		(3,482)		(0,029)		
S&P 400	0,008	***	-0,041	*	0,362	***	0,797		0,313
	(22,594)		(-1,870)		(4,460)		(-0,261)		
S&P 600	0,011	***	-0,031		0,356	***	-1,745		0,278
	(24,338)		(-1,491)		(4,119)		(-0,557)		
2017									
S&P 500	0,007	***	-0,015		0,107		6,081		0,045
	(29,731)		(-0,407)		(0,836)		(0,599)		
S&P 400	0,008	***	-0,053	**	0,470	***	-12,792	*	0,191
	(27,945)		(-2,094)		(4,591)		(-1,915)		
S&P 600	0,009	***	-0,039	*	0,460	***	-11,693	**	0,186
	(28,899)		(-1,789)		(4,923)		(-2,398)		
2018									
S&P 500	0,007	***	-0,022		0,331	***	-4,364	***	0,292
	(29,393)		(-1,446)		(6,721)		(-2,936)		
S&P 400	0,009	***	-0,031	*	0,361	***	-4,682	**	0,278
	(29,723)		(-1,669)		(6,085)		(-2,467)		
S&P 600	0,011	***	-0,027		0,306	***	-3,277	*	0,219
	(31,581)		(-1,464)		(5,207)		(-1,866)		

2019									
S&P 500	0,008	***	-0,039	*	0,273	***	-4,147		0,129
	(27,291)		(-1,769)		(3,765)		(-1,389)		
S&P 400	0,009	***	-0,026		0,354	***	-4,678		0,215
	(26,240)		(-1,281)		(4,653)		(-1,514)		
S&P 600	0,011	***	0,041	**	0,428	***	-8,498	***	0,188
	(28,328)		(-2,004)		(5,576)		(-3,033)		
2020									
S&P 500	0,011	***	0,006		0,401	***	-0,589		0,419
	(16,256)		(0,306)		(6,637)		(-0,854)		
S&P 400	0,011	***	0,022		0,484	***	-0,690		0,577
	(16,260)		(1,172)		(9,401)		(-1,313)		
S&P 600	0,013	***	0,038	*	0,435	***	0,785		0,605
	(16,003)		(1,861)		(7,174)		(1,238)		
2021									
S&P 500	0,009	***	-0,046	*	0,483	***	-11,984	**	0,154
	(22,085)		(-1,747)		(4,279)		(-2,109)		
S&P 400	0,011	***	-0,024		0,326	***	-3,636		0,184
	(24,587)		(-1,228)		(3,999)		(-1,219)		
S&P 600	0,012	***	-0,015		0,292	***	-2,696		0,143
	(23,942)		(-0,745)		(3,474)		(-1,004)		
2022 (1.1 - 14.2.2022)									
S&P 500	0,011	***	-0,024		0,204		-0,649		0,091
	(8,331)		(-0,446)		(0,648)		(-0,048)		
S&P 400	0,011	***	0,006		0,566	*	-15,891		0,201
	(8,014)		(0,157)		(1,842)		(-1,152)		
S&P 600	0,013	***	0,046		0,397		-8,454		0,109
	(9,324)		(0,946)		(1,449)		(-0,775)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

The per year testing yields highly interesting and significant results. Table 7 shows negative and statistically significant γ_3 coefficients for multiple indices in several years, demonstrating strong evidence of the occurrence of herd behavior. Proceeding from the top down, only 2009, 2011, 2016, 2020 and the shorter period of 2022 produce no statistically significant evidence of herding for all indices. This means that only 4 out of 17 full year tests show no significant evidence of herding. None of the years show a positive γ_3 coefficient for all three indices, meaning all years indicate herding occurring in at least one of the indices, although some without statistical significance.

2005 shows statistically significant evidence of herding in large- and midcap indices and 2006 in all three. In 2006, S&P 400 displays significance at the 5% level, while S&P 500 and S&P 600 show significance at the 10% level. 2007 reveals statistically significant (10% level) evidence of herding only in the small-cap index. The 2008 financial crisis caused severe volatility in stock markets but interestingly, the only significant indication of herding is gathered from the S&P 500. This may be due to relatively typical investor behavior, where capital is allocated from riskier investments toward safer large-cap value stocks in crisis situations, resulting in a herding formation toward the S&P 500. The results are partially consistent with Christie and Huang (1995) who state that herding is more profound in the state of crisis.

