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Herding during COVID-19 pandemic

Evidence from Finnish stock market

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ABSTRACT:

Herding represents an occurrence in investors' decision-making process which roots from animal behaviour and has been extended to characterize analogous human behaviour in financial markets. Both individual and institutional investors exhibit this behaviour, with key differences being the reasons to herd and the outcomes of herding. This thesis examines whether a behavioural bias called herding occurs in Finnish stock market. The focus is to find out whether a sudden global health crisis has affected in investors herd mentality.

Utilizing the Cross-sectional Standard Deviation (CSSD) and Cross-sectional Absolute Deviation (CSAD) models, this study aims to detect market-wide herding to be prominent in Finnish stock market during time periods of 01.01.2018 – 31.12.2019 and 01.01.2020 – 31.12.2021. In continuation, the intensity of herding between the two sample periods is compared. The study hypothesizes herding to be more prominent during the second time period due to increased market uncertainty caused by the negative news about COVID-19 pandemic.

Following the research hypotheses this thesis presents the existing literature on herding on different markets. Hypotheses of herding to be present in Finnish stock market are based on existing literature and studies on topic exhibiting the presence of herding in various markets. The literature review discusses the fundamentals of herding as a part of behavioural finance. In continuation, examples of other behavioural biases strongly connected to herding are presented. Different forms of intentional and spurious herding are explained and traditional financial theories such as efficient market hypothesis, CAPM, three factor model and five factor model are discussed and challenged by behavioural finance.

Data of the study consists of daily closing prices for 25 most actively traded stocks in Finnish stock market. Despite hypothesized increase in herding in Finnish stock market during the COVID-19 time period, the results of the study exhibit herding to be absent in Finnish stock market during both of the observed time periods. When considering herding to cause the market to be irrational, Finnish stock market seems to function rationally, as evidenced by the CSSD and CSAD results. Despite the increased uncertainty in the market, Finnish stock market appears to be rather resilient to impacts of global health crisis. Absence of herding in Finnish stock market especially during the COVID-19 time period highlights the importance of considering other behavioural biases to explain market movements and investors' decision making.

KEYWORDS: Herding, Behavioural finance, COVID-19, Pandemic, Cross-sectional standard deviation, Cross-sectional absolute deviation, Finnish stock market, Market efficiency

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TIIVISTELMÄ:
Laumakäyttäytyminen on osa käyttäytymistiedettä, joka juontaa juurensa eläimistä. Ihmisten laumakäyttäytymistä esiintyy rahoitusmarkkinoilla sijoittajien sijoituspäätöksissä. Laumakäyttäytymiselle alttiita ovat sekä yksityiset, että institutionaaliset sijoittajat. Sekä syyt miksi yksityiset- ja institutionaaliset sijoittajat laumautuvat, että seuraukset heidän laumautumisestaan eroavat. Tämä tutkielman tarkoituksena on löytää koko markkinan laajuista laumakäyttäytymistä Helsingin pörssistä. Pääpainona tutkielmassa on tarkastella, onko maailmanlaajuisella terveyskriisillä ollut vaikutusta sijoittajien laumautumiseen.

Tarkastelu tehdään Cross-sectional Standard Deviation (CSSD) ja Cross-sectional Absolute Deviation (CSAD) malleilla. Malleilla on tarkoitus löytää koko markkinan laajuista laumakäyttäytymistä ajanjaksoilta 01.01.2018 – 31.12.2019 ja 01.01.2020 – 31.12.2021. Tutkielma tarkastelee, mikäli laumakäyttäytyminen on ollut näkyvämpää jommankumman jakson aikana. Hypoteesina on, että laumakäyttäytyminen näyttäytyisi voimakkaampana jälkimmäisen ajanjakson aikana. Tämän oletetaan johtuvan kasvaneesta epävarmuudesta osakemarkkinoilla, joka taas on seurausta median luomista uhkakuvista liittyen COVID-19 pandemiaan.

Hypoteesien jälkeen, tutkielma esittelee kirjallisuutta ja relevantteja tutkimuksia aiheeseen liittyen. Tämän tutkielman hypoteesit on muodostettu jo olemassa olevien relevanttien tutkimusten tulosten pohjalta. Laumakäyttäytymistä on useaan otteeseen löydetty eri markkinoilta, jonka vuoksi tutkielma olettaa sitä esiintyvän myös Suomen osakemarkkinoilla. Kirjallisuuskatsaus koostaa kokonaiskäsityksen laumakäyttäytymisen eri muodoista. Tämän lisäksi kirjallisuuskatsauksessa esitellään relevantit perinteiset rahoitusteoriat, joita behavioristinen rahoitus haastaa.

Tutkimuksen data koostuu Helsingin pörssin 25:n aktiivisimmin vaihdetun osakkeen päivittäisistä päätöshinnoista. Tutkimuksen tulokset osoittavat, että Helsingin pörssissä ei esiinny laumakäyttäytymistä näinä valittuina ajanjaksoina. CSSD- ja CSAD-mallien tuloksista huomataan, että jos epärationaalisuutta mitataan laumakäyttäytymisen määrällä, Helsingin pörssissä sijoittajien voidaan sanoa toimivan rationaalisesti. Vaikka markkinoiden epävarmuustekijöiden määrä nousi COVID-19 pandemian alkamisen jälkeen, se ei vaikuttanut sijoittajien laumakäyttäytymiseen Suomessa. Markkinoiden liikehdintää tulisikin tarkastella jostain muusta behavioristisen rahoituksen näkökulmasta, sillä liikehdintä Helsingin pörssissä ei vaikuta olevan seurausta sijoittajien laumakäyttäytymisestä.

AVAINSANAT: Laumakäyttäytyminen, behavioristinen rahoitus, COVID-19, pandemia, Cross-sectional standard deviation, Cross-sectional absolute deviation, Helsingin pörssi, markkinatehokkuus

List of contents

1 Introduction 7

1.1 Purpose and structure of the study 8

1.3 Research hypotheses 9

2 Literature review 12

2.1 Behavioural finance and herding 13

2.2 Forms of herding 16

3 Herding in stock markets 23

3.1 Efficient market hypothesis 24

3.1.1 Security Market Line and Capital Asset Pricing Model 27

3.1.2 Three Factor Model 28

3.1.3 Five Factor Model 29

3.1.4 Efficient Market Hypothesis and herding 31

3.2 Financial bubbles and herding 33

4 Methodology 34

4.1 CSSD Model 34

4.2 CSAD Model 36

5 Data 39

5.1 Data sample and market overview 39

5.2 Descriptive statistics 42

6 Herding results 47

7 Conclusions 53

References 55

Figures

Figure 1. Forms of herding 18

Figure 2. Levels of market efficiency 25

Figure 3. Security Market Line 27

Figure 4. OMXHPI Index 01.01.2018 - 31.12.2021 39

Figure 5. OMXH25 Index 01.01.2018 - 31.12.2021 40

Figure 6. OMXHPI Index 01.01.2018 - 31.12.2019 40

Figure 7. OMXHPI Index 01.01.2018 - 31.12.2021 41

Figure 8. Relationship between CSSD and market return 2018 – 2019 45

Figure 9. Relationship between CSAD and market return 2018 – 2019 45

Figure 10. Relationship between CSSD and market return 2020 – 2021 46

Figure 11. Relationship between CSAD and market return 2020 – 2021 46

Tables

Table 1. Daily cross-sectional standard deviations (CSSD) and daily market returns (R_m) for Finnish stock market 01.01.2018 – 31.12.2019 42

Table 2. Daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for Finnish stock market 01.01.2018 – 31.12.2019 43

Table 3. Daily cross-sectional standard deviations (CSSD) and daily market returns (R_m) for Finnish stock market 01.01.2020 – 31.12.2021 43

Table 4. Daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for Finnish stock market 01.01.2020 – 31.12.2021 44

Table 5. Christie & Huang (1995) Cross-sectional standard deviation for OMX Helsinki 01.01.2018 – 31.12.2019 48

Table 6. Christie & Huang (1995) Cross-sectional standard deviation for OMX Helsinki 01.01.2020 – 31.12.2021 48

Table 7. Christie & Huang (1995) Cross-sectional absolute deviation for OMX Helsinki 01.01.2018 – 31.12.2019 50

Table 8. Christie & Huang (1995) Cross-sectional absolute deviation for OMX Helsinki 01.01.2020 – 31.12.2021 50

Abbreviations

CAPM	Capital Asset Pricing Model
CSSD	Cross-sectional Standard Deviation
CSAD	Cross-sectional Absolute Deviation
EMH	Efficient Market Hypothesis
SML	Security Market Line

1 Introduction

Herding is a phenomenon which originates from psychology of human behaviour. (Spyrou, 2013, p. 175). Initially observed in animals, herding has also been identified among human who, as mammals, tend to mimic actions and decisions of other humans within social groups (Spyrou, 2013). Early sociologists and economists examined changes in consumer behaviour, particularly in fashion and fads, by applying behavioural phenomena that had previously been mostly studied in social psychology (Rook, 2006). Visible examples of humans herding based on actions of other people would for example be teens who follow fashion trends or young adults frequenting trendy clubs.

Individuals replicating each other’s actions and decision is noticed to occur also in financial markets. If the actions of other investors influence investors' decisions, investors may be considered members of a herd (Bikhchandani & Sharma 2001, p. 280) Stock return volatility is frequently attributed to herding, in which investors deviate from rational decision-making processes and rather follow larger market trends (Christie & Huang, 1995). This phenomenon is commonly referred to market-wide herding (Henker, Henker & Mitosis 2006, p. 197).

As information asymmetry, rumours and other market dynamics often causes herding to arise, this thesis examines the occurrence of market-wide herding in Finnish stock markets prior to and during the COVID-19 pandemic, as well as how herding behaviour changes during market stress caused by global health crisis. The outbreak of the pandemic in early 2020 caused unprecedented volatility in global financial markets. For instance, the S&P 500 Index had a quick decline to 2237.40 in March 2020 before rebounding to 3386.15 in late February 2020 (S&P Global, 2023). The OMXH25 index, which consist of 25 most actively traded stocks in the Finnish stock market, fell from 4589.41 to 2905.76 between February and March 2020 (NASDAQ, 2023). As stock markets have been rather fluctuate after the beginning of the pandemic, this thesis aims to find herding to increase during crises and present the reasons for herding.

