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## **Herding behaviour during the COVID-19**

Evidence from the German, US and UK stock markets

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**UNIVERSITY OF VAASA****School of Accounting and Finance**

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**ABSTRACT :**

This thesis investigates market-wide herding behaviour in the German, US, and UK stock markets during the COVID-19 pandemic, comparing investor behaviour before, during and after the crisis. In particular, it examines whether the uncertainty caused by the pandemic led to herding behaviour, which is typically absent in developed markets. The study analyses daily stock returns from January 1, 2018, to May 30, 2023, applying the Chiang and Zheng (2010) methodology to measure market-wide herding. It also examines whether herding was asymmetric, occurring only during up or down-market movements.

The results indicate that herding behaviour was not present across the entire sample period. However, herding behaviour was observed pre-COVID-19, while no significant herding was detected in the pandemic and post-pandemic periods in the German, US, and UK markets. Notably, herding was asymmetric in both the German and UK markets during COVID-19, occurring only on negative market days, suggesting that heightened uncertainty may drive herding behaviour during declining markets. The contribution of this study is to confirm and refine previous findings on herding behaviour in developed markets, especially before the onset of crises. In line with previous literature, this thesis shows that the intensity of herding behaviour in developed markets peaks in the days just before the crisis and declines rapidly after the onset of the crisis. This provides new insights into how investor behaviour in developed markets changes at different stages of the crisis, offering a deeper understanding of investor psychology and market dynamics in the run-up to the crisis.

Tässä tutkielmassa tutkitaan markkinoiden laajuista laumakäyttäytymistä Saksan, Yhdysvaltojen ja Iso-Britannian osakemarkkinoilla COVID-19-pandemian aikana verraten sijoittajien käyttäytymistä ennen kriisiä, sen aikana ja sen jälkeen. Erityisesti tutkitaan, johtiko pandemian aiheuttama epävarmuus laumakäyttäytymiseen, jota ei yleensä esiinny kehittyneillä markkinoilla. Tutkimuksessa analysoidaan osakkeiden päivittäisiä tuottoja 1. tammikuuta 2018 ja 30. toukokuuta 2023 väliseltä ajalta. Chiangin ja Zhengin (2010) menetelmää sovelletaan markkinoiden laajuisen laumakäyttäytymisen mittaamiseksi. Tutkimuksessa tarkastellaan myös sitä, oliko laumakäyttäytyminen epäsymmetristä eli esiintyikö sitä vain markkinoiden nousu- tai laskupäivien aikana.

Tulokset osoittavat, että laumakäyttäytymistä ei esiintynyt koko tarkastelujakson aikana. Laumakäyttäytymistä havaittiin kuitenkin ennen COVID-19-pandemiaa, kun taas pandemian aikana ja sen jälkeen ei havaittu merkittävää laumakäyttäytymistä Saksan,

Yhdysvaltojen ja Iso-Britannian markkinoilla. Erityisesti Saksan ja Iso-Britannian markkinoilla laumakäyttäytyminen oli epäsymmetristä COVID-19:n aikana, ja sitä esiintyi vain negatiivisina markkinapäivinä, mikä viittaa siihen, että lisääntynyt epävarmuus voi johtaa laumakäyttäytymiseen laskevien markkinoiden aikana. Tämän tutkimuksen tavoitteena on vahvistaa ja tarkentaa aiempia havaintoja laumakäyttäytymisestä kehittyneillä markkinoilla erityisesti ennen kriisien puhkeamista. Aiemman kirjallisuuden mukaisesti tämä tutkielma osoittaa, että kehittyneiden markkinoiden laumakäyttäytymisen voimakkuus on suurimmillaan juuri ennen kriisiä ja vähenee nopeasti kriisin puhjettua. Näin saadaan uutta tietoa siitä, miten sijoittajakäyttäytyminen kehittyneillä markkinoilla muuttuu kriisin eri vaiheissa, ja saadaan syvällisempi käsitys sijoittajien psykologiasta ja markkinoiden dynamiikasta kriisin alkuvaiheessa.

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**KEYWORDS:** Asymmetric herding, Behavioural Finance, COVID-19, Cross-sectional absolute deviation, Developed markets, Market-wide herding

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## 1 Introduction

According to Baker and Ricciardi (2014), traditional finance is generally understood as a normative theory that describes how people should behave in the financial market. For example, according to the Efficient Market Theory (EMT) presented by Fama (1970) investors are rational and will always act in their own best interest to maximise returns. In the stock market, investors are assumed to be unemotional and rational. Their decisions are based on all available information and markets are informationally efficient. In reality, however, investors behave irrationally in the market and emotions influence their decisions. Therefore, the perspective of behavioural finance could be a better approach to evaluate the behaviour of investors in the stock market than traditional finance. Research related to behavioural finance began to appear increasingly at the end of the 1980s, as more and more evidence was presented against the EMT. However, it was not until the 1990s that behavioural finance became widely known.

The behavioural approach aims to consider both economic and psychological and behavioural perspectives. Behavioural finance explains deviations of stock market prices from fundamentals and EMT by herding behaviour, which can be broadly defined as imitating the actions of others. Following the actions of others is a consequence of the basic human need to belong to a group. In the stock market, investors tend to imitate the trading behaviour of more knowledgeable investors without regard to their own beliefs or private information (Bikhchandani & Sharma, 2000). The monitoring of other investors' actions is either conscious or unconscious. Bikhchandani and Sharma (2000) distinguish between intentional herding, where investors are willing to imitate others, and spurious herding, where groups of investors facing similar decision problems and data sets make similar decisions.

The literature on herding has grown steadily over three decades, but the evidence on the existence and extent of herding across asset markets and countries remains unclear. The existing literature proves that herding behaviour is not expected in developed markets, while in emerging markets the presence of inexperienced agents, speculative

trading, weak regulations and low liquidity are common and plausible explanations to influence overreaction and herding behavior (Chang et al. 2000; Pochea et al. 2017). However, a significant body of research on herding behaviour shows that during periods of financial uncertainty, investors are prone to herding behaviour, which can lead to excessive market volatility (Pochea et al., 2015; Bogdan et al. 2022; Clements et al., 2017; Jirasakuldech & Emekter, 2021). During periods of uncertainty, such as the COVID-19 pandemic, herding behaviour may be particularly pronounced as investors seek safety in numbers and look to the actions of others to guide their own investment decisions.

The COVID-19 pandemic, which began in 2020, is currently affecting the entire world, causing a significant distortion of economic activity. This pandemic has affected the financial market in many ways. In the early days of the COVID-19 pandemic, the stock market experienced significant volatility as investors grappled with the potential economic impact of the virus and the policy responses of governments and central banks. This volatility was exacerbated by herding behaviour, as investors sought to match the actions of others and avoid being left behind as the market moved in a particular direction.

As a result, some stocks experienced significant price movements, with some experiencing large gains and others experiencing steep declines, often with little fundamental basis for these moves. While herding behaviour can be a natural reaction to uncertainty and help to provide a degree of stability in markets, it can also lead to irrational market movements and ultimately create opportunities for savvy investors who are able to see through the noise and identify value.

## **1.1 Purpose of the study**

The purpose of this study is to examine, and compare the behaviour of investors before, during and after the COVID-19 pandemic in the developed markets. More specifically, this thesis examines whether market-wide herding behaviour occurs in the German, US and UK stock markets over the period 1.1.2018-30.5.2023. In addition, this thesis

examines whether the selected stock markets exhibit asymmetric herding behaviour on a market-wide basis, i.e., whether it only occurs in the up or down market. Although the German, US and UK stock markets are developed markets, which according to existing research should not exhibit herding behaviour, the study of herding behaviour is attractive due to the uncertainty caused by the pandemic. The research therefore aims to answer the question of whether there is herding behaviour in developed markets during the COVID-19 pandemic.

Many recent studies have used the Cross Sectional Absolute Deviation (CSAD) (Duygun et al., 2021; Espinosa-Méndez & Arias, 2021; Ferreruella & Mallor, 2021; Susana et al., 2020), first used by Chang et. al (2000), to determine whether stock market herding behaviour occurs. This study also uses the CSAD methodology so that the results are easily comparable with previous studies. The CSAD methodology aims to determine whether the relationship between cross-sectional return dispersion and squared market returns is non-linear. To this end, a non-linear regression model is used. According to traditional asset pricing models, the relationship between cross-sectional returns and squared market returns should always be positive and linear. Herding behaviour occurs when the relationship is decreasing. Herding asymmetry tests are conducted on the German, US and UK stock markets before and during the COVID-19 pandemic.

## **1.2 Scope of the study**

This study includes the DAX, DIJA and FTSE 100 indices to represent the German, US and UK stock markets. The DAX and FTSE 100 are among the most important indices in Europe and the DIJA is one of the most important indices of the US. These three indices have been chosen in order to get as broad a picture as possible of the markets in Europe and the United States.

This study focuses on empirically investigating only the existence of herding behaviour during the COVID-19 pandemic. Reasons for potential herding behaviour of investors are presented based on herding theory and previous studies. A separate method for

observing the decision-making process of investors would be required to empirically investigate the reasons for possible herding behaviour of investors.

### **1.3 Structure of the study**

The structure of this thesis is as follows. The first chapter introduces the topic and the purpose and scope of the study. The second chapter explains the theoretical background of the study. By comparing behavioural finance theories with traditional finance theory, the theoretical background is presented. The third chapter discusses the literature on herding behaviour, based on which a research hypothesis is formulated. The fourth chapter presents the chosen methodology for the empirical research, the selected data and the descriptive statistics. The fifth chapter discusses the results of the empirical research and compares them with existing research. The limitations of the empirical research conducted and the chosen topic are discussed in chapter six. Finally, the last chapter presents all the findings and discusses their practical implications. In addition, possible future research opportunities are considered.

## **2 Theoretical background**

This section presents the relevant theoretical background to herding behaviour. In general, financial theory distinguishes between traditional finance and behavioural finance. By comparing behavioural finance with traditional finance, this study aims to explain the theoretical background of herding behaviour. Traditional finance theory is an important foundation for behavioural finance, although the existing literature has shown that its assumptions and theories are not valid. According to traditional finance, investors' decisions are based on a rational evaluation of available information and they act to maximise their own interests (Donyetta et al., 2023). On the other hand, according to Donyetta et al. (2023), behavioural finance theory attempts to explain the pricing of securities in terms of factors that influence investor behaviour. They state that behavioural finance seeks to understand the cognitive and emotional factors behind investment decisions. Traditional finance theory assumes that all information in the financial markets is free and available to everyone (Donyetta et al., 2023). Behavioural finance, on the other hand, suggests that not all information is available to all investors (Donyetta et al., 2023). The next chapter discusses traditional financial theories, after which this thesis considers the theories of behavioural finance. Finally, the thesis takes a closer look at herding behaviour.

### **2.1 Traditional finance**

According to Baker and Ricciardi (2014), the traditional view of finance is based on classical decision theory, which states that decision-making is rational and takes into account all possible factors that affect the final outcome. They state that rational decision makers seek to find the optimal choice by maximising expected utility. In addition, financial theorists assume that rational individuals are risk averse and require compensation for taking risks. Thus, traditional financial theories assume that investors are risk neutral. Based on these principles, financial theorists develop models to analyse critical financial decisions such as portfolio composition and asset pricing.

According to Baker and Ricciardi (2014), classical decision theory is concerned with how people make decisions under uncertainty. It takes a normative stance and aims to identify the optimal decision in different situations. This theory assumes that individuals are rational actors who prioritise their self-interest and optimise within given constraints. According to Baker and Ricciardi (2014), while rationality takes different forms, classical decision theory focuses primarily on decision-making under conditions where the probabilities of outcomes are known, known as risky environments. Despite the prevalence of uncertainty in real-world scenarios, classical decision theory is primarily concerned with decision-making under risk.

Rationality and utility play a central role in classical decision theory. According to Baker and Ricciardi (2014), a rational individual is characterised by consistent preferences, even under complex circumstances. When faced with risk, rational decision makers rely on the theory of expected utility (EUT), developed by von Neumann and Morgenstern in 1944. EUT posits that individuals, assuming rational preferences and a preference for more over less, make decisions under uncertainty based on a utility function. Baker and Ricciardi (2014) explain that this function assigns measurable rankings to alternatives, with higher numbers indicating preferred outcomes. Each person has a unique utility function, making comparisons between individuals impractical. Expected utility is determined by evaluating the utility of each possible outcome and weighting it by its probability. Rational decision makers then choose the outcome with the highest expected utility from the available set of alternatives.

### **2.1.1 Efficient market theory**

The traditional theory that has dominated financial theories in recent decades is the efficient market theory. The efficient market theory (EMT) was first introduced by Fama (1970). The primary function of financial markets is to allocate capital to the most socially beneficial objectives. The ideal situation in the market would be for security prices to provide accurate signals for resource allocation. Accordingly, companies can make investment decisions and investors can choose their investment objectives with

confidence that the prices of securities fully reflect all available information. EMT suggest that when companies release information about matters affecting their business, this information is immediately reflected in share prices. This is because there are many investors and public information is immediately available to all.

According to Fama (1970), the market is always efficient when security prices "fully reflect" all available information. For security prices to "fully reflect" all information in capital markets, there should be no transaction costs or taxes in the market. In other words, the market must be frictionless. In addition, all available information should be free to all market participants, and all would agree on the impact of current information on the current price and the distribution of future prices. In other words, all investors act rationally to maximise returns.

However, the efficient market described above, does not translate into practice in the market. Even if these conditions of an efficient market do not materialise in practice, the market can still be efficient (Fama, 1970). For example, the irrationality of individual investors does not threaten the efficiency of the market as a whole; it is enough that most investors behave perfectly rationally (Fama, 1970). In an efficient market, competition among many rational participants results in prices that are a good estimate of their true value (Fama, 1995).

