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Herd behavior in the Baltic equity markets during the COVID-19 pandemic

School of Accounting and Finance
Master’s thesis in Finance
Master’s Degree Programme in Finance

Vaasa 2025

UNIVERSITY OF VAASA
School of Accounting and Finance
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Title of the thesis: Herd behavior in the Baltic equity markets during the COVID-19 pandemic
Degree: Master of Science in Economics and Business Administration
Discipline: Master's Degree Programme in Finance
Supervisor: Sami Vähämaa
Year: 2025 **Pages:** 77

ABSTRACT:
Herd behavior has been extensively studied, with contradictory results regarding its existence in different market situations. Herding is a behavioral bias that causes humans to follow each other's actions without perfectly evaluating the reasons or motivations for them. It is derived from animals and, therefore, embedded in our DNA, making it difficult to overcome.

Herding poses challenges to fundamental finance theories as it can stem from irrational behavior. For instance, asset pricing models, such as the Capital Asset Pricing Model, rely on the assumption of a perfect capital market, which entails that financial agents are rational self-utility maximizers. Prior literature shows that herding can lead to stock market bubbles and other temporary market inefficiencies, which directly contradict the Efficient Market Hypothesis.

This thesis aims to assess whether herd behavior can be noticed in the Baltic equity markets during a global pandemic, namely the recent Coronavirus disease (COVID-19) pandemic. The sample period of this thesis is divided into three sub-periods: the pre-COVID period, the COVID period, and the post-COVID period, which are studied separately alongside the entire sample period. Additionally, this thesis reviews fundamental finance theories closely associated with herding and how such bias may affect them. To add context to the empirical results, previous literature related to herd behavior in stock markets is discussed.

The methodology of this thesis is based on a regression analysis that uses stock return dispersions to determine whether market-wide herding can be observed. This thesis employs the cross-sectional absolute deviation model, which was introduced by Chang et al. (2000) and is a more advanced version of the cross-sectional standard deviation model introduced by Christie and Huang (1995).

All three suggested hypotheses can be rejected based on the empirical results obtained from the Baltic equity markets. Estonia is the only country that exhibits herd behavior, but only during pre-pandemic and post-pandemic periods. The results, however, are not statistically significant, and therefore, they can be seen as inconclusive. Lithuania, however, produces evidence of anti-herding behavior during the pre-pandemic period that is significant at a 5% level. This implies that investors acted rationally regarding herd behavior in Lithuania before the pandemic.

KEYWORDS: Herd behavior, behavioral finance, COVID-19, Cross-sectional absolute deviation, Baltic equity markets, global pandemic, market-wide herding, market efficiency

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen akateeminen yksikkö

Tekijä:	Matias Rusi		
Tutkielman nimi:	Herd behavior in the Baltic equity markets during the COVID-19 pandemic		
Tutkinto:	Kauppatieteiden maisteri		
Oppiaine:	Rahoitus		
Työn ohjaaja:	Sami Vähämaa		
Valmistusmisvuosi:	2025	**Sivuja:**	77

TIIVISTELMÄ:
Laumakäyttäytymistä on tutkittu laajasti, ja sen olemassaolosta eri markkinatilanteissa on saatu ristiriitaisia tuloksia. Laumakäyttäytyminen on käyttäytymisharha, joka saa ihmiset seuraamaan toistensa toimia arvioimatta täydellisesti niiden syitä. Se on juurtunut ihmisen DNA:han, minkä vuoksi on haastavaa olla antamatta sen vaikuttaa yksilön päätöksentekoprosessiin.

Laumakäyttäytyminen asettaa haasteita rahoituksen perusteorioille, koska sen syynä voi olla epärationaalisuus. Esimerkiksi osakkeiden hinnoittelumallit, kuten Capital Asset Pricing Model, perustuvat oletukseen täydellisistä pääomamarkkinoista, joka olettaa, että markkinatoimijat ovat rationaalisia oman hyödyn maksimoijia. Aikaisempi kirjallisuus osoittaa, että laumakäyttäytyminen voi johtaa osakemarkkinoiden kupliin ja muuhun tilapäiseen markkinoiden tehottomuuteen, mikä on suoraan ristiriidassa tehokkaiden markkinoiden hypoteesin kanssa.

Tämän tutkielman tarkoituksena on arvioida, voidaanko Baltian osakemarkkinoilla havaita laumakäyttäytymistä maailmanlaajuisen koronavirus (COVID-19) pandemian aikana. Tämän tutkielman otantajakso on jaettu kolmeen osajaksoon: COVID-pandemiaa edeltävään jaksoon, COVID-jaksoon ja COVID-jakson jälkeiseen jaksoon, joita tutkitaan erikseen koko otantajakson ohella. Lisäksi tässä tutkielmassa tarkastellaan laumakäyttäytymiseen läheisesti liittyviä rahoituksen perusteorioita ja sitä, miten tällainen harha voi vaikuttaa niihin. Empiiristen tulosten kontekstin lisäämiseksi käsitellään osakemarkkinoiden laumakäyttäytymiseen liittyvää aiempaa kirjallisuutta.

Tämän tutkielman metodologia perustuu regressioanalyysiin, jossa käytetään osakkeiden tuottohajontaa markkinoiden laajuisen laumakäyttytymisen havaitsemiseen. Täten tutkielmassa käytetään cross-sectional absolute devation -mallia, jonka on kehittänyt Chang et al. (2000) ja joka on kehittyneempi versio Christien ja Huangin (1995) kehittämästä cross-sectional standard deviation -mallista.

Kaikki kolme esitettyä hypoteesia voidaan hylätä Baltian osakemarkkinoilta saatujen empiiristen tulosten perusteella. Viro on ainoa maa, jossa esiintyy laumakäyttäytymistä, mutta vain pandemiaa edeltävänä ja sen jälkeisenä ajanjaksona. Tulokset eivät kuitenkaan ole tilastollisesti merkittäviä, joten niiden perusteella ei voida tehdä johtopäätöksiä. Liettuassa on kuitenkin laumakäyttäytymistä vastustavaa näyttöä pandemiaa edeltävänä aikana, ja se on merkittävää 5 prosentin tasolla. Tämä viittaa siihen, että sijoittajat toimivat rationaalisesti laumakäyttäytymisen suhteen Liettuassa ennen pandemiaa.

AVAINSANAT: Herd behavior, behavioral finance, COVID-19, Cross-sectional absolute deviation, Baltic equity markets, global pandemic, market-wide herding, market efficiency

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Abbreviations

AMH	Adaptive Market Hypothesis
BSM	Black-Scholes-Merton Model
CAPM	Capital Asset Pricing Model
COVID	Coronavirus disease
CSAD	Cross-sectional absolute deviation
CSSD	Cross-sectional standard deviation
DCF	Discounted cash flow
EMH	Efficient Market Hypothesis
OTC	Over-the-Counter
REIT	Real Estate Investment Trust
S&P	Standard & Poor’s
SML	Security market line
UAE	United Arab Emirates
US	United States
VaR	Value at Risk
VIX	Volatility Index
WACC	Weighted average cost of capital

1 Introduction

Humans tend to make decisions that might not be the most beneficial or the most reasonable for them. Whether it is about sleeping ten minutes later in the morning than intended or not brushing your teeth in the evening. It is normal and even characteristic for a human to satisfy basic needs – enough sleep and rest in this case. If considered a situation where a person has to choose a restaurant to eat dinner at. People seem to stand in a queue in front of the first option. Everyone is excited, and the place looks high-quality. The second option, on the other hand, is empty. Nobody seems to be dining there even though the “open” sign is lit. The choice is easy to make. The queue does not guarantee the quality of the food, but it makes up an illusion about the superiority of the restaurant. People want to go to the same restaurant as everyone else because the human intrinsic tells them so. After all, a human is an animal that works intrinsically by its nature.

The phenomenon introduced above is called herd mentality, herd behavior, bandwagon effect, or simply herding (Ah Mand et al., 2021). Another concrete example related to the topic of this thesis could be consumers’ buying behavior during the COVID-19 pandemic. As people started to fear that the pandemic could affect the availability of basic household items, they started irrationally hoarding things, such as toilet paper. Looking back, it was obvious that any of the items mentioned above were not to run out, but people hoarded them because other consumers did so as well. There was neither reason nor need to buy excessive amounts of canned food, pasta, or rice, but it felt like a safe option for many. People feared that if they did not engage in hoarding, they would be left without items necessary for living. The same phenomenon could also be noticed in physical cash, which led to a 12.20 percent jump in physical euros in circulation in 2020-2021 (Arnold, 2021). That said, fear is one of the fundamental reasons behind irrational decisions. Fear is also an essential driver for herd behavior in the stock market (Economou et al., 2018; Huang & Wang, 2017) due to the increased irrationality.

Even though there is a significant difference between hoarding household items and making financial decisions on the stock market, similar psychological factors affect the decision-making process. Investors tend to choose stocks that have received positive ratings from stock analysts or mimic a well-known investor without adequately evaluating the reasons for their actions. They might also choose the stock because a friend or relative bought the same stock a few days earlier. It does not guarantee that the stock will perform well but it feels like a good and safe decision. If a big group, like a whole group of friends, buys a certain stock or participates in a certain Initial Public Offering, the need to belong to the group might arise in those who have not done so. Alternatively, the ones not doing so might experience FOMO – The Fear of Missing Out. A good case in point is the GameStop short squeeze that led thousands of investors to buy GameStop stock as it felt like an opportunity to get rich quickly (Vasileiou, 2021).

The same phenomenon can also be recognized in different financial market conditions. When prices rise, also known as a bull market, people tend to get overwhelmed and rush to buy stocks. On the contrary, when prices fall, and the bull market switches to the bear market, investors get anxious and scared and tend to realize their portfolios. They let their emotions affect their decision-making, leading to irrational actions with possibly destructive consequences regarding portfolio performance. If people acted rationally, they would do the opposite: buy when the prices are falling and sell when they are rising. There is a saying on Wall Street that is sometimes even referred to as an index: *when your taxi driver starts giving you stock recommendations, it is time to sell*. In addition to its actual meaning, it narrates much about the psychology behind investing. The driver cannot probably evaluate the correct price of a stock using all the information available following a well-educated decision to either buy or sell the stock. Instead, he has formed his opinions and further the tips based on the crowd's opinion. This is the bandwagon effect, also known as the heard bias.

The COVID-19 pandemic had several adverse effects on the global economy, such as an increase in global poverty and inequality, an increase in governments' expenditures

(World Bank Group, 2023), a decrease in the world's collective gross domestic product (Dyvik, 2024), dramatic falls in the stock market (Baker, 2024) et cetera. These further translated into decreased demand, postponed investments, disrupted supply chains, and a general negative consensus on the expectations of the firms' outlooks (Stemmler, 2022). This ultimately led to consequences, such as decreased sales and firms' liquidity and increased layoffs, temporary closings, and general uncertainty. For example, out of more than 100,000 businesses, 84 percent of them across 51 countries reported a decrease in sales during the period from April through August 2020 (World Bank Group, 2023). These kinds of effects often cause heightened volatility in the stock market, and it could also be noticed during the COVID-19 pandemic as the volatility index (VIX) rose to the all-time highest, closing at 82.69. As herd behavior should be more noticeable during periods of high volatility (Christie and Huang, 1995), this thesis evaluates whether this notion applies in the Baltic stock market during a global health pandemic.

1.1 Purpose of the study

The purpose of this study is to examine whether herding can be noticed in the Baltic countries' equity market during the COVID-19 pandemic. More precisely, the purpose is to find out whether the degree of herd behavior varies before, during, or after the COVID-19 pandemic in Estonian, Latvian, and Lithuanian equity markets. The primary reason for choosing the Baltic markets for the scope of this thesis is the lack of previous herding-related literature during the COVID-19 pandemic. As the Baltic countries are relatively homogenous in terms of size and both demographic and economic characteristics, this thesis will also examine whether significant differences can be noticed between the Baltic countries. These similarities as well as the proximity to Finland is the secondary reason to choose the Baltic countries for this study. Provided that herding can be recognized to some degree, its impacts are also evaluated. As herding is a direct implication of irrational behavior, this thesis also assesses whether several financial theories, such as the Capital Asset Pricing Model, are based on unrealistic assumptions. In addition, as one direct effect of herding is the price movements of stocks, this thesis also assesses the market efficiency in the Baltic countries.

While behavioral finance is an interesting, important, and relevant subject in its own right, what is even more interesting is to find whether either retail or institutional investors can benefit from it. Therefore, the ultimate motivation for this study is to examine how participants in the Baltic stock market act to provide information that can potentially be exploited to achieve abnormal returns. Alternatively, this thesis can provide helpful insight for regulators, especially during crisis periods. As this is not part of the main scope of this thesis, it will not be examined or analyzed further. It could, however, be a topic of how this thesis could be continued in the future by implementing, for example, an asset allocation strategy that benefits from the findings of this paper.

In addition to the abovementioned motivations, this thesis also aims to contribute to previous literature on herding in the European equity markets. More specifically, the original motivation of this thesis was to contribute to previous studies on herding in the Baltic stock market, such as Maria (2015) and Pavlovska and Berisha (2015), by studying the phenomenon during the period of heightened volatility. As there are some previous studies conducted during other events of heightened volatility in the Baltics, such as the Global Financial Crisis (Angela-Maria et al., 2015), this study's goal was to be the first one studying the same topic during the COVID-19 pandemic. At the time of starting this thesis, no other studies were examining herding in the Baltic stock market during the crisis. However, several months later, Legenzova et al. (2024) published a paper that studies herding in the Nordic and Baltic stock markets during upward and downward market movements in global disruptive events, that is, the COVID-19 pandemic. As the uniqueness aspect of this study was partly eliminated after the beforementioned publication, the way this thesis contributes to previous literature changed. The revised contribution consists not only of studying the Baltics as a whole but also concentrating on the differences between the results from Estonian, Latvian, and Lithuanian stock markets. As Legenzova et al. (2024) only study one out of three countries, leaving Estonia and

Latvia out of their scope, this study might reveal differences between Baltic nations. In addition, to the best of my knowledge, no other papers besides Legenzova et al. (2024) have been published that study solely herding in all three Baltic nations during the pandemic. Therefore, this paper also either validates or contradicts the findings of Legenzova et al. (2024).

