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Herding behavior in emerging equity markets during COVID-19

An investigation of Russian, Taiwanese, and Vietnamese stock markets

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ABSTRACT:

This thesis investigates market-wide herding within Russian, Taiwanese, and Vietnamese stock markets during the COVID-19 pandemic. Moreover, the existence of asymmetric herding and industry-specific herding are also examined in more detail by utilizing OLS regressions. Due to the recency of the pandemic and the inconclusive evidence that has been published within the research field, there exists a clear need for further herding-related studies. Thus, an in-depth examination is conducted for three emerging markets that can be considered to be appealing areas for research. At the time of publication, this thesis is also one of the few academic studies to test how market-wide herding has emerged inside the Russian stock market.

The main methodology for this study is based on regression analysis where stock return dispersions are used to quantify the level of herding. Moreover, herding is measured by utilizing the cross-sectional absolute deviation (CSAD) approach which can be seen to ultimately stem from the studies conducted by Christie and Huang (1995) and Chang et al. (2000). Besides observing herding during the chosen sample period (01.01.2018-06.05.2022), regression tests are also conducted during shorter subperiods as the sample period is divided into three separate time periods: pre-COVID period, outbreak period, and post-COVID period.

The results of this thesis suggest that market-wide herding exists mainly inside Vietnamese stock markets. Surprisingly – and in contrast to numerous previous academic studies – no herding is detected within the Taiwanese stock markets. Inversely, the regression tests imply that Russian and Taiwanese markets have been more prone towards anti-herding behavior during the pandemic time. Based on the results of the empirical part, Russia and Vietnam seem to experience market-wide herding only during down-market days whereas no herding is observed during rising market days in any of the three markets. Finally, industry-specific herding is found to exist only within Vietnamese stock markets.

As the findings of this thesis are considered as a whole, it is justified to state that the observed results are inconclusive to a large extent. Due to the unique market characteristics of the chosen stock markets and their historical tendency for market anomalies, one could have expected more pronounced herding-results. In general, it is reasonable to argue that the current research methods within the research field include several limitations and thus can be seen as a partial reason for the inconclusive evidence that highlights herding-related research. Therefore, it is suggested that future research would concentrate more on the shortcomings of the current measures and steer focus towards the development of new herding-related methodologies.

KEYWORDS: Asymmetric herding, COVID-19, Cross-sectional absolute deviation, Emerging markets, Industry-specific herding, Market-wide herding

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Abbreviations

APT	Arbitrage Pricing Theory
BV	Book Value
CAPM	Capital Asset Pricing Model
CML	Capital Market Line
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
EMH	Efficient Market Hypothesis
ECSAD	Expected Cross-Sectional Absolute Deviation
EUT	Expected Utility Theory
MC	Market Capitalization
MPT	Modern Portfolio Theory
P/E	Price-to-Earnings
SIC	Standard Industrial Classification
SML	Security Market Line

1 Introduction

Herding behavior among investors has been a widely researched topic during the last decade. According to a bibliometric study conducted by Choijil et al. (2022), there has been a significant growth in herding-related research especially after the well-known subprime crisis which occurred in 2008. Increased interest towards herding has initiated researchers to examine the topic from varying perspectives, which has caused the research field to fragment into several separate subareas. Despite of this, the general perception of herding and its different dimensions is often narrower and more simplistic in public as the underlying research field and its subareas are not taken into consideration.

In his literature review of herding inside the financial markets, Spyrou (2013) emphasizes that public typically associates herding with extreme market events and perceives it as the underlying explanation for these events. By looking at history, it is possible to detect several classical examples of market events which have been born as a consequence of investor herding. One of the most famous example can be considered to be the so-called Tulip Mania that occurred in Holland in 1637. At the time, the prices of tulips rose to absurd prices due to the herding behavior of people. Similar incident took place during the dot-com bubble in 2000 when the prices of internet stocks soared to unjustifiable levels. Alan Greenspan, a former chairman of the Federal Reserve Board, famously described investors' behavior as "irrational exuberance" at the time (Shiller, 2015). More recently, same kinds of herding traits have been detected within the U.S equity markets and the cryptocurrency markets for instance (Bouri et al., 2019; Lyócsa et al., 2021).

Even though these kinds of market events easily draw the attention of public and highlight herding explicitly as an underlying explanation for extreme market incidents, the reality seems to be less straightforward as scientific results do not fully support this viewpoint. In his paper, Welch (2000) emphasizes this notion as he states that herding is often considered as a widespread phenomenon although the empirical evidence regarding the matter is actually quite sparse. Spyrou (2013) extends this remark further as he sheds light on the underlying dimensions of herd behavior. According to Spyrou, herding is a multidimensional phenomenon that is highly dependent on its context. First of all, the concept of herding varies greatly if it is observed in different research fields outside finance and economics. Secondly, when herding is observed under financial context, there prevails several subareas that complicate the conduction of research. Spyrou also notes that the complexity of the topic and the varying research methods that have been used in the past have been some of the possible reasons for the inconclusive results that have been published within the research field. However, even though some might interpret this as a flaw for herding-related research, it also makes the production of new research valuable and needed. This notion also serves as one of the main motivations for this thesis.

1.1 Purpose of the study

The purpose of this study is to investigate market-wide herding inside emerging stock markets during the COVID-19 pandemic. More specifically, this thesis examines how market-wide herding has occurred within Russian, Taiwanese, and Vietnamese stock markets between a time period of 01.01.2018-06.05.2022. Besides investigating if market-wide herding exists within the selected stock markets, the possible existence of asymmetric herding (herding during up- and down-market days) and industry-specific are also studied in more detail. Because of the unique stock market characteristics of Russia, Taiwan, and Vietnam, they can all be considered to be appealing areas for herding-related research. Moreover, recent world events such as the outbreak of the pandemic and the military conflict between Ukraine and Russia generate an attractive research setting to study herding.

The motivation for this thesis stems from three separate factors. First, the lack of consensus and coherent evidence inside herding-related research motivates one to provide new research and observe if previous results can be validated further. Second, several studies have outlined the need for new research within emerging equity markets (Demirer et al, 2010; Spyrou, 2013; Vo & Phan, 2017). Even though numerous researchers have already extended their investigation towards these markets, a considerable number of prior studies can be argued to concentrate especially on the Asia-Pacific region and especially on the Chinese stock markets. Actually, at the time of writing, there seems to be only one study that investigates market-wide herding solely within Russian stock markets, which highlights the need for further research in this specific area. In contrast, Taiwan and Vietnam have gathered more interest from academics although the existing evidence for these markets can be still considered to be notably concentrated especially for Vietnam. Furthermore, both of these markets are also known for their distinctive market structures as individual investors account for most of the trading that takes place within the countries' marketplaces (Dang and Lin, 2016; Hung et al., 2010; Taiwan Stock Exchange Corporation, 2022). Additionally, previous studies have reported significant herding-results for both Taiwan and Vietnam which further supports the inclusion of these markets for this study. Due to the abovementioned reasons, the decision to examine Taiwan and Vietnam alongside with Russia can be seen to provide an interesting combination from the perspective of herding-related research.

Lastly, the outbreak of COVID-19 serves as an evident motivation for this study as a limited number of academic studies have yet investigated market-wide herding during the pandemic time. Thus, this thesis strives to utilize generalized research methods and investigate how the outbreak of the pandemic has affected investor herding and if the observed results deviate significantly from prior market crises.

1.2 Contribution to the prevailing literature

In line with the abovementioned motivations, the intended contribution of this thesis is three-fold. First, this thesis provides up-to-date information of market-wide herding during the COVID-19 pandemic. Due to the recency of the pandemic, there exists several herding-related research areas which have not been investigated under the pandemic setting. For instance, two of these subareas can be considered to be asymmetric herding and industry-specific herding as only few of the existing studies have yet investigated these areas inside Russian, Taiwanese or Vietnamese stock markets after the outbreak of COVID-19. Second, due to the rapid spread of the virus, stock markets around the world have undergone periods of severe market volatility which have been last experienced during previous market crises such as the subprime crisis in 2008 and the dot-com bubble in 2000. Thus, this study contributes to the existing literature by examining if there has been variation in market-wide herding in different times during the pandemic and if these results are in line with prior market crises. Finally, this thesis provides relevant information of market-wide herding within emerging markets. Moreover, the investigation of Russian stock markets contributes to the current research field as there is an evident lack of herding-related research in this specific area.

1.3 Structure of the study

The structure of this thesis is the following. The first chapter includes an introduction to the study as the purpose of this thesis and its intended contribution are outlined. During the second chapter, the theoretical background is presented and explained through a comparison of the prevailing theories within traditional and behavioral finance. The third chapter provides a literature review of herding on the basis which the research hypotheses are then formed. The fourth chapter describes the chosen methodology for the empirical part whereas the fifth chapter describes the underlying data and the descriptive statistics. The sixth chapter presents the empirical findings and considers them in the light of prior studies. The seventh chapter contains discussion about the existing limitations with the chosen topic and the conducted study. Finally, the last chapter concludes all the findings and discusses about their practical implications. Possible avenues for future research are also considered.

2 Theoretical background

A common division made inside financial theory is the separation into traditional and behavioral finance. Generally, traditional finance has been regarded as a normative theory which states how people are ought to act inside the financial markets. In contrast to this, behavioral finance is often considered as a descriptive theory which pursues to explain the reasons behind people's decisions (Baker & Ricciardi, 2014). Even though it has been shown that certain assumptions and models inside traditional finance do not hold in reality, they still serve as central building blocks for the existing theories within modern finance. Next, an overlook on the underlying theories of traditional and behavioral finance will be provided. Afterwards, a closer examination of investor herding will be conducted so that one is able to understand the different dimensions that exist behind the phenomenon.

2.1 Traditional finance

Baker and Ricciardi (2014) state that traditional finance can be seen to ultimately stem from the principles of the classical decision theory. According to the authors, the classical decision theory assumes that investors are able to act rationally under different conditions that are characterized by uncertainty. Because investors are rational, they are able to make the optimal choice and thus maximize their utility even when there are multiple choices available. Without diving into the details of the expected utility theory (EUT), it is important to understand that many of the assumptions and models that exist in modern finance essentially culminate to the expectation that investors are always trying to act rationally and achieve the best possible outcome that is available for them at the time. Within finance, the classical decision theory is affected by risk which greatly influences the decision-making process of investors. In their publication, Baker and Ricciardi emphasize that investment choices are fundamentally affected by the trade-off that exists between risk and return. This trade-off plays a central role in finance as it builds the core for the ground-breaking financial concepts such as the modern portfolio theory

(MPT), security market line (SML), capital asset pricing model (CAPM), and the efficient market hypothesis (EMH).

2.1.1 The Efficient Market Hypothesis

The efficient market hypothesis has been one of the leading paradigms at the center of financial theory for several decades. The born of EMH dates back to 1950s as Kendall and Hill (1953) observed that stock prices were not following any predictable price patterns. At the time, this observation created confusion among financial experts as it implied that markets were dominated by investor irrationality. However, the interpretation of Kendall and Hill's findings quickly reformed as the unpredictability of stock prices were seen as a sign of market efficiency. In other words, it was believed that instead of market irrationality, stock prices were actually reflecting all available information that was available. If new information emerged, this would lead to a reaction in stock prices that was unpredictable. This notion was famously cited as the *random walk* of stock prices, and it led to the born of the random walk theory in traditional finance (Baker & Ricciardi, 2014; Bodie et al., 2018).

A generalized three-level classification of the efficient market hypothesis roots from a paper published by Fama (1970). According to the author, EMH can be divided into three different categories based on the information that stock prices are believed to reflect. First, the *weak-form efficiency* implies that stock prices are reflecting all historical information successfully. Thus, it makes no sense for an investor to conduct any technical nor fundamental analysis on stocks as their prices are already reflecting past information. In contrast, the *semi-strong-form efficiency* suggests that stock prices already incorporate all available public information in addition to historical information. Under this assumption, there should be no possibility for investors to utilize new information such as market announcements or earnings reports and achieve abnormal returns. Lastly, the *strong-form efficiency* states that all information should be perfectly reflected in stock prices. Thus, even people who work inside companies and possess monopolistic access to private information should not be able to earn abnormal returns by exploiting this information. As Fama emphasizes in his paper, the strong-form efficiency should not be taken as an exact demonstration of reality. Rather, it should be used as a benchmark when conducting tests for market efficiency. This remark seems logical as it is evident that corporate insiders might possess restricted access to their company's information and thus have investment opportunities that are not available for other investors.

According to Shiller (2015), one of the most common argument that supports EMH stems from the fact that the timing of trades seems to be extremely challenging for investors. The author states that if one aims to make money, (s)he must beat the smartest investors that operate inside the stock market. Moreover, Shiller remarks that if the smartest investors are able to earn profits by buying low and selling high, this would ultimately steer prices of stocks towards their actual values assuming that EMH holds. The logic behind this notion comes from the assumption that the smartest investors would be lifting the prices of underpriced stocks and inversely driving the prices of overpriced stocks down. As this would happen, the smartest investors would gain more and more influence on the market and thus achieve increased power to remove mispricing.

Despite of the previous example, Shiller (2015) states that the theory behind EMH fundamentally assumes that no one should be able to achieve superior profits because of one's individual abilities or expertise. Based on this notion, professional investors should not be able to earn greater returns because their superior knowledge is already absorbed into stock prices. Thus, it would make no sense for investors to try to look for investment opportunities on the basis of one's own skill. As Schiller points out, the fact that professional operators such as hedge fund managers, stock analysts, and other financial professionals do not seem to be able to outperform the stock market in general as a group also supports this argument.

As one might expect, EMH has also faced a considerable amount of critique from numerous academics after the publications of Kendall and Hill (1953) and Fama (1970).

According to Malkiel (2003), the existing consensus among academics started to change as the beginning of the twenty-first century had been reached. Moreover, a growing number of academics began to think that the prices of stocks might be predictable at least to some extent. As emphasized by Malkiel, the underlying reason for this change stemmed from the fact that many researchers began to give more weight on the influence of investor psychology and behavioral characteristics. In line with this remark, Baker and Ricciardi (2014) state that the rising number of reported market anomalies served as an underlying driver behind behavioral finance and its generalization among academics.

One of the first studies to test if behavioral characteristics can forecast market anomalies was conducted by De Bondt and Thaler (1985). In their paper, the authors show that investors tend to consistently overreact to new information thus providing contrarian evidence against the assumptions of EMH. Similar results have been reported by several other researchers such as Howe (1986), Dissanaike (1997), and Baytas and Cakici (1999) who also provide evidence of the overreaction anomaly and its existence. In addition to investor overreaction, numerous other market anomalies have been reported through time which has unarguably shaken the theoretical foundations of EMH. Despite the critique that has been presented towards the efficient market hypothesis, it still serves as a central paradigm inside modern finance. Moreover, it brings one to the edge of another essential financial concept – asset pricing.

2.1.2 The Capital Asset Pricing Model and the Security Market Line

The efficient market hypothesis assumes that assets are priced correctly on the stock market. If markets are believed to be efficient, then the models that are used to price assets must be reflecting the true value of stocks. Thus, an alternative explanation for the failure of EMH might root from the underlying asset pricing models and their incapability to represent reality. Regarding asset pricing, one of the most famous models to be used is the capital asset pricing model (CAPM) which origins from the 1960s. As stated by Bodie et al. (2018), CAPM can be regarded as one of the cornerstones for financial theory. Even though the born of CAPM is often linked to the publications of William Sharpe (1964), John Lintner (1965), and Jan Mossin (1966), the theoretical foundation for CAPM already stems from the insights of modern portfolio theory (MPT), which was presented by Harry Markowitz (1952).

The underlying idea of MPT roots from Markowitz's realization that even though the complete return of a portfolio is calculated from the average returns of each stock multiplied by their weights, the calculation of portfolio's volatility does not follow the same logic. Moreover, by increasing the number of stocks in a portfolio, investors are able to reduce the variance of the portfolio assuming that the returns of the chosen stocks are not perfectly correlated with each other. In other words, investors can decrease the overall risk of their portfolios by choosing securities whose correlations are as small as possible. Based on this observation, it must be that the risk of an individual security cannot be analyzed in separation of other securities when determining an optimal portfolio. Additionally, if investors can reduce their risk-levels through diversification, then it follows that no one should be compensated for this type of risk which can be already dealt with. Thus, the only risk that must be rewarded for is the risk that affects all securities. This type of risk is also known as systematic risk whereas diversifiable risk is commonly cited as unsystematic risk (Baker & Ricciardi, 2014; Markowitz, 1952).

The underlying logic of CAPM builds around the abovementioned notions of systematic and unsystematic risk. If investors are not credited for the risk that they can diversify away, then the risk of an individual asset should be measured relative to the market portfolio. A central assumption of the CAPM is that all investors are assumed to optimize the mean-variance relations of their portfolios' returns. In other words, every investor is expected to find the best possible portfolio in terms of its risk-return trade-off. In addition to this, CAPM also assumes that investors are operating inside a universal marketplace where their expectations are homogenous. Thus, it follows that every investor arrives to the same optimal risky portfolio when determining their optimal investment choices. Furthermore, if the risky portfolio is same for all market participants, then it must be that this portfolio represents the market portfolio. This insight serves as a cornerstone for the capital market line (CML), which depicts the risk-return trade-off for all efficient portfolios (Baker & Ricciardi, 2014; Bodie et al., 2018).

