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Herding in Financial Markets and Its Impact on Stock Market Volatility

Evidence from European stock markets

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ABSTRACT :

Herd behavior, or the action of investors following other investors, has been widely discussed in academic literature in the field of behavioral finance. Behavioral finance anomalies can have important implications for stock market dynamics, particularly with respect to market volatility. This paper examines the presence of herding in the European financial markets between the years 2017 to the beginning of the year 2023. The herding behavior is being examined in the European stock markets using the Cross-Sectional Standard Deviation, CSSD, model by Chang and Huang (1995) and the Cross-Sectional Absolute Deviation, CSAD, model by Chang, Cheng and Khorana (2000). Furthermore, this paper examines whether herd behavior has had an impact on market volatility and vice versa. This is being measured by combining the herding measures with two different volatility measures, Generalized Autoregressive Conditional Heteroskedasticity, GARCH, and Exponentially Weighted Moving Average, EWMA, models.

From the empirical research this study finds that herding has occurred during the most bearish days during the period between 1.1.2020 to 31.1.2023, which is referred as the crisis period since there has been global Covid-19 pandemic and the outbreak of the Russo-Ukrainian war during the crisis period. Moreover, both herding measures showed increasing herding compared to the crisis period. No herding was detected during the pre-crisis period. This study also found that herding has a decreasing effect on market volatility both during the pre-crisis and crisis periods. The results showed no clear pattern that an increase in volatility automatically increases herding but showed that herding does increase during the most volatile period in the European stock market.

The effect of herding on volatility has been an open issue and the result from this study supports the most recent study conducted of the matter but contradicts some of the earlier studies. Overall, this thesis provides valuable insights into the investor's behavior during turbulent market conditions, and the impact of that behavior on market volatility. The results are valuable for investors to better manage risks when acting in the financial markets.

KEY WORDS: Herding behavior, Behavioral finance, Stock market Volatility, Market efficiency, Euronext100

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TIIVISTELMÄ :

Laumakäyttäytymisestä, eli sijoittajien tavasta imitoida muita sijoittajia, on ollut laajasti keskustelua akateemisessa kirjallisuudessa käyttäytymistaloustieteen viitekehyksessä. Käyttäytymistaloustieteen tunnistamilla rationaalisen käyttäytymisen poikkeamilla voi olla tärkeitä vaikutuksia osakemarkkinoiden dynamiikkaan, erityisesti markkinoiden volatiliteetin osalta. Tässä tutkielmassa tarkastellaan laumakäyttäytymisen esiintymistä Euroopan rahoitusmarkkinoilla vuosien 2017 ja 2023 alun välillä. Laumakäyttäytymistä tutkitaan Euroopan osakemarkkinoilla käyttämällä Christien ja Huangin (1995) CSSD-mallia ja Changin, Chengin ja Khoranan (2000) CSAD-mallia. Lisäksi tässä tutkimuksessa tutkitaan, onko laumakäyttäytymisellä ollut vaikutusta markkinoiden volatiliteettiin ja päinvastoin, sekä voiko volatiliteetti laukaista laumakäyttäytymisen. Tätä mitataan yhdistämällä laumakäyttäytymisen mittarit kahteen erilaiseen volatiliteettimittariin, GARCH ja EWMA-malleihin.

Empiirisen tutkimuksen perusteella tämä tutkimus osoittaa, että laumakäyttäytymistä on havaittavissa markkinoiden suurimpina laskupäivinä aikavälillä 1.1.2020 - 31.1.2023, jota kutsutaan kriisijaksoksi. Kriisijakso sisältää Covid-19 pandemian ja Venäjän aloittaman hyökkäyssodan Ukrainaan. Lisäksi molemmat laumakäyttäytymistä havaitsevat mittarit osoittivat lisääntyvää laumakäyttäytymistä verrattuna kriisijaksoon. Ennen kriisijaksoa ei havaittu laumakäyttäytymistä. Tämä tutkimus osoittaa myös, että laumakäyttäytymisellä on hillitsevä vaikutus markkinoiden volatiliteettiin sekä ennen kriisijaksoa että sen aikana. Tulokset eivät osoittaneet selkeää kaavaa, jonka mukaan volatiliteetin lisääntyminen automaattisesti lisää laumakäyttäytymistä, mutta osoittivat, että laumakäyttäytyminen lisääntyy markkinoiden volatiileimpien jaksojen aikana Euroopan osakemarkkinoilla.

Laumakäyttäytymisen vaikutus volatiliteettiin on ollut avoin kysymys ja tämän tutkimuksen tulos tukee osittain viimeisintä aihetta käsittelevää tutkimusta, mutta on ristiriidassa joidenkin aikaisempien tutkimusten kanssa. Tämä tutkimus tarjoaa näkemystä laumakäyttäytymisestä turbulenttien ajanjaksojen aikana sekä sen vaikutuksesta markkinoiden volatiliteettiin. Tulokset ovat hyödyllisiä sijoittajien riskinhallinnan kannalta.

KEY WORDS: Herding behavior, Behavioral finance, Stock market Volatility, Market efficiency, Euronext100

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Abbreviations

BRICS	Brazil, Russia, India, China and South Africa
CAPM	Capital Asset Pricing Model
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
EMH	Efficient Market Hypothesis
EWMA	Exponentially Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
WHO	World Health Organization

1 Introduction

In finance, everything can be mathematically proven. Different formulas aim to explain asset pricing, market movements, values and so on, but one key component is usually missing: humans are not always rational, nor can their behavior be precisely mathematically calculated. Bounded rationality of investors can reflect to the stock markets and create an abundance of anomalies, inefficiencies, to the way in which stock market works.

Behavioral finance is a field of finance that explains stock market anomalies, such as herding, by proposing psychology-based theories. In the context of finance, herding means the act of investors following the actions of other investors. Bikhcandani and Sharma (2000) state that herding can be unintentional where a group of investors come to the same conclusion with the given information. They continue that it can also be intentional where investors knowingly abandon their own initial decisions and follow other investors instead. There are several different reasons why investors would practice intentional herding and the reasons are covered in this study. In theory, herding behavior can drive stock prices from their fundamentals and exacerbate volatility which makes markets more inefficient. Academic literature is interested in the intentional herding because it has the power to make the financial system more fragile.

This study will cover the concept of herding behavior in depth and the different scenarios that could contribute to investors herding. There are different mathematical models that can be used in determining whether a market faces herding behavior or not, these models will be covered. Through empirical research, this study will assess whether herding has occurred in European stock markets during two different time periods. The first is the pre-crisis period where nothing substantial occurred in the financial markets that could have disturbed the stock market balance in a noteworthy way. The second period under examination includes the outbreak of the Covid-19 pandemic as well as the

Russian invasion of Ukraine, and in addition, the entire period has been marked by accelerating inflation.

The first step is to recognize the market anomalies and then to have a method to calculate and quantify the magnitude of the anomalies. Only after this it is possible to draw conclusions about the effect on financial markets. Investors want to have all the available knowledge about the stock markets and one key aspect of investing is risks. Volatility creates not only opportunities but also risks to investors. It is a commonly known fact that investors tend to want greater profits for a very volatile, thus risky, asset (Sharpe, 1964.) This study will cover the relationship between herding in the financial markets and volatility. Through empirical research this paper aims to find whether these behavioral characteristics in financial markets can create more volatile market conditions.

1.1 Purpose of the study

The purpose of this study is to investigate the presence of herd behavior in European stock markets and to examine how the herd behavior has affected market volatility and vice versa. Moreover, the study aims to identify whether there has been evidence of herding amongst investors during the time period between 2017 to early 2023 in European stock markets and to examine the extent to which this behavior has contributed to the market volatility. The period is split in two to investigate the herd behavior in two different market conditions.

By examining the existence of herding in different market conditions, this study seeks to shed light on the underlying factors that may have contributed to the volatility in financial markets. Therefore, the results of this study may provide insights that can influence future risk management strategies. The results could also have implications for investors, and they have more knowledge in their decision-making process.

1.2 Research Hypotheses

Herding behavior has been widely discussed in the field of behavioral finance during recent years. There is some controversy whether herding behavior exists or not and to what extent. There are studies that state herding to be a phenomenon that merges during specific market conditions (e.g. Dang & Lin, 2016; Blasco, Corredor & Ferreruela, 2017). Some studies show signs of widespread herding among investors (e.g. Hwang & Salmon, 2004; Zhang & Giouvris, 2022). Some of the earliest studies have found so little evidence of herding that they state that herd behavior does not exist in financial markets (e.g. Lakonishok, Shleifer & Vishny, 1992). This study uses a recent data and includes a period of turbulent market conditions, thus the first hypothesis is as follows:

H1: Herding does occur in stock markets.

Stock market volatility, or the fluctuation in asset prices, is an important factor in investors' decision-making process as it can affect the asset returns and the investors' risk management strategies. There is evidence that herd behavior amongst investors can lead to an increase in volatility in developed markets (e.g. Blasco et al., 2012). The issue is still ongoing whether herding amplifies the price movements or flattens them, for example Zhang & Giouvris (2022) found that herding decreases volatility in emerging markets. This study is aimed to examine the Euronext100 index that includes stocks from developed countries in Europe, therefore the second hypothesis is as follows:

H2: Herding causes an increase in volatility.

While herding could be identified as a potential cause of increased volatility, it is also possible that the relationship works in reverse: that is, increase in volatility triggers an increase in the magnitude of herd behavior amongst investors. It seems logical that whenever volatility spikes up, investors get more anxious and outsource the decision-making proses to other investors or they start to panic and imitate other investors rather than trust their own analysis. Therefore, the last hypothesis is:

H3: Volatility causes more herding.

This study suggests that herd behavior is an anomaly that occurs in the financial markets and that herding and volatility are interrelated phenomena and one causes the other. Each of these hypotheses propose a different relationship between these two factors, herding and volatility, but to accept hypothesis two and three, the hypothesis one needs to be accepted. Moreover, if there is no herding in the financial markets, there could not be an impact on volatility by herding, but herding can exist without having an impact on market volatility. Testing these hypotheses empirically will provide insights into the behavior of investors and the impact of that behavior on the stock markets.

2 Framework

Even though the concept of herding may sound clear and easy to grasp on, there are many ways to differentiate the concept. Herding can be divided by the intentionality, rationality, and reasons behind the herding action (Bikhandani & Sharma, 2000). Some studies focus on the rationality of herding and try to differentiate it from irrational herding, whereas some studies simply dismiss the reasons why herding happens in a certain situation, and they focus on the outcome. In this next chapter, the concept of herding is explained and further divided into more categories to provide broader understanding of the main subject of the paper.

2.1 What does herd behavior mean?

Herd behavior has many descriptions in the literature. Lakonishok et al. (1992) describe herding behavior as the average tendency of a group of investors to buy or sell the same stocks simultaneously. Banerjee (1992) has a simplified description; he describes herding as people who do what others are doing rather than use their own information. Avery and Zemsky (1998) define herding as investors who ignore their own initial assessment and start to follow the trend in previous trades. Bikhcandani and Sharma (2000) conclude that herding is an obvious intent by investors to copy the behavior of other investors. Moreover, Sias (2004) describes herding as a group of investors who follow each other into and out of the same securities over some period. Even though there are many different descriptions of herd behavior and what it means, they all have in common the tendency of investors copying each other.

Bikhcandani and Sharma (2000) makes a clear distinction between "intentional herding" and "spurious herding". By spurious herding they mean a type of herding where groups facing similar decision problems and information make a similar decision. They do this without being influenced by others. This type of herding is not herding according to the definition of herd behavior, even though a herd is created. This type of herding is seen as efficient because it simply uses given news to make the most efficient outcome and it does not include irrational human behavior. Intentional, or true herding occurs when an investor abandons their own initial trading decision and follows other investors instead. This kind of herding is not efficient since it does not reflect on firms' fundamental values.

The distinction between these two types of herding may seem clear theoretically, but Bikchandani and Sharma (2000) acknowledge that in real life, distinguishing the two from each other is hard, even impossible, because usually a multitude of different factors play a role in the investment decisions made by people. One way these two herding phenomena could possibly be distinguished from each other is by timing. Intentional herding happens after other investors have already made their moves, so an investor who is intentionally herding concludes to make the investment decision later than an investor who is unintentionally herding. Investors who are unintentionally herding think they came up with the trading decision by themselves. In a more recent study Park (2011) examine herding that occurs with the absence of news. When herds are formed without any relevant news, it suggests that the herd behavior occurring is intentional.

