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Testing for Herding in the Finnish Equity Market: A CSSD and CSAD Approach During Periods of Uncertainty

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ABSTRACT:

Behavioural finance is a theoretical framework at the intersection of finance and psychology. It describes the irrational behaviour of individuals within an economic context. The basis of behavioural finance is to understand individual financial decision-making. Sometimes however, investors can behave irrationally as a group. This phenomenon is described as herding.

This thesis tests whether the Finnish equity markets exhibit herding behaviour during the sample period of 2019 – 2024. The research is twofold. Firstly, it focuses on the full sample of 2019 – 2024 to test whether the Finnish equity markets exhibit herding behaviour in general. Secondly, it splits the time period into three sub-periods to focus on specific periods that contain events that exhibit market stress. Notably, the COVID-19 pandemic and the escalation of the war in Ukraine during early 2022.

The empirical testing methodology used is a combination of two cross-sectional dispersion models: the cross-sectional standard deviation and the cross-sectional absolute deviation models. The data used for the tests is composed of the daily returns of 18 companies within Nasdaq Helsinki, and the OMXH25 index is used as a proxy for the market. A total of 1508 observations are included within the period.

The empirical results of the cross-sectional standard deviation and the cross-sectional absolute deviation models suggest anti-herding behaviour within the Finnish equity market. Return dispersion tends to widen during periods of large market movements, contradicting with the convergence pattern of herding. However, these findings should not be interpreted as definitive evidence that herding does not happen within the Finnish equity market. Both models are based on theoretical assumptions of CAPM and market efficiency, suffering from the joint hypothesis problem. Thus, they may fail to capture varying types of herding in different market environments. The presence of multiple market stress periods during the sample period applies stress to the markets, which could amplify herding. This herding might not be fully captured by the cross-sectional standard deviation and cross-sectional absolute deviation approaches.

KEYWORDS: behavioural finance, CSSD, CSAD, herding, return dispersion, equity markets

ChatGPT was used in the thesis for grammar purposes.

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Abbreviations

CAPM	Capital Asset Pricing Model
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
EMH	Efficient Market Hypothesis
EUT	Expected Utility Theory
IPO	Initial Public Offering
WTA	Willingness to Accept
WTP	Willingness to Pay

1 Introduction

Imitation has for a long time been a fundamental aspect of human behaviour through a multitude of varying domains (Devenow & Welch, 1996). Despite this, theories within the field of finance assume investors to act within theoretical rational frameworks. Ever since the introduction of the Efficient Market Hypothesis (EMH) by Fama (1970), extensive research has been published debating for and against the efficiency of the markets and the role of investor psychology within the financial markets.

The efficiency of the markets has consistently been questioned in the financial literature. Often questioned in the aftermath of crises such as the global financial crisis (Economou, 2011) and the European financial crisis (Galariotis et al., 2016a). In these contexts, human behaviour is often suggested as at least one of the reasons for such crises (Bekiros et al., 2017). If the markets were efficient as Fama (1970) states, individual irrationality would be suppressed away by the market as a collective, as sugegested by Shleifer (2000). Contrary to the expectation, research indicates that human behaviour and its biases have an effect on the financial markets across geographies (Blasco et al., 2012; Caparrelli et al., 2004) investor types (Akepanidtaworn et al., 2019), and asset classes (Memon et al., 2022; Galariotis et al., 2016a; Galariotis et al, 2016b). The everlasting debate between efficient and inefficient markets, and the contradicting results within the behavioural finance literature, have motivated me to write my thesis within the field of behavioural finance. To specify, this thesis investigates the presence of investor herding within the Finnish equity markets.

The thesis focuses on the Finnish market, particularly during the period of 2019 to 2024, a time period with significant market uncertainty, favourable for potential investor herding. The time period includes the onset of the COVID-19 pandemic during the beginning of 2020 and the escalation of the Russo-Ukrainian war at the start of 2022, the time period provides a recent context in which to examine investor herding under uncertainty.

1.1 Purpose of the study and contribution

The purpose of the study is to empirically examine whether investor herding is present within the Finnish equity market during the sample period of 2019 – 2024. Further, the time period is split into three sub-periods of 2019 – 2020, 2021 – 2022, and 2023 – 2024. The splitting of the time period into sub-periods allows for more intricate empirical analysis on whether herding behavior differs during different states of uncertainty. This is achieved by applying two simple and established methodologies of herding detection, the cross-sectional standard deviation (CSSD) (Christie & Huang, 1995) and the cross-sectional absolute deviation (CSAD) (Chang et al., 2000) to the daily return data of the OMXH25 index as a market proxy and a selection of 18 constituents of the index.

This thesis contributes to the existing literature by applying two models: the CSSD by Christie and Huang (1995) and the CSAD by Chang et al. (2000) to examine herding behaviour within the Finnish equity market, and by the discussion on whether these models are truly reliable on actual herding detection. These models have been used in various market contexts, their application to the Finnish market over the period of 2019 – 2024 and the sub-periods show somewhat updated insight into investor behaviour under recent forms of uncertainty. This timeframe includes recent periods of uncertainty such as the COVID-19 pandemic and the Russo-Ukrainian War, both events that have directly affected Finland and by extension the Finnish equity markets, introducing conditions under which investor herding behaviour may plausibly occur.

1.2 Research question and hypotheses

The general research question of the paper is whether investors exhibit herding behaviour within the Finnish equity market. The *general* definition of herding in this thesis is a phenomenon in which investors ignore their own beliefs and imitate others' thoughts, feelings and actions (Bekiros et al., 2017). During the empirical tests within this thesis however, CSSD an CSAD will be used as theoretical proxies for herding due their simplistic nature and their extensive use in the herding literature. The thesis-specific definition of herding under these two models will be discussed in further detail in the theoretical background chapter. Although, the general definition of herding by Bekiros et al. (2017) is closer to reality, it is broader and more complex.

Herding is argued to occur more often during times of additional market distress (Mobarek et al., 2014). Thus, the time period with its chosen sub-periods is favourable for the thesis,as the time period includes several abnormal market events. Previous literature suggests that herding is apparent in both emerging markets (Chiang et al., 2010; Boyer et al., 2006) and developed markets (Galariotis et al., 2016b; Bekiros et al., 2017) and that herding is more apparent during market distress (Mobarek et al., 2014). Thus, inspired by the spread of herding througought a vast array of markets, the first hypothesis is formed below to test for general herding within the sample period as follows:

H_1^1: The Finnish equity market displays signs of herding behaviour during the sample period.

H_0^1: The Finnish equity market does not display signs of herding behaviour during the sample period.

The first hypothesis tests for the presence of herding over the full sample period (2019–2024), which is not uniformly defined by a distinct event that generates uncertainty. It aims to determine whether Finnish investors generally exhibit herding behaviour. The second hypothesis is motivated by the findings of Mobarek et al. (2014), who examined herding behaviour in European equity indices from 2001 to 2012. Their results indicated no significant herding during the full sample period but revealed significant evidence of herding during episodes of extreme market stress, specifically the global financial crisis and the Eurozone crisis. These findings inspire the second hypothesis to test whether herding is more pronounced in the Finnish equity market during periods of abnormal market uncertainty. In this context the abnormal market uncertainty is represented by the COVID-19 pandemic and the escalation of the Russo-Ukrainian war.

H_1^2 : Herding behaviour is more pronounced during periods of abnormal market uncertainty within the Finnish equity market.

H_0^2: Herding behaviour is not more pronounced during periods of abnormal market uncertainty within the Finnish equity market.

1.3 Structure of the thesis

This thesis is structured into six chapters. The first chapter acts as the introduction, presenting the motivation behind the study, the hypotheses, their underlying rationale, and the overall structure of the thesis. The second chapter outlines the theoretical framework, focusing on behavioural finance, herding within a behavioural finance context, and the theory behind the methodology of CSSD and CSAD measuring herding behaviour, and importantly the limitations of these models.

The third chapter provides a literature review, discussing academic contributions within the field of behavioural finance. The fourth chapter details the data and methodology used to process the data. The fifth chapter uses the previous chapters by combining the theoretical framework with the methodology to process the data. It begins with descriptive statistics, followed by regression analysis. This chapter concludes with a discussion of the empirical findings in relation to the stated hypotheses. Finally, the sixth chapter offers a discussion of the thesis as a whole, focusing on the findings, the limitations of the thesis, and suggests future research ideas.