This study examines stock return dispersion using the cross-sectional standard deviation (CSSD) model, which was first introduced by Christie and Huang in 1995. The examination also includes the cross-sectional absolute deviation (CSAD) model developed by Chang, Cheng, and Khorana in 2000. Given the exploration of distinct time periods with markedly different market conditions, the use of both models is reasonable. The CSSD model is expected to be effective at detecting instances of herding, especially during market stress when regressions are linear. In contrast, the CSAD model is expected to provide a more robust measure in typical stable up or down markets (Christie & Huang, 1995; Chang et al., 2000). In studies on herding, the deviations are usually explained by investors copying each other's actions in quickly buying or selling same stocks. This behaviour causes market swings as many people execute similar trades in a short period of time. It contradicts the assumption of efficient markets, in which investors should make decisions based on all the available information on stock's fundamentals. Herding as a bias occurs in financial markets, as evidenced by previous literature on behavioural finance. Herding is a one of a variety of phenomena explaining market's inefficiency.

As previous literature provides hints of herding to occur in Finnish stock market and the phenomenon to be more prominent during crises, this thesis tries to find out if market-wide herding occurs in Finnish stock market and if it has increased in after the global health crisis hit Finland.

1.1 Purpose and structure of the study

This study contributes to the existing body of research on herding in financial market by investigating the changes in herding in the Finnish stock market caused by the global health crisis. The study defines herding as a market anomaly and investigates whether it occurs in the Finnish stock market. Furthermore, the study reviews prior research on topic and provides a model for measuring herding. In continuation, the study seeks to determine whether information about the COVID-19 pandemic had an impact in investors' decision-making process and resulted in investors to herd.

This study begins with an introduction to the phenomenon of herding. Following the introduction, the research hypotheses are defined, serving as the basis for the empirical study. Subsequently, an extensive review of existing literature and theoretical background on herding is discussed. After the literature review, the methodology for the empirical study is presented. Chapter 5 presents an exposition of the selected data and a comprehensive analysis using descriptive statistics, allowing for a more detailed understanding of the dataset and its relevance to the study's objectives. The chapter after that, provides a review of the study's findings using empirical evidence to assess the validity of the research hypotheses. Finally, the final chapter contains an overview of the thesis, providing a comprehensive summary of the research, its contributions, limitations, and suggestions for future research.

1.2 Research hypotheses

Efficient market hypothesis assumes that stock returns and dispersions are normally distributed, and the returns reflect all the available information. Market anomalies affect in stock returns resulting them not reflecting all the available information. According to Davis, Hansen and Seminario-Amez (2020) news and new information explain only half of the volatility in the returns while the other half is explained by psychological biases of investors, especially during large market swings (Nofsinger, 2017 pp. 3 – 4). COVID-19 pandemic stopped the world and global markets responded quickly to changes such as travel restrictions and pandemic-related news. Crises intensify the global uncertainty which reflects to the stock markets due to news about potential threats of the crisis. The COVID-19 epidemic has caused a significant spike in uncertainty, shifting from a healthcare crisis to an economic crisis (Baker, Bloom, Davis & Terry, 2020). The extensive media coverage of turmoil in the markets and the salient news about the threats of the pandemic generates favourable conditions for cognitive biases to intensify. During the pandemic, there was a flood of news and information regarding the virus, its effects on businesses, and government responses. This information overload may have caused investors to rely on heuristic shortcuts and reckon others making correct decisions rather than conducting a broad analysis themselves, as the human mind capacity is limited (Kahneman 1979; Baker & Nofsinger, 2010 pp. 56 – 57). During times of market stress and uncertainty, investors exhibit risk aversion (Kahneman & Tversky, 1979). Seeking safety in familiar assets, they may lean towards recommendations of others that are considered more reliable than their own analyses. Shear, Ashraf and Sadaqat (2020) found out that investors refrained making new stock purchases during COVID-19 pandemic.

The hypotheses are formed with an assumption of herding to be present in the Finnish stock market. In addition, herding is expected to increase after the outbreak of the COVID-19 pandemic as previous research have found herding to increase during and after crises (Ferreruela & Mallor, 2021; Nouri-Goushki & Hojaji, 2023). To inspect whether market anomaly herding occurs generally in the Finnish stock market and causes returns to deviate from normal distribution, the null hypothesis is formed as follows:

$H10$: *Market-wide herding does not occur in Finnish stock market.*

The first hypothesis inspects whether a behavioural bias occurs in Finnish stock market. The object of the hypothesis is to address if herding is prominent in Finnish stock markets during the sample periods. Thus, the first hypothesis is:

$H1$: *Market-wide herding is present in Finnish stock markets during both sample periods.*

The second hypothesis inspects the change in herding between the two sample periods. Knowing that cognitive biases intensify during market stress (Kahneman & Tversky

1979) and fluctuate market conditions tend to increase herding in markets (Yao, Ma & He, 2014), and herding has been found to be prominent during large market swings (Chang et al., 2000), the second hypothesis assumes that herding occurs differently during the two sample periods. The second hypothesis is:

H20: Market-wide herding did not increase during COVID-19 pandemic in Finnish stock market.

$H2$: *Market-wide herding increased during COVID-19 pandemic in Finnish stock market.*

2 Literature review

Traditional financial theories suggest that the idea of rational investment decisions is that the decisions are made using all the available information (Scharfstein & Stein 1990). However, the capacity of the human mind is limited, and investors must form their decisions using only the information they are able to process. (Kahneman, 1973) Also, the amount of attention capacity varies. When something arouses an individual's interest, there is more capacity available than when arousal is low (Kahneman, 1973). When humans are not able to take all the information into consideration, they are prone to focus on the information that is prominent. Salience of information causes humans to neglect information that do not stand out from the crowd and use heuristic shortcuts (Baker & Nofsinger, 2010, p. 299; Scharfstein & Stein, 1990). Simon assumed in 1986 that humans' irrationality origins from limitations in their ability to process information. A couple of years earlier Kahneman and Tversky (1979) discovered that humans are prone to using heuristic shortcuts when making decisions. Heuristic shortcuts enable humans to ignore complex information processing. Heuristics can be seen as "rules of thumb," which are cognitive shortcuts for quick decision-making, as Baker and Nofsinger (2010) define them. Heuristics have the potential to ease decision-making by simplifying and speeding up the process. However, relying on such rules of thumb are prone to lead into biased decision-making because individuals are unable to consistently determine whether their decisions are 100% correct, as stated by Kahneman (2013).

The cognitive biases such as the availability bias and the representativeness heuristic are prone to generate herding in financial markets. Availability bias occurs when investors rely heavily on readily available salient information while overlooking less accessible or contradictory data. The representativeness heuristic, on the other hand, causes investors to base their decisions on previous experiences or stereotypes rather than objectively evaluating current market conditions. (Kahneman & Tversky, 1979)

2.1 Behavioural finance and herding

Herding challenges traditional financial theories by suggesting that individuals' decisions are affected by group psychology, specifically decisions made by other individuals (Scharfstein & Stein, 1990). Human decision-making frequently leans towards mimicking actions of others as the process of conducting a comprehensive individual analysis is heavy for human brain. As a part of behavioural finance, herding is defined as an alignment of behaviours of an individual investor in a group of people. The behaviour occurs withinside the group without coordinating (Raafat, Chater & Frith, 2009). Herding behaviour is result of psychological phenomena in which social norms cause individuals to share similar expectations (Kameda & Hastie 2015). Individuals who suffer from herding are following the actions of a group of other individuals for a specific period of time even though their own information would guide them to act differently (Banerjee 1992, p. 798; Hwang & Salmon, 2004). Herding occurs when investors base their decisions on beliefs of other decision makers or market movements rather than on their own beliefs and information. Bikhchandani and Sharma (2001, p 280) state that when investors are conscious of other market participants and influenced by the actions of them, they are considered a part of a herd.

Herding originates from the fundamental characteristics of human mind's ability to adapt to different social norms (Kameda & Hastie, 2015). According to Herbert Simon (1990) the main grounds of humans' decision making are the recommendations and suggestions of other people. When an individual feels like he is a part of a group of investors, he tends to be under a significant influence from other members of the group. The feeling of belonging to a group strengthens herding and causes individuals to rely less and less on their own information. Herding is inclined to increase in low information cost environment. Banerjee's (1992, p. 798) definition of herding "*everyone doing what everyone else is doing, even when their information suggests doing something different*." implies that it would be irrational to herd. Commonly herding is considered irrational. Even very skilled and influential investors are known to base their investment decisions on other investors actions and recommendations (Devenow &

Welch 1996). Hence, behavioural biases and constraints in the human mind must be assumed to have a strong impact in asset prices. Commonly, herding is considered to destabilize the markets (Alevy, Haigh & List, 2007; Scharfstein & Stein, 1990). However, herding is also argued to drive the asset prices to their equilibrium values and speed up the formation of the price (Hirshleifer, Subrahmayan & Titman, 1994).

Herding has been studied widely in behavioural finance. As investor herds are prone to drive stock prices away from their fundamental values, the effect interests' practitioners on the stock markets, as herding might generate profitable trading opportunities for them. On the other hand, the behavioural effect in stock prices and the changes in the risk and return characteristics arouses interest among economists (Tan, Chiang, Mason & Nelling, 2008, p. 61-62). Initially, herding in social psychology has been seen irrational and unconscious occurrence of human mind. The broader studies on herding reveals it to arise from individuals will to understand and fit into the social reality (Rook 2006). In behavioural finance, according to Spyrou (2013, p. 176) the empirical analysis of herding consists of two different approaches. Commonly, studies either assume herding to be intentional and rational or unintentional and non-rational. In addition, some researchers study herding focusing only on a certain group of investors, for example stock analysts or individual investors while others focus on the whole market considering herding to be a market-wide phenomenon. (Spyrou 2013, p. 179) Market-wide herding occurs when a group of investors focus on the movements of the market instead of examining a particular stock or a group of stocks (Henker J. et al. 2006, p. 197).

Herding is a form of informational cascades, which are caused by imperfect information, that can help explain various observed phenomena. Informational cascade occurs when an individual has followed the consensus of previous actions while ignoring his or her own information (Kameda & Hastie, 2015). An example of an informational cascade-based action is when an individual has negative private information about a certain stock but ends up purchasing it because few analysts recommend the stock.

(Devenow & Welch, 1996, p. 609-610). Stock analysts' recommendations carry more weight than individual private negative information. (Devenow & Welch, 1996, p 609). However, these cascades are fragile and susceptible to disruption from various types of shocks, such as the arrival of individuals with new or better information or the dissemination of new public information (Bikhchandani & Hirshleifer & Welsch, 1998, p. 157).