2.2 Dividing herding into subcategories

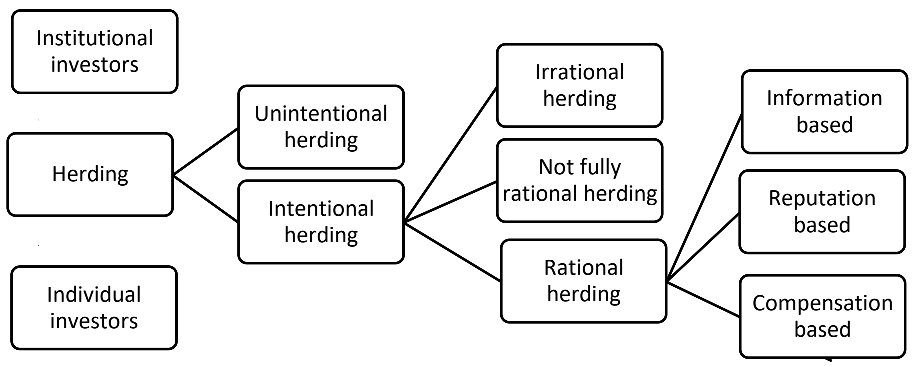

Figure 1. Division of herding (Bikhandani and Sharma, 2000; Spyrou, 2013).

Bikhandani and Sharma (2000) divide herding into these categories illustrated above. They do not dive into the irrationality of herding, but it has been mentioned in other studies (e.g. Spyrou, 2013). Previous studies acknowledge that both institutional and individual herd which is also illustrated in figure 1 (Bikhcandani & Sharma, 2000; Lakonishok et al., 1992; Spyrou, 2013). This chapter will not go through unintentional and intentional herding since those have been already covered, but the rest of the figure above will be explained.

Intentional herding can be irrational or not fully rational. Irrational herding occurs when irrational investors make trades in the market. These investors are also called noise traders and they are often described as investors who make poor and mindless trades. These decisions by noise traders are usually due to psychological or social conventions. It is argued that irrational herding can lead to higher demand on stocks that are not fundamentally worth the stock price, and this can lead to a price bubble. (Spyrou, 2013.) Furthermore, intentional herding is divided to not fully rational herding. This kind of herding means it has characteristics from irrational and rational herding which is done by investors who use the momentum strategy. Momentum strategy is a strategy where a trader purchases a stock that has started to rise in value. This can arguably be rational, since the investor is using historical data that shows the trend of that specific stock. It is also arguably irrational, since there is no proof that something that has happened previously will happen again. (Bikhcandani & Sharma, 2000.)

Then going through the figure 1 above, there is rational herding, which has further been divided into three subcategories: information-based, reputation-based and compensation-based herding. These three herding categories are more so to explain the reasons why rational herding can occur. Bikhcandani and Sharma (2000) suggest that there can be moments where herding can be a rational and voluntary act. They explain this through an example. Let there be a situation where a young analyst gains their first job in the field and makes a bold forecast of a stock that clearly deviates from the market consensus. They are more likely to get fired from their job if that forecast turns out to be false. If they follow other analysts and make a similar forecast and that turns out to be wrong, they are not that likely to get fired because the reason why they made that forecast can easily be understood. Therefore, it can be argued that in this case it was rational to follow the common market consensus to secure one's career, which Bikhcandani and Sharma (2000) state to be an example of reputation based herding.

Bikhcandani and Sharma (2000) continue to explain informational herding. This occurs when an investor has a firm belief that other investors have more information, better insight, and more knowledge of the market than they do. An investor then observes the actions taken by other investors and makes their investment decision based on those Bikhcandani & Sharma (2000). Arguably this kind of herd behavior is rational if the other investors truly have more information therefore making the investor dependent on other investors decisions. This kind of herding is fragile in the sense that the decisions made by informational herders might change easily when new information arrives.

Lastly, there are compensation-based herding and reputation-based herding. Bikhcandani and Sharma (2000) link both to employment, thus making them interconnected. Compensation-based herding occurs when a person's salary depends on their performance. Taking risks and going against the market consensus can either gain an employee a great salary, or a very low salary. Risky decisions may also lead to unemployment, so it might or probably will be safer for the person to follow other successful investors. Reputational herding occurs when an investor's reputation may be damaged if they make an error in their decisions. This fear of losing one's reputation is often seen amongst stock analysts. If an analyst deviates from a common consensus of a firm's performance and it turns out to be incorrect, the analyst can receive distrust from investors who are expecting correct predictions. This will decline the analyst's reputation and ultimately make them lose their job. These both can be seen as rational herding since there is clear reasoning behind the decision to follow the common market consensus. This is only efficient for a person's own career and life but is often inefficient to the whole market. Rational herding should not be efficient since it may lead to fragile market, excess volatility, and systematic risk. (Bikhcandani & Sharma, 2000.)

2.3 Efficient-market hypothesis

Many of the commonly known and accepted economic theories are based on the hypothesis that human beings are rational and there are no inefficiencies in the markets. This is of course the polar opposite of what behavioral finance and the concept of herding stand for. This study will introduce the efficient-market hypothesis and the capital asset pricing model. This is because an abundance of the later herding models and theories utilize these two theories. These theories have been utilized mostly from the point of view of why they are not working precisely and how introducing herding to them could make them more realistic. In the end of this chapter this study will also introduce the debate between these theories and behavioral finance.

The efficient market hypothesis, EMH, was established by Fama (1970). The central of this hypothesis is, that all security prices always fully reflect all available information. The efficient market hypothesis relies on three assumptions. Firstly, investors are always rational and value assets rationally, thus the stock prices should always reflect their fundamental values. Secondly, if there are irrational investors, their trades are random and cancel each other out. Lastly, rational investors eliminate the arbitrage possibilities caused by irrational investors. Even though the efficient market hypothesis suggests that investors are rational and use the information given rationally, the EMH states that in scenarios where investors are not rational, the market itself still stays efficient. (Shleifer, 2000.)

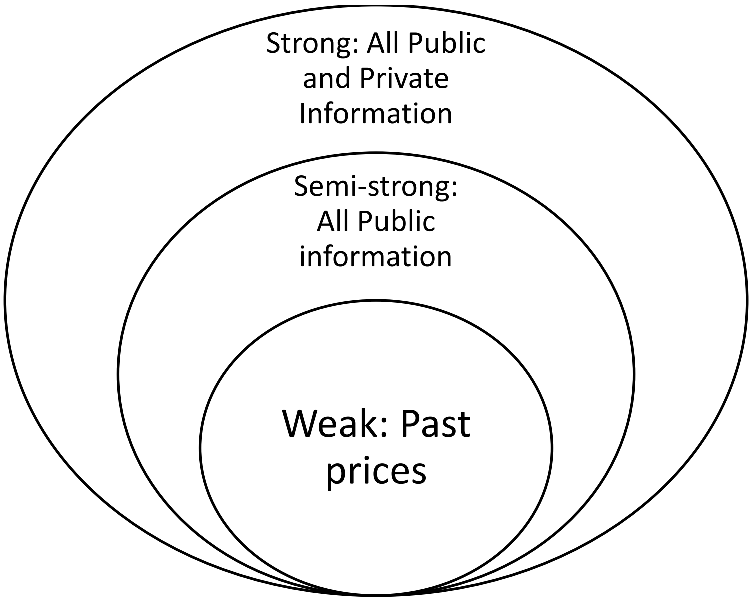

Figure 2. Forms of Efficient Market Hypothesis (Fama, 1970).

The market efficiency hypothesis can be divided into three different forms according to Fama (1970). These categories are: Strong, Semi-strong and Weak. In the strong form of market efficiency, prices reflect all information, private and public. Investors have monopolistic access to any information relevant to the asset price formation. In this case, an investor should have all the information about the private companies as well as the overall economy. Fama (1970) himself admits that the strong form is an extreme model and is not an exact description of the world.

The second category is the state of semi-strong information. Fama (1970) explains that on this occasion the investor has all the public information available in the decision-making process but not the private information. Here the prices in the stock market reflect all the past prices in addition to all public information (Fama, 1970). In other words, the investors can use the historical data of the prices as well as the public information which may include, for example, company news and performance reviews.

The lowest level in the EMH categories is the level of weak market efficiency. Fama (1970) explains that here the prices reflect only the past information of the chosen investment.

Investors should not be able to make any predictions or use any trading strategy that will lead to earning abnormal returns in the markets (Fama, 1970). The study shows that this is the most voluminous form of market efficiency.

Efficient market hypothesis is a widely used model for a framework to future studies on market efficiency and capital pricing. It creates a basis for different stock market models. However, because it clearly relies on human rationality, researchers started to question that. For the last decades researchers have recognized that investors are influenced by psychological and sociological factors when acting in the stock markets. Since the start of the field of behavioral finance, researchers have indicated many anomalies, such as herd behavior, that violate the core principles of efficient market theories.

2.4 Capital Asset pricing model

The Capital Asset Pricing model, CAPM, was developed by different researchers during the sixties. Economists who were involved in the making of the CAPM were Jack Treynor (1962), William Sharpe (1964), John Linter (1965). The function of CAPM is to calculate the expected return for an investment, taking into account the risk of that investment. (Perold, 2004.) The basis for the CAPM is that there are no taxes involved, there are no frictions that would intervene buying or selling assets, the actions of one investor has no effect on the prices, investors are utility maximizers and investors do not seek risks (Treynor, 1962). From these bases, it can already be seen that this model does not take into account the human behavior factor during investment decision-making process.

2.5 Behavioral finance versus efficient markets

After receiving criticism towards the efficient market model, Fama (1998) defends his model and discusses the anomalies seen in the markets. He states that in an efficient market, anomalies such as overreaction and underreaction, both occur frequently, thus they cancel each other out and the market stays efficient. Fama (1998) says that long-term return anomalies are affected by the methodology used and they tend to disappear when an alternative approach is used. He states that even though the market efficiency hypothesis is not a perfect model, it is unacceptable to replace it with a hypothesis that is not as strong as the EMH model. According to him, market anomalies are only methodological illusions, thus he concludes that markets are efficient and there is not enough proof against this statement.

Over the years, behavioral finance has gained a great amount of support and skepticism about market efficiency has risen. Shleifer (2000) concludes that behavioral finance has been able to provide evidence which suggests that the arbitrage is limited, and asset prices are likely to be away from their fundamental values. Markets are faced with many anomalies, that affect market prices and that cannot be explained any other way but through human behavior. Another argument is that arbitrage will eventually catch up and diminish at least the most frequently occurring anomalies, but it takes a long time which is why the efficiency of markets can be questioned (Shleifer, 2000).

3 Literature review

Since herding is usually related to many psychological factors, quantifying, and measuring it is difficult. There are still many theoretical models built to measure herding. The first model was built by Lakonishok et al. in 1992 and after that many researchers have followed and created new models to measure herding.

Spyrou (2013) divides different empirical herding measures roughly into two categories. In the first category researchers investigate the existence of herding on specific investor types such as institutional investors. The first herding measure of this first category was established by Lakonishok et al. in 1992 and followed by Sias in 2004. In the second category researchers investigate herding as a market wide phenomenon. Measures in this category are relatively easy to calculate because they are based on observed returns of stock market data and do not require microdata of individual trading activities such as the model established by Lakonishok et al. (1992). Christie and Huang were the first ones to establish a model of the second category in 1995, followed by Chang et. al. in 2000, who modified the first model, and Hwang and Salmon in 2004. This paper presents these models briefly and discusses the findings to answer the question, is there herding in the markets.

3.1 LSV Model

The first study this paper presents is by Lakonishok, Shleifer and Vishny from 1992. Later, their model got the name LSV model due to the names of its founders. Their study investigates whether institutional trading has an impact on stock prices or not. They tested if institutional trading shows characteristics of herding and positive-feedback trading, which means relying on historical data and buying past winners and selling past losers. At that time, these two concepts were argued to cause stock prices to drift away from their fundamentals. (Lakonishok et al., 1992.) This paper will concentrate on the herding part of the study since the second aspect is not important for this paper.

There are different reasons that Lakonishok et al. (1992) introduce about why it would be logical that institutional investors destabilize stock prices and by doing so, increase long-run price volatility. One reasoning is that when institutional investors trade, they have a stronger impact on the stock prices than individual investors because they have significantly larger holdings than individual investors. Moreover, if institutional investors herd, the impact could be so strong that it could drive a stock price away from its fundamental value. One explanation they give about herd behavior by institutions is that they all follow the same indicators, therefore coming to the same conclusion of selling or buying decisions is natural. As stated above, this kind of herding is referred to as spurious or unintentional herding, which does not contradict the efficient market hypothesis (Bikhcandani & Sharma, 2000). This type of herding speeds up the information in the market and by doing so, makes markets more efficient. As discussed previously (see Bikhcandani & Sharma, 2000); Lakonihok et al. (1992) also establish that institutional investors might want to herd because they do not want to stain their reputation by doing bold and unique moves.