The market price of securities need not always be equal to their true value for the market to be efficient (Fama, 1970). Disagreement among market participants about how new information affects the value of securities leads to discrepancies between the prices of securities and their true values (Fama, 1995). In an efficient market, market price deviations from the true value of the security should be incidental and unpredictable (Fama, 1970). This means that securities are equally likely to be overvalued or undervalued (Fama, 1970). Thus, in an efficient market, no investor is able to achieve outsized returns through a particular investment strategy (Fama, 1970). However, the fact that individual investors beat the market does not mean that the market is not efficient (Fama, 1970).

In efficient markets, inefficiencies occur regularly and disappear immediately as investors find and exploit them (Fama, 1970). In this case, an individual investor can beat the market.

Fama (1970) has defined three different levels of market efficiency: weak form, semi-strong form and strong form. These three levels of market efficiency differ in the extent to which the theory assumes all available information. In a market that satisfies weak forms, security prices reflect historical information such as trading volumes and past price performance. In a market that satisfies semi-strong forms, all current publicly available information is incorporated into security prices. For example, public information includes financial statements, earnings forecasts, patents and stock splits. Historical information is also incorporated into stock prices, as past price movements and trading volumes are clearly public information. Finally, in a strong-form market, share prices reflect all undisclosed private information in addition to historical and public information. Thus, even with inside information, it is almost impossible to achieve abnormal returns (Fama, 1970).

### **2.1.2 Random walk**

The random walk theory presented by Fama (1995) is closely related to the EMT because in the efficient market the returns of securities follow a random walk. According to Fama (1995), the random walk means that the prices of securities change randomly. Therefore, changes in the price of securities are not correlated with any variable. It is therefore impossible for investors to predict the future returns of securities with a particular investment strategy. Fama (1995) states that the random walk theory means that the stock market has no memory, and that the history of price changes has no effect on future returns. Consequently, future returns cannot be predicted from past price changes because prices only change when new information enters the market, and this new information cannot be predicted in advance (Fama, 1995).

According to Fama (1995), in an efficient market, the prices of individual securities reflect the effects of information that is already occurring at any given time. This information is based on both past and future events that the market expects to occur. This is due to the competition among many intelligent participants in an efficient market. The overall impact of the new information on the intrinsic values of securities is reflected "instantaneously" in their actual prices due to competition in efficient markets (Fama, 1995).

Fama (1995) notes that because the effect of new information on price changes in securities is uncertain or vague, the immediate adjustment has two effects. First, it is equally likely that the prices of securities will initially adjust either above or below the changes in their intrinsic values (Fama, 1995). In other words, as new information enters the market, the price of securities is equally likely to be overstated or understated relative to their true value. Second, according to Fama (1995), the full adjustment of the actual prices of securities to their new intrinsic values is itself a random variable. In this case, the market anticipates a change in the intrinsic values of securities and their actual prices will adjust even before the basis for the change in intrinsic values has occurred. Thus, successive price changes of individual securities are independent due to the "instantaneous adjustment" of efficient markets (Fama, 1995).

### **2.1.3 Capital asset pricing model**

The Capital Asset Pricing Model (CAPM) is a widely used financial theory that examines the relationship between risk and expected return for individual assets or investment portfolios. Although William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) are generally credited with developing the CAPM, the theoretical background can be traced back to the insights of Modern Portfolio Theory (MPT) introduced by Markowitz (1952) (Bodie et al., 2023). The CAPM is based on the EMT which assumes that assets are accurately and fairly priced in the stock market. Consequently, all available information is reflected in asset prices.

The basic concept behind the MPT stems from Harry Markowitz's (1952) realisation that while the total return of a portfolio can be calculated by taking the weighted average of individual stock returns, the calculation of portfolio volatility does not follow the same simple logic. Furthermore, Markowitz (1952) observed that by increasing the number of stocks in a portfolio, investors could effectively reduce the portfolio's volatility, provided the stocks chosen were not perfectly correlated with each other. In simpler terms, by selecting stocks with minimal correlations, investors could reduce the overall risk of their portfolios through diversification. This insight led to the conclusion that the risk associated with an individual security cannot be assessed in isolation when trying to construct an optimal portfolio. Moreover, if diversification allows investors to mitigate risk, this implies that no one should expect to be compensated for this type of risk because it can be managed. Consequently, the only risk that deserves compensation is the one that affects all securities in the market. This type of risk is commonly referred to as systematic risk, while diversifiable risk is often referred to as unsystematic risk.

The CAPM relies on two categories of assumptions. These are individual behaviour and market structure. One of the key assumptions regarding individual behaviour is that all investors use mean-variance optimisation. This assumption is related to the systematic and unsystematic risk. The risk of an individual asset should be measured relative to the market portfolio if investors are not allowed to diversify away the risk. The CAPM assumes that all investors achieve the best possible portfolio in terms of its risk-return trade-off. It also assumes that they are rational and have the same investment time horizon. In addition, all investors rely on a consistent information, as evidenced by their use of identical input lists. The market structure assumptions are that investors can borrow or lend at a common risk-free rate. The CAPM also assumes that all assets are publicly owned and traded on public exchanges, and that there are no taxes or trading costs. Because of these assumptions, when investors make their optional investment choices, they all end up with the same optional risky portfolio. Since the risk portfolio is the same for all market participants, the risk portfolio is the same as the market portfolio. The

Capital Market Line (CML) is based on this insight. The CML is a linear relationship between the risk of the asset and the expected return of the asset.

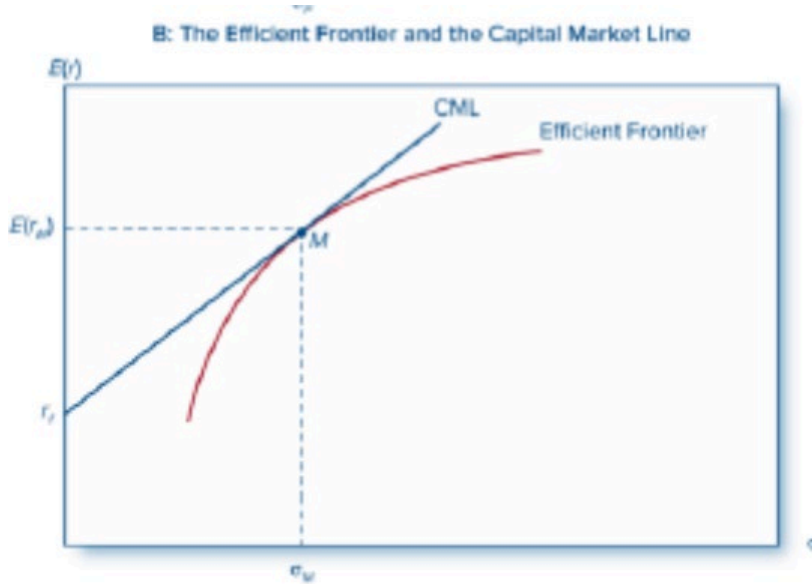
According to Bodie et al. (2023), the CAPM is typically explained by examining its mean beta relationship. The CAPM evaluates the risk of an individual asset by considering its contribution to the overall market portfolio. It uses the beta coefficient to accurately measure the sensitivity of that asset's returns to broader market. In other words, a beta of one means that the asset's returns move in the perfect tandem with the market. A beta greater than one indicates that asset's returns are more responsive to market fluctuations. Conversely, a beta of less than one indicates that the asset's returns are less responsive to changes in market prices. Bodie et al. (2023) illustrate that beta can be derived by following the principles of market equilibrium, which states that the risk-return relationship should be consistent across investments. Consequently, one can construct an equation that equates the risk-return of an individual investment to that of the market portfolio. This leads to the well-known expression of the CAPM, which is summarised in the following formula:

$$E(r_i) = r_f + \beta_i[r_m - r_f] \quad (1)$$

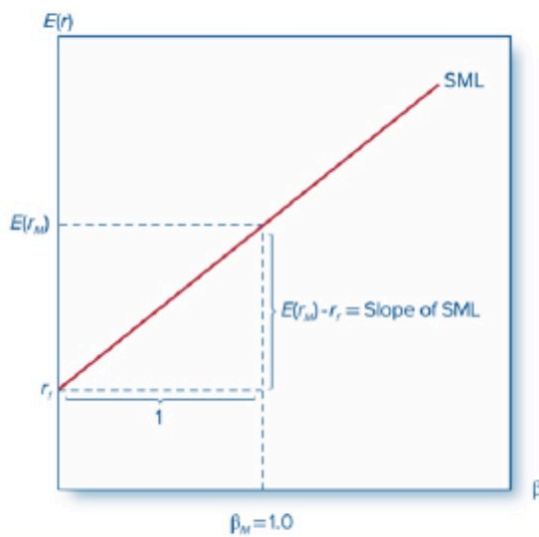
In this CAPM formula,  $E(r_i)$  is the expected return of an asset,  $r_f$  is the risk-free rate,  $\beta_i$  is the beta of an asset and  $r_m$  is the expected market return. Hence,  $[r_m - r_f]$  is the market risk premium.

As mentioned above, the mean-variance relationship, i.e. the risk-return trade-off for efficient portfolios, is represented by the CML. Similarly, the relationship between mean returns and beta for individual assets is represented by the Security Market Line (SML). The main difference between these two models is that the CML shows the risk premium of efficient portfolios in terms of their variance, while the SML shows the risk premium of individual assets in terms of their beta values. The SML can also be used for efficient

portfolios (Bodie et al., 2023). Visual representations of the CML and SML are shown in Figure 1 and Figure 2 below.



**Figure 1.** Capital market line (Bodie et al., 2023, p. 435)



**Figure 2.** Security market line (Bodie et al., 2023, p. 444)

The SML serves as a benchmark for assessing the performance of an investment. It provides the expected return that investors require in return for taking beta risk and considering the time value of money. When assets are "fairly priced", they are exactly in line with the SML. In other words, their expected returns are commensurate with the level

of risk associated with them. In a state of market equilibrium, all securities fall along the SML. If the security or portfolio is above the SML, it is undervalued or is perceived as an attractive buy. The expected return on these securities is higher than the equilibrium return determined by the SML. Conversely, securities below the SML are overvalued and their expected return is below the equilibrium return indicated by the SML.

## **2.2 Behavioral finance**

Although there are many useful insights provided by traditional finance, the assumptions of traditional finance theories are unrealistic and there are many empirical studies that have shown that its theories are not valid. Traditional finance models cannot explain the behavioural biases of investors. Consequently, these models can fail because people behave irrationally contrary to the assumptions of traditional finance.

Behavioural finance draws on insights from a range of scientific and business disciplines to gain a deeper understanding of the decisions made by investors. Psychologists and other experts in the social sciences have conducted extensive research on human behaviour, accumulating a wealth of evidence about the decision-making process. According to Baker and Ricciardi (2014), using advanced technologies, neuroscientists are now able to understand how brain function can influence financial decisions in the emerging field of neuroeconomics, or neurofinance. They note that rather than fixating on the end results, researchers in these alternative disciplines focus on unravelling the mechanisms that lead decision-makers to those results. Unlike traditional finance theory, which offers prescriptive guidelines for how investors should make decisions, behavioural finance seeks to understand the underlying reasons for the decisions that investors make (Baker & Ricciardi, 2014).

Kahneman and Tversky (1979) developed one of the most important theories in behavioural finance, the prospect theory, which accelerated the spread of behavioural finance. Prospect theory was developed to challenge the traditional finance view that expected utility theory served as the basis for decision-making under risk. Unlike expected

utility theory, prospect theory assumes that investors are not risk neutral. Prospect theory is based on an individual's actual behaviour, unlike utility theory, which determines how individuals should behave. According to Tversky and Kahneman (1979), individuals often make inconsistent decisions and suggests that losses have a greater emotional impact on an individual than an equivalent amount of gain. Tversky and Kahneman (1981) showed that individuals tend to be risk-averse for gains but risk-seeking for losses. In other words, individuals take more risk when losses are presented in the decision-making environment. Expected utility theory, on the other hand, assumes that individuals consistently choose either the risk-averse or the risk-seeking option when making decisions. If investors change their preference from risk-averse to risk-seeking, expected utility theory cannot explain it. In contrast, this behaviour is one of the main observations of prospect theory. Prospect theory therefore suggests that individuals seek to maximise value rather than expected utility. Individuals tend to value outcomes in terms of changes in wealth rather than the final state.

### **2.2.1 Herding in stock market**

Herding behaviour is a prominent concept in behavioural finance, which explores how psychological factors influence financial decision-making. There are several definitions of herding behaviour offered by the foundations of empirical research. Bikhchandani and Sharma (2001) characterise herding behaviour as a clear intention to imitate the actions of other market participants, often without conducting thorough independent analysis or relying on one's own judgment. In addition, the decisions of others are followed even if they are not based on rational analysis or information. As highlighted by Spyrou (2013), it is a common assumption among the public that herding behaviour is prevalent among both individual and institutional investors. This herding behaviour is seen as a fundamental factor contributing to periods of significant market volatility and uncertainty. Well-known historical examples of investor herding, such as the tulip mania in 1637, the dotcom bubble in 2000 and the subprime crisis in 2008, have reinforced this belief. However, it is important to note that while many people tend to associate herding with

extreme market events and consider it a widespread phenomenon, the empirical evidence, as pointed out by Welch (2000) in his paper, does not necessarily support such a universal perception.

While the first studies focusing on herding emerged mainly in the 1990s, the concept of investors emulating the actions of others dates to the 1930s, as noted by Keynes (1936). In his paper, Keynes (1936) drew an analogy between financial markets and a beauty contest, where judges judge beauty (analogous to stock prices) based on their expectations of other judges' judgments. According to Keynes (1936), the metaphor implies that rational investors try to judge future stock prices based on how others perceive them, even though these judgments may differ from the fundamental value of the stock. This perspective leads to an important insight about herding: it doesn't necessarily have to be driven by purely irrational behaviour.