As Bodie et al. (2018) state, CAPM is usually expressed by observing its mean-beta relationship. Because the risk of an individual asset is determined on the basis of its contribution to the market portfolio, CAPM incorporates beta to quantify how sensitive the return of an individual asset is in comparison to the market. If beta equals one, then it follows that the returns of an asset move identically with the market. If beta is higher than one, then the asset's returns are more sensitive to market movements. Similarly, a beta lower than one indicates the opposite which means less sensitive reactions to changes in market prices. In their publication, Bodie et al. demonstrate that beta can be derived based on the principles of market equilibrium, which states that the ratio between risk and return should be same for all investments. Thus, one is able to form an equation where the risk-reward ratios of an individual asset and market portfolio equal each other. By utilizing this logic, one arrives to the following formula which is known as the most common expression of the CAPM:

$$E(r_i) = r_f + \beta_i[r_m - r_f], \tag{1}$$

where $E(r_i)$ is the expected return of an asset i, r_f is the risk-free rate, β_i is the beta of an asset i, r_m is the expected market return, and thus $[r_m - r_f]$ is the market risk premium.

As stated, the mean-variance relationship (risk-return trade-off for efficient portfolios) is demonstrated by the CML. Similarly, the mean-beta relationship is given by the security market line (SML), which portrays the returns of an individual asset in relation to its beta. The main difference between these two models is that when the CML depicts the efficient portfolios' risk premiums in relation to variance, the SML illustrates individual asset's risk premiums in relation to beta (Bodie et al., 2018). Visual illustrations of the CML and SML are given below in figure 1.

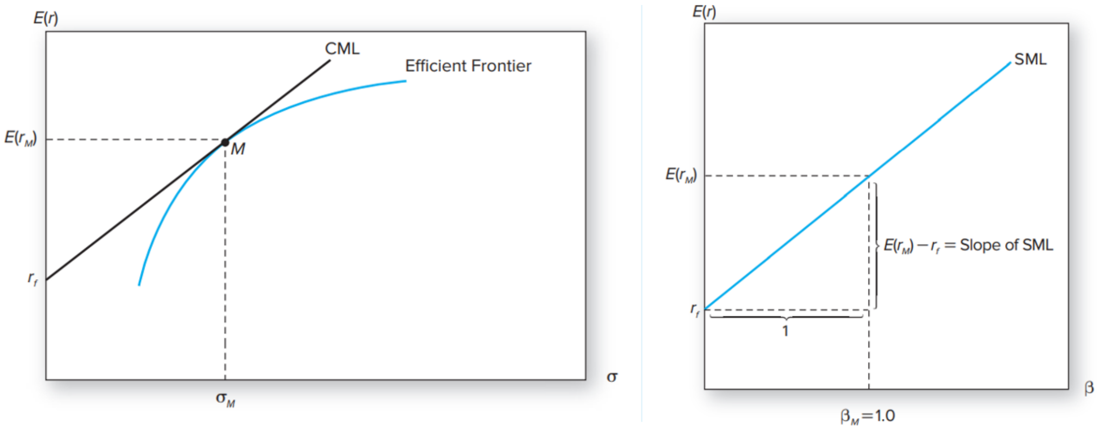

Figure 1. Capital and Security market line (Bodie et al., 2018, p. 279, 286)

After the publication of the CAPM, numerous studies have provided empirical evidence against the model's functionality. It is fair to assume that the fair amount of criticism that CAPM has undergone stems from the unrealistic assumptions that are incorporated into the model. According to Bodie et al. (2018), the suppositions of CAPM can be divided into two categories which relate to investor behavior and market structure. As stated, one central assumption of CAPM is that all investors are believed to be so-called mean-variance optimizers who act rationally. Second, the model assumes that the time horizons of investors are limited into a single horizon, and that every investor has similar expectations for the future. Regarding market structure, CAPM assumes that all assets are traded in public and that they are also held by the public. Additionally, the model assumes that lending and borrowing is possible with the common risk-free rate. Finally, CAPM also presumes that investors are able to short sell and that there are no transaction costs nor taxes inside the marketplace.

Evidently, the assumptions of CAPM can be considered to be highly restricted and impractical. Although Sharpe (1964) acknowledges this in his paper, he also states that even though the underlying assumptions are not in line with reality, this does not necessarily mean that the implications of the model would be useless. In retrospect, the problem with Sharpe's argument is that numerous researchers have now provided contrarian evidence of the functionality of the CAPM. Thus, several extensions of the model have been developed that try to depict reality more successfully by dealing with the restrictions of the original single-index CAPM. As emphasized later in this thesis, this same exact notion can be observed also within herding-related research as researchers have attempted to extend the traditional herding measures further to attain more realistic models.

One of the studies to provide damaging evidence against the CAPM has been published by Fama and French (1992) who show that between a fifty-year time period in 1941-1990, the relationship between beta and the average returns is nearly non-existent. As Fama and French state in their paper, numerous other researchers have also provided strong evidence against CAPM and shown for instance that market capitalization seems to be a prominent explanatory factor for average returns. Even though the increasing amount of empirical evidence that has been presented against the CAPM has led to the development of several other asset pricing models, Bodie et al. (2018) emphasize that all of these models are surrounded by the same fundamental idea that the original CAPM already incorporates: The only risk that should be compensated for is the systematic risk that affects all market participants.

2.1.3 Multifactor models

The development of the arbitrage pricing theory (APT) has played an essential role in offering an alternative way to price assets in comparison to CAPM. According to Roll and Ross (1980), an essential element of the APT is that it allows the usage of several risk factors whereas the original single-index CAPM only utilizes one. In other words, APT can be expanded into so-called multifactor models which enable one to utilize multiple risk factors when quantifying systematic risk. The basic equation for a multifactor model is following:

$$R_i = E(R_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + e_i, \tag{2}$$

where R_i is the excess return on asset i, $E(R_i)$ is the expected excess return of asset i, β_{i1} is the beta for a risk factor F_1, β_{i2} is the beta for a risk factor F_2, and e_i is the firm-specific surprise in the return of asset i which is also known as the zero-mean residual. Equation (2) represents a two-factor model where the expected value of every factor equals zero. This is because each factor quantifies the level of unexpected surprise within the systematic factor (Bodie et al., 2018).

One of the most popular multifactor model that has been developed is the three-factor model provided by Fama and French (1992, 1993). According to the authors, the size of the firm and the book-to-market ratio serve as effective explanatory factors for the average stock returns during a time period between 1963-1990. Fama and French state that the average returns of smaller firms have been found to be better in comparison to larger firms measured by the level of market equity. Second, the relation between the proportion of firm's book-value (BV) to its market capitalization (MC) and the firm's stock returns has been found to be positive. In other words, it has been shown that firms with higher BV/MC ratios tend to outperform firms whose ratios are lower. Following the logic of equation (2), Fama and French's three-factor model is defined as follows:

$$R_i = E(R_i) + \beta_{i1}\left[E(r_m) - r_f\right] + \beta_{i2}(SMB) + \beta_{i3}(HML) + e_i, \tag{3}$$

where in addition to equation (2), β_{i1} is the beta for the excess return of the market index $[E(r_m) - r_f]$, β_{i2} is the beta for the size factor (SMB), and β_{i3} is the beta for the value factor (HML). For clarification, Fama and French (1993) determine the (SMB) and the (HML) factors by constructing value weighted size- and value-factor portfolios. (SMB) factor represents the return that is gotten when the return of the portfolio that contains big stocks is subtracted from the return of the portfolio that comprises of small stocks. The logic remains similar for the (HML) factor although the calculation of the underlying portfolios is not identical (Bodie et al., 2018).

The three-factor model has been widely utilized in financial research although it has been extended further by researchers. In his paper, Carhart (1997) suggests that momentum can be considered as an additional fourth factor as it seems to be a powerful explanatory factor for the performance of mutual funds. Based on the observation that past winners are prone to offer better returns in comparison to past losers, Carhart's four-factor model has become a generalized extension for the three-factor model. However, Fama and French (2015) have also provided a further extension to their original three-factor model due to the problems that have been detected with it after its publication. According to the authors, the empirical evidence of the existing studies shows that the three-factor model does not successfully explain stock return variation associated with profitability and investments. Thus, the authors have come up with a five-factor model that incorporates these dimensions and which has proven to outperform their original three-factor model. In a more recent study, Fama and French (2018) extend their model even further by adding momentum as the sixth factor and thus presenting a six-factor model for asset pricing. At the same time, the authors emphasize that the endless inclusion of new factors might lead to the situation where the existing factor models do not serve their purpose anymore as they are built on prior patterns of stock returns. As Fama and French note, this is a problem which one does not need to worry about when using the original single-index CAPM.

2.2 Behavioral finance

The starting point of behavioral finance can be linked to the late 1980s when an increasing amount of academic research started to emerge related to the topic. There had been several papers that addressed the subject before this but it did not reach the awareness of the public until the 1990s. One of the main reasons for the change in the perception of academics and the generalization of the behavioral viewpoint can be seen to root from the growing amount of evidence that was presented against the efficient market hypothesis. As stated, the idea of perfectly efficient markets began to perish as new reports of market anomalies started to arise among researchers. This seemed to suggest that stock prices might in fact be predictable to some extent. Thus, one of the main problems with the traditional approach was that it was not able to explain the observed behavior that occurred within the stock markets. It is justified to argue that this served as one of the main reasons for the decline in the popularity of traditional finance (Baker & Ricciardi, 2014; Shiller, 2015; Shleifer, 2000).

As stated, the traditional approach differs from the behavioral viewpoint as it states how people are ought to make decisions as they are operating inside the financial markets. Thus, traditional finance can be defined as a normative theory which is based on the assumption that investors act rationally even in situations that are characterized by uncertainty. In contrast to this viewpoint, behavioral finance is often defined as a descriptive theory which tries to shed light on the observed financial phenomena and their underlying causes. Furthermore, it attempts to estimate possible future patterns in financial behavior based on what has already been observed. Because many of the models and the underlying assumptions inside traditional finance have not been in line with realized stock market behavior, it is easy to understand why behavioral finance has gained increasing acceptance during the last decades.

One of the main reasons for the rapid spread of behavioral finance has been the development of prospect theory. In 1979, Kahneman and Tversky (1979) published a paper where they criticized the use of the expected utility theory as a descriptive theory. The authors suggested that an alternative model, also known as the prospect theory, would be a better choice for describing the decision-making process of investors. According to the authors, people's decision-making process under risk incorporates several dimensions that the EUT fails to capture. In their article, Kahneman and Tversky illustrate multiple examples of situations where the preferences of people contravene with the assumptions of EUT. For instance, the authors show that humans are often more tendent to choose a certain outcome in situations where other (non-certain) options may offer higher overall utility. Furthermore, it is also shown by the authors that when losses are introduced to the decision-making setting, people tend to take more risks. According to

Kahneman and Tversky, this suggests that risk averse behavior is more common in the so-called gain domain whereas risk seeking behavior dominates the loss domain.

Kahneman and Tversky's (1979) study proves that the underlying assumptions of EUT might actually provide a misleading image of reality. As the authors show, it is highly likely that many of the observed violations of the EUT are outcomes of human irrationality. Furthermore, this irrationality can be considered to be due to the behavioral biases that root from people's psychological habits. The insights of Kahneman and Tversky have had a great influence on the increased acceptance of the psychological aspects that exist inside finance. They have also served as plausible explanations for number of market anomalies such as investor overreaction, anchoring, and herding, the latter of which will be the focus of this thesis.

2.2.1 Herding in financial markets

According to Spyrou (2013), herding refers to the phenomenon where people are prone to act in line with each other and base their decisions upon the decisions of others. Thus, the imitation of other investors and the abandonment of one's own beliefs can be classified as common characteristics for herding. As Spyrou emphasizes, it is often presumed by the public that herding is a general phenomenon among individual and institutional investors and that it serves as an underlying reason for times that are characterized by severe market volatility and uncertainty. As already mentioned, there exists numerous classical examples of investor herding such as the Tulip Mania in 1637, the dot-com bubble in 2000, and the subprime crisis in 2008. However, even though the vast majority of people often link herding to these types of extreme market events and consider it to be somewhat of a universal phenomenon, the empirical evidence regarding the matter does not suggest the same as Welch (2000) remarks in his paper.

Many of the first studies to concentrate solely on herding date back to 1990s as behavioral finance began to gain more attention from academics. However, the concept of investors imitating the actions of others has been highlighted already in the 1930s by Keynes (1936). In his publication, Keynes compares financial markets to a beauty contest where judges evaluate beauty (stock prices) based on the expected assessments of other judges. According to Baker and Ricciardi (2014), Keynes' metaphor suggests that rational investors attempt to evaluate future stock prices on the basis how other people perceive them even though these valuations might differ from the fundamental value of the stock. This notion brings one to the edge of an important element of herding, which states that herding does not have to be solely irrational.

Several different studies provide their own definitions for herding. In one of the early studies to investigate the phenomenon, Lakonishok et al. (1992) examine the trading of institutional investors and define herding as money managers' tendency to buy or sell the same asset at the same time with other managers. In turn, Banerjee (1992) argues that herding refers to investors abandoning their own private information and following the actions of others as other investors might possess information which is not available for them. Furthermore, De Bondt and Forbes (1999) investigate if financial analysts are prone to herd. The authors define herding as analysts' "excessive agreement" in their earnings forecasts. Based on the studies above, it seems that the core definition of herding remains largely the same even though the exact definition might slightly vary depending on the context of research.

However, although the definition of herding can be considered to be somewhat universal, the same cannot be said for the phenomenon itself. As mentioned in the introduction, herding can be considered to be a complex phenomenon which includes several different dimensions. For instance, an essential part that affects the level and the form of herding relates to the type of investors that can be identified behind the phenomenon. Inside finance, a common assumption is that individual investors are prone to act less rationally than institutional investors. In other words, individual investors are often regarded to be more inclined towards different kinds of behavioral biases such as herding. This argument can be supported with the fact that institutional investors are presumably more educated in comparison to individual investors who do not have the same resources nor the same professional expertise when it comes down to investing.

Based on the bibliometric study of Choijil et al. (2022), it seems that the vast majority of prior herding-related studies focus either on the herding behavior of institutional investors or on the whole market. Inversely, a considerably smaller number of academic studies seem to concentrate solely on the herding of individual investors although some exceptions exist. A logical explanation for this notion might be related to the fact that institutional investor herding and market-wide herding can be measured more easily as one can utilize widely known measures such as performance indices when quantifying the level of herding. However, there have been some studies such as Barber et al. (2009) and Hsieh et al. (2020) that have limited their research exclusively into individual investors. For example, Hsieh et al. show that Google searches might serve as a functional proxy for retail investor herding. Furthermore, a more common approach for measuring herding among smaller investors is to measure market-wide herding in markets that are dominated by individual investors. This approach will also be utilized in this thesis.

It is highly likely that the complexity of herding has been one of the main reasons for the inconclusive results that have been reported inside the research field. Besides of the varying investor types that can cause herding, there exists several other dimensions that can have significant effects on the phenomenon. To make matters worse, the underlying reasons for herding can also vary as Spyrou (2013) states in his paper. For these reasons, it is essential to have a clear understanding of the phenomenon itself and its different dimensions so that one is able to form an appropriate research setting which allows the measurement of the desired research areas. This can be considered as one the greatest challenges for herding-related research as it has been proven to be extremely difficult to quantify the level of herding without having to deal with the possibility of several different unknown factors affecting the results.

2.2.2 Different dimensions of herding

According to Bikhchandani and Sharma (2000), herding can be divided into two different categories based on how market participants react to new information. For example, if investors receive same information and face analogous decision-making problems, this can lead to a situation where investors herd simply because their decision-making setting is identical. The authors define this kind of herd behavior as *spurious herding* and state that it leads to market outcomes that are efficient. Moreover, the opposite form of herding is defined as *intentional herding* where herding is a consequence of investors abandoning their own information and imitating the behavior of other market participants. Thus, intentional herding can lead to inefficient market outcomes if investors decide to imitate the actions of others due to their behavioral biases for instance.

Indārs et al. (2019) further the definition of herding as the authors state that intentional herding can be an outcome of either rational or irrational behavior. As Bikhchandani and Sharma (2000) emphasize in their study, *rational herding* can stem from several factors such as reputation concerns, compensation arrangements, and inadequate information. *Irrational herding* on the other hand is often considered to be an outcome of behavioral biases that root from investors' psychological traits. Furthermore, Indārs et al. point out that prior literature has suggested that irrational herding might be an end product of investors who interpret new information unsuccessfully. This notion relates closely to Black's (1986) definition of noise-trading which will be discussed in more detail shortly.

In addition to the abovementioned dimensions, Indārs et al. (2019) include fundamental and non-fundamental components into their research setting. According to the authors, both of these factors can drive spurious and intentional herding behavior. For example, if new fundamental information is released in stock markets, this might create an identical reaction from investors which can translate into spurious herding. In contrast, if investors interpret new information incorrectly, this can also lead to spurious herding with the difference that herding is now based on non-fundamental information. Panic selling serves as another example for this as investors end up selling their investments simultaneously due to psychological factors, most commonly because of fear. The outbreak of COVID-19 can be considered as a prime example of this as investors began to liquidate their positions due to the uncertainty that temporarily took over the markets.

As stated, intentional herding can be separated into rational and irrational herding. In line with the abovementioned logic, both of these forms of herding can be driven by fundamental or non-fundamental factors. For instance, if uneducated investors choose to imitate the actions of professional investors who base their investment decisions on non-fundamental information, herding can be considered to be intentional, rational, and non-fundamental. Moreover, if investors mimic the actions of other investors thoughtlessly, they expose themselves to intentional and irrational herd behavior (Indārs et al., 2019). It is justified to say that the aforementioned examples illustrate the complexity of the topic and show the prevailing challenge that herding-related research faces. All of the different dimensions that have been discussed so far are demonstrated below in figure 2, which has been constructed based on the publications of Contreras (2019) and Indārs et al. (2019). Figure 2 should be considered merely as a rough representation of the varying dimensions behind herding rather than as a conclusive description of reality.