No statistically significant evidence of herding is found in 2009, as is the case in 2011. 2010 displays robust evidence of herding, yielding significant and negative γ_3 coefficients for all three indices. The S&P 400 tests significant at the 1% level. Tests for 2012, 2013, 2014, and 2015 reveal negative γ_3 coefficients for all indices in each year. Only some of the results are statistically significant, and significance levels rotate between the indices, meaning that none of the indices display consistent statistical significance from year to year. This remains true throughout table 7.

Tests for 2016 result in no evidence of herding, and only S&P 600 presents a negative γ_3 coefficient. Corresponding to figure 7, 2016 is period of relatively low volatility. 2017, 2018, and 2019 all result in statistically significant evidence of herding for at least some of the indices. The γ_3 coefficients are mostly negative and again significance levels vary. Throughout the table, significance at the 1% level is relatively rare, but here the large cap yields 1% level reliability in 2018 and the S&P 600 in 2019. 2018 saw high volatility due to threats of tightening monetary policy and trade wars among other issues. Interestingly, the table shows highly negative coefficients and statistically significant evidence of herding in all indices for 2018.

The last three years of the empirical test, 2020, 2021, and 2022, all show varying results. 2020 displays negative coefficients for some of the indices but no statistical significance. The result is interesting since 2020 was turbulent, experiencing a rapid downtrend and an even stronger bull market. The test results for 2021 are equally compelling, since only the S&P 500 shows a significant and highly negative γ_3. Corresponding to figures 3-5, the index saw the largest increase in value of the three, and the result may support the hypothesis that return chasing among large-cap growth stocks has been prevalent in recent years. As discussed earlier, the growth portfolio forms almost a quarter of the S&P 500 measured in market capitalization. Also, the S&P 500 shows a steady increase in 2021 while the mid- and small caps have saturated. The short sample period of 2022 shows no evidence of herding behavior.

The yearly period tests yield interesting results. H0 is rejected in all but four years, and covering the sample period as a single entity, H0 is rejected. The tests demonstrate reliably that herding behavior occurs in stock markets, thus leading to the acceptance of H1. H2 assumes that market capitalization matters for herds. The results remain inconclusive since the table does not show an index consistently yielding a more negative and significant γ_3. The indices seem to experience more herding depending on the year. However, an interesting observation from the table is that in 2008, 2018, and 2021 the S&P 500 displays the most significant and negative γ_3. The results coincide with proximity to the largest crisis during the sample period, meaning market cap seems to matter when market sentiment is most uncertain.

7.3.2 Growth versus value

Table 8.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Yearly periods)

	α		γ_1		γ_2		γ_3		Adj. R^2
2005									
GP	0,008	***	-0,071		0,900	***	-29,244		0,104
	(11,078)		(-1,193)		(3,346)		(-1,556)		
S&P 600	0,007	***	-0,009		0,612	***	-4,206		0,742
	(31,617)		(-0,801)		(9,806)		(-1,401)		
2006									
GP	0,008	***	-0,072		0,687	***	-10,462		0,101
	(11,191)		(-1,142)		(2,659)		(-0,675)		
S&P 600	0,008	***	-0,005		0,589	***	-4,271	*	0,700
	(32,465)		(-0,412)		(10,794)		(-1,968)		
2007									
GP	0,007	***	-0,068		0,769	***	-13,626	**	0,192
	(10,180)		-(-1,567)		(4,626)		-(-2,118)		
S&P 600	0,008	***	0,005		0,635	***	-4,065	*	0,573
	(19,418)		(0,267)		(8,433)		(-1,665)		
2008									
GP	0,010	***	-0,023		0,499	***	-0,241		0,53
	(11,739)		(-1,114)		(6,912)		(-0,276)		
S&P 600	0,011	***	0,038	***	0,648	***	-0,568		0,833
	(20,574)		(3,127)		(15,379)		(-1,055)		
2009									
GP	0,007	***	-0,018		0,536	***	-2,581		0,367
	(9,880)		(-0,757)		(6,127)		(-1,407)		
S&P 600	0,013	***	-0,005		0,558	***	-0,091		0,726
	(21,932)		(-0,369)		(9,686)		(-0,089)		
2010									
GP	0,010	***	-0,0001		0,427	***	-3,116		0,117
	(13,169)		(-0,002)		(2,896)		(-0,659)		
S&P 600	0,009	***	-0,014		0,478	***	-2,493	**	0,751
	(35,477)		(-1,530)		(12,583)		(-2,542)		