Numerous studies have offered their own interpretations of herding. In one of the earliest studies of the phenomenon, Lakonishok et al. (1992) looked at the trading behaviour of institutional investors. They characterised herding as the tendency of money managers to buy or sell the same asset simultaneously with other managers. On the other hand, Banerjee (1992) proposed a slightly different view of herding. According to him, herding involves investors abandoning their own private information and instead mirroring the actions of other investors, often in response to the belief that these other investors possess information that is not available to them. In a different line of research, De Bondt and Forbes (1999) examined whether financial analysts are prone to herding behaviour. They defined herding in this context as the "excessive agreement" among analysts in their earnings forecasts. In summary, while these studies present different nuances in their definitions, the basic concept of herding remains largely consistent, notwithstanding slight variations that may arise due to the the specific context of the research.

However, while the definition of herding can be seen as fairly consistent across contexts, the actual manifestation of this phenomenon can vary considerably. Herding is a

multifaceted concept that encompasses several dimensions. A critical aspect influencing the extent and nature of herding is the category of investor associated with the phenomenon. In finance, individual investors are generally considered to be more prone to irrational behaviour than institutional investors. Put simply, individual investors are often thought to be more prone to various behavioural biases, including herding. This may be reinforced by the fact that institutional investors are assumed to have higher level of education and expertise than individual investors, who may not have the same resources and expertise around investing.

According to the bibliometric study conducted by Choi et al. (2022), it appears that a significant proportion of previous research on herding has focused primarily on two main areas: the herding behaviour of institutional investors or the collective behaviour of the market. In contrast, a significantly smaller number of academic studies seem to specifically address the herding tendencies of individual investors, although there are exceptions to this trend. A plausible explanation for this observation could be related to the ease of measurement. Institutional herding and market-wide herding are easier to quantify, often using well-established measures such as performance indices. However, there are also cases, such as the studies by Barber et al. (2009) and Hsieh et al. (2020), where the research focuses exclusively on individual investors. For example, Hsieh et al. (2020) suggest that Google search trends can serve as a practical proxy for capturing herding behaviour among individual investors. In addition, a more common approach to measuring herding among smaller investors is to assess market-wide herding, particularly in markets where individual investors have a significant presence.

The complexity of herding is likely to be a major factor contributing to the inconclusive findings in this area of research. Herding is not only influenced by different types of investors, but also by various other factors that can significantly affect this phenomenon. To add to the complexity, the underlying motivations that drive herding may also differ, as highlighted by Spyrou (2013) in his paper. Given these considerations, it is crucial to gain a thorough understanding of herding itself and its various dimensions. This

understanding is essential to establish a research framework that effectively captures the specific aspects of interest. This poses a significant challenge for herding-related research, as quantifying the extent of herding is extremely complicated, and researchers must contend with the possibility of numerous unknown variables influencing their findings.

### **2.2.2 Different forms of herding**

Bikhchandani and Sharma (2000) divided herding behaviour into 'spurious' and 'intentional' herding. Spurious herding refers to groups with comparable decision challenges and access to the same information tent to make similar decisions, whereas intentional herding refers to investors who deliberately mimic the actions of their peers. Bikhchandani and Sharma (2000) note that spurious herding can be an efficient outcome, unlike intentional herding, which does not necessarily lead to efficiency, for example in fragile markets, excessive volatility, and systemic risk. However, it is important to note that empirically distinguishing between spurious herding and intentional herding is a challenging task and may even be impossible. This is because various factors can typically influence investment decisions, making it difficult to attribute herding behaviour to a specific cause.

According to Bikhchandani and Sharma (2000), spurious herding is based on fundamentals. When fundamental information changes, investors may change their investment strategy. Bikhchandani and Sharma (2000) give the example that a sudden rise in interest rates makes stocks less attractive as an investment option and, based on this change in fundamentals, investors would prefer bonds to stocks. Thus, investors are responding to public information, namely rising interest rates, and not to the investment decisions of others, so this is not herding behaviour according to Bikhchandani and Sharma (2000).

According to Bikhchandani and Sharma (2000), spurious herding can also occur when different groups of investors with different investment options make apparently coordinated decisions. Bikhchandani and Sharma (2000) give the example of a scenario with

domestic (D) and foreign (F) investors, where D investors can only invest in the domestic stock and bond markets, while F investors can also invest in foreign markets. This occurs when F investors increase their holdings in domestic markets due to changes in the foreign market, creating the appearance of a "buying herd" by F investors and a "selling herd" by D investors in domestic markets. However, these decisions are individual and efficient given the constraints on D investors.

According to Hirshleifer and Theoh (2003), intentional herding behaviour can be divided into rational and irrational herding. They state that rational herding refers to a situation where investors believe that the decisions and analysis of information by others are better than their own ability to make decisions. By making decisions in line with the crowd, it is believed that the risk of making a mistake is reduced. Rational herding behaviour is based on new information or market signals that lead to a consensus among investors on a particular investment or trading strategy. When information is limited or difficult to interpret, the rational approach is to rely on the decision of others as a signal to do the right thing. While rational herding is based on valid information, there is still a risk of overreaction to new information or events. Collective action caused by herding behaviour can lead to accelerated price changes that are not supported by fundamental information. Rational herding can exist within the framework of the EMT, which suggest that asset prices reflect all available information. In such cases, herding is a rational response to new information, even within the context of EMT.

According to Lakonishok et al. (1992), irrational herding behaviour is due to fashionable trends, cognitive or emotional biases. Ignoring private information and making investment decisions by blindly following other investors are key characteristics of irrational herding behaviour. This behaviour can disrupt markets and amplify fluctuations in volatility. For example, Chang et al. (2000) note that during large stock market fluctuations, some investors buy and sell large numbers of stocks, and as a result of irrational herding behaviour, other investors also follow and repeat their buying and selling, ignoring other information. They argue that irrational herding behaviour, based on emotion and social

influence rather than rational decision-making, can disrupt the functioning of capital markets. This can manifest itself in information uncertainty, price inaccuracy and financial system fragility, threatening market stability.

### **2.2.3 Different causes of herding behavior**

Bikhchandani and Sharma (2000) identify three reasons for rational herding behaviour. The reasons for herding behaviour are diverse. For example, the most important reasons for herding behaviour are imperfect information, reputation concerns, and compensation structures. For example, analysts may herd to protect their reputation, institutional investors may herd to protect their compensation, and investors may infer information from the actions of previous investors or react to the arrival of fundamental information.

The basic models of information-based herding proposed by Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) assume universal access to investment opportunities at the same price, implying a perfectly elastic supply. In the scenario described, individuals face similar investment decisions under uncertainty and private (but imperfect) information about the optimal course of action. This private information may come from the research findings of an investor. Alternatively, all the information relevant to the investment may be public, but there is uncertainty about its quality, such as concerns about the government's manipulation of economic data or its true commitment to economic reform. An individual's assessment of the quality of publicly available information remains private.

According to Bikhchandani and Sharma (2000), individuals can observe each other's actions, but not the private information or signals that each player receives. This assumption is justified by the concept that "actions speak louder than words", even when private information is communicated. If individuals have a particular view about the appropriate course of action, then the actions taken can be used to infer an investor's private information. This setting allows for the emergence of herding behaviour, where individuals follow the actions of others. This behaviour is shown to be fragile, easily disrupted

by a small amount of new information. It is also idiosyncratic, with the nature of the behaviour determined by random events and the choices of the initial players.

Bikhchandani and Sharma (2000) present a simple example to illustrate the main ideas of information-based herding. Investors decide sequentially whether to invest in a stock, industry, or country. The payoff ( $V$ ) for each investor is either +1 or -1 with equal probability relative to the next best investment. Each investor has a private signal (good, G, or bad, B) about the payoff of the investment. The probability distribution of the signal depends on whether the payoff is +1 or -1, introducing an element of uncertainty. In addition to their private signals, each investor observes the decisions (but not the private signals) of their predecessors, which contributes to the observability of actions in the absence of perfect information.

Scharfstein and Stein (1990), Trueman (1994), Zweibel (1995) and Graham (1999) present a herding theory based on the reputational concerns of fund managers or analysts. Reputational concerns arise from uncertainty about the manager's ability or skill. The central idea is that conformity with other investment professionals helps to preserve uncertainty about the manager's ability, to the manager's advantage, especially when there is uncertainty about the ability of several professionals. For example, two investment managers are faced with an identical investment opportunity. Each manager may be of high or low ability, and their ability levels are chosen independently. A high ability manager receives informative signals, while the signal from the low ability manager is pure noise. Uncertainty about each manager's ability persists throughout the decision-making process.

A herding equilibrium emerges in which one manager imitates the decision of the other, regardless of their own signal. This occurs because each manager is uncertain about their ability, which leads him or her to avoid making decisions that contradict the other manager and risk a negative evaluation. If several managers decide in sequence, the herding behaviour continues, leading to inefficiencies. Herding is idiosyncratic, based on the

signal of the first individual realisation, and fragile, based on minimal information. Similar to the models of Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992), the investment opportunity is assumed to be available to all individuals at the same price. The extent to which market prices mitigate inefficiencies in the Scharfstein and Stein model is not clear, raising questions about the effectiveness of price movements in well-functioning markets in addressing the identified inefficiencies.

Bikhchandani and Sharma (2000) discuss the impact of compensation structures on the behaviour of investment managers. If investment managers' compensation is based on how well they perform relative to other professionals, their incentives are distorted, resulting in an inefficient portfolio and potentially leading to herding behaviour. Bikhchandani and Sharma (2000) consider a scenario where a risk-averse investor receives higher compensation for personal performance, but lower compensation if she/he underperforms a benchmark. Both the risk-averse investor and the benchmark have imperfect private information about stock returns. The risk-averse investor tends to mimic the actions of the benchmark, driven the incentive to imitate and the compensation structure that penalises underperformance. Writing a relative performance contract is considered optimal for the employer in situations of moral hazard or adverse selection. This ensures that the risk-averse investor's compensation is aligned with the performance of the benchmark. While this "constrained efficiency" may be appropriate due to moral hazard or adverse selection constraints, it prioritises the employer's profit over societal welfare. The constrained efficiency presented by Bikhchandani and Sharma (2000) is based on the assumption of a single risky asset, while Admati and Pfleiderer (1997) challenge this in a multiple risky assets model. They find that benchmark-based compensation contracts are inefficient because they do not optimise risk sharing and do not address moral hazard and adverse selection issues in a multiple risky assets model. Unlike in a single risky asset model, a benchmark-adjusted return is insufficient to capture the agent's private information, leading to divergent results between the two models.

### **3 Literature review and hypothesis development**

There are two main categories of empirical research on herding behaviour. On the one hand, there are studies that focus specifically on the herding behaviour of institutional investors, such as the work of Kraus and Stoll (1972), Lakonishok et al. (1992). On the other hand, there are research efforts that use market-wide data to investigate herding tendencies towards the market consensus, such as the research by Chang et al. (2000), Christie and Huang (1995). This chapter first presents the methodologies used in the existing literature to measure herding behaviour. This is followed by a discussion of the herding behaviour of institutional investors. Finally, this thesis focuses on market-wide herding behaviour.

#### **3.1 Measurements of herding behaviour**

In empirical research, there are two main categories of how herding behaviour is measured. First, there are studies that use micro or proprietary data to investigate whether certain types of investors engage in herding. Lakonishok et al. (1992) and Sias (2004) present two commonly used measures for this type of research. Other studies of existing research rely on aggregate price and market activity data to investigate herding tendencies towards the market consensus. Christie and Huang (1995) and Chang et al. (2000) present two commonly used measures for this other category. This thesis first presents the models proposed by Lakonishok et al. (1992) and Sias (2004) and then discusses two measures presented by Christie and Huang (1995) and Chang et al. (2000).

One common measure used to assess the herding behaviour of institutional investor is that proposed by Lakonishok et al. (1992), known as the LSV measure. The underlying concept of the LSV measure is simple: if there is a trend among money managers to buy or sell a particular stock disproportionately, indicating a collective position on one side of the market, then herding at the individual stock level can be inferred. The calculation of herding involves determining the proportion of net buyers. This is calculated as the number of money managers increasing their holdings in a stock over a given quarter

relative to the total number of money managers trading that stock, adjusted by a factor that decreases as the number of active money managers in that stock increases. In the absence of herding, the expected value of this measure should be consistent across periods. However, in the presence of herding, significant cross-sectional variation in this measure is expected. The LSV herding measure, denoted as  $H$ , is calculated as follows:

$$H(i) = \left| \frac{B(i)}{B(i)+S(i)} - p(t) \right| - AF(i) \quad (2)$$

In the equation,  $B(i)$  is the amount of money managers that are net buyers,  $S(i)$  is the amount of money managers that are net sellers or reduce their holdings,  $p(t)$  is the expected fraction of money managers that are buying in the quarter relative to the total active money managers. The adjustment factor,  $AF(i)$ , reflects the expected value of  $\left| \frac{B}{B+S} \times p \right|$  under the null hypothesis of no herding. Lakonishok et al. (1992) point out that, for any given stock,  $AF$  diminishes as the number of active money managers in that stock increases.