2 Theoretical framework

This chapter provides the theoretical framework for the thesis. It starts by comparing behavioural finance with traditional finance. Following this, the concept of herding behaviour in financial markets is examined. The chapter finally turns onto the theories of detecting herding within the market, and the essential limitations of these methodologies. Particular emphasis will be on the theory of CSSD introduced by Christie and Huang (1995) and the theory of the CSAD approach introduced by Chang et al. (2000).

2.1 Behavioural finance foundations

Traditional finance in general is largely based on the idea of rational market participants, as proposed in the EMH (Fama, 1970). According to the EMH of Fama (1970) asset prices reflect all available information. According to Shleifer (2000) the whole of the EMH is based on three key principles:

1. Investors are assumed to be rational and value securities on the basis of maximum economic utility.
2. Rational use of arbitrage will eliminate the actions of inefficient market participants.
3. If an investor was to be irrational, their effect on the market prices is offset by the randomness of their actions.

These statements can be undermined by basic human psychology and emotions, exemplified by the animal spirit theory of Keynes (1936). The animal spirit theory of Keynes (1936) argues that economic decisions are made under intuition and emotion. The EMH has always been a debated topic within the broader finance literature. Early arguments against the EMH can be found from cognitive psychology, through which human judgement has been studied. According to Kahneman & Tversky (1974) humans have a tendency to use heuristics, these are shortcuts in human thinking, to make decisions. The heuristics discussed by Kahneman & Tversky (1974) are representativeness, availability and anchoring. Representativeness is the act of making a decision based on an event representing a previous pattern or event, possibly neglecting key information. Availability is the act of overweighting memorable or recent, available, information within decision-making. Anchoring is the heuristic of anchoring your decisions on a previous baseline, relying heavily on initial information, leading to skewed judgement. Also a critical flaw of the EMH is the joint hypothesis problem, which will be discussed in detail within the theory of herding measurements chapter.

To comprehensively understand behaviourial finance, key theories such as the Prospect Theory (Kahneman & Tversky, 1979) must be discussed. According to the Prospect Theory, economic agents, make decisions in an asymmetrical manner. For example, humans tend to feel more pain when they experience a loss, than they feel pleasure when experiencing a gain of similar volume (loss aversion). This is the opposite of the expected utility theory (EUT) first proposed by Morgenstern and Von Neumann (1944), which is a foundational assumption of decision-making, claiming that individuals make decisions rationally, weighing decisions on outcomes and probabilities. This of course contradicts the findings of Kahneman and Tversky (1979) regarding the asymmetrical response to a win/loss of the same intensity. The EUT can also be argued as logically flawed, as investors in the actual financial markets have to do decision under varying level of uncertainty, as discussed next.

Bounded Rationality (Simon, 1955) is a theory that focuses on the boundaries of decision making. The theory challenges the traditional rational economic thinking portrayed by the EUT (Morgenstern & Von Neumann, 1944). It claims that humans make their decision under constraints such as time, cognitive capacity and information. Interestingly, while the theory of bounded rationality is a part of economic behaviour, it and heuristics like it can be seen as an evolutionarily rational survival strategy. Kinoshita et al. (2013) argue that biases such as loss-aversion and anchoring may be evolutionary survival strategies in uncertain environments such as the financial markets. Their findings suggest that under certain conditions, heuristic-based decisions may outperform purely rational decisions. This implies that bounded rationality reflects not just constraint, but a form of subconcious adaptation to uncertainty, in the financial context volatility and information scarcity.

2.2 Herding behaviour in financial markets

As discussed in the preceding chapter, humans have developed multiple different mental models for decision-making through evolution, that are also now being used in economic decision-making (Kinoshita et al., 2013). The presence of these mental models does undermine the EMH (Fama, 1970). When it comes to uncertainty in the financial markets, investor herding is a prime example of inefficient investor behaviour, especially prevalent in extreme market conditions (Bekiros et al., 2017). Herding has been a part human cognition naturally. Raafat et al. (2009) present herding as a multifaceted phenomenon, that could be extended into the financial markets. According to the Raafet et al. (2009) herding involves social influence which leads to emotional contagion, such as fear and panic in the financial markets, which can be seen as a driving force during decision-making in the uncertain financial markets.

Herding in financial markets refers to the phenomenon in which investors imitate the actions of others (Bekiros et al., 2017). This herding can cause asset prices to divert from their intrinsic values, driven by market price deviations and reflexive feedback loops described by Soros (1994). This sort of herding has a direct effect on market volatility (Blasco et al., 2012). As information or misinformation spreads rapidly, financial markets can evolve into self-reinforcing systems, where reflexivity amplifies initial movements (Filimonov et al., 2012), potentially fuelling bubbles or panics and detaching prices from the fundamentals.

In the papers by Humayun (2017) and it is outlined how during the 2008 financial crisis herding was evident, more so during periods of extreme volatility. Although on the other hand, Galariotis et al. (2016a) point out that there was no noticeable herding before, during or after the European sovereign debt crisis in the bond markets during the early 2010s following the global financial crisis of 2008. This juxtaposition implies that herding could be situational on the specific market, the current market events at hand and the amount of uncertainty regarding the event and its possible consequences.

As herding is context-specific shaped by the asset, market, or specific market events, it can be argued that retail investors are more prone to herding due to their relatively limited access to information (Bohl et al., 2017). Bouri et al. (2018) find that the cryptocurrency market exhibits pronounced herding behaviour, with its intensity fluctuating across different market cycles. Youssef (2020), using the CSAD methodology of Chang et al. (2000), demonstrates that herding tendencies among cryptocurrency investors increase during periods of heightened uncertainty, typically reflected in high market volatility. Interestingly, Youssef (2020) also notes that rising indicators such as the S&P 500 index or a strong US dollar acted as negative herding signals. This may suggest that investors interpret a strong equity market or stable macroeconomic environment as reducing the need for alternative assets like cryptocurrencies. On the contrary, it is known that institutional investors also exhibit irrational behaviour (Akepanidtaworn et al., 2019) and herding (Kremer & Nautz, 2013). The findings imply that herding is a prevalent factor in both retail and institutional investors, which is logically sound, as both investor types are humans and exhibit intuition and emotions, that will affect economic decision making (Keynes, 1936).

Herding can be both intentional and unintentional. Intentional herding occurs for example when fund managers subconsciously or consciously align their decision-making with their peers to avoid career risk (Li, 2002). This type of behaviour can also be interpreted as social herding, as described by Raafat et al. (2009). Unintentional herding arises from a lack of private information and increased reliance on public signals. Kremer and Nautz (2013) offer suggest that unintentional herding among institutional investors is primarily driven by the widespread use of similar risk models. This raises a critical question. If an investor base uses a suitable or not suitable risk model systematically, arguably herding around it, what kind of implications does this have for the financial markets?

Different stock markets often exhibit differing behavioural patterns (Economou, 2011). Significant variation exists in the presence and intensity of herding across markets. Spyrou (2013) argues that herding is not a universal phenomenon. There are also vast differences in the herding literature on market maturity and the amount of herding. Emerging markets are more prone to herding than developed nations (Bohl et al., 2017). This emerging market herding is especially apparent when it revolves around institutional investors and their trades in emerging markets (Chiang, 2010). When it comes to market conditions, herding can also be detected both in rising and falling markets environments, though it is more pronounced during market stress (Chang et al., 2000). Earlier models such Christie & Huang (1995) hypothesized herding to be a market stress induced phenomenon. Papers such as Hwang & Salmon (2004) suggest that herding is prevalent regardless of market conditions.

2.3 Theory of measuring herding

The theory behind measuring herding begins with the capital asset pricing model (CAPM) by Lintner (1965), Mossin (1966), and Sharpe (1964), which assumes that asset returns differ due to systematic and idiosyncratic risk factors. Under the EMH (Fama, 1970), large market movements should be accompanied by increased return dispersion among stocks, reflecting the nature of the stock betas and idiosyncratic characteristics. However, when herding occurs, investors mimic collective behaviour, leading to a contraction in return dispersion. In the following three sub-chapters, the theory of measuring herding is discussed in relation to each of the fundamental frameworks.

2.3.1 Capital Asset Pricing Model and the joint hypothesis problem

The CAPM developed by Lintner (1965), Mossin (1966), and Sharpe (1964) is a theoretical asset pricing model developed to describe the relationship between an asset's expected returns and the systematic risk, illustrated in Equation (1).