The study by Lakonishok et al. (1992) is carried out by using a time frame from 1985 to 1989 and sample size of 769 funds that are being managed by 341 different money managers. They calculate whether institutional investors end up on the same side, sell or buy, of the markets in a certain stock in a certain time frame. If a bigger proportion of money managers increase or decrease in the same stock in each time frame, herding occurs amongst that individual stock. Lakonishok et al. (1992) evaluate herding as the proportion of net buyers relative to the institutional investors who trade the certain stock minus an adjustment factor, this factor decreases when the number of active traders increases. If herding does not exist, then the expected value does not vary between different time periods. An important aspect of their study is the distinction between the trading strategies in large and small stocks amongst institutional investors. This happens because information does not flow as fast in small stocks as with large stocks, so investors may rely on other investors more in hopes of them having some new information. Because of this, Lakonishok et al. (1992) wanted to study these stocks separately, so the results would be more accurate.

From the study by Lakonishok et al. (1992), there is weak evidence of herding for smaller stocks and little evidence of herding for larger stocks. They find that larger stocks constitute the majority of all the trading of institutional money managers. The fact that there was little evidence of herding for larger stocks was a critical fact that led to the conclusion that from this study, there is not enough evidence of herding amongst institutional investors. The study concludes that there is no solid evidence that institutional trading destabilizes prices of individual stocks (Lakonishok et al., 1992).

3.2 Sias Model

Even though LSV model did not give strong evidence of institutional investor herding, Sias (2004) studied the subject with altered approach due to strong theoretical foundations of institutional investor herding behavior. Sias (2004) divides the theoretical background into five categories, first one being informational cascades which occur when investors ignore their own information and trade with the herd because they collect information from each other's trades. The second one is investigative herding, which occurs when investors information positively correlates to others, which could be a sign that institutional investors follow the same signals when making decisions. The third one is reputational herding, which has already been covered previously, but which means that institutional investors do not want to lose their reputation by possibly making wrong decision that deviates from the herd. The fourth category is that institutional investors may simply follow different fads, causing herding behavior. Lastly herding might be caused by characteristic herding, which means that investors are attracted to securities with specific characteristics. (Sias, 2004.) Besides all these logical theories, still in 2004 the empirical evidence of institutional investors herding behavior was lacking. Thus, the goal of this study by Sias (2004) was to answer the question, do institutional investors herd.

A study by Sias (2004) uses cross-sectional correlation for institutional demand between two different time frames. Herding occurs if institutional investors follow each other into and out of the same stocks. He also studied whether institutional investors follow their own trades they made in the previous period. If institutional investors in fact do herd, the amount of institutions buying in the current time frame will be positively correlated with the amount of institutions buying in the previous time frame. The way in which Sias (2004) approach is different from Lakonishok et al. (1992) is that Sias (2004) measures the cross-sectional temporal dependence directly between two subsequent quarters whereas Lakonishok et al. (1992) measure the cross-sectional temporal dependency indirectly within periods.

Whereas the LSV model fails to reveal herding behavior amongst institutional investors, Sias (2004) manages to conclude that institutional investors do in fact herd. The results show that the number of institutional investors buying in the second time frame is strongly related to the number of investors buying in the first time frame. This is attributed by both actions: institutions following their own previous trades and institutions following other institutions previous trades. The results are more consistent with the hypothesis that institutional investors herding is a result of institutions inferring information from each other´s trades. Even though there is strong evidence of herding detected, Sias (2004) concludes that there is still no proof that institutional herding drives stock prices from their fundamental values. Sias (2004) suggests that institutional herding reflects the manner in which information is impounded into stock prices.

3.3 CH Model

Christie and Huang (1995) had a different approach when it comes to measuring herding. Whereas Lakonishok et al. (1992) and Sias (2004) investigated whether specific investor type herd, in their case institutional investors, Christie and Huang (1995) studies herding as a market wide phenomenon. They measure herding towards the market consensus by using daily and monthly data from the market. This is a convenient way to calculate herding because this does not require specific and detailed information about trading activities, making this type of data more effortless to collect.

Christie and Huang (1995) study whether herding occurs in the US stock market from 1925 to 1988. There was evidence of herding behavior from the field of social psychology that states that an individual is likely to agree a group decision even though the individual perceives the group to be wrong. Thus, Christie and Huang (1995) draw a conclusion that investors are drawn to the market consensus because they make their investment decisions solely on the collective actions of the market. If this is true, an investor's individual returns should be similar to the market return. During periods of market stress, the CAPM model predicts large changes in returns and that would translate into an increase in dispersion. Whereas Christie and Huang (1995) suggest, that in a presence of herding, the returns will not be scattered and there would not be increase in dispersion. Therefore, the study of Christie and Huang (1995) is interested in the times of market stress to reveal herding. As dispersion reveals the average proximity of individual returns to the mean, Christie and Huang (1995) conduct a return dispersion-based model. Their model derives from estimating the cross-sectional standard deviation, CSSD, of returns.

Christie and Huang (1995) suggest that herd behavior is most likely to form during periods of market stress. The reasoning behind this is that because herding is referred to as an action where individuals suppress their own beliefs and follow the market consensus, the stock returns will be diminished along with the market, so they study whether dispersions are lower than average during extreme market movements. Their strategy compares the predictions of herd behavior and those of rational asset pricing models during market downturns or large price movements. Christie and Huang (1995) find that dispersions increase significantly during large price changes, which implies that individual returns do not gather around the market consensus during market stress. This of course implies that herding does not occur during large price changes. They also examine whether herding is an attribute of market stress only during extreme market downturns or not. The study shows that the predicted dispersion and the actual dispersion of returns are very similar. With these outcomes, Christie and Huang (1995) conclude that herding is not a significant factor when determining equity returns during periods of market stress. The study states that the evidence supports the predictions of rational asset pricing models.

3.4 CCK Model

Even though the study executed by Christie and Huang (1995) gave results that stated that herding behavior has no significant impact, Chang, Cheng and Khorana (2000) decided to use the original study by Christie and Huang (1995) and extend that. Their study investigates the herd behavior in different international markets, such as the US, Hong Kong, Japan, South Korea, and Taiwan. The study extends the original study by three different dimensions. Firstly, new, and stronger approach to detect herding. Secondly, investigating herding both in developed and developing markets. Thirdly, testing if herd behavior has shifted after the liberalization of Asian financial markets. To execute these extensions, Chang et al. (2000) uses the cross-sectional absolute deviation, CSAD; of returns instead of the cross-sectional standard deviation of returns and compare that to the overall market return. If herding occurs, the return dispersion will decrease, and the market return will increase. The reason why they decided to study herding both in developing and developed markets is that the market conditions in these are rather different. Chang et al. (2000) state that the relations between institutional and individual investors are different, the quality and availability of information is different, the level of sophistication of derivatives markets are different etc. and all these factors have an impact on the behavioral side of financial markets.

The herding model by Chang et al. (2000) is also inspired by the rational asset pricing model, CAPM, that was introduced in chapter two. The CAPM model links the inherent linearity of individual stock returns with market portfolio returns. Chang et al. (2000) use this information and try to find deviations from this linearity to detect herding. If there is no herding in the market, their model, CSAD, should have an increasing and linear relation to market returns, otherwise, there is proof that herding exists (Chang et al., 2000). As already stated, behavioral finance is trying to detect the errors in financial theories that lean on investors' rationality, hence behavioral finance believes that investors have bounded rationality when acting on the markets. This does not mean that models that lean on the efficient market hypothesis are useless. Rather it means that behavioral finance could improve these models to make them more usable in the real world where real people with bounded rationality act.

The study shows no significant herding in the US markets, making the results consistent with those of Christie and Huang (1995). Chang et al. (2000) find no evidence of herding neither in the Hong Kong nor in the Japanese markets. Still, they manage to detect herding in both emerging markets, Taiwan, and Korea. In both markets, the stock return dispersion decreases with an increase in the absolute value of the market returns during both extreme up and down price movement days. Chang et al. (2000) suggest that the reason why these two emerging markets show signs of herding is because these markets show symptoms of incomplete information distribution. Their tests suggest that in these two countries, macroeconomic information plays a greater role in the decision-making process of market participants. The CSAD model is still a widely used method to detect herding albeit many new researchers modify it. This can be because the data for these models that use the deviation of returns is relatively easy to collect and the CSAD model has proven to be effective.

3.5 Model by Hwang and Salmon

A study executed by Hwang and Salmon (2004) is also linked to the one executed by Christie and Huang (1995) and Chang et al. (2000) in the literature. That is not far-fetched because Hwang and Salmon (2004) also use the information held in the cross-sectional movement of the market. But the difference is that they focus on the cross-sectional variability of factor sensitivities, not the returns. Against the common belief that herding is more intense during large market movements, Hwang and Salmon (2004) argue that herding behavior can also emerge during calm market conditions. According to Hwang and Salmon (2004), the problem with the CH herding measure is that it does not exclude the movements in assets fundamentals. This means that it is impossible to determine whether the market is moving towards a more efficient outcome by adjusting to fundamentals or is it moving towards a more inefficient outcome by investors' herding. The cross-sectional standard deviation of stock returns is not independent of volatility, hence it is impossible to say if the possible herding behavior detected is truly herding, or is it just changes in volatility which occur when investors are reacting to good or bad news. Therefore, Hwang and Salmon (2004) use the cross-sectional variability of factor sensitives, not the returns in their model. The conventional CAPM model assumes that betas used in the model do not change over time, but empirical studies suggest otherwise. Huang and Salmon (2004) argue that betas become biased. When the movements of dispersion of betas are conditioned to what happens in the fundamental changes it allows them to eliminate the idiosyncratic components.

They, as well as all former researchers introduced, argue that herding leads to mispricing the assets because the decision-making is no longer rational which further affects the views of expected returns and assets. This would mean that the assumptions of the capital asset pricing model would not hold anymore. Hwang and Salmon (2004) test their model in the US and South Korean markets and report significant herding behavior from both markets. Given that herding leads to mispricing the assets, it is important to note that during their study period there were multiple times that herding was a major concern and statistically significant in the US market. (Hwang & Salmon, 2004.) This was an interesting finding since former studies conducted on the US market failed to reveal herding behavior. Christie and Huang (1995) concluded that the CAPM model holds. Even though Hwang and Salmon (2004) do not state after their study whether the CAPM model is an accurate measure of asset pricing or not, it could be clearly seen, that according to them, the CAPM model should be adjusted by taking into account the significant herding in different markets.

3.6 Is herd behavior real?

After introducing five different methods for detecting herding, it could be clearly seen that the results are at least inconclusive. Lakonishok et al. (1992) do not manage to find proof that institutional investors herd. There was little evidence of herding amongst smaller stocks, but not any significant findings. Sias (2004) also examines whether institutional investors herd and manage to find significant herding amongst institutional investors. His study still states that the herding behavior of institutional investors does not drive prices away from their fundamental values. Christie and Huang (1995) study whether herding occurs in the US stock markets and conclude that it does not, and they give their support to the CAPM model. Later in 2000, Chang et al. conduct an improved version of the model previously made by Christie and Huang (1995) and find significant herding in the two emerging markets, Taiwan and Korea. Hwang and Salmon (2004) examine herding in the US and South Korean markets. Their results are opposite compared to the previous ones. They detect significant herding both in the US and South Korean financial markets.

The only two studies that do not detect any herding are those conducted by Lakonishok et al. (1992) and Christie and Huang (1995). Study by Lakonishok et al. (1992) is deficient by two dimensions according to Bikhcandani and Sharma (2000). Firstly, the measure does not consider the amount of stocks that institutional investors buy or sell. The model only considers whether the investor buys or sells. Secondly, Bikhcandani and Sharma (2000) state that the LSV measure fails to inform whether there are even some fund managers that continue to herd if it is given that all fund managers do not herd. The CH model has been criticized for the fact that it only tests whether a specific form of herding occurs in the markets and fails to show whether, for example, the prices of all assets in a specific market change in the same direction (Bikhcandani & Sharma, 2000). The model by Chang et al. (2000) has been criticized in the same manner (Bikhcandani & Sharma, 2000).

Even though the results introduced in this chapter are inconclusive, herding has been studied in an abundance of different countries using these different methods. Batmunkh et al. (2020) find that herding occurs both in bull and bear market periods in the Mongolian stock market. Ulussever and Demirer (2017) find herding in the crude oil markets in Saudi Arabia, Qatar, Kuwati, Bahrain, Dubai, and Abu Dhabi. Mäki (2019) studies herding behavior in the Chinese stock market and concludes that market-wide herding exists in the Chinese stock market. Rouvinen (2018) studies herding in the Nordic countries and his study shows evidence of herding behavior in the Swedish stock market. The list goes on. It is not clear why the evidence is so inconsistent. One reason given by researchers is that emerging markets are more affected by unequal distribution of information (e.g. Chang et al., 2000). Blasco et al. (2017) state that lack of information is the most important reason why herding occurs, so it is logical that herding occurs in these countries more significantly. Even though the results are inconsistent, and the studies have differences in which market conditions herding is the strongest etc. there is still a significant amount of evidence that herding is a real anomaly that occurs in the stock markets.