Traditional finance includes several theories based on certain assumptions. One widely known assumption is that investors act rationally and make perfectly rational decisions. As previous studies, such as Legenzova et al. (2024), Bogdan et al. (2022), Spyrou (2013), and Nofsinger and Sias (1999), show, herding might include characteristics of irrationality, and therefore, this thesis also contributes to the literature opposing this widely accepted assumption. Consequently, this thesis challenges the foundations of some of the most fundamental theories in the field of finance.

1.2 Research hypotheses

As mentioned above, this thesis contributes to previous behavioral finance literature by studying whether herding can be noticed in the Baltic stock market during a period of heightened volatility, the COVID-19 pandemic in this case. As history shows, investors have provided evidence of herd behavior in the stock markets during several abnormal market occurrences, such as the Dotcom bubble at the beginning of the 21st century (Galariotis et al., 2014), the Global Financial Crisis in 2008 (Xing et al., 2024), and the GME Short squeeze in 2021 (Lin et al., 2021). By reflecting on the events above, there is a credible reason to believe that herding also occurs during the COVID-19 pandemic. The prediction is backed by the findings of Adem and Sarıoğlu (2020) and Kabir and Shakur (2018), who find a positive correlation between the increased volatility and the level of herding behavior. In addition, as the COVID-19 pandemic was a global crisis and touched more or less every single country in the world, there is also a credible reason to believe that the effects of the COVID-19 pandemic can be noticed in the Baltics as well. Therefore, the first hypothesis is defined as follows:

H1: Evidence of market-wide herding can be found in the Baltic equity markets during the outbreak period of COVID-19 pandemic

It is, however, worth mentioning that the level of herd behavior did vary between nations during the Global Financial Crisis and the COVID-19 pandemic (Xing et al., 2024; Ferreruela & Mallor, 2021). Therefore, there could also be differences between the Baltic countries when studying herding behavior during the different periods of the COVID-19 pandemic. On the other hand, studies such as Nikkinen et al. (2012), Brännäs et al. (2012), and Dubinskas & Stungurienė (2010) find evidence of Baltic stock markets' co-integration and bidirectional relationship. They also noticed feedback effect between the markets, and therefore, they should correlate at least to some extent in the context of COVID-19. Considering the studies mentioned above, there is also a credible reason to believe that the level of herd behavior did not radically change between the countries. This leads to the second hypothesis:

H2: Investors' behavior did not significantly change between the different Baltic stock markets during the entire sample period in terms of market-wide herding

As this study is divided into three different periods, the pre-COVID-19 period, the COVID-19 period, and the post-COVID-19 period, the differences between these periods will be studied as well. As previous studies, such as Galariotis et al. (2015), show, herd behavior did increase during previous crises, but once the crisis is over, no evidence of herding can be found. By extending the first hypothesis, the third hypothesis is defined as follows:

H3: No evidence of market-wide herding can be found once the outbreak period is over

Although it would be interesting to see results similar to those of previous studies, finding opposing evidence could be even more salutary, as it could reveal new branches of study. Defining the end of the pandemic unambiguously is relatively complex, so defining the post-COVID-19 period differently could also produce deviating results.

1.3 Structure of the study

The first chapter of this thesis discusses the theoretical background linking herd behavior to relevant and well-known financial theories. The second part discusses the most widely known asset pricing models and how herd behavior affects them. The third part introduces herding as a phenomenon, how it affects markets, and reviews the previous related literature. The fourth section examines the data, the sub-periods studied in this thesis, and descriptive statistics. The fifth part provides insight into the methodology and models used to recognize herd behavior, and the sixth part discusses the main results and findings of the empirical part. Lastly, the seventh part includes a conclusion that summarizes the main concepts and findings and discusses how the study could be continued. References are listed at the end of this thesis.

2 Theoretical background

The following chapters explore the widely debated Efficient Market Hypothesis (EMH) and its more modern version, the Adaptive Market Hypothesis (AMH). These concepts are closely associated with herd behavior, which is often viewed as a direct contradiction to the former theory. As mentioned in the purpose of this study, one of the primary goals is to assess whether herd behavior contradicts the EMH in the Baltic equity markets during a global pandemic.

2.1 The Efficient Market Hypothesis

The main purpose of capital markets is to be an efficient trading center for buyers and sellers to trade currencies, stocks, bonds, derivatives, and other financial instruments. More precisely, capital markets are often split between the stock market and the bond market as they are the most common ones. One of the most important prerequisites for capital markets to function correctly is the correct securities pricing. For markets to be fully efficient, all the information available at any given time should be reflected in the prices of securities. An ideal market has been widely regarded as one where the security price fully reflects all the information available at any given time. One of the financial world's most well-known hypotheses is the Efficient Market Hypothesis (EMH), which explains the phenomenon of market efficiency and its different levels.

Eugene Fama can partly be held as a father of the EMH as it mainly derives from the concepts of his research (Fama, 1970). However, in his earlier paper, Fama states that the EMH is a theoretical premise and that an efficient market does not factually exist (Fama, 1965). The idea of efficient markets being a theoretical premise stems from Kendall's (1953) research. In the research, Kendall studies economic time series and discovers that future stock prices cannot be predicted because the prices are determined randomly. The name "random walk" was subsequently coined as a result of various other studies on the same topic inspired by Kendall's (1953) publication.

The ultimate finding Fama (1970) makes is that it is nearly impossible to sell overvalued stocks or buy undervalued ones as stocks always trade at their fair value. He finds an abundant amount of supporting evidence of the efficient market model. However, the amount of contrary evidence is slight. A market is considered "informationally efficient" if prices at any given time reflect all available knowledge about future values. Fama (1970) presents three variations of the EMH: the weak, semi-strong, and strong forms, which will be discussed in more detail later in this chapter. The main difference between the forms is how well they reflect the information and what kind of information they reflect. One of the most critical findings Fama (1970) makes, especially from a retail investor's point of view, might be the fundamental contention that it is essentially impossible to beat the market constantly. He states that investors might buy a stock that performs exceptionally well occasionally. Still, they cannot reasonably expect to achieve significantly higher returns than the market average over the long term. The contention mentioned earlier is particularly important, for example, when shifting from the field of market efficiency to the field of portfolio management. The idea that investors cannot achieve significantly higher returns by picking stocks is essential to understand when studying asset allocation and, for example, choosing between mutual funds and common stocks.

Herd behavior contradicts the EMH in two key ways. As discussed in the following chapters, several previous studies provide evidence of herding. Since herding can directly influence asset prices, causing temporary inefficiencies, it contradicts one of the fundamental principles of the EMH, which asserts that asset prices only react to new information. The EMH also assumes that economic agents (i.e., market participants) are rational utility maximizers. This, however, is clearly not true, as herd behavior often stems from irrational behavior. These topics are discussed more extensively in the following chapters.

The EMH is commonly divided into three different forms: weak, semi-strong, and strong. These versions differ in how they define the term "all accessible information" (Bodie et al., pp. 353). The weak-form hypothesis states that current stock prices represent all information that can be found by examining market trading data, including transaction volume, price history, and short interest. Therefore, the current price of stock includes all historical information. If historical data included signals about future price movements, investors would learn to exploit them, making them lose their value. The hypothesis of the semi-strong form assumes that the stock price reflects all the available public information regarding the firm's prospects. Therefore, the stock price must reflect information about past prices, the firm's product portfolio, management's capabilities, financial statements, patents, future cashflows, and bookkeeping methods. According to the strong-form hypothesis, the stock price must reflect all available relevant information regarding the firm. Therefore, the information available only for employees and other insiders should also be reflected in the stock price. The strong form can be considered relatively problematic and controversial as there are strict rules and laws controlling insider trading. The corporate officers, owners, and such are obligated to report their trades to prevent them from benefiting from their position. Regardless, the strong form of the EMH suggests that information only available to insiders should also be reflected in the stock price. The characteristic shared by all of the versions is that reflected information should be available. Thus, the EMH does not expect traders to be aware of information that is not available (Bodie et al. pp. 353-354).

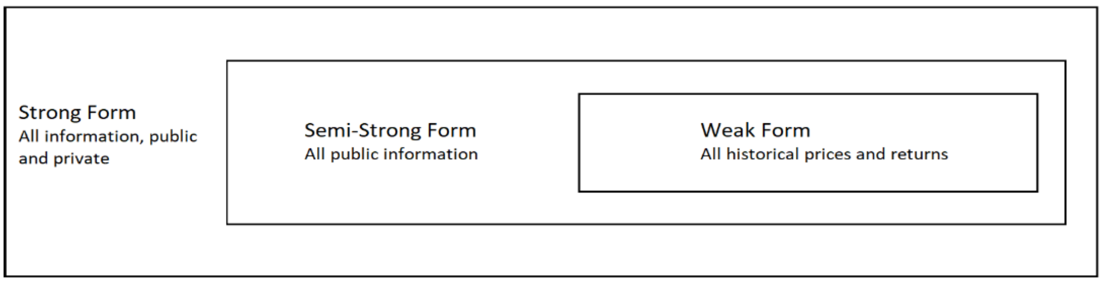

Figure 1. Different versions of the EMH with information levels visualized

2.2 The Adaptive Market Hypothesis

As discussed above, the Efficient Market Hypothesis is one of the most fundamental and well-known theories in the field of finance. When something is highly well-known and publicly available, it often arouses controversy – so does the EMH. Things like hypotheses tend to get better and more accurate when they can be examined critically and publicly. The Adaptive Market Hypothesis (the AMH) is an excellent example of how a hypothesis can have roots in relatively old, fundamental studies. Still, when it is combined with more recent research, it sparks new ways of thinking and seeing phenomena. In this case, the AMH widens the interpretation of efficient markets compared to the traditional EMH.

Lo (2004) examines the present debate over the classic version of the EMH in his paper. In addition, he offers a fresh viewpoint that integrates the two divergent schools of thought. He calls the integration AMH as it is a combination of revolutionary findings in the field of economics and recent studies in cognitive neurosciences. Lo's work is significant, particularly because the traditional EMH does not consider cognitive biases and neuroscience widely when evaluating markets' efficiency. As mentioned in the paper, cognitive neuroscience has been transforming and revitalizing the intersection of psychology and economics (Lo, 2004).

Lo (2004) states that the preferences and behavior of investors are the basis of the EMH's most persistent criticism. According to him, the EMH has been criticized, especially by psychologists and economists studying market participants' behavior. He lists various behavioral biases, such as overconfidence and loss aversion, which can be considered criticism of the EMH, arguing that investors tend to act irrationally. This is backed by several previous studies, such as Baker and Wurgler (2006), who have found that investor sentiment affects the cross-section of stock returns. On the other hand, EMH supporters often argue that there are opposing forces that void the effects of such biases, making them cancel one another.

There are four major findings, or practical implications, as Lo (2004) describes them in the paper. The first implication is that there is a relation between risk and reward, however, it is improbable to remain standard over time. The author explains this with institutional aspects and differences in sizes and preferences of different groups participating in the market. Another implication is that, in contrast to the traditional EMH, there are occasionally arbitrage possibilities in the AMH. This is explained in the paper with Grossman and Stiglitz's observation about the lack of arbitrage opportunities. According to the observation, people will not gather information as they have no incentive to do so, and because of this, the price discovery aspect of financial markets will collapse. A third implication is that different investment strategies will experience highs and lows, doing well in certain situations and poorly in others. The author portrays an example by computing the rolling first-order autocorrelation of monthly returns of the S&P composite index from January 1871 through April 2003. He finds that the autocorrelation varies over time, although it should remain zero according to the random walk hypothesis. A fourth implication is that to survive, investors must innovate as market conditions, and therefore, the risk/reward ratio relation changes over time. The ultimate objective for investors is to survive, and thus, aspects such as profit maximization are subsidiaries, according to him.

Urquhart and McGroarty (2016) examine stock markets' efficiency in their paper by studying stock return data gathered from four major stock indexes from January 1990 to May 2014. They conduct the study by using a variance ratio test, AR-GARCH process, and BDS test. Lastly, they apply the tests to fixed-length moving subsample windows to see if there is a relationship between the degree of market circumstances and stock return predictability. Urquhart and McGroarty (2016) discover that return predictability is not a stable, unchanging phenomenon. Instead, it varies gradually in every market. There are highs when significant predictability occurs and lows when no predictability is found. According to Urquhart and McGroarty (2016), due to the variation in predictability, market efficiency cannot be seen as a binary, yes or no type of phenomenon. Instead, it varies depending mainly on market conditions, the market itself, and the time frame.

Zhou and Lee (2013) study the evidence of the AMH from the REIT market in their paper using Choi's automatic variance ratio test and Escanciano and Lobato's automatic portmanteau test. The authors test two implications of the AMH by applying them to the REIT market. The first is that market efficiency cannot be considered a binary condition, and the second is that market conditions impact market efficiency. Zhou and Lee (2013) make similar findings in their research as Urquhart and McGroarty (2016), as their empirical findings support both implications. They discover strong evidence of fluctuations over time in the degree of REIT return predictability. They also demonstrate that market conditions impact how predictable REIT returns are, as factors such as inflation and the degree of market development appear to be major drivers for REIT market efficiency.

Kılıç (2020) studies whether evidence of the AMH in the Turkish Stock Market can be found. He examines the predictability of the Borsa Istanbul 100 index returns from January 2013 to 2019. Kılıç discovers that the evidence he gathered from the Borsa Istanbul index does not support the AMH. He examines the predictability for both entire sample period and sub-periods of 300, 400, and 500 days. The findings are similar: market conditions do not cause market efficiency to vary over time. Kılıç (2020) concludes that stock prices cannot be predicted, and investors cannot seek unusual returns there. The result is particularly interesting because it differs from the studies discussed earlier.

