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HERDING BEHAVIOR IN FRONTIER NORDIC COUNTRIES

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Abstract: This paper investigates herding behavior of investors in three frontier Nordic countries from July 1, 2002 until July 30, 2021, under different market conditions and during three crises that occurred in this period. As estimation methods, we use both OLS and quantile regression and determine that both up and down market, high and low volatility induce a weak herding behavior for at least one quantile in almost all Nordic countries examined, except for Latvia. At the same time, we find that crises determine a more prominent herding behavior in Nordic countries, but do not influent the behavior of investors from Latvia, that tend to remain rational even in stressful conditions.

JEL Classification: G01, G14, G40

Keywords: Herding behavior; Market states; Financial Crises; Cross-sectional absolute deviation of returns.

1. Introduction

As the researchers start doubting Efficient Market Hypothesis and the fact that all investors act rational while make a decision when to sell or to buy a stock, a new field appears, Behavioral Finance, that attempts to observe and explain how people perform in real life, and not how they should act.

One of the discussed and studied topic is herding behavior, which consist in ignoring own information and mimicking the other market players' actions or following the market consensus. This behavior may be caused by informational cascades, concern for reputation and/or compensation scheme, the main reason of offering so much attention to this behavioral bias is due to the consequences induced by it in the financial markets, such as leading to misevaluation of asset prices and bubbles, destabilizing market stability and its efficiency.

The paucity of previous studies concentrating on investor herding behavior in Nordic countries inspired us to conduct this research. Therefore, this paper contributes to the existing herding literature by examining herding behavior in three

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emerging Nordic countries under various market states, specifically up or down market, high or low volatility. Furthermore, we fill the gap in the literature by analyzing how crises affect the herding behavior in Nordic countries, such as Global Financial Crisis, the European Sovereign Debt, and the Covid-19 crisis.

To the best of our knowledge, this is the first study to look into and disclose the incidence of herding behavior in emerging Nordic countries during market ups and downs, high and low volatility, the Global Financial Crisis, European Sovereign Debt, and Covid-19 pandemic.

The study is structured as follows: section 1 presents the theoretical background regarding herding behavior and reviews some of the scientific articles written on the subject of interest, the second section evokes the data used and describes the way of methods and regressions used for estimating the occurrence of this phenomenon, the following section reports the obtained results and highlights the main ideas concerning the presence of herding behavior in examined Nordic countries. The study ends with conclusions and an overview of future research pursuits. The supporting materials are to be found within the Appendices.

2. Literature Review

Herding behavior is defined as being present in a market when investors opt to replicate the trading practices of those, they assume to be well-informed and more experienced or mimic the market consensus, rather than acting upon their own knowledge and beliefs (Blasco et al., 2012), even if they are unsure that other investors have made the correct decision (Banerjee, 1992).

Herding also necessitates a coordination mechanism, according to Devenow and Welch (1996), which can be either a widely diffused rule to coordinate based on some signal, such as price movement, or a direct ability to observe other decision makers.

Due to the importance of herd behavior implications, such as asset price misevaluation, risk management, performance evaluations, and the threat to financial market stability and efficiency, a growing body of literature has explored the prevalence and causes of herding in recent years (Hirshleifer and Teoh, 2003; Hwang and Salmon, 2004; Chiang and Zheng, 2010). Galariotis et al. (2016), for example, claim that irrational herding is a major cause of financial instability and increasing yield discrepancies. Furthermore, herding may exacerbate the financial system's vulnerability and lead to bubbles (Galariotis et al., 2016).

The studies that have already investigated this subject concluded that the occurrence of herding behavior may be observed in a variety of markets, such as stock markets, commodity markets, cryptocurrency markets, oil markets, REITs in different volatility regimes (Coskun et al., 2020). Irrespective of the market in which the rational type of herding behavior can be observed, it is determined mainly by one of the three potential causes conceived by Bikhchandani and Sharma (2000), specifically the imperfect information, concern for reputation and compensation structures.

On the other hand, Choijil et al. (2021) conclude in their study of the literature review available regarding this subject that there is no yet a general agreement explaining the causes of the herding behavior. Nonetheless, the emergence of the new perspectives and issues inspires the specialists in developing and elaborating new studies on this phenomenon. All the new researches start from the fundamental theories and previous assumptions, and after that investigate new suppositions, observe various markets, and drag a conclusion. The basic theoretical framework on the subject of herding behavior involves also the causes mentioned above and described further.

The consequences of imperfect information on asset prices are amplified through a mimicking investment behavior during a transmission mechanism commonly known as an “informational cascade” (Filip et al., 2015).