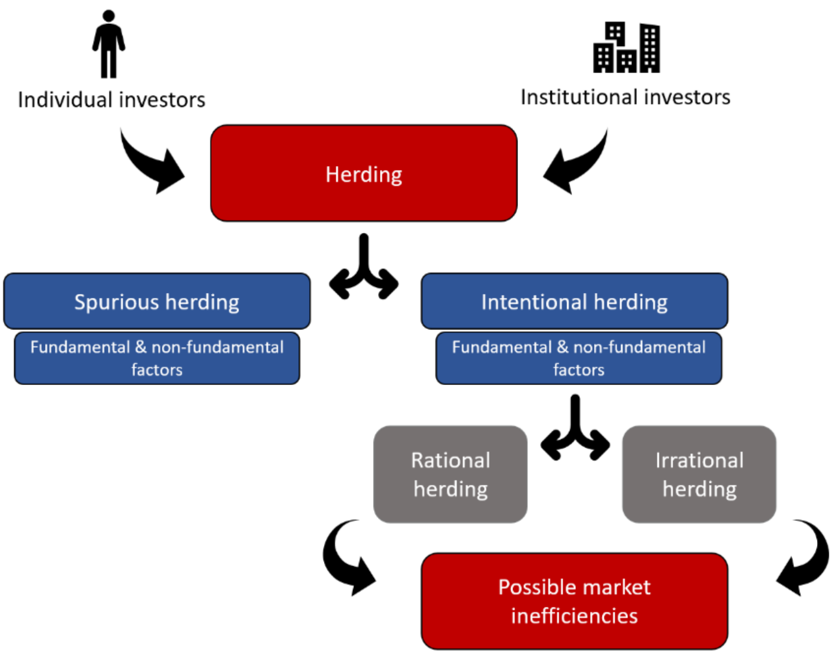

Figure 2. Different dimensions of herding

2.2.3 Root causes of herding

In public, herding is commonly explained exclusively by investors' tendency to act irrationally. As it has become clear, this argument does not hold in reality as there are several reasons that might cause market participants to herd. This notion is also emphasized by Spyrou (2013) as the author demonstrates how the underlying reasons for herding can vary. For example, one alternative explanation for the phenomenon concerns investors who reinforce herding as they try to profit from it. This kind of behavior is often initiated by speculative investors who possess short investment horizons. According to Froot et al. (1992), short-term speculators tend to imitate other investors as they try to leverage from their information. If many speculators participate in this kind of behavior, then it will be advantageous to obtain information early on as this will lead to greater profits. A more recent study conducted by Ferreruela and Mallor (2021) also emphasizes the cost and time in processing information during extreme market conditions. According to the authors, investors have a stronger incentive to herd around the market under times of extreme uncertainty. The sooner one is able to acquire information, the better the chance to profit from it.

Another possible reason for herding is related to reputation and compensation. As Spyrou (2013) states, analysts may be prone to follow announcements of other analysts as an attempt to profit from their private information and thus gain higher reputation. Moreover, the imitation of other analysts may also be beneficial if analyst forecasts turn out bad. By acting in line with others, one is able to hide behind the consensus and avoid reputational damages that would occur if (s)he would fail in isolation of others. The same logic applies also for compensation. Bikhchandani and Sharma (2000) argue that if the compensation of investment managers is dependent on how well they perform in comparison to their rivals, this creates an incentive to mimic their actions. The authors state that it makes more sense for managers to follow their rivals' behavior as this minimizes the risk for underperforming. If one acted alone and underperformed competitors, this would translate as a decline in one's compensation.

Besides reputation and compensation, an additional explanation for herding relates to noise traders. According to Black (1986), investors who base their investment decisions on so-called *noise* can be defined as noise traders. Although Black does not provide an exact definition of noise in his paper, he emphasizes that the term is at odds with information. Within finance, noise traders are often considered as irrational investors whose trading is characterized by emotions and non-fundamental trading behavior. According to Black, the likeliest candidates for fulfilling the role of a noise trader are individual investors. However, if noise cannot be considered as accurate information, then why would investors trade on it? Black argues that there are two possible reasons for this. First, it might be that individual investors simply enjoy basing their trading decisions on speculative information. Another explanation is that investors are not actually aware of the noise that surrounds them, and thus they improperly interpret it as correct information. Regardless of the underlying reason, noise can translate into herding if a considerable number of investors end up reacting similarly to it.

As stated, spurious herding is a consequence of investors reacting identically to the arrival of new information. Although spurious herding is often considered as an efficient market reaction, there can be instances where the overall reaction of investors is not efficient. In their study, Balashov and Nikiforov (2019) offer an example of this as the authors examine investors tendency for confusion trading. In 2013, Twitter's (TWTR) plans for an initial public offering became public. After the news reached the stock markets, a company named Tweeter Home Entertainment Group (TWTRQ) experienced an 1400 % increase in its stock price. According to the authors, this phenomenon can be explained by investor confusion as investors mixed the ticker symbols of the two companies. This shows that herding might also root from misinterpretation of market information even though these kinds of market events are usually short-lived.

Possibly the most common explanation for herding is related to psychological and sociological factors. It is a well-known fact that humans have a tendency to follow crowds in situations where they do not feel comfortable of acting alone. This kind of behavior roots from human nature and is often referred as herd mentality, which can be considered to stem from biases in people's cognitive and emotional factors as Baker and Ricciardi (2014) state in their publication. Evidently, these biases impact investor behavior especially under times of significant uncertainty. As noted, investor psychology is often argued to be an underlying cause for market crises and bubbles that are commonly characterized by irrational herding. According to Baker and Ricciardi, numerous different models have been developed to measure the level of irrational herd behavior. As one might expect, the task is not easy nor straightforward as most human biases are products of people's psychological characteristics and personality traits. Thus, the influence that these factors have on investor herding remains largely vague. Despite of this, the existing models can serve as useful indicators if one keeps in mind that even though they do not describe reality perfectly, this does not necessarily mean that the models would be useless. For instance, the CAPM serves as a great example of this as the model is still taught as one of the most central paradigms inside finance even though its practical failures have been known for decades.

Because the underlying reasons for herding can vary notably, it is relatively difficult to construct strong arguments of the reasons behind the phenomenon when measuring herding. In an optimal situation one would be able to restrict all irrelevant factors and create a research setting that would measure the desired dimensions of the phenomenon. However, as prior research has shown, this task can be rather difficult and in some situations it may be more sophisticated to claim that herding is likely a combination of various factors. Partly for this reason, this thesis will measure herding by utilizing some of the most established measures inside herding-related research. The limitations that come with the chosen methodology will be discussed in more detail after the empirical part.

3 Literature review and hypothesis development

The inconclusive results of previous studies highlight the importance of determining a clear research setting as one conducts new herding-related empirical research. Next, a comprehensive literature review will be conducted so that meaningful research hypotheses can be built for the empirical part. Because the main purpose of this thesis is to investigate the existence of market-wide herding, the following chapters provide an overlook on the methods and results that have been previously published within this branch of research. Each of the hypotheses presented at the end of this chapter are formed on the basis of prior studies and their main findings. Logically conducted literature review will serve as an essential tool for the upcoming empirical part as it helps to build sensible and testable research hypotheses.

3.1 Overlook on herding-related research

Herding behavior of investors has attracted a growing amount of interest among academics during the last two decades. As mentioned, the bibliometric study conducted by Choijil et al. (2022) shows that an increasing number of herding-related academic studies began to emerge especially after the subprime crisis in 2008. Factors such as the globalization of the financial markets, the increasing easiness to participate in trading activities, and the enhanced information transparency among investors can be argued to be some of the most major reasons for this as these factors have made stock markets around the world increasingly more dependent from each other especially during times of market turmoil. Thus, one could argue that herding has become a more meaningful topic to study as its effects have become more pronounced on a global scale in comparison to past decades. Even though it is difficult to pinpoint the exact starting point for herding-related research, it is logical to assume that most of the earliest in-depth studies were conducted shortly after the criticism towards rational asset pricing models started to arise.

As noted, the complexity of the topic and the different subareas of herding are some of the most significant reasons for the inconclusive results that have been published inside the research field. In his literature review of herding, Spyrou (2013) explores possible reasons that might have led to the current lack of consensus. First, the author remarks that the empirical evidence regarding herding is controversial. For example, by observing U.S stock markets, researchers Christie and Huang (1995) and Chang et al. (2000) detect no signs of market-wide herding whereas Hwang and Salmon (2004) document inverse results within U.S. However, it is essential to note that Hwang and Salmon utilize different methodology for quantifying the level of herding which might serve as a plausible explanation for the conflicting results. Besides market-wide herding, Spyrou also notes that inconclusive empirical results can be detected in other subareas of herding. For instance, the author states that researchers have published mixing results of herding among institutional investors. Studies conducted by Lakonishok et al. (1992) and Grinblatt et al. (1995) provide limited evidence on behalf of institutional investor herding whereas later studies from Sias (2004) and Choi and Sias (2009) record the opposite as institutional investors are found to herd.

Secondly, Spyrou (2013) remarks that there prevails a clear inconsistency between the existing theoretical assumptions and the ways these assumptions can be measured. Even though this remark dates back to 2013, it can still be considered as a central challenge for herding-related research as many of the more recent studies utilize the same models and methods that have been used since the start of the 21st century. The challenge with most of the existing measures is that they do not allow one to measure the desired aspects of herding directly, which in turn reduces the explanatory power of the observed results. Furthermore, the availability of proper data might also challenge the conduction of meaningful tests if one does not have access to relevant databases as Spyrou notes.

Lastly, Spyrou's (2013) final remark concerns the varying measures that are used to detect herding. According to the author, the empirical methods that are applied in herding-related research can be divided into two main categories from which one concentrates on herding of specific investor types. For this branch of research, the herding behavior of mutual funds has been a popular topic especially after Lakonishok et al. (1992) introduced a direct measure to quantify the level of mutual fund herding. In its simplicity, Lakonishok et al.'s metric is based on measuring the buying and selling behavior of mutual fund managers. According to Spyrou, this has been a widely adopted practice for mutual fund and institutional investor herding although numerous alternative measures have also been later developed.

The second empirical approach – and the approach that this thesis utilizes – focuses on investigating the existence of market-wide herding. Unarguably, this has been one of the most popular research areas for herding-related research in the past. In his paper, Spyrou (2013) defines market-wide herding as "herding towards the market consensus". The underlying logic for measuring herding on a market-wide scale is to observe how stock return dispersions change over time. If dispersions are detected to decrease, this can be considered as an indication of market-wide herding as a reduced deviation in stock returns suggests a strengthened market consensus. One of the first studies to propose this idea and present a generalizable herding-measure has been conducted by Christie and Huang (1995). Shortly after this, researchers Chang et al. (2000) presented a slightly modified version of Christie and Huang's measure, which quickly became a popular approach inside the research field and which is still widely utilized today. Even though the measures proposed by Christie and Huang and Chang et al. are not the most recent anymore, they are unarguably still some of the most well-known measures for detecting market-wide herding. Several later studies have introduced further specifications for these measures, but despite of this, the underlying logic has remained the same to a large extent.

3.2 Traditional measures for market-wide herding

As noted, Christie and Huang (1995) were the first researchers to knowingly utilize stock return dispersions as a measure for market-wide herding. In their paper, the authors investigate if deviations in stock returns serve as an explanation for herding under times of market stress. The underlying idea for the study stems from the notion that investors are likely to herd when the market is experiencing significant increase in volatility. According to the authors, this is due to investors' tendency to change their own beliefs towards the market consensus when unexpected changes occur inside the stock markets. Thus, the main hypothesis of the authors is that stock return deviations tend to be low when investors herd. Christie and Huang also state that their hypothesis contradicts the assumptions of rational asset pricing models which in turn suggest that dispersions should be higher during times of market stress because the sensitivity of individual stocks and market returns are not identical and thus should differ. To measure the dispersion of stock returns, the authors calculate daily and monthly cross-sectional standard deviations (CSSD) for each of their samples by using the following formula:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}, \tag{4}$$

where N is the number of companies, $R_{i,t}$ is the observed stock return of industry i at time t, and $R_{m,t}$ is the cross-sectional average of the N returns in the portfolio at time t. It is essential to note that the CSSD itself does not serve as a metric for herding. As Christie and Huang (1995) emphasize in their study, stock return deviations are assumed to be low when herding is present, but low dispersions do not guarantee that herding exists. Thus, the authors define the following linear regression model which enables one to test if herding occurs during periods of market stress:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_{t,} \tag{5}$$

where D_t^L is a dummy variable which equals one if the market return on day t places within the extreme lower tail of the return distribution and zero otherwise. In turn, D_t^U equals one if the market return on day t places within the extreme upper tail of the return distribution and zero otherwise. The constant coefficient α represents the average

CSSD of the entire sample disregarding the areas that the dummy variables already cover. According to Christie and Huang (1995), statistically significant negative coefficients β_1 and β_2 indicate that herding exists within the observed markets. Thus, rational asset pricing models expect the opposite, which is that the coefficients β_1 and β_2 should be positive.

After the publication of Christie and Huang (1995), the authors' methodology for measuring market-wide herding has spread widely among researchers. However, even though the underlying logic for the measure has become a well-established practice within the research field, the linear regression model has been developed further. Shortly after the publication of Christie and Huang's paper, Chang et al. (2000) extended the existing herding model by addressing an issue associated with the model's linearity. In their paper, Chang et al. show that rational asset pricing models not only assume that the dispersions of stock returns increase with market returns, but that the relationship between these two is linear. Thus, if herding exists, this linear relationship should not hold which means that the relation can increase or decrease non-linearly.

Based on this notion, Chang et al. (2000) first derive a formula for the expected cross-sectional absolute deviation (ECSAD) by using the conditional CAPM:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m|E_t(R_m - \gamma_0), \tag{6}$$

where β_i is the systematic risk on any asset i, β_m is the systematic risk on an equally weighted market portfolio, R_m is the return on the market portfolio, and γ_0 is the return on the zero-β portfolio. After deriving the formula for the ECSAD, the authors then define the linear and increasing relationship between stock return dispersions and market returns as follows:

$$\frac{\partial ECSAD_t}{\partial E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| > 0, \tag{7}$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(R_m)^2} = 0 \tag{8}$$

Equations (7) and (8) represent the expectation of rational asset pricing models. Because a non-linear relation would be an indication of herding, Chang et al. (2000) suggest an additional factor that takes the possible non-linearity into account. The authors come up with the following regression model where the squared market return $R_{m,t}^2$ is set to capture the possible non-linear relationship, and where a negative γ_2 factor implies that herding is present:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{9}$$

After the publication of Chang et al. (2000), the non-linear regression model has been specified further by Chiang and Zheng (2010) who slightly modify Chang et al.'s model by including an additional $\mathrm{R_{m,t}}$ factor to the equation. By doing this, Chiang and Zheng are able to take investors' asymmetric behavior into account during different market states. In line with the logic in equation (9), the authors state that a negative γ_3 factor serves as an indication of herding:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{10}$$

More recently, several studies conducted by researchers such as Galariotis et al. (2015), Dang and Lin (2016), and Indārs et al. (2019) extend the abovementioned regression models further by including factors that take non-fundamental and fundamental information into account. This is done by incorporating the impact of macroeconomic announcements into the research setting as this enables one to examine if herd behavior is driven more strongly either by fundamental or non-fundamental factors. As Indārs et al. note, herd behavior that is based on non-fundamental information can be interpreted as informational inefficiency for the observed markets. In contrast, herding based on fundamentals might suggest that markets are operating efficiently, which could in turn serve as a partial explanation for spurious herding as demonstrated in chapter two.

The idea of modifying the original regression equations of Christie and Huang (1995) and Chang et al. (2000) has allowed researchers to include new aspects into the research setting. For instance, a more recent study conducted by Arjoon et al. (2020) examines how different aspects of market microstructure such as volatility and liquidity might impact market-wide herding. Utilizing the same logic as presented in equation (10), the authors define their regression models by including additional factors which take liquidity and volatility into account. As emphasized, even though numerous extensions have been offered for the original measures, the underlying logic for most empirical tests has remained largely the same. In line with many of the studies that investigate market-wide herding, this thesis will use the regression model presented by Chiang and Zheng (2010) as the main model for empirical testing. However, it is important to understand that the abovementioned factors such as macroeconomic announcements and different aspects of market microstructure are likely to impact the results.

3.3 Market-wide herding in emerging equity markets

After the publication of the CSSD and the CSAD methodologies, academic studies have highlighted the need to extend herding-related research towards markets that are not as well-known as the main equity markets among developed countries (Chang et al., 2000; Demirer et al., 2010; Spyrou, 2013; Vo & Phan, 2017). At the time of writing, numerous researchers have already expanded their research towards emerging markets although there still exists various countries which require more thorough investigation. Although the field of herding-related research and the results it has provided in the past can be considered to be fragmented on many levels, there seems to prevail some sort of consensus when it comes down to results regarding market-wide herding in emerging markets. More specifically, numerous researchers have argued that market-wide herding tends to be more prominent within emerging countries.