2011									
GP	0,01	***	0,012		0,417	***	-3,246		0,124
	(12,388)		(0,356)		(3,829)		(-1,328)		
S&P 600	0,009	***	0,004		0,380	***	0,337		0,832
	(32,899)		(0,620)		(13,936)		(0,725)		
2012									
GP	0,015	***	0,045		0,096		-4,222		-0,009
	(14,240)		(0,597)		(0,310)		(-0,267)		
S&P 600	0,008	***	-0,005		0,510	***	-5,751	*	0,505
	(28,352)		(-0,368)		(7,413)		(-1,950)		
2013									
GP	0,014	***	-0,025		0,280		-20,091		-0,005
	(12,785)		(-0,293)		(0,847)		(-1,158)		
S&P 600	0,008	***	-0,012		0,410	***	-3,025		0,478
	(33,528)		(-0,824)		(7,221)		(-1,208)		
2014									
GP	0,010	***	-0,043		0,690	***	-31,607	**	0,018
	(11,759)		(-0,642)		(2,690)		(-2,275)		
S&P 600	0,008	***	-0,006		0,389	***	-3,561		0,384
	(28,546)		(-0,451)		(5,930)		(-1,278)		
2015									
GP	0,010	***	0,042		0,166		2,263		0,038
	(13,715)		(0,969)		(1,156)		(0,437)		
S&P 600	0,009	***	-0,011		0,455	***	-6,965	**	0,302
	(27,836)		(-0,615)		(6,423)		(-2,467)		
2016									
GP	0,008	***	-0,020		0,463	**	-7,808		0,052
	(11,779)		(-0,364)		(2,483)		(-0,973)		
S&P 600	0,011	***	-0,031		0,356	***	-1,745		0,278
	(24,338)		(-1,491)		(4,119)		(-0,557)		
2017									
GP	0,008	***	-0,008		0,057		2,840		-0,008
	(13,970)		(-0,101)		(0,188)		(0,117)		
S&P 600	0,009	***	-0,039	*	0,460	***	-11,693	**	0,186
	(28,899)		(-1,789)		(4,923)		(-2,398)		

2018										
GP	0,010	***	0,003		0,391	***	-3,299		0,089
	(15,149)		(0,091)		(2,991)		(-0,833)		
S&P 600	0,011	***	-0,027		0,306	***	-3,277	*	0,219
	(31,581)		(-1,464)		(5,207)		(-1,866)		
2019									
GP	0,009	***	0,043		0,248		-1,566		0,027
	(13,686)		(0,852)		(1,506)		(-0,230)		
S&P 600	0,011	***	0,041	**	0,428	***	-8,498	***	0,188
	(28,328)		(-2,004)		(5,576)		(-3,033)		
2020									
GP	0,013	***	0,010		0,300	***	-1,595	*	0,077
	(14,211)		(0,361)		(3,512)		(-1,634)		
S&P 600	0,013	***	0,038	*	0,435	***	0,785		0,605
	(16,003)		(1,861)		(7,174)		(1,238)		
2021									
GP	0,008	***	-0,048		0,837	***	-28,536	***	0,081
	(11,054)		(-0,984)		(4,047)		(-2,736)		
S&P 600	0,012	***	-0,015		0,292	***	-2,696		0,143
	(23,942)		(-0,745)		(3,474)		(-1,004)		
2022 (1.1-14.2.2022)									
GP	0,014	**	-0,076		-0,039		49,650		0,109
	(2,764)		(-0,357)		(-0,319)		(0,959)		
S&P 600	0,013	***	0,046		0,397		-8,454		0,109
	(9,324)		(0,946)		(1,449)		(-0,775)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 8 shows the yearly data regression results for the growth portfolio (marked GP). S&P 600 results are identical to table 7 but are repeated for the purposes of clarity and comparison. The table corresponds to hypothesis 3, which is that large-cap growth stocks see a more prevalent herding effect compared to value stocks. The focus is on the growth portfolio, as S&P 600 results were discussed more extensively in the previous chapter. As mentioned, the growth portfolio constitutes a large portion of the entire S&P 500 index. The purpose is to seek evidence of herd behavior and see if results have shifted over time.