This concept of “informational cascade” was introduced by Bikhchandani et al. (1992). According to them, this occurs when an individual, after observing the actions of investors ahead of him, determines that it is best to follow the previous individual’s behavior regardless of his own information. In case of stock markets, the investment decisions of early individuals are reflected in the subsequent price of the investment. Consequently, in a sequential decision model, agents herd rationally when they believe that other investors have better information and this fact is reflected in their investment decision, so they ignore their private information and act only based on the knowledge obtained from the previous decisions.

Banerjee (1992) emphasizes that these informational cascades can influence rational people and lead to the creation of bubbles. A bubble appears when an asset price is significantly different from its fundamental value, that is based on the discounted sum of expected future earnings (Cuñado et al., 2007). Kaliva and Koskinen (2008) believe that, generally, a bubble is followed by a crash. At the same time, Kreuser and Sornette (2017) affirms that even if the market price blows up, it is always possible that the price will reverse smoothly without a crash, but it is a scenario that becomes less and less probable the higher the price is.

On the other hand, herding can occur being determined by reputational reasons. Fernández et al. (2011) maintain that concern for reputation is a relevant explaining factor only for money managers who invest on behalf of others. Additionally, Lao and Singh (2011) enumerate traders, fund managers and analysts, that are employees or agents in a financial institution, because their performance evaluation is done on a comparative basis, being a relative measure rather than absolute one.

Therefore, when a manager is not sure regarding his professional skills, he might mimic the actions of other managers, completely ignoring his private information, in order to protect his reputation. Based on the statement of Scharfstein and Stein (1990) that money managers herd due to their fear of being poorly assessed or judged by others if they make the wrong decision, Spyrou (2013) asserts that this type of herding is driven also by psychological incentives and restraints, such as “pressure from social circles and/or social conventions”.

At the same time, the wages of the analysts are assumed to increase linearly with the reputation of the analyst. Consequently, in order to maximize his income, the analyst choose a strategy that increases the probability that investors will think he is smart and high-skilled. Due to the fact that the analyst is uncertain about his own ability and the risk to lose his reputational capital in the market, he does not take a decision contrary to another analyst, even if his private information tells otherwise.

Villatoro (2009) argues that financial intermediaries with a good reputation are more likely to invest in information, whereas those with a bad reputation will are more likely to copy the portfolio decisions of other financial intermediaries (Khan, 2011). Devenow and Welch (1996), on the other hand, claim that if enough bad managers herd on a bad decision, even better managers will herd instead of taking the risk of being the lone manager investing in what might turn out to be an ex-post poor decision. Demirer and Kutan (2006) affirm that it may also occur among individual investors, in order to obtain a performance that is not below the market average.

Both information-based and reputation-based herding are more likely to occur in emerging and frontier markets, according to Pochea et al. (2017), due to factors such as weak reporting requirements, poorer accounting standards, ambiguous regulatory enforcements, and costly information, all of which contribute to a lack of transparency.

As previously mentioned, the performance of money managers is more a relative measure rather than an absolute one and therefore, their compensation structures are also competitive with respect to a benchmark, either it is a similar group of professionals or a market index. Thus, another important issue causing herding behavior is the incentives provided by the compensations scheme.

According to Maug and Naik (1995), the compensation contracts, which are optimal for the employer of the money manager, induce herding. This type of compensation contracts is, in fact, relative performance contract in which the bonus paid to the money manager depends on how well he does relative to the benchmark. In case the benchmark is a separate group of investors, then an intentional herding occurs: the benchmark investor, that similarly with the agent, has imperfect, private information about stock return, makes his decision first. Then, the agent being motivated by the fact that his reward decreases if he underperforms the benchmark causes the agent to imitate the benchmark's actions. Conversely, in case the benchmark is a market index, then a spurious herding occurs.

As acknowledged formerly, herding is a subject of interest for researchers and the number of already written articles prove this fact. Furthermore, Choijil et al. (2021) consider that the subprime crisis represents the critical point for the analysis of this concept. For instance, from 1990 until 2007, during a period of 18 years were published only 65 articles with 1944 citations, while in the following 5 years, specifically from 2008 until 2012, 74 articles with 2913 citations that were published. This represents a 14% increase in case of the published article regarding herd behavior and 67% increase if referring to the number of citations. Additionally, Choijil et al. (2021) show that during 2014 – 2020 another 168 articles with 10,155 citations were issued, that exceed the 161 articles and 5,745 citations published in earlier 24 years, from 1990 until 2013.