For instance, the literature reviews of Chiang and Zheng (2010) and Indārs et al. (2019) list numerous previous studies which show that herding is stronger when the research setting is moved outside advanced markets. According to Dhall and Singh (2020), this notion is commonly explained by the fact that emerging markets offer less accurate and accessible information, which leads investors to act in line with the market consensus. Furthermore, Lao and Singh (2011) state that market inefficiencies – which are predominantly characteristics of emerging countries – serve as plausible explanations for more prominent herd behavior. According to the authors, market features such as the lack of regulation, investor education, and central bank interventions are examples of market inefficiencies and explain why investors in developing markets are more prone to herd. For these reasons, one can arguably state that emerging markets offer a more ideal research setting for market-wide herding as these markets might have inefficiencies and other unique market characteristics which ultimately lead to a higher likelihood for detecting herding behavior. Therefore, this thesis will investigate Russian, Taiwanese, and Vietnamese stock markets in more detail which knowingly possess some unique market characteristics.

3.3.1 Characteristics of Russian equity markets

There exists a very limited amount of research of market-wide herding in Russia. At the time of writing, there seems to be only one academic paper that comprehensively examines the existence of market-wide herding inside the Russian equity markets. This study has been conducted by Indārs et al. (2019) who carry out a thorough investigation of herding inside the Moscow Exchange which is the largest stock exchange inside Russia. According to the authors, no prior study has yet investigated herding inside the Moscow Exchange despite its considerable role among major stock exchanges. Thus, it is evident that there exists a clear need for further research in one of the world's leading emerging markets.

Russian equity markets possess several unique characteristics which differ from many other markets. First, they are highly influenced by the global demand and supply of natural resources. Because of the significant exposure to natural resources, major price movements in raw materials such as oil and gas have a substantial impact on the development of Russian markets. Second, several inefficiencies can be detected inside the Moscow Exchange as it is known for its information asymmetries, non-educated retail investors, lack of investor protection, and its delicate market microstructure. Third, the ownership structure of Russian equity markets can be considered to be notably concentrated as the level of state-ownership has been high in comparison to many other markets. For this reason, there might exist a greater danger for investor herding as public information is less transparent. If investors trust less on public information, they might be more prone to rely on the actions of others (Indārs et al., 2019). Additionally, a recent study conducted by Djalilov and Ülkü (2021) states that approximately 38 % of the trading value in Russian stock markets is produced by individual investors. Finally, the last notion regarding the equity markets of Russia is related to the war between Ukraine and Russia which began on the 24th of February in 2022. Despite of the tragic nature of this event, it is evident that it has created a new kind of market setting in Russia. Even though the concentration of this thesis will not be on this crisis and its effects on Russian market dynamics, the need for future research in this area is apparent.

3.3.2 Characteristics of Taiwanese equity markets

In contrast to the limited evidence regarding market-wide herding in Russia, Taiwanese equity markets have gathered considerably more attention from researchers. Several researchers such as Chang et al. (2000), Chen et al. (2012), Demirer et al. (2010), and Huang and Wang (2017) have investigated how herd behavior occurs inside the Taiwanese stock markets. A possible explanation for academics' strong interest towards Taiwanese markets might be partly associated with the fact that majority of Taiwan's market participants are individual investors (Hung et al., 2010). Thus, the market structure in Taiwan differs greatly from many other markets where institutional investors generally possess most of the market power. This unique characteristic of Taiwanese equity markets makes the country an extremely interesting area for herding-related research. As Huang and Wang point out in their study, retail investors are commonly believed to be more tendent towards herding.

According to a study conducted by Hung et al. (2010), approximately 80 % of the trading volume in the Taiwanese stock market comes from individual investors. However, the authors also point out that the mutual fund sector has experienced some rapid growth within the country. This remark is also emphasized by Demirer et al. (2010) who state that after the easing of Taiwan's trading restrictions in 2000, the number of foreign investors has increased notably. According to the latest report of the Taiwan Stock Exchange Corporation (2022), domestic individual investors accounted for 67,7 % of the trading in Taiwan Stock Exchange (TWSE) between the time period of January 2021 and June 2021. Thus, it seems that the proportion of individual investors has remained relatively high despite of the reported increase in the number of foreign investors.

Besides of the market structure, Taiwanese markets are characterized by several unique features. According to Chen et al. (2012), the Price-To-Earnings (P/E) ratios of stocks, stock turnovers, market volatility, and the excessive use of margin trades can be considered to be particularly high in Taiwan. Additionally, the authors also note that individual investors in Taiwan tend to be more inclined towards trading on noise. It is justified to assume that the notable dominance of individual investors has had a direct impact on the born of the abovementioned market characteristics. As Chen et al. note in their study, Taiwanese investors might rather rely on the trading strategies of professional investors as professionals have greater resources and knowledge to operate inside a market that has several unusual market characteristics. Demirer et al. (2010) support this notion by stating that is common for individual investors to lack the professional expertise. The authors also point out that individual investors suffer from information availability as they cannot access information as easily and accurately as professional investors. As a consequence of information asymmetry, individual investors might be more prone to imitate the actions of others and thus cause herding. In addition to this, Huang and Wang (2017) note that Taiwanese markets differ from other emerging markets as the daily prices of listing stocks are regulated by the TWSE. Thus, regulation may also have considerable influence on the flow of information causing the existence of information inefficiencies and herding.

3.3.3 Characteristics of Vietnamese equity markets

In line with Taiwan, Vietnamese equity markets have received significantly more attention from academics in contrast to Russia. An overlook to the existing literature shows that the number of herding-related studies related to Vietnam has been increasing steadily during the last two decades. In their paper, Dang and Lin (2016) state that Vietnamese equity markets have been experiencing rapid growth especially after the start of the 21st century, which can be seen as one plausible explanation for the increased interest among researchers. Furthermore, a more recent study conducted by Vo and Phan (2019) also highlights the relevance of Vietnamese markets as the authors note that Vietnam has started to receive increasingly more attention both from local and foreign investors. Thus, Vietnam serves as an appealing research area with Taiwan and Russia as it has become a significant frontier market in Asia and as its equity markets also possess some unique market characteristics.

According to Vo and Phan (2017), one notable characteristic of Vietnamese equity markets concerns insufficient information transparency. The authors remark that the state of information transparency has been a problem for Vietnam as its equity markets have faced several issues related to illegal trading activities, price distortions, and breaches in information disclosure. It is reasonable to assume that these issues can be largely explained by the lack of regulation and governmental management that have existed within Vietnamese markets as the authors point out. In a more recent study, Vo and Phan (2019) state that the regulatory framework and the overall investing environment in Vietnam has been developing although the transparency issue still remains present and serves as one of the main reasons behind herding.

Like many other emerging markets, Vietnamese markets are characterized by high volatility as they are easily exposed to economic shocks. In case of Vietnam, high volatility can be considered to highlight even more as the country’s financial system is yet far from established due to its issues related to areas such as regulatory control and market development (Vo, 2015). Furthermore, another unique characteristic of Vietnamese equity markets concerns restrictions that have been placed on foreign ownership. According to Dang and Lin (2016), Vietnam has set limits on the amount that foreign investors can hold in publicly traded companies. Comparing this notion to Taiwanese markets, it is reasonable to assume that the restricted access of foreign and institutional investors has increased the influence of individual investors also in Vietnam. Indeed, the authors state in their paper that several reports suggest that the impact of retail investors can be considered to be significant within the country’s stock markets. Finally, Dang and Lin also argue that noise trading is a probable outcome for Vietnamese markets. This can be considered as a reasonable argument due to the abovementioned issues with information transparency, volatility, and foreign trading restrictions.

3.4 Herding under extreme market conditions

As stated, herding is often considered as an underlying reason for extreme market events. Numerous prior studies have examined how market-wide herding occurs during periods of uplifted market stress and recorded mixing results depending on the observed stock market (Spyrou, 2013). In the earliest studies of market-wide herding, Christie and Huang (1995) and Chang et al. (2000) state that one can expect increased herding under times of severe market uncertainty because individuals tend to suppress their own beliefs and act in line with the market consensus. This notion has been emphasized already in the

1930s by the famous economist John Maynard Keynes who knowingly highlighted the importance of herding and remarked that individuals rather imitate the actions of others instead of taking the risk of failing in isolation of others (Schmitt and Westerhoff, 2017).

Although the above assumptions of increased herding under stressful times might feel logical, the scientific results concerning the matter have been varying. The evidence provided by Christie and Huang (1995) shows that herding does not play an important role as regards to U.S equity returns under times of market stress. In line with these results, Chang et al. (2000) find no evidence of herding in U.S nor Hong Kong during periods of radical price movements. Applying a different kind of methodology, Hwang and Salmon (2004) record positive results for market-wide herding in U.S and South Korean equity markets during both bull and bear markets. However, the results of Hwang and Salmon are independent from market conditions, and thus they do not support the idea that herding would appear merely during market crises. In contrast, the authors document that herding often increases prior to a crisis period and then declines just before the actual crisis takes place.

In line with the findings of Hwang and Salmon (2004), other researchers such as Choea et al. (1999), Economou et al. (2011), and Ferreruela and Mallor (2021) document that herding tends to vary under extreme market conditions. In their paper, Choe et al. investigate how foreign investors affect stock returns during the Korean economic crisis that occurred in 1997. Consistent with the findings of Hwang and Salmon, the authors find that foreign investors tend to herd before the crisis. However, the authors find that during the actual crisis period itself, herding ceases to exist. Economou et al. strengthen this observation as the authors examine Southern European equity markets during the 2008 financial crisis and show that the cross-sectional dispersions of stock returns increase inside the equity markets of Greek and Spain. Similarly, a more recent study conducted by Ferreruela and Mallor (2021) validates the aforementioned findings as the authors review the 2008 financial crisis and find that herding rises prior to the crisis period but disappears during the crisis itself. Furthermore, Ferreruela and Mallor also find that herding reemerges after the tipping point of the financial crisis.

Based on the presented findings, it seems that market-wide herding is prone to vary under extreme market conditions. More specifically, empirical evidence shows that in many cases herding appears to be stronger before and after the crisis whereas this is the opposite during the actual crisis phase itself. Intuitively, this observation might feel controversial to a large extent. However, as highlighted on several occasions during this thesis, it is essential to remember that the measures used to quantify herding are far from perfect and thus the results can vary considerably depending on the chosen methodology and the research setting. Nevertheless, the observation of varying herding during times of markets stress will be incorporated into the empirical part of this thesis by dividing the observation period into shorter subperiods. By doing this, it is possible to investigate if similar results are received during the COVID-19 crisis.

3.5 Herding during up- and down-markets

Another popular topic within the field of herding-related research concerns the investigation of asymmetric herding during up- and down-markets. Numerous researchers such as Arjoon et al. (2021), Chang et al. (2000), Chiang and Zheng (2010), and Indārs et al. (2019) have examined if herding emerges differently in rising and declining market days. In line with the findings of market-wide herding during extreme market conditions, prior studies have reported mixing results when it comes down to observing herding during positive and negative market days. Based on the notion that herding is often associated with extreme market events that are characterized by negative stock returns, one could expect that herding would be greater during declining markets. However, by investigating market-wide herding in Taiwan, South Korea, U.S, Japan, and Hong Kong, Chang et al. find that there seems to be no asymmetries present between positive and negative market movement days. Similar results are documented also by Hwang and Salmon (2004) who utilize an alternative herding-methodology and examine market-wide herding in U.S and South Korean markets. Likewise, the findings of Chiang and Zheng further validate these results as the authors investigate eighteen different countries and show that herding is present regardless of the market state in most of the observed equity markets.

In contrast to the abovementioned results, numerous studies have inversely found that market-wide herding appears to be stronger in either rising or declining markets. In their paper, Demirer and Kutan (2006) show that stock return dispersions tend to be lower during down-market days within Chinese stock markets, which indicates that investors are more prone to act in line with the market consensus during periods of declining price movements. By examining Hong Kong Stock Exchange, Zhou and Lai (2009) report analogous results as the authors find that sell-side herding is more profound in comparison to buy-side herding. Furthermore, Mobarek et al. (2014) conduct a cross-country analysis for European countries and detect significant market-wide herding during negative market days in several countries such as in Germany, Sweden, and Greece. According to Mobarek et al., their results suggest that investors are far more likely to face market-wide herding during periods of negative market returns.

Several studies have also reported asymmetries in terms of positive market returns. Even though Chiang and Zheng (2010) find no asymmetries in market-wide herding in most of the observed equity markets, the authors specify that Asian markets serve as an exception to their results. Furthermore, Chiang and Zheng report stronger herding in China, Hong Kong, and Japan during rising markets. An earlier study conducted by Tan et al. (2008) partly supports these findings as the authors investigate how market-wide herding occurs within Chinese stock markets between A- and B-class shares. Tan et al. observe more profound herding within A-class shares during rising markets whereas the authors find no asymmetries in B-class shares. More recent results from Asia are provided by Lam and Qiao (2015) and Arjoon et al. (2021) as their studies examine market-wide herding in Hong Kong and Singapore. Both of the studies document more pronounced herding during rising market days.

Based on the abovementioned studies, it seems that there exists no apparent consensus whether market-wide herding is more profound in either up- or down-markets. However, it is justified to assume that if herding-related asymmetries appear, they are strongly influenced by the observed stock market and the chosen time period. This argument is supported by the results of the previously mentioned studies which show that even though some markets do not seem to exhibit asymmetric herd behavior, other markets might provide completely opposite results. As demonstrated, numerous prior studies have documented asymmetries especially inside the Asia-Pacific region even though the results cannot be considered to be fully conclusive (Arjoon et al., 2021; Chiang & Zheng, 2010; Demirer & Kutan 2006; Lam and Qiao; 2015).

3.6 Industry-specific herding

The idea of investigating market-wide herding inside specific industries stems from the original article of Christie and Huang (1995). As stated, the authors find no evidence of market-wide herding as their results show that stock return dispersions rather increase instead of decreasing during times of large price movements. However, Christie and Huang remark that a possible reason for insignificant herding-results might be due to the fact that investors tend to herd around companies which possess similar characteristics. Furthermore, the authors suggest that examining herding across different industries might yield differing results. To measure the possible effect of industry-specific herding, the authors utilize a popular classification method where companies are categorized based on their Standard Industrial Classification (SIC) codes. By categorizing companies using SIC codes, the authors are able to investigate if herding exists inside specific industries. This methodology has been later utilized by numerous researchers, and the results regarding the matter have been varying.

Existing studies and their results of industry-specific herding can be divided into two separate categories: the studies which have documented herding within industries and the studies that have inversely found no evidence of the phenomenon. Being one of the first to examine the matter, Christie and Huang (1995) stand inside the latter category as the authors find no evidence of industry-specific herding inside the U.S markets. According to the authors, stock return dispersions act in line with the assumptions of rational asset pricing models as they are found to increase in all of the observed industries. A later study conducted by Henker et al. (2006) reports similar findings as the authors investigate intraday herding within the Australian equity markets. Utilizing both the CSSD and the CSAD measures, Henker et al. find no signs of industry-specific herding. Lam and Qiao (2015) also arrive to identical conclusions in their study as the authors examine herding in the Hong Kong stock market and find no evidence on behalf of herding inside industries.

In contrast to the abovementioned results, several researchers have reported opposing findings. In their literature review of herding inside the financial markets, Bikhchandani and Sharma (2000) emphasize that herding always requires two participants: the buyers and the sellers. According to the authors, if one wants to observe herding, (s)he must find a sufficient group of investors who act in line with each other under the same decision setting. Therefore, it is more likely that herding is observed within industries that consist of group of stocks that possess similar characteristics. Concentrating on Chinese equity markets, Lee et al. (2013) provide evidence on behalf of the existence of industry-specific herding. Using the CSAD approach, the authors find that between a ten-year time period of 2001 and 2011, herding is present in all of the observed 22 industry sectors within China's A-share markets. Similar findings are reported by Yao et al. (2014) who also investigate herding inside the Chinese equity markets between years 1999 and 2008. In contrast to the study conducted by Lee et al., Yao et al. utilize a slightly different methodology as they measure industry-specific herding within China's A- and B-share markets by using the CSSD approach. Even though the authors do not detect any herding on the aggregate market level, they document positive results of industry-specific herding inside most (15/21) of their observed industry portfolios.

Zheng et al. (2017) continue the investigation of herding inside industries within Asian equity markets. The authors examine nine different stock markets using daily stock data and detect that herding is present in most of the observed markets. Furthermore, the authors report that the strongest herding is observed inside financial and technology industries whereas utility industry is associated with the weakest herding-results in all markets. According to the authors, this finding is in line with the study conducted by Lee et al. (2013) who document identical results inside the Chinese equity markets. Moving outside the Asia-Pacific region, Ukpong et al. (2021) examine industry-specific herding inside the U.S equity markets between years 1990 and 2020. In line with the findings of Yao et al. (2014), the authors find no evidence of herding on the aggregate market level. However, Ukpong et al. document some evidence of industry-specific herding although these findings are not that strong as the authors record positive herding-results in three out of ten industries.

Following the logic of previous chapters, the results regarding industry-specific herding remain inconclusive. However, based on the presented empirical evidence, it seems that industry-specific herding is generally more profound within the Asia-Pacific region and especially inside the Chinese equity markets (Lee et al., 2013; Yao et al., 2014; Zheng et al., 2017). It is justified to assume that this notion partly results from the unique characteristics of Chinese stock markets. As Tan et al. (2008) remark in their study, Chinese stock markets are divided into A- and B-share markets with the difference that only local investors are allowed to participate in the A-share market whereas B-share market allows trading exclusively for foreign investors. Thus, there exists notable contrast in market dynamics as the A-share market is dominated by local retail investors and B-share market is inversely controlled by foreign institutional investors. Therefore, the large dominance of individual investors might have considerable influence on the observed levels of herding as it is common to assume that individual investors are more tendent towards different kinds of behavioral biases such as herding (Huang & Wang, 2017). This notion closely relates with the observation made regarding Taiwanese and Vietnamese stock markets where majority of the market participants have been reported to consist of local individual investors (Dang & Lin, 2016; Taiwan Stock Exchange Corporation, 2022).