2.3 Asset Pricing Models

The fundamental idea of the whole concept of investing is to let the money grow and compound over time. This can be achieved by investing in fixed-income assets, which are relatively easy to predict: a 10-year corporate bond with a face value of €1,000 and a coupon rate of 5.00% will pay €50 per year. Investors can apply a simple net present value formula to calculate the bond price and discount the future cashflows into present value. The method works because the investor knows the expected return, that is, the bond's yield, beforehand. As long as the issuer stays solvent, the bondholder will get paid according to the pre-agreed terms. This, however, is not possible for equities. When screening stocks, the expected rate of return will not be shown on the broker's terminal as there are no pre-agreed rates of return. Hence, it is the investor's task to analyze and evaluate the correct rate of return for a stock and further decide whether it is enough for one's portfolio. To tackle this problem, researchers have developed different asset pricing models as a tool for investors to calculate and "predict" the returns.

Herd behavior and different asset pricing models are strongly interrelated, as herd behavior can distort the outcomes of these models. Alternatively, as the EMH assumes, all the stocks on the market are priced correctly. As proven, the EMH does not hold, which leads to the hypothesis that the asset pricing models used to value the stocks cannot precisely reflect reality. This can be considered relatively crucial as, for example, the Capital Asset Pricing Model is widely used by finance professionals in the business world and academics in academic research.

2.3.1 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), developed by William Sharpe (1964) and further studied by Lintner (1965) and Mossin (1966), describes the linear relationship between the expected return and risk of a security. Although the model was initially introduced by the researchers mentioned above, its roots can be traced back to the 1950s. This can be explained by Markowitz's previous work (1952), which introduced the modern portfolio theory on which the CAPM is based.

The modern way of thinking about portfolio formation stems from the findings of Markowitz (1952). As discussed above, Sharpe (1964) introduced the CAPM, which describes the linear relationship between the expected return and risk of a security. That is, the riskier the asset, the higher the returns; conversely, the safer the asset, the lower the returns. This is a widely accepted premise in all financial markets – investors require compensation for taking risks (i.e., risk premium) in the form of higher returns

(Jagannathan & Wang, 1996). Investors can, however, escape this relationship by investing in several assets instead of just one or two. The saying “Do not put all your eggs in one basket” stems from Markowitz’s realization that by combining stocks with varying levels of risk, investors can create a portfolio with the highest expected return on a given level of risk. The fundamental idea of diversification lies in the observation that by combining stocks with low correlation with each other, investors can decrease the portfolio's risk without sacrificing virtually any returns. The word “virtually” is included in the previous sentence because it has been debated whether investors actually sacrifice some returns. The findings of Markowitz were later tested by several researchers, Evans and Archer (1968), for example, most of whom found a strong negative correlation between risk and the number of assets in the portfolio. Hence, the widely accepted implication is that investors should not be compensating for taking risks that can be eliminated by diversifying the portfolio (i.e., unsystematic risk). Instead, investors should be rewarded for taking higher market risk (i.e., systematic risk), which is associated with any investment and, therefore, cannot be diversified away.

The fundamental idea of the CAPM is that the expected return of an asset equals the sum of the risk-free rate and market risk premium multiplied by the investment’s beta. As investors require compensation for taking systematic risk, the formula includes the risk premium multiplied by the investment's beta (i.e., riskiness). Therefore, the CAPM can be denoted as follows:

$$ER_i = R_f + \beta_i\left(ER_m - R_f\right) \tag{1}$$

where $\left(ER_m - R_f\right)$ is the market risk premium, ER_i is the expected return of an asset, R_f is the risk-free rate, and β_i is the beta of an asset *i*, which can be composed as:

$$\beta_i = \frac{COV(R_i, R_m)}{\sigma^2(R_m)} \tag{2}$$

where R_i is the return of asset *i*, R_m is the market return, $\sigma^2(R_m)$ is the variance associated with the market return, and $COV(R_i, R_m)$ is the covariance between the return of asset *I* and the return of the market.

This implies that assets with higher beta have higher correlations with market returns. According to CAPM, investors should be rewarded for taking more market risk, that is, systematic risk, as discussed above. Conversely, assets that do not move in parallel with market returns have lower correlations and, therefore, will be predicted to have lower expected returns.

The fundamental problems of the model are the assumptions on which it is based. As Watson and Head (2016) outline, the CAPM is based on the idea of a perfect capital market. One of the most fundamental violations of the perfect capital market in terms of behavioral finance, and especially herd behavior, is the assumption that investors act rationally. As discussed in Chapter 3, herd behavior might stem from investors' irrationality, and it might be an irrational choice by itself. Several studies have found evidence of irrational herding, which is direct evidence against one of the most fundamental assumptions on which the CAPM is based. Hence, the rationality assumption in the concept of a perfect capital market is arguably unrealistic and wrong. In addition, as discussed in the following chapters, stock returns in the Baltic markets are not normally distributed during any of the subperiods. This is problematic as one of the assumptions the CAPM is built on is the normality of returns.

In addition to the issue surrounding the irrationality assumption, several studies suggest that an asset's beta alone is relatively weak in explaining the cross-section of expected returns. For instance, Black, Jensen, and Scholes (1972) analyze all the securities listed on the New York Stock Exchange from 1926 to 1966 and form portfolios based on their betas. To derive the monthly returns of a market portfolio, they calculate the returns that would have been earned by holding every security listed on the NYSE at the beginning of each month. They discover that the returns of portfolios with low betas were systematically lower than those predicted by the CAPM. Conversely, high beta portfolios produced returns that were systematically higher than predicted by the CAPM. According to the authors, this indicates that the security market line (SML)—a graphical representation of the CAPM demonstrating the linear relationship between a security's expected return and its systematic risk—is too flat. Jagannathan and Wang (1996), on the other hand, find that instead of being static (i.e., remain constant over time), market risk premiums and the betas of assets vary over time. Based on this observation, they form the concept of conditional CAPM with multiple betas, which performs significantly better in predicting the cross-section of stock returns compared to the original "static CAPM". Whereas the two previous studies find divergent evidence regarding the functionality of the CAPM, Frazzini and Pedersen (2014) find strong, purely contradicting evidence of the model's explanatory power regarding the cross-section of stock returns. By observing global stock markets between 1926 and 2012, they find evidence of low-beta stocks outperforming high-beta stocks even after adjusting them for risk. This "Betting against beta" anomaly contradicts the fundamental idea of the CAPM, as, according to it, high beta stocks should outperform low beta stocks.

Roll (1977), however, not only criticizes the results of the CAPM but dismisses the whole foundation of the model. He argues that it is not possible to construct a true market portfolio with every single risky asset that is perfectly diversified. This economic concept is also known as *Roll's Critique,* which suggests that every instrument in every market, including, for example, commodities, should be covered in the portfolio to be considered a true "market portfolio." Hence, Roll's Critique also challenges one of the most fundamental components of the CAPM and, therefore, criticizes its usefulness in predicting expected returns. The findings of Jagannathan and Wang (1996) are in line with Roll (1977) as they agree with the idea that the market portfolio is unobservable. This could be the reason for the findings of Black, Jensen, and Scholes (1972) regarding the flatness of the security market line.

A perfect capital market includes several other unrealistic assumptions in addition to the ones discussed above. For example, the nonexistence of transaction or brokerage costs is virtually untrue, as even institutional investors pay minor, privately negotiated commissions to execute trades (O'Donoghue, 2022). A perfect capital market also assumes that a large number of buyers and sellers are constantly present in the market so that individual participants cannot virtually affect the securities prices. A great example of market participants driving up the price of a security from the 2020s is GameStop's short squeeze in 2021 (Umar et al., 2021). This explicitly contradicts the assumption that market participants are unable to affect the prices of the securities. In addition, this contradicts the EMH discussed above, as the price movements were not information-based. Instead, the price soared plainly due to a significant increase in (artificial) demand.

Lastly, the idea of a perfect capital market (and, therefore, also the CAPM) is based on the assumption that individuals and institutions have equal access to different investment instruments and information. As several investment instruments – hedge funds, certain private equity funds, or Over-the-Counter (OTC) instruments, for example, are only available to big institutional investors, it is arguably wrong to suppose that all the investors have similar access to investment opportunities. Equal access to information, on the other hand, can be considered an unrealistic assumption as even all individual investors do not have equal access to information, not to mention the differences between retail investors and institutions. Factors such as wealth (Li et al., 2017) and the relationships associated with it might provide access to privileged information that is not publicly available. In addition, Bushee et al. (2017) find that selective access, that is, the opportunity to meet privately with a company's management, can lead to information advantages. Institutions also tend to have faster and broader access to information due to different terminals, databases, service providers, et cetera, that are not realistically within reach of individual investors due to their price and/or general exclusivity.

The CAPM is arguably the most popular and widely used asset pricing model in finance due to its straightforwardness and simplicity. It has been taught, researched, and applied extensively, serving as a foundation for other, more complex multifactor asset pricing models discussed in the following chapters. In addition to listed equities, the CAPM is also commonly applied in other areas of finance, such as corporate finance. For instance, firms often use the CAPM to calculate the cost of equity, one of the components in the weighted average cost of capital (WACC) (Arditti, 1973). WACC is then used as the discount rate to discount future free cash flows to present value using the discounted cash flow (DCF) model in M&A deals, for example. This is an important consideration, as even slight deviations in the DCF model can significantly impact the final closing price if the underlying models (i.e., CAPM) are based on unrealistic assumptions.

2.3.2 Fama and French Three-Factor Model

As discussed in the previous chapter, Black, Jensen, and Scholes (1972) find that the results of the CAPM are systematically wrong. In addition to them, researchers such as Basu (1977), Banz (1981), and Lakonishok et al. (1994), among several others, have found contradicting evidence of securities' beta's explanatory power as the only variable. This inspired Fama and French (1992; 1993) to extend the work of Sharpe (1964), Lintner (1965), and Mossin (1966) by creating an asset pricing model that could capture the risk exposure of securities more accurately. The new model, the Fama and French Three-Factor Model, is based on the finding from the US stock market from 1963 to 1990 that, in addition to the asset's beta, its size and book-to-market ratio can explain a significant proportion of the expected returns (Fama and French, 1992). According to them, these two variables account for the underlying risk of the assets. Hence, they extend the original CAPM by adding two additional factors: the size (measured by total market capitalization) and the value (measured by book-to-market ratio). The two additional variables are represented by portfolios, SMB_t which denote the difference between the returns of a portfolio consisting of firms with high market capitalization and low market capitalization. Similarly, HML_t denotes the difference between the returns of a portfolio consisting of firms with high book-to-market ratios and low book-to-market ratios. Hence, the Fama and French Three-Factor model can be written as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + \varepsilon_{it} \qquad (3)$$

where $E(R_{it})$ is the expected return on security *i*, R_{ft} is the risk-free interest rate, R_{mt} is the return on the market portfolio, $E(R_{mt})$ is the expected return of the market, SMB_t is the size factor, HML_t is the value factor, β_i, s_i, h_i are the sensitivities of an asset to the different factors, and α_i is the intercept that should equal to zero if the factors perfectly explain the cross-section of the returns.

The Fama-French Three-Factor Model represents a significant advancement in asset pricing theory by addressing the limitations of the traditional CAPM. In addition to the market risk, by adding size (SMB) and value (HML) factors, the model provides a more robust framework for explaining the cross-section of stock returns. Empirical evidence shows that stocks with low market capitalization and high book-to-market ratio tend to outperform their counterparts, even after adjusting for market risk. This further provides investors, portfolio managers, risk officers, and many other professionals a method to evaluate and manage the risks they are taking.

Although Fama and French's three-factor model (1992; 1993) is a step in the right direction regarding the sophistication and accuracy of the asset pricing models, it has also received criticism. For example, Mclean and Pontiff (2015) find that many stock market anomalies – such as those related to size and value – tend to weaken or even disappear after they are published in academic research. Therefore, they argue that the Fama and French three-factor model cannot be considered enduring. Instead, its ability to explain the stock returns will decline over time. Lakonishok et al. (1994) find similar evidence, stating that the value premium captured by HML should be considered a behavioral anomaly caused by investors' overreaction instead of a risk factor. Banz (1981) argues that the size effect is not linear in the market value; rather, it is skewed, with very small firms generating significantly higher returns, while average-sized and large firms exhibit relatively indifferent returns. Lastly, Davis et al. (2000) conclude that even though the three-factor model explains the value premium more efficiently than its relatively well-known competitor, Daniel and Titman's (1997) characteristics model, the three-factor is rejected by the Gibbons et al. test. Therefore, it should be considered just a model instead of a realistic description of expected returns. Daniel et al. (2001) find similar evidence from the Japanese stock market as, according to their tests, the Fama and French three-factor model is rejected, whereas Daniel and Titman's characteristic model is not.

2.3.3 Carhart Four Factor Model

The Carhart (1997) Four-Factor Model is built on the foundations of Fama and French's (1992; 1993) Three-Factor Model, incorporating their findings with those of Jegadeesh and Titman (1993). By studying the best-performing mutual funds versus the worst-performing mutual funds, he noticed that the predictive power of the original Three-Factor Model could be improved by adding the additional momentum factor into the equation. The underlying idea of a momentum strategy is to buy stocks that have performed well and sell stocks that have performed poorly. By combining the market, size, and value factors with the momentum factor, the equation can be written as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it} \qquad (4)$$

where, in addition to the factors discussed in the previous chapter, MOM_t is the momentum factor denoting the difference in returns of winning portfolios and losing portfolios. m_i is the sensitivity to the momentum factor.

2.3.4 Fama and French Five-Factor Model

After publishing the original Fama and French Three-Factor model (1992; 1993), several researchers found additional factors that could explain the cross-section of the average stock returns. For example, Novy-Marx (2013) finds that average stock returns and the firm's profitability have a strong correlation. He finds that firms with higher gross profits-to-assets ratios yield significantly higher returns. In addition, Aharoni et al. (2013) find a weak but statistically significant correlation between the firm's investment policies and the average stock returns. According to them, firms that invest less yield higher risk-adjusted returns than those investing more. Hence, Fama and French (2015) decided to develop their previous Three-Factor Model further and introduced the new five-factor model. Thus, the Fama and French Five-Factor Model can be written as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it} \qquad (5)$$

where, in addition to the previous factors, RMW_t denotes the difference between the returns of portfolios consisting of high operating profitability equities and weak operating profitability equities and CMA_t denotes the difference between the returns of portfolios consisting of conservative and aggressive stocks. Respectively, r_i and c_i are the sensitivities to the given factors.