It can quickly be determined that the growth portfolio does not show statistically significant evidence of herding as often compared to the indices in table 7. Only 2007, 2014, 2020, and 2021 display statistically significant and negative γ_3 coefficients. Negative coefficients are found in all but three years, which are 2015, 2017, and 2022, meaning that there is indication of herd behavior in most years, but the test is unable to capture statistical significance. Conversely, the S&P 600 shows statistically significant evidence in eight out of eighteen years, although with various levels of significance.

Between 2005 and 2011, the growth portfolio displays statistically significant evidence of herding only once, which occurs in 2007, where the result is significant at the 5% level. H3 can only be accepted in 2007 from 2005-2011. An interesting observation from the table is that although the growth portfolio results do not demonstrate statistical significance in most years, the γ_3 coefficient is consistently more negative compared to the small-cap index. Between 2005-2011 this is true in every year.

In 2012-2019, tests for the growth portfolio result in a significant and negative γ_3 only once, 2014. The result is significant at the 5% level. Another observation from the period is that coefficients for the growth portfolio continue to be much more negative compared to the S&P 600. This remains relatively consistent, excluding 2012 and 2019. 2015 and 2017 result in positive coefficients, thus demonstrating no evidence of herd behavior. H3 can reliably be accepted only in 2014 during this period.

2020 and 2021 show very interesting results regarding H3. 2020 displays statistically significant evidence of herding at the 10% level for the growth portfolio. Tests for 2021 result in a significant and negative γ_3 at the 1% level. Tests for mid-/small-cap value stocks present no statistically significant evidence of herding in the two years. 2022 shows no evidence of herding for either. The results are interesting since H3 assumes that large-cap growth stocks experience higher levels of herding compared to value stocks. The hypothesis concerns the entire sample period, but the phenomena of significant returns yielded by large cap growth stocks seems to have gained momentum particularly in recent years. The growth portfolio consisting of FAANG stocks and Tesla has yielded outstanding returns since the 2020 Covid-19 induced bear market.

H3 can reliably be accepted for 2007, 2014, 2020, and 2021. Other years indicate stronger evidence of herding in the growth portfolio compared to the S&P 600 but lack statistical significance. The results from the last few years are highly interesting, since evidence from 2020 and 2021 coincide with the almost historical rally of the S&P 500. It is arguable that herding toward FAANG stocks and Tesla have uplifted the entire index, since the stocks form such a large portion of it. From the viewpoint of volatility, the years that produce the strongest evidence of herding in the growth portfolio correlate rather well with times of higher volatility.

7.4 Rising and falling market tests

The last tables of the chapter display the regression results of tests conducted for rising and falling markets. Equation 7 is applied for calculating the results. The results introduce a new coefficient which is marked γ_4. The tests are run by using daily data from the entire sample period. If herding occurs, coefficients γ_3 and γ_4 are negative and statistically significant. The γ_3 coefficient reflects herding during rising markets while γ_4 reflects herding during falling markets.

7.4.1 Market capitalization

Table 9.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Up and down market days)

	α		γ_1		γ_2		γ_3		γ_4		Adj. R^2
S&P 500	0,007	***	0,403	***	0,406	***	0,499	*	0,086		0,508
	(85,497)		(28,106)		(30,596)		(1,897)		(0,393)		
S&P 400	0,008	***	0,448	***	0,468	***	1,001	***	-0,093		0,616
	(87,652)		(31,992)		(39,637)		(3,672)		(-0,559)		
S&P 600	0,009	***	0,402	***	0,459	***	2,991	***	0,731	***	0,635
	(90,823)		(25,289)		(36,150)		(9,061)		(4,000)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

Table 9 demonstrates no evidence of herding concerning all indices. The large cap index yields positive coefficients, as does the small-cap index. The S&P 400 has the only negative coefficient in γ_4. None of the results are both negative and statistically significant, thus indicating that herding does not occur during the rising and declining days when examining the sample period as a single entity.