3.7 Research hypotheses

As emphasized, market-wide herding has been researched under several contexts in prior literature. Previous studies have not only concentrated on the sections that were addressed in the chapters above, but also on numerous other areas. For instance, several studies have included factors such as firm size, market microstructure, and the role of fundamental and non-fundamental information into their research setting and tested how these might influence the level of market-wide herding. Even though the versatile testing of varying perspectives brings more clarity to herding as a phenomenon, one could argue that the vast range of different approaches explains the current fragmentation that can be detected inside the field of herding related research. Furthermore, another probable reason for inconclusive results stems from the varying research methods that have been used by researchers as Spyrou (2013) emphasizes in his paper. For all these reasons, this thesis utilizes established research methods for research areas that already possess some previous results within the research field. By doing this, one is able to compare results to previous studies as the underlying logic for empirical testing remains consistent.

The null hypothesis for this thesis is based on the efficient market hypothesis. According to EMH, stock return dispersions should follow a normal distribution. In contrast, behavioral viewpoint suggests the opposite as it assumes that anomalies such as herding can cause stock return dispersions to deviate from their expected values. Thus, if stock return dispersion are not normally distributed, one can confidently argue that there exists a possibility for market-wide herding. Based on these notions, the following null hypothesis is formed:

H0: During the entire sample period, stock return dispersions are normally distributed in Russian, Taiwanese, and Vietnamese stock markets.

If the null hypothesis is rejected successfully, one can assume that there is a possibility for herding. The following step is to then investigate if market-wide herding exists inside the observed stock markets. Regarding Taiwan, numerous researchers have recorded significant herding inside the country's equity markets (Chang et al., 2000; Demirer et al., 2010; Huang & Wang, 2017; Lin et al., 2007). Similarly, several prior studies have reported positive herding-results also within Vietnamese markets (Dang & Lin, 2016; Dao & Tu, 2014; Vo & Phan, 2017; Vo & Phan, 2019). Thus, based on the results of previous research, it is reasonable to expect that this thesis will provide analogous results. In contrast to Taiwan and Vietnam, there is a limited amount of empirical research available regarding market-wide herding in Russia. Being one of the first to assess the phenomenon in Russian equity markets, Indārs et al. (2019) document positive herding-results under certain market conditions. Moreover, the authors report that investors are prone to herd on non-fundamental information during unexpected financial crises. Based on the findings of Indārs et al. and the fact that market-wide herding is often coupled with periods of market turmoil, one can justifiably argue that in the light of this thesis, there is a good probability for detecting market-wide herding also in Russian markets. Thus, based on these notions, the first hypothesis is determined as follows:

H1: Herding is prevalent in Russian, Taiwanese, and Vietnamese stock markets during the entire sample period.

Since the publication of Christie and Huang's (1995) study, many researchers have investigated how herding occurs during periods of market crises. A common approach has been to divide the crisis period into smaller subperiods, which enables one to observe if the level of herding changes during different time intervals. For instance, recent studies conducted by Dhall and Singh (2020) and Ferreruela and Mallor (2021) follow this logic as the authors examine market-wide herding under the pandemic time by using several subperiods. This thesis utilizes a similar methodology as three separate sample periods are used based on the start of the COVID-19 pandemic: pre-COVID period, outbreak period, and post-COVID period. The entire sample period and the exact dates for each subperiod are defined as follows:

Entire sample period:	01.01.2018-06.05.2022
Pre-COVID period:	01.01.2018-30.01.2020
Outbreak period:	30.01.2020-01.06.2020
Post-COVID period:	01.06.2020-06.05.2022

The main reason for dividing the entire sample period into smaller subperiods roots from the results of previous studies. As stated, several researchers have found that market-wide herding tends to vary under times of market stress. More specifically, in many cases herding has been detected to increase before a crisis but as the actual crisis occurs, herding has been found to decrease (Choea et al., 1999; Ferreruela & Mallor, 2021; Hwang & Salmon, 2004). Thus, it will be meaningful to test if this kind of herd behavior can be detected also during the pandemic crisis. Based on these notions, the following hypothesis is formed:

H2: Herding varies during different subperiods in Russian, Taiwanese, and Vietnamese stock markets.

Besides examining market-wide herding under periods of uplifted market stress, Christie and Huang (1995) also incorporate an investigation of up- and down-market days in their original study. After their publication, this approach has been utilized by several studies as researchers have examined if asymmetries exists between positive and negative market days. As demonstrated during the previous chapters, prior studies have shown mixing results of herding-asymmetries. Furthermore, many studies have reported asymmetries inside Asian stock markets whereas some studies have found no signs of the phenomenon (Arjoon et al., 2021; Chiang and Zheng, 2010; Demirer and Kutan, 2006; Lam and Qiao, 2015). Due to inadequate evidence, this thesis will observe if market-wide herding emerges asymmetrically by testing the following hypothesis:

H3: Herding is asymmetrical within Russian, Taiwanese, and Vietnamese stock markets in up- and down-market days during the entire sample period.

The motivation for the final hypothesis stems from the observations that were made during the previous chapter concerning industry-specific herding. Again, following the logic of the aforementioned hypotheses, numerous prior studies provide conflicting evidence of industry-specific herding. As shown, many researchers such as Christie and Huang (1995), Henker et al. (2006), and Lam and Qiao (2015) find no evidence of herding inside specific industries whereas several other studies inversely find positive herding-results (Lee et al., 2013; Yao et al., 2014; Zheng et al., 2017). Based on the fact that most of the previously mentioned studies that document industry-specific herding concentrate on Chinese stock markets, one can arguably expect that Taiwanese and Vietnamese stock markets might offer corresponding results. This assumption can be justified with the fact that Chinese, Taiwanese, and Vietnamese markets all seem to be characterized by a high proportion of individual investors who possess considerable market power. Finally, the fourth hypothesis is formed to test if industry-specific herding exists inside Taiwanese and Vietnamese stock markets:

H4: Herding is prevalent in different industries inside Taiwanese and Vietnamese stock markets during the entire sample period.

4 Methodology

Christie and Huang (1995) can be considered to be the first researchers to come up with a meaningful method to quantify the level market-wide herding. Numerous different modifications have been later developed to make the measurement of herding more meaningful and accurate. Furthermore, different kinds of factors such as macroeconomic news and market microstructure have been later introduced into the research setting so that their possible impact on herding can be observed. Despite of the new approaches that have been developed, the fundamental logic of measuring market-wide herding has largely remained the same and can be argued to ultimately stem from the studies of Christie and Huang and Chang et al. (2000).

To detect if market-wide herding exists inside Russian, Taiwanese, and Vietnamese stock markets, this thesis utilizes the same methodology as Chiang and Zheng (2010). As stated, their approach for measuring market-wide herding is a slight modification of the method proposed by Chang et al. (2000). First, the cross-sectional standard deviations are defined as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|, \tag{10}$$

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

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t, \tag{11}$$

where in addition to equation (10), γ_0 is the constant coefficient, γ_1 is the coefficient for market return on day t, γ_2 is the coefficient for absolute market return on day t, $\left|R_{m,t}\right|$ is the absolute market return on day t, γ_3 is the coefficient for the squared market return on day t, $R_{m,t}^2$ is the squared market return on day t (representing the non-linear component), and ε_t is the error term.

The strength of Chiang and Zheng's (2010) method is that it includes an additional factor $R_{m,t}$ in comparison to the presented regression equations of Christie and Huang (1995) and Chang et al. (2000). By doing this, the authors are able to take possible asymmetries into account that might occur in investor behavior. However, the main concentration should be on the final coefficient γ_3, which serves as a coefficient for the non-linear component of the regression equation. As a reminder, rational asset pricing models assume that the relation between the deviations of stock returns and the market return is linear. Thus, a statistically significant and negative value for γ_3 can be interpreted as an indication of market-wide herding.

The first two hypotheses of this thesis will be tested by using equation (11). However, the third and fourth hypotheses require some further specifications. Utilizing the logic of Chiang and Zheng (2010), the following regression equation is formed to test if asymmetries exist between up- and down-market days within the observed stock markets:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 D\left|R_{m,t}\right| + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 D R_{m,t}^2 + \varepsilon_t, \quad (12)$$

where in addition to equation (11), D is a dummy variable which equals one if the market return is negative ($R_{m,t}$ < 0) and zero if the market return is positive ($R_{m,t}$ ≥ 0). Thus, a statistically significant and negative coefficient γ_3 suggest that market-wide herding is present during rising market days whereas statistically significant and negative coefficient γ_4 implies herding during declining market days.

Lastly, to test if industry-specific herding exists, one needs to assign stocks into industry portfolios so that herding can be observed separately within industries. As stated, a generalized approach has been to divide companies based on their Standard Industrial Classification codes. This thesis utilizes the same method as stocks are assigned to different industries based on their broad industry type classification code (two-digit SIC): Agriculture, Forestry and Fishing (01-09), Mining (10-14), Construction (15-17), Manufacturing (20-39), Transportation and Public utilities (40-49), Wholesale trade (50-51), Retail trade (52-59), Finance, Insurance and Real estate (60-67), Services (70-89), and Public Administration (90-99). Due to data restrictions, the underlying dataset has 18 companies that do not have SIC codes specified for them (3 in Taiwan, 15 in Vietnam). These companies will be excluded from the sample before forming industry portfolios. Furthermore, the minimum size of an industry portfolio is determined to be 10 stocks so that the portfolio sizes are meaningful in terms of diversification. Thus, all of the abovementioned industries are not included into the examination because there exists industries with less than ten stocks according to the underlying data. After constructing portfolios for Taiwanese and Vietnamese stock markets, industry-specific herding is measured by using equation (11).

5 Data and descriptive statistics

Next, an overlook to the underlying data that is used in the empirical part will be provided. All the necessary data specifications and the descriptive statistics will be presented below in detail. Additionally, some further graphical representations are included to illustrate the stock index developments and the cross-sectional absolute deviations inside the observed equity markets.

5.1 Data

The data for this study has been gathered from the Refinitiv Datastream and it consists of the major stock indices of Russia, Taiwan, and Vietnam. The Taiwan Capitalization Weighted Stock Index (TAIEX) is a capitalization-weighted stock index that comprises of all of the publicly listed stocks in the Taiwan Stock Exchange. At the time of writing, TAIEX includes 941 companies and has a base value of 100. Sharing similar characteristics, the Vietnam Ho Chi Minh Stock Index (VN) is also a capitalization-weighted stock index that consist of all of the companies listed on the Ho Chi Minh City Stock Exchange and the Hanoi Stock Exchange. The index has a base value of 100 and currently includes 416 companies.

The RF Russia 50 Index (RF Russia 50) is a capitalization-weighted stock index that includes some of the largest and most liquid stocks of the Moscow Exchange. At the time of writing, the number of companies included in the RF Russia 50 stands at 35. Initially, the plan was to use the MOEX Russia Index which is the main index of Russian stock markets. However, due to data restrictions, there was no available listing of the stocks that have been included in the index during the whole observation period. Thus, if one would have preferred to use MOEX Russia for empirical testing, (s)he must have searched for the current composition of the index and handpicked all of the index's stocks for the entire sample period. Because the available compositions of MOEX Russia seemed to vary depending on the data provider, RF Russia 50 was chosen to represent Russia as it already provided a complete listing of the stocks that have been part of the index during the observation period.

The time period for the gathered data places between 01.01.2018-06.05.2022. All stock returns are reported in local currencies: RF Russia 50 in Russian rubles (RUB), TAIEX in Taiwanese dollars (TWD), and VN in Vietnamese dongs (VND). An important notion that needs to be considered is related to the structure of the chosen stock indices. It is natural for an index to vary over time as stocks might be excluded from it due to changes in companies' market capitalization. Inversely, new stocks might be included to an index if one is able to gather new capital and surpass other companies currently included in the index. This fluctuation issue will be controlled by giving neutral values for those stocks that have been either included or excluded from the index during the entire sample period. More specifically, the missing returns of these stocks are replaced by the average daily return of the market portfolio.

After accounting for index fluctuations, the data consists of 3181 observations in overall. The number of observations differs between markets since the number of non-trading days varies in each country. For example, stock markets are usually closed during national holidays which differ depending on the observed country and its stock market. Another reason for the variation is related to Russia as its stock markets were temporarily closed due to the military conflict that began in February 2022. Thus, the underlying data does not provide any records of RF Russia 50's stock returns after 25.02.2022. After taking these limitations into account, the daily stock returns are calculated by using the following equation:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{12}$$

where R_t is the daily change in stock's closing price between time t-1 and time t, $\ln$ is a 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 prior to time t.

5.2 Descriptive statistics

As stated, the null hypothesis assumes that the dispersions of stock returns are distributed normally in all three equity markets. In this case, the null hypothesis can be tested by providing descriptive statistics for the underlying data and observing central variability measures. Furthermore, if one detects that the level of skewness and kurtosis is significant in terms of stock returns, (s)he can reject the null hypothesis and state that the stock returns do not follow a normal distribution. In other words, one can confidently argue that there prevails a possibility for herding. Descriptive statistics are reported below in table 1 separately for each of the observed stock markets.

Table 1. Descriptive statistics of cross-sectional absolute deviations

Market	Russia		Taiwan		Vietnam	
	CSAD	Rm	CSAD	Rm	CSAD	Rm
Mean	0,0119	0,0002	0,0136	0,0004	0,0186	0,0003
Median	0,0107	0,0010	0,0127	0,0008	0,0175	0,0014
Maximum	0,1243	0,1897	0,0432	0,0617	0,0366	0,0486
Minimum	0,0047	-0,3674	0,0074	-0,0652	0,0113	-0,0691
Std. Dev.	0,0065	0,0188	0,0040	0,0106	0,0045	0,0126
Skewness	8,4568	-6,7138	2,2279	-0,7127	1,3446	-1,0966
Kurtosis	119,6398	154,2437	11,9523	9,2056	4,8812	7,5172
Observations	1045	1045	1055	1055	1081	1081

This table reports the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily market index returns (Rm) for Russian, Taiwanese, and Vietnamese stock markets. The sample period is 01.01.2018-06.05.2022.

The skewness of a normal distribution should equal zero. As it can be seen from table 1, the reported skewness is significantly negative for market returns (Rm) in each of the observed markets. The kurtosis of a normal distribution should equal close to three. However, highly significant and positive measures for kurtosis are reported in all three markets. Based on these observations, one can reject the null hypothesis.

According to table 1, the means of the daily market returns are close to zero in all markets. Regarding the maximum and minimum values, the most extreme values can be detected inside the Russian stock market. As seen in table 1, the lowest daily market return for the RF Russia 50 Index equals -36,74 %. Based on the underlying data, this observation is recorded on the 24th of February in 2022, which is the exact date for the beginning of the military conflict. The highest daily market return is documented right after this date as the 25th of February offers a positive market return of 18,97 % in Russia. The skewness (-6,7) and kurtosis (154,2) also illustrate the extreme market movements within the Russian stock market as these measures rise to abnormal levels.

As regards to Taiwanese and Vietnamese markets, the minimum and maximum values of daily market returns do not deviate as strongly as in Russia. The lowest daily return (-6,52 %) for the TAIEX index is recorded on the 11th of October in 2018. In turn, TAIEX offers its highest daily return (6,17 %) on the 20th of March in 2020 as global stock markets recovered after plunging due to the outbreak of the COVID-19 pandemic. In line with this notion, VN index also offers its highest return in the aftermath of the pandemic as the maximum market return (4,86 %) is documented on the 6th of April in 2020. VN records its lowest return on the 28th of January in 2021 as the index has experienced a daily drop of -6,91 %.

The maximum and minimum daily returns can be detected below in figure 3, which represents the price developments of the RF Russia 50, TAIEX, and VN. Even though there exists clear similarity in the long-run trends of the three price indices, there are differences as one compares their development under different subperiods. During the pre-COVID period, RF Russia 50's price level has experienced notable increase as its value has risen over 35 %. TAIEX has also offered positive market returns during this time period as the index has risen approximately 15 % in overall. In contrast, VN has undergone some notable up- and down-price movements during the pre-COVID period and remained around the same price level as the start and end dates of this time period are compared to each other.