Herding certainly is certainly more complex than just investors imitating others’ investment decisions. It involves a variety of behaviours and actions among investors in various levels, occurring in certain groups and even as market-wide phenomenon. Commonly herding is associated with turbulent and stressful market conditions. However, herding is found to be prominent also during periods of market boom. The most noteworthy studies are discussed also in this thesis.

Few main previous studies in addition to the studies of Christie and Huang (1995) and Chang et. al (2000) to mention are for example studies by Cheng and Khorana (2000), Hwang and Salmon (2004), Chiang and Zheng (2010), Spyrou (2013), and Lakonishok, Shleifer and Vishny (1992). Lao and Singh (2011) find evidence of herding in China and India. In China, herding is more prominent during market downturns, while herding in Indian stock market is more prominent while market prices are going up (Lao & Singh, 2011). Demirer, Kutan & Chen (2010) applied the CSSD and CSAD models developed in this study to the Taiwanese market and discovered evidence of prominent herding during large market movements. The original creators of the CSAD model, Chang et al (2000), were able to find significant evidence of herding in South Korea and Taiwan, which is consistent with the study of Demirer et al. (2010). Chang et al. (2000) found no evidence of significant herding in the United States or Hong Kong, which is consistent with Christie and Huang's (1995) findings, who also found no evidence of herding in US stock markets.

Previous research has shown that herding occurs in a variety of markets under both stable and fluctuating market conditions. Furthermore, previous research has shown that herding increases during market turmoil and crisis (Chang et al., 2000). In the Athens stock market, herding was found to be stronger with rising markets. However, the presence of herding was discovered to be significant during and after the 1999 stock market crisis (Caporale, Philippas, & Economou, 2008). More recent studies have found crises to increase herding. Nouri-Goushki and Hojaji (2023) found evidence of herding to increase in Iranian stock market during the COVID-19 pandemic. In Spain and Portugal Ferreruela and Mallor (2021) found herding to occur just before and after the crises but not at the time of the crisis when they observed the financial crisis of 2008 and COVID-19 crisis.

The phenomenon of herding in Nordic financial markets has not been studied excessively yet. However, a few studies have looked into herding in this region. For example Mobarek, Mollah and Kasey (2014), had their interest in Finnish stock market. Similarly, Grinblatt and Keloharju (2000), and Kyröläinen and Perttunen (2003) were focusing on Finnish stock market as well. Ohlson (2010) conducted research in Sweden and found evidence of herding. In addition, Saastamoinen (2008) investigated herding among Finnish stock market investors. Notably, Saastamoinen used CSSD and CSAD models, which are also used in this study, to find hints of herding behaviour on the Helsinki stock exchange.

2.2 Forms of herding

Lakonishok, Shleifer and Vishny started to examine herding in 1992 with their LSV model (Lakonishok et al., 1992). In their study the focus was on pension fund managers. The researchers tried to find evidence of fund managers imitating each other's decisions. The evidence of fund managers following each other was not found, however they suggested unintentional herding to be greater in large-cap companies than in small-cap companies (Lakonishok et al, 1992). The reason was assumed to be that information about large-cap companies was easier to access compared to small-cap companies. The easy access of information, in turn, leads investors to form unilateral similar decisions without even having a thought of others' decisions, as they all have the same information available (Bikhchandani & Sharma, 2001). In general, larger companies are followed by a greater number of stakeholders than smaller ones. As a result of the increased visibility, investors may accidentally align their investment decisions, resulting in unintentional herding. Smaller companies, on the other hand, are prone to be not followed so precisely, making them vulnerable to intentional herding effects, in which investors ignore the comprehensive analysis of fundamental factors and rather follow the decisions made by others (Lakonishok et al., 1992; Bikhchandani & Sharma, 2001).

Later research expanded and developed the approach of dividing herding into intentional and unintentional herding. Gavriilidis, Kallinterakis, & Ferreira (2013) propose herding to be either intentional or spurious. Intentional herding occurs when an investor's decision-making process is influenced by the actions of other investors. Spurious herding occurs when an investor follows the same strategy as other investors without actively monitoring or modelling their decisions (Bikhchandani & Sharma, 2001, p. 281). In such cases, decisions are made without conducting a thorough examination of other investors' actions, relying solely on the same information others are using (Bikhchandani & Sharma 2001, p. 281). This form of decision-making typically avoids fundamental analysis as investors tend to follow the consensus of the market rather than conduct independent anlysis (Lakonishok et al., 1994; Devenow & Welch, 1996).

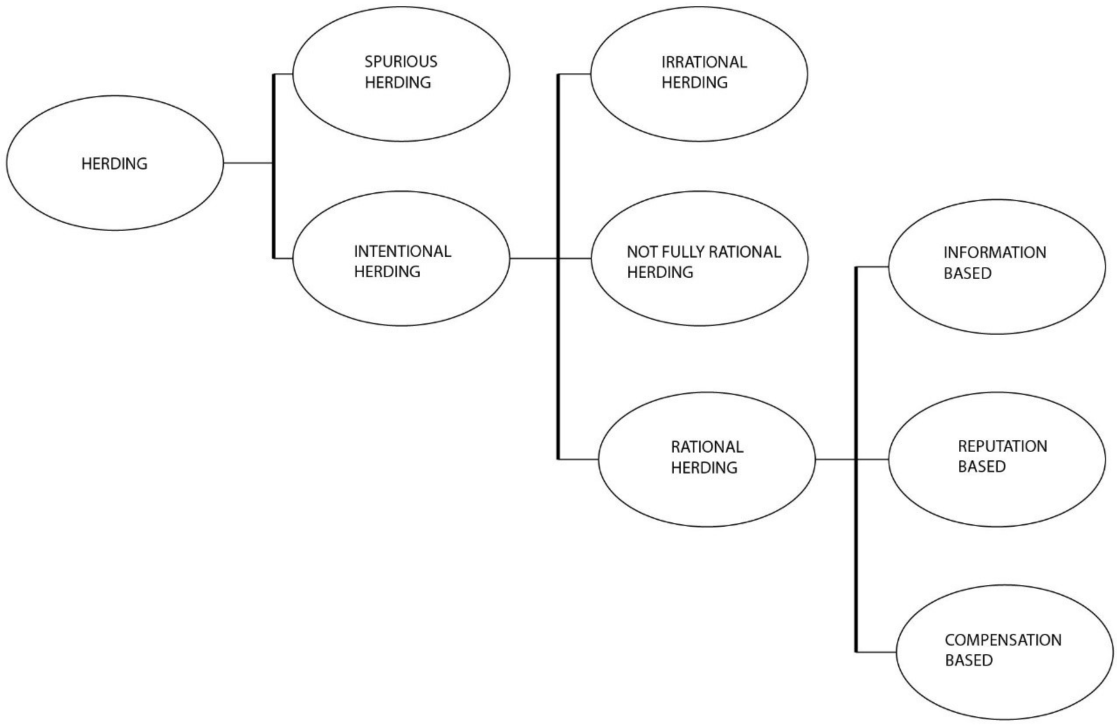

Figure 1. Forms of herding (Bikhchandi & Sharma, 2001; Spyrou, 2013)

Figure 1 presents the division of herding. Bikhchandani and Sharma (2001) divided the concept of herding into two types: intentional and spurious. According to the authors, intentional herding can be further divided into three subcategories: irrational herding, partially rational herding, and rational herding. Furthermore, Bikhchandani and Sharma (2001) divide rational herding strategies into three types: information-based, reputation-based, and compensation-based.

To begin with spurious, and intentional herding it might be almost impossible to tell apart by just looking at the data (Bikhchandani and Sharma, 2001). A large group of investors might trade on the same side of the market caused by the change in fundamentals. It is possible that everyone reacts to fundamentals independently and simultaneously (Bikhchandani & Sharma, 2001, p. 281). The decisions are not caused by herding, but the effect is the same. The price change of an asset is probably greater than the change in fundamentals would justify. In this kind of situation, it is basically impossible to tell which part of the trading is driven by herding and which is based on change in fundamentals. As stated earlier, professional investors are more likely prone to choose herding intentionally which in certain situations it might be considered rational (Gavriilidis et al., 2013) Meanwhile retail investors tend to herd spuriously (Gavriilidis et al., 2013).

A scenario in financial markets where an increase in interest rates causes stocks to become less profitable investments might result in spurious herding (Bikhchandani & Sharma, 2001, p. 281). As a result of this new information, investors are less interested in holding onto stocks in their portfolios. While there is a collective trend among investors to reduce stock allocations within portfolios, this behaviour does not constitute herding. Rather, it reflects individual reactions to public information and market dynamics concerning interest rates (Bikhchandani & Sharma, 2001, p. 281). In financial markets, spurious herding and its consequences are viewed as an efficient outcome, as opposed to intentional herding, which is not regarded as an efficient phenomenon (Bikhchandani & Sharma, 2001, p. 281). Furthermore, spurious herding may occur in situations where investment opportunities differ due to legal constraints (Contreras, 2022). This type of spurious herding can be considered as "fundamentals-driven," because investors' decisions are influenced by common facts and environmental variables. In this context, the term "fundamentals" refers to the factual and environmental factors that influence financial decisions. The outcomes and subsequent changes observed in financial markets as a result of this "fundamentals-driven" spurious herding are considered efficient (Contreras, 2022).

Retail investors are prone to herd spuriously (Gavriilidis et al., 2013). Conversely, as previously stated, institutional investors herding is often intentional, which under certain conditions can be considered rational (Gavriilidis et al., 2013). However, it is worth to note that intentional herding occurs among retail investors as well (Contreras, 2022) Intentional herding occurs when an individual investor bases their decision making solely on the decisions and behaviours of other investors (Contreras, 2022). In this context, intentional herding refers to the disregard of personal information, with such decisions unaffected by individual insights.

When intentional herding is not considered rational, it is often the result of an individual's unconscious and involuntary decisions (Shiller, 2016). Investors who herd irrationally tend to make sudden, unexpected, and poor investment decisions based on incomplete information. According to Spyrou (2013), this behaviour is motivated by external social influences and societal norms. However, even professional, and experienced investors may herd irrationally when there is a lack of reliable information (Baddeley, Curtis & Wood, 2004).

Not fully rational herding falls between rational and irrational herding behaviours. Bikchandani and Sharma (2001) define not fully rational herding as actions aligned with an investment strategy that lacks complete rationality (e. g. momentum strategies). This type of herding occurs when investors attempt to gain profit on past winners, as advocated by the momentum strategy, in which investors buy past winners while selling past losers (Kyröläinen and Perttunen, 2003). The partially rational momentum investor systematically monitors previous market consensus and asset performance. However, the lack of empirical evidence for the reliability of historical asset performance in guiding investment decisions makes reliance on momentum strategies irrational (Bikhchandani & Sharma, 2001).