Similarly, Sias (2004) suggests that if institutional investors are herding or replicating their own trades in the same securities, the proportion of institutional investors buying in the current quarter will have a correlation across assets with the proportion of institutional investors buying in the previous quarter. Therefore, to assess herding, one can measure the cross-sectional correlation between institutional investors' demand for a given asset in the current quarter and their demand for the same asset in the previous quarter. Sias (2004) first estimates the position of each institutional investor in each asset as a fraction of the outstanding shares of the asset at both the beginning and the end of each quarter. If an institutional investor increases (decreases) its holding in a stock, it is labelled a buyer (seller). For each stock quarter, the proportion of institutions buying is calculated, referred to as the "raw fraction of institutions buying", expressed in the equation:

$$Raw\Delta_{k,t} = \frac{BI_{k,t}}{BI_{k,t} + SI_{k,t}} \quad (3)$$

In the equation,  $BI_{k,t}$  represents the number of institutions buying asset  $k$  in quarter  $t$ , and  $SI_{k,t}$  represents the number of institutions selling asset  $k$  during quarter  $t$ . To facilitate aggregation over time and comparison across different market capitalisations and investor types, Sias (2004) standardises the fraction of institutional investors buying asset  $k$  in quarter  $t$  as follows:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_{k,t}}}{\sigma(Raw\Delta_{k,t})} \quad (4)$$

This is followed by a cross-sectional regression:

$$\Delta_{k,t} = \beta \Delta_{k,t-1} + \varepsilon_{k,t} \quad (5)$$

The underlying idea is that "if institutional investors follow each other into and out of the same securities (herding), or if individual institutional investors follow their own trades of the previous quarter, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter" (Sias, 2004). Sias (2004) emphasises that the key difference between the LSV and Sias (2004) measures is that the former indirectly tests for cross-sectional temporal dependence within periods, while the latter is a direct test of whether institutional investors follow each other's trades in subsequent periods.

Christie and Huang (1995) offer an alternative approach by presenting a measure of investor herding towards the market consensus. They argue that during periods of large market movements, investors are more likely to suppress their individual beliefs and follow the market consensus. As a result, returns are expected to be close to the market return, resulting in relatively low return dispersion. If stocks have different sensitivities to the market, rational asset pricing suggests that dispersion will increase. To measure

herding behaviour, Christie and Huang (1995) introduce the Cross-Sectional Standard Deviation (CSSD), which is calculated using the formula:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N-1}} \quad (6)$$

In this formula,  $R_{i,t}$  is the observed return of asset  $i$  at time  $t$ , and  $R_{m,t}$  is the cross-sectional average of the returns of the  $N$  assets in the aggregate market portfolio at time  $t$ . In essence, the metric presented by Christie and Huang (1995) reflects how close the returns of an asset are to the realised average.

Christie and Huang (1995) then use a regression model to investigate whether return dispersion is significantly lower during periods of extreme market movements:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (7)$$

The use of dummy variables allows us to distinguish investor behaviour in extreme positive and negative market conditions from normal market conditions. According to Christie and Huang (1995), rational asset pricing implies positive coefficients on the dummy variables during extreme market conditions. Statistically significant negative coefficients, on the other hand, may indicate investor herding during these extreme conditions.

A methodology related to the approach of Christie and Huang (1995) is proposed by Chang et al. (2000). They note that if investors tend to follow aggregate market behaviour during periods of large average price movements, the typical linear and increasing relationship between dispersion and market return may become non-linearly increasing or even decreasing. Consequently, they use a non-linear regression specification to estimate the relationship between cross-sectional absolute deviation of returns and market return. Chang et al. (2000) start with the conditional version of the Black (1972) Capital Asset Pricing Model (CAPM) to define the expected cross-sectional absolute deviation of stock returns (ECSAD) in period  $t$ . This is expressed as follows:

$$ECSAD_t = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| E_t(R_m - \gamma_0) \quad (8)$$

In this formula,  $R_m$  is the return of the market portfolio,  $\gamma_0$  is the return of the zero-beta portfolio,  $\beta_m$  is the systematic risk of each asset  $i$ . Chang et al. (2000) show that the typical increasing and linear relationship between dispersion and time-varying market expected returns can be expressed as:

$$\frac{\partial ECSAD_t}{\partial E_t(R_m)} = \frac{1}{n} \sum_{i=1}^N |\beta_i - \beta_m| > 0 \quad (9)$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(R_m)^2} = 0 \quad (10)$$

Based on this relationship, CCK propose a herding test that includes a parameter to account for potential non-linearity in the relationship between asset return dispersion and market return. They use the cross-sectional absolute deviation at time  $t$  (CSAD $_t$ ) as a proxy for the unobservable ECSAD $_t$ . CSAD is calculated as the average absolute value of the deviation of each stock relative to the return of the equally weighted market portfolio.

The rationale behind this approach is that if herding is present during periods of extreme market conditions, there should be a less than proportional increase (or even decrease) in the CSAD measure. It's important to note that CSAD is not used as a direct measure of herding; rather, herding is identified through the relationship between CSAD and the market return. CCK then runs regressions to test whether the degree of herding is asymmetric in rising (UP) and falling (DOWN) markets. The regressions are reported as follows:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} |R_m^{UP}| + \gamma_2^{UP} (R_{m,t}^{UP})^2 + \epsilon_t \quad (11)$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} |R_m^{DOWN}| + \gamma_2^{DOWN} (R_{m,t}^{DOWN})^2 + \epsilon_t \quad (12)$$

If investors tend to herd into the market during periods of extreme market conditions, there should be a negative non-linear relationship between CSAD and the average market return should exist, as captured by the coefficient on the non-linear term.

### 3.2 Institutional investors and herding

There are many studies on herding behaviour that focus on the trading behaviour of institutional investors. The herding behaviour of institutional investors was first studied by Kraus and Stoll (1972). They describe the herding behaviour of institutional investors as parallel trading. In parallel trading, institutional investors trade the same stock in the same direction over a period, as defined by Kraus and Stoll (1972).

There is a large body of research on the herding behaviour of institutional investors from the US market. Early research by Christie and Huang (1995) examined the presence of herding behaviour among institutional and individual investors in the US stock market. They found evidence of herding, particularly among institutional investors. The research of Nofsinger and Sias's (1999) research showed a remarkable relationship between annual fluctuations in institutional ownership and returns in the US markets. Their findings supported the view that these fluctuations were the result of the greater impact of institutional herding on prices, as opposed to herding by individual investors.

A more recent study by Choi and Sias (2009) presents compelling empirical evidence of herding behaviour within the US institutional industry. They find a significant cross-sectional correlation, averaging 39 per cent, between the proportion of institutional traders buying stocks within given industry in one quarter and the proportion that did so in the previous quarter. Their research also shows that this institutional herding is primarily driven by the decisions of fund managers. It contributes to the momentum trading observed in the institutional sector and is more pronounced in smaller and more volatile

sectors. Furthermore, the results suggest that such institutional herding can lead to industry market values deviating from their fundamental underpinnings.

Zheng et al. (2015) study the impact of institutional investors' herding behaviour on future excess stock returns in the Chinese stock market. In their study, they use the LSV measure developed by Lakonishok et al. (1992) to measure institutional investors' herding behaviour. The results of Zheng et al. (2015) suggest that both short- and long-term stock excess returns appear to be positively related to the Lakonishok et al. (1992) metric of herding behaviour. Moreover, they show that the herding effect is significant mainly for buy-side herding behaviour, and that the effect of herding behaviour on stock excess returns is stronger in times of crisis. Zheng et al. (2015) provide evidence that the price effect is stronger and earlier when the herding behaviour of institutional investors is directed towards larger, value or liquid stocks. In contrast, the price effect is significantly longer when the herding behaviour of institutional investors is directed towards smaller, growth or illiquid stocks. Finally, they find that long-term continuous herding behaviour is positively correlated with stock excess returns in the short and medium term, but negatively correlated with stock excess returns in the long term.

### **3.2.1 Herding and fund performance**

Many early studies of institutional investor herding behaviour suggest that herding is less common in mutual funds, but herding has been observed in the smallest stocks. In an important early study by Lakonishok et al. (1992), they analysed data from 769 tax-exempt equity funds in the United States between 1985 and 1989. They used the LSV measure to examine two behaviours in financial markets: herding and positive-feedback trading. The results of the study indicated that, for the most part, pension fund managers, did not show strong tendencies towards either herding or positive-feedback trading. However, Lakonishok et al. (1992) found some evidence of herding behaviour among pension fund managers, particularly in smaller stocks. Importantly, this herding behaviour in smaller stocks did not have a destabilising effect on stock prices.

Grinblatt et al. (1995) also used LSV to study the US mutual fund industry, focusing on momentum and herding behaviour. The results of the study revealed evidence consistent with the existence of momentum behaviour, suggesting that mutual fund managers tended to follow market trends. However, the study did not find strong evidence of herding behaviour among these fund managers. A study by Wermers (1999) also found limited evidence of herding among US mutual funds when it came to the typical or average stocks. However, the results of the study indicated a much greater degree of herding in the trading activity of smaller stocks and in the trading activity of funds that focused on growth-oriented investments.

However, research by Nofsinger and Sias in 1999 found a notable relationship between annual fluctuations in institutional ownership and returns in US markets. They suggested that this relationship could be due either to a greater degree of positive-feedback trading by institutional investors relative to individual investors, or to the greater influence of institutional herding on prices relative to herding by individual investors. The results of the study support the idea that both factors contribute to explaining the observed relationship.

### **3.3 Market-wide herding**

Market-wide herding behaviour has been studied extensively, especially in times of crises, because stressful events trigger emotional reactions in investors, leading to irrational decisions. Following the recent COVID-19 pandemic there has been a proliferation of academic articles on financial market distortions. The pandemic has created unexpected uncertainty with negative consequences not only for public health, but also for financial markets and economies worldwide (Bogdan et al. 2022). Several studies (Lyócsa et al. 2020; Liu et al. 2020; Al-Awadhi et al. 2020; Zhang et al. 2020) have shown that investor fear and anxiety are the cause of the negative impact of the COVID-19 pandemic on financial markets. In addition, investors' fear and anxiety about the pandemic leads to herding behaviour, as less informed investors tend to follow more informed market participants during market disruptions. However, according to Bogdan et al. (2022), the

impact of global crises such as the COVID-19 pandemic varies across regions and markets. For example, the prevalence and impact of herding behaviour varies between developed and emerging markets.

The phenomenon of herding behaviour in stock markets has been studied in both developed and emerging markets, with varying results. This is influenced by the time period and research methods used. According to Chang et al. 2000 and Pochea et al. 2017 emerging markets are more prone to herding due to the characteristics and incentives of their participants, who are generally less experienced than those in developed markets. Factors such as information asymmetries, speculative trading, lack of transparency, low trading volumes, low liquidity and weak regulatory frameworks further encourage herding in these markets (Chang et al. 2000; Pochea et al. 2017). Conversely, herding is less prevalent in well-established markets. However, as mentioned earlier, a number of studies show that herding tends to be higher in developed markets during periods of market stress, leading to higher volatility (Bogdan et al. 2022; Clements et al. 2017; Jirasakuldech and Emekter 2020).

For the purposes of this study, emerging and developed markets are defined according to Morgan Stanley Capital International's (MSCI) Market Classification Framework 2023. The MSCI market definition requires a market to meet certain criteria in terms of economic development, market size and liquidity, and accessibility. The economic development requirement for developed markets is that a country's GNI per capita must be 25% above the World Bank's high-income threshold for three consecutive years. There are no economic development requirements for emerging markets. For both developed and emerging markets, the size and liquidity requirements include the size of listed companies and securities and the liquidity of securities. Both developed and emerging markets have their own thresholds for the above criteria. Developed markets have higher thresholds. The openness of emerging market to foreign ownership, ease of capital inflows, efficiency of the operating framework and institutional stability should be very high in developed markets according to the MSCI market definition. For emerging markets, the

MSCI scale for these criteria ranges from high to significant. Only the institutional stability requirement scale for emerging markets is modest. Availability of investment instruments should be unlimited in developed markets and high in emerging markets. This study focuses on developed markets and more specifically on the German, UK and US markets.

### **3.3.1 Characteristics of German stock market**

The German economy is the largest economy in the EU, and the German stock exchange is the largest in continental Europe in terms of market capitalisation. Germany has several stock exchanges but the two most important are the Frankfurt Stock Exchange (FSE) and the Xetra electronic trading system. Despite the size of the market, there is relatively little literature on herding in German stock markets. This may be since the German stock market has a short history of development and is relatively small compared to the US or UK. Although the FSE was founded in 1585 and is one of the oldest stock exchanges in the world, the Finanzplatz Deutschland initiative to promote Frankfurt as a financial centre and to develop the German stock market was only launched in the mid-1980s (Hein & Detzer 2015; Detzer et al. 2017). Traditionally, the FSE was a floor trading exchange, but it now operates both floor and electronic trading. Xetra is an electronic trading system that was launched after the Finanzplatz Deutschland initiative in 1997.

For example, Walter and Moritz Weber (2006) study herding behaviour in German stock markets. They find that fund managers engage in both herding behaviour and positive feedback trading, examining the trading performance of German mutual funds between 1998 and 2002. Kremer and Nautz (2013) find evidence of herding behaviour in the German stock market at the daily level by analysing the daily trading lags of financial institutions in the German stock market. Moreover, in their study, they find that herding behaviour causes price volatility in the short run, as they observe return reversals in the German stock market.

Mobarek et al. (2014) find that herding behaviour only occurs significantly during asymmetric market conditions and crises in European liquid indices between 2001 and 2012. They also find that the cross-sectional dispersion of returns in individual country markets is affected by the cross-sectional dispersion of returns in other countries. They find that the cross-sectional dispersion of German markets has the largest impact on regional cross-country herding behaviour. In other words, the degree of herding behaviour in the German market has a large impact on the degree of herding behaviour in stock markets in other European countries. Espinosa-Mendez and Arias (2021) also conclude that crises lead to an higher level in herding within European stock markets. They focus on the study of herding behaviour during the COVID-19 pandemic and found that COVID-19 increased the level of herding behaviour in the DAX index, which is the main stock market index in Germany. The study by Ouarda et al. (2013) also confirms that herding behaviour occurs in European markets, particularly during periods of high volatility. Thus, the previous literature suggests that herding behaviour occurs in the German stock market, during periods of high volatility and especially during market crises.