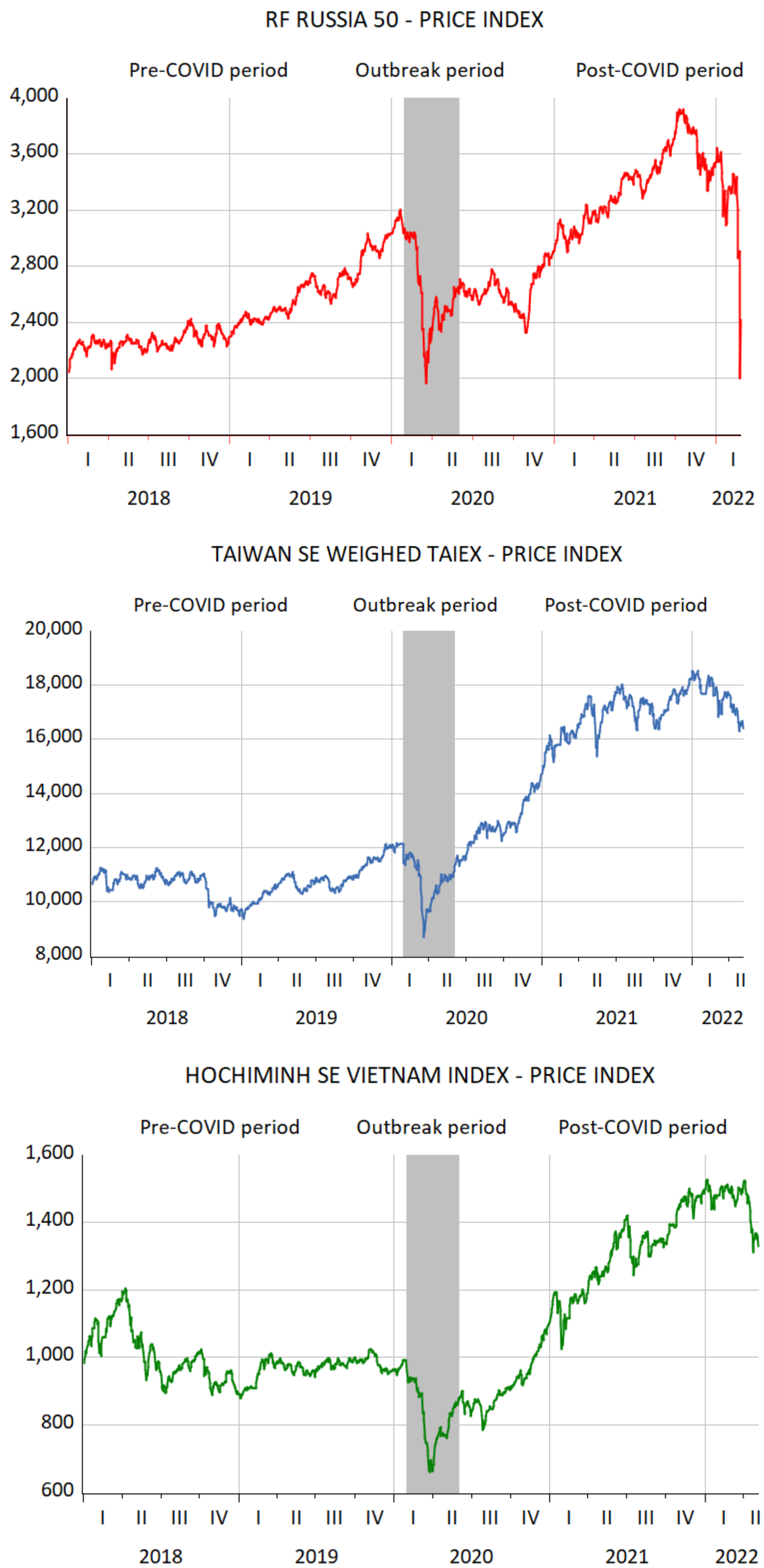

Figure 3. The price developments of the RF Russia 50, TAIEX, and VN reported in local currencies

The outbreak period has been somewhat identical for all of the observed indices as the grey areas in figure 3 demonstrate. Even though none of the stock indices document their lowest daily return during the outbreak period, this period has included one of the most severe monthly market declines during the entire sample period in all three markets. Regarding the post-COVID period, all indices experience a significant surge in their price levels. An obvious exception to this is the RF Russia 50, which has crashed down immediately after the start of the war between Ukraine and Russia. The widespread impact of this event can also be seen in the TAIEX and VN as both indices suffer a clear decline in their price levels after the first quarter of 2022.

The descriptive statistics in table 1 show that there are no significant differences in the means of the cross-sectional absolute deviations when the three markets are compared with each other. However, as emphasized in chapter 3.2, the CSAD itself is not a measure for herding and thus it makes no sense to observe it alone. Rather, a more meaningful approach is to observe the relationship between the CSADs and stock market returns as a non-linearly increasing or decreasing relation can be interpreted as an indication of market-wide herding (Chang et al., 2000).

In line with the study conducted by Chang et al. (2000), the aforementioned relationship is demonstrated below in figure 4 by using scatter plot charts. As the figure shows, stock return dispersions (CSADs) increase as the market return deviates from zero regardless of the market. As one examines the dispersions more closely, some interesting differences can be detected between markets. For instance, dispersions seem to be more significant within Taiwan during negative market days although the density of these observations is not that notable. Regarding Vietnam, it seems that the stock return dispersions increase more rapidly in comparison to Russia and Taiwan as the market return differs from zero. In other words, a smaller deviation in market return leads to a higher reaction in CSADs. When making interpretations of the scatter plot charts, it is essential to notice that the scaling of the charts varies slightly between markets due to the fact that the observations are concentrated / spread differently.

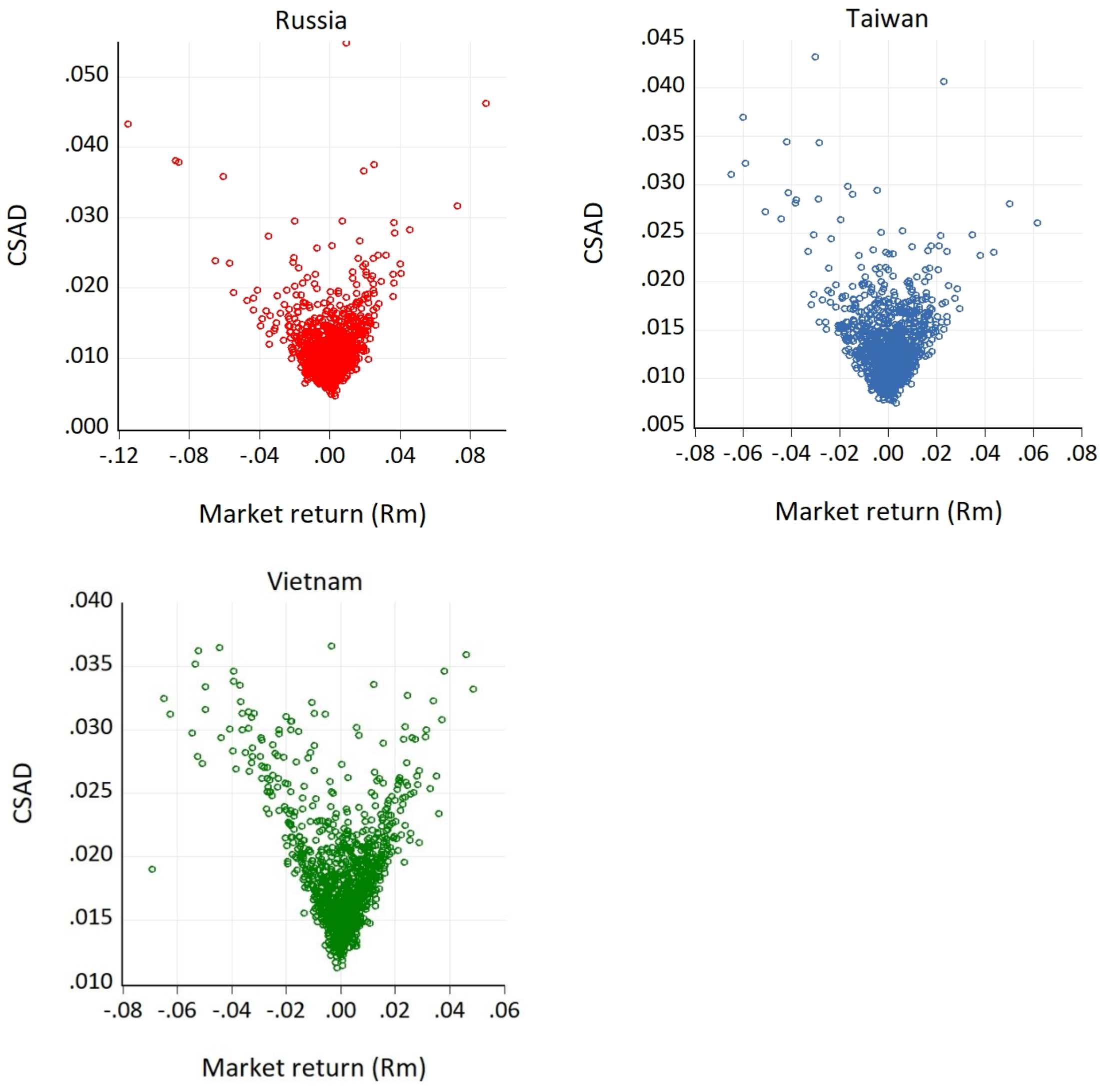

Figure 4. The relationship between the daily cross-sectional absolute deviations (CSAD) and market returns (Rm) for Russian, Taiwanese, and Vietnamese markets

Based on figure 4, all three markets provide a fairly linear pattern as the relationships between the CSADs and market returns are examined during the entire sample period, which implies that herding might not be present in any of the observed markets. However, by observing Vietnam, one can see that the observations are in general more scattered. Moreover, there seems to be increased variation in dispersions especially when the market return is close to -2 %. Thus, if herding is present, one could assume that Vietnam would be the most potential candidate for detecting it. However, one cannot make certain conclusions merely on the basis of graphical figures. Next, empirical tests will be conducted to investigate herding in more detail.

6 Empirical results

The empirical part is divided into four different sections on the basis of the presented hypotheses. Each section is built around the following logic: statement of the hypothesis, interpretation of results, and comparison of the stated assumptions and results. All of the hypotheses presented in chapter 3.7 will be tested by utilizing regression tests as described in the methodological part.

6.1 Market-wide herding during COVID-19

As stated, it reasonable to expect that Russian, Taiwanese, and Vietnamese stock markets have experienced market-wide herding during COVID-19 based on the results of prior research. However, as it was shown in figure 4, the initial regression charts suggest the opposite as the CSADs seem to follow a relatively linear pattern as they are observed along with market returns. Thus, this contradiction will be explored by testing the first hypothesis:

H1: Herding is prevalent in Russian, Taiwanese, and Vietnamese stock markets during the entire sample period.

H1 will be tested by using regression equation (11). For a reminder, the squared market return ($R_{m,t}^2$) represents the non-linear component of the equation and its coefficient (γ_3) denotes the level of herding. Thus, if the following regression tests provide a negative and statistically significant value for γ_3, this implies that herding is present. The regression results for H1 are reported below in table 2.

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

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

	γ_0	γ_1	γ_2	$\boldsymbol{\gamma_3}$	Adj. R^2
Market					
Russia	0,008 ***	0,089 ***	0,372 ***	-0,039	0,679
	(52,101)	(12,254)	(28,705)	(-0,754)	
Taiwan	0,011 ***	-0,021 **	0,288 ***	1,113 **	0,409
	(69,286)	(-2,259)	(11,134)	(1,775)	
Vietnam	0,015 ***	-0,015 **	0,517 ***	**-3,896** ***	0,607
	(101,556)	(-2,026)	(23,529)	(-7,318)	

This table reports the estimated coefficients for equation (11). A negative and statistically significant coefficient γ_3 represents herding. The sample period is 01.01.2018-06.05.2022. The T-statistics are reported in parantheses.

* 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, Vietnam seems to be the only market to experience herding during the entire sample period as its γ_3 coefficient is negative and statistically significant. Regarding Russia and Taiwan, neither one of the markets provide evidence on behalf of herding although Russia's γ_3 coefficient is also negative. However, due to the lack of explanatory power, the regression results are not statically significant for the market. In contrast to Vietnam, the regression tests provide a positive and statistically significant γ_3 coefficient for Taiwan, which suggests that the market has experienced anti-herding behavior (negative herding).

The abovementioned results provide opposing evidence for H1 excluding Vietnam where positive herding behavior is documented. Based on the results of previous studies and the similar market characteristics that Taiwan possesses with Vietnam, it is a bit surprising that the results are found to be completely opposite for Taiwan. However, even though Taiwan does not show signs of herding during the entire sample period, the results might change as the time period is being adjusted. Next, market-wide herding will be examined in more detail during separate subperiods.

6.2 Market-wide herding during different subperiods

As stated in chapter 3.4, several prior studies show that herding tends to vary under times of severe market uncertainty. Moreover, the level of herding seems to fluctuate as the actual breaking point of the crisis is being reached (Choe et al., 1999; Economou et al., 2011; Ferreruela & Mallor, 2021; Hwang & Salmon, 2004). This notion will be next examined by dividing the entire sample period into shorter subperiods. Market-wide herding will be examined separately during the pre-COVID period, outbreak period, and post-COVID period. The possible variation in herding during COVID-19 will be investigated by testing the second hypothesis:

H2: Herding varies during different subperiods in Russian, Taiwanese, and Vietnamese stock markets.

The methodology for testing H2 remains the same as equation (11) will be utilized to quantify the level of herding. The only difference is that there will be three separate regression tests for each stock market as the entire sample period is observed in three distinct time windows. The regression results for H2 can be found in table 3.

In line with the findings of previous regression tests, table 3 shows that Vietnam seems to be the only market to experience market-wide herding during shorter subperiods. More specifically, herding is documented during the outbreak period and the post-COVID period whereas the pre-COVID period shows no indication of herding behavior within the market. Interestingly, herding seems to be at its strongest during the post-COVID period as Vietnam's γ_3 coefficient is notably negative (-6,104) and statistically significant at the 1 % level. This observation seems to be partially in line with the findings of Ferreruela and Mallor (2021) who report more prominent herding inside the Spanish stock markets after the tipping point of the COVID-19 crisis period has been passed. As regards to Russia and Taiwan, neither one of the markets provide negative γ_3 coefficients under any of the observed subperiods.

Table 3. Analysis of market-wide herding during different subperiods

Regression results of market-wide herding during different subperiods.

Panel A: Pre-COVID period

	γ_0	γ_1	γ_2	$\boldsymbol{\gamma_3}$	Adj. R^2
Market					
Russia	0,009 ***	0,052 ***	0,237 ***	1,920 ***	0,432
	(47,662)	(4,362)	(9,044)	(3,780)	
Taiwan	0,010 ***	-0,002	0,296 ***	0,929 *	0,610
	(76,698)	(-0,241)	(13,093)	(1,699)	
Vietnam	0,014 ***	0,014 **	0,447 ***	0,740	0,846
	(112,743)	(2,014)	(20,558)	(1,146)	

Panel B: Outbreak period

	γ_0	γ_1	γ_2	$\boldsymbol{\gamma_3}$	Adj. R^2
Market					
Russia	0,012 ***	0,023	0,113	2,981 ***	0,638
	(10,790)	(1,022)	(1,318)	(3,046)	
Taiwan	0,012 ***	-0,063 ***	0,317 ***	0,084	0,698
	(16,957)	(-3,397)	(4,119)	(0,061)	
Vietnam	0,018 ***	-0,005	0,471 ***	**-3,372** **	0,679
	(30,288)	(-0,273)	(6,798)	(-2,604)	

Panel C: Post-COVID period

	γ_0	γ_1	γ_2	$\boldsymbol{\gamma_3}$	Adj. R^2
Market					
Russia	0,009 ***	0,135 ***	0,351 ***	0,112	0,750
	(31,344)	(12,817)	(16,356)	(1,469)	
Taiwan	0,014 ***	-0,016	0,100 *	6,175 ***	0,251
	(45,368)	(-1,064)	(1,904)	(3,702)	
Vietnam	0,016 ***	-0,055 ***	0,511 ***	**-6,104** ***	0,459
	(64,182)	(-4,232)	(13,784)	(-6,646)	

This table reports the estimated coefficients for equation (11). A negative and statistically significant coefficient γ_3 represents herding. The subperiods are:

Pre-COVID period - 01.01.2018-30.01.2020
Outbreak period - 30.01.2020-01.06.2020
Post-COVID period - 01.06.2020-06.05.2022

Another noteworthy observation from table 3 concerns Taiwan. In line with the results of H1, significant anti-herding behavior is being documented during the post-COVID period as the γ_3 coefficient is highly positive (6,175) and statistically significant.

Furthermore, anti-herding behavior is being documented also within the Russian stock market during the pre-COVID period and the outbreak period. According to Gębka and Wohar (2013), anti-herding behavior suggests that stock return dispersions have exceeded the expectations of rational asset pricing models, which means that the cross-sectional absolute deviations have been exceptionally high. This implies that investors have been more prone to ignore the overall market consensus and rather followed views that are predominant among a smaller subgroup of investors. As the authors remark, this kind of behavior could be explained by different phenomena such as localized herding, investor overconfidence or "flight-to-quality" phenomenon.

As noted, researchers such as Hwang and Salmon (2004) and Ferreruela and Mallor (2021) have found that the level of herding is often less prominent during the actual crisis period itself whereas significant herding is being documented before / after the breaking point of the crisis. In the light of table 3, these kinds of conclusions cannot be made. Furthermore, as one considers how herding has varied during different subperiods, it is not meaningful to make strong conclusions on the basis of table 3 since the observed results clearly differ between markets.

6.3 Market-wide herding during up- and down-market days

Even though herding is commonly linked to market crises that are characterized by fear and highly negative market returns, it has been shown that herding also occurs during rising market states (Arjoon et al., 2021; Chiang and Zheng, 2010; Lam and Qiao, 2015; Tan et al., 2008). Although numerous previous studies have already investigated the existence of asymmetric herding and reported conflicting results of the matter, a limited number of studies have yet examined the topic during the COVID-19 pandemic. Furthermore, COVID-19 offers an interesting research setting for asymmetric herding as the global stock markets experienced a rapid surge after first declining drastically due to the outbreak of the pandemic as seen in figure 3. To see if asymmetric herding has existed during the pandemic time, the following H3 will be tested:

H3: Herding is asymmetrical within Russian, Taiwanese, and Vietnamese stock markets in up- and down-market days during the entire sample period.