3.7 Herding during crises

This study is interested in whether there is any difference between the herding magnitude between the time before the crisis period and the crisis period. The crisis period is marked to began when the Covid-19 pandemic had its outbreak. The period also covers the start of Russo-Ukrainian war in Europe and the increase of inflation. Moreover, before the crises the financial markets were calmer and with the crises also more turbulent times began in the financial markets. There is already a handful of studies conducted about the herding magnitude during the Covid-19 outbreak, but no published studies cover the Russo-Ukrainian war period in Europe.

Most of the studies that have examined herding during the Covid-19 period have used either the CSSD method by Christie and Huang (1995) or the CSAD method by Chang et al. (2000). The interpretation of when the Covid-19 period started varies in the studies. Jiang et al. (2022) study herding during Covid-19 period in the Asian equity markets. They use both of these, CSSD and CSAD, methods to determine whether herding has occurred or not and they start calculating the effects on stock market from beginning of February in 2020. They find that herding has clearly been present in the Asian stock markets during the period studied. Moreover, they conclude that herding peaked when the financial markets crashed during the Covid-19 outbreak which means that the pandemic has influenced the herding magnitude.

Rubesam and Júnior (2022) conduct a comprehensive study examining the effect of Covid-19 on herding in ten different equity markets. They find evidence of herding in European stock markets from Italy and Sweden. Overall, they find little evidence of herding during Covid-19 with United States being the only market in addition to Sweden and Italy to show evidence of herding. Contradicting the findings by Jiang et al. (2022) Rubesam and Júnior (2022) do not find enough evidence to conclude that herding has been present during the Covin-19 period in China. The difference is that Rubesam and Júnior (2022) use the method by Hwang and Salmon (2004) to study the existence of herding. Moreover, they point out that there have been results showing herding during the pandemic period using CSAD model, so they study the ten markets with CSAD as well. With the CSAD model they can find herding also in other countries than USA, Italy and Sweden, including China, but because the results are so inconsistent and dependent on the time period studied, they cannot conclude existence of herding from these other countries.

Kizys et al. (2021) conduct an even more comprehensive study and examine the herd behavior during the Covid-19 period in 72 countries. They also use both CSSD and CSAD methods as Jiang et al. (2022). They find evidence of herding during the first three months after Covid-19 outbreak in 2020. They find that in countries with stricter Covid-19 rules imposed by the governments decreases the amount of herd behavior. Kizys et al. (2021) suggest that this could be an effect of decreasing the fear sentiment amongst investors. Moreover, they state the investors might feel safer when the Government gives clear and strict rules on how to behave.

As stated above, the evidence of herding during the Covid-19 period also seems to have conflicting results. A common result seems to be that with the CSSD model by Christie and Huang (1995) and with the CSAD method by Chang et al. (1995) it is possible to find even somewhat consistent evidence on herding during the Covid-19 period. The herding seems to be more intense at the beginning of the Covid-19 outbreak. This should be logical since the information about the disease was scarce, which could have led to fear and uncertainty amongst investors. A study by Ferreruela and Mallor (2021) supports this since they could not find evidence of herding with the CSSD and CSAD methods in Spain and Portugal except from the most bullish days during the pandemic. Moreover, they could not find evidence when looking at the whole sample, but as the study by Rubesam and Júnior (2022), they managed to find evidence at certain market conditions and with using the CSAD model.

Reflecting the results from previous studies conducted of the crisis period of Covid-19 outbreak and the hypothesis one in this study, it can be expectable that with the use of CSSD and CSAD models it is possible to find evidence of herding in the European financial markets. It can also to be expected that the results show stronger evidence of herding during the crisis period compared to the before crisis period. At the time of the pandemic outbreak the information flow was fast paced and continuously changing. This should have brought a level of uncertainty in the market that could lead investors to reject their own strategies and start following the market consensus. The uncertainty between facing an unknown pandemic and a war maybe cannot be compared, but the fear sentiment amongst investors should rise during both of the events. This is why it is logical to assume that herding has been present at the outbreak of the Russo-Ukrainian war as well in the European stock markets.

4 The impact on equity market and market outlook

This study has already covered the situations and reasons that may drive investors into herding behavior in previous chapters. It is important to acknowledge what kind of market inefficiencies, anomalies, herding can cause. Schmitt and Westerhoff (2017) create a model where investors follow a linear mix of technical and fundamental trading rules to determine their orders. In their model uncertainty plays a role that drives investors to observe other investors more closely and drives them into herding behavior. Due to the herding behavior the market faces a less balanced excess demand and adjusts prices more strongly, driving the markets to face more volatile conditions. Their aim is to prove that herd behavior can lead to a high volatility period. In their hypothesis, when investors are faced with increased uncertainty, investors start to follow each other more closely and will end up on the same side of the markets, either on the sell side or buy side. Their model can produce several inefficiencies in the markets: bubbles and crashes, excess volatility, fat-tailed return distributions, uncorrelated returns, and volatility clustering. In light of this herding can effect volatility in theory, but it is a different question can this be empirically proven.

4.1 Relationship between herding and market volatility

This part of the study will concentrate on the excess volatility that herding can allegedly cause. In a scenario where the efficient market hypothesis is true, stock prices would instantly or quickly adjust to new information (Fama, 1970). If this were true, volatility could only be caused by this action of investors rationally reacting to good or bad news. However, as this study has already introduced multiple studies that have proven herd behavior to exist, it is reasonable to assume that there are other factors impacting volatility besides rational trading decisions. Herding behavior of investors debunks the statement that investors always act rationally. Therefore, it raises a question, whether volatility could only be caused by continuous adjustment of stock prices to new information or can herding have an impact on it. First this study will shed some light on the existing literature whether herding has an impact on volatility or not. Then this matter is viewed when the market conditions are different. Blasco et al. (2012) conclude that Friedman found a link between investors behavior and market volatility already in the 1953. They say that Friedman argued that there are so many irrational investors in the markets that they can destabilize prices. These investors usually buy stocks when prices are high and then sell stocks when prices are low. When, on the other hand, rational investors lead the prices towards their fundamental values by buying stocks when the prices are low and selling them when prices are high (Blasco et al., 2012).

Park (2011) argues that herding behavior can lead to a panic situation and high increase in volatility even without any significant news. In efficient markets, the increase in volatility should be caused by the arrival of new information, resulting also in a rise of trading volumes. He executes his study in South Korean markets, since it is known to exhibit severe herding. He concludes that herding behavior does lead to high increase in volatility but not in trading volume. He even states that strong persistence in volatility is more likely to be caused by herd behavior rather than arrival of news.

A study by Venezia et al. (2011) investigates the correlation between professional and amateur herding to market volatility. The study shows that amateur investors tend to herd more severely than professionals and herding is more prominent within large firms' stocks than small firms' stocks. This is logical, as it has already been stated that the most significant reason for herding is the lack of information. However, this does not mean that professional investors do not herd, the study by Venezia et al. (2011) shows that professional's herd as well. The study also shows that the herding behavior of amateur investors has a greater correlation between the market volatility than professional investors herding. This suggests that amateur investors pose a bigger threat to market stability. Finally, they state that herding, both amateur and professional, is significantly correlated with the stock market volatility. Blasco et al. (2012) suggest that herding variables should be used when forecasting volatility and further on in the decision-making process if volatility is considered a key factor. In their study they find that herding does have a direct linear impact on volatility in the Spanish stock markets. They highlight that even though herding is a factor that has an impact on volatility, intensity of that impact variates between different market conditions. Messis and Zapranis (2014) find that herding has a significant linear effect on all volatility measures in the Athens stock market. This would imply that stock markets that are facing higher levels of herding behavior, for instance emerging markets, also face higher volatility. Their study also shows that herding can cause volatility, but high volatility does not cause herding, this was also found by Venezia et al. (2011).

The previous studies conducted about the effect of herding on volatility have found significant correlation between rising magnitude of herding and the increase in volatility as introduced above. Although the question is still not answered in an unambiguous way, the overall consensus is that herding leads to an increase in volatility. There are studies that have found results contradicting this consensus. Zhang & Giouvris (2022) have conducted one of the most recent and broadest studies about the issue. They study the magnitude of herding and the effects on stock market volatility in Brazil, Russia, India, China and South Africa, also referred as the BRICS countries. They use the previously introduced CSAD model and multitude of volatility measures. Contradictory to the previous studies, they find that an increase in the level of herding actually decreases the market volatility in all BRICS countries and during different market conditions.

Alemanni and Ornelas (2008) also find somewhat contradictory results from their study. They study the magnitude of herding and the consequences of that on the financial markets in emerging markets. As no surprise they find the presence of herding which supports the evidence that herding is more likely to be present in the emerging financial markets. Although they find strong evidence of the presence of herding they do not find any significant impact on market volatility. Moreover, their study concludes that herding does not have increasing nor decreasing effect on stock market volatility. They still find some impacts of herding on financial markets such as fat tails of equity return's distribution.

From these previous studies it can be concluded that the effect of herding remains an open issue. The empirical research conducted previously on the issue shows that the results are still inconclusive. There are multitude of different variables that can cause these wide range of results. As discussed, emerging markets and developed markets face a different scenario when investors are making investment decisions. There is a higher level of institutional investors in developed countries which should be more knowledge-based investors instead of emotions-based decision making. The information flow also seems to be better in developed countries. Moreover, the market conditions from the time periods these studies have examined are different. The methods of measuring the level of herding, the magnitude of volatility and the relationship between these two also differ and could have led to a difference of results. These mixed results might also indicate that there still is not an efficient enough way to measure the relationship between these two that would generate more coherent results.

4.2 Can volatility trigger herding?

This study has discussed the effects of herd behavior on the market volatility, but a different question is, can market volatility trigger herding. It is important to acknowledge the different relationships between market volatility and herding. There is evidence that herding magnitude is greater in riskier markets. For example, Lakshman, Basu and Vaidyanathan (2013) study herding in Indian financial markets and the effect of volatility to the herding magnitude. They find that the impact of volatility is significant to the increase of herding tendency. They conclude that regulators should watch out for herding tendencies when volatility starts to increase.

Results from Zhang & Giouvris (2022) study are consistent with the study by Lakshman et al. (2013). They also find significant results of increasing volatility triggering more herding. The similarity from the studies that show volatility causing increasing herding is that they are conducted in financial markets that are considered to be a part of the emerging markets, BRICS markets. Zhang & Giouvris (2022) conclude that the BRICS countries do face more volatile market conditions, so it might be more logical that these economies also face more “side effects” of that volatility. This study is examining whether volatility triggers herding in developed markets, which could generate different results, such as Blasco et al. (2012).

The reasons behind the increase in volatility that seem to lead to an increase in herd behavior are interesting. Lakshman et al. (2013) argue that investors are not aware when the volatility is high, they only realize the magnitude of volatility as it has already happened. They argue that because investors are not aware of the volatility at the time, their instincts take over and they start to herd instead of following their own investment strategies. This explanation appears somewhat peculiar, since it hints that investors do know that something is happening since they change their investment strategies but also that the reason is investors not being aware of the volatility. Zhang & Giouvris (2022) suggest that this is because volatility can trigger fear and anxiety sentiment amongst investors, thus hampering their ability to stay analytical and objective. This then leads investors to question their own ability to make investment decisions and they somewhat outsource the decision making to the market consensus.

4.3 Effect on volatility during bull and bear markets

Herding behavior is usually at its strongest when market shows extreme conditions, both bull and bear markets. Blasco et al. (2017) argue that in the presence of bad news or crisis periods, more intense herding behavior appears. Therefore, herding can exaggerate the effects of a crisis period because that is a time where herding behavior is most likely going to be at its peak. The common belief is that the crisis period creates more stress to the investors, resulting in herding, whereas during bull markets the investors are left with a calmer mindset (Blasco et al., 2017). Even though in theory, it is harder to rationalize why the investors behavior during bullish market would have an impact on the volatility, there are few suggestions in the literature. One reasoning being that herding is a rational strategy for less sophisticated investors, because they try to follow the more successful investors and not do the research on their own (Blasco et al., 2017). Furthermore, during extreme market stress, both bear and bull markets, there is more information generated, which the less sophisticated investors cannot process (Blasco et al., 2017). Thus, the herding behavior can be more significant and have an impact on volatility also in the bull markets.

There is evidence that contradicts the statement that herding is more prominent during market downturns and crisis periods. Dang and Lin (2016) find that herding is more prominent during market upturns than downturns in Vietnam.