The factors included in the Five-Factor Model have been studied extensively, but the findings are somewhat inconclusive. As previous literature shows, the profitability factor is proven to have the most explanatory power for equity returns in emerging stock markets (Mosoeu & Kodongo, 2020), which is backed by Cox and Britten (2019) as they find similar evidence from the Johannesburg stock exchange. On the other hand, Kubota and Takehara (2017) find no statistically significant evidence of the explanatory power of either the investment factor or the profitability factor in Japan’s stock market. This is in line with the findings of Huang (2018), as he finds evidence of only minor increases in the performance of the model when the profitability and investment factors are added.

3 Literature Review

Herd bias, also referred to as the herding effect, herd mentality, or bandwagon effect, is a behavioral bias that occurs when market participants follow the actions of others without evaluating available information efficiently. In other words, investors' tendency to mimic other investors' actions is known as herding in the stock market. According to Chiang and Zheng (2010), the correlation in transactions resulting from interactions between investors is frequently referred to as herding. According to Bikhchandani and Sharma (2000), herding can be divided into two different categories. The first is “spurious” herding, which occurs when investors face similar information and thus make similar decisions. The second is “intentional” herding, which occurs when investors intentionally mimic or copy other investors (Spyrou, 2013).

3.1 Early assessments

When addressing herd behavior, it is worth drawing a line between herd behavior as a human characteristic and a part of human psychology and herding in the stock market as a part of behavioral finance. Herding in a stock market is undeniably a part of human psychology, but this thesis aims to study the topic more from behavioral finance’s perspective. A clear bifurcation between the two can be seen when studying the early assessment of herd behavior. As discussed in the following paragraph, the roots of academic research on herd behavior in the stock market go back to the early 19th century, whereas the first studies regarding herd behavior as a part of fundamental human psychology reach the late 18th century. Le Bon (1895) studies the behavior of crowds during the French Revolution and finds several characteristics of crowd psychology, such as *“impulsiveness, irritability, incapacity to reason, the absence of judgment and of the critical spirit, the exaggeration of the sentiments, and others”.* Le Bon’s book influenced Sigmund Freud (1921) to develop his modified theories based on the notions of Le Bon. Even though the publications mentioned above are often considered to be the most fundamental pieces of work regarding herd behavior, Wilfred Trotter (1916) had a significant impact on popularizing the term “herding” by publishing his book, which was also based on the ideas and concepts of Le Bon (1895).

The first hints of herding behavior as a research topic can be traced back to early economic theories that addressed the collective behavior of individuals. According to one interpretation, Adam Smith was the first to study the impact of market sentiment on investor behavior in his seminal work “The Wealth of Nations” in 1776. Kahneman and Tversky (1979) and Bikhchandani et al. (1992), however, had a significant impact on identifying the modern definition of herding in the stock market. Still, it can be seen to have roots as far back as the 1930s when John Keynes studied price fluctuations in the stock market in 1936. Other researchers worth mentioning are Froot et al. (1992) and Banerjee (1992), who identified and studied herding and its effects on the stock market.

3.2 Causes for herd behavior

Some could, and do, argue that herding stems from a lack of experience or knowledge, which can, in fact, be partly true. It is easy to mimic the actions of professional investors with great track records, especially if one is relatively inexperienced and lacks sufficient skills in, for example, firm valuation or financial statement analysis. It cannot, however, be argued that inexperience is the root cause of herd behavior as studies, such as Wermers (1999), Nofsinger and Sias (1999), Dasgupta et al. (2011), and Choi and Skiba (2015) find evidence of herding among institutional investors and money managers, which are generally considered professional and experienced market participants. In addition, Lee and Lee (2015), Graham (1999), Hong et al. (2000), and Welch (2000), among many others, find evidence of herding behavior among financial analysts. On the other hand, Jiang and Verardo (2018) propose an opposing opinion, theorizing that less-skilled individuals may be more prone to follow the actions of their predecessors. In contrast, more advanced ones tend to “follow their own path”, and deviate from the general public and past actions, showing even antiherding behavior.

The root cause for the herd mentality and further herd behavior stems from the very basic human psychology. As human beings can be identified as gregarious animals, it is natural for investors to exhibit herd behavior. Some studies, however, provide some insights on why investors tend to herd. Salem (2019), for example, finds that Arab women tend to herd more than Arab men in Saudi Arabia. This can be explained by factors such as lower investment knowledge, risk tolerance levels, and confidence that women tend to have compared to men. This supports Chang et al.'s (2012) statement that the lack of confidence is one of the major drivers of herd behavior. On the other hand, Banerjee (1992) introduces the concept of informational cascades, where individuals ignore their own beliefs and follow the actions of others because they believe that other investors may have superior or more relevant information. Bikchandani et al. (1992) find similar evidence, suggesting that investors engage in herding when they believe that their information is inferior compared to their peers.

3.3 The rationality of herd behavior

While it is challenging to define the characteristics of rational and irrational herding objectively and unambiguously, existing literature outlines certain aspects that help differentiate the two types. It is particularly difficult to determine whether a specific action is rational. A rational investor might be viewed as one who avoids losses, as they consistently make the best possible decisions.

The following chapters present the literature on the differences between rational and irrational herding. As rationality belongs to human psychology rather than economics, this thesis will not explore it too deeply. However, rationality will be discussed on a general level, as understanding the basic concepts of rationality is vital to understanding herd mentality.

3.3.1 Irrational herding

Herd bias could be considered particularly harmful because it may lead investors to make decisions blindly and irrationally. In these kinds of situations, investors make decisions without using their own judgment and analysis efficiently. Decisions are not based on the idea of the individual's maximum benefit. Instead, they are based on factors such as FOMO – the fear of missing out or the belief that some specific action is exceptionally good because a certain proportion of people are also doing so. The choice can naturally also be good, but in this case, it is a matter of flipping a coin; the choice can also be good as bad. If the choice turns out to be bad, the investor cannot plausibly argue what should have happened according to their calculus, analysis, or evaluation.

One essential reason for investors' irrational herding is a lack of confidence, as stated by Chang et al. (2012). According to Spyrou (2013), investors' irrationality may cause bubble-like phenomena and trigger herd behavior. Spyrou argues that psychological factors, such as pressure from social circles and social conventions, might cause irrational herding among investors, especially during periods of uncertainty. Nokia could be considered a good example of such social convention causing herding in Finland; it has been the Finnish crown jewel for centuries, causing people to perceive it as a safe stock to invest in. Herding behavior can also have a significant impact on stock prices and market movements, as large groups of investors can drive prices up or down based on their collective actions. A great example is GameStop stock, which rose from a few 32 dollars to as high as over 80 dollars because people collectively bought the stock. A good case in point from the bond market is the sell-off of European bonds, which took place in November 2010. Consequently, the Spanish ten-year government bond yield spreads rose to 5.35 percent, the Portuguese spreads to 7.23 percent, and the Irish spreads to 9.42 percent (Spyrou, 2013).

As Bogdan et al. (2022) find, emerging and frontier markets are often characterized by irrational herding that is not driven by market fundamentals but is a consequence of market participants mimicking each other's actions. In addition, they find that frontier markets, that is, markets that are too small, illiquid, or carry too much risk, tend to exhibit more herding behavior than developed markets. Blasco and Ferreurela (2008) find similar evidence, as, according to them, Spanish mutual funds tend to herd more on stocks with low market capitalization and trading volumes. Hence, it is credible to argue that Estonia, Latvia, and Lithuania, i.e., the Baltics, show higher levels of herding behavior during the COVID-19 pandemic than Finland, Sweden, or Norway, for example. Vidya et al. (2022) and Jiang et al. (2022) also find evidence of a higher level of herding in the frontier or less developed markets in Asian markets, which, however, might not be perfectly comparable to the results of the Nordics per se. On the other hand, Legenzova et al. (2024) study the differences between the Nordic stock markets (Iceland, Denmark, Finland, and Sweden) and the Baltic stock market, Lithuania in this case, and find that the Nordic markets produce more evidence of herding than the frontier market. They theorize that investors in more advanced countries tend to enjoy higher living standards, which further translates into bounded rationality due to lower levels of resiliency to the pressures caused by COVID-19 and, therefore, also lower investment risk resiliency. According to the authors, investors in Nordic countries tend to have access to better information and analytical tools, which should supposedly give investors better prerequisites to rational decisions. Despite this, investors in the Nordic countries, for example, followed the market and liquidated their investments when the effects of the pandemic hit the stock market. As history shows, the stock markets have recovered from all the previous market crashes or crises, which suggests that liquidating one’s investments after they have suffered from significant price drops due to a crisis is not a rational choice supposing that one’s investment period is ten(s) of years.

Legenzova et al. (2024) further explain that investors’ irrational decisions stem from the abundant amount of negative information on the market, which leads to disorientation and further proneness to following the actions of other investors. This, however, raises the question of whether herding can be considered irrational or not. It could be inferred that if a large amount of negative information causes herd behavior, the root cause in this case is most likely fear, which, on the other hand, is a natural part of human behavior.

Therefore, it could be argued that it is rational for investors to act in such a way. Previous papers, such as Economou et al. (2018), confirm this by studying whether herd behavior and fear have a connection, and they find statistically significant evidence of fear as a major driver for herding.

3.3.2 Rational herding

On the other hand, according to Spyrou (2013), herd behavior can be considered a rational choice in some circumstances. For example, a young analyst can face a higher risk of being fired if their forecast deviates strongly from the consensus. Therefore, it is beneficial and rational for the young analyst to agree with the consensus. This is in line with Graham's (1999) findings, which state that analysts are inclined to herd in certain circumstances. Factors such as high reputation, low ability, and strong public information inconsistent with the analyst's private information tend to lead analysts to engage in herd behavior. According to him, herding can also have characteristics of a rational choice if investors' horizons are short as they are trying to learn what their peers know.

Chang et al. (2012) argue that herding can be rational for individual investors in the form of investigative herding, which occurs when investors utilize the same or very similar information. As discussed earlier, Bikhchandani and Sharma recognize this type of herding as "spurious" (Spyrou, 2013). According to Chang et al. (2012), investigative herding is more characteristic of institutional investors as they acquire their information from similar sources or apply identical methodology more often than retail investors. Another form of rational herding the authors mention is unintentional herding, which fundamentally means that investors are influenced to make the same trading decisions when they have similar preferences or dispositions toward specific stock characteristics. Like investigative herding, unintentional herding is more common among institutional investors. However, Blasco and Ferreruela (2008) find contradicting evidence of this as, according to them, mutual funds tend to exhibit intentional herding on the Spanish stock market.

Chiang and Zhen (2010) report similar discoveries as Spyrou (2013) as herding can be held as rational for less sophisticated investors whose actions and choices strongly correlate with successful and famous investors. They tend to mimic investors they trust or believe to make desirable investment decisions. The rationality can be justified by the fact that using their own information would incur a higher cost than mimicking successful investors. In addition, they discover that herding behavior might lead to asset prices deviating from their fundamentals due to investors herding around 33 the market consensus. As discussed above, this could ultimately lead to asset mispricing and affect market efficiency.

Previous studies, such as Adem and Sarıoğlu (2020) or Kabir and Shakur (2018), show that volatility positively correlates with herding behavior, implying that investors tend to herd more during high volatility periods. Gleason et al. (2004) explain this with the comfort that investors seek. According to them, investors find it more comfortable to follow the market consensus by herding as by doing so, they can expect to achieve the average return of the market. This can be considered rational, as by doing so, investors aim to avoid significant losses they could face by not engaging in herding behavior. As investors tend to be risk averse, they tend to feel more sorrow for significant losses than joy for substantial gains. The findings of Adem and Sarıoğlu (2020) and Kabit and Shakur (2018) are in line with the findings of Christie and Huang (1995), the founders of the widely known Cross Sectional Standard Deviation -model, which will also be used in this thesis to recognize herding.

Lux (1995) argues that investors should have information about assets' fundamental values to be able to make rational (or irrational) decisions. In the absence of fundamental values, investors have no choice but to rely on the market movements and make their decisions based on them. This implies that investors' herd behavior cannot be seen irrational if they are not aware of the fundamental values. Therefore, according to Lux (1995), investors' rationality or irrationality cannot be assessed without evaluating the level of information investors have.

To conclude, the difference between rational and irrational herding stems from the purpose and the drivers for herd behavior. As Chang et al. (2000) outline, rational herding is often associated with the principal-agent problem, in which the managers engage in herding to maintain their reputation. By following the herd, it is easier to explain the possible errors, given that the majority of other managers made the same errors as well. Hence, the manager is aware of their surroundings and prior knowledge but decides to follow others' actions because it can be seen as beneficial. Irrational herding, on the other hand, is associated with disregarding prior beliefs and following the crowd blindly.

3.4 Evidence of herd behavior

Mand et al. (2021) study whether evidence of herd behavior can be found in emerging economies' stock markets. They conduct their study by examining daily data from the Malaysian stock market between 1995 and 2016, using Chang et al.'s herding behavior model. The study is relatively unique because, in addition to just examining data from the entire Malaysian stock market, the authors also study whether herd behavior varies among investors in Islamic and conventional stocks. They find no significant evidence of herding on the whole Malaysian stock market during the given time frame, either during the upmarket or downmarket. On the contrary, Mand et al. (2021) discover evidence of herd behavior both during up and down markets when examining the data from Islamic, Shariah-compliant stocks. The study provides no apparent reason why Islamic stocks produce abundant evidence of herd behavior, whereas the whole market does not. The reason might be related to certain norms and moral principles of Islam, which influence investors' behavior on the stock market. As mentioned in the study, no previous research has been done on the herding behavior of Shariah-compliant stocks in Malaysia. Differing from both categories above, data obtained from conventional stocks demonstrates evidence of herding during the down market only.