Equation (1)

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

Where:

$E(R_i)$= expected return of asset i

R_f= risk-free rate

β_i= beta of asset i

$E(R_m)$= expected return of the market

CAPM is the fundamental model for this thesis, as the following theories and methodologies on measuring herding rely heavily on CAPM's use of beta as a risk factor. Under the CAPM framework, asset returns vary due to varying levels of systematic risk, captured by each asset's beta. This implies that in a theoretical rational market under the EMH (Fama, 1970), the cross-sectional dispersion of individual stock returns around the market return should increase. Stocks with different sensitivities to market movements (different betas), are expected to react differently, resulting in wider return dispersions. This relationship provides the theoretical groundwork for the two models: CSSD (Christie and Huang, 1995) and CSAD (Chang et al., 2000) that are used to empirically detect herding behaviour in this thesis.

When discussing the CAPM and the EMH, the joint hypothesis problem (Fama, 1970) cannot be overlooked. It is the problem that arises when testing for any form of market efficiency. An asset pricing model is always required to test whether information is properly reflected in prices (Fama, 1991). This leads to indirectly testing both the asset pricing model and the efficiency of the markets simultaneously, leading to difficulties on interpreting results of market efficiency studies. Furthermore, in the case of this thesis, when testing for herding, the joint hypothesis problem is multi-dimensional. To test for herding, the thesis is simultaneously testing for market efficiency, while simultaneously testing CAPM, as both the CSSD and the CSAD are based on CAPM on a theoretical level. Moving forward in the thesis, this relationship is to be kept in mind when interpreting the findings.

The two primary models employed in this thesis to capture such effects are the CSSD introduced by Christie and Huang (1995) and the CSAD introduced by Chang et al. (2000). Both models assess the degree to which actual return dispersion deviates from expectations, allowing for the empirical testing of herding under different market conditions. The models are discussed in the following sub-chapters. The return dispersion within both CSSD and CSAD will be used as a proxy for herding within this thesis' empirical section. This decision is made as there is extensive herding literature using these models. Although, the amount of literature using these models does not correspond with the reliability of these models, especially taking into account the joint hypothesis problem.

2.3.2 Cross-sectional Standard Deviation

CSSD is an early approach by Christie & Huang (1995). The key theory behind the CSSD methodology is to compare stock returns to the market returns during a specific time period. As each stock has their own beta and react to information idiosyncratically, the return dispersion should in theory widen during periods of high volatility, however if investors are herding, the opposite would in theory happen. Each stock having different betas and idiosyncratic behaviour to information, during a period of herding the deviation in stock returns would shrink. The CSSD equation illustrated in equation (2).

(2) Cross-sectional Standard Deviation

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

Where:

N=	Number of stocks
$R_{i,t}$=	Return of stock i at time t
$R_{m,t}$=	Return of the market at time t

The raw CSSD values provides a measure of how dispersed individual stock returns are relative to the market return at time t. However, these values alone do not reveal whether the observed dispersion is related to investor herding. To test this, CSSD is regressed against dummy variables that represent extreme market conditions. A significant decrease in dispersion during these extremes would under the theory of CSSD suggest that investors are imitating each other (Christie & Huang, 1995), opposing the EMH (Fama, 1970). Equation (3) illustrates the regression of CSSD.

(3) Cross-sectional standard deviation regression model

$$CSSD_t = \alpha + \beta_1 D_t^{UP} + \beta_2 D_t^{DOWN} + \varepsilon_t$$

Where:

α=	constant when all returns are zero
$\beta_1 D_t^{UP}$=	dummy variable for extreme positive returns
$\beta_2 D_t^{DOWN}$=	dummy variable for extreme negative returns
ε_t=	error term

2.3.3 Cross-sectional Absolute Deviation

CSAD by Chang et al. (2000) is theoretically similar to the CSSD approach of Christie and Huang (1995). It examines the relationship between the dispersion of individual stock returns across market movements. The key difference between the two however is that where CSSD uses squared deviations, CSAD uses absolute deviations. This refinement for the model makes it so that outliers in the squared deviations are not as likely to distort the results, making the CSAD model less sensitive to outliers. CSAD at time t, shown in equation (4), represents the average absolute deviation of individual stock returns from the market return.

(4) Cross-sectional Absolute Deviation

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

Where:

N=	Number of stocks
$R_{i,t}$=	Return of stock i at time t
$R_{m,t}$=	Return of market at time t

Like CSSD, the raw CSAD values do not provide conclusive evidence of herding on their own. Under theoretical asset pricing models such as the CAPM, return dispersion is expected to increase with market movements, as different assets have different betas. Higher CSAD during large market movements reflects rational investor behaviour. To detect herding, it is necessary to isolate nonlinear patterns in the relationship between CSAD and market returns. In theory under CSAD, herding is identified when CSAD increases at a decreasing rate as large market movements happen. This behaviour can be captured through the CSAD regression model, illustrated in equation (5).

(5) Cross-sectional absolute deviation regression model

$$CSAD_t = \alpha + \beta_1 R_{m,t} + \beta_2\left|R_{m,t}\right| + \gamma_1 R_{m,t}^2 + \varepsilon_t$$

Where:

α=	constant when all returns are zero
$\beta_1 R_{m,t}$=	linear component
$\beta_2\left|R_{m,t}\right|$=	absolute component
$\gamma_1 R_{m,t}^2$=	non-linear component

$\varepsilon_t =$ error term

2.3.4 Limitations of CSSD and CSAD

Although the CSSD (Christie & Huang, 1995) and CSAD (Chang et al., 2000) models are widely cited within the herding literature, the models have limitations. Firstly, as noted earlier, CSSD is more sensitive to outliers. Secondly, these models are time period sensitive, particularly whether the time period includes a crisis or not, the models might miss herding during non-crisis periods. Thirdly, unexpectedly low return dispersion relative to market return is not inherently indicative of herding. Finally, the joint hypothesis problem does undermine the results of these models. Refinements of the CSSD and CSAD models have been made.

Bekiros et al. (2017) modify the CSAD model by introducing implied volatility as measure of risk expectations. The evolution of these models will address the limitations of the models with time. Bohl et al. (2017) argue against the use of the CSSD model of Chang et al. (2000) by showing that the true coefficient of herding under CSAD is positive, rather than the significantly negative coefficient on the squared excess market return suggested by Chang et al. (2000). Under the argument of Bohl et al. (2017), the CSAD model is biased against finding herding. They present evidence of this by examining the S&P500 and the EuroStoxx 50 indices.

3 Literature review

This section of the paper discusses the fundamental research on the topic of herding in the financial markets. Behavioural economics started to take shape in the 1970s with the notable works of psychologists Daniel Kahneman and Amos Tversky. Prospect theory (Kahneman & Tversky, 1979) laid the groundwork for behavioural finance. Following that Thaler (1985) built on the findings of Kahneman and Tversky, bridging psychology and economics. He did it by applying cognitive biases such as loss aversion and framing into real world economics. Thaler (1985) emphasized how people often act irrationally in a systematic way. A famous example of this is the true willingness to pay (WTP) and willingness to accept (WTA) of an individual (Kahneman & Thaler, 1991). For example, Thaler (1985) demonstrated how individuals have a willingness to pay higher prices for a beer at a fancy hotel when compared to a grocery store.

De Bondt and Thaler (1985) examined whether the stock market overreacts to new information. They found that the stock market consistently overreacts in both market downturns and growth periods. They note how stocks that had underperformed during the previous three to five years were likely to outperform stocks that had performed well during the same time period. Again, contradicting with the EMH of Fama (1970). Such investor behaviour and market overreaction can contribute to herding dynamics. Building on the work of overreaction in the financial markets, Hoitash and Krishnan (2007) show that mimicking in the stock market, especially in highly speculative stocks, is a key component in driving the profits of momentum strategies. The findings of Hoitash and Krishnan (2007) imply that informational mimicking, herding, could be quantified and potentially used to predict future returns.

3.1 Studies on herding behaviour

Herding behaviour in financial markets has been studied for decades. Early research (Keynes, 1936) suggests that economic behaviour mirrors patterns observed in everyday social life. Individuals tend to gravitate toward ideas or actions that others have already adopted. What is perceived as the right way to act in a given context is often shaped by the actions of others within that environment (Banerjee, 1992). Examples of this include choices such as which school to attend, how new technologies are adopted, or how voters respond to opinion polls, often shifting their preferences in line with prevailing trends (Cukierman, 1991).