### **3.3.2 Characteristics of US stock market**

The United States has one of the largest and most influential stock markets in the world, with several major stock exchanges. The New York Stock Exchange (NYSE) is one of the main stock exchanges. Founded in 1792, the NYSE is one of the oldest and largest stock exchanges in the world. The NYSE lists a wide range of domestic and international companies, including many large-cap companies. In addition to the NYSE, the US also has the world's first electronic trading platform, NASDAQ, which was founded in 1971, long before, for example, Germany's Xetra. The NASDAQ is another major stock exchange, alongside the NYSE, and is known for listing many technology and biotechnology companies.

As the US market already has a long history and is one of the largest and most influential markets, there is a lot of literature on herding behaviour in the US stock market. Studies on herding behaviour in the US stock market provide conflicting results. Neither Christie

and Huang (1995) nor Gleason et al. (2004) found evidence of herding behaviour in the US stock market, while Chang et al. (2000) studied both Asian and US markets but found no evidence of herding behaviour in the US stock market. In contrast, they found evidence of herding behaviour in Asian markets. Chiang and Zheng (2010) find similar results. They also find no evidence of herding behaviour in US stock markets but find evidence of herding behaviour in other developed Asian markets.

On the other hand, there is a large body of literature providing evidence of herding behaviour in the US market. From previous studies, Hwang and Salmon (2004) show that herding behaviour is present in the US stock market. In particular, the literature that studies herding behaviour in sub-periods provides evidence of herding behaviour in the US stock market. For example, Galariotis et al. (2015) provide evidence of herding behaviour in the US stock market when they divide their sample into sub-periods of time. On the other hand, they do not find herding behaviour for the entire sample period. Klein (2013) also shows that the degree of herding behaviour in the US stock market varies under different market conditions. As mentioned above, according to Ouarda et al. (2013), herding behaviour can be observed in several sectors when market volatility increases. For example, volatility accelerates in markets during crises, and studies that find herding behaviour in US markets typically select sub-periods according to known crises. Thus, previous literature suggests that herding behaviour is not found in US sub-markets in the long run, but that herding behaviour may be found in shorter periods of high volatility.

### **3.3.3 Characteristics of British stock market**

There are several stock exchanges in the UK, the main one being the London Stock Exchange (LSE). The LSE was founded in 1801 and is one of the oldest stock exchanges in the world, along with Germany and the United States. The LSE is also one of the largest stock exchanges in the world, along with the US market. The London Stock Exchange lists companies from a variety of sectors, including finance, energy, healthcare, consumer goods, technology, and more. It offers different segments for companies of different

sizes and stages of development, such as the Main Market for larger, established companies, and the Alternative Investment Market for smaller, growth-oriented companies. Because the LSE offers a wide range of opportunities to invest in companies of all shapes and sizes, the UK stock market attracts a wide range of investors, including individual retail investors, institutional investors such as pension funds, insurance companies, and investment funds, as well as foreign investors.

There has been much research on herding behaviour in the UK market and, as in the US stock market, the results are contradictory. For example, Bogdan et al. (2022) found no herding in the UK stock market. However, as in the German and US stock markets, herding is found in the UK stock market when the sample period is divided into shorter sub-periods or when herding is examined in bullish and bearish markets. Galariotis et al. (2015) suggest that herding behaviour is found in the UK market, particularly during financial crises. In addition, Aslam et al. (2021) find evidence of herding in UK stock markets. Asim et al. (2024) also examine herding behaviour in UK stock markets over different time periods and find evidence of herding. Their findings are confirmed when they further investigate the effect of economic uncertainty on herding behaviour. The study by Asim et al. (2024) shows that herding occurs in the UK stock market during the global financial crisis of 2007-2008 and the COVID-19 pandemic. Thus, as in the US and German markets, the existing literature suggests that herding occurs in the UK market in shorter sub-periods and during crises.

#### **3.3.4 Market-wide herding in developed markets**

Several studies provide evidence of herding in developed stock markets. In Europe, Espinosa-Méndez and Arias (2021) study the impact of the COVID-19 pandemic on the capital markets of France, Germany, Italy, the United Kingdom and Spain. They use the CSAD model to study herding behaviour in this market. The results of the study provide strong evidence that herding behaviour is higher during the COVID-19 pandemic. Espinosa-Méndez and Arias (2021) argue that due to fear and uncertainty during the pandemic, less informed investors tend to follow the decision of more informed investors.

Ferreruela and Mallor (2021) study on the herding behaviour of investors during market crises, focusing on developed markets. Specifically, they study herding behaviour during the 2008 financial crisis and the COVID-19 pandemic in the Spanish and Portuguese markets. In their study, Ferreruela and Mallor (2021) use daily cross-sectional standard deviations (CSSD) and daily cross-sectional absolute deviations (CSAD) for the period 2000-2021 to measure herding behaviour in Portuguese and Spanish markets. The study is divided into pre-crisis, crisis and post-crisis periods. They find that, herding behaviour is more pronounced in the pre-crisis and post-crisis periods, while it is not present during the financial crisis. However, Ferreruela and Mallor observed herding behaviour in the Spanish and Portuguese markets during the COVID-19 pandemic on days with high volatility. In other words, herding behaviour was stronger before and after the pandemic than during it.

On the contrary, Espinosa-Méndez and Arias (2020) find that the COVID-19 pandemic increases herding behaviour in the developed Australian stock market. The sample used in their study includes the daily returns of all listed companies in Australia between June 2008 and June 2020. Like Ferreruela and Mallor (2021), Espinosa-Méndez and Arias (2020) use the CSAD model proposed by Chang et al. (2000) in their study. Their results show that herding occurs in Australian markets during COVID-19. Thus, the study by Espinosa-Méndez and Arias (2020) shows that herding behaviour can occur in developed markets during a COVID-19 pandemic.

Bogdan et al. (2022) also looked at herding behaviour during a COVID-19 pandemic and they found no herding behavior in developed markets. They investigate whether herding is due to the pandemic and compare herding behaviour across different European stock markets. Bogdan et al. (2022) selected European countries from three different categories for their study: developed markets, emerging markets, and frontier markets. Within developed markets, Bogdan et al. (2022) selected Austria, the UK, Italy, and France for their study to represent the developed markets. Hungary, Greece, the Czech Republic,

Poland, and Turkey were selected from the European emerging markets, while Estonia, Romania, Lithuania, Slovenia, and Croatia were selected from the frontier markets. Bogdan et al. (2022) used the CSAD model of Chang et al. (2000) to detect herding behaviour during the COVID-19 pandemic. In their study, herding was not observed in any market prior to the COVID-19 pandemic. During the COVID-19 pandemic, herding was observed in emerging and frontier markets, but not in developed markets.

Wen et al. (2021) investigate the existence of herding behaviour before and during the COVID-19 pandemic in the Hong Kong market. They examine the Heng Sang Index over the period from August 2019 to July 2020. They define the pre-pandemic period as August 2019 to January 2020 and the period between February 2020 and July 2020 as the COVID-19 pandemic period. Wen et al. (2021) use the CSAD model of Chang et al. (2000) in their study, as does other literature. Wen et al. (2021) do not observe herding behaviour during the COVID-19 pandemic in Hong Kong markets but do observe some minor herding behaviour before to the pandemic started. According to Wen et al. (2021), the emergence of herding behaviour prior to the pandemic was probably due to the socio-economic chaos in Hong Kong. Just before the pandemic, Hong Kong liberalised land and housing policies to balance housing supply and demand, which had a huge impact on Hong Kong's real estate and banking sectors.

Contrary to the study by Wen et al. (2021), Aslam et al. (2021) find herding behaviour during a COVID-19 pandemic in developed markets. In their study, they compare herding behaviour in European and Asian markets during the COVID-19 pandemic. For their study, they select the stock markets of India, China, Japan, the UK, France and Spain for the period from 1 January 2020 to 3 December 2020. According to the MSCI market definition, Japan, the UK, France, and Spain can be classified as developed countries in the study.

In contrast to other post-pandemic COVID-19 studies of herding behaviour, Aslma et al. (2021) use as their research methodology the Multifractal Detrended Fluctuation

Analysis method introduced by Kantelhardt et al. (2002) together with the Generalised Hurst Exponent and the Magnitude of Long Memory index proposed by Khuntia and Patanayak (2020). By using these methods together on a quarterly basis Aslam et al. (2021) are able to study herding behaviour through multifractality, long memory and efficiency level and thus gaining a different perspective on herding behaviour during the COVID19 pandemic.

The results of Aslam et al. (2021) show that herding behaviour occurs in different quarters in the European and Asian markets. They find that European stock markets are more likely to exhibit herding behaviour because they are more sensitive to asset losses. The most pronounced herding behaviour was observed in European markets in the second quarter of 2020. The third wave of the COVID19 pandemic affected Asian countries more, as reflected in the study by Aslam et al. (2021), where herding behaviour only appeared in Asian markets in the third quarter of 2020. In the European market, however, it was already evident in the first two quarters. According to Aslam et al. (2021), the COVID19 pandemic had the largest negative impact on Spain of all European countries, which is why herding behaviour was present in the last three quarters of 2020 in their study. This contrasts with the study by Ferreruella and Mallor (2021), who only found herd behaviour on high-volatility days in the Spanish stock markets during the COVID19 pandemic.

Prior to the COVID-19 pandemic, bubbles in financial markets, such as the dot-com bubble and the housing bubble, have received considerable attention in the context of herding in developed markets. Addressing a gap in existing literature, Galariotis et al. (2015) investigate the herding behaviour towards the market consensus of leading stocks in the US and the UK by considering the impact of major macroeconomic announcements. The results show that in the US, investors tend to exhibit herding behaviour on days when important macroeconomic data are released. In addition, there were instances of herding spillovers from the US to the UK during previous financial crises. The study also reveals notable differences in herding behaviour between the two markets. In the US, both fundamental and non-fundamental herding is observed during different crisis periods. In

the UK, on the other hand, herding is primarily driven by fundamental factors and is particularly evident during the bursting of the dotcom bubble. These results underline the idea that the drivers of herding behaviour are context-specific and vary across time and country.

Ouarda et al. (2013) study herding behaviour in European markets, focusing on the prevalence of herding behaviour in different sectors and its impact on returns, volatility, and transaction volume. They also study herding behaviour in European markets during the financial crisis and show that herding behaviour does occur in European markets, i.e. in developed markets, during crises. Like many other studies on herding behaviour, Ouarda et al. (2013) use the CSAD model presented by Chang et al. (2000) in their study. The data for this study consisted of the Stoxx 600 index, which represents 10 different sectors in Europe. Ouarda et al. (2013) used firm-level data from this index for the period January 1998 to 2010 in their study. They found herding behaviour at the monthly level for most of the individual industry sectors, except for the consumer goods sector.

The study by Ouarda et al. (2013) suggests that herding behaviour exists in both bullish and bearish markets, with evidence of stronger herding in months when certain sectors experience declines. Furthermore, during periods of high volatility, significant herding is observed in various sectors, including consumer goods. However, the impact of herding on volatility seems to be more pronounced than on trading volume. Furthermore, Ouarda et al. (2013) find that during the 2007-2008 financial crisis, herding behaviour, especially in the financial and technology sectors, was affected by the subprime crisis due to interdependence and contagion effects.

Pochea et al. (2017) study herding behaviour in developed markets, focusing on stock markets in Central and Eastern Europe. Their sample focuses on the daily stock prices of 384 firms over the period January 2003 to December 2013. Pochea et al. (2017) use the CSAD method developed by Chang et al. (2000) in their study. They find herding behaviour in all countries in their sample except Poland and Romania. The study by Pochea et

al. (2017) shows that herding behaviour occurs during both market booms and declines in developed markets. When investors are excited and optimistic about a market boom, they abandon their own information and mimic other investors in their stock purchases, which is a sign of herding behaviour in a market boom. In a market downturn, herding behaviour is manifested by investors overselling, as panicked and fearful investors follow the market and do not trust their own information.

Based on the evidence presented, it appears that there is market-wide herding behaviour in developed markets. In particular, empirical evidence has shown in many cases that herding behaviour is stronger before or after a crisis than during it (Ferreruela and Mallor, 2021; Wen et al., 2021). On the other hand, there are many studies that show that herding behaviour becomes stronger during crises or when markets are more volatile (Espinosa-Méndez & Arias, 2020; Aslam et al., 2021; Galariotis et al., 2015; Ouarda et al., 2013; Pochea et al., 2017). The cross-correlation between studies is also increased by the fact that, for example, Bogdan et al. (2022) did not find herding behaviour in developed markets at all. The variability in results is due to the fact that measures of herding behaviour are far from perfect, and that study designs and methods vary across studies (Spyrou, 2013).

### **3.4 Hypotheses of the study**

As highlighted in the previous chapters, research on herding behaviour follows a variety of perspectives and methodologies. The main trends in herding literature are institutional herding and market-wide herding. Within these trends, there are many different areas of research on herding behaviour. Research on market-wide herding is mainly divided into research on developed markets and research on emerging markets. This is because emerging markets exhibit herding behaviour more frequently and outside of crisis periods due to market volatility and a variety of other factors. In addition, previous literature has examined other factors that influence market-wide herding. First, by examining how firm size, market microstructure and fundamental and non-fundamental information affect market-wide herding behaviour. The field of research on herding

behaviour is highly fragmented and the results are sometimes contradictory due to the wide range of methodologies and multiple approaches. According to Spyrou (2013), the contradictory nature of the research findings can be partly explained by the diversity of research methods used by researchers. However, a comprehensive study can contribute to a better understanding of the phenomenon of herding behaviour. This study therefore draws on established research methods in areas where previous research already exists. This is done to compare new findings with previous research and to maintain the consistency of the methods used in the empirical work.