Medhioub and Chaffai (2018) present similar findings in their study of Islamic stocks' herding. Their study concentrates on Bahrain, Kuwait, Qatar, Saudi Arabia, and the UAE stock markets. Qatar and Saudi Arabia are the only markets where they discover evidence of herding, which can be recognized only during down-market periods. In addition, they recognize a correlation between conventional stocks and Islamic stocks in Kuwait and the UAE regarding herd behavior.

According to Chiang and Zhen's (2010) study, herd behavior can be recognized in all the 18 countries they study except the US and Latin America, consisting of Argentina, Brazil, Chile, and Mexico. They find an abundant amount of evidence to support the existence of herding in advanced markets, such as Australia, France, or Germany, and in Asian markets, such as China, Thailand, or Singapore, which contradicts earlier literature that displays no evidence of herding in the markets mentioned above. In addition to just discovering evidence of herding, they also categorize it as being present in both bullish and bearish markets except for Asian markets, in which herding is more focused on periods of the bull market. Chiang and Zhen (2010) also ascertain that financial crises often trigger herding activity in the countries from which crises originated. This causes crises to spread to surrounding countries as a contagion effect. Evidence of herding behavior in the US and Latin America can also be found in these circumstances.

Herd behavior is characteristic of both men and women, but Zheng et al. (2021) find evidence of women herding more in the Chinese stock market. Women especially tend to follow the actions of their peers (i.e., other women investors). As herding negatively affects portfolio performance, women also tend to lose more money and perform worse on the stock market from a herding's point-of-view. Both genders tend to herd more stocks with specific characteristics, such as higher market value and better market liquidity. Market conditions also affect how intensively investors herd, as the data shows that the degree of herd bias is higher during a bull market than a bear market. Hence, investors also tend to lose more money during a bull market. Salem (2019) also discovers positive evidence of a higher level of herd behavior among Arab women than Arab men in Saudi Arabia.

Considering the evidence discussed above, it is reasonable to conclude that herd bias affects investors' financial decision-making. As mentioned, it is undeniable that it affects how investors behave; however, to determine whether it positively or negatively impacts an individual's portfolio performance, research should focus on the consequences of herding rather than merely assessing whether evidence of herding exists. According to Chang et al. (2012), investment strategies based on buy- and sell-herding produce significant positive returns, particularly for retail investors. Messis et al. (2023) also find evidence supporting herding as a systematic driver of returns, indicating that herding behavior positively affects portfolio performance. Conversely, investors who engage in herding tend to underperform compared to market and non-herd portfolios, according to Mavruk (2022). This perspective is further supported by Zheng et al. (2021), whose research indicates that the more investors herd, the more money they lose. Zaremba et al. (2021) identify a connection between high market breadth and herding, along with a negative correlation between high market breadth and portfolio performance, suggesting that herding might have a negative effect on portfolio performance. When examining institutional investors, evidence suggests negative impacts on their portfolio performance and construction due to herd bias (Gavrilakis & Floros, 2022). Additionally, herding can lead to heightened correlations between assets, anomalies, and return distortions that challenge the EMH. Consequently, herding may be beneficial in some situations, while in others, it may lead to outcomes ranging from neutral to negative. From a macroeconomic perspective, several authors frequently link herd behavior with the emergence and eventual burst of asset bubbles. This phenomenon is driven by stock mispricing, where stock prices deviate from their fundamental values due to herding behavior, as outlined in Mavruk's (2022) research. However, this starkly contrasts Spyrou's (2013) findings, which suggest that investors' irrational behavior leads to bubbles and subsequently triggers herding.

3.5 The effects of herd behavior

Herd behavior has various effects both on the stock market as well as on the global economy, as explained below. One of the most fundamental effects could be considered as the overruling of the various fundamental finance theories, such as the CAPM (Sharpe, 1964) or the Efficient Market Hypothesis (Fama, 1970), as discussed above. Even though the assumption about investors' perfect rationality rarely (if ever) holds, several more recent finance theories, models, or assumptions are based on these fundamental phenomena. If investors' bounded rationality can be proven to be true, it partly eliminates the relevance of such theories as it predicts them to be systematically wrong.

Galariotis et al. (2015) study herd behavior in the context of the European debt crisis and find that herd behavior played a significant role in the emergence of the aforementioned crisis. The authors categorize herding using Bikhchandani and Sharma's (2001) "spurious" and "intentional" herding and find strong evidence of herd behavior motivated by changes in fundamentals, i.e., spurious herding. Changes in the US Federal Funds rate and the Bank of England rate, as well as other significant macroeconomic information, led to herding and further to the clustering of bond returns during the European debt crisis. In other words, herd behavior can be seen as an accelerative factor regarding the spread of certain crises. Choe et al. (1999) study Korean stock market during the 1997 Asian financial crisis and find similar evidence. According to them, foreign investors were net sellers during the crisis, whereas domestic investors were net buyers, providing liquidity to the market. The selling pressure caused by foreign investors led to both significant price declines and increased volatility, suggesting that the collective herd-like behavior contributed to the destabilization of the Korean stock market during the Asian financial crisis. This further amplified the market downturn, that is, acted as an accelerative factor in terms of the crisis. The findings of the two studies are backed by Ghorbel et al. (2022), who find that herd behavior played a significant role in the spread of market shocks across countries. Herd behavior also amplified the contagion effect, as investors in one country reacted to the actions of investors in other countries. This further led to synchronized market declines.

In contrast to the study discussed in the previous paragraph, papers such as Wermers (1999) and Sias (2004) find evidence of price-stabilizing characteristics in herd behavior. Instead of being a phenomenon that accelerates the spread of instability, Wermers (1999) demonstrates that stocks actively bought by institutional investors, mutual funds in this case, tend to outperform stocks that mutual funds heavily sell over the following six months. Sias (2004) finds similar evidence, concluding that stocks bought by institutional investors tend to attract other institutional investors the following quarter. A particularly interesting finding in the paper is that even though institutional investors tend to follow the momentum strategy (i.e., exploiting volatility by buying rising stocks and selling falling ones) to a large extent, a relatively small portion of the momentum trading results from actually following the strategy. Instead, institutional investors tend to exhibit characteristics of momentum trading due to the herd mentality.

Nofsinger and Sias (1999) find evidence of herd behavior on institutional investors similar to Sias (2004). They study both institutional and individual investors from 1977 to 1996 and find that institutional investors' herd activity is positively correlated with past returns. They engage in positive feedback trading, buying past winners and selling past losers. The high volumes characteristic for institutional investors contribute to price momentum as herding amplifies existing price trends. Therefore, stocks heavily bought by institutional investors experience short-term price increases; conversely, stocks sold by institutions experience short-term price decreases. This can be seen as problematic regarding the EMH (Fama, 1970), as the price fluctuations are not information driven. Instead, they are driven by psychological factors, which should not be possible according to the EMH. Nofsinger and Sias (1999), however, find that the price changes are (at least) partially reversed in the long term, and therefore, the mispricing should be seen as a short-term and temporary phenomenon. Hence, institutional investors' herd behavior may temporarily distort the stock prices so that they deviate from their fundamental values.

Blasco and Ferreruela (2008) study Spanish mutual funds from 1994 to 2001 and find similar evidence of price distortion due to institutional investors' herding activity as Nofsinger and Sias (1999). The price distortion effect can be noticed, especially in less liquid, unfamiliar stocks. The authors define unfamiliar stocks as ones with low market capitalization and trading volumes. Conversely, stocks with higher market capitalization and trading volumes (i.e., familiar stocks) herding is more difficult to notice, and it has a more minor impact on the prices. As discussed in the previous paragraph, herd behavior might contradict the fundamental idea of the EMH, which is backed by the findings of Blasco and Ferreruela (2008). This, however, is more prominent when studying stocks with small market capitalization and low trading volumes compared to stocks with high market capitalization and high trading volumes.

In addition to the above findings, Chang et al. (2000) find that investors need more securities to achieve the same level of diversification when investing in an economy where market participants tend to engage in herding behavior around the market consensus. Therefore, herd behavior could affect portfolio formation and asset allocation. This also partly contradicts the fundamental idea of Markowitz's (1952) Modern Portfolio Theory, as diversification may lose some of its usefulness due to herd behavior.

4 Data and descriptive statistics

4.1 Data

The data for this thesis consists of daily stock index returns and individual stock ret ranging from January 1st, 2019, to May 31st, 2021. The study uses data from the Baltic stock market, namely Estonia, Latvia, and Lithuania. The data is collected from Thomson Reuters Datastream. As the indices are relatively small, consisting of around 15 firms each, 6 of the most liquid stocks will be picked from each index to calculate the cross-sectional absolute deviation from the market index.

The data will be gathered from the Baltic stock gross indices, which include Estonia's OMX Tallinn, Latvia's OMX Riga, and Lithuania's OMX Vilnius. All of the mentioned indices are all-share gross indices consisting of all the shares listed on both the Main and Secondary lists of each country's Stock Exchange. The effects will likely be relatively similar since these countries have several shared characteristics, such as geography and demographics. Additionally, the Baltic countries exhibit similarities in their economic structures and the factors influencing economic growth. However, there are also differences between the countries and economic asymmetries in the region (Poissonnier, 2017), which may explain potential deviations in the results.

The total number of observations across all three studied markets is 606. These markets fall under the Nasdaq Baltic umbrella, meaning the trading days are identical. This eliminates the need for data adjustments, further enhancing its robustness and objectivity.

As all studied countries are located in the European Union and use the Euro as their local currency, the returns are in Euros. An important point to be considered, as the data used in this thesis is from different indices, is that the structure of the indices might have changed over time. Firms might have been added or removed from specific index, which changes its structure. To tackle this problem, the stocks not included in the indices for the entire period (from January 1st, 2019, to May 31st, 2021) are given the market portfolio's average value.

Hence, the daily logarithmic return is calculated as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{6}$$

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

4.1.1 Sample period

Since the work of Christie and Huang (1995), the phenomenon of herding during financial crises has been a topic of several studies. A common method in these studies involves breaking down crisis periods into smaller timeframes, which enables analyzing how herd behavior fluctuates across different phases. For example, Ferreruela and Mallor (2021) and Bogdan et al. (2022) employ this method to study market-wide herding during the pandemic by analyzing several subperiods. Similarly, this thesis categorized the timeframe surrounding the COVID-19 pandemic into three distinct phases: the pre-COVID period, the outbreak period, and the post-COVID period. Given the minor variations across studies in defining the subperiods, I will adopt the same outbreak and post-COVID period dates as Ferreruela and Mallor (2021). As they do not define the pre-COVID period in their study, I define it as a little over a year before the beginning of the outbreak period. Hence, each of these phases, along with their specific date ranges, is delineated as follows:

Entire sample period:	**01.01.2019 – 31.05.2021**
Pre-COVID period:	01.01.2019 – 19.02.2020
Outbreak period:	20.02.2020 – 27.11.2020
Post-COVID period:	28.11.2020 – 31.05.2021

As it is relatively challenging, or nearly impossible, to unambiguously define the end date for the COVID-19 pandemic, I solely follow the judgment of Ferreruela and Mallor (2021). According to their study, the worst of the pandemic's effects on markets were thought to have subsided by November 2020 as a result of positive news from AstraZeneca, Pfizer-BioNTech, and Moderna regarding their vaccines. They also support their decision with the performance of the Ibex-35 and PSI-20 indices as, according to them, November 2020 was the break-even point, which allowed the indices above to return to pre-pandemic levels. Given that there are no compelling reasons to favor one date over another, a similar study could be conducted by adjusting the timeframe (or subperiods) to test whether the results remain consistent. One reasonable adjustment could be to designate the post-COVID period to begin on OMX Tallinn's, OMX Riga's, or OMX Vilnius's break-even point, which was earlier for the latter two. However, the break-even point for OMX Tallinn came later than that for the Spanish Ibex-35 and Portuguese PSI-20 indices, as shown in Figure 2. I find this particularly interesting as the other two indices had identical break-even dates at the end of the second quarter of 2020.

4.1.2 Index returns

Figures 2, 3, and 4 show that the sample period was relatively consistent across all the studied indices. All three indices exhibited stable growth before the outbreak of the pandemic. However, once news of the virus's spread in Europe began to surface, price levels experienced a sharp decline. OMX Riga experienced the most significant losses, with the index falling by over 16 percent in a single day, whereas OMX Tallinn decreased by more than 10 percent, and OMX Vilnius nearly 7 percent. Remarkably, the largest intraday price drops occurred on March 13th and March 16th, 2020, even though the first confirmed COVID-19 cases in Europe were reported in late January 2020. Considering that the virus started spreading more violently in Europe in mid-February 2020, it can be concluded that it took some time for markets to react to this as an all-time low was in late March 2020 for the sample period.