Devenow and Welch (1996, p. 604) propose that there are only two contradictory forms of herding – rational and non-rational. The approach of Devenow and Welch (1996) focuses on external factors and takes into consideration that forming optimal decisions might be impossible when there are issues with information or incentives as outlined by Scharfstein and Stein (1990), Banerjee (1992) and Bikhchandani et al. (1998). Rational herding occurs in an environment where, for example information is incomplete or reputation concerns and compensation structures exists. (Bikchandani & Sharma, 2001, p 283)

The first form of rational herding, known as information-based herding, occurs when an investor mimics the decisions of others, believing that those individuals have more reliable information or more resources in processing information (Bikhchandani and Sharma, 2001; Gavriilidis et al., 2013). For information-based herding to be considered rational, other investors in the market must genuinely have more information or have information that is significantly more accurate.

The other two forms of rational herding are closely related to employment and are more prominent among institutional investors. Reputation-based herding occurs when investors base their investment decisions on the actions of successful competitors, motivated by a will to maintain their reputation as skilful investors (Spyrou, 2013). This phenomenon is evident, for example, among stock analysts, who may refrain from deviating from the common consensus on a company's performance in order to avoid being considered as untrustworthy analysts (Spyrou, 2013).

Scharfstein and Stein (1990) have developed a model to demonstrate how herding can arise due to reputational concerns. Their model assumes that managers are either smart or dumb and receive either informative (true) or uninformative (noise) signals about an investment decision. Smart managers are assumed to have correlated signals, while dumb managers have uncorrelated signals. However, in the model, managers are unsure whether they are smart or dumb, and the outcome of an investment decision is not known until all managers commit to it. If a suboptimal investment is chosen, its poor quality will become apparent only if other managers do not make the same decision. When enough less competent managers agree on a suboptimal decision, even skilled managers may choose to follow the crowd in order to avoid the possibility of investing in a potentially bad product. This strategic alignment is done to protect their reputations, as they prioritise conformity over the risk associated with investing in a product, they believe is superior (Scharfstein and Stein, 1990).

Compensational herding might happen when investors' salary is connected to their performance (Spyrou, 2013). For an individual to maintain their job, and get constant salary, it is safer to follow the consensus of the markets and not make risky actions which deviate strongly from the actions of other investors. Both employment-based forms of herding can be considered rational as they are a guarantee for an individual to uphold their reputation and maintain the constant income (Spyrou, 2013).

3 Herding in stock markets

Thomas Lux (1995) stated that the overall efficiency of stock markets must be doubted as the stock prices are found out to be more volatile than the fundamentals or expected returns would allow them to be. The unexplained volatility in the markets raised a question about the efficiency of the markets (Lux, 1995). West (1988) concluded that it might be needed to consider sociological and psychological mechanisms when inspecting the volatility of returns. A phenomenon which has been found to have an impact in stock market efficiency is herding (Christie & Huang, 1995).

After several financial crises in financial markets, the term "herd effect" has become negatively viewed in finance (Bikhchandani & Sharma, 2001). Investors and fund managers are often depicted as acting like a "herd" during times of financial crisis. Blindly following each other into risky decisions without proper information or justification for their decisions. (Bikhchandani & Sharma, 2001). When the first signs of trouble arise, these investors quickly flee to safer options. (Bikhchandani & Sharma, 2001). This herding behaviour contributes to market volatility and highlights the fragility of the financial markets as a whole. The question remains: what are the underlying factors that motivate investors who have similar information and share the goal of maximising profit to coordinate their actions, and which theoretical frameworks explain this phenomenon? (Bikhchandani & Sharma, 2001).

Herding is prone to cause overreaction in the markets. Even though herding would occur towards someone else's rational decision, overreaction tends to result in assets to be mispriced (Fu & Lin, 2010). The common approach in measuring and modelling herding is the usage of return dispersions. The first return dispersion -based model was created by Christie and Huang (1995) followed by the model of Chang et al. (2000). Both models have been widely used in previous studies on herding. This thesis uses the cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) models developed by Christie and Huang (1995) and Chang et al. (2000), respectively, to analyse herding in the Finnish stock markets.

3.1 Efficient Market Hypothesis

Classical finance theories assume that market prices should reflect the real fundamentally based values of assets. Meaning that markets are efficient if the prices reflect all available fundamental information (Bodie, Kane & Marcus, 2014; Singh, Babshetti & Shivaprasad, 2021). Fama's (1965) random walk model suggests stock price fluctuations are completely unpredictable, with the hypothesis that future price changes of individual stocks are unaffected by their previous movements. However, investors are limited in their ability to process and respond to the entire range of available information in an appropriate pace (Peng & Xiong, 2006). This causes prices to move in an irregular response to new information, slowing down the balancing of supply and demand for stocks. (Kaufman, 2019, p. 3). Because of the constraints in the human capacity to process information, supply and demand factors are not immediately balanced. When market prices do not immediately reflect the newly available information, this indicates market to be inefficient, which may result in historical performance influencing future performance. Bodie et al. (2014) proposed that even when market prices do not fully reflect all available information, the random walk phenomenon exists. However, informational inefficiencies may still occur as the relevance of the information reflected in prices might be irrelevant (Bodie et al., 2014, pp. 350-409).

In 1970 Fama introduced the Efficient Market Hypothesis ("EMH"), which combined the concepts of market efficiency and random walk theory. The EMH assumes that all available information include:

1. Historical information – past prices/performance,
2. Public information – e. g., credit ratings, interim reports, and analysts' analyses.
3. Insider information – information available only for the company and its insiders.

In addition to these three levels of information, Fama (1970) proposed three types of market efficiency:

1. Weak form of market efficiency – prices reflect all historical movement.
2. Semi-strong form of market efficiency – prices reflect all public information.
3. Strong form of market efficiency – prices reflect all information, including insider information (Fama, 1970).

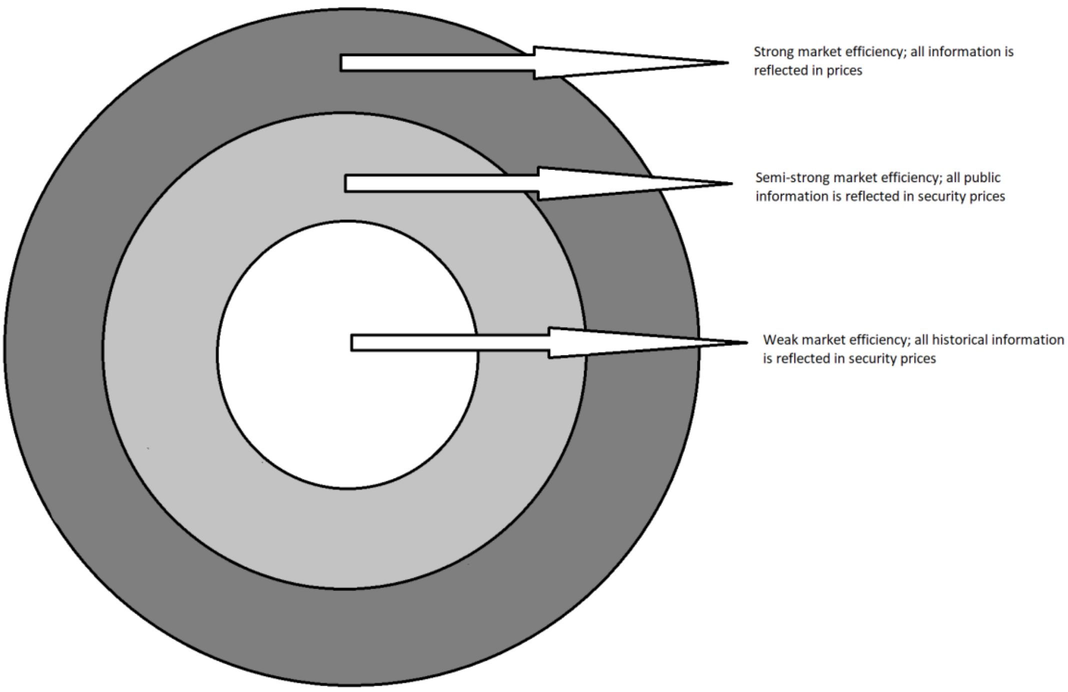

Figure 2. Levels of market efficiency (Fama, 1970).

The Efficient Market Hypothesis (EMH) states that financial market securities fully reflect all available fundamental information (Fama, 1970). However, due to cognitive limitations, investors are unable to process and respond to all available information. As a result, when investors do not respond fully to available information, markets can’t be completely efficient. In the strongest form of market efficiency, prices should reflect all available information, including insider information (Fama, 1970). Nonetheless, Fama (1970) acknowledges that this assumption is not strictly valid, citing evidence that investors do not consistently use insider information in markets. Furthermore, investors' cognitive limitations, such as attention constraints, call into question the EMH's overall validity. Given the human brain's limitations in processing information, let alone determining its relevance, even if all information, including insider information, were available, investors would still struggle to effectively process and leverage such information.

In continuation, the EMH assumes that investors are rational and seeking to maximize their utility. According to Fama (1970) and Shleifer (2002), the impact of decisions made by irrational investors should be eliminated by the decisions made by other irrational investors. According to Barberis and Thaler (2002) in addition to psychology, behavioural finance originates also from limits to arbitrage If the prices end up being inefficient, the arbitrageurs should correct the prices. The arbitrage limits are argued to cause irrational investment decisions, as the transaction costs cause investors to avoid utilizing arbitrage opportunities (Barberis & Thaler 2002). If transaction costs keep investors avoiding arbitrage opportunities, arbitrageurs will not correct the prices of mispriced assets, which ends up asset prices not to reflect all the information. Hence, efficient market hypothesis cannot be true.

3.1.1 Security Market Line and Capital Asset Pricing Model

In financial markets, investments can be divided in risk-free investments and risky investments. Return of a risk-free investment is already known before the investment decision. However, the outcome of a risky investment is not known beforehand. Investors have expectations about the return of the investment. The difference between the actual return of the investment and the expected return of the investment is the risk (Sharpe, 1964). The deviation can be displayed with the security market line. SML displays the expected rate of return of an individual asset as a function of systematic risk (Sharpe, 1964).