Banerjee (1992) argues through a sequential decision model that optimizing individuals usually look at what decisions other individuals in the same context made. The Assumption being that these observed individuals might have some information that the observer does not have. Banerjee (1992) shows that the decision-making of the optimizing individuals observing others will be in fact characterized by herding behaviour. The same paper also shows that equilibrium following the described herding behaviour is inefficient. This inefficient equilibrium stems from the sequenced decisions, if a decision maker has a signal, they follow their own signal, but if they do not, they tend to follow the previous decision maker’s action. One can easily see, how this sort of behaviour can drift investors away from a rational equilibrium.

Bikhchandani et al. (1992) developed the concept of informational cascades. The thoery is that individuals ignore their personal signals and may follow the previous individuals’ action. This may become a self-enforcing loop when the actions of multiple individuals align, and observers mimic, similarly to herding. This is an interesting concept around behavioural finance, as it factualizes investors’ tendency to outsource decision-making. This challenges the traditional assumption of the EUT (Morgenstern & Von Neumann, 1947), which claims that economic decision making is characterized by the probabilistic utlitity an individual can gain from the decision. Informational cascades also argue for the act of herding even in the absence of irrationality, as investors expect that multiple previous investors have better information about an event or a company, than the sole investor.

Reinforcing the findings of Bikhchandani et al. (1992) Cipriani and Guarino (2008) show that when traders have private information, they may start making the same decisions together, regardless of the individual information of each trader leading to informational cascades. This could be seen as a detrimental to theoretical market efficiency, as it prevents new private information from flowing into the markets, as the traders are mimicking traders within the informational cascade. Cipriani and Guarino (2008) argue that the likelihood of an informational cascade depends the how precise the private information is, and how different the traders are.

The key concept being that an investor with high-precision private information is likely to act on their own private information. They have high conviction on the information, preventing informational cascades and simultaneously injecting new information onto the market. However, Cipriani and Guarino (2008) note that if the private information is low-precision, it can lead investors into informational cascades, as the investors are more uncertain about their own information. Cipriani & Guarino (2008) argue that investors with low-precision information are more likely to follow suit of the earlier traders of investors with high-precision information, such as early investments into IPOs. This can lead to information cascades. These findings are supported by Wang et al. (2017) who noted similar herding around IPOs in Taiwan.

Cipriani and Guarino (2008) also discuss the concept of herding contagion in financial markets by introducing the idea of trades as signals. An investor observing a series of purchases of asset A may infer that it is undervalued, despite lacking direct information to support this view. The critical insight is that this perceived information, whether accurate or not, can spill over into related assets Cipriani and Guarino (2008). If asset B is correlated with asset A, the initial herding behaviour around asset A may spread, influencing the valuation of asset B as well. In this way, contagion can extend beyond a single asset and affect broader segments of the market. The results of Lux (1995) suggesting that boundedly rational traders can mimic others and transmit optimistic or pessimistic sentiment about prices.

Interestingly, Avery et al. (1998) report findings that complement with Bikhchandani et al. (1992) regarding informational herding. Avery et al. (1998) show that herding is less likely in simple environments, but more prevalent in complex settings such as financial markets. This is attributed to the sheer volume and complexity of the information in the financial markets. This makes it objectively difficult for individuals to process all relevant data in real time, especially as new information is continuously injected into the market. This is in line with the theory of bounded rationality (Simon, 1955). However, Avery et al. (1998) also argue that herding is unlikely to persist in the long run, as more investors are processing and incorporating available information into market prices. Contrary to the short term nature of herding suggested by Avery et al. (1998).

Devenow and Welch (1996) outline multiple forms through which herding behaviour can become apparent. Non-rational herding refers to psychology-driven behaviour, where individuals follow others without independent evaluation, closely resembling the previously discussed concept of social herding by Raafat et al. (2009). Rational herding, on the other hand, occurs when individuals use the actions of others as informational signals in the absence of their own information. Finally, Devenow and Welch (1996) introduce the concept of near-rational herding, which involves the use of heuristics under the theory of Bounded Rationality (Simon, 1955). Within this framework, decision-makers operate under cognitive and informational constraints, relying on mental shortcuts rather than full optimisation. This type of behaviour was found in regards to institutional investors by Akepanidtaworn et al. (2019).

Devenow & Welch (1996) also argue that the herding literature as a whole is still lacking rigorous empirical evidence. They note that empirical studies on herding only use price and price-related statistics such as volatility for the empirical portions. The paper argues that this is a lacking way of conducting herding research, as it is missing the complex component of investor communication amongst each other. This conclusion on the difficulties on empirical research of herding is also supported by the previously mentioned paper by Avery & Zemsky (1998). Although papers published afterwards show additional empirical rigour, the methodologies used for herding are still often the CSSD (Christine & Huang. 1995) and CSAD (Chang et al., 2000), even if they are flawed due to the joint hypothesis problem and biased towards finding anti-herding behaviour (Bohl et al., 2017). This leads us to the following section of reviewing notable literature on the measurement of herding.

3.2 Studies on empirical measurements of herding

To detect herding at a market level the herding literature often result to using simplistic models focusing on the dispersion of individual stock returns relative to the overall market return, such as the CSSD (Christie & Huang, 1995) and the CSAD (Chang et al., 2000). The theory behind CSSD and CSAD being that under normal and efficient market conditions, cross-sectional return dispersion increases as market movements intensify. In theory, this is because stocks should theoretically (CAPM) respond differently to market changes due to varying betas and idiosyncratic factors, resulting in a wider spread of returns. Conversely, during herding under CSSD/CSAD this dispersion decreases (Christie & Huang, 1995; Chang et al., 2000). In herding episodes stocks begin to move more uniformly, regardless of their individual characteristics. This behaviour contradicts the expectations of the EMH (Fama, 1970), which assumes that stock prices reflect all available information and should therefore exhibit dispersed reactions to market movements. Under the theory of CSSD and CSAD, a reduction in dispersion indicaties that market participants are following the crowd rather than acting on distinct, stock-specific information.

An early approach of measuring herding in the financial markets is to use the CSSD to measure return dispersion (Christie & Huang, 1995). In the paper Christie and Huang (1995) looked for unusually low dispersion during large market moves as signs of herd behaviour within the US equity market. The hypothesis of this notable paper was that herding emerges during periods of market stress. Christie and Huang (1995) found that the return dispersion increased significantly during periods of large market changes. This implies that individual returns do not cluster around each other during higher volatility, and that the markets are working as the EMH would suggest.

A criticism of Christie and Huang (1995) is that the methodology used was the CSSD method. Instead of using absolute returns, the paper used squared returns, which could in theory distort the results, if the sample had large outliers. A second possible flaw in the paper is the use of a single-market sample. On one hand this could be seen as a flaw as it only views herding in one market context, but on the other hand, it could be beneficial, if the focus is on getting this information for the US market alone. Finally, the CSSD model is also suffering from the joint hypothesis problem. On the contrary, however, Caparrelli et al. (2004), a paper that uses same methods described in Christie and Huang (1995) find that in the Italian stock market herding is apparent during extreme market conditions, indicating that herding is indeed a context-specific phenomenon.

The empirical foundation for measuring herding was established by Christie and Huang (1995) and further refined by Chang et al. (2000) in their influential study on herding behaviour in the international financial markets. Unlike Christie and Huang (1995), which focused solely on the US market, Chang et al. (2000) broadened the scope to include multiple markets: the US, Hong Kong, Japan, South Korea, and Taiwan. This diversification of markets reduces the risk of drawing conclusions based on data of a single market, when the goal is to study the global financial markets.

This sample of multiple markets include both developed and emerging markets, which is interesting as it brings forth the topic of differences in herding behaviour across differing market maturities. From a methodological standpoint, the paper improves upon the CSSD approach used by Christie and Huang (1995) by employing CSAD, which is less sensitive to outliers due to its use of absolute rather than squared deviations.

Chang et al. (2000) introduce a non-linear regression framework, arguing that under rational asset pricing, CSAD should increase approximately linearly with the absolute value of market returns. This reflects the idea that stocks typically respond differently to market movements based on their individual characteristics. However, during periods of extreme market movement, investors may suppress their individual judgement and act in a uniform manner. This could lead to a flattening or even a decline in CSAD, implying herding under the CSAD framework. The non-linear model thus allows for the detection of both expected behaviour under rational pricing and deviations from it, capturing more nuanced forms of herding. Bohl et al. (2017) however argue that the CSAD approach used by Chang et al. (2000) is fundamentally biased towards getting anti-herding evidence. The argument of Bohl et al. (2017) and the presence of the joint hypothesis problem draw extra attention to the relaiblity of the CSAD model.