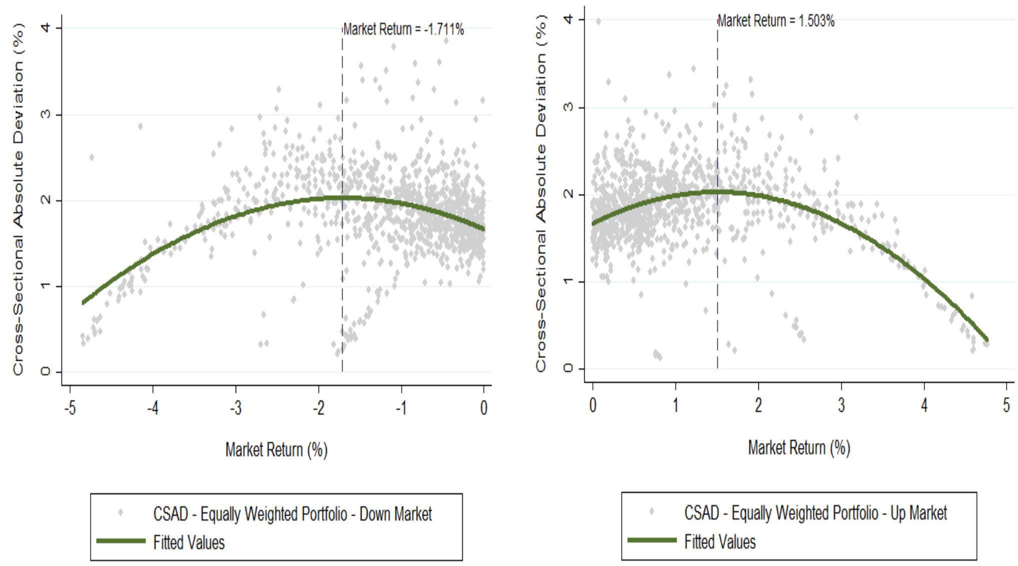

Figure 3. CSAD during market downturns and upturns. (Dang & Lin, 2016.)

These pictures show how the values of Cross-Sectional Absolute Deviation are slightly more scattered during market downturns than during market upturns. The different results are reported from different markets; thus, it could be an indicator that there is something in the way different cultures act in the financial markets and that would also reflect on the herding behavior. The results of Dang and Lin (2016) support the previous findings from Asian markets. Herding that is more prominent in the market upturns and downturns are found especially from China, Japan, and Hong Kong (Dang & Lin, 2016).

Blasco et al. (2017) expanded their study on the herding behavior impact on volatility in the Spanish stock market and studied the impact on volatility during extreme market movements. They test whether herding exists during extreme down days and extreme up days. Their study shows that during extreme bearish days investors herd on the buy side more than on the sell side and during extreme bullish days, herding is more prominent on the sell side. They suggest that this occurs because given the market conditions, these acts are seen as extraordinary, hence those are intensively followed. Blasco et al. (2017) also provides another reason for this, an anomaly called disposition effect. The disposition effect occurs when investors quickly sell stocks that have increased in value since purchase and keep stocks that generates losses (Kaustia, 2011). Blasco et al. (2017) conduct tests with 5% of the lower and upper tail days and only 1% of the lower and upper tail days tests. Their study shows that the herding in the buy/sell side is even more intense when only including the 1% of the lower/upper tail. This is logical since these days are the most extreme down or up days in the period they study.

Blasco et al. (2017) use the realized volatility measure and the conditional volatility to detect whether the amount of herding affects the daily volatility during financial crises. The study shows that during extreme bearish days herding makes volatility rise more than usual. Their study shows that the behavior of investors, herding, affects volatility to a higher degree during extreme bearish days than during calm days. This is due to a panic caused by the decline in the markets (Blasco et al., 2017). They suggest that during extreme market downturn days many psychological biases arise, thus having the chance to affect the whole financial system. According to Blasco et al. (2017), adding elements which include behavioral factors can be highly valuable in the field of risk management.

Despite the presence of herding on the sell side during extreme bullish days, the study shows that herding increased volatility less than the rest of the days. Blasco et al. (2017) suggests that this is because during market upturn periods, investors are calmer compared to market decline periods. This might not be the case in all markets. As already shown, Asian markets face more prominent herding during market upturns that downturns (Dang & Lin, 2016). This could possibly suggest that in these countries, herding could have more significant implications in the volatility during market upturns than downturns, but to state that, it would need more evidence.

4.4 The effect of fear on herding and volatility

According to the Keynes (1936) animal spirit theory, individuals are driven by their fear and panic during uncertainty which leads individuals to act by their instincts rather than knowledge. This would mean that during turbulent market conditions more irrational investors would make trades in the markets leading to increased volatility. (Bekiros et al., 2017.) Fear is an emotion that encourages investors toward herding (Huang & Wang, 2017). During extreme market downturns, the amount of fear amongst investors rises. Fear is not easy to calculate and quantify, but the VIX index try to accomplish that. VIX index, also called “fear index” in the common language, measures how much uncertainty, or fear, is at the stock market (Economou et al., 2018). It tries to predict the future volatility over the next 30 days based on the S&P500 options (Economou et al., 2018). That being said, it has to be acknowledged that the market sentiment cannot be accurately measured, so the volatility expectation can always differ from the realized volatility.

Huang and Wang (2017) reveal through their study conducted to the Taiwan stock market, that there is an asymmetry in the way investors react to news. They state that investors react more quickly to bad news than to good news when their fear arises. This suggest that the trading volume increases during periods of fear, which they show in their study. They demonstrate that when the volatility measure, VIX, increases, so does the amount of herding. This shows that fear drives investors to herd, which creates excess volatility in the market. Economou et al. (2018) also study the investors fear using the VIX index and the correlation with herding. Their study indicates that in US, UK and German markets clearly herd towards the volatility measure, VIX. Their study also provides evidence that fear and herding are intertwined.

As stated in the beginning of this study, the time of the COVID-19 pandemic and the beginning of Russo-Ukrainian war has been a highly volatile period for the stock market. It has raised a question whether herding and fear has been involved for the stock market downfall an upturn. Espinosa-Méndez and Arias (2020) have studied the events. They find that herd behavior has indeed increased in Europe. They conclude that investors' fear has risen in front of an unusual market situation which had led to the less informed investors abandoning their own beliefs and following the more informed ones. As has already been stated, an increase in fear could lead to increase in herd behavior which could have an effect on volatility when considering the previous studies (e.g. Blasco et al., 2012; Zhang & Giouvris, 2022).

4.5 Market conditions outlook

The core reason to study whether herding influences volatility is to generate more knowledge for the investors and for the companies. The investors can use the knowledge to their decision-making processes and companies for the risk management strategies. The financial markets are not flat without crises, but it is more fruitful to study the effects of herd behavior to volatility during a volatile period. During periods where the countries face different types of crises the volatility is usually higher due to uncertainty (e.g. Blasco et al., 2017). Also, companies are usually facing a different operating environment which is reflected in the financial markets. For example, during the lockdowns due to Covid-19 some companies could not provide their services to people because the services require face-to-face interaction with customers. After Russia attacked Ukraine, the EU quickly set restrictions towards importing goods to Russia which of course led some companies to lose customers because they needed to leave from Russia. Therefore, the market reactions are also rational during crisis periods, but the phenomena this study is interested in, is the way that markets are not rational.

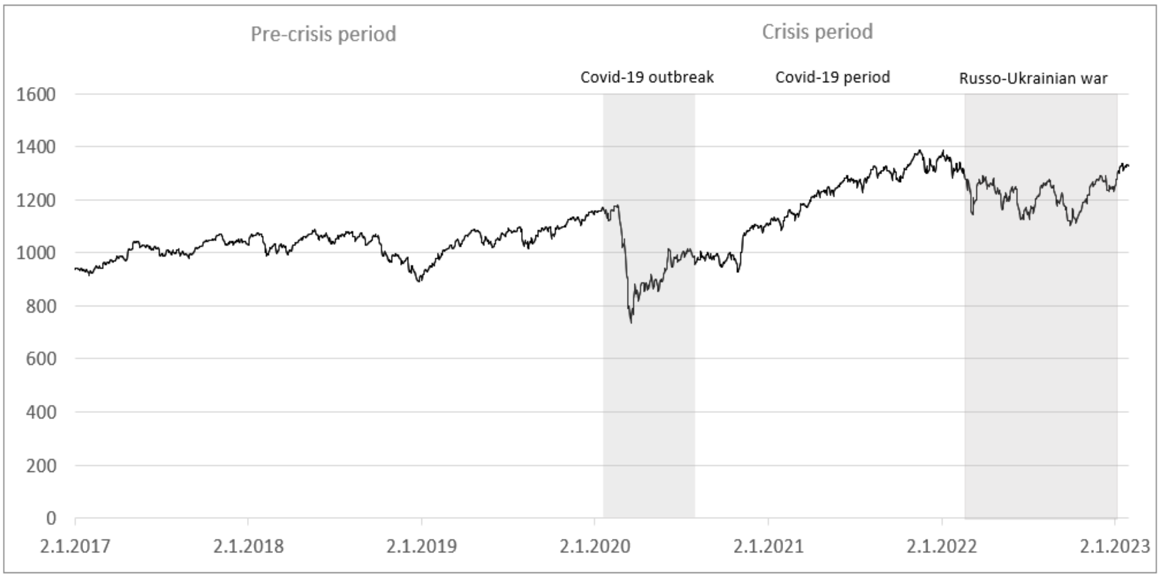

Figure 4. The price development of Euronext100 in Euros.

At the outbreak of the pandemic the Euronext100 index, as well as many other indexes crashed at the beginning of 2020. It can be seen from figure 4 above, that the market bounced back rather quickly. After a year the markets exceeded the before pandemic level. This is an interesting phenomenon since the World Health Organization, WHO, has not confirmed the pandemic to be over from the beginning of the Covid-19 to the end of this study period. This is still expected since historically, financial markets have recovered from these types of shocks rather fast. For example, David et al. (2021) study the effects of Covid-19, Ebola, MERS and SARS pandemics to the stock markets and find that after the initial shock markets start to recover fast. They find that Covid-19 had the longest recovery time, and the volatility was higher compared to the other pandemics. The outbreak of Covid-19 is highlighted in grey in figure 4 above and the initial shock and the recovery can be seen from the figure clearly.

The impact of the Russo-Ukrainian war to the Euronext100 index is illustrated in figure 4 as well. It can be seen that the initial shock was not as great as it was for the pandemic, but it can be seen that the war has caused clear volatility to the markets. Historically as well wars tend to have decreasing effects on the financial markets (e.g. Schneider & Troeger, 2006). Although war creates demand for some sectors of the economy, the overall sentiment in the financial markets is more anxious and the uncertainty makes the markets act more quickly, for example, to bad news (e.g. Schneider & Troeger, 2006). As it can be seen from the figure above, after the shock to the Covid-19 outbreak, the index started to recover quite steadily. With the case of the war, the initial shock has not been as dramatic, but the index has declined and increased multiple times.

Overall, the financial markets in Europe have faced more volatile and uncertain conditions for the so-called crisis period in comparison with the pre-crisis period. The lowest price of the Euronext100 index from the pre-crisis period is 891,8EUR compared to crisis period where the lowest price is 733,9EUR which equals to -18% decrease. The highest price of the pre-crisis period is 1 156,6EUR and during the crisis period 1 388,1EUR, which equals to 20% increase. Moreover, the index price has fluctuated between +/- 30% during the pre-crisis period and +/- 89% during the crisis period, showing a much greater volatility for the crisis period.

The same can be detected from the daily returns of Euronext100. Before the Covid-19 outbreak the greatest decrease in daily returns of Euronext100 has been -3,42% and the greatest increase has been 3,48%. Compared to the greatest decrease in daily returns during the crisis period has been -11,98% and increase of 8,18%. This goes to show that the overall market conditions during the periods studied in this paper have been both calm and turbulent, which makes the study of the different periods interesting. Neither the Covid-19 pandemic nor the Russo-Ukrainian war have been announced to be over during the sample period studied, but as it can be seen from figure 4, the Covid-19 does not seem to have much of an impact on the Euronext100 index after the initial shock and the recovery. Moreover, it would still be ignorant to not acknowledge that the Covid-19 pandemic is still present, and the effects of the more intense pandemic period could still have reflected to the reactions for the Russo-Ukrainian war.

5 Methodology and Data

The methodology consists of three different parts, first it needs to be tested whether herding can be detected during the time period of pre-crisis (1.1.2017 - 31.12.2019) and during the crisis period (1.1.2020 – 31.1.2023). Second, volatility measures need to be conducted to state the level of volatility during the study period. After this the second hypothesis can be tested using a regression model that detects whether herding has had an impact on volatility during the study period. Then the same data and mathematical formulas can be used to detect whether volatility triggers herding using differently divided sample periods.