The results are consistent with Chiang and Zheng (2010) who find no asymmetric herding in the developed markets. However, Ohlson (2010) reports the occurrence of herding in rising market days and Keasey, Mobarek and Mollah (2014) report evidence from declining days, indicating that the results are also inconsistent with some research. The differences may be attributed to different sample periods and different markets and conditions, and possibly to limitations of the CSAD-model to capture herding in full sample testing.

7.4.2 Growth versus value

Table 10.

Analysis of herding behavior in US stock markets

Sample period 1.1.2005-14.2.2022 (Up and down market days)

	α		γ_1		γ_2		γ_3		γ_4		Adj. R^2
GP	0,010	***	0,351	***	0,402	***	0,120		-0,859	*	0,159
	(59,988)		(12,280)		(15,225)		(0,230)		(-1,959)		
S&P 600	0,009	***	0,402	***	0,459	***	2,991	***	0,731	***	0,635
	(90,823)		(25,289)		(36,150)		(9,061)		(4,000)		

*** Significant at the 0,01 level
** Significant at the 0,05 level
* Significant at the 0,10 level

The growth portfolio is similarly tested with equation 7. The portfolio is the only one of the four subjects that produces statistically significant evidence of herding behavior. It shows to have experienced herding during falling markets, i.e., days when markets have declined. This is demonstrated by the negative γ_4 coefficient for the growth portfolio. The result is statistically significant at the 10% level. The rest of the coefficients are positive and show no evidence of herding.

Results for the growth portfolio are noteworthy since none of the indices produce evidence of herding when testing for rising and declining days. Equation 7 is also the only specification which produces evidence of herding in full sample testing, although only concerning the growth portfolio. More importantly, the S&P 500, where all the tested growth stocks reside, does not yield similar evidence. H0 is rejected only concerning the growth portfolio and H1 and H3 are accepted. The results are consistent with Keasey et al. (2014), while inconsistent with Chiang and Zheng (2010).

7.5 Summary of the results

Chapter 7 displays all the meaningful results derived from the regressions conducted for this study. Data is tested with different samples and conditions, and with two different empirical specifications, which are equations 6 and 7. The results are partially inconsistent with previous research, which is common among studies conducted on herding. The differences can mostly be explained by heterogeneous data sets. The sample period, the target indices and stocks, and the location of the markets under observation can all affect the results significantly.

Full sample testing results in no statistically significant evidence of herding concerning all four targets, which are the S&P 500, S&P 400 MidCap, S&P 600 SmallCap and the growth portfolio. The portfolio yields the single negative γ_3 but it is not significant. H0 is accepted for all targets with full sample testing.

Weekly, monthly, quarterly, and yearly data testing offers various results. With some of the noise cancelled out, weekly and quarterly data produce robust evidence of herding. Conversely, monthly and yearly data provide no evidence of herding, although some negative γ_3 coefficients. The reason for the differences remains unclear, although the timing of quarterly reporting may have something to do with it. With this data arrangement, large- and mid-capitalization stocks present stronger evidence of herding compared to small-cap stocks and allows the acceptance of H1 and H2. The growth portfolio presents negative γ_3 coefficients for all but monthly data. Weekly and quarterly results are statistically significant, and the coefficients are consistently more negative than the corresponding small-cap values. With the specific data arrangement, H1 and H3 are accepted, meaning the results indicate stronger presence of herding in large-cap growth stocks.

Yearly period testing provides the most interesting results concerning the hypotheses. The tables show transformation from year to year, and no consistent pattern is present. Regarding market capitalization, all indices display negative γ_3 coefficients in most years and approximately half of them are statistically significant. Each index demonstrates the strongest evidence of herding in at least one of the years, i.e., γ_3 is most negative and significant at the 1% level at least once.