The findings of Chang et al. (2000) indicate that herding is not broadly apparent in developed markets, in their sample the US and Hong Kong, but find partial herding in Japan. Notably, Chang et al. (2000) find significant evidence of herding in emerging markets, which in this case were South Korea and Taiwan. Furthermore, Chang et al. (2000) find that macroeconomic information has a broader impact on investor herding when compared to firm-specific information.

Chang et al. (2000) also find that the dispersion of returns is more apparent during days of market rise, and on days of market decline the dispersion is less apparent, indicating that herding as a phenomenon could be more likely in downturns rather than during periods of market growth. This finding is supported by papers like Mobarek et al. (2014) which imply no significant herding is found in the European markets during normal times, but significant herding is displayed during crises. To conclude, Chang et al. (2000) suggest that herding as a phenomenon is context-based, more apparent during periods of market distress, and possibly more apparent in emerging markets, possibly due to less efficient information distribution, leading to informational cascades.

As mentioned before, the empirical approach to herding research has been quite one-dimensional with its focus mostly on the dispersion of stock returns. Hwang and Salmon (2004) expand on the previous CSSD and CSAD by developing a new model. The model is based on the cross-sectional dispersion of factor sensitivities of the assets. This approach allows the user to evaluate whether there is herding within a specific market sector or style of investing (Hwang & Salmon, 2004).

The modified approach of Hwang and Salmon (2004) to herding methodology differs from the traditional CSSD and CSAD approaches as it focuses on herding towards a common factor, instead of price activity clustering, while also automatically adjusting for market conditions and volatility. Thus, it could be seen as a more advanced version of the CSSD/CSAD models, as it allows for potential detection of herding even when other models are not able to do so. Specifically, Hwang and Salmon (2004) argue that with their model of herding they were able to notice herding where Christine and Huang (1995) were not able to. According to Hwang and Salmon (2004), this occurs because herding tends to subside before a crisis unfolds, with the onset of the crisis triggering a flight-to-fundamentals. In other words, herding may act as a precursor to market crises, gradually alleviating as investors shift their focus back to fundamentals when uncertainty escalates.

Bekiros et al. (2017) challenge the CSAD approach by Chang et al. (2000) and modify it by introducing implied volatility as a measure of risk expectations. Bekiros et al. (2017) find that herding tends to be more apparent during market stress, and during crisis periods herding becomes insignificant towards the end of the crisis. Notably, Bekiros et al. (2017) find that the OLS estimation results reported absence of herding during crisis, but their quantiles approach deteced herding behaviour.

To conclude the section on measuring herding, Devenow and Welch (1996) highlight the initial lack of rigorous empirical evidence in the herding literature. While this concern has been since addressed, a methodological lack still persists, with most studies relying heavily CSSD by Christie and Huang (1995) and the CSAD by Chang et al. (2000). This is additionally concerning taking into account research such as Bohl et al. (2017), claiming that the CSAD model is biased towards anti-herding. Although more advanced techniques have emerged, such as the model proposed by Hwang and Salmon (2004) or Bekiros et al. (2017), the CSSD and CSAD approaches remain dominant arguably due to their simplicity, replicability, and widespread application in empirical research on herding.

3.3 Herding in different market contexts

The herding literature suggests that herding is context based (Chang et al., 2000; Mobarek et al., 2014) reveals that the extent and nature of herding can vary significantly across different market types and conditions. To explore these variations, this section will discuss herding literature in three different contexts: (1) herding during market crises, (2) herding differences between emerging and developed economies, and (3) herding differences across asset classes.

3.3.1 Herding during market crises

During market stress investors face a heightened level of uncertainty, leading to sharp and often quickly varying sentiment shifts, as was the case with the COVID-19 crash and the following quantitative easing. A vast number of research documents how during times of crises, herding becomes more pronounced compared to normal times. Mobarek et al. (2014) examined European stock indices during 2001 – 2012 and found no herding during normal times but heightened and even extreme herding during crises such as the global financial crisis and the following Eurozone crisis. Implying that the European investor base did not at least systematically herd during calmer market segments, but significant herding occurred during market turmoil, leading to converged behaviour. Kabir (2017) used the CSAD model and examined evidence of similar crisis-induced herding in the US financial sector during the global financial crisis and adverse herding during normal times.

Notably, crisis-induced herding does not seem to be a universal phenomenon. Contrary evidence is presented by Economou et al. (2011) who examined herding behaviour in the Greek, Portugues, Italian and Spanish markets during the time period of 1998 – 2008. Economou et al. (2011) present evidence that no herding was found in Portugal and Spain. Evidence was however found for the Italian and Greek markets. The most noteworthy finding of the paper however was that the global financial crisis did not induce any more intense herding behaviour in any of the four markets, contradicting the findings of Kabir (2017) and Mobarek et al. (2014) on crisis-induced herding. It is noteworthy that Economou et al. (2011) used the CSAD approach, which could have anti-herding biased results as suggested by Bohl et al. (2017). Contradicting the hypothesis of herding only happening during crises Chiang and Zheng (2010) showcase evidence suggesting herding in both rising market environments and market downturns. Chiang and Zheng (2010) also suggests that herding asymmetry, meaning difference in herding strength between market states, is more prevalent in Asian markets during rising markets.

Based on the discussion, it could be suggested that crisis-induced herding is generated due to each crisis representing a unique type of uncertainty. As investors have to manage new types of information under distress and bounded rationality (Simon, 1955), they are more likely to be in a position of low-precision information, unable to behave rationally and more likely to follow peers in the market. This idea will be empirically tested in this thesis within the Finnish equity market context with the second hypothesis regarding abnormal market uncertainty within the Finnish equity market.

3.3.2 Herding in market types and participants

Apart from timely contexts such as crisis periods, differences in herding activity can be induced by market types such as emerging versus developed economies. Emerging markets are more often prone to herding (Chang et al., 2000), potentially due to the less efficient distribution of information withing emerging markets. Chang et al. (2000) showcase how emerging markets had significant herding while as the developed markets in their sample did not. Contradicting Chang et al. (2000), Chiang et al. (2010) note that in their sample of 18 countries with the time frame of 1988 – 2009, there was significant differences in the strength of herding between the countries, but emerging markets did not show significantly more herding compared to the developed countries in the sample. The absence of herding in developed economies in Chang et al. (2000) suggests that as a market gathers more depth and information efficiency, the investors do not have to rely as much on herding for their decision making, due to lower amount of low-precision information.

In the context of this thesis, market participants can be broadly categorised into institutional and retail investors. Logically, institutional investors could be viewed as more informed and analytically equipped. Thus, they would exhibit less herding behaviour due to fewer instances of low-quality information.

Lakonishok et al. (1992) studied the trading behaviour of institutional investors and found weak evidence of herding, but somewhat stronger evidence of trend-chasing previous winner stocks. With large market capitalization stocks, institutional investors did not display clear herding tendencies. Lakonishok et al. (1992) conclude that institutional herding was not evident. However, following research by Wermers (1999) challenges this conclusion. Wermers (1999) finds that institutional money managers do engage in herding more than previously thought, particularly among growth-oriented funds. These funds often employ positive-feedback trading strategies, amplifying herding behaviour. The finding is in line with Kremer and Nautz (2013) who display evidence of institutional herding in short-term trades. Choi and Sias (2009) also found that US institutuional investors have a tendency to herd.

More recent findings by Guo et al. (2024) also focus on institutional herding. Their study suggests that institutional investors are more prone to herd during periods of high market sentiment, which is in line with the hypothesis of crisis-induced herding. Moreover, Guo et al. (2024) show that institutional herding has different effects depending on market sentiment. When market sentiment is low, the price impact of herding is not impactful. In high market sentiment periods herding leads to greater price distortions, with a more pronounced destabilising effect in firms with small market capitalisations. These findings also support the idea of herding as a context-based phenomenon.