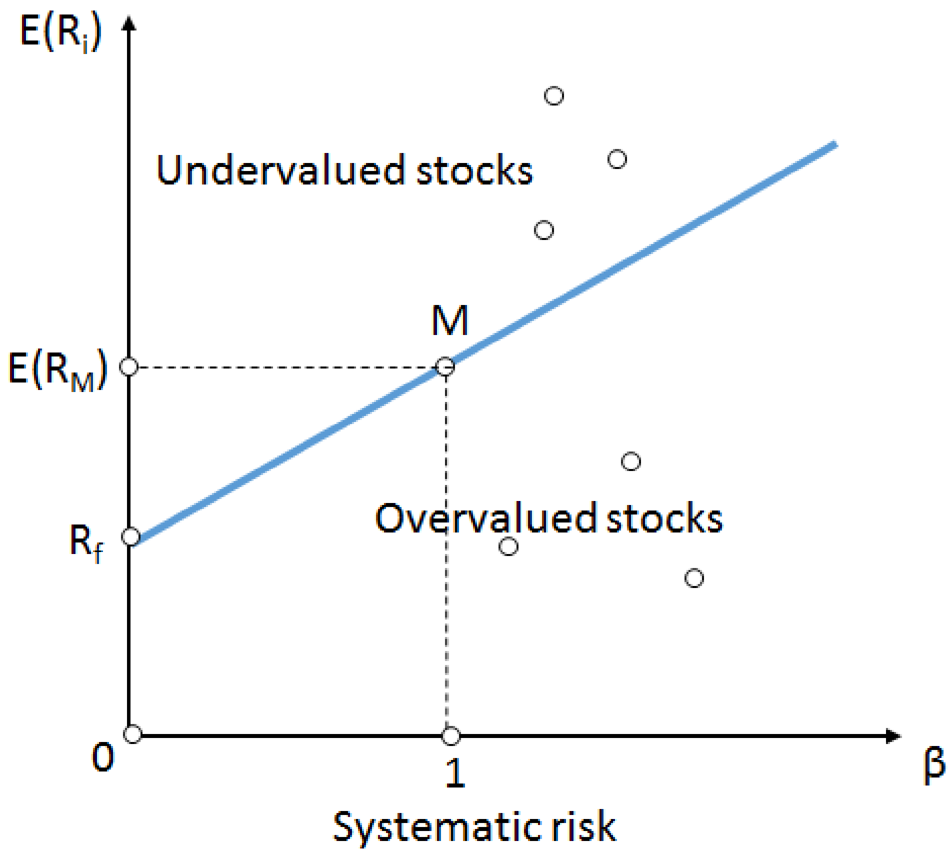

Figure 3. Security Market Line (Sharpe, 1964).

Capital Asset Pricing Model (CAPM) is a pricing model which can be used for calculating the expected return of an asset. The model was first introduced by Jack Treynor (1962). It relies on the portfolio theory model developed by Harry Markowitz (1952). CAPM describes the relationship between systematic risk and the expected return for assets. The model suggests that the expected return of an asset is equal to the risk-free return, plus a risk premium of the market multiplied by the company-specific beta. CAPM indicates the demanded long-term return for an asset. However, volatility might cause the expected return to be different in short and medium term (Treynor, 1962; Sharpe, 1964). The CAPM equation is as follows:

$$E(r_i) = r_f + \beta_i[r_m - r_f]$$

Where:

$E(r_i)$ =	expected return of an asset
r_f =	risk-free return
β_i=	beta of the security
r_m=	expected return of the market.

3.1.2 Three-factor model

Fama and French (1992) stated that using CAPM is not completely accurate when measuring returns of value companies (high book-to-market ratio) and small-cap companies (Public company with a market capitalization from $300 million to $2 billion). Asset returns cannot be completely explained by the market premium factor of CAPM. Fama and French (1992) examined how the size and the value of a company affect to the expected returns of a certain stock. Three-factor model originates from tendency of high value and small-cap companies to outperform the market (Fama & French, 1993).

The size factor – Small Minus Big – inspects what is the impact of company's size to its stock returns. Past returns of small-cap companies have generally been greater than returns of large-cap companies. Hence, the equation of the factor is the difference between the stock returns of small-cap companies and stock returns of large-cap companies (Fama & French, 1992). The value factor of the model seeks to explain whether the value of a certain company has an impact in its stock returns. The value, known as High Minus Low, is formed by calculating the difference of returns of low book-to-market value companies (also commonly referred as growth companies) and high book-to-market value companies (Fama and French 1993). The equation of three-factor model is as follows:

$$E(r)_a = r_f + \beta_a\left(r_m - r_f\right) + \beta_b(SMB) + \beta_c(HML) + e_i$$

Where:

$E(r_i)$ =	expected return of an asset
r_f =	risk-free return
β_i=	beta of the security
r_m=	expected return of the market.
β_b =	sensitivity of asset to SMB
(SMB) =	Small Minus Big factor
β_c =	sensitivity of asset to HML
(HML) =	High Minus Low factor
e_i =	zero-mean residual

3.1.3 Five-factor model

In 2015 Fama and French formed a new model called five-factor model based on the three-factor model as it received criticism of it not being capable to explain the momentum effect on the stock market. Fama and French (2015) updated the model to explain the market anomalies more accurately by adding the profitability factor and investment factor into the model. Fama and French conducted a study in 2017 to test the robustness of the model. The results of the empirical study which included North America, Europe, Japan and Asia Pacific markets suggests the five-factor model to be more accurate than the three-factor model (Fama & French 2017). Despite the better results, Fama and French (2015) claimed that the five-factor mode is still not perfect.

The profitability factor – Robust Minus Weak – is the average difference in returns between robust operating profit companies and weak operating profit companies. The investment factor in the model – Conservative Minus Aggressive – measures difference between conservative investment companies and aggressive investment companies. The equation of five-factor model is as follows:

$$E(r)_a = r_f + \beta_a(r_m - r_f) + \beta_b(SMB) + \beta_c(HML) + \beta_d(RMW) + \beta_e(CMA) + e_i$$

Where:

$E(r_i)$ =	expected return of an asset
r_f =	risk-free return
β_i=	beta of the security
r_m=	expected return of the market.
β_b =	sensitivity of asset to SMB
(SMB) =	Small Minus Big factor
β_c =	sensitivity of asset to HML
(HML) =	High Minus Low factor
β_d =	sensitivity of asset to RMW
(RMW) =	Robust Minus Weak factor
β_e =	sensitivity of asset to CMA
(CMA) =	Conservative Minus Aggressive
e_i =	zero-mean residual

3.1.4 Efficient Market Hypothesis and herding

Traditional asset pricing models are supposed to measure the actual price of an asset when there is nothing else that has an impact in the price. However, in real world full of humans' whose cognitive capacity has constraints, it is not possible that no other factors would not affect the prices. Traditional asset pricing models do not take into consideration the human component. The models always assume investors to be completely rational and making decisions based on information they receive (Hirshleifer, Lim & Teoh, 2009). The capital asset pricing model, three-factor model and the five-factor model all assume linearity of expected returns.

Behavioural finance can be viewed as a theory which doubts the accuracy of the linear asset pricing models that presume the efficient market hypothesis to be accurate and investors being rational. Herding is just one example of behavioural biases that causes asset prices to deviate from the prices traditional asset pricing models suggest. As behavioural finance suggests, most humans act irrationally and are prone to make decisions based on feelings, recommendations, and hunches. (Banerjee, 1992; Baker & Nofsinger, 2010) Behavioural finance provides another viewpoint of investors' decision-making by suggesting that it is not only measurable variables that have an impact on humans' decision-making. In real life, investors react differently to recommendations, salient information, or for example past returns (Bikhchandani & Sharma, 2001). Individuals' own experiences affect to their investment decisions. When different investors react to the same information differently or use different information (not only the absolute values provided by traditional asset pricing models) the efficient market hypothesis cannot be true. Herding is an area in behavioural finance which focuses on how investors react to information about investment decisions of other investors (Froot, Scharfstein & Stein, 1992).

For the EMH to be true it is needed that two of the assumptions are true. First one being the assumption that prices move according to random walk, and the price changes of assets are not predictable. The second assumption is that the prices reflect all the available information and the market fundamentals (Fama, 1970). Behavioural finance assumes EMH not to be true in a real world. The traditional asset pricing models including for example the efficient market hypothesis are not able to predict the movements of asset prices accurately enough.

Dang and Mi (2016) stated that a group of investors are prone to parallel trading over time. If investors tend to herd around the consensus in the markets, the trading decisions are likely to move asset prices in a way that cannot be explained by their fundamentals The stocks end up being improperly priced, usually overpriced. For individual investors, herding causes purchases at inefficient prices. Institutional investors should usually be more aware of the fundamentals affecting to the asset price as they usually have better resources in processing information.

However, the assumption of better information processing resources is also prone to cause herding. Institutions tend to herd into undervalued stocks (Bailey, Cai, Cheung & Wang, 2009). Herding of institutional investors tends to correct the inefficient prices that the herding of individual investors is causing.

During high uncertainty sociological factors might drive humans to imitate each other's actions, i. e. herd (Keynes 1936). Investors base their actions on past decision makers' choices, ignoring the non-obvious aspects of those choices (Hirshleifer, 2001; Simonsohn & Ariely, 2008). Individual investors tend to believe that past returns are a reliable indicator of future performance (Lakonishok et al., 1994). On the other hand, investors are prone to suffer from disposition bias and they tend to sell past winners and keep the losers (Shefrin & Statman, 1985).

Institutional investors, who typically have better information processing capabilities, have different reasons for non-rational herding than individual investors. Institutional investors' irrational behaviour is typically caused by noise, such as news headlines (Schleifer & Summers, 1990). These investors frequently use momentum or contrarian trading strategies, which are based on historical performance. However, relying on past performance frequently results in assets being overvalued or undervalued (Grinblatt, Titman & Wermers, 1995). Nevertheless, despite their greater ability to process information than individual investors, institutional investors may choose to align their decisions with the opinions and actions of other market participants when there is not enough information to process (Devenow and Welch, 1996).

3.2 Financial bubbles and herding

After big financial crises, herding has drawn attention in research on behavioural finance. The crises have raised the interest to research whether herding towards financial markets tends to generate financial bubbles (Spyrou 2013, p. 178). No matter whether the investor who is herding is institutional or individual, herding is prone to cause market inefficiency, which again, in extreme situations might generate financial bubbles (Spyrou 2013, p. 178). If herding is strong enough, it is possible that it would generate a strong inflation of certain assets or even markets. If the demand for those assets is strong enough it might end up in asset prices to deviate from their fundamental values so greatly that it would form a pricing bubble (Spyrou 2013 p. 178).