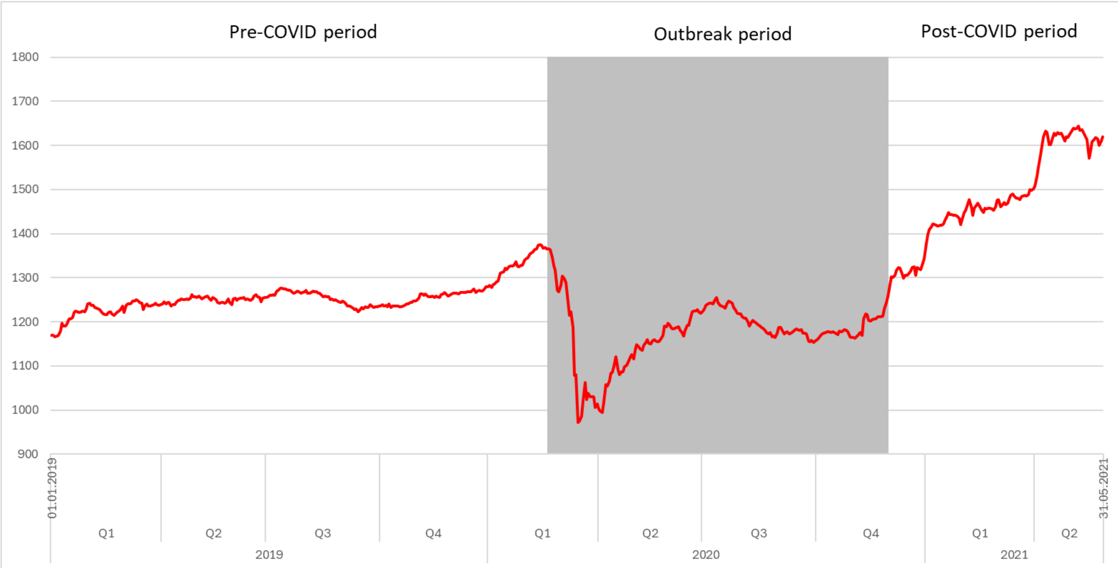

Figure 2. The price development of Estonia's OMX Tallinn index from 01.01.2019 to 31.05.2021

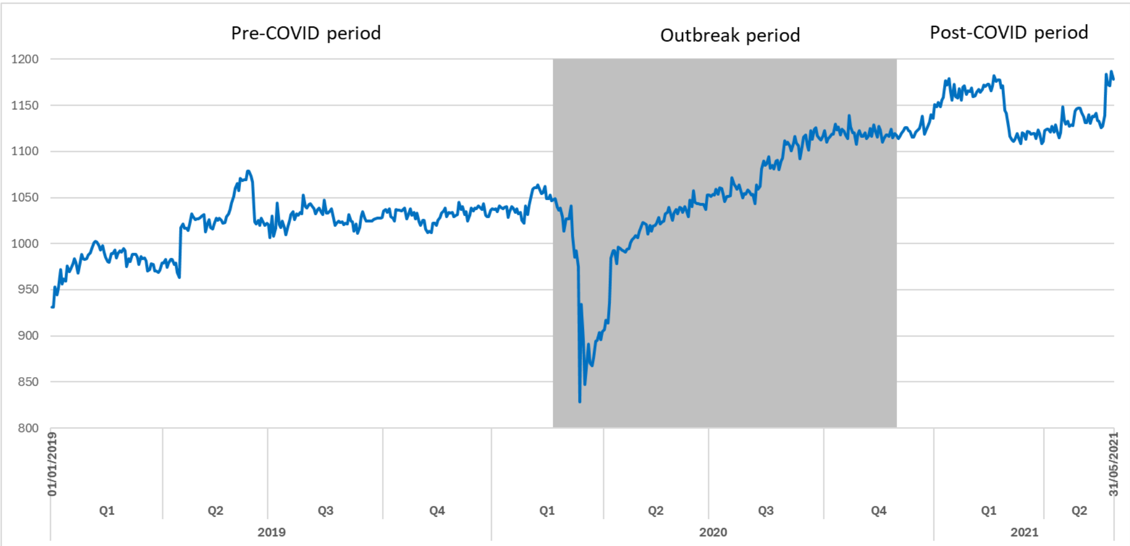

Figure 3. The price development of Latvia's OMX Riga index from 01.01.2019 to 31.05.2021

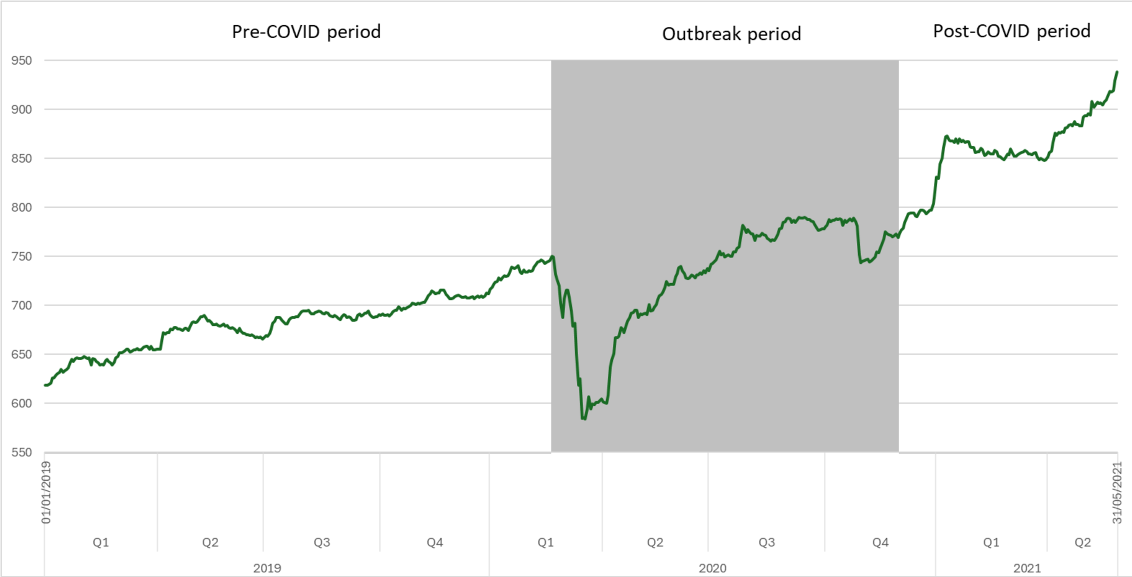

Figure 4. The price development of Lithuania's OMX Vilnius index from 01.01.2019 to 31.05.2021

The figures, however, indicate that the outbreak period varied across the markets. OMX Tallinn recovered significantly more slowly than OMX Riga and OMX Vilnius, with the latter two indices reaching their break-even points in the following quarter. In contrast, OMX Tallinn did not achieve its previous all-time high during the entire outbreak period. This discrepancy may be due to differences in the structure of the indices. If OMX Tallinn included more companies that were more directly impacted by the COVID-19 pandemic, it could have resulted in a slower recovery. Another plausible explanation for the disparities could be the looser COVID-19 restrictions in Latvia and Lithuania, which may have led to more minor disadvantages for the firms. Lastly, one could argue that the differences stem from investors' varying interpretations of the damage caused by the pandemic as well as general consensus.

4.2 Descriptive statistics

According to fundamental financial research, the distributions of stock returns should conform to a normal distribution for markets to function correctly (Kendall, 1953; Osborne, 1959). In addition, several fundamental financial theories, such as the CAPM, Black-Scholes-Merton Model (BSM), and JP Morgan's Value at Risk (VaR) metric, assume that the returns of securities are normally distributed. This, however, is usually not true, as stock returns exhibit characteristics such as high peaks and fat tails due to informational asymmetries, over- or underreactions, biases, and other market inefficiencies. The normality of stock returns in the Baltic countries is tested using the Jarque-Bera test which is discussed in the following sections.

Table 1 presents descriptive statistics for the daily cross-sectional absolute deviations (CSAD) and market returns (R_m) for the three studied markets: Estonia, Latvia, and Lithuania. The sample period is 01.01.2019 – 31.05.2021, and the number of observations is 606 for all three markets.

According to table 1, the maximum CSAD values for Estonia and Lithuania are relatively close to each other, whereas the maximum value for Latvia is almost two times higher than the others. Similar observations can be made when studying the mean, median, and standard deviation values of CSAD in different countries; Estonia and Lithuania produce similar results, whereas Latvia is (significantly) higher. The results appear to repeat themselves as the minimum values for Estonia and Lithuania are almost identical (0.0001742 for Estonia and 0.0001696 for Lithuania), whereas the minimum value for Latvia is zero. It is interesting to see whether the differences in the above values affect the final results. Still, the statistics suggest that there could be a strong positive correlation between Estonia and Latvia.

Table 1. Descriptive statistics of cross-sectional absolute deviations and daily market returns.

Full sample-period

Market	**Estonia**		**Latvia**		**Lithuania**	
	CSAD	R_m	*CSAD*	R_m	*CSAD*	R_m
Mean	0,0102	0,0005	0,0152	0,0004	0,0093	0,0007
Median	0,0078	0,0007	0,0120	0,0004	0,0068	0,0007
Standard deviation	0,0104	0,0092	0,0152	0,0121	0,0100	0,0068
Kurtosis	46,8121	52,3718	115,6076	72,2642	54,5548	29,7649
Skewness	5,8178	-4,4740	8,5189	-2,4014	6,1204	-2,6500
Minimum	0,0002	-0,1060	0,0000	-0,1634	0,0002	-0,0667
Maximum	0,1134	0,0411	0,2565	0,1209	0,1309	0,0459
Observations	606	606	606	606	606	606
JB-Test	58750,833	71277,648	344799,20	132440,88	78933,00	23079,499
JB-Test *P*-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Pre-COVID period

Market	**Estonia**		**Latvia**		**Lithuania**	
	CSAD	R_m	*CSAD*	R_m	*CSAD*	R_m
Mean	0,0082	0,0005	0,0144	0,0004	0,0068	0,0007
Median	0,0073	0,0005	0,0126	0,0004	0,0062	0,0007
Standard deviation	0,0047	0,0035	0,0102	0,0080	0,0042	0,0031
Kurtosis	3,5277	2,4880	31,0331	9,6022	36,4948	1,8964
Skewness	1,5234	0,4202	3,8427	0,7049	4,3712	0,3239
Minimum	0,0002	-0,0116	0,0009	-0,0409	0,0011	-0,0114
Maximum	0,0313	0,0145	0,1128	0,0545	0,0486	0,0129
Observations	285	285	285	285	285	285
JB-Test	258,0096	81,8955	12137,668	1118,5088	16723,545	47,6870
JB-Test P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

COVID period

Market	**Estonia**		**Latvia**		**Lithuania**	
	CSAD	R_m	*CSAD*	R_m	*CSAD*	R_m
Mean	0,0135	-0,0004	0,0171	0,0003	0,0125	0,0002
Median	0,0088	0,0001	0,0119	0,0003	0,0088	0,0009
Standard deviation	0,0162	0,0143	0,0224	0,0180	0,0140	0,0107
Kurtosis	19,3642	25,0063	71,0702	45,1609	29,1714	13,3866
Skewness	4,0245	-3,4619	7,3649	-2,4042	4,5158	-2,0783
Minimum	0,0007	-0,1060	0,0000	-0,1634	0,0009	-0,0667
Maximum	0,1134	0,0411	0,2565	0,1209	0,1309	0,0459
Observations	197	197	197	197	197	197
JB-Test	3609,6895	5526,3075	43240,964	16930,711	7654,6202	1612,7557
JB-Test P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Post-COVID period

Market	Estonia		Latvia		Lithuania	
	CSAD	R_m	*CSAD*	R_m	*CSAD*	R_m
Mean	0,0094	0,0020	0,0140	0,0004	0,0100	0,0016
Median	0,0079	0,0016	0,0118	0,0003	0,0077	0,0007
Standard deviation	0,0055	0,0074	0,0092	0,0077	0,0103	0,0048
Kurtosis	2,2101	2,0427	4,7012	4,8061	49,6097	1,9022
Skewness	1,3409	-0,1990	1,9638	0,9310	5,9889	1,1850
Minimum	0,0003	-0,0264	0,0018	-0,0231	0,0002	-0,0070
Maximum	0,0310	0,0257	0,0571	0,0381	0,1009	0,0175
Observations	124	124	124	124	124	124
JB-Test	62,3942	22,3764	193,8926	137,2593	13457,069	47,7144
JB-Test P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

This table reports the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily market index returns (R_m) for Estonia's, Latvia's, and Lithuania's markets from the beginning of the pre-COVID period (01.01.2019) to the end of the post-COVID period (31.05.2021) as well as during different sub-periods.

According to Table 1, the descriptive statistics show that markets do not function correctly as, according to the financial theory discussed above, returns should be normally distributed, and hence, skewness should equal zero. As discussed above, Estonia and Lithuania exhibited similar results when studying other statistical values, but regarding skewness, Estonia seems to produce significantly higher results. By comparing Estonia's -4,4740 to Latvia's -2,4014 or Lithuania's -2,6500, it can be concluded that market returns in Estonia are more negatively skewed than in the two remaining countries. This is not direct evidence of herding, but it could indicate that Estonia exhibits a higher degree of herding than Latvia and Lithuania. The kurtosis of the market returns also implies that none of them are normally distributed, as the widely accepted value for kurtosis is around three to be considered normally distributed. Similarly to skewness, kurtosis does not imply herding per se, but the market returns' deviation from normal distribution might predict inefficiencies, such as biases, on the market. High kurtosis also implies that there were many deviations from the average return (i.e., a high level of volatility) during the sample period, which should not be a surprise considering the occurrence of the COVID-19 pandemic. Normality of the market returns is also tested using the Jarque-Bera normality test. As Table 1 shows, the p-value of the Jarque-Bera is significantly lower than the chosen significance level (0.05), and therefore, the assumption of the market returns' normality can be rejected. This implies that the stock returns are not normally distributed during any of the studied periods.

As can be observed from Table 1, the means of CSADs do not vary significantly between different markets during any of the periods. CSAD, however, does not imply herding alone; instead, one should observe how the stock market returns and CSADs are related to each other. As Chang et al. (2000) find, an increase or decrease in non-linearity can be interpreted as herding on the stock market. Therefore, the main topic of interest is the relationship between CSADs and market returns.

Following Chang et al.'s (2000) methodology, scatter plot charts can be used to illustrate the relationship between CSADS and market returns. As can be observed from Figures 5, 6, and 7, stock return dispersions, that is, the CSAD values increase when moving away from neutral market returns. As the number of observations is relatively small, it is challenging to make undisputed interpretations. Still, it can be seen that the dispersions are more prominent on days of negative market returns. This is in line with the findings of Legenzova et al. (2024), as they explain that investors' irrational behavior stems from an abundant amount of negative information on the market. As negative market returns (at least in theory) should be caused by negative information on the market, as implicated by the EMH (Fama, 1970), the finding above links the underlying theory with the findings. However, Latvia differs from Estonia and Lithuania in this respect, as the observations are nearly identical when comparing negative and positive market days.