In Taiwan the initial public offerings (IPOs) are primarily only for individual investors, and the Taiwan stock exchange announces subscription demand information before listing (Wang et al., 2017). The study by Wang et al. (2017) showcases how investors are more likely to subscribe IPOs that have preliminarily high demand This suggests retail investor herding, where the subscribes expect the others to have had better information, thus the later subscribers dismiss their own judgment and follow the herd. Wang et al. (2017) argue for irrational herding behaviour, specifically overreaction to the demand announcements during the sample. However, this statement begs the question whether the IPOs are herded around irrationally, for example through informational cascades or rationally, as the firm which's IPO is at hand, just happens to have strong fundamentals supporting the demand. Sirri and Tufano (1998) showed that retail investors are investing disproportionately more into funds with strong earlier returns. This could be seen as sign of herding.

3.3.3 Herding across asset classes

Although cryptocurrencies are not the focus of this paper, the herding behaviour surrounding them is noteworthy. Koch and Dimpfl (2023) find that by using google searches and Twitter tweets as a proxy for attention, rising amount of google searches and tweets lead to more price synchronicity in popular cryptocurrencies such as Bitcoin, Ethereum, Litecoin and Monero. This suggests herding behaviour as apparent in cryptocurrencies, and the nature of google searches and tweets could be seen as retail investor activity due to the casual nature of them. Wang et al. (2023) also studied herding in cryptocurrencies utilizing CSSD and CSAD and found no statistically significant herding. Interestingly, Wang et al. (2023) find that cryptocurrencies with lower market capitalizations exhibit more herding than ones with higher market capitalizations. investors.

Regarding Fixed income assets Galariotis et al. (2016a) examined the herding of euro-area sovereign bond markets during the Eurozone crisis. They found no empirical evidence of herding in the European government bonds. Galarioitis et al. (2016a) showcase their findings support “spurious” herding. Spurious herding is herding behaviour that is motivated by fundamental changes in macroeconomics and could be seen as herding, when it is not. Memon et al. (2022) studied multiple different commodity markets during two crises, the global financial crisis, and the COVID-19 crisis. They found evidence for herding behaviour during crises, supporting the crisis-induced herding behaviour hypothesis.

4 Data and methodology

This section presents the data and methodology employed in this thesis. It begins by elaborating on why the specific companies and the specific time frame were chosen, and how the data was acquired. The methodology section details how the data was processed and how the models of Christie and Huang (1995) and Chang et al. (2000) are applied to detect herding behaviour in the Finnishe equity market during the sample period.

4.1 Data description

The dataset consists of the daily simple returns for 18 companies listed on the OMXH25 index of the Nasdaq Helsinki. The OMXH25 is composed of the 25 most traded blue-chip companies in the Helsinki Stock Exchange. The index is chosen as the proxy for market returns for the study, as it is the most commonly used Finnish stock index. Table 1 showcases the companies selected for the study. These 18 companies specifically were selected, as all of them were continuously part of the OMXH25 index throughout the time period of 1.1.2019 – 31.12.2024, ensuring that the data stays consistent and comparable. Other companies were excluded as the index itself had some structural changes during the time period due to merger activity. The data itself includes 1508 daily return observations.

Table 1. Companies of the data set.

Count	Company name	Ticker	Sector
1	Elisa	ELISA	Communication Services
2	Fortum	FORTUM	Utilities / Energy
3	Huhtamäki	HUH1V	Consumer Staples / Packaging
4	Kesko B	KESKOB	Consumer Staples / Retail
5	Kojamo	KOJAMO	Real Estate
6	Kone	KNEBV	Industrials / Machinery
7	Konecranes	KCR	Industrials / Machinery
8	Neste	NESTE	Energy / Renewables
9	Nokia	NOKIA	Information Technology

Count	Company name	Ticker	Sector
10	Nokian Renkaat	TYRES	Auto Components
11	Orion B	ORNBV	Health Care / Pharmaceuticals
12	Outokumpu	OUT1V	Materials / Metals & Mining
13	Sampo A	SAMPO	Financials / Insurance
14	Stora Enso R	STERV	Materials / Paper & Forest Products
15	TietoEVRY	TIETO	Information Technology / IT Services
16	UPM-Kymmene	UPM	Materials / Paper & Forest Products
17	Valmet	VALMT	Industrials / Machinery
18	Wärtsilä B	WRT1V	Industrials / Capital Goods

The sample period of 1 January 2019 to 31 December 2024 was chosen due to the period being recent and due to it having multiple significant market events: the pandemic induced crash of COVID-19, the subsequent recovery fuelled by ultra-low interest rates, inflationary surges, monetary tightening and the volatile and unpredictable geopolitical climate triggered by the escalation of the war in Ukraine. The Finnish market context could be particularly sensitive to the latter due to its proximity and historical economic ties to Russia.

Hwang and Salmon (2004) suggest that herding behaviour could precede crises. Multiple reviewed studies (Humayn (2017); Chang et al. (2000); Kabir (2017)) indicate that herding behaviour amongst investors is more prevalent in extreme uncertainty or crises. All of the previously discussed factors indicate that Finland has been under high amounts of uncertainty during the examined time frame. Given the market events within the time period, the selected time frame is well-established for examining behaviour herding in the Finnish markets.

4.2 Methodology

To empirically test for herding in the Finnish equity market during the time period of 2019 – 2024, this study applies two widely used return dispersion methodologies: the CSSD introduced by Christie and Huang (1995) and the CSAD proposed by Chang et al. (2000). The CSSD methodology is designed to detect herding in extreme market movements by measuring if stock return dispersion compresses under market stress. However, the CSSD methodology alone is susceptible to outliers in sample market data as it uses squared returns. To address this limitation, the CSAD model is used in parallel.

The CSSD and the CSAD methodologies are not perfect, but are chosen for the thesis due to their simplicity, replicability, and wide usage across the herding literature. As stated before, CSSD and CSAD are used as proxies during the empirical analysis. The choice is made acknowledging the argument of Bohl. et al (2017) regarding the CSAD model being potentially biased towards anti-herding.

The methodology is straightforward. Firstly, arithmetic simple daily returns for each stock in the sample, and the market proxy, are calculated. After that, the CSSD is calculated and then regressed. Following, the CSAD is calculated and then regressed.

The daily return for each of the 18 stocks and the market index was calculated using the simple arithmetic return formula illustrated in equation (6).

(6) Arithmetic simple daily return

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

Where:

$P_{i,t}$= Closing price of stock i during time period t

$P_{i,t-1}$= Closing price of stock i during time period t-1

The daily returns are then processed through the CSSD (Christie & Huang, 1995) model, displayed in equation (2).

(2) Cross-sectional Standard Deviation

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

Where:

N=	Number of stocks
$R_{i,t}$=	Return of stock i at time t
$R_{m,t}$=	Return of the market at time t

The daily CSSD values are then regressed by using the equation (3) described below.

(3) Cross-sectional standard deviation regression model

$$CSSD_t = \alpha + \beta_1 D_t^{UP} + \beta_2 D_t^{DOWN} + \varepsilon_t$$

Where:

α=	Constant when all returns are zero
$\beta_1 D_t^{UP}$=	Dummy variable for extreme positive returns
$\beta_2 D_t^{DOWN}$=	Dummy variable for extreme negative returns
ε_t=	Error term

The dummy variables for daily returns were calculated using 95% as the right tail (UP) cut off and 5% as the left tail (DOWN) cut off, which is consistent with the Christie and Huang (1995) approach. Meaning, that all daily returns above the UP-threshold and under the DOWN-threshold are considered as extreme tail cases. The calculated UP-threshold for the whole time period is 1.67% and the DOWN-threshold is -1.72%, indicating a slightly left-skewing return distribution.

The CSAD approach (Chang et al., 2000) is displayed in equation (4).

(4) Cross-sectional Absolute Deviation

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

Where:

N=	Number of stocks
$R_{i,t}$=	Return of stock i at time t
$R_{m,t}$=	Return of market at time t

The daily CSAD values are then regressed using the regression model described in equation (5).