According to the efficient market hypothesis, the dispersion of stock returns should follow a normal distribution. In contrast, behavioural theory suggest that herding behaviour causes the dispersion of stock returns to deviate from their expected values. Therefore, the EMT serves as the null hypothesis base for this thesis. Market-wide herding behaviour is possible if the dispersion of stock returns is not normally distributed. Hence, the null hypothesis is:

$H_0$ : There is no herding behaviour in developed markets.

The possibility of herding exists if the null hypothesis is successfully rejected. This thesis then examines whether herding behaviour occurs in developed markets, focusing on the US, the UK and German stock markets. Previous literature has found herding behaviour in various developed markets, especially during crises. For example, Galariotis et al. (2015) present findings on herding in the US and UK markets. In addition, Aslam et al. (2021) find herding behaviour in UK markets. There are also many studies on the markets of different European countries and on the European market in general. These studies find herding behaviour in different parts of the hemisphere (Ferreuela & Mallor, 2021; Aslam et al., 2021; Ouarda et al., 2013; Pochea et al., 2017). Evidence of herding behaviour in developed markets is also found in Australia and Hong Kong (Espinosa-Méndez & Arias, 2020; Wen et al., 2021).

Following the publication of Christie and Huang (1995) research, there has been an increasing amount of literature studying herding behaviour during market crises. A common way to measure herding behaviour during market crises is to divide the crisis period into smaller intervals. This allows the change in herding levels between these intervals to be measured. The market-wide herding behaviour of interest rates during a pandemic is studied by Dhallin and Singh (2020) and Ferreruela and Mallor (2021) using several different time periods as proxies. This study uses a similar methodology to investigate herding behaviour during COVID-19 pandemic. The time periods sampled in this study are defined as a corona based on the onset of the pandemic as follows:

Entire sample period: 01.01.2017-31.05.2023

Pre-COVID period: 01.01.2017-30.01.2020

Outbreak period: 30.01.2020-01.06.2020

Post-COVID period: 01.06.2020-31.05.2023

The existing literature suggests that herding behaviour is lower after the crisis breaks out and higher before the crisis occurs. (Espinosa-Méndez & Arias, 2020; Ferreruela & Mallor, 2021; Aslam et al., 2021; Galariotis et al., 2015; Ouarda et al., 2013; Pochea et al., 2017). Thus, it can be assumed that when the sample in this study is divided into smaller sub-periods, herding behaviour occurs just before the outbreak period of the crisis. Therefore, the first hypothesis is formulated as follows:

$H_1$ : Herding behaviour is higher before the outbreak period of the COVID-19 pandemic in developed stock markets.

The motivation for the second hypothesis comes from the observations in the previous literature. Since Christie and Huang (1995), many studies have investigated the sensitivity of herding behaviour to different market situations. They investigated the asymmetry of herding behaviour between up and down-market days. Previous studies present contradictory results on the asymmetry of herding behaviour. According to Chang

et al. (2000), Chiang and Zheng (2010), Demirer et al. (2010) and Philippas et al. (2013) herding behaviour is more prevalent on negative market days. To the contrary, Tan et al. (2008) and Economou et al. (2015) present evidence of significant asymmetries in herding behaviour during positive market days. Given the conflicting, this thesis investigates if herding behaviour in developed markets is asymmetric during up and down-market days by testing the following hypothesis:

$H_2$ : Herding behaviour is asymmetric and is more prevalent on down-market days on a market-wide basis in the developed stock markets.

## 4 Methodology, Data and Descriptive Statistics

### 4.1 Methodology

Market-wide herding can be said to be based on studies by Christie and Huang (1995) and Chang et al (2000). Following these studies, different versions of measuring herding behaviour have been created to make the measurement more meaningful. For example, different variables, such as macroeconomic news and market microstructure, have been added to the models to study their impact on herding behaviour. However, the basic rationale for measuring market-wide herding behaviour has remained the same since the models developed by Christie and Huang (1995) and Chang et al (2000).

This thesis uses Chiang and Zheng's (2010) approach to measure whether market-wide herding occurs in the German, US and UK stock markets. The measurement method Chiang and Zheng (2010) differs slightly from the method proposed by Chang et al. (2000). Cross-sectional standard deviations are defined as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (13)$$

where  $R_{i,t}$  is the return of a stock  $i$  on day  $t$ ,  $R_{m,t}$  is the market return on day  $t$ , and  $N$  is the total number of stocks. After the daily CSADs are calculated, Chiang and Zheng (2010) define their CSAD regression equation as follows:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \quad (14)$$

where in addition to the first equation,  $\gamma_0$  is the constant coefficient,  $\gamma_1$  is the coefficient for market return on day  $t$ ,  $\gamma_2$  is the coefficient for absolute market return on day  $t$ ,  $|R_{m,t}|$  is the absolute market return on day  $t$ ,  $\gamma_3$  is the coefficient for the squared market return on day  $t$ ,  $R_{m,t}^2$  is the squared market return on day  $t$  (representing the non-linear component), and  $\varepsilon_t$  is the error term.

There may be asymmetries in investor behaviour, which Chiangin and Zhengin (2010) have accounted for by adding a factor  $R_{m,t}$  to the regression equations presented by Christie and Huang and Chang et al. (2000). In rational asset pricing models, the relationship between stock return deviations and market returns is assumed to be linear. Therefore, it is important to focus on the coefficient of the nonlinear component of the regression equation,  $\gamma_3$ . Indeed, a statistically significant and negative  $\gamma_3$ , is interpreted as an indication of market-wide herd behaviour.

The first regression is used to test the first and the second hypothesis. The third hypothesis requires some further specification. In order to measure if asymmetries exist between up and down-market days within the observed stock markets this thesis utilise the methodology of Chiang and Zheng (2010) and the following equation is:

$$CSAD_t = \gamma_0 + \gamma_1(1 - D)R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3(1 - D)R_{m,t}^2 + \gamma_4DR_{m,t}^2 + \varepsilon_t \quad (15)$$

Where,  $D$  is a dummy variable which equals one if the market return is negative ( $R_{m,t} < 0$ ) and zero if the market return is positive ( $R_{m,t} \geq 0$ ). Consequently, when the coefficient  $\gamma_3$  is statistically significant and negative, it indicates that market-wide herding behaviour exist during the rising market days. On the other hand, a statistically significant and negative coefficient  $\gamma_4$  suggest herding behaviour during days when the market is declining.

## 4.2 Data

The study uses data from the German, US and UK stock markets in order to measure herding behaviour in these specific markets during COVID19. The data includes three major stock indices: Deutscher Aktienindex (DAX) for the German stock market, Dow Jones Industrial Average Index (DJIA) for the US stock market and FTSE100 for the UK stock market. As the DAX, FTSE 100 and DIJA are often compared with each other and

are similar in terms of their company ranges, these indices have been chosen in this thesis to reflect the markets of different countries.

The DAX is the most famous stock market index for the German market, consisting of the 40 largest German companies in terms of trading and volume on the Frankfurt Stock Exchange. The DAX is a market value-weighted index, which means that the shares are weighted according to the market value of the companies. In addition, it is a total return index, in other words dividends paid are included in the graph. The DAX index is widely followed and is an influential European index, with Germany being the largest single economy in Europe. DJIA tracks the share prices of 30 major US companies and is one of the oldest equity indices in the world. The aim of the index is to provide a snapshot of the US stock market, focusing on large companies. The DJIA index was originally designed to facilitate the tracking of industrial stocks in the US stock market. Although the index focuses on industrial companies, other companies have been added to the index over the years. Stock prices determine the weight of a stock in the DJIA index. The higher the stock price, the greater the weight of the stock in the index. The FTSE 100 Index is the most widely followed stock index on the London Stock Exchange and comprises the 100 largest companies listed on the London Stock Exchange by market capitalisation.

All returns are measured in local currency. DAX returns are measured in EUR, DJIA returns in USD and FTSE 100 returns in GBP. The sample period is January 1.1.2017-30.5.2023. The DAX index has 40 stocks, the DJIA index has 30 stocks, and the FTSE 100 index has 100 stocks, but new stocks have been added to the indices over the sample period. Due to these changes, it has been decided that for stocks added to the index after the start of the sample period, the average return of the market index for the days when the stock was not in the index will be added.

The total number of observations is 1737 for the German market, 1723 for the US market and 1729 for the UK market. The difference in observations between markets is due to several factors, but mainly to national holidays when the stock exchange is closed.

National holidays are different for each stock exchange. Daily returns for stocks and indices are calculated using the daily closing prices. Daily returns are calculated using the following formula:

$$R_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \quad (16)$$

where  $R_t$  describes the daily change in the closing price of a stock between time  $t - 1$  and  $t$ .  $\ln$  is the natural logarithm,  $P_t$  is the closing price of the stock at time  $t$  and  $P_{t-1}$  is the closing price of the stock the day before time  $t$ .

### 4.3 Descriptive statistics

Since the null hypothesis suggests that the dispersion of stock returns in all three stock markets is normally distributed, the null hypothesis can be tested by presenting descriptive statistics and observing key variables on the data presented earlier. The null hypothesis can be rejected if it is found that the level of skewness and kurtosis is significant for stock returns. In this case, it can be concluded that the distribution of stock returns does not follow a normal distribution, and it can be argued that herding behaviour is possible in this market. The descriptive statistics are shown in Table 1 below, separately for each of the observed stock markets.

**Table 1.** Descriptive statistics of cross-sectional absolute deviations

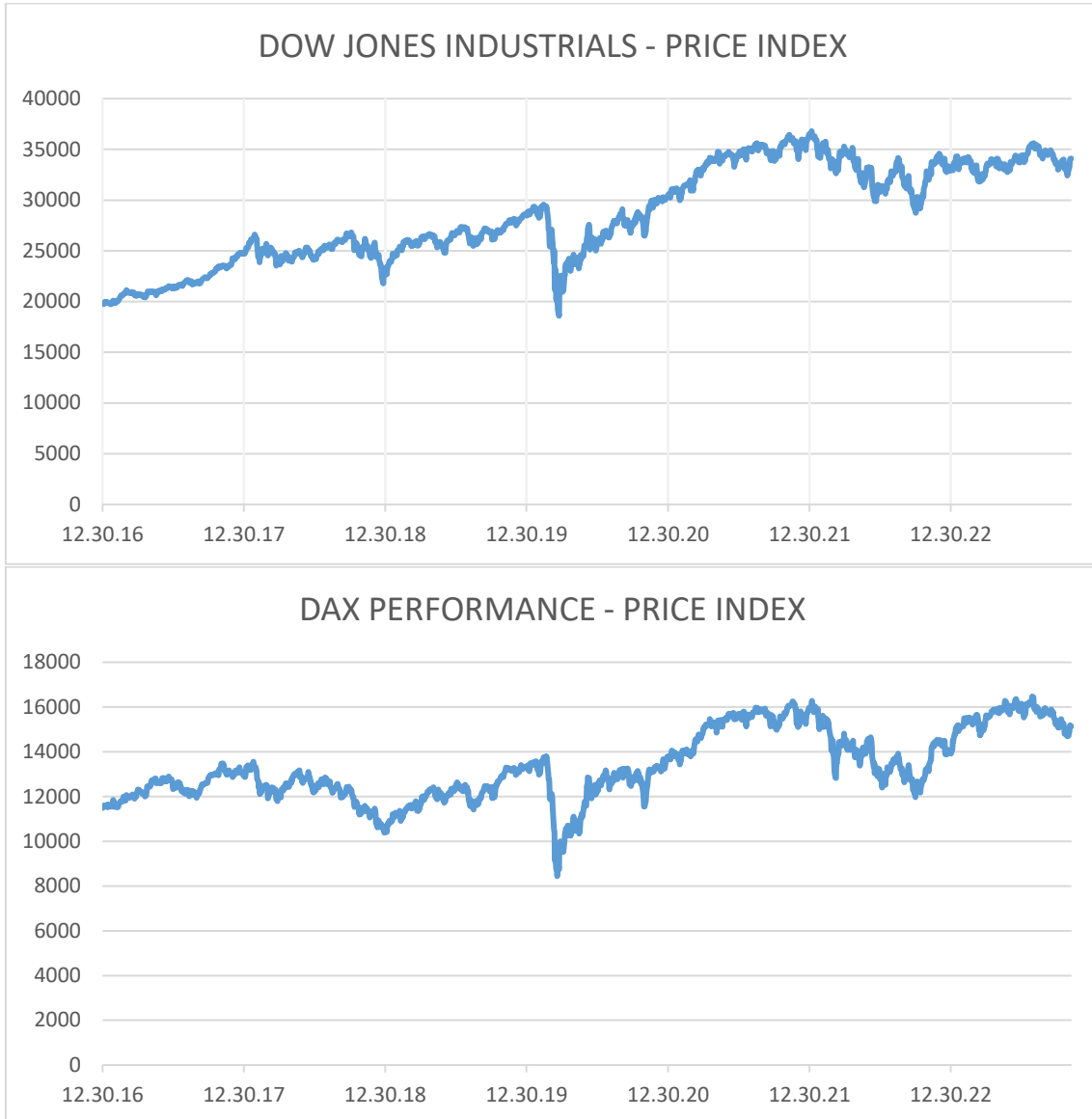
Market	Germany		US		UK	
	<i>Rm</i>	<i>CSAD</i>	<i>Rm</i>	<i>CSAD</i>	<i>Rm</i>	<i>CSAD</i>
Mean	0,0002	0,0105	0,0004	0,0089	0,0000	0,0110
Median	0,0006	0,0096	0,0007	0,0080	0,0006	0,0099
Std. Dev.	0,0122	0,0046	0,0122	0,0042	0,0102	0,0048
Kurtosis	14,3321	13,9937	22,4008	30,0046	16,5371	21,6512
Skewness	-0,6698	2,8402	-1,0030	3,8623	-1,1294	3,5418
Minimum	-0,1305	0,0033	-0,1384	0,0024	-0,1151	0,0039
Maximum	0,1041	0,0451	0,1076	0,0590	0,0867	0,0610
Observations	1737	1737	1723	1723	1729	1729