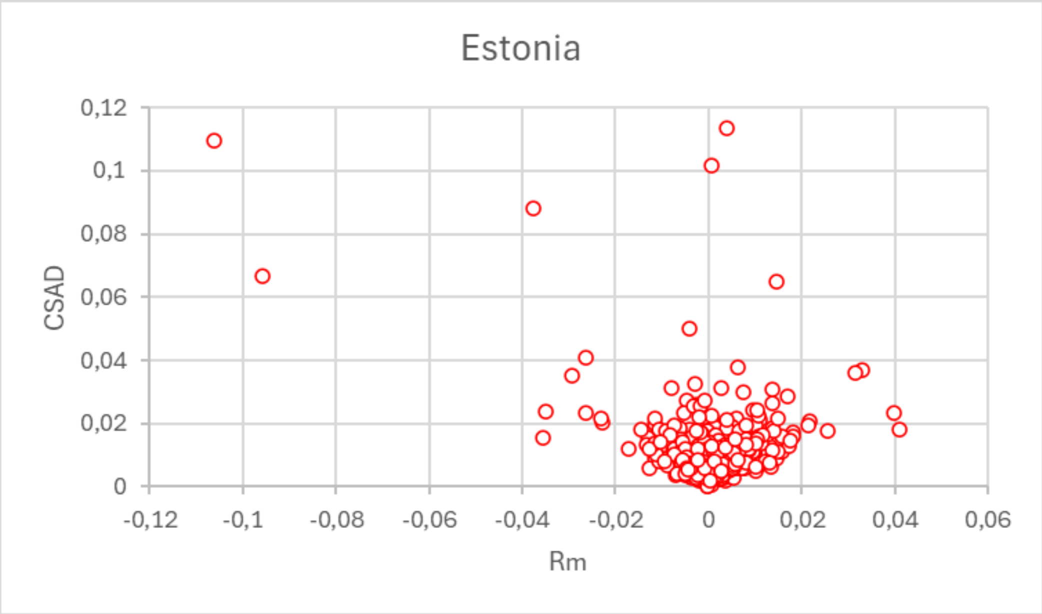

Figure 5. The relationship between the market returns (Rm) and cross-sectional absolute deviations (CSAD) for the Estonian stock market

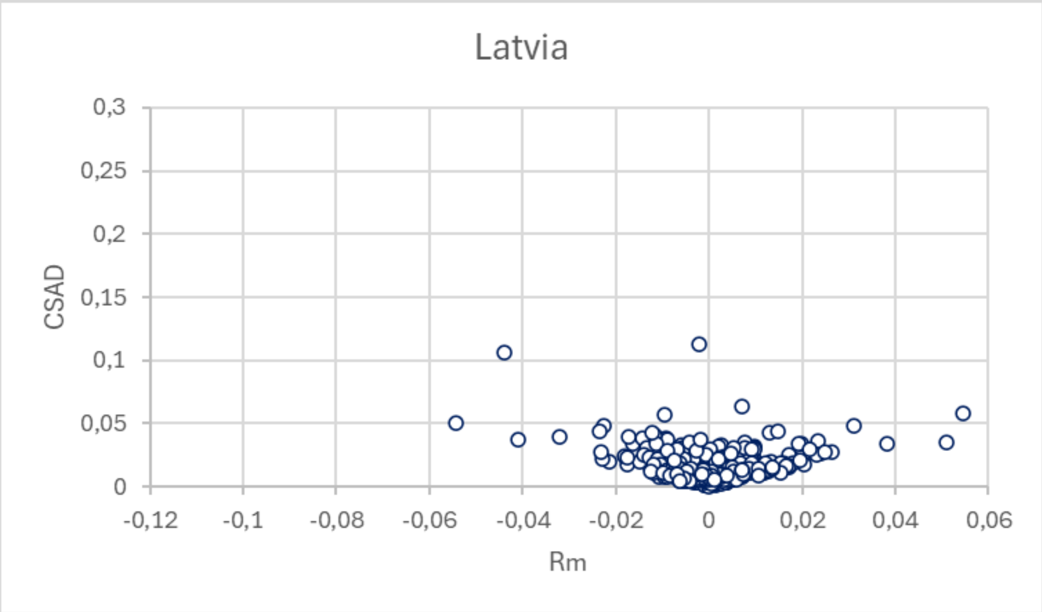

Figure 6. The relationship between the market returns (Rm) and cross-sectional absolute deviations (CSAD) for the Latvian stock market

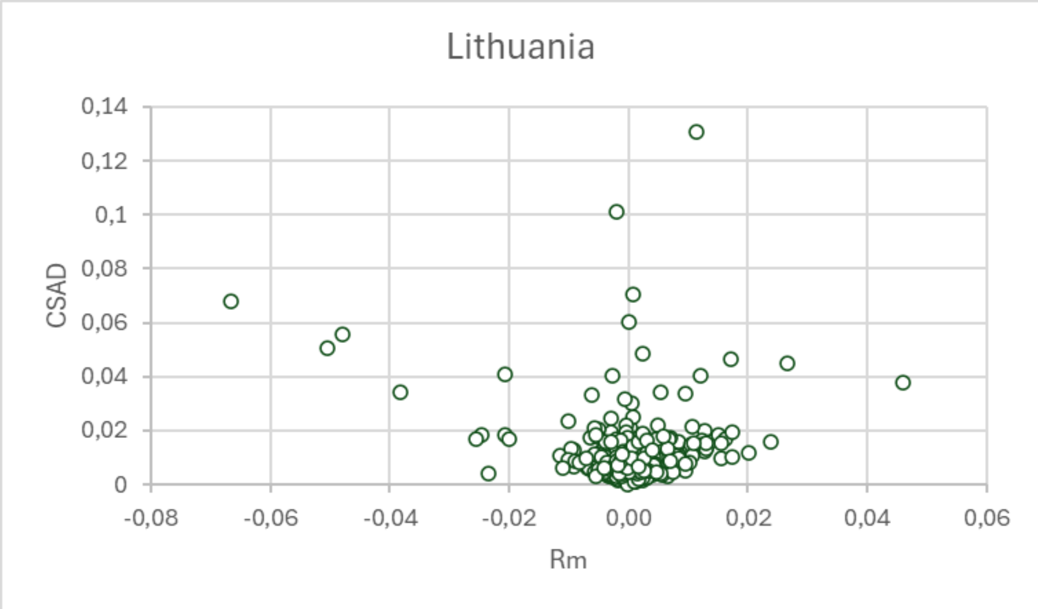

Figure 7. The relationship between the market returns (Rm) and cross-sectional absolute deviations (CSAD) for the Lithuanian stock market

By observing Figures 5, 6, and 7, it can be noticed that the CSADs increase as market returns move away from 0. Therefore, all three markets provide evidence of the linear relationship between market returns and CSADs. Due to the small number of stocks and relatively short timeframe, the relationship is somewhat difficult to illustrate, that is, if the number of observations was higher, the relationship could be more straightforward to show visually. According to Chang et al. (2000), the linear relationship should indicate that no herding can be observed during the given time frame. As discussed above, Latvia differs from the other two Baltic countries regarding the presented observations, as it exhibits virtually identical CSAD values during positive and negative market days. Considering the findings of Legenzova et al. (2024), Latvia could provide evidence of anti-herding behavior when studying the entire sample period. According to them, investors' irrational behavior stems from negative information on the market.

5 Methodology

Two different methods for recognizing and quantifying market-wide herding are presented in this thesis. The first is the Cross-Sectional Standard Deviation model, introduced by Christie and Huang (1995). The second is the Cross-Sectional Absolute Deviation model, introduced by Chang et al. (2000) and Chiang and Zheng (2010). The following chapters discusses these two models in more depth.

Huang & Wang (2017) do not find evidence of herd behavior among investors in the Taiwan stock market during periods of increased volatility using the CSSD-model introduced by Christie and Huang (1995). However, by applying the nonlinear CSAD-model of Chang et al. (2000), they find evidence of herding during the 2007-2008 Global Financial Crisis. As discussed in the following paragraphs, the CSAD-model is considered more robust and, therefore, more suitable for recognizing market-wide herding. Thus, this paper utilizes the CSAD-model to recognize herding on the Baltic stock markets. Still, the CSSD-model is also introduced briefly, as the CSAD-model is based on the fundamentals of the CSSD-model.

5.1 CSSD-Model

Christine and Huang (1995) can be considered the first ones to introduce a plausible method for recognizing market-wide herding. This model is called the cross-sectional standard deviation model (CSSD), which uses individual stock returns and cross-sectional returns for the market portfolio to recognize herding in the stock market. The fundamental idea of the model is to compare the market's average return to individual stocks' return. Herding should cause stock prices to deviate from their intrinsic values due to irrational investor behavior. This, further on, should cause the deviation between stock returns to decrease due to investors' decisions to follow market performance and abandon their own analysis. Ultimately, the lower the value the CSSD model produces, the higher the degree of herding (Christie and Huang, 1995). Hence, the cross-sectional standard deviation is calculated as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{it} - R_{mt})^2}{(N-1)}} \tag{7}$$

where N is the number of stocks, R_{it} is the observed return of the stock at time t, and R_{mt} is the cross-sectional return for the market portfolio at time t.

According to Christie and Huang (1995), the degree of herding should be higher during events of high market movements, such as crises, and lower during more stable periods. During stable periods, stock prices should follow a random walk and, therefore, deviate from the market index. Hence, it is highly probable that COVID-19 would produce lower CSSD values, implying a higher level of herd behavior on the market.

5.2 CSAD-Model

Due to criticism towards CSSD-Model regarding its inaccuracy in measuring herd behavior, the more robust cross-sectional absolute deviation model (CSAD) introduced by Chang et al. (2000) is utilized. According to Chiang and Zheng (2010), the CSSD-model is relatively sensitive to outliers, and it can detect herding only in certain market conditions. The CSAD-Model is based on the principles of Christie and Huang’s (1995) CSSD-model but it can be seen as an improved version of CSSD-model. The fundamental difference between these two models is that CSAD-model includes the entire dataset instead of extreme movements only. As CSAD and its different variants are the most popular way to test herding nowadays, it will be the primary model for testing the degree of herding in this thesis.

The underlying idea of the model is to examine whether herding can be noticed in the market by observing the degree of return dispersion measured by the cross-sectional absolute deviation of returns. According to Chang et al. (2000) and Chiang and Cheng (2010), the stock market and cross-sectional absolute deviation should demonstrate a linear relationship during rational investor behavior. Conversely, when investors act irrationally and engage in herding activity, abandoning their own analysis and following the crowd, this linear relationship will no longer hold. Therefore, the market returns and CSADs are expected to exhibit a non-linear relationship during extreme market movements.

This thesis employs the same variant of the original CSAD model as the one used by Chiang and Zheng (2010) in their paper to test whether market-wide herding can be noticed in the Baltic equity markets. Cross-sectional standard deviations are initially calculated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{8}$$

where N is the sample size, $R_{i,t}$ is the return of the stock at time t, and $R_{m.t}$ is the return of the market portfolio at time t.

Once the daily cross-sectional absolute deviations are calculated, following the methodology of Chiang and Zheng (2010), the regression equation can be defined as follows:

$$CSAD_t = y_0 + y_1 R_{m,t} + y_2\left|R_{m,t}\right| + y_3 R_{m,t}^2 + \varepsilon_{t,} \tag{9}$$

where, in addition to equation (8), y_0 is the constant term, $\left|R_{m,t}\right|$ is the absolute market return on day t, $R_{m,t}^2$ is the squared market return on day t (the “linearity component”), y_1 is the coefficient for market return on day t, y_2 is the coefficient for absolute market return on day t, y_3 is the coefficient for the squared market return on day t, and ε_t is the error term.

As Chang et al. (2000) state in their paper, investors' herd behavior during periods of heightened volatility should lead to a non-linear relationship between cross-sectional absolute deviations and market returns. This non-linear relationship should be captured by a negative and statistically significant y_3 coefficient. Conversely, a positive and statistically significant y_3 coefficient should imply that the market participants behave rationally by exhibiting antiherding behavior. It is also worth noting that the strength of Chiang and Zheng's (2010) method is that it takes the possible asymmetries into account by incorporating the $R_{m,t}$ factor into the equation.

This paper follows solely the methodology used by Chiang and Zeng (2010). Due to its robustness compared to other herding measurements, this model is virtually the most used to recognize market-wide herding.

6 Empirical results

This chapter discusses the empirical results obtained using the regression analysis described in the previous chapter. Based on the studied periods, the chapter is divided into two sections: the first discusses the findings during the entire sample period, and the second discusses different sub-periods. The hypotheses are tested and discussed against the obtained results.

6.1 Market-wide herding during the entire sample period

As discussed in previous chapters, several previous studies have found evidence of herding during different periods across different markets. Additionally, according to previous studies, it is likely that the Baltic markets, that is, Estonian, Latvian, and Lithuanian stock markets, exhibit herd behavior to some extent. However, as discussed in chapter 4.2., Figures 5, 6, and 7 contradict this by showing a linear relationship between cross-sectional standard deviations and the market returns. However, as can be seen from Figure 6, data points in the Latvian stock market differ from those in the Estonian and Lithuanian markets. Therefore, it could provide a hint of differing results. Hence, the difference is being tested by discussing the second hypothesis:

H2: Investors' behavior did not significantly change between the different Baltic stock markets during the entire sample period in terms of market-wide herding

The second hypothesis is tested using equation (9) in the regression analysis. As discussed in the methodology section, the regression analysis focuses on the equation's non-linear component, the squared market return ($R_{m,t}^2$). More specifically, its statistically significant negative coefficient y_3 indicates whether market-wide herding can be recognized during the given time frame.