As prices increase due to increasing demand from herding, investors might get overconfident and believe that the trend will continue for ever. This can lead to excessive risk-taking and speculative behaviour, raising prices even higher. Conversely when the bubble bursts, panic selling tends to increase herding, magnifying the extent of the market downturn. The concern of herding generating huge market disturbances has motivated researchers to study the reasons and origins of herding (Bikhchandani & Sharma, 2001).

4 Methodology

The following chapter describes the herding models used in this study. Unlike traditional asset pricing models based on the assumption of investor rationality and market efficiency, these models recognise that market participants may engage in irrational behaviour, such as herding. The methodology employed in this study is focused on identifying market-wide herding. Such herding occurs when market participants ignore the individual characteristics of stocks and follows the overall performance of the market (Henker et al., 2006, p. 197).

The following herding models have been able to detect herding and irrationality under certain circumstances. Both, CSAD and CSSD models have been widely used and herding has been detected with those models in previous studies, such as those by Chiang & Zheng (2010) and Caporale et al. (2008) in addition to studies of Christie and Huang (1995) and Chang et al. (2000). Therefore, if herding exists in Finnish stock market, it is reasonable to expect that the models will detect it in study also. The models presented in this chapter are not only ones existing, but rather represent those widely used in previous literature.

4.1 CSSD-model

Christie and Huang (1995) introduced a pioneering method for identifying herding. They proposed that dispersion, which quantifies the amount to which individual returns correlate with market returns, is an appropriate tool for assessing the impact of investor herds on the market. Dispersions are bounded from below zero, and an increase in dispersions occurs when individual returns differ from the market return. Hence, a decrease in dispersions would indicate market-wide herding. CSSD model is a linear regression model which can find herding among investors. During high market volatility and market stress, Christie and Huang (1995) propose that investors form their decisions according to others’ actions rather than relying on traditional asset pricing models. Authors assume that herding ends up the in a market condition where the deviation between returns of individual assets and the return on the market index decreases (Christie & Huang, 1995). Additionally, they suggested that during periods of large market movements, investors are more likely to base their investment decisions solely on the market's performance, resulting in individual returns that do not differ significantly from the market return. Consequently, the level of dispersion, i. e., CSSD, will be lower than during normal market conditions, which contrasts rational asset pricing models that assume an increase in dispersion during large market movements. Furthermore, Chang et al. (2000) introduced the cross-sectional absolute deviation (CSAD) as a measurement.

With CSSD model it is possible to measure dispersion between individual asset's returns and the market index's return (Christie & Huang, 1995). The bigger the gap between individual asset's returns and the market index return is, the bigger the dispersion is (Christie & Huang, 1995). Random walk suggests that individual assets price movements are not related to other assets price movements. Hence, dispersion between all the individual assets and the market index should be notable. However, market-wide herding causes individual asset prices to follow prices of other assets and move accordingly to market index. Therefore, the dispersion decreases.

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

Where:

$R_{i,t}$ = observed stock return on stock i at time t

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

Christie and Huang (1995) argue that investors tend to exhibit herding towards the market consensus, particularly during periods of market stress. Hence, they conduct empirical verification of this proposition using regression analysis with the following model:

(2) $$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$$

Where:

D_t^L = 1, if the market return on a day t is on the extreme low tail of the distribution, and 0 otherwise.

D_t^U= 1, if the market return on a day t is on the extreme up tail of the distribution, and 0 otherwise

ε_t = error term at time t

The α coefficient represents the sample's mean dispersion after excluding the segments defined by the two dummy variables. These dummy variables are meant to capture differences in investor behaviour during days of significant up- or down-market movements and days of stable markets (Christie & Huang 1995).

4.2 CSAD-model

As CSSD model has been criticized for the linearity of the model and reliability only in under certain market conditions, the cross-sectional absolute deviation (CSAD) model, introduced by Chang, Cheng & Khoarna (2000) detects herding even when the relation between dispersions and the market return is non-linear. Chang et al. (2000) assume that the presence of herding in the market would lead to a non-linear correlation between the dispersions of individual asset returns and the market portfolio's return. This implies that the cross-sectional absolute deviation would either decrease or increase at a rate less than proportional to the market return. Chang et al. (2000) utilize a CSAD-model that is based on the conditional version of the Capital Asset Pricing Model (CAPM) to indicate this potential linearity. Therefore, they measure CSAD as:

(3) $$CSAD_t = \frac{1}{N}\sum_{i=1} N|R_{it} - R_{mt}|$$

$R_{i,t}$ = return of a stock i time t

$R_{m,t}$ = return of market index at time t

Chang et al. (2000) assume that according to traditional asset pricing models, the dispersion between individual asset prices and market return should increase. Therefore, the dispersion should be non-linear. The model forecasts that herding occurs in two ways: a decline in dispersion and a non-linear correlation between dispersion and market returns (Chang et al., 2000). For the latter to exist, the rate of change in dispersion must be less proportional to the market return (Chang et al., 2000). The CSAD-model can detect herding and provide stronger evidence of it under more stable typical up- and down-market conditions.

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

Where:

$CSAD_t$ = measure for return dispersion

$R_{m,t}$ = return of market index at time t

$\left|R_{m,t}\right|$ = absolute-term

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

ε_t = error term at time t

According to Chang et al. (2000), the relationship between CSAD and the average market return will be non-linear relationship if all market participant herd towards the consensus of the markets during large market swings. For herding to be evident, the CSAD value should be negative or at least increase less than proportional rate compared to the market return. For herding to be evident, the CSAD value is expected to be either negative or increase at a rate less than proportional compared to the market returns. Thus, the non-linearity is captured with γ_3 coefficient if the value is negative and statistically significant. Chang et al. (2000) tested the significance of estimated coefficients and t-statistics at 1% and 5% percent levels.

5 Data

The data used in the study is gathered from University of Vaasa's database. It contains the daily closing prices of stocks included in OMXH25 index in the end of 2021. OMX Helsinki 25, which belongs to OMX group, is a leading stock index in Finland. The index includes 25 most traded stocks in the Helsinki Stock Exchange. The Index is revised twice a year. Stocks of which market capitalizations has decreased will be exchanged with stocks that have gained the market capitalization (Nasdaq 2023).

5.1 Data sample and market overview

The sample period consists of the daily prices of the 25 stocks from the beginning of 2018 to the end of 2021. The period is divided into two sub-periods as the market conditions experienced a significant change in the beginning of 2020 due to the COVID-19 pandemic. As this thesis aims to compare the change in market wide herding in Finnish stock market between stable and fluctuate markets, the time periods inspected are 01.01.2018 – 31.12.2021. OMXH25 index and OMXHPI index, which includes all the stocks listed in the Helsinki Stock Exchange, are presented below. The indexes aim to reflect the status and changes in the Finnish stock market.

Figure 4. OMXHPI Index 01.01.2018 - 31.12.2021

Figure 5. OMXH25 Index 01.01.2018 - 31.12.2021

As Figure 4 above state, the Finnish stock market experienced modest fluctuations during 2018-2019, but can be considered rather stabile. The stabile market conditions were followed by significant volatility and downturns in 2020 caused by the COVID-19 pandemic. Looking at figure 5, the OMXH25 index was rather stable during 2018 and early 2019. During years 2018 – 2019 the Finnish stock market did not experience any major external shocks. Figures exhibits that the uncertainty in the market began in the beginning of 2020, already before the 16th of March. Especially during February and March 2020, the market experienced significant fluctuations and sharp declines caused by investors reactions to increase uncertainty caused by the pandemic. Subsequently, in 2021, the market showed signs of recovery and stability as the vaccination became available for everyone and the restrictions in travelling and meeting people were relaxed. Although the market remained vulnerable to pandemic-related developments as well as other global economic factors. From late 2020 to mid-late 2021 the market can be considered rather stabile rising market.

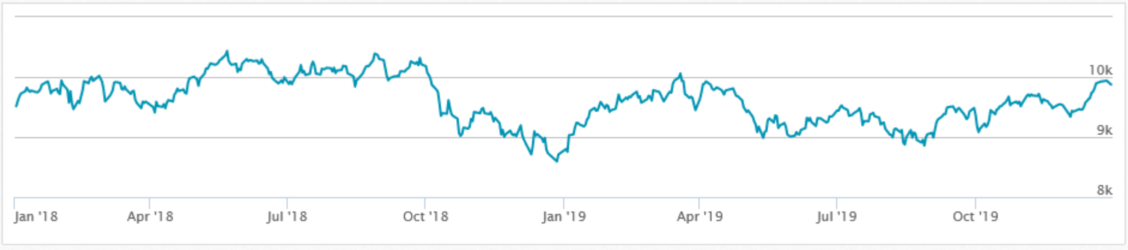

Figure 6. OMXHPI Index 01.01.2018 - 31.12.2019

Figure 7. OMXHPI 01.01.2020 - 31.12.2021

The beginning of Covid-19 pandemic in Finland is commonly considered to be 16th of March 2020 when the state of emergency started in Finland (Valtioneuvosto, 2020). The OMX Helsinki reached its lowest point of the chosen time period in 18th of March 2020. However, there were several Covid-19 cases in Finland already before that, and the media had started to inform about all the possible threats in late 2019 and early 2020. The Covid-19 can be considered to have an impact in markets already in the beginning of 2020. The news in Finland covered for example headlines about China confirming coronavirus to transmit from human to human on 20th of January (Ramelli & Wagner, 2020), first confirmed coronavirus infection in Finland on 29th of January (Yle, 2020), Lockdown of Italy on 23rd of February (Ramelli & Wagner, 2020) and the Rise of Covid-19 infections in Finland on 11th of March (Yle, 2020).

5.2 Descriptive statistics

Tables 1, 2, 3 and 4 exhibits the descriptive statistics for CSSD and CSAD measures and the market returns for each of the time periods selected. CSSD values are similar across both observed time periods. The only significant difference between the periods is the maximum value, which is 0.084 during the 2018-2019 period and deviates significantly from the maximum value of 0.055 during the 2020-2021 period. The CSAD values show a lack of significant differences. Throughout the 2018-2019 period, the values are close to the values observed during 2020-2021 period. Market returns, in turn, vary slightly more between the two time periods. Notably, the maximum return for 2020-2021 is twice that of 2018-2019. In contrast, the minimum return in 2020-2021 is four times smaller than during 2018-2019. Significant deviations in maximum and minimum return imply the market fluctuations during the pandemic time frame to be stronger.

Table 1. Daily cross-sectional standard deviations (CSSD) and daily market returns (R_m) for Finnish stock market 01.01.2018 – 31.12.2019.