(5) Cross-sectional absolute deviation regression model

$$CSAD_t = \alpha + \beta_1 R_{m,t} + \beta_2 |R_{m,t}| + \gamma_1 R_{m,t}^2 + \varepsilon_t$$

Where:

α=	constant when all returns are zero
$\beta_1 R_{m,t}$=	linear component
$\beta_2 \|R_{m,t}\|$=	absolute component
$\gamma_1 R_{m,t}^2$=	non-linear component
$\varepsilon_t =$	error term

The CSAD approach of Chang et al. (2000) continues on to the CSSD model of Christie and Huang (1995) due to its (slightly) more refined capability to capture herding in more varied market contexts, and not only under extreme market tail cases, as is the case with the CSSD approach. To summarize the methodology, the CSAD model introduced by Chang et al. (2000): unlike earlier models such as CSSD (Christie & Huang, 1995), which only allow for herding detection under extreme cases, the CSAD approach allows for a more detailed study of non-linear relationships between the return dispersions and market movements under both normal and extreme market conditions. The CSSD and CSAD approaches are well established and have been continuously usedin different market contexts throughout herding literature, such as different emerging markets (Chiang & Zheng, 2010), Chinese markets (Demirer & Kutan, 2006) and South European markets (Economou et al., 2011). This thesis will use both, as it allows for a more reliable outcome, resulting from the comparison of the results of both the CSSD and the CSAD models, fully acknowledging the bias of the CSAD model (Bohl et al., 2017).

To address the first hypothesis, the full sample of daily returns from 2019 to 2024 will be used in the analysis. To test the second hypothesis, the same methodology will be applied to three sub-periods, each representing a phase of abnormal market uncertainty.

The first sub-period (2019 – 2020) captures the onset and immediate impact of the COVID-19 pandemic. The second sub-period (2021 – 2022) captures the escalation of the war in Ukraine. The final sub-period (2023 – 2024) encompasses the ongoing effects of the Russo-Ukrainian war. This segmentation allows for a comparative empirical test of herding behaviour across different periods of uncertainty.

5 Empirical results and discussion

This chapter presents the results of the empirical test described in the Data and methodology chapter. The research question of the paper was whether the Finnish market displays signs of herding. The chapter begins with general statistics, followed by the regression results for both CSSD (Christie & Huang, 1995) and CSAD (Chang et al., 2000) models across all time periods.

5.1 Dsecriptive statistics

Table 2 presents the descriptive statistics for both CSSD and CSAD during the full sample period and during all the three sub-periods. The highest mean CSSD and CSAD values occur in the first sub-period (2019 – 2020), which includes the COVID-19 crisis. This suggests relatively high dispersion. Additionally, the highly positive skewness in both CSSD and CSAD suggests a potential bias towards anti-herding results in the following sections, in line with the argument Bohl. et al (2017) regarding the anti-herding bias of CSAD.

Table 2. Descriptive statistics of CSSD and CSAD

	Full Sample	**2019 - 2020**	**2021 - 2022**	**2023 - 2024**
Mean CSSD	0,01529	0,01610	0,01584	0,01394
Std. CSSD	0,00743	0,00844	0,00720	0,00636
Mean CSAD	0,01102	0,01181	0,01135	0,00992
Std. CSAD	0,00475	0,00576	0,00438	0,00368
Kurtosis CSSD	7,92954	9,51274	4,84650	4,37713
Skewness CSSD	2,24428	2,57858	1,73951	1,91375
Kurtosis CSAD	8,39002	8,90572	1,56593	3,89747
Skewness CSAD	2,15484	2,47864	1,10664	1,57782
MIN CSSD	0,00374	0,00527	0,00374	0,00488
MAX CSSD	0,07148	0,07148	0,05977	0,04298
MIN CSAD	0,00315	0,00418	0,00315	0,00386
MAX CSAD	0,04572	0,04572	0,03009	0,02991
N	1508	501	504	501

Figure 1 acts as an anchor for the analysis of investor behaviour by displaying the development of the OMXH25 index during the sample period. The graph shows several distinct market moves. Most notably the start of 2020 with the pandemic and the start of 2022 with the escalation of the war in Ukraine. These two points of time are particularly important to focus on, as the literature suggests that herding in the financial markets is often market stress-induced herding (Kabir, 2017; Mobarek et al., 2014). The market shifts support the rationale behind the time-based segmentation applied in the empirical testing.

Figure 1. Development of the OMXH25 index during the sample period

Figures 2 and 3 below follow the approach of Chang et al. (2000) and plot the relationship between equally-weighted market return with CSSD and CSAD for each day. Graphs of the data provide insights into the relationship between market returns and return dispersion before the actual regressions. Both Figure 2 and 3 show an increase in dispersion as market returns move away from zero in either direction.

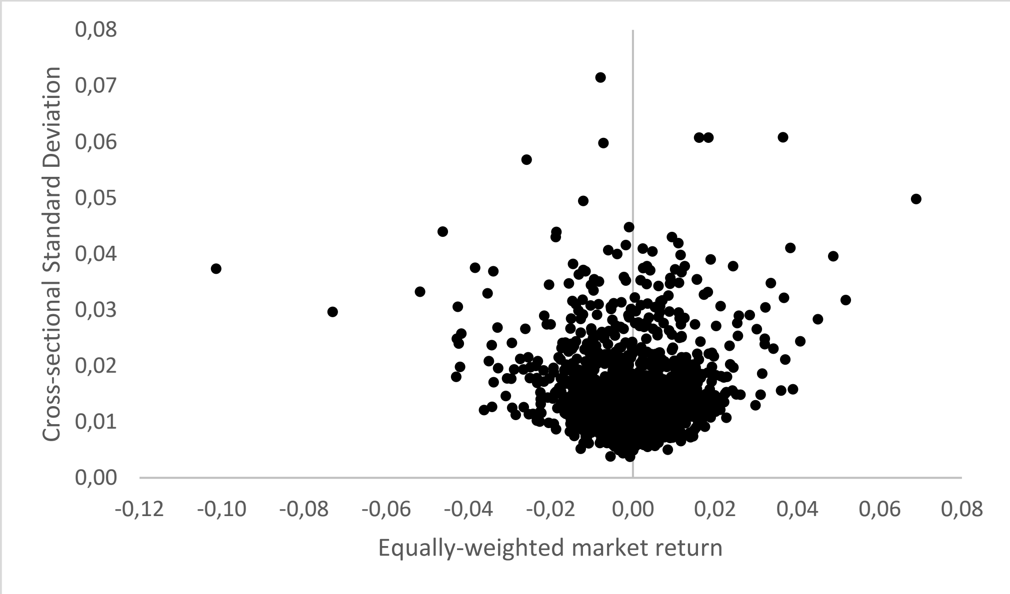

Figure 2. Relationship of CSSD and equally-weighted market returns

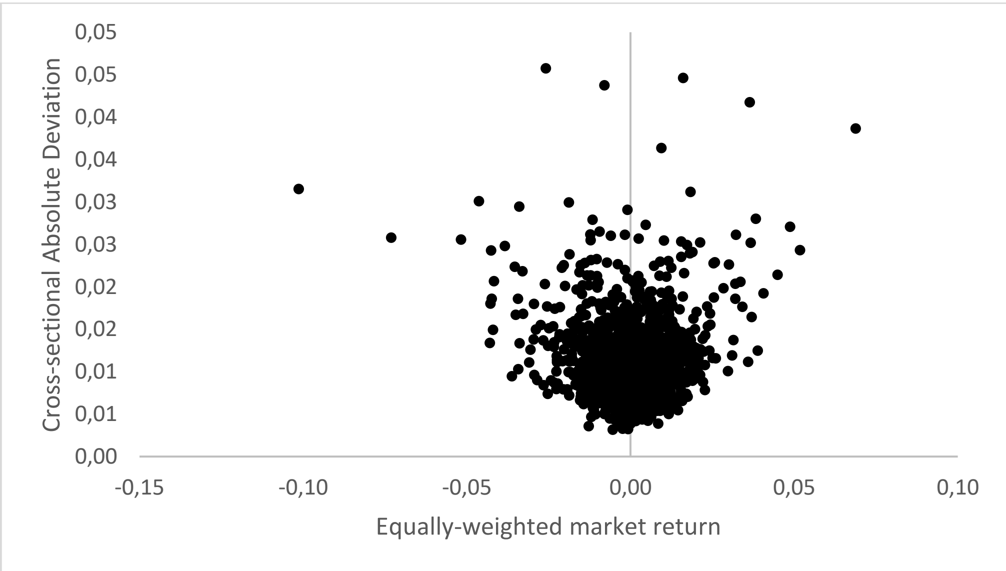

Figure 3. Relationship of CSAD and equally-weighted market returns

5.2 Regression results

Following the methodology of Christie and Huang (1995), Table 3 reports the CSSD regression coefficients at the 5% criterion. Following the methodology of Chang et al. (2000) Table 4 reports the CSAD regression coefficients at 5% criterion.