Table 2. Regression results of market-wide herding during the entire sample period

Regression results of market-wide herding during the entire sample-period

	y_0	y_1	y_2	y_3
Market				
Estonia	0,007 ***	-0,060	0,698 ***	0,694
	(14,541)	(-1,213)	(7,946)	(0,531)
Latvia	0,009 ***	0,221 ***	0,928 ***	1,796 ***
	(15,192)	(6,1456)	(11,654)	(2,671)
Lithuania	0,007 ***	0,059	0,625 ***	5,353
	(12,728)	(0,945)	(0,453)	(1,612)

This table reports the estimated coefficients for equation (9) with the T-statistics in the parentheses. A negative and statistically significant coefficient $\gamma 3$ represents herding. The sample period is from 01.01.2019 to 31.05.2021.
* The coefficient is significant at the 10 % level
** The coefficient is significant at the 5 % level
*** The coefficient is significant at the 1 % level

As Table 2 shows, no signs of herding can be detected throughout the entire sample period in the Baltic stock markets due to the absence of negative and statistically significant y_3 coefficients. Therefore, according to the methodology of Chiang and Zheng (2010), market participants in the Baltic markets behave rationally regarding herding. However, the results for Estonia and Lithuania are not statistically significant because the coefficients lack explanatory power. As discussed above, it is probable that Latvia differs from Estonia and Lithuania, which can be observed by examining the scatter plot charts. This can be confirmed through the regression analysis, which provides a positive and statistically significant value at the 1% level for the coefficient y_3 for Latvia. This implies that the market participants in Latvia show signs of antiherding behavior, and therefore, it can be concluded that they act rationally (i.e., do not engage in herding).

None of the markets studied show any signs of market-wide herding. However, as discussed in the previous paragraph, investors in Latvia exhibit statistically significant antiherding behavior during the entire sample period whereas investors in Estonia and Lithuania do not exhibit any statistically significant behavior at all. Therefore, the second hypothesis can be rejected as it can be argued that investors' behavior did change between the markets. The assumption that herding can be found is based on the existing literature, but as the results of regression analysis show, no herding is present during the given time frame. As discussed in the previous chapters, the Baltic countries share several characteristics related to size, geography, demographics, economic structures, and the factors driving economic growth. In addition, previous studies, such as Nikkinen et al. (2012), Brännäs et al. (2012), and Dubinskas & Stungurienė (2010) find evidence of Baltic stock markets' co-integration and bidirectional relationship. Therefore, similar results between countries were relatively expected. The degree of antiherding behavior is highest in Lithuania (5,353) and lowest in Estonia (0,694); however, as both of the values lack statistical significance, it is not relevant to compare them to each other.

6.2 Market-wide herding during different sub-periods

As discussed in the first chapter, several previous studies find evidence of herd behavior during periods of increased market volatility. Occurrences such as the Dotcom bubble (Galariotis et al., 2014), the Global Financial Crisis in 2008 (Xing et al., 2024), and the GME Short squeeze in 2021 (Lin et al., 2021) provide evidence of herding. Economou et al. (2018) and Huang and Wang (2017) find that fear is a fundamental driver of herd behavior, which (through logical reasoning) is driven by negative information on the market. Legenzova et al. (2024) confirm this by explaining that an abundant amount of negative information tends to trigger herd behavior among investors. This is backed by Chang et al. (2000) as, according to them, macroeconomic information tends to stimulate market participants to engage in herd behavior more than firms-specific information. Hence, the effect of the COVID-19 pandemic (and the increased volatility caused by it) will be tested to either reject or accept the first and the third hypotheses:

H1: Evidence of market-wide herding can be found in the Baltic equity markets during the outbreak period of COVID-19 pandemic

H3: No evidence of market-wide herding can be found once the outbreak period is over

Table 3. Regression results of market-wide herding during the different sub-periods

Regression results of market-wide herding during the pre-COVID period

Market	y_0	y_1	y_2	y_3
Estonia	0,007 ***	0,001	0,692 **	-2,221
	(12,655)	(0,016)	(2,521)	(-0,087)
Latvia	0,010 ***	-0,083	0,855 ***	0,251
	(11,233)	(-1,227)	(4,918)	(0,052)
Lithuania	0,006 ***	0,003	-0,125	62,124 **
	(12,937	(0,039)	(-0,443)	(2,138)

This table reports the estimated coefficients for equation (9) with the T-statistics in the parentheses. A negative and statistically significant coefficient $\gamma 3$ represents herding. The pre-COVID period ranges from 01.01.2019 to 19.02.2020.

Regression results of market-wide herding during the COVID-period

Market	y_0	y_1	y_2	y_3
Estonia	0,008 ***	-0,094	0,683 ***	0,351
	(6,293)	(-1,002)	(3,743)	(0,142)
Latvia	0,007 ***	0,373 ***	1,101 ***	1,218
	(6,319)	(7,549)	(8,276)	(1,209)
Lithuania	0,008 ***	0,126	0,703 ***	4,248
	(6,292)	(1,317)	(2,950)	(0,819)

This table reports the estimated coefficients for equation (9) with the T-statistics in the parentheses. A negative and statistically significant coefficient $\gamma 3$ represents herding. The COVID-19 period ranges from 20.02.2020 to 27.11.2020.

Regression results of market-wide herding during post-COVID period

Market	y_0	y_1	y_2	y_3
Estonia	0,006 ***	0,068	0,643 ***	-1,593
	(7,448)	(1,202)	(3,087)	(-0,164)
Latvia	0,010 ***	-0,192 *	0,791 ***	2,038
	(7,226)	(-1,796)	(2,632)	(0,183)
Lithuania	0,009 ***	-0,291	0,330	16,864
	(5,179)	(-0,950)	(0,450)	(0,326)

This table reports the estimated coefficients for equation (9) with the T-statistics in the parentheses. A negative and statistically significant coefficient $\gamma 3$ represents herding. The post-COVID period ranges from 28.11.2020 to 31.05.2021.

* The coefficient is significant at the 10 % level

** The coefficient is significant at the 5 % level

*** The coefficient is significant at the 1 % level

By observing the first panel of Table 3, it can be concluded that no statistically significant evidence of herding can be found in any of the Baltic markets during the pre-COVID period. It is worth noting that the coefficient y_3 is negative in Estonia (-2.221), implying herd behavior; however, due to the lack of statistical significance, it cannot be ruled out that the negative coefficient is purely due to random chance. Latvia shows weak evidence of antiherding behavior with a y_3 coefficient of 0,251, but differing from the full sample period, it is not statistically significant. On the other hand, Lithuania shows strong evidence of antiherding behavior with a y_3 coefficient of 62,124, which is statistically significant at a 5% level. This finding aligns partially with the findings of Ferreruela and Mallor (2021), as they find no evidence of herding during the pre-COVID period in Spanish markets. Bouri et al. (2021) study herding in international stock markets and similarly found no evidence of herding during the pre-pandemic period either. Taking the previous studies into account, the results for the pre-COVID period were relatively expected, as there were no plausible reasons for some countries to exhibit signs of herd behavior based on factors such as macroeconomic information.

The second panel in Table 3 shows the regression results during the COVID-19 outbreak period, which is the primary focus of this study. As the panel shows, the results during the outbreak period are relatively similar to those of the whole sample period. Instead of herding, all of the markets show evidence of antiherding behavior with positive y_3 coefficients of 0,351 for Estonia, 1,218 for Latvia, and 4,248 for Lithuania. This, however, is not statistically significant for any of the markets. An interesting observation is that the ratio of the y_3 coefficients between the markets is virtually identical to the entire sample period. The lack of evidence of herd behavior is in line with studies such as Xing et al. (2024) and Ferreruela and Mallor (2021). Rubesam and de Souza Raimundo (2022) and Hwang and Salmon (2004) agree with this by stating that investors tend to herd more during periods of low volatility as they are confident in which direction the market is moving. Legenzova et al. (2024), however, find evidence of herd behavior in Lithuania during the pandemic with different sample period and market index. Bogdan et al. (2022), on the other hand, find evidence of herding during the pandemic when incorporating

Estonian and Lithuanian markets with three other European frontier markets. Kizys et al. (2021), as well as Ghorbel et al. (2022) study herding in international stock markets during the pandemic and find statistically significant evidence of herd behavior. Espinosa-Méndez and Arias (2020) find evidence of fear and uncertainty-driven herding in Europe during the pandemic, confirming the findings of Economou et al. (2018) and Huang and Wang (2017). Evidence of herd behavior, however, can be considered contradictory as Yang and Chuang (2022) state. Several authors find evidence of such behavior during different market occurrences, whereas others do not when studying the same sample period in different countries. Rubesam and De Souza Raimundo (2022) exemplify this by finding evidence of herding in three countries (i.e., Italy, Sweden, and the United States) out of a total of 10 countries studied.

The third panel in Table 3 shows the regression results for the post-pandemic period. Although Estonia's y_3 negative coefficient (-1,593) indicates herding, it is not statistically significant. By observing the coefficients of Latvia (2,038) and Lithuania (16,864), one can find evidence of antiherding behavior in these countries. However, similarly to Estonia, these values are not statistically significant, and therefore, no conclusion can be made regarding the presence of herd behavior. Despite this, it is interesting to notice that Lithuania provides much stronger evidence of antiherding behavior than Latvia during all of the given sub-periods.

By observing Table 3 and analyzing the regression results for different sub-periods, it is fair to conclude that no statistically significant evidence of herd behavior can be found during any of the periods. By comparing the pre-COVID and COVID-period in Table 3, it can be concluded that the value of y_3 coefficient did increase in Estonia and Latvia, implying that the level of herd behavior decreased (or the level of antiherding behavior increased). Investors in Estonia exhibited herd behavior during the pre-COVID period but during the COVID-period, they exhibited weak antiherding behavior. Latvian market participants exhibited weak antiherding behavior during the pre-COVID period, whereas during the COVID-period they provide evidence of stronger antiherding behavior.

Lithuania, on the other hand, shows evidence of strong antiherding behavior during the pre-COVID period but during the COVID-period, the level of antiherding behavior is significantly lower. Hence, the results can be considered inconclusive as the only statistically significant finding is strong antiherding behavior in Lithuania during the pre-COVID period. Therefore, the first hypothesis does not hold due to the lack of statistically significant evidence of market-wide herding during the outbreak period. By observing the post-COVID period in Table 3, it can be concluded that Estonia exhibits statistically insignificant evidence of market-wide herding, whereas Latvia and Lithuania provide statistically insignificant evidence of antiherding behavior. Therefore, the third hypothesis should be accepted as no statistically significant evidence of herding in the Baltic equity markets during the post-COVID period can be found. Interestingly, market participants in the Estonian market tend to engage in herd behavior before and after the pandemic but not during it. However, it is not relevant to analyze the obtained results further because they lack explanatory power, as discussed above. Due to the lack of explanatory power, there is a chance that the results are negative or positive due to random chance.

7 Conclusions

Herd behavior is deeply embedded in human DNA and plays a significant role in human psychology. As the actions of market participants in the equity markets are greatly influenced by human psychology, it is reasonable to believe that this behavior becomes even more prominent in the decision-making process during a global pandemic. Given that several side effects of COVID-19, such as grocery hoarding, were driven more by psychology than by rationality, it is reasonable to predict that market participants exhibited similar behavior in the Baltic equity markets. Herd behavior is problematic in terms of fundamental traditional finance theories, such as the Efficient Market Hypothesis and asset pricing models. According to the EMH, asset prices fully reflect all available information, yet several previous studies have found evidence of market inefficiencies caused by herding. Furthermore, herd behavior may lead to asset mispricing, which directly contradicts asset pricing models.

This thesis examines the presence of market-wide herding in three European frontier markets during the global pandemic caused by the Coronavirus disease (COVID-19). The sample period is further divided into pre-COVID, COVID, and post-COVID periods to analyze whether any differences can be noticed between the periods. By doing so, the hypotheses defined in the first chapter of this thesis can be either accepted or rejected which is discussed more in depth in the next paragraph.

By observing the regression results of the outbreak period in Table 3, it can be concluded that neither of the countries provides negative nor statistically significant y_3 coefficient. This implies that no market-wide herding can be found during the outbreak period, and therefore, the first hypothesis *H1: Evidence of market-wide herding can be found in the Baltic equity markets during the outbreak period of COVID-19 pandemic* can be rejected. Regression results in Table 2, on the other hand, show that investors in Estonia and Lithuania provide no evidence of statistically significant behavior at all during the entire sample period, whereas investors in Latvia exhibit strong antiherding behavior. Hence, the second hypothesis *H2: Investors' behavior did not significantly change between the* *different Baltic stock markets during the entire sample period in terms of market-wide herding* can also be rejected. Lastly, by observing the regression results of the post-pandemic section of Table 3, it can be concluded that no statistically significant evidence of herding can be found in any of the countries studied. Estonia's y_3 coefficient is arguably negative, but due to the statistical insignificance, it lacks explanatory power. Hence, the third hypothesis, *H3: No evidence of market-wide herding can be found once the outbreak period is over*, can be accepted.

As discussed in the previous chapter, the findings of this study were relatively likely. According to prior literature, herding is a contradictory phenomenon in the sense that it cannot be predicted in advance. Although the COVID-19 pandemic was an event that could have predicted herding, no signs of it were observed in the Baltic equity markets. It is interesting to notice that previous studies have, in fact, identified signs of herding in, for instance, Nordic and other European equity markets during the pandemic. Therefore, future research could aim to identify factors that may predict market-wide herding at the country or market level. For example, Ghorbel et al. (2022) find that the number of COVID-19-related deaths increased the level of herding in international stock markets. Consequently, one direction for further study could be to assess whether the coefficients and the number of deaths are correlated with each other.

Since the empirical part did not reveal any statistically significant evidence of herding, no direct potential implications can be discussed. Despite this, it could be argued that market participants in Latvian equity markets seem to exhibit rational (i.e., antiherding) behavior. This implies that the possible abovementioned finance theories, that is, the EMH and the asset pricing models, should not be contradicted in terms of herd behavior in Latvian markets.

This thesis contributes to previous studies on herding and behavioral finance in general by providing evidence of the absence of herd behavior in the Baltic equity markets during a global pandemic. More specifically, this thesis shows that no evidence for or against herd behavior can be found during the given sample period. Due to their size, the Baltic equity markets are studied relatively little, so this thesis also contributes to the related literature. The findings are interesting since several previous studies have found statistically significant evidence of market-wide herding during periods of heightened volatility, for example, during the Global Financial Crisis. On the other hand, several studies also find no statistically significant evidence of market-wide herding during such periods.

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