5.1.1 Herding measure

In order to test hypothesis one, it is needed to test whether herding is occurring during the sample periods. The sample period is divided into two different periods: pre-crisis (1.1.2017 - 31.12.2019) and crisis (1.1.2020 – 31.1.2023). These sample periods are compared with each other to find how the herding magnitude evolves during different market conditions. The sample period is studied as a whole as well.

Two different herding models are being used to get a reliable result. The first model used is the CSSD-model introduced in 1995 by Christie and Huang. In the model the cross-sectional standard deviation (CSSD) of returns of chosen stocks in a certain market are calculated as seen in the equation (1). Christie and Huang (1995) suggest that if herding is occurring in the given market, the dispersion would be lower than could be expected compared to a market where herding did not occur. The equation is written as follows:

$$CSSDt = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-R_{M,t}\right)^2}{N-1}} \tag{1}$$

Where $R_{i,t}$ is the stock return i at time t ; $R_{M,t}$ is the equally weighted average return of the N stocks listed in the market at the time t. It is possible to observe visually whether herding occurs in a certain market or not when drawing a scatter diagram with the CSSD values and market returns, shown in figures 5, 6 and 7. To draw statistically significant conclusions, it needs to assess whether the dispersion of returns is significantly lower or not. Moreover, Christie and Huang (1995) suggest that herding is most significant during periods of extreme market returns. This is the reason Christie and Huang (1995) propose the following regression to assess whether herding occurs in the studied market or not:

$$CSSDt = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \tag{2}$$

Where, D_t^L is a dummy variable that takes the value of 1 if the market return $R_{M,t}$ is located at the lower tail of the distribution of returns and if not, then the value of 0; D_t^U is a dummy variable that takes the value of 1 if the market return $R_{M,t}$ is located in the upper tail of the distribution of returns and if not, then the value of 0. In this study the lower and upper 5% and 1% are studied to get comprehensive results. Moreover, it is stated that the coefficients need to be negative and statistically significant in order to state that the market has experienced herd behavior by investors (Christie & Huang, 1995).

The second herding measure used to detect herd behavior in the market is the Cross-sectional absolute deviation, CSAD, model by Chang et al., (2000). The CSAD formula can be written as follows:

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

Where, the $R_{i,t}$ equals return on stock i, at a time t ; $R_{m,t}$ equals market return at time t ; N equals the number of sample stocks and $CSAD$ is the cross-sectional absolute deviation of returns. Chang et al., (2000) propose that if investors engage in herd behavior the linear relationship between the market return and CSAD will no longer hold, and the relationship will become non-linear. Chang et al. (2000) propose the following to capture the nonlinearities in the relationship between dispersion and market return:

$$CSAD_t = a_1 + a_2\left|R_{m,t}\right| + a_3\left(R_{m,t}^2\right) + \varepsilon_t \tag{4}$$

If there is herding detected during the chosen time period, then the coefficient a_3 will be significant, and negative (Chang et al., 2000).

Moreover, because the time periods studied differ and it is expected that the time periods have different levels of herding both the CSSD equation (2) and the CSAD equation (4) should be adjusted accordingly. The models are modified to evaluate the effects of a crisis on herding and is as follows:

$$CSSD_t^{pre-crisis/cris} = \alpha + \beta^L D_t^{L^{pre-crisis/cris}} + \beta^U D_t^{U^{pre-crisis/cris}} + \varepsilon_t \tag{5}$$

$$CSAD_t^{pre-crisis/cris} = a_1 + a_2\left|R_{m,t}\right|^{pre-crisis/cris} + a_3(R_{m,t})^{pre-crisis/cris} + \varepsilon_t \tag{6}$$

5.1.2 Volatility measures

For the second hypothesis, it needs to be tested whether herding has an effect to the market volatility. For testing the hypothesis, a volatility measure needs to be conducted. There are multiple volatility models in the literature and to gain the necessary level of certainty, two different volatility measures will be used. First, the conditional volatility, GARCH, measure introduced by Bollerslev (1986) is used. This is used to detect the effects of herding on conditional volatility. The GARCH model is as follows:

$$R_{m,t} = a + \beta R_{m(t-1)} + \varepsilon_t$$

$$\sigma_{GARCH(t)} = \sqrt{a + \beta\sigma GARCH(t-1)^2 + \delta\varepsilon_t - 1^{2+\eta}} \tag{7}$$

Where, $R_{m(t-1)}$ is the first-order lagged variable of $R_{m,t}$; $\sigma GARCH(t-1)^2$ is the first-order lagged variable of $\sigma GARCH^2$; ε_t is a residual term at t ; ε_{t-1^2} is the square of first-order lagged variable for ε_t and $\sigma GARCH$ is the conditional volatility. The square root of σ is used to obtain the standard deviation for the calculations.

Second volatility measure that is being used, is the Exponentially Weighted Moving Average Volatility, EWMA, model. The EWMA model addressed the issue of "Ghost Feature". Ghost Feature means, that there are extreme events occurred in the data period, and these events can influence the volatility forecasting, which could cause the results being unreliable (Zhang & Giouvris, 2022). The time period contains the beginning of Covid-19 pandemic and Russo-Ukrainian war, therefore it can be expected, that the time period contains at least some extreme events that affect the market volatility. The difference between EWMA and the historical volatility calculations is that EWMA does not weigh equally the past variance, it attracts higher weights in recent observations rather than weighing each observation equally. The EWMA method is stated by J.P. Morgan to be a slightly more reliable method to predict volatility, because its ability to take external shocks into account and because of the assumption of conditional distributed returns (Longerstaey & Spencer, 1996). The EWMA model is being written as follows:

$$\sigma_{EWMA}(t) = \sqrt{\lambda \sigma_{EWMA}(t-1)^2 + (1-\lambda) R_{mt^2}} \tag{8}$$

Where, $\sigma_{EWMA}(t)$ is EWMA volatility at time t ; $\sigma EWMA(t-1)$ is first-ordered lagged volatility and Initial Volatility ($\sigma EWMA(0)$) in the initial return squared. The lambda λ can have many values, however in this study the widely used 94% will be used.

5.1.3 Herding model and volatility models

To test the second hypothesis, the CSAD and the two volatility measures need to be combined. Following Zhang and Giouvris (2022), this is done by following regression models:

$$\eta_t = a + \beta CSSDt + \varepsilon_t \tag{9}$$

$$\eta_t = a + \beta CSADt + \varepsilon_t \tag{10}$$

Where, η_t is the true volatility, calculated with the GARCH and EWMA models. The true volatility is denoted as $GARCH(t)$ and $EWMA(t)$. With the regression, it can be detected whether herding has an affect on volatility. Moreover, if the coefficient of $CSSDt$ or $CSADt$ is significant, then it can be concluded that the second hypothesis can be accepted, and herding does have an impact on market volatility.

With the same data it is possible to test the third hypothesis. The whole sample period needs to be divided into smaller sample sizes based on the level of volatility. The sample is divided into four subsamples based on where in the volatility distribution it lays on. Then the same CSAD regression introduced earlier, formula 4, will be conducted for each subsample period. If the coefficient $a_3\left(R_{m,t}^2\right)$ decreases as the volatility increases, then a conclusion can be drawn that volatility triggers herding.

5.2 Data

The largest stock exchange in Europe is Euronext (Statista, 2022). At the end of March 2022 the market capitalization of the listed companies in Euronext was 6.6 trillion Euros (Euronext, 2022). Euronext is a stock exchange that was founded in 2000 when the Stock exchange of Brussels, Amsterdam and Paris merged. After that also Dublin, Lisbon, Milan and Oslo have merged into Euronext (Euronext, 2022). When studying herding in Europe, using data from the stocks in the index Euronext100 gives a proper picture of the stock exchange movements in Europe.

The data used is daily stock returns from the Euronext100 index between 1.1.2017 and 31.1.2023. The data is studied as three different timespans: as a whole sample (1.1.2017-

31.1.2023), as a before crisis period (pre-crisis 1.1.2017-31.12.2019) and as a during the crisis period (crisis 1.1.2020-31.1.2023). During the years of 2017 to 2019 nothing significantly impacting the financial markets occurred, but during the years 2020 to the beginning of 2023 two significant events have occurred. The first suspected case of the Covid-19 has been reported on 31.12.2019 and this is why the crisis period is taking place at the beginning of 2020. Russia attacked Ukraine on 24.2.2022 when the world was still recovering from the pandemic.

Moreover, the inflation started to spike due to the coronavirus pandemic when there was shortage of raw materials due to the guarantees when people could not physically go to the workplaces and the prices started to rise rapidly. It is inconvenient to study when these crises occurred and affected the financial markets from a behavioral finance point of view, therefore the period of 1.1.2020-31.1.2023 is studied as a whole and it is suspected that these crises have had an effect on the financial markets more or less during the whole time period.

All these aspects have increased volatility in the markets, thus it is fascinating to investigate herding, because as stated previously, herding should be most prominent when there is distress in the markets (e.g. Blasco et al., 2017). The reason for using daily data instead of weekly or monthly is that the time span is rather short, and the market movements have been rapid. Therefore, it is important to use daily data instead of weekly or monthly data to be able to capture the rapid downturns and upturns.

The daily returns are calculated with the following formula:

$$R_t = 100 \cdot \left(log(P_t) - log(P_t - 1) \right) \tag{11}$$

where: Rt is the market index daily closing price; Pt is the market index price at time t and $Pt{-}1$ is the market index price at $t{-}1$.

5.3 Descriptive statistics for herding

In the case of a perfectly functioning financial market that is not affected by market anomalies, the distribution of market returns should be normal. Moreover, if this is not the case, it raises a question of market anomaly such as herding occurring. With this in mind, the data can be skimmed through with more simple statistical methods.

Table 1. Descriptive statistics of cross-sectional standard deviations and cross-sectional absolute deviations

	Whole Sample			**Pre-Crisis**			**Crisis**		
	CSSD	*CSAD*	*Rm*	*CSSD*	*CSAD*	*Rm*	*CSSD*	*CSAD*	*Rm*
Mean	0,0149	0,0107	0,0003	0,0126	0,0087	0,0003	0,0171	0,0126	0,0003
Median	0,0136	0,0096	0,0007	0,0119	0,0086	0,0006	0,0157	0,0114	0,0009
Standard Deviation	0,0066	0,0046	0,0113	0,0049	0,0021	0,0074	0,0072	0,0055	0,0141
Kurtosis	34,9068	24,7508	14,0716	160,0018	3,3121	2,4123	14,7723	18,0894	10,5666
Skewness	4,2986	3,8122	-0,9783	9,5599	1,2345	-0,3550	3,0630	3,4316	-0,9455
Minimum	0,0053	0,0040	-0,1198	0,0053	0,0040	-0,0342	0,0061	0,0047	-0,1198
Maximum	0,1028	0,0561	0,0818	0,1028	0,0209	0,0348	0,0721	0,0561	0,0818
Count of Days	1 558	1 558	1 558	764	764	764	794	794	794
Count of Stocks	96	96	96	96	96	96	96	96	96

This table reports the descriptive statistics of daily cross-sectional standard deviations (CSSD), cross-sectional absolute deviations (CSAD) and daily market index returns (Rm) for the whole sample period 1.1.2017-31.1.2023, pre-crisis period 1.1.2017-31.12.2019 and crisis period 1.1.2020-31.1.2023.

For a market not being affected by anomalies the returns should be normally distributed, this means that the skewness of the market returns should equal to zero. As it can be seen from table 1 above, the skewness for each time period does not equal zero, albeit being close especially during the pre-crisis period. When comparing the time before crisis and the crisis period it can be seen that the skewness moves further away from zero. This on its own does not offer much but it indicates the possibility of herding occurring at the crisis period. The kurtosis of a normally distributed market returns should be around three. As it can be seen again, during the pre-crisis period the kurtosis is much closer to three when comparing to the crisis period when the kurtosis is much higher.

Again, indicating that during the crisis period the market could have been affected by herding.

Looking at table 1, the minimum value for returns during the pre-crisis and crisis periods indicates more volatility during crisis period as well. The minimum value for returns was recorded on 12.3.2020, -11,98% and maximum on the same month on 24.3.2020, 8,18%. This shows that the covid-19 has had more impact on the volatility in Euronext100 when comparing to the Russo-Ukrainian war.

The relationship between CSSD and CSAD with the market return can be illustrated using a scatter diagram. The scatter diagram does not give any precise answers but can indicate whether there is anything to even start to calculate. If the points of CSSD and CSAD start to flock together, it is a sign that there might be herding amongst investors in the specific market under investigation. The scatter diagrams from different time periods are illustrated below.