The only relatively consistent pattern seems to correlate with volatility. Stocks in the S&P 500 experience significant herding and, more importantly, most of the three indices in years 2008, 2013, 2018, and 2021. As mentioned, corresponding to figure 7, the years are in close proximity to the largest crisis during the sample period, excluding 2013. Conversely, mid- and small-cap stocks present the most evidence in 2007, 2010, 2012, 2015, 2017, and 2019. The years correlate with times of relatively low volatility. The evidence is not robust, but the above information indicates that investors may herd more toward large-cap stocks in crisis periods and toward mid- and small-caps in more stable times. While looking at the yearly period tests as a single entity, H2 is accepted. Market capitalization seems to matter depending on market sentiment and conditions.

The yearly tests for the growth portfolio yield similarly interesting results. As mentioned, while examining the entire sample period, the portfolio does not show consistent evidence of more herding compared to the small-cap value index. Large-cap growth stocks experience most herding, and more than the S&P 600, in 2007, 2014, 2020, and 2021. Interestingly, the years are very close to the years when the S&P 500 experiences most herding, where the portfolio stocks also locate. As a reminder, the growth portfolio stocks make up almost a quarter of the S&P 500 in market value. It is possible that investors move toward the study's portfolio stocks in turbulent times, forming a herd. This then consequently lifts the entire large-cap index. The evidence is again inconclusive, but it may be a viable theory. The growth portfolio shows significant evidence of herding after 2019, resulting in the acceptance of H3 between 2020-2021. As an entity, results of yearly tests lead to the rejection of H3. Lastly, concerning the large-cap growth stocks, it is important to emphasize how they produce easily the most negative coefficients relatively consistently, strongly indicating the occurrence of herding. However, the test is not able to show statistical significance which may possibly be attributed to some of discussed limitations of the CSAD-model.

Tests for rising and falling markets are conducted with all available data points. Full sample testing for rising and declining days produces no statistically significant evidence of herding. The only relevant and negative coefficient is from the growth portfolio, but it does not demonstrate statistical significance. H0 is accepted for rising and falling market tests. In the next and final chapter, the results are further discussed in correspondence with relevant literature, and we make suggestions for future research.

8 Conclusions

Herding behavior is a concept linked strongly to human psychology. Given that efficient market theory assumes rational investor behavior at all times, herding is a phenomenon that directly opposes the EMH. This study finds statistically significant evidence of herding behavior in major stock indices in the US equity markets during the period 2005 through early 2022. Moreover, the study supports the notion that psychological factors influence the movement and pricing of markets. The thesis examines herding behavior from the viewpoint of market capitalization (i.e., if herds tend to move toward stocks withs certain market values). Furthermore, the thesis examines if herding formations are more prevalent in large-cap growth stocks compared to smaller-cap value stocks.

As discussed, it seems that results of herding research have experienced a transformation over time. Results of this study are partially consistent with Chiang and Zheng (2010), and even more consistent with Galariotis et al. (2015), Choi and Skiba (2015), Bohl et al. (2017), Deng et al. (2018) and Jiang and Verardo (2018) who all examine individual or institutional herding in US equity markets. The results are mostly inconsistent with Christie and Huang (1995) and Chang et al. (2000).

More recent studies seem to produce stronger evidence of herding compared to earlier research. One common factor with recent literature and this study is more recent data. The phenomenon can be attributed to enhanced research methods, but there is a possibility that the generalization of the internet has reduced information asymmetry, resulting in easier conditions for investors to follow each other, and especially those who are perceived as experts in the investment field. Choi and Skiba (2015) report the strongest evidence of herding from markets with low levels of information asymmetry, and as Kahneman and Tversky (1979) pointed out, most people simply do not want to be left out of the group.

This study finds that herds in the investment field are adaptable and mobile, as they are in nature. All three examined stock indices experienced most herding in at least some years during the sample period. The study produces significant evidence of stock characteristics (i.e., market cap) being a factor for herd movement, although the results do not show consistent herding toward one particular capitalization size. As discussed in the summary of chapter 7, the only relatively harmonious pattern is the herd movement in periods of high and low volatility. Therefore, H2 is accepted; yet there is no specific capitalization size or constant capitalization-based herding result. Overall, it seems to depend on market conditions as to how market capitalization matters for herding. In other words, herding occurs and market capitalization matters, but these results depend largely on volatility extremes (i.e., high or low levels).