The regression tests for H3 differ from the first two hypotheses as dummy variables are introduced to the regression equation as presented in equation (12). Thus, the interpretation of results also changes as an additional coefficient (γ_4) is taken into consideration. Moreover, if the following regression tests yield a negative and statistically significant γ_3 coefficient, this implies that herding has existed during rising market days. In contrast, a statistically significant and negative γ_4 coefficient means that market-wide herding has been detected during declining market days. Table 4 below reports the findings of the regression tests.

Table 4. Analysis of market-wide herding during up- and down-market days

Regression results of market-wide herding during up and down-market days during the entire sample period.

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Market						
Russia	0,009 ***	0,318 ***	0,290 ***	1,501 ***	**-0,114** **	0,711
	(55,765)	(16,830)	(19,973)	(10,078)	(-2,315)	
Taiwan	0,011 ***	0,288 ***	0,295 ***	0,211	1,593 **	0,409
	(68,976)	(9,288)	(9,838)	(0,227)	(2,196)	
Vietnam	0,015 ***	0,404 ***	0,549 ***	0,242	**-4,569** ***	0,613
	(100,222)	(13,038)	(22,148)	(0,225)	-8,315	

This table reports the estimated coefficients for equation (12). A negative and statistically significant coefficient γ_3 represents herding during rising market states whereas a negative and statistically significant coefficient γ_4 represents herding during declining market states. The sample period is 01.01.2018-06.05.2022.

According to table 4, market-wide herding is being documented only during declining markets. Moreover, herding is detected within Russian and Vietnamese stock markets whereas Taiwanese markets do not seem to reveal any evidence on behalf of herding. Following the logic of the previous regression tests, anti-herding behavior is reported within Russian and Taiwanese markets as Russia shows signs of anti-herding during positive market days and Taiwan during negative market days. Based on these results, it seems that asymmetric herding has been present during COVID-19 as only down-market days provide positive herding results. As one considers these findings in the light of prior expectations, it is justified to say that the results feel logical to a large extent. Even though the observed stock markets have experienced a clear rise in their price levels during the entire sample period (excluding Russia and the impact of the war), market events such as the outbreak of the pandemic and the war between Ukraine and Russia have led to sudden and extreme market reactions which can be considered as possible explanations for herding during negative market days. In contrast to these notions, the regression tests continue providing surprising evidence for Taiwan as considerable anti-herding behavior is being documented inside the country's stock market.

6.4 Industry-specific herding

The last area of the empirical part concerns industry-specific herding. Due to data restrictions, the last hypothesis will be tested only for Taiwanese and Vietnamese stock markets. More specifically, because the RF Russia 50 Index only includes 35 stocks in comparison to TAIEX and VN which both comprise of several hundreds of stocks, it would not be meaningful nor possible to divide the stocks of the RF Russia 50 into ten different industry portfolios. To see if industry-specific herding has existed in Taiwan and Vietnam during the pandemic time, the following H4 will be tested:

H4: Herding is prevalent in different industries inside Taiwanese and Vietnamese stock markets during the entire sample period.

In contrast to previous hypotheses, the examination of industry-specific herding requires some further processing of the underlying data as the stocks need to be categorized into industry portfolios. As stated in chapter 4, the stocks of TAIEX and VN will be divided into ten different industry portfolios based on their broad industry type classification codes (two-digit SICs). Since the division of stocks will not be equal, all portfolios consisting of under ten stocks will be excluded from the upcoming regression tests. All of the industry portfolios and their compositions can be seen below in table 5.

Table 5. Compositions of industry portfolios

Compositions of industry portfolios			
Panel A: Taiwan		Panel B: Vietnam	
	Number of stocks		Number of stocks
Industry portfolio		Industry portfolio	
Agriculture, Forestry and Fishing	0	Agriculture, Forestry and Fishing	0
Construction	54	Construction	58
Finance, Insurance and Real estate	45	Finance, Insurance and Real estate	71
Manufacturing	706	Manufacturing	131
Mining	1	Mining	13
Public Administration	0	Public Administration	0
Retail trade	24	Retail trade	16
Services	32	Services	18
Transportation and Public utilities	39	Transportation and Public utilities	62
Wholesale trade	37	Wholesale trade	33
Total	938	Total	402

This table reports the compositions of different industry portfolios. Portfolios have been formed on the basis of broad industry type classification codes (two-digit SICs). All of the portfolios whose number of stocks is under 10 are highlighted in red and will be later excluded from the regression tests.

As it can be seen from table 5, there are three industries in overall which consist of under ten stocks and which will be removed from the upcoming regression tests. Furthermore, the compositions of the portfolios reveal that most of the stocks in both markets belong to the “Manufacturing” portfolio based on their reported SICs. This is highlighted especially within Taiwan where approximately 75 % of the market’s stocks belong to this particular portfolio. In line with the logic of testing H1 and H2, identical regression tests are conducted for each of the industry portfolios. Thus, when interpreting results, the point of interest should be on the γ_3 coefficient as it denotes the level of herding. The results of the industry-specific regression tests are reported in table 6.

On the basis of table 6, all of the industry portfolios (8/8) in Vietnam report positive and statistically significant herding results. In line with the previous findings of this thesis, no industry-specific herding is detected within Taiwan as none of the portfolios (0/7) provide negative and statistically significant γ_3 coefficients. The only industry portfolios to offer statistically significant results in Taiwan are “Manufacturing” and “Wholesale trade” portfolios, which seem to experience anti-herding behavior.

Table 6. Analysis of industry-specific herding during the entire sample period

Regression results of industry-specific herding during the entire sample period.

Panel A: Taiwan

	γ_0	γ_1	γ_2	γ_3	Adj. R^2
Industry					
Construction	0,009 ***	0,005	0,333 ***	-0,327	0,376
	(51,573)	(0,480)	(12,604)	(-0,511)	
Finance, Insurance and Real estate	0,006 ***	0,010	0,292 ***	-0,097	0,408
	(44,610)	(1,244)	(13,190)	(-0,180)	
Manufacturing	0,012 ***	-0,028 ***	0,267 ***	1,509 **	0,364
	(68,892)	(-2,813)	(9,485)	(2,214)	
Retail trade	0,008 ***	-0,001	0,405 ***	0,078	0,439
	(44,725)	(-0,104)	(13,684)	(0,109)	
Services	0,010 ***	-0,002	0,388 ***	-0,052	0,378
	(47,546)	(-0,163)	(12,219)	(-0,068)	
Transportation and Public utilities	0,010 ***	-0,005	0,439 ***	-1,006	0,171
	(27,026)	(-0,264)	(7,735)	(-0,732)	
Wholesale trade	0,009 ***	0,001	0,306 ***	1,075 *	0,421
	(53,155)	(0,081)	(11,772)	(1,708)	

Panel B: Vietnam

	γ_0	γ_1	γ_2	γ_3	Adj. R^2
Industry					
Construction	0,017 ***	-0,015	0,485 ***	**-3,776** ***	0,345
	(72,983)	(-1,256)	(13,947)	(-4,481)	
Finance, Insurance and Real estate	0,013 ***	-0,037 ***	0,509 ***	**-5,092** ***	0,365
	(62,551)	(-3,337)	(15,840)	(-6,536)	
Manufacturing	0,015 ***	-0,006	0,486 ***	**-3,747** ***	0,345
	(103,911)	(-0,750)	(21,718)	(-6,918)	
Mining	0,016 ***	-0,043 ***	0,529 ***	**-5,147** ***	0,229
	(52,134)	(-2,614)	(11,218)	(-4,510)	
Retail trade	0,016 ***	-0,024	0,534 ***	**-3,982** ***	0,308
	(57,134)	(-1,644)	(12,528)	(-3,860)	
Services	0,015 ***	-0,021	0,514 ***	**-2,108** *	0,328
	(50,565)	(-1,310)	(11,251)	(-1,906)	
Transportation and Public utilities	0,013 ***	-0,001	0,530 ***	**-3,011** ***	0,612
	(84,325)	(-0,094)	(22,103)	(-5,181)	
Wholesale trade	0,016 ***	-0,013	0,580 ***	**-4,552** ***	0,340
	(56,527)	(-0,914)	(13,903)	(-4,509)	

This table reports the estimated coefficients for equation (11). A negative and statistically significant coefficient γ_3 represents industry-specific herding. The sample period is 01.01.2018-06.05.2022.

Based on the compositions of industry portfolios, it would have been reasonable to assume that there was a possibility for industry-specific herding within Taiwan. Since the "Manufacturing" portfolio includes most of the stocks within the TAIEX, it has more notable influence on results when they are observed on an index-level. Despite of this, only three industries within Taiwan report negative γ_3 coefficients which are all statistically insignificant. Vietnam serves as a complete opposite for this as every industry reports significant herding at the 1 % significance level apart from the “Services” portfolio. Based on table 6, it seems that “Finance, Insurance and Real estate” and “Mining” are the portfolios to record the most significant herding during the entire sample period. These observations validate the results received from the other three hypotheses as Vietnam is found to be the market to experience the most pronounced herding behavior. In general, the observed results can be considered to be the most surprising for Taiwan as no herding is detected within the country in any of the conducted regressions tests. The results of this thesis seem to suggest that Taiwan has been more tendent towards anti-herding behavior during the pandemic time.

7 Limitations

Due to the complex nature of herding, it is evident that one must make assumptions that are not necessarily in line with reality when conducting empirical tests. Thus, it is essential that one is able to identify all the central limitations that are related to the topic and the chosen research methodology. Regarding this study, the major limitations will be approached from three separate perspectives: underlying theoretical assumptions, the CSAD measure, and the chosen methodology.

7.1 Underlying theoretical assumptions

The mainstream methodology for market-wide herding relies on the assumption that non-linearly increasing or decreasing stock return dispersions serve as a sign for market-wide herding as rational asset pricing models expect the opposite. However, if rational asset pricing models such as CAPM are incapable of describing reality as it has been unarguably shown, why should one expect that an inverse reaction of CAPM would be an indication of market-wide herding? This question is also emphasized by Xie et al. (2015) who note that the lack of CAPM's explanatory power ultimately weakens the reliability of the results that are achieved by using mainstream herding models. However, even though the inverse assumption of CAPM can be considered as a limitation for these models, they have still prevailed as some of the most utilized measures within herding-related research. Perhaps this is due to the intuitive logic and the simpleness that the mainstream models possess in comparison to many other alternative approaches that have been offered in the past.

Secondly, there exists a notable disparity between the theoretical assumptions and the empirical tests. For instance, it is well-acknowledged among researchers that herding itself is a multitude phenomenon that has several forms and root causes. Despite of this, majority of the methods that are utilized for herding-related research can be seen to be highly limited in the sense that they cannot usually distinguish different dimensions of herding from each other. As Spyrou states (2013), the empirical methods and the past advances in the underlying theory have not developed in line which has caused an imbalance between them. According to the author, this has led to a situation where one is required to make strong assumptions and conduct empirical tests that are measuring herding indirectly. Thus, it is justified to argue that one of the greatest limitations within herding related research concerns the lack of proper methodologies.

In the light of this thesis, the abovementioned limitations should be kept in mind as further conclusions are made based on the achieved empirical results. Even though this thesis detects market-wide herding mainly within Vietnamese stock markets, one must bear in mind that these results are merely representing one aspect of herding. Furthermore, it is not meaningful to argue whether these results stem from intentional, spurious, rational, or irrational herding based on the findings of this study. Thus, one can only form educated guesses of the possible reasons behind market-wide herding in this case.

7.2 CSAD measure

According to Spyrou (2013), the empirical methods for measuring herding can be divided into two separate categories. The first category relies mainly on microdata as it aims to understand if certain types of investors such as institutional investors herd. The second category, which is also the focus of this thesis, relies on aggregate market data as the goal is to observe how stock prices move in relation to the market consensus. As stated, the method of using cross-sectional absolute deviations of stock returns has become an established practice inside the research field after the publications of Christie and Huang (1995) and Chang et al. (2000). Although the authors' original measures have been later developed further, it is evident that the current modifications of these measures are still far from perfect as they are able to capture herding only to a certain extent. As Spyrou remarks, the CSSD measure (and its further extensions) only detect herding in the direction of the market consensus, which means that it disregards other types of herding.

Another drawback of using the CSAD (and the CSSD) as a measure for herding is its incapability of distinguishing intentional herding from spurious herding. According to Hwang and Salmon (2004), it is essential that one is able to differentiate these forms of herding from each other as spurious herding can be considered as an efficient market reaction. Thus, even though the CSAD measure would suggest that herding is present, it may simply be that this is a result of investors reacting efficiently to new fundamental market information. Furthermore, the underlying causes for herding also remain unknown with the CSAD measure as it cannot separate rational herding from irrational herding. As Spyrou (2013) states, it is important to clearly specify the type of herding that is being examined and then utilize proper measures for empirical testing. This can be considered as one of the biggest challenges not only for the CSAD measure, but also for the whole research field.

In addition to the abovementioned limitations, Xie et al. (2015) point out that the original CSAD measure of Chang et al. (2000) include assumptions that do not hold in reality. Moreover, as presented in equation (6), Chang et al. derive a formula for the expected cross-sectional absolute deviation by using the conditional CAPM. Furthermore, the authors then construct equation (7) which represents the linear and increasing relation of expected stock return deviations and the expected returns of the market. Based on this derivation, Chang et al. construct a test for herding as the authors utilize CSADs and realized market returns to test for the undetectable ECSAD. As demonstrated in equation (9), this is done by creating a regression equation with an additional market factor ($\gamma_2 R_{m,t}^2$) so that one is able to capture the non-linear component, which is believed to serve as a signal for herding. However, as Xie et al. note in their study, the above logic has a clear limitation as it might not be suitable to utilize CSADs and market returns as a proxy for the undetectable ECSAD. The authors support this argument by using the CAPM and deriving a formula for the expectation of CSAD at time t. The derivation of Xie et al. shows that the beta of an equally weighted market portfolio is expected to be one even though this is rarely the case in reality. Thus, one might end up to false conclusions due to the fact that the ECSAD might actually differ significantly from the expectation of CSAD.

Based on all of the abovementioned notions, it should be apparent that the CSAD measure includes limitations that must be kept in mind when assessing the final results and making further conclusions.

7.3 Chosen methodology

Lastly, there exists some limitations in the chosen methodology that should be addressed. As stated, the possible structural changes of indices have been taken into account by giving neutral values for those stocks that are missing returns in the data sample. The challenge with index fluctuations is that they can influence the average deviations of stocks versus the market index significantly, which in turn can falsify the final results. For example, if one is processing data that consists of many years of worth of stock returns, there is a great risk that the observed indices have experienced numerous changes in their structure. As a consequence, the underlying data and its stocks do not always match the content of the actual indices, which inevitably leads to distortions in the observed results. Thus, one must make the decision between excluding all the stocks that are lacking values in the data or as it has been done in this thesis, giving neutral values for the missing returns i.e. replacing them with the average return of the market portfolio.

Besides structural changes, another important notion concerns the chosen time windows that one uses when measuring market-wide herding. Regarding this thesis, the research setting has been divided into three shorter time periods (pre-COVID period, outbreak period, and post-COVID period) as prior literature has shown that herding tends to vary under extreme market conditions. However, it should be noted that by adjusting the length of the time periods that are utilized in empirical testing, one can affect the end-results significantly. Additionally, the chosen time intervals for calculating the CSADs also influence the results. For instance, Tan et al. (2008) utilize daily, weekly, and yearly time intervals in their study and show that herding tends to be stronger during daily intervals.

In their study, Chiang and Zheng (2010) address a further herding-related limitation that had not been taken into consideration before the authors' publication. As the authors point out, most of the previous studies have focused solely on measuring herding inside local stock markets. In contrast, the possible impact of cross-country herding has been bypassed even though empirical evidence suggests that events such as market shocks are international phenomena that tend to spread across markets. Thus, when interpreting the results of this thesis, one needs to keep in mind that the reported results in each of the observed markets might be impacted by cross-country herding. As Chiang and Zheng (2010) emphasize, one of the main issues of measuring herding merely in local markets is that the underlying regression equations might end up lacking important explanatory variables. However, it is justified to argue that in the case of Taiwan and Vietnam, it is likely that these markets are not as tendent for cross-country herding due to their restricted accessibility for foreign investors.

Finally, the last limitation concerns the formation of industry portfolios. Even though it has been common for researchers to divide companies based on their SIC codes and this way quantify the level of industry-specific herding, one must keep in mind that companies might not be perfect representations of their own industries. Thus, the industry-specific results of this study should not be interpreted as an absolute truth, but rather as an indication of possible herding patterns. Actually, a more optimal approach could be to handpick companies that are known to correspond with the observed industries and this way form industry portfolios that serve as better illustrations of reality.

8 Conclusions

This thesis has investigated the existence of market-wide herding in three different emerging markets during the COVID-19 pandemic. The results of the empirical part show that herding seems to exist mainly within Vietnamese stock markets. More specifically, market-wide herding is being documented only in Vietnam when the entire sample period is observed. Likewise, when herding is examined during shorter time periods, Vietnam is the only market to show statistically significant results as herding is recorded during the outbreak period and the post-COVID period. Furthermore, Russia and Taiwan provide conflicting results as both markets seem to be experiencing anti-herding behavior during varying subperiods. Due to the inconclusive evidence, the first two hypotheses of this study are rejected.

In contrast to the abovementioned results, positive herding is found in the Russian stock market as asymmetric herding is being investigated. More specifically, herding is documented within Russia and Vietnam during declining market days whereas Taiwan continues to show signs of significant anti-herding behavior. Regarding rising market days, no herding is observed in any of the three markets excluding Russia which provides evidence on behalf of anti-herding. Based on the observed results, the third hypothesis is accepted as herding seems to be more pronounced during declining markets. Lastly, by investigating Vietnamese and Taiwanese markets, the empirical tests show that industry-specific herding is only present within Vietnamese markets. Following the results of the first three hypotheses, no herding is detected within any of the industries inside Taiwan. Based on these results, the final hypothesis is partially accepted.