2018 - 2019	**CSSD**	R_m
Mean	0,015	0,000
Median	0,014	0,001
Max	0,084	0,031
Min	0,006	-0,026
Std. Dev	0,007	0,009

Table 2. Daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for Finnish stock market 01.01.2018 – 31.12.2019.

2018 - 2019	CSAD	R_m
Mean	0,011	0,000
Median	0,010	0,001
Max	0,041	0,031
Min	0,005	-0,026
Std. Dev	0,004	0,009

Table 3. Daily cross-sectional standard deviations (CSSD) and daily market returns (R_m) for Finnish stock market 01.01.2020 – 31.12.2021.

2020 - 2021	CSSD	R_m
Mean	0,017	0,001
Median	0,015	0,001
Max	0,055	0,064
Min	0,005	-0,102
Std. Dev	0,008	0,014

Table 4. Daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for Finnish stock market 01.01.2020 – 31.12.2021.

2020 - 2021	CSAD	R_m
Mean	0,012	0,001
Median	0,011	0,001
Max	0,043	0,064
Min	0,004	-0,102
Std. Dev	0,005	0,014

Daily CSSD and CSAD measures as well as their corresponding equally weighted market returns are plotted in for both selected time periods. Figures 8, 9, 10 and 11 below present the relationship between the daily cross-sectional standard deviation (CSSD) and absolute deviation (CSAD) and their corresponding equally weighted market returns. All figures below exhibit nonlinearity in the CSSD and CSAD market relationships. Lack of a linear relationship in the figures implies that it is reasonable to conclude that linear relationship models are not suitable for this analysis.

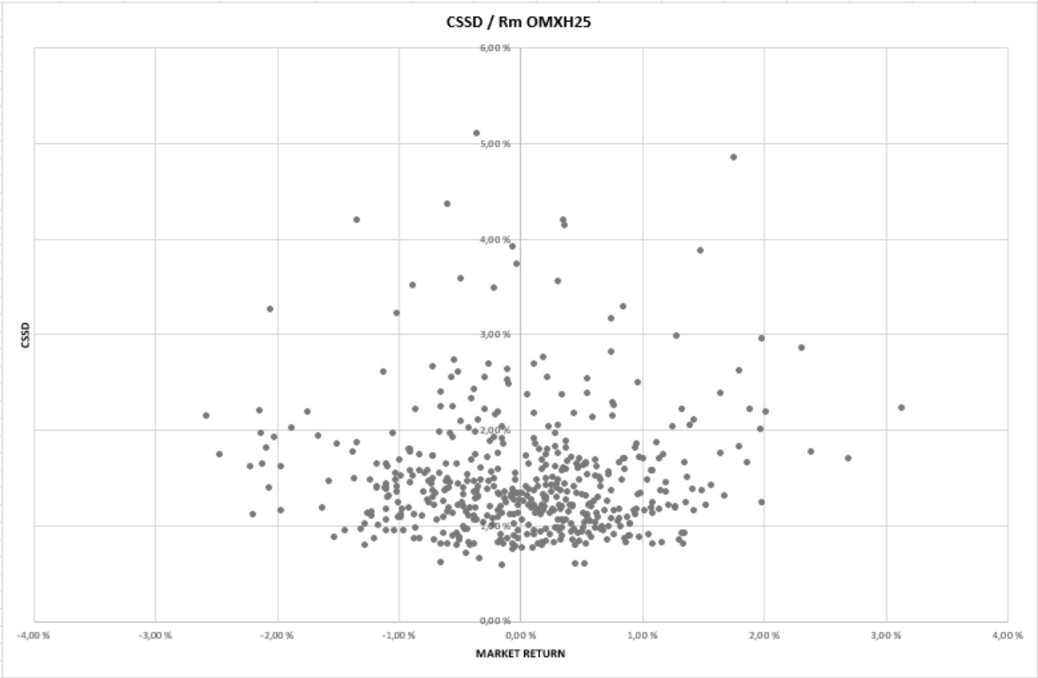

Figure 8. Relationship between CSSD and market return 2018 – 2019

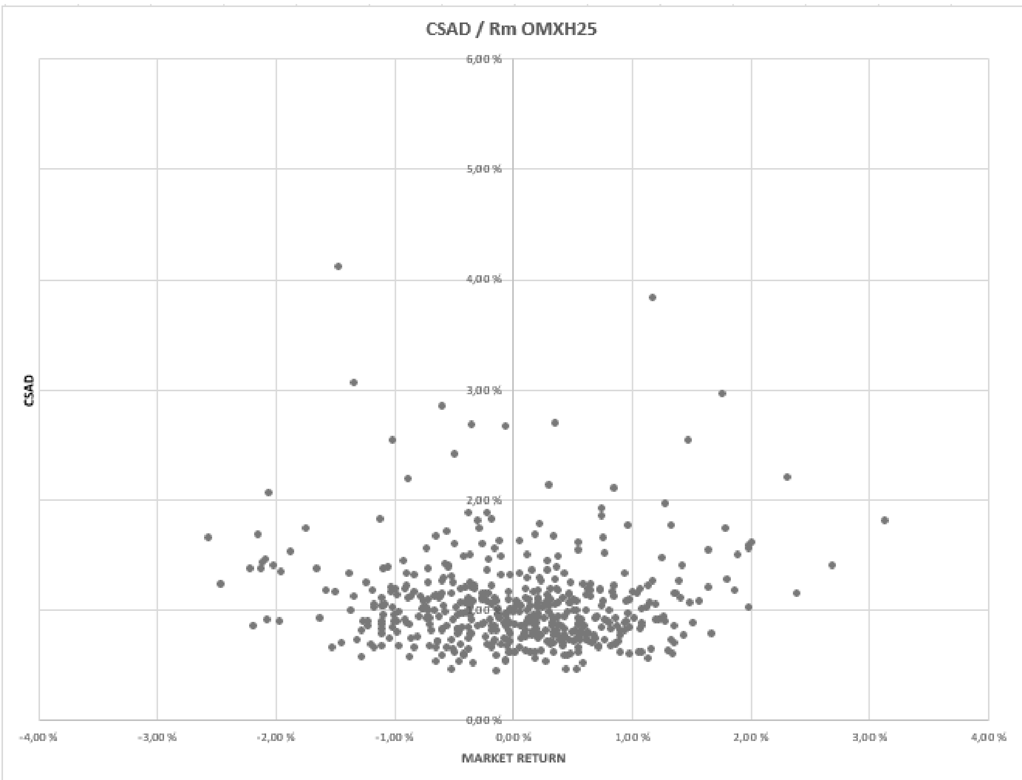

Figure 9. Relationship between CSAD and market return 2018 - 2019

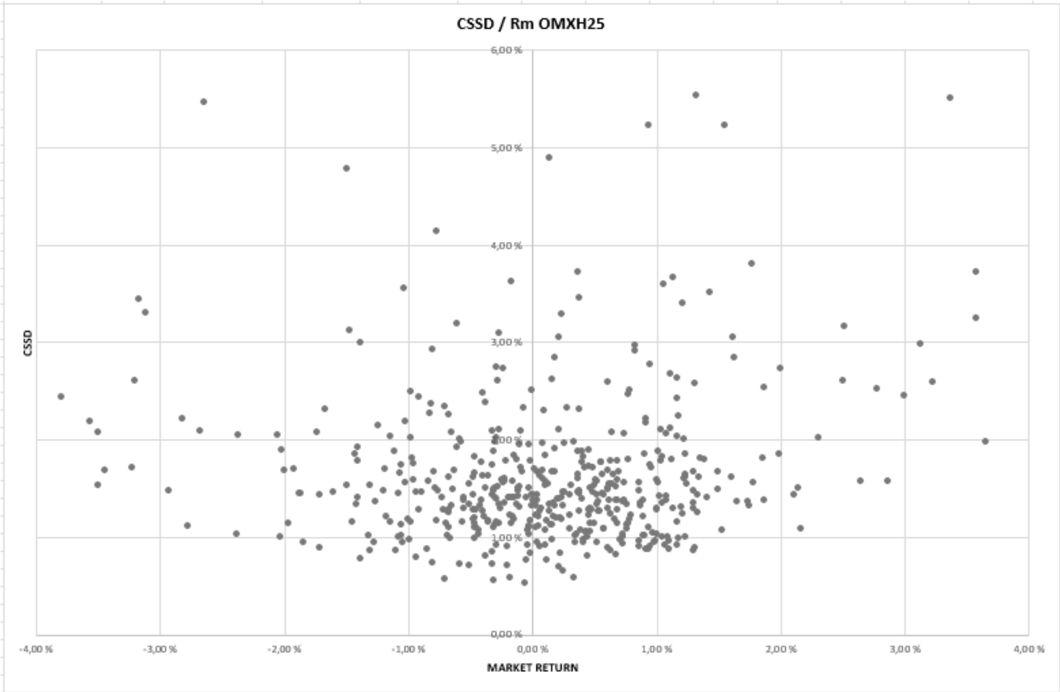

Figure 10. Relationship between CSSD and market return 2020 – 2021.

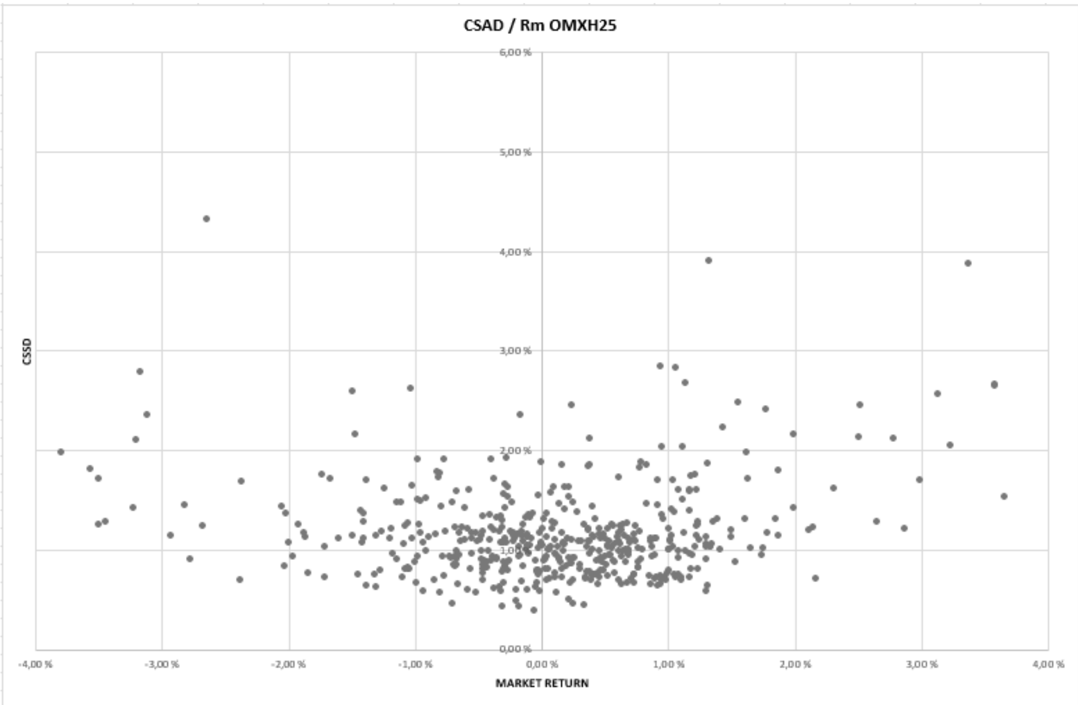

Figure 11. Relationship between CSAD and market return 2020 – 2021.