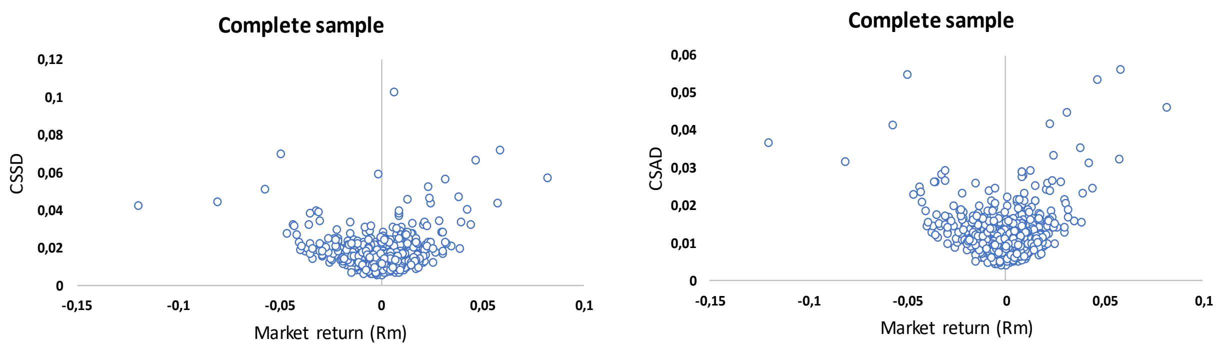

Figure 5. CSSD & CSAD - Market return for whole sample

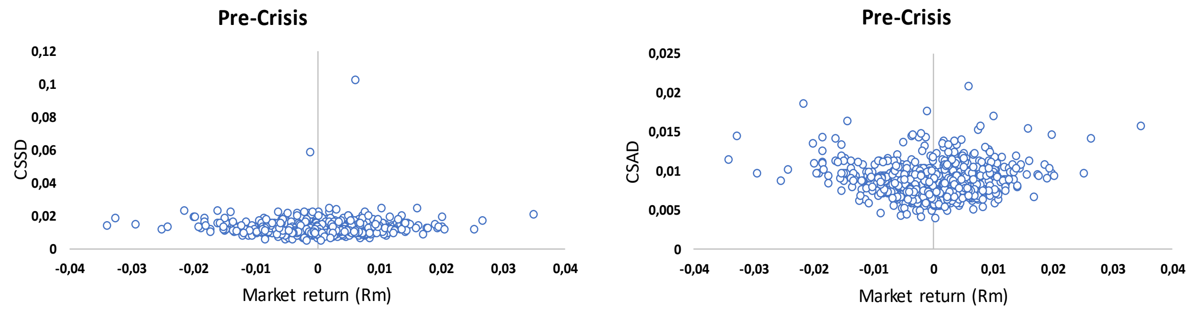

Figure 6. CSSD & CSAD - Market return for pre-crisis period

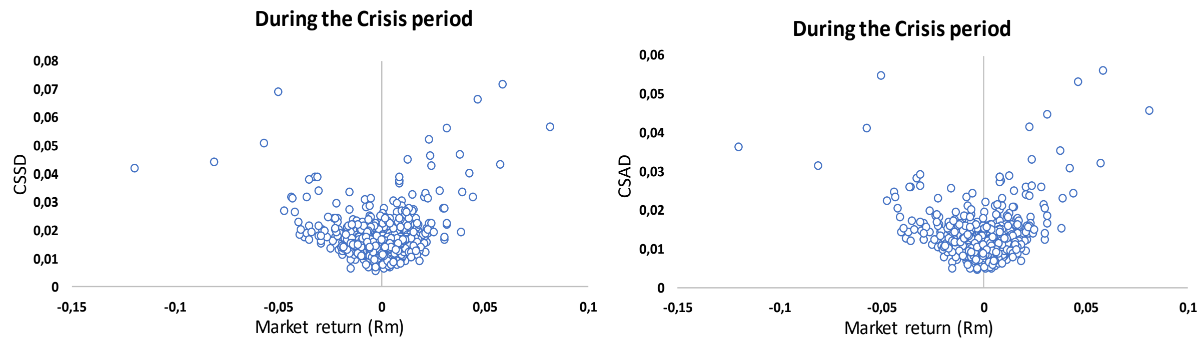

Figure 7. CSSD & CSAD - Market return for crisis period

The figures 5, 6 and 7 illustates the relationship between cross-sectional standard deviations or cross-sectional absolute deviations with the market returns. When comparing the figures between pre-crisis period and crisis period the difference is obvious. There seems to be positive and more linear relationship between CSSD / CSAD and market returns during the time of crisis, but no linearity is found during the pre-crisis period.

5.4 Descriptive statistics for volatility

The descriptive statistics for both of the volatility measures used are displayd in table 2 below. The GARCH volatilities are calculated using the formula 7 and the EWMA volatilities are calculated using the formula 8.

Table 2. Descriptive statistics for the volatility measures

	Whole sample		Pre-Crisis		Crisis	
	GARCH	*EWMA*	*GARCH*	*EWMA*	*GARCH*	*EWMA*
Mean	0,0101	0,0130	0,0074	0,0055	0,0127	0,0207
Median	0,0085	0,0048	0,0068	0,0030	0,0112	0,0080
Standard Deviation	0,0053	0,0356	0,0018	0,0075	0,0063	0,0493
Kurtosis	23,4110	153,1566	7,2348	15,7142	16,7693	79,3944
Skewness	3,9328	10,7313	2,3114	3,4711	3,4635	7,8403
Minimum	0,0053	0,0000	0,0055	0,0000	0,0070	0,0000
Maximum	0,0611	0,6651	0,0180	0,0580	0,0632	0,6651
Count of Days	1 558	1 558	764	764	794	794

This table reports the descriptive statistics of the two volatility measures used: Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponentially Weighted Moving Average (EWMA). The whole sample period is 1.1.2017-31.1.2023, pre-crisis period is 1.1.2017-31.12.2019 and crisis period is 1.1.2020-31.1.2023.

The pattern of increased volatility when moving from pre-crisis period to the crisis period can be seen from table 2 above. Both volatility measures show this change when comparing the mean of the volatilities from the pre-crisis to the crisis period. This goes to show that the Covid-19 pandemic and the war have had an impact on volatility as seen already from figure 4. The differences between the minimum and maximum values support this.

Perhaps the most noticeable difference between the two volatility measures, and between the sample periods are in the kurtosis and skewness. As stated above, a kurtosis of a normal distribution is zero, neither of the time periods have a normally distributed volatility but there is a noticeable spike from the pre-crisis period compared to the crisis period. The higher kurtosis indicates that the distribution is more peaked and has thicker tails. During the crisis period the kurtosis of 16,7693 (GARCH) and 79,3944 (EWMA) suggests that there is frequent and significant fluctuations in the volatility. The figure 4 illustrating the price development of Euronext100 during the whole sample period supports these results.

The difference in the kurtosis between these two volatility measures is most likely due to the fact that the EWMA model puts more weight to the most recent price changes and the effects of war are the most recent effects in this period, thus giving the highly volatile period more emphasis. Moreover, the GARCH measure assumes that the volatility changes over time and allows both negative and positive autocorrelation in the variance. This can of course lead to an lower kurtosis of the sample because the measure accounts for the changes in the volatility. Therefore, the kurtosis measured with the EWMA model in this case has a higher value because the end of the crisis period is so volatile. The GARCH model, on the other hand captures the changes in volatility over time lowering the number.

The skewness shows the same pattern. During the crisis period the skewness is noticeably higher and positive, implicading that the change of experiensing extreme events is more likely. The same difference in the skewness as in the kurtosis between the two volatility measures is also logical and most propably caused by the same reason as the difference between the kurtosis. Moreover, it can be concluded also from this descriptive statistics table that the volatility in Euronext100 is, as assumed, greater during the crisis period compared to the pre-crisis period.

6 Empirical results

As the research is divided into three parts, the empirical part is also divided into three parts. First the results of hypothesis one are presented and interpreted following the results for hypotheses two and three.

6.1 Herding during two different market conditions

Table 3. Estimates of herd behavior with the CSSD measure

		α	$D_t^L 5\%$	$D_t^U 5\%$	α	$D_t^L 1\%$	$D_t^U 1\%$
Complete sample	Coef.	0,0141***	0,0073***	0,0094***	0,0145***	0,0171***	0,0242***
	(Prob.)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
Pre-crisis	Coef.	0,0124***	0,0026***	0,0020**	0,0125***	0,0040**	0,0032*
	(Prob.)	(0,0000)	(0,0012)	(0,0146)	(0,0000)	(0,0871)	(0,0299)
Crisis	Coef.	0,0190***	-0,0027***	0,0195***	0,0198***	-0,0037***	0,0378***
	(Prob.)	(0,0000)	(0,0001)	(0,0000)	(0,0000)	(0,0000)	(0,0000)

This table reports the estimates for coefficients for the formula (2). The sample period for pre-crisis is 1.1.2017-31.12.2019 and for the crisis period 1.1.2020-31.1.2023. The coefficients are estimated using both 5% and 1% tails. The P-value is presented in parentheses and illustrated with ***, ** and * which represents statistical significance at the 1%, 5% and 10% levels.

The data analysis for the herding part for both CSSD and CSAD models in this study was conducted using Excel's LINEST function, which enables linear regression analysis. Although the LINEST function does not account for heteroscedasticity of errors, it provides a simple measure of observation dispersion and was, thus appropriate for the phenomenon under investigation.

H1 : Herding does occur in stock markets.

To analyse whether herding has occurred during the different sample periods attention needs to be paid for the beta coefficients presented in the table 2. The model calculates whether the dispersions are low during extreme market movements. In this case, the lower and upper tails are calculated and from table 2 it can be seen that during the pre-crisis period herding is not detected either in the upper nor the lower tails of the return distribution. The beta values are positive as well as statistically significant, that means that there has not been herd behavior during the most bullish or bearish days for the pre-crisis period in Euronext100.

During the crisis period the model detects negative beta values for the lowest 5% and the lowest 1% of the returns distribution. These negative beta values are also statistically significant at the 1% level. This indicates that investors have a tendency to herd during the extreme market downturns. Interestingly, there is no indication of herding during the days of the most bullish days. These findings are consistent with, for example, Jiang et al. (2022) and Blasco et al. (2017) who find that during the periods of market distress investors are more likely to herd. This might rise from the feeling of fear and even panic during the extreme bullish days (Blasco et al., 2017).

When only considering the results from the CSSD model, it seems that the H1 can be accepted. There is a statistically significant result of herd behavior when looking at the lower tail of the return distribution. Even though this result is enough to carry on to the effects of this herd behavior to the volatility measures, to get more comprehensive results the presence of herding is also calculated with the formula 4, cross-sectional absolute deviation.

Table 4. Estimates of herd behavior with the CSAD measure

		α	γ_1	γ_2	γ_3
Complete sample	Coef.	0,0083***	0,0520***	0,3030***	0,9870***
	(Prob.)	(0,0000)	(0,0000)	(0,0000)	(0,0014)
Pre-crisis	Coef.	0,0080***	0,0078	0,1023***	2,0923
	(Prob.)	(0,0000)	(0,4196)	(0,0019)	(0,1507)
Crisis	Coef.	0,0094***	0,0587***	0,3165***	0,6589*
	(Prob.)	(0,0000)	(0,0000)	(0,0000)	(0,0973)

This table reports the estimates for coefficients for the formula (4). The sample period for pre-crisis is 1.1.2017-31.12.2019 and for the crisis period 1.1.2020-31.1.2023. The P-value is presented in parentheses and illustrated with ***, ** and * which represents statistical significance at the 1%, 5% and 10% levels.

The results when using formula 4, CSAD method are illustrated in table 3. The results are much more inconclusive when comparing to the results when using the CSSD methods. When reading table 3, the results for the coefficient γ_3 are the most important ones. If there is herding detected, the coefficient γ_3 is negative and statistically significant. As can be seen from table 3 above the coefficient for the pre-crisis period is highly positive, but not statistically significant. For the crisis period the coefficient is only significant at the 10% level and positive. It can be still stated that when comparing the coefficient during the pre-crisis period and crisis period the coefficient decreases from 2,0923 to 0,6589 meaning that there is significantly less deviation during the crisis period and some level of mimicking of other investors might have occurred.

The CSSD is better at catching herd behavior during the extreme market movements because the model is carried out by using the tails of the return distribution and this is the reason it could catch the herd behavior during the extreme bearish days during the crisis period. The CSAD model did not detect herding but indicated that there has been a greater level of mimicking of other investors during the crisis periods. From these results the hypothesis one can be partially accepted. The models did not show herding during the pre-crisis period, therefore it can be stated that during market distress investors are more likely to engage in herd behavior. These results are opposite to the results by Zhang and Giouvris (2022) who found herding to be prevalent characteristics of financial markets and is not dependent on the market movements but consistent with results by Blasco et al. (2017) who found that during the most bearish days the herding increases.