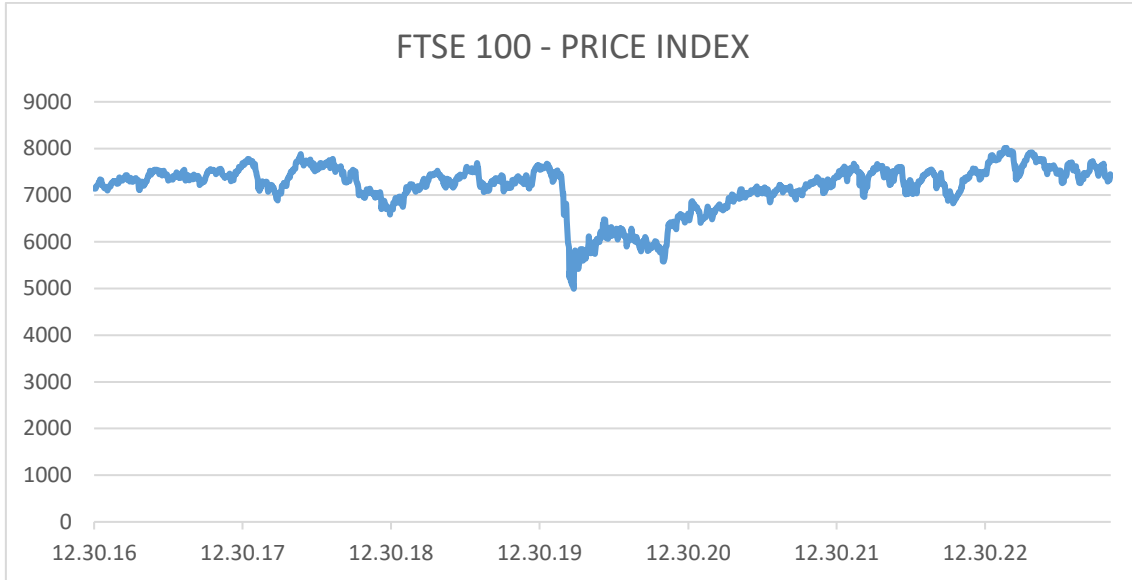
This table reports the descriptive statistics of daily market index returns (*Rm*) and daily cross-sectional absolute deviations (*CSAD*) for German, US and UK stock markets. The sample period is 1.1.2017-30.5.2023.

If the dispersion of stock returns is normally distributed, the skewness of a normal distribution should equal zero. For market returns (*RM*) in each observed market, the reported skewness is significantly negative, as it can be seen from table 1. The kurtosis of a normal distribution should be close to three. However, highly significant and positive measures of kurtosis are reported for all three markets. Based on these observations, the null hypothesis can be rejected.

According to Table 1, the US and German markets have mean daily market returns close to zero and the UK market has a mean of zero. The minimum and maximum daily market returns are at the same level for all markets. For the US and German markets, the maximum values are between 10% and 11% and the minimum values between -13% and -14%. The minimum and maximum daily market returns for the UK market are closer together, with a minimum value of -11.5% and a maximum value of 8.7%. Based on the underlying data, the minimum daily market returns for each market were recorded with the outbreak of the COVID-19 pandemic. Minimum values were recorded in the US market on 31 January 2020, in the German market on 30 January 2020 and in the UK market a few days later 4 February 2020. Maximum market returns were recorded in all markets one week after the minimum return occurred, in the US market

on 6 February 2020, in the German market on 7 February 2020 and in the UK market on 12 February 2020. The largest variation in market returns therefore occurred during the outbreak of the COVID19 pandemic.





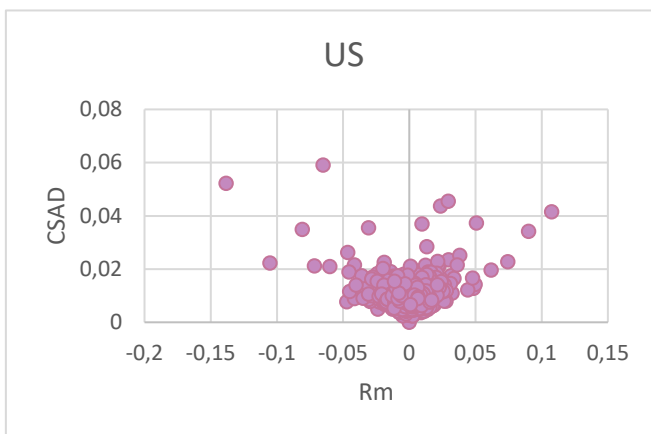
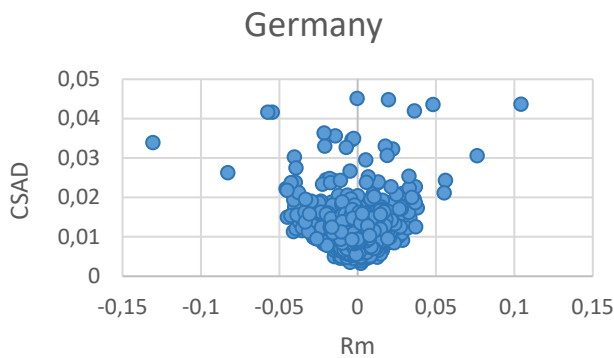
**Figure 3.** The daily returns of the DIJA, DAX and FTSE100

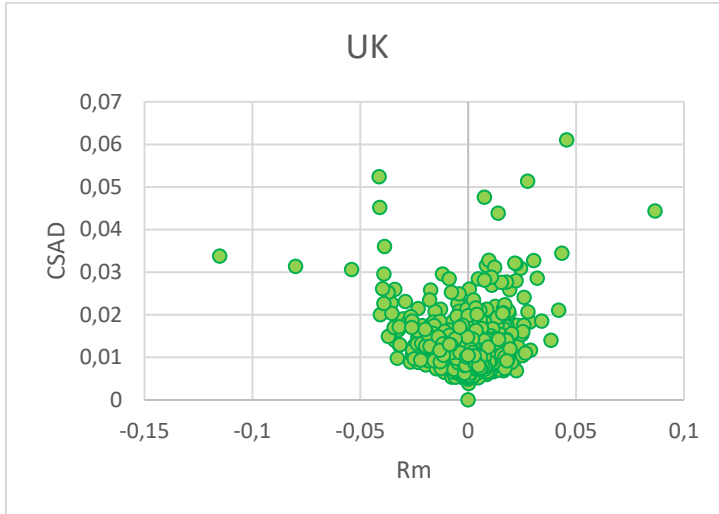
The outbreak period of the COVID19 pandemic was similar for all three indices, as observed in the outbreak areas of the graphs. Figure 3 shows that during the sample period, the lowest daily return for each index was observed at the outbreak site, as already noted earlier in Table 1. The price levels of the Dow Jones index and the DAX index have followed a similar trend. For both indices, the price level increased after the COVID-19 pandemic and is higher than before the pandemic. The FTSE 100 index has also risen since the pandemic but is not risen higher than before the pandemic during the sample period.

For all three markets, the means and standard deviations of the cross-sectional absolute deviation (CSAD) are close, as shown in Table 1. However, Chang et al. (2000) point out that CSAD alone is not a measure of herding. Chang et al. (2000) argue that market-wide herding behaviour should be examined through the relationship between CSAD and stock market returns. An indication of market-wide herding behaviour is a non-linear increasing or decreasing relationship between CSAD and stock market returns.

Figure 4 below shows the relationship between CSAD and stock market returns. In all three markets, non-zero market returns increase the dispersion of stock returns

(CSAD). Looking more closely at the observations in Figure 4, it can be seen that in the US market, in contrast to the other markets, the largest dispersion of stock returns was observed on the day of the negative market return. In the UK market, the largest dispersion of stock returns was observed on the day of a positive market return. In Germany, the largest dispersion of stock returns was also observed on a positive market return day, but as can be seen from the graph, the dispersion of stock returns is at the same level on both negative and positive market return days. Figure 4 shows that in all markets the dispersion of stock returns increases at a similar rate when the market return deviates from zero. As observations are concentrated or dispersed differently across markets, the scaling may not vary across markets. This is important to keep in mind when analysing the dispersion plot.





**Figure 4.** The relationship between the daily cross-sectional absolute deviations and market returns for German, the US and the UK markets

The relationship between CSAD and market returns in all three markets is fairly linear throughout the sample period, as can be seen in Figure 4. This may indicate that herding does not occur in any of the three markets. However, in each market the dispersion of stock returns shows the largest individual variations when market returns are either above 5% or -5%, which may lead to the detection of herding behaviour. However, it is not possible to draw firm conclusions from the graphs alone. In the next chapter, herding will be better studied through empirical research.

## 5 Empirical results

The empirical part is divided into two parts, organised according to the proposed hypotheses. Both parts follow a structured approach: stating the hypothesis, analysing the results, and assessing the match between the assumptions made and the obtained results. The hypotheses formulated in section 3.4 are tested using the regression model presented in the methodology section.

### 5.1 Market-wide herding in German, US and UK markets

As the previous literature shows, it is reasonable to assume that herding takes place in the developed markets. Moreover, as noted earlier, the null hypothesis was rejected, implying that herding behaviour occurs in developed markets. The first hypothesis is tested by dividing the sample period into shorter sub-periods, but first we investigate the prevalence of herding behaviour over the whole sample period in the developed markets. To test for the whole sample period, equation (11) is used.

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \quad (11)$$

As stated earlier, in equation (11) the coefficient  $\gamma_3$  defines the level of herding behaviour and the squared market return  $R_{m,t}^2$  represents the non-linear component of the formula. Herding behaviour occurs in the market if the regression test provides a negative and statistically significant value of  $\gamma_3$ . Table 2 below shows the regression results for the whole sample period from 01.01.2017 to 31.05.2023.

**Table 2.** The regression results for the whole sample period

<b>Market:</b>	Germany	US	UK
<b>Coefficients:</b>			
Intercept	0,0078*** (53,643)	0,0066*** (53,780)	0,0082*** (54,070)
$\gamma_1$	0,0105 (1,302)	0,0079 (1,102)	0,0338** (3,236)
$\gamma_2$	0,3062*** (17,438)	0,2658*** (17,252)	0,3769*** (17,366)
$\gamma_3$	-0,2902 (-1,070)	0,2717 (1,313)	-0,2710 (-0,709)
Adjusted R-squared	0,2954	0,3613	0,2911

Table 2 shows that the regression test for the whole sample period does not provide any statistically significant findings on herding behaviour in developed markets. A negative and statistically significant  $\gamma_3$  coefficient would imply that herding behaviour is present in the market. Although the  $\gamma_3$  coefficient is negative for the German and UK markets, the results are not statistically significant due to lack of explanatory power. Thus, the finding of herding behaviour over the whole sample period is random. In contrast to the German and UK markets, the  $\gamma_3$  coefficient for the US market is positive, which would imply that the US market has experienced anti-herding behaviour throughout the sample period. This result is also not statistically significant, so it cannot be concluded that the US market has experienced anti-herding throughout the sample period. In conclusion, testing the regression over the entire sample period does not establish the prevalence of herding behaviour but does not reject its existence either. In addition, according to previous literature, the presence of herding behaviour varies depending on the period used in the regression. Follow-up market-wide herding behaviour in developed markets is examined in more detail in different sub-periods.

## 5.2 Market-wide herding during different time periods

As discussed in section 3.3.4, many previous studies show that the level of herding behaviour varies in times of crisis. More specifically, the previous literature suggests that herding behaviour occurs in developed markets, especially just before the outbreak period of crises (Espinosa-Méndez and Arias, 2020; Ferreruella & Mallor, 2021; Aslam et al., 2021; Galariotis et al., 2015; Ouarda et al., 2013; Pochea et al., 2017). Having previously rejected the null hypothesis and found that herding does occur in developed markets, this paper now explores this finding further by dividing the full sample size into three shorter time periods. We investigate the variation in market-wide herding in developed markets before the COVID-19 pandemic, during the outbreak period and after the pandemic. To test the first hypothesis, we investigate the variation in the level of herding behaviour, and at which point in the crisis it occurs.

$H_1$ : Herding behaviour is higher before the outbreak period of the COVID-19 pandemic in developed stock markets.

First hypothesis is tested using formula 11 to examine the level of herding behaviour. In a departure from the testing of the first hypothesis, we conduct three separate regression tests for each of the three stock markets. The regression test is conducted for the period before COVID-19, the outbreak period of COVID-19 and the period after COVID-19. The regression results for the second hypothesis can be seen in table 3 below.