In conclusion, the results of this thesis provide inconclusive evidence for the observed markets. As stated, the greatest surprise concerns Taiwan as numerous prior studies have reported significant herding within the country’s equity markets. The fact that Taiwan and Vietnam have shared many similar market characteristics such as their high proportion of individual investors and the restricted access of foreign investors highlight the unexpected results all the more. However, as emphasized during the previous chapter, there exists several limitations which might serve as underlying reasons for the unintuitive results. For instance, a plausible explanation for the differing results between Taiwan and Vietnam could stem from the differences in the countries' market micro-structures such as price determination and trading practices for example.

The abovementioned findings and the general insights that have been presented during this thesis contain many potential implications as one considers them in the light of practical decision making. Furthermore, the practical implications of this study can be approached from two separate perspectives based on the type of decision makers. First, it is apparent that by understanding herding as a phenomenon, financial entities such as financial institutions, portfolio managers, and other financial professionals are directly benefited as they seek to make profits through investment activities. For example, if some stock markets show signs of constant herding behavior, one might be able to form trading strategies that temporarily benefit from this information. Moreover, the findings of prior studies and this thesis suggest that especially Vietnamese markets may offer this kind of opportunity as market-wide herding seems to be a rather robust phenomenon inside the country's markets especially during times of market turmoil. In addition to this, the knowledge of cross-country herding might also serve as another factor that benefits financial entities in terms of capital allocation. If there exists differences in countries' tendency for cross-country herding, one might be able to decrease the level of correlation in an investment portfolio by allocating capital into markets that are not as prone for these herding-related spillover effects.

Besides financial entities whose aim is to maximize profits, the insights of this thesis can be also considered from the perspective of governmental policy makers and regulators. As demonstrated with Chinese, Taiwanese, and Vietnamese markets, investor-specific trading restrictions and the large proportion of individual investors seem to be linked with the existence of market-wide herding (Dang & Lin, 2016; Huang & Wang, 2017; Lee et al., 2013). Thus, by understanding how trading restrictions influence the level of herding in a stock market, one might be able to minimize the occurrence of extreme herding events. This notion is supported by Kizys et al. (2021) who investigate governmental actions in international stock markets and show that regulatory responses ultimately mitigate herding behavior. In line with these findings, Jiang et al. (2018) examine herding behavior within online peer-to-peer trading platforms and document that government's regulatory actions have a significant downward effect on herding. Based on these results, it is justified to argue that governmental policy makers and regulators may have considerable influence on herding behavior through regulatory events.

Lastly, it is evident that there prevails numerous areas that remain unsolved within the field of herding-related research. As one considers future research directions, it could be logical to first observe the dominating limitations inside the research field and consider if these challenges could be answered somehow. For instance, as it has been emphasized on several occasions during this thesis, one of the greatest herding-related challenges concerns the existing measures that are currently used to quantify the level of herding. Thus, the main suggestion of this study is the development of new methodologies when future research is considered. If one was able to come up with a method that would separate different forms of herding from each other and compute the level of herding in a more meaningful way, this could have significant implications on the research field. More specifically, this could create clarity to the results that have been highly fragmented till this day.

Since the development of new measures can take time, another approach is to study the shortcomings of the currently used measures and demonstrate their weaknesses through empirical tests. By doing this, the existing issues with the most utilized measures such as the CSAD would become more knowledgeable within the research field, which in turn could stimulate the development of new methodologies. For instance, a possible avenue for future research could be to investigate how index drops and add-ins affect the CSAD measure. As noted during the previous chapter, index fluctuations can have a considerable effect on the validity of empirical tests due to the fact that the observed stock returns might not actually match the actual content of an index. Thus, the longer the observation period, the greater the risk for distortions in results. If one was able to demonstrate the possible impact that the structural changes of an index have on the CSAD measure, this would create clarity on the distortions that are currently part of empirical testing.

Another suggestion for future research concerns the time intervals that are used to calculate the CSADs. As Andrikopoulos et al. (2017) state in their study, the bulk of prior herding-related research has concentrated on investigating herding by utilizing time intervals that vary from daily to annual. Thus, due to the fact that herding tends to be a short-lived phenomenon, the examination of intraday herding could be a meaningful area for future research. Even though Andrikopoulos et al. point out that intraday herding has already attracted interest from academics, it can be argued that this branch of research is still considerably less explored in contrast to numerous other herding-related areas. Furthermore, as the authors note in their study, the recent advancements in financial technology have increased the relevance of short-frequency trading, which in turn can be seen to support the investigation of this specific research branch.

In addition to the abovementioned research possibilities, the recent war between Ukraine and Russia offers another opportunity for future studies. In fact, the initial plan of this thesis was to examine the impact of this event in more detail. This would have been a meaningful area for investigation as there seems to be no studies which would examine herding explicitly under wartime. However, due to unavailable Russian stock market data, the empirical tests could not be carried out. If one was able to find available data, future studies could examine herding under wartime and extend the prevailing research towards areas which have not been investigated yet. Finally, the last proposal for future research concerns industry-specific herding. As stated at the end of the previous chapter, a more ideal approach for investigating herding within industries could be to build specified industry portfolios instead of using SIC codes. For instance, one could test if this kind of approach would lead to differing results in markets where industry-specific herding has been weak or non-existent according to previous studies. As it can be seen, there exists numerous different research possibilities which ultimately stem from the inconclusive results that currently dominate herding-related research. Even though the lack of clarity can be interpreted as a clear limitation for the research field, it also makes herding an extremely appealing area for future research.

References

Andrikopoulos, P., Kallinterakis, V., Ferreira, M. P. L., & Verousis, T. (2017). Intraday herding on a cross-border exchange. *International Review of Financial Analysis*, *53*, 25-36. https://doi.org/10.1016/j.irfa.2017.08.010

Arjoon, V., Bhatnagar, C. S., & Ramlakhan, P. (2020). Herding in the Singapore stock exchange. *Journal of Economics and Business*, *109*, 105889. https://doi.org/10.1016/j.jeconbus.2019.105889

Baker, H. K., & Ricciardi, V. (2014). *Investor behavior: The psychology of financial planning and investing*. John Wiley & Sons. https://doi.org/10.1002/9781118813454

Balashov, V. S., & Nikiforov, A. (2019). How much do investors trade because of name/ticker confusion? *Journal of Financial Markets*, *46*, 100499. https://doi.org/10.1016/j.finmar.2019.06.002

Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817. https://doi.org/10.2307/2118364

Barber, B. M., Odean, T., & Zhu, N. (2009). Do retail trades move markets? *The Review of Financial Studies*, *22*(1), 151–186. https://doi.org/10.1093/rfs/hhn035

Baytas, A., & Cakici, N. (1999). Do markets overreact: International evidence. *Journal of Banking & Finance*, 23(7), 1121-1144. https://doi.org/10.1016/S0378-4266(98)00133-2

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279–310. https://doi.org/10.2307/3867650

Black, F. (1986). Noise. *The Journal of Finance*, 41(3), 528–543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

Bodie, Z., Kane, A. & Marcus, A. J. (2018). *Investments* (Eleventh edition, international edition.). McGraw-Hill Education.

Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, 29, 216-221. https://doi.org/10.1016/j.frl.2018.07.008

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679. https://doi-org.proxy.uwasa.fi/10.1016/S0378-4266(99)00096-5

Chen, Y. F., Yang, S. Y., & Lin, F. L. (2012). Foreign institutional industrial herding in Taiwan stock market. *Managerial Finance*. https://doi.org/10.1108/03074351211201442

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, 34(8), 1911-1921.

Choi, N., & Sias, R. W. (2009). Institutional industry herding. *Journal of Financial Economics*, 94(3), 469-491. https://doi.org/10.1016/j.jfineco.2008.12.009

Choijil, E., Méndez, C. E., Wong, W. K., Vieito, J. P., & Batmunkh, M. U. (2022). Thirty years of herd behavior in financial markets: A bibliometric analysis. *Research in*

International Business and Finance, *59*, 101506. https://doi.org/10.1016/j.ribaf.2021.101506

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, 51(4), 31-37. https://doi.org/10.2469/faj.v51.n4.1918

Contreras, C., & Contreras, Á. (2019). Herding in financial markets: Why do financial investors herd. *La revista Análisis Financiero*. Retrieved 23rd of June 2022 from https://www.analisisfinanciero.ieaf.es/publicaciones-la-revista-analisis-financiero-4/la-innovacion-tecnologica-y-financiera/122-herding-in-financial-markets-why-do-financial-investors-herd

Dang, H. V., & Lin, M. (2016). Herd mentality in the stock market: On the role of idiosyncratic participants with heterogeneous information. *International Review of Financial Analysis*, *48*, 247–260. https://doi.org/10.1016/j.irfa.2016.10.005

Dao, B., & Tu, N. (2014). Herding behavior: Overview and evidence in Vietnam stock market. *Available at SSRN 2543723*. https://dx.doi.org/10.2139/ssrn.2543723

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of finance*, *40*(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F., & Forbes*, W. P. (1999). Herding in analyst earnings forecasts: evidence from the United Kingdom. *European financial management*, *5*(2), 143–163. https://doi.org/10.1111/1468-036X.00087

Demirer, R., & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets? *Journal of international Financial markets, institutions and money*, *16*(2), 123-142. https://doi.org/10.1016/j.intfin.2005.01.002

Demirer, R., Kutan, A. M., & Chen, C. D. (2010). Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. *Journal of Economic Behavior & Organization*, *76*(2), 283-295. https://doi.org/10.1016/j.jebo.2010.06.013

Dhall, R., & Singh, B. (2020). The COVID-19 pandemic and herding behaviour: Evidence from India's stock market. *Millennial Asia*, *11*(3), 366–390. https://doi.org/10.1177%2F0976399620964635

Dissanaike, G. (1997). Do stock market investors overreact?. *Journal of Business Finance & Accounting*, 24(1), 27-50. https://doi.org/10.1111/1468-5957.00093

Djalilov, A., & Ülkü, N. (2021). Individual investors' trading behavior in Moscow Exchange and the COVID-19 crisis. *Journal of Behavioral and Experimental Finance*, *31*, 100549. https://doi.org/10.1016/j.jbef.2021.100549

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of financial economics*, *128*(2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012

Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *The North American Journal of Economics and Finance*, *58*, 101531. https://doi.org/10.1016/j.najef.2021.101531

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of Finance*, *47*(4), 1461–1484. https://doi.org/10.1111/j.1540-6261.1992.tb04665.x

Galariotis, E. C., Rong, W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. *Journal of Banking & Finance*, 50, 589-598. https://doi.org/10.1016/j.jbankfin.2014.03.014

Gębka, B., & Wohar, M. E. (2013). International herding: Does it differ across sectors?. *Journal of International Financial Markets, Institutions and Money*, *23*, 55-84. https://doi.org/10.1016/j.intfin.2012.09.003

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review*, 1088-1105. https://www.jstor.org/stable/2950976

Henker, J., Henker, T., & Mitsios, A. (2006). Do investors herd intraday in Australian equities? *International Journal of Managerial Finance*, 2(3), 196-219. https://doi.org/10.1108/17439130610676475

Hsieh, S. F., Chan, C. Y., & Wang, M. C. (2020). Retail investor attention and herding behavior. *Journal of Empirical Finance*, *59*, 109–132. https://doi.org/10.1016/j.jempfin.2020.09.005

Howe, J. S. (1986). Evidence on stock market overreaction. *Financial Analysts Journal*, *42*(4), 74–77. https://doi.org/10.2469/faj.v42.n4.74

Hung, W., Lu, C. C., & Lee, C. F. (2010). Mutual fund herding its impact on stock returns: Evidence from the Taiwan stock market. *Pacific-Basin Finance Journal*, *18*(5), 477–493. https://doi.org/10.1016/j.pacfin.2010.06.001

Huang, T. C., & Wang, K. Y. (2017). Investors' fear and herding behavior: evidence from the taiwan stock market. *Emerging Markets Finance and Trade*, *53*(10), 2259–2278. https://doi.org/10.1080/1540496X.2016.1258357

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, 11(4), 585-616. https://doi-org.proxy.uwasa.fi/10.1016/j.jempfin.2004.04.003

Indārs, E. R., Savin, A., & Lublóy, Á. (2019). Herding behaviour in an emerging market: Evidence from the Moscow Exchange. *Emerging Markets Review*, *38*, 468–487.

Jiang, Y., Ho, Y. C., Yan, X., & Tan, Y. (2018). Investor platform choice: Herding, platform attributes, and regulations. *Journal of Management Information Systems*, *35*(1), 86–116. https://doi.org/10.1080/07421222.2018.1440770

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Kendall, M. G., & Hill, A. B. (1953). The analysis of economic time-series-part i: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11-34. https://doi.org/10.2307/2980947

Keynes, John Maynard, 1936, The General Theory of Employment, Interest and Money. London: Macmillan.

Kizys, R., Tzouvanas, P., & Donadelli, M. (2021). From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. *International Review of Financial Analysis*, 74, 101663. https://doi.org/10.1016/j.irfa.2021.101663

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of financial economics*, 32(1), 23-43. https://doi.org/10.1016/0304-405X(92)90023-Q

Lam, K. S., & Qiao, Z. (2015). Herding and fundamental factors: The Hong Kong experience. *Pacific-Basin Finance Journal*, *32*, 160–188.

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian economics*, *22*(6), 495–506. https://doi.org/10.1016/j.asieco.2011.08.001

Lee, C. C., Chen, M. P., & Hsieh, K. M. (2013). Industry herding and market states: evidence from Chinese stock markets. *Quantitative Finance*, *13*(7), 1091–1113. https://doi.org/10.1080/14697688.2012.740571

Lin, A. Y., Huang, L. S., & Chen, M. Y. (2007). Price comovement and institutional performance following large market movements. *Emerging Markets Finance and Trade*, *43*(5), 37-61. https://doi.org/10.2753/REE1540-496X430503

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Lyócsa, Š., Baumöhl, E., & Výrost, T. (2021). YOLO trading: Riding with the herd during the GameStop episode. *Finance Research Letters*, 102359. https://doi.org/10.1016/j.frl.2021.102359

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), 59–82. https://doi.org/10.1257/089533003321164958

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77-91. https://doi.org/10.2307/2975974

Mobarek, A., Mollah, S., & Keasey, K. (2014). A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, *32*, 107–127. https://doi.org/10.1016/j.intfin.2014.05.008

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*(4), 768–783. https://doi.org/10.2307/1910098

Roll, R., & Ross, S. A. (1980). An empirical investigation of the arbitrage pricing theory. *The journal of finance*, *35*(5), 1073–1103. https://doi.org/10.1111/j.1540-6261.1980.tb02197.x

Schmitt, N., & Westerhoff, F. (2017). Herding behaviour and volatility clustering in financial markets. *Quantitative Finance*, 17(8), 1187-1203. https://doi.org/10.1080/14697688.2016.1267391

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shiller, R. J. (2015). *Irrational exuberance* (3rd ed.). Princeton University Press.

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*. Oup Oxford.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies*, 17(1), 165-206. https://doi.org/10.1093/rfs/hhg035

Spyrou, S. (2013). Herding in financial markets: a review of the literature. *Review of Behavioral Finance*. https://doi.org/10.1108/RBF-02-2013-0009

Taiwan Stock Exchange Corporation. (2022). *Guide to investing in Taiwan 2021: Individual Investors and Institutional Investors*. Retrieved 25th of April 2022 from https://www.twse.com.tw/en/page/about/company/guide.html#16

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin finance journal*, *16*(1–2), 61-77. https://doi.org/10.1016/j.pacfin.2007.04.004

Ukpong, I., Tan, H., & Yarovaya, L. (2021). Determinants of industry herding in the US stock market. *Finance Research Letters*, *43*, 101953. https://doi.org/10.1016/j.frl.2021.101953

Vo, X. V. (2015). Foreign ownership and stock return volatility–Evidence from Vietnam. *Journal of Multinational Financial Management*, *30*, 101-109. https://doi.org/10.1016/j.mulfin.2015.03.004

Vo, X. V., & Phan, D. B. A. (2017). Further evidence on the herd behavior in Vietnam stock market. *Journal of Behavioral and Experimental Finance*, *13*, 33-41. https://doi.org/10.1016/j.jbef.2017.02.003

Vo, X. V., & Phan, D. B. A. (2019). Herd behavior and idiosyncratic volatility in a frontier market. *Pacific-Basin Finance Journal*, *53*, 321–330. https://doi.org/10.1016/j.pacfin.2018.10.005

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, *58*(3), 369–396. https://doi.org/10.1016/S0304-405X(00)00076-3

Xie, T., Xu, Y., & Zhang, X. (2015). A new method of measuring herding in stock market and its empirical results in Chinese A-share market. *International Review of Economics & Finance*, *37*, 324–339. https://doi.org/10.1016/j.iref.2014.12.004

Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance*, *29*, 12-29. https://doi.org/10.1016/j.iref.2013.03.002

Zheng, D., Li, H., & Chiang, T. C. (2017). Herding within industries: Evidence from Asian stock markets. *International Review of Economics & Finance*, *51*, 487-509. https://doi.org/10.1016/j.iref.2017.07.005

Zhou, R. T., & Lai, R. N. (2009). Herding and information based trading. *Journal of Empirical Finance*, *16*(3), 388–393. https://doi.org/10.1016/j.jempfin.2009.01.004