Table 3. CSSD regression coefficients

	α	$\beta_1 D_t^{UP}$	$\beta_2 D_t^{DOWN}$
CSSD, full sample	0,01464	0,00692	0,00623
t-stat	75,20467	8,13627	7,32663
p-value	0	8,44757E-16	3,833E-13
CSSD, 2019 - 2020	0,01520	0,01076	0,00730
t-stat	40,42482	6,55973	4,45006
p-value	0	1,35291E-10	1,0601E-05
CSSD, 2021 - 2022	0,01544	0,00358	0,00564
t-stat	46,54284	2,47272	3,89462
p-value	0	0,01374	0,00011
CSSD, 2023 - 2024	0,01361	0,00250	0,00405
t-stat	45,96885	1,93432	3,13749
p-value	0	0,05364	0,00180

The regression results show that across the full sample and the sub-periods the coefficients of the dummy variables are positive and statistically significant. These results indicate that return dispersion increases during extreme market conditions. The results of this CSSD test imply anti-herding behaviour during all of the sample periods, in line with the original findings of Christie and Huang (1995). However, the highly positive skewness of CSSD portrayed in Table 2 indicates that the model could be inclined towards showing anti-herding results. The CSSD test alone suggests that the first hypothesis could be rejected assuming CSSD as a proxy for herding, but the CSSD alone is not enough of evidence to justify the rejection of the hypothesis. The second hypothesis could also be rejected on the same assumption, as all of the sub-periods' dummy variables, except the B_1D_tUP coefficient of the 2023 – 2024 period, are positive and statistically significant. However, again, CSSD alone does not justify rejecting the hypothesis. Logically, the absence of herding under CSSD does not imply the absence of herding under the general definition of it. Finally, as the limitations of the model are known, results cannot be concluded from CSSD alone.

Table 4. CSAD regression coefficients

	α	$\beta_1 R_{m,t}$	$\beta_2 \lvert R_{m,t} \rvert$	$\gamma_1 R_{m,t}^2$
CSAD, full sample	0,00915	0,01179	0,20645	1,07905
t-stat	48,39055	1,22421	8,37325	2,15859
p-value	0	0,22106	1,3E-16	0,03104
CSAD, 2019 - 2020	0,00939	0,05103	0,23088	0,92724
t-stat	25,05369	3,07153	5,27209	1,27837
p-value	0	0,00225	2E-07	0,20172
CSAD, 2021 - 2022	0,00989	-0,02681	0,13513	2,06153
t-stat	26,92764	-1,74632	2,27851	1,18278
p-value	0	0,08137	0,02312	0,23746
CSAD, 2023 - 2024	0,00874	-0,03079	0,15027	2,65598
t-stat	26,61966	-1,64761	1,90127	0,70441
p-value	0	0,10006	0,05784	0,48151

The regression results reported in table 4 follow the methodology of Chang et al. (2000). When analysing the results, the main focus is on the squared returns coefficient, within the right-most column. Using CSAD as a proxy for herding, indicated by the statistically significant positive squared returns coefficient, no herding is detected in the Finnish equity market during the sample period. Thus, the first hypothesis under the theory of CSAD could be rejected, based on the CSAD regression results, and whilst using CSAD as a proxy for herding. For the sub-periods, while the squared return coefficients remain positive, they are not statistically significant. Thus, the second hypothesis remains inconclusive on the basis of the CSAD results. The inconclusive outcome is further supported by the finding of Bohl et al. (2017) indicating that the model is biased towards anti-herding results. Secondly, the highly positive skewness of CSAD in Table 2 suggests bias towards anti-herding results.

5.3 Discussion of results

The empirical results from both CSSD (Christie & Huang, 1995) and CSAD (Chang et al., 2000), when using CSSD/CSAD as a proxy for herding, indicate that the Finnish equity market did not exhibit herding behaviour during the sample period of 2019 – 2024. However, the joint hypothesis problem makes the CSSD and CSAD models somewhat uncertain. Additionally, the skewness data in Table 2 indicate that the models might be biased towards anti-herding. Finally, the research regarding the anti-herding bias of CSAD (Bohl et al., 2017) suggests that using CSAD to reject either of the hypotheses would be unjustified.

The absence of herding in both of the CSSD and CSAD models does not directly mean that herding is not a phenomenon within the Finnish equity market during the time frame, especially if using the general definition for herding by Bekiros et al (2017). Taking into account the events of high uncertainty during the sample period and the literature supporting the idea of herding being more prevalent during periods of market stress (Mobarek et al., 2014) a total lack of herding in the Finnish equity market would be illogical.

There is a distinct contradiction in the results. The CSSD and CSAD models under the theories of Christie and Huang (1995) and Chang et al. (2000) are implying anti-herding behaviour both in the full sample period and during all three sub-periods. Contradicting this is the more recent research of Bohl et al. (2017) indicating the CSAD model has bias towards anti-herding results. Additionally, the research of Bekiros et al. (2017) on a more efficient model shows that CSAD could use refining. Finally, the joint hypothesis problem combined with the skewness data presented in Table 2 challenges the reliability of drawing conclusions about herding in the Finnish equity market based solely on CSSD ans CSAD models. Thus, the first hypothesis and the second hypothesis of this thesis both remain inconclusive.

6 Conclusion

The research objective of the thesis was to study whether the Finnish equity market exhibited herding behaviour during the period of 2019 – 2024. The time period included two periods of significant uncertainty, namely the COVID-19 crisis and the escalation of the war in Ukraine in the beginning of 2022. Given prior literature suggesting that herding is more prevalent in market downturns (Chang et al., 2000) and during market crises (Mobarek et al., 2014; Bekiros et al., 2017), the selected sample period is justified.

The thesis used the CSSD model introduced by Christie and Huang (1995) and the CSAD model introduced later by Chang et al. (2000) to empirically test whether the Finnish equity market exhibited herding behaviour during the sample period, or any of the three sub-periods of 2019 – 2020, 2021 – 2022 and 2023 – 2024. CSSD and CSAD were used as proxies for herding due to their simplicity and the widespread use of both of the models within the herding literature. Both of the models suggested that the Finnish equity market exhibited anti-herding behaviour. The reliability of these results was questioned on the basis of three points. Firstly, the joint hypothesis problem. Secondly, the CSSD and CSAD skewness data presented in Table 2, suggesting anti-herding bias. Finally, most notably on the basis of more recent literature, that has questioned the accuracy of the CSAD model (Bekiros et al., 2017) and the CSAD's bias towards anti-herding results (Bohl et al., 2017). Therefore, the contradiction between the results of the models, and the potential anti-herding bias of the models themselves made rejecting the hypotheses purely on the basis of the CSSD/CSAD results unjustifiable. Thus, the first hypothesis and the second hypothesis both remain inconclusive.

There are a few limitations to the study that should be discussed. Firstly, the joint hypothesis problem described by Fama (1970). As any test of herding is simultaneously testing market efficiency, which is testing the underlying asset pricing model (in this case CAPM). To take it even further, the CSSD and CSAD models' theory is based on CAPM, thus, the problem becomes increasingly complex. For example: if the CSSD and CSAD models were to hypothetically show lower than expected dispersion of returns, it would indicate herding, but this relies on the assumption that CAPM is working as expected. If CAPM was wrong, the observed pattern may not reflect herding at all. Second limitation is the use of simplistic models to measure a complex phenomenon. Even though the methodologies of Christie and Huang (1995) and Chang et al., (2000) are widely referenced throughout the herding literature, the literature would benefit from adopting more novel ways of measuring herding. The approaches of Hwang and Salmon (2004) and Bekiros et al., (2017) exemplify this well. The third limitation is the potential bias of the CSAD model against results of herding behaviour (Bohl et al., 2017). If a model favours one outcome, its usefulness in detecting herding becomes questionable.

Future research builds on the limitations of the paper. Most notably, the future herding research would highly benefit from developing a model that could be as extensively used as the CSSD and CSAD models are still being used today. Hwang and Salmon (2004), Bekiros et al., (2017) and Bohl et al. (2017) all show some modifications of the CSAD model. Future research could explore intra-day herding dynamics, specifically related to macroeconomic uncertainty, as Chang et al. (2000) suggest that macrospecific information is more likely to amplify herding than firm-specific information. Research into how investors adjust during quick geopolitical developments would be compelling.

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