**Table 3.** The regression results for different sub-periods.

<b>Market:</b>	Germany	US	UK
<b>Coefficients:</b>			
Intercept	0,0065*** (39,368)	0,0055*** (39,562)	0,0075*** (41,545)
y1	-0,0082 (-0,759)	-0,0101 (-0,912)	-0,0376 (-2,591)
y2	0,3083*** (7,933)	0,3288*** (10,668)	0,3456*** (7,152)
y3	-4,4027** (-2,634)	-5,2517*** (-4,999)	-9,3009*** (-3,944)
Adjusted R-squared	0,1948	0,2032	0,1007
<b>Pre-COVID period: 01.01.2017-30.01.2020</b>			
<b>Market:</b>	Germany	US	UK
<b>Coefficients:</b>			
Intercept	0,0100*** (6,609)	0,0099*** (6,951)	0,1093*** (6,291)
y1	0,0461 (1,478)	0,0017 (0,069)	0,0743. (1,867)
y2	0,4100*** (4,263)	0,2754** (3,308)	0,6105*** (5,059)
y3	-1,4262 (-1,539)	-0,0772 (-0,099)	-3,1133* (-2,339)
Adjusted R-squared	0,3345	0,4437	0,3474
<b>Outbreak period: 30.01.2020-01.06.2020</b>			
<b>Market:</b>	Germany	US	UK
<b>Coefficients:</b>			
Intercept	0,0097*** (43,154)	0,0077*** (40,621)	0,0099*** (43,168)
y1	-0,0102 (-0,915)	0,0093 (0,808)	0,0253. (1,797)
y2	0,1837*** (5,504)	0,2262*** (7,410)	0,1357** (2,910)
y3	1,8330* (2,189)	-0,3605 (-0,401)	6,2831*** (3,917)
Adjusted R-squared	0,2227	0,1659	0,2168
<b>Post-COVID period: 01.06.2020-31.05.2023</b>			

In line with the results of regression tests in the previous literature, Table 3 shows that herding behaviour occurs in all markets just before the COVID-19 pandemic. As can be seen in Table 3, the  $\gamma_3$  coefficient is clearly negative and statistically significant in all three markets in the pre COVID-19 period. The reliability of the findings is confirmed by the fact that the results for the UK and US markets are highly statistically significant, with a p-value of less than 0.001. In addition, the result for the German market is highly statistically significant with a p-value below 0.01.

During the outbreak period only the UK stock market shows herding behaviour, although at a lower level, with a  $\gamma_3$  coefficient of -3.1133, compared to a pre COVID-19 period with a  $\gamma_3$  coefficient of -9.3009. Moreover, although the result is statistical significance, it is slightly less significant with a p-value below 0.05. For the US and German stock markets, the  $\gamma_3$  coefficient is also negative, which would imply that herding behaviour occurs during the outbreak period. However, the results are not statistically significant, so it cannot be confidently concluded that the results are anything other than coincidence.

According to Table 3, the UK and German stock markets are rationally performing without herding, in the post COVID-19 period. For the UK market, the  $\gamma_3$  coefficient is extremely positive at 6.2831 and statistically significant with a p-value below 0.001. For the German market, the  $\gamma_3$  coefficient is slightly lower at 1.8330 and statistically significant with a p-value below 0.05. These results show that after the pandemic subsided, the UK and German stock markets levelled off and rationed. For the US stock market, the  $\gamma_3$  coefficient is negative according to Table 3, but not statistically significant, so a negative  $\gamma_3$  coefficient is random according to this regression test.

In summary, based on the results in Table 3,  $H_1$  is acceptable as herding behaviour is observed in the pre COVID-19 period, and the results are statistically significant. Furthermore, in the post COVID-19 period, the stock markets levelled off and rationed and no herding behaviour is observed in the UK and German markets. The variation in the

level of herding behaviour between the pre and post COVID-19 period is evidenced by the fact that in both the UK and German stock markets have statistically significant and different coefficients in both periods.

### **5.3 Market-wide herding during up and down-market**

Herding is often associated with market crises, when panicked and frightened investors overreact and distrust their own information. However, previous literature has shown that herd behaviour also occurs on positive market days (Ourda et al., 2013; Pochea et al., 2017; Tan et al., 2008; Economou et al., 2015). During market booms, investors are enthusiastic and optimistic, abandoning their own knowledge and emulating the stock purchases of others. Much previous literature has examined asymmetric herding, i.e. whether herding occurs more on positive or negative market days. The results of the existing research are contradictory. According to Chang et al. (2000), Chiang and Zheng (2010), Demirer et al. (2010) and Philippas et al. (2013), herding behaviour is more common on negative market days. In contrast, Tan et al. (2008) and Economou et al. (2015) provide evidence of significant asymmetries in herding behaviour on positive market days.

Although there is a large body of research on asymmetry, little research has been done on asymmetry during the COVID-19 pandemic. Figure 3 shows that during the outbreak of the COVID-19 pandemic, stock markets fell rapidly, followed by a rapid rise. This makes it interesting to investigate asymmetric herding behaviour during the COVID-19 pandemic. By testing  $H_2$ , we investigate whether herding behaviour is asymmetric during the COVID-19 pandemic in the German, US and UK markets.

$H_2$ : Herding behaviour is asymmetric and is more prevalent on down-market days on a market-wide basis in the developed stock markets.

To test  $H_2$ , a different regression formula is used than for  $H_1$ . To test  $H_2$ , formula 12 is used as presented in section 4.1. As presented in section 4.1, formula 12 uses dummy variables. In addition, the formula 12 used to test  $H_2$  has an additional coefficient  $\gamma_4$ .

$$CSAD_t = \gamma_0 + \gamma_1(1 - D)R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3(1 - D)R_{m,t}^2 + \gamma_4DR_{m,t}^2 + \varepsilon_t \quad (12)$$

Since the regression model has an additional coefficient  $\gamma_4$ , the interpretation of the results differs from  $H_1$ . Herding occurs on positive market days when the coefficient  $\gamma_3$  is negative and statistically significant. A negative  $\gamma_4$  implies that herding is observed on negative market days. Table 4 shows the results of the regression.

**Table 4.** The regression results for up and down-market days

<b>Market:</b>	Germany	US	UK
<b>Coefficients:</b>			
Intercept	0,0079*** (53,681)	0,0066*** (53,287)	0,0083*** (54,126)
y1	0,2801*** (12,152)	0,2731*** (13,433)	0,3531*** (12,012)
y2	0,3109*** (15,470)	0,2581*** (14,297)	0,3601*** (14,536)
y3	0,7391 (1,645)	0,2853 (0,827)	1,7850* (2,457)
y4	-0,7205* (-2,329)	0,2668 (1,136)	-0,8298* (-1,991)
Adjusted R-squared	0,2983	0,3609	0,2951

Table 4 shows that the results are only statistically significant for the German and UK markets. In both markets, the  $\gamma_4$  coefficient is negative, indicating that herding occurs in the German and UK markets on negative market days during the sample period. For both markets, the results are statistically significant with a p-value below 0.05. Furthermore, for the UK market, the regression test shows that the coefficient  $\gamma_3$  is positive and statistically significant with a p-value below 0.05, indicating that herding did not occur in the UK market on positive market days during the sample period. On the other hand, the US market shows no evidence of herding during the sample period according

to the regression test, but the results are not statistically significant, so the coefficients are random.

The results of the regression test show that herding behaviour was asymmetric in the German and UK markets during the COVID-19 pandemic, as only negative market days showed herding behaviour. The results seem logical in relation to previous assumptions. The results may be explained by the fact that the sample period includes both the COVID-19 outbreak and the war in Ukraine, which caused large stock market reactions. These may explain the fact that the results of the regression tests suggest that herding occurs in the German and UK markets on negative market days.

## 6 Limitations

There are several limitations associated with this study that need to be acknowledged when reviewing the empirical results presented in this study. The limitations of this study relate to the assumptions of the CSAD model used as the methodology for the empirical test, which do not necessarily correspond to reality. In addition, results obtained from the CSAD measure can be sensitive to the chosen time frame of analysis and the quality and availability of the data used in the study.

CSAD model of Chang et al.(2000) used in this study relies on specific statistical assumptions that may not always hold in real-world market conditions. First, the CSAD model assumes that the return distributions are homoscedastic, i.e. the dispersion of stock returns is constant over time. In reality, stock market volatility can vary considerably, especially during market shocks or economic crises, which can affect the reliability of the CSAD measure. Second, CSAD assumes that stock returns follow a normal distribution. Equity returns are often abnormally distributed, especially during extreme market events. This can lead to erroneous conclusions about herding behaviour. Third, the model assumes that the deviations of all stock returns from the mean are equally important and independent of each other. Stocks may be correlated with each other, for example within the same sector, which may lead to underestimation or overestimation of herding behaviour. Lastly, the CSAD model assumes a linear relationship between stock returns and market returns. Stock market behaviour can be non-linear, especially during exceptional market conditions. This may affect the ability of the model to accurately capture herding behaviour.

The time frame chosen for CSAD analysis will affect the effectiveness of the CSAD measure. The time frame must be long enough to detect significant herding behaviour phenomena. Short time frames may miss long-term trends in herding behaviour and long-time frames may mask short-term episodes. Previous literature has shown that the level of herding behaviour varies under volatile market conditions. Therefore, in this thesis, the whole sample period is divided into three shorter time periods before

the COVID-19 pandemic, the out-break period and the post COVID-19 period. The selected periods have the potential to significantly affect the results of the empirical test, which should be considered when examining the results of this thesis.

Finally, the completeness and representativeness of the data available to study herding behaviour over the whole period of analysis is a limitation of empirical research. Gaps in the data, such as missing data or low frequency data, can skew the CSAD measure and lead to biased results. For example, new stocks have been added to the indices included in the data for this thesis empirical study over the sample period. Due to these changes, it has been decided that for stocks added to the index after the start of the sample period, the average return of the market index for the days when the stock was not in the index will be added. In addition, different numbers of observations are obtained for the market indices of different countries, mainly due to national holidays when the stock market is closed. These factors may distort the CSAD model. Furthermore, according to Sproy (2013), herding behaviour is problematic to study if detailed datasets and private information of investors prior to trading are not available. It is difficult to test whether investors mimic the behaviour of others and discard their own private information. Thus, in this study, too, the empirical research has been done implicitly by assumptions.

## 7 Conclusion

This thesis studies the herding behaviour in the developed stock markets during the COVID-19 pandemic. The main purpose of this study is to investigate and compare the behaviour of investors in these markets before and during the COVID-19 pandemic. More specifically, this thesis examines whether market-wide herding behaviour occurs in the British, German and US stock markets on a time frame 1.1.2018-30.5.2023. The second purpose is to investigate if the selected stock markets have an asymmetric herding behaviour on a market-wide basis, i.e. whether it only happens in the market up or down.

The empirical results of this thesis show that when the sample period is divided into shorter sub-periods before the pandemic, the pandemic out-break period and the post-pandemic period, herding behaviour occurs in all three markets. In all three markets, herding behaviour was clearly evident before the onset of the pandemic. In addition, it was also present in the UK market during the pandemic outbreak period. In the post COVID-19 period, the UK and German stock markets are rationally performing without any herding behaviour.

As the literature suggests, herding behaviour should be stronger before or after a crisis than during a crisis in the developed markets. On the other hand, there are many studies showing that herding should be stronger during crises or when markets are more volatile. In addition, there is literature suggesting that herding behaviour should not be found in developed markets. As noted earlier, the results of existing research on herding behaviour are contradictory and the results of empirical research on herding behaviour can be significantly influenced by varying the sample period. The results of this thesis also vary depending on the time frame of the sample. No statistically significant results on herding behaviour was observed over the whole sample period, but in shorter sample periods herding behaviour was observed in all markets before the outbreak of the pandemic.

This thesis uses a dummy variable to examine asymmetric herding behaviour over the sample period. In other words, the use of a dummy variable allows us to examine whether herding behaviour occurs more on positive or negative market days. Asymmetric herding behaviour is expected to occur in developed markets, but existing research is conflicting on whether herding is asymmetric on positive or negative market days. The results of this thesis show that herding behaviour was asymmetric in the German and UK markets during the COVID-19 pandemic. In these markets, herding occurs on negative market days. Empirical evidence suggests that herding was not asymmetric in the US market.

This thesis covers the daily returns of the DAX, FTSE100 and DJIA, the major indices of the German, US and UK markets, for the period 1.1.2017-30.5.2023, providing the latest available data for studying herding behaviour in these markets. Thus, the empirical findings and general insights of this thesis are timely and relevant for comparison by other researchers. Furthermore, this thesis contains implications that can be considered in the light of practical decision making. Once herding behaviour is understood as a phenomenon by financial institutions, portfolio managers and other financial professionals, as well as individual investors, it can be used in the trading strategies to pursue profit. Trading strategies can be constructed according to the prevalence of herding behaviour. For example, the results of this study suggest that herding behaviour is strong in the German, UK and US markets just before the onset of the crisis, which could be used to inform trading strategies in these markets in times of crisis and high volatility.

Future research could take a closer look at the limitations and how to respond to the challenges they pose. There are many limitations to the measures used to study herding behaviour that can undermine the reliability of the results. For example, the CSAD model used in this, and many other studies of herding behaviour has many limitations and assumptions that have been highlighted several times in this thesis. Therefore, for future research, methodological improvements would bring reliability to the results of the studies. In addition, this would make the studies on herding behaviour more in line with each

other and reduce contradictions. In addition, research on future needs to better address what leads to herding behaviour. It would be important to be able to distinguish spurious herding from intentional herding. In other words, does herding behaviour result from investors making similar principal trades because they all have the same information and react to the same changes in fundamental factors, or does herding behaviour result from investors rejecting their own private information when trading and intentionally following the actions of other investors. This is currently difficult to investigate as it would require detailed datasets and private information from investors prior to trading.

In conclusion, times of crisis offer a remarkable perspective for studying herding behaviour, especially in developed markets. As markets are more efficient in developed markets than in emerging markets, herding behaviour is less prevalent in developed markets. However, it is also important to study herding behaviour in developed markets, as it can be used in investment strategies in the search for profit. For future studies, it is very important to develop models to measure herding behaviour to make the results more reliable and consistent across studies.

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