6.2 The effect of herding on volatility

Table 5. The effect of herding on volatility

Panel A: The effect of CSSD				
		Complete sample	Pre-crisis	crisis
GARCH	CSSD	0,4699***	0,0320*	0,6319***
	(Prob.)	(0,000)	(0,0606)	(0,0000)
Ewma	CSSD	0,01887***	0,0033***	0,0241***
	(Prob.)	(0,000)	(0,0045)	(0,000)
Panel B: The effect of CSAD				
		Complete sample	Pre-crisis	crisis
GARCH	CSAD	0,7766***	0,1494***	0,8723***
	(Prob.)	(0,000)	(0,0000)	(0,0000)
Ewma	CSAD	0,03116***	0,0177***	0,03289***
	(Prob.)	(0,000)	(0,000)	(0,000)

This table represents the results for formulas (9) and (10). The sample period for pre-crisis is 1.1.2017-31.12.2019 and for the crisis period 1.1.2020-31.1.2023. The P-value is presented in parentheses and illustrated with ***, ** and * which represents statistical significance at the 1%, 5% and 10% levels.

Table 4 represents the regression results when calculated the effects of herding on the two volatility measures used. From the table it can be seen that with both volatility measures, GARCH and EWMA, the regressions generated statistically significant results. The effect of herding on volatility was calculated using both herding measures to investigate whether they generated different results.

H2 : Herding causes an increase in volatility.

When looking at the pre-crisis period, both CSSD and CSAD seem to have a positive effect on volatility when using the GARCH volatility measure. Low or negative CSSD / CSAD indicates that investors mimic each other and there is herding present in the financial markets which could have an effect on the market volatility. If there is a positive relationship between volatility and CSSD / CSAD, such as these results show, then it means that a decrease in CSSD / CSAD means increase in herding and a decrease in volatility. For both pre-crisis and crisis periods this seems to be the case although the effect during the crisis period is more substantial. These results generated using the GARCH volatility model are in line with the results by Zhang and Giouvris (2022) who also found no implications that herd behavior increases the volatility.

Using the EWMA volatility measure the results for both CSSD and CSAD seem to have the same positive relationship as did the GARCH volatility measure. The relationship between pre-crisis and crisis periods also seems to be the same. The decreasing effect on volatility is greater during a crisis period than during the pre-crisis period. Interestingly the effect on volatility, although being statistically significant, is less when calculated with the EWMA volatility measure. This might be caused by the so called "smoothing factor", lambda. For example, the most volatile periods in the crisis period sample are at the beginning of the sample period, but with the EWMA measure those most volatile periods do not get as much weight as the most recent volatility changes in the sample period. The results with the EWMA method are also consistent with the study conducted by Zhang and Giouvris (2022).

From these results the second hypothesis that states that herding causes an increase in volatility can be rejected. This study shows that herding leads to less volatility. The study supports the results by Zhang and Giouvris (2022), although in their study herding generated a greater impact on volatility when measured with the EWMA volatility measure. In this study the difference is not that great but can still be noted from the results. These results do not support the conclusions of the study by Blasco et al. (2012). They found that herding increases volatility in the Spanish stock markets.

6.3 The effect of volatility on herding

Whether herding affects volatility is calculated with the formula 4 that calculates the herding intensity, but the data is divided into four different samples based on the volatility levels. The effect of volatility on herding is calculated only by using the CSAD method. This is because the CSSD gives the results of herding level at the ends of the return distributions and because the sample is already divided into four it is more suitable to look at the subperiods as a whole, not just the ends of the periods. Moreover, the samples would be too small to measure herding if the CSSD was used and the results would not be reliable.

Table 6. The effect of volatility on herding

Panel A: Volatilities Level < 25% of Volatilities Distribution		
	GARCH	Ewma
CSAD	12,2571	-5,0279
(Prob.)	(0,5269)	(0,9877)
Panel B: Volatilities Level 25% - 50% of Volatilities Distribution		
	GARCH	Ewma
CSAD	3,5675***	31,6098***
(Prob.)	(0,0001)	(0,0147)
Panel C: Volatilities Level 50% - 75% of Volatilities Distribution		
	GARCH	Ewma
CSAD	5,0787	35,2718***
(Prob.)	(0,3482)	(0,0004)
Panel D: Volatilities Level > 75% of Volatilities Distribution		
	GARCH	Ewma
CSAD	1,1961**	-0,9084
(Prob.)	(0,0407)	(0,1634)

This table represents how different levels of volatility effects the herding measure CSAD. The whole sample period is divided into four subperiods based on the volatilities distribution. The table shows results for volatilities distribution calculated both with the GARCH method and EWMA method. The P-value is presented in parentheses and illustrated with ***, ** and * which represents statistical significance at the 1%, 5% and 10% levels.

When the herding intensity rises the CSAD coefficient decreases. Moreover, it can be said that there is herding present if the coefficient is negative, but if the coefficient decreases significantly the conclusion can be drawn that investors have started to mimic each other more compared to periods when the coefficient is larger. For this test the results presented in table 5 above, the coefficients are mostly not statistically significant. This is probably because the sample sizes are quite small when the whole data is divided into four subperiods compared to only two.

H3 : Volatility causes more herding.

From table 5 above it can be detected that there seems to be substantial herding during the least volatile period when the volatilities are divided into subgroups using the EWMA method. It can also be seen that the p-value is 0,9877 which means that this result is nowhere near being significant and it can be considered as an error. During the subgroups two and three there is clear indication that herding has not occured and those results are statistically significant. Between those groups there is an indication that there is even less herd-like behavior when the volatilities are at the second upper end of the volatilities distribution, which indicates that volatility does not trigger herding. During the last subperiod, which is the subperiod of most volatile period it seems like herding is detected, but again the result is not statistically significant with the p-value of 0,1634.

When the volatilities are divided into subgroups using the GARCH method the results are more consistent between the different periods. The same can be detected comparing to results with using the EMWA volatility measure that the third subperiod shows less herd-like behavior compared to the second subperiod. There is a decrease on the CSAD coefficient during the most volatile subperiod and the result is also statistically significant at 5% level.

Even though the results show a decrease on the CSAD coefficient during the most volatile periods, walking through the table, the results are not consistent enough to make a conclusion that volatility triggers herding. Therefore, the third hypothesis is not supported in this study. This result contradicts the results by Zhang and Giouvris (2022) who find increased volatility to trigger herding. Moreover, these results are in line with the results by Blasco et al. (2012) and Venezia et al. (2011). Neither of these studies found implications of volatility causing herding. This result is consistent with the result that there seems to be herding during the extreme bearish days which this study showed. This study showed no herding during the extreme bullish days. It is most likely that both extreme up and down days show in the most volatile periods and that is why the CSAD coefficient decreases but not enough to be significantly lower or negative. Also, in order to make a conclusion that volatility triggers herding the table should have showed consistent decrease in the CSAD coefficient when moving from least volatile period to the most volatile period.

To reflect on the three hypotheses it can be summed up that only the first hypothesis is partially accepted. The CSSD and CSAD methods showed that during the crisis periods the coefficients decreased or turned negative. The second hypothesis is rejected since the results show that herding has an opposite effect on volatility than predicted. Herding decreases volatility and not vice versa. The third hypothesis is rejected since there was not enough consistency in the results. It can still be stated that it seems like during the most volatile periods investors are more likely to start mimicking each other.

7 Conclusion

The research objective in this study was to examine whether herd behavior exists in the European stock markets, and the implications of the herd behavior to the market volatility. This study has introduced a wide range of previous studies about herding. Both original studies which introduce different herding models and studies that use these models in order to detect herding from different financial markets during different market conditions. Moreover, previous studies conducted about the relationship between herd behavior and stock market volatility have been discussed. Herding is a concept that belongs to the field of behavioral finance, thus being strongly connected with human psychology. Moreover, the concept of herding contradicts the broadly accepted theory of efficient market hypothesis.

This study shows through empirical research that herding does exist during the more turbulent times in the European stock markets. Through the CSSD and CSAD analysis herding exists during the extreme negative market return days and when comparing the pre-crisis period and crisis period the analysis shows a clear pattern of decreasing dispersion, which shows that more investors outsource their investment decisions to the markets and start to follow other investors instead of their own analysis. The previous findings about herding existing in financial markets and in which market conditions differ from each other. Findings from this study support the previous studies, for example from Blasco et al. (2017) and Espinosa-Méndez & Arias (2020).

By using regression models to combine two different volatility measures, GARCH and EWMA, and the two herding models CSSD and CSAD, this study finds that herding and volatility have a statistically significant and positive relationship. This means that when the level of herding increases (CSSD or CSAD decreases) in the financial markets, the volatility decreases. This has been an open issue in academic literature and these findings are contradicting for example the findings of Blasco et al. (2012) but support the findings of Zhang & Giouvris (2022).

This study found no clear, nor significant implications of greater volatility causing greater herding. The empirical results show that during the most volatile period herding exists, however the results were not consistent enough to state that whenever volatility increases, the level of herding increases. The evidence of volatility causing more herding can be seen from the study by Zhang & Giouvris, (2022). Yet in conclusion, this study could not find enough evidence or a clear pattern between the volatility distribution subsections of increasing herding which is consistent with the results of Blasco et al. (2012) and Venezia et al. (2011).

7.1 Limitations

Even though this study found statistically significant evidence of herd behavior and the implications of that to the volatility, the models used do not come without limitations. Firstly, the Cross-Sectional Standard Deviation (CSSD) and the Cross-Sectional Absolute Deviation (CSAD) models used to detect herding do not take into account the differences of stocks in the index. They do not recognize differences in liquidity, market capitalization or the fact that the stocks represent different industries. This could affect the results since it could be that for example there is herding amongst a certain industry, or amongst the most liquid stocks but not in all of the stocks used in this study.

Secondly, both of the volatility measures used, Exponentially Weighted Moving Average (EWMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, assume that volatility is a stationary process. The EWMA model is able to respond quickly to changes due to giving more weight to most recent data, while the overall distribution remains stationary. The GARCH model is able to capture the volatility clusters because it assumes that the conditional variance of the data is a function of past values of the variance and the squared error terms. The limitation is that the same assumptions are both stationary processes. The limitations of stationary processes are discussed in the academic literature (e.g. Xu, 2008). In conclusion, the stationary assumption of these models is based on an assumption that the statistical properties of the data sample studied remains constant over time. This may not reflect the reality because the data taken from real world can exhibit non-stationarity. For example, in this data studied, especially during the crisis period, the data exhibited different trends, which violates the assumption of stationarity.

There are limitations with the statistical methods used. While all the models, CSSD, CSAD, EWMA and GARCH are widely used in academic research, it would be ignorant to not leave room for the assumption that there may be other statistical or econometric models that could generate even more accurate results. These limitations do not debunk the results found, but researchers should be aware of the limitations while using these methods.

7.2 Future research suggestions

With the field of behavioral finance, only the imagination is the limit for future research. Traditionally investors have been viewed as rational actors in the financial markets, which might have been the case before when investing was more exclusive to smaller groups of people. Nowadays investing is seen as much more as a low threshold action and more and more young investors enter to the financial markets. Also, the flow of information and misleading news coverage is more rapid. This highlights the importance of the field of behavioral finance. It is important to be able to make implications to the real financial markets, ergo find how the behavioral finance anomalies manifest in the financial markets or what aspect of the markets the anomalies effect and how.

This study has covered the beginning of the Russian invasion to Ukraine, and as this study is being written, the financial markets in Russia has been declined greatly. It would be interesting to study the magnitude of herding in the Russian markets during this period. Herding is usually seen either to manifest when the markets are turbulent, or the investors are unsure how to act (e.g. Blasco et al., 2017). In the case of Russia there could be a sentiment of punishment from the investors towards Russia and it manifests as a loss of investors in the market. Moreover, it would be interesting to study what is the amount the markets should have declined based on the fundamentals, and what is the role of herding in the decrease.

The question of the relationship between herding and market volatility remains an open issue. This field needs still more studying to be able to draw a conclusion what is the significance of herding to the volatility in financial markets. It is possible that the relationship can be different in different markets, for example it is possible that the influence to the volatility can vary in developed and emerging markets due to different market conditions. It would be important to draw conclusions of whether herding can influence the volatility so greatly, that it needs to be taken into account in the volatility calculations.

7.3 Contribution

This study has contributed to the existing academic literature of herd behavior and market volatility by advancing the understanding of herd behavior and the implications this anomaly has in the financial markets. The findings in this study shed light to the effects of herd behavior in financial markets that could be useful for researchers, investors and policymakers who seek to deepen their knowledge and to better manage market risks.

The research conducted on the implications of herding to market volatility provides new nuances to understand the dynamics of different behavioral factors in financial markets and the matters that cause asset price fluctuations in financial markets. The findings could be used by investors to better manage the risks in their portfolios.

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