Chang et al. (2000) and Galariotis et al. (2015) form market capitalization-based portfolios for their research, and, among other investment styles, the latter also test for value vs growth. Chang et al. (2000) report evidence from the emerging markets that herding formations persist irrespective of market capitalization. Galariotis et al. (2015) study the US market during 1989-2011 and report evidence of herding toward the consensus in US stock prices. The writers suggest that herding is not driven by investment style but rather coincides with releases of important macroeconomic information. The results of this study also do not argue that herding is consistently driven by market capitalization, rather investors may herd toward different market caps in different conditions. In other words, market capitalization is not the catalyst of herding behavior, but it may be a destination of herds in various circumstances and is therefore meaningful.

Galariotis et al. (2015) also test for value versus growth in US markets. The cross-over of their sample period with this study is rather short, and the results displayed in chapter 7 indicate that large-cap growth stocks have experienced increased levels of herding in recent years. The findings of Choi and Skiba (2015) support the hypothesis that herding has increased rather than decreased. For large-cap growth stocks, this seems to be particularly true since the Covid-19 related stock market crash in early 2020. As discussed, H3 is not accepted for the entire sample period but it would be interesting to examine if return chasing has been prevalent in FAANG stocks in recent years, what level of herding they have experienced, and how it may have affected the pricing of the S&P 500.

Another subject of interest for this study is how the results correspond with the suggestion that CSAD-values and other herding measurements are mostly a substitute for volatility. Full sample testing is useless in this regard, but the yearly period tests show some linearity with periods of high volatility. The weakest consecutive evidence of herding from the yearly tests of all targets (indices and growth portfolio) are calculated between 2011 through 2017. Figure 7 shows this to be a time of low volatility. It is entirely possible that investors resort to herding in periods of high uncertainty and otherwise invest more independently, relying more on fundamental information in more stable periods. However, the results and the strong correlation shown in Figure 7 can also be interpreted as an artifact of the CSAD measure indicating robust herd behavior in high volatility periods and less in low volatility periods. In other words, it is possible that herding research results follow the VIX index and simply display changes in volatility, not investors' tendencies to herd. The plausibility of that explanation also depends on the level of belief in investors' full rationality and fundamental-based decision making in periods of low volatility.

The topic is highly interesting and grants further investigation. As discussed in chapter 1, to absolutely prove that an investment decision is herding, in this context defined as making an investment decision based solely on the actions of others, researchers would essentially need mind-reading abilities. Chapter 3 introduces spurious herding (Bikhchandani & Sharma, 2000), which is a form of unintentional herding where investors receive similar fundamental information at the same time and carry out homogeneous investment decisions based solely on fundamentals, resulting in an unintentional herd. Galariotis et al. (2015) and Choi and Skiba (2015) attribute at least part of their results to this form of herding. Although this form of herding is a useful concept in the herding literature, it is important to point out that in a traditional economic context spurious herding is not herding, but rather rational investors acting simultaneously. Spurious herding is action in accordance with the assumptions of EMH, and it is arguable that the term could be removed from the behavioral finance literature.

To conclude, the information gathered from this study is highly interesting. The thesis discusses theory, reviews the relevant literature, and conducts empirical tests with a specified focus. Whether plausible or not, it has been noted that traditional EMH based theory suggests that herding behavior may result in, or at least support, efficient outcomes. The literature review and empirical study support the existence of herd behavior in the US stock markets. By extension, it is relatively safe to assume that the psychological phenomenon exists in global markets.

Lastly, even though it is widely used as empirical framework for finance research on herding, as well as used in this thesis, this study questions the CSAD-model as a herding research method. The results with CSAD are inconsistent and often seem to yield less evidence of herding than could be assumed. As mentioned, the phenomenon is difficult to examine and reliably prove, which brings this paper to a final point which applies to this thesis, various finance theories and models, and even research in general: humans tend to act as sheep (Shiller, 2015), but do not want to be perceived as such. In short, and largely out of fear of being rejected by the flock, we tend to use research methods and approaches approved by the herd, regardless of accuracy or efficacy. The CSAD-measure and this thesis are not exceptions to this type of herd behavior.

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