6 Herding results

This study aims to find herding within the Finnish stock market during two different time periods. The selected time periods show significant differences in market conditions. Given the assumption of Cross-Sectional Standard Deviation (CSSD) model detecting herding only during extreme up and down markets and the power of Cross-Sectional Absolute Deviation (CSAD) model do detect herding in more stable market conditions, it is reasonable to employ both models as the market conditions for the time periods are different.

Measuring the dispersion between individual returns and market return was done the same way Christie and Huang (1995) did in their study using the CSSD-model. Periods of market stress and abnormally high price movements are prone to disclose the differences in predictions based on traditional asset pricing models and behavioural finance. According to traditional asset pricing models, the dispersion increases as individual securities sensitivity to market return differs. In contrast, when individual returns herd around the market, the dispersion decreases. (Christie & Huang, 1995.) Following Christie and Huang's (1995) approach this study separated the level of dispersion into two extreme tails of the distribution of market returns in order to determine whether the extreme market return tails deviate significantly from the typical levels of dispersion that do not include the outermost market returns.

Table 5. Christie & Huang (1995) Cross-sectional standard deviation for OMX Helsinki 01.01.2018 – 31.12.2019.

	Christie & Huang (1995) CSSD Regression estimates 2018 – 2019		
	$\boldsymbol{\beta_1 D_t^L}$	$\boldsymbol{\beta_2 D_t^U}$	**Intercept**
Coefficient	0,0054*** (3,5910)	0,0061*** (4,0569)	0,0147*** (42,5950)
Standard error	0,0015	0,0015	0,0003
	0,0532	0,0073	
	13,9473	496	
	0,0015	0,0264	

The numbers in the parentheses are t-statistics.
*Statistical significance at the 10% level
**Statistical significance at the 5% level
***Statistical significance at the 1% level

Table 6. Christie & Huang (1995) Cross-sectional standard deviation for OMX Helsinki 01.01.2020 – 31.12.2021.

	Christie & Huang (1995) CSSD Regression estimates 2020 – 2021		
	$\boldsymbol{\beta_1 D_t^L}$	$\boldsymbol{\beta_2 D_t^U}$	**Intercept**
Coefficient	0,0074*** (4,9503)	0,0097*** (6,4408)	0,0158*** (45,9696)
Standard error	0,0015	0,0015	0,0003
	0,1114	0,0073	
	31,4162	501	
	0,0034	0,0269	

The numbers in the parentheses are t-statistics.
*Statistical significance at the 10% level
**Statistical significance at the 5% level
***Statistical significance at the 1% level

Tables 1 and 2 displays the regression results of CSSD model in Finnish stock market for both observed periods separately. Coefficient of the dummy variables, which indicate whether the return is either on extreme up tail (95%) or extreme low tail (5%) of the return distribution, is positive during both observed periods. Positive coefficients imply market to function rationally before and during the pandemic. Christie & Huang (1995) presume herding to occur if estimates of $\beta_1 D_t^L$ and $\beta_2 D_t^U$ are negative and statistically significant. The positive coefficient exhibits the CSSD to increase in the left tail and the right tail. Tables 1 and 2 displays the coefficients to be statistically significant. Hence, the results suggest that investors form decisions rationally without herding towards market signal or actions of other investors and key influences. All coefficients being positive and statistically significant, CSSD was not able to detect herding in Finnish stock market neither before nor during the pandemic. While the difference in coefficients between the two periods is small, the slightly higher coefficients during the 2020-2021 period suggests the market to function even more rationally onset of the pandemic than in the pre-pandemic era based on the intensity of herding.

Table 7. Chang et. al. (2000) Cross-sectional absolute deviation for OMX Helsinki 01.01.2018 – 31.12.2019.

	Chang, Cheng & Khorana (2000) CSAD Regression estimates 2018 - 2019			
	γ_3	γ_2	γ_1	**Intercept**
Coefficient	9,9950***	-0,0055	-0,0108	0,0100***
	(2,2148)	(-0,0563)	(0,4967)	(24,1503)
Standard error	4,5128	0,0979	0,0218	0,0004
	0,0689	0,0042		
	12,2122	495,0000		
	0,0006	0,0086		

The numbers in the parentheses are t-statistics.
*Statistical significance at the 10% level
**Statistical significance at the 5% level
***Statistical significance at the 1% level

Table 8. Chang et. al. (2000) Cross-sectional absolute deviation for OMX Helsinki 01.01.2020– 31.12.2021.

	Chang, Cheng & Khorana (2000) CSAD Regression estimates 2020 - 2021			
	γ_3	γ_2	γ_1	**Intercept**
Coefficient	0,1049	0,2642***	0,0420***	0,0095
	(0,1647)	(6,9043)	(2,7459)	(29,6236)
Standard error	0,6367	0,0383	0,0153	0,0003
	0,2741	0,0044		
	62,9401	500,0000		
	0,0036	0,0096		

The numbers in the parentheses are t-statistics.
*Statistical significance at the 10% level
**Statistical significance at the 5% level
***Statistical significance at the 1% level

The regression results of CSAD model are presented in the table 3 and 4 above. The variable of interest, the non-linear component, coefficient γ_3 during the pandemic period is close to zero, although it is not negative. Tables exhibit the non-linear term for the period 2018 to 2019 being significantly larger than the corresponding coefficient for the period 2020 to 2021. The positive value implies the market to function rationally without herding occurring. Since CSAD should be able to detect herding on more fluctuate markets, it should be safe to conclude herding not occurring in Finnish stock market during 2020 – 2021. Although, the coefficient being noticeably smaller would indicate the markets moving towards irrationality during the time of a global health crisis and market stress. However, as the Table 4 exhibits, the coefficient γ_3 is not statistically significant even at 10% level, suggesting the possibility of the value to be 0,1049 just by a random chance alone.

Regressions on tables 3 and 4 display that market wide herding is not present in the Finnish stock market during either of the periods. The findings imply that investors do not blindly follow the herd or disregard particular stocks' unique qualities. Hence, the first hypothesis: *Market-wide herding is present in Finnish stock markets during both sample periods.* is rejected as markets are found to function rationally. The results contradict the study of Kyröläinen and Perttunen (2003), who found herding in the Finnish stock market. However, since coefficient in this study is closer to zero in more volatile market conditions, the findings bear some resemblance to a study of Saastamoinen (2008) who found potential hints of investors' behaviour to shift towards herding under certain market conditions. Results of this study are inconsistent with the results of Christie and Huang (1995), who suggest herding to occur during periods of large market movements. These results however can be rather considered consistent with the study of Chang et al. (2000) and traditional asset pricing models. Despite the absence of detectable herding behaviour, the findings show a smaller increase in dispersion under more fluctuate market conditions during the pandemic compared to the pre-pandemic period. Given the absence of herding during both time-periods, any increase in herding activity during the COVID-19 can’t be detected. Hence the second hypothesis: *Market-wide herding increased during COVID-19 pandemic in Finnish stock market.* is rejected as well.

7 Conclusions

This thesis investigated the phenomenon of herding behaviour in the Finnish stock market, focusing on two distinct time periods: 2018-2019 and 2020-2021, the latter coinciding with the outbreak of the COVID-19 pandemic. The empirical study utilized CSSD and CSAD models to determine whether herding occurs in Finnish stock market and whether there were any discernible shifts in herding between these time periods.

The observed dispersions given by the CSSD and CSAD models indicate that Finnish investors did not rely on the actions of other market participants, either before or during the pandemic. Herding cannot be said to explain the movements of the market during either of the time periods. The onset of global stock market turbulence began with the outbreak of the pandemic (Baker et al., 2020). Despite the market uncertainty the Finnish stock market seems to function rationally, when examining whether herding caused markets to be irrational, as evidenced by the CSSD and CSAD results. While previous studies have reported instances behavioural biases, including herding, in various global markets, the absence of herding in the Finnish stock market highlights the importance of considering other behavioural biases to explain market movements and investors' decision making. Notably, significant market downturns in March and October 2020 are probably better explained by uncertainty generated through media-driven threat scenarios than by herd behaviour among investors. The observed dispersions highlight investors' rational responses to information about both stock market dynamics and current global conditions.

Despite the tendency for crises to evoke fear and uncertainty, potentially leading to herding, the Finnish stock market appears to be rather resilient to such influences. Alternative factors appear to play a role in explaining market dynamics. These findings suggest avenues for further research in the field of behavioural finance in the context of the global health crisis. Further studies could look into whether the COVID-19 pandemic and other global crises have increased other behavioural biases.

Although the findings of this study show that there was no increase in herding in the Finnish stock market in response to the COVID-19 pandemic, there are opportunities for future research to investigate potential variations in herding across other markets. Future research could expand beyond the OMXH25 stocks to include all stocks traded in Finnish market, increasing the sample size, and providing a more accurate analysis. Furthermore, looking at data over a longer time period than the four years examined in this study may provide insights into the presence or absence of herding behaviour under various market conditions. Conversely, examining a larger number of shorter time periods, particularly at the beginning of the COVID-19 pandemic when market movements were most prominent, could provide evidence of herding behaviour during brief market fluctuations.

In conclusion, this thesis adds to the growing body of literature on herding by providing empirical evidence of its absence in the Finnish stock market during 2018 – 2021. In addition, this thesis provides evidence of the global health crisis not causing investors to herd. Despite the global health crisis, travel restrictions, increased market fluctuations, and disseminated information about the pandemic's potential threats, no discernible effects on herding in the Finnish stock market were observed. The findings of this study imply the Finnish stock market to function rather rationally as indicated by the lack of herding.

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