It is important to mention that this enhancement of publications and citations enabled the researchers to develop sub-areas of interest in order to study herding. Choijil et al. (2021) enumerate five groups. The first one tries to obtain a wider understanding of herding behavior. The second group focuses on evidencing the occurrence of this phenomenon in various financial markets and concentrates on find the motives in order to explain this behavior. There are also researchers, belonging to the third group, that analyses herding behavior in period of financial crisis. The fourth group examines how the profile of investor influences the herding behavior, while the fifth group investigates the effects of herding behavior on portfolio management.

Regardless the increasing number of articles written on this subject, the great majority of them assess the occurrence of herding behavior in markets from the US (Guo et al., 2020), the UK (Galariotis et. al, 2015), and Asian countries, such as South Korea (Yao and Li, 2020; Choi, 2016), China (Demirer and Kutan, 2006), Taiwan (Chen et al., 2020), Pakistan (Javed et al., 2017). There are also studies regarding herding behavior in ten stock markets from Central and Eastern Europe (Filip et al., 2015; Pochea et al., 2017).

Furthermore, there are comparative studies between different countries. For instance, Chiang and Zheng (2010) estimates herding behavior under asymmetric market conditions in 18 countries: Australia, France, Germany, Hong Kong, Japan, the UK, the US; Latin American markets, such as Argentina, Brazil, Chile, and Mexico; Asian markets, such as China, Indonesia, Malaysia, Singapore, South Korea, Taiwan and Thailand.

Determined by the lack or previous studies focusing on herding behavior in Nordic countries, we aim to estimate the herding behavior in Latvia, Lithuania, and Iceland. As far as we are concerned, our paper represents the first work in revealing the herding behavior in emerging Nordic countries, under up and down market, high and low volatility, in case of Global Financial Crisis, European Sovereign Debt Crisis, and Covid-19 pandemic.

3. Methodology

For detecting herding behavior in Nordic countries, we applied the cross-sectional absolute deviation (CSAD) of returns, developed by Chang et al. (2000). This is one of the most common measures used in this sense, providing a more robust data and the possibility to estimate herding behavior during the all period considered even if the market is calm or under extreme conditions, experiencing large price fluctuations. In order to determine CSAD, firstly, should be computed the daily logarithmic rates of returns for the equity market indices and for each company that constitutes the index, by using the following formulas:

$$R_{i,t} = ln \ (\frac{P_{i,t}}{P_{i,t-1}}) \quad (1)$$

$$R_{m,t} = ln\left(\frac{P_{m,t}}{P_{m,t-1}}\right) \quad (2)$$

where $\mathrm{P_{i,t}}$ and $\mathrm{P_{m,t}}$ represent the closing price of day t for stock i, respectively market index m. The CSAD is calculated as follows:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{n}|R_{i,t} - R_{m,t}| \quad (3)$$

where n represents the number of observations, $R_{i,t}$ and $R_{m,t}$ are the return of the company i at time t and, respectively return of the market m, at time t, for which the computation formulas, (1) and (2), were presented previously.

For estimating herding behavior, Chang et al. (2000) developed the following model that measures the relationship between the CSAD and the market return:

$$CSAD_t = \beta_0 + \beta_1 \cdot |R_{m,t}| + \beta_2 \cdot R_{m,t}^2 + \varepsilon_t \quad (4)$$

The explanation behind this regression is related to the Capital Asset Pricing Model, according to which if investors are fully rational, then the stocks return and market return are linearly related, so that the coefficient β_2 is positive and statistically significant in the absence of herding behavior. On the other hand, a non-linear negative relationship between these two variables reveals the existence of herding behavior in the analyzed market. Consequently, the negative and statistically significant coefficient β_2 denotes the presence of herding behavior in market under examination.

According to Barnes and Hughes (2002), the quantile regression analysis is more appropriate than OLS in analyzing CSAD in the distribution tails. This is due to the fact that, OLS estimators being based on the mean as a measure of location, do not consider the information regarding the tail of the distribution. Therefore, in this study, we also consider the quantile regression analysis for estimating the $CSAD_t$, expressed as follows:

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_{1,\tau} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (5)$$

where $CSAD_t$ denominates the cross-sectional absolute deviation of returns of quantile τ, which can take values between 0 and 1.

Asymmetric Effects of Market Return on Herding Behavior

Previous studies demonstrated that herding behavior is more probable to occur during extreme market fluctuations, which create uncertainty, fear, and determine the traders to follow the observed trend, leading in this way, to a more prominent herding behavior. At the same time, according to Economou et al. (2018), there is also evidence of asymmetric herding behavior during up-market periods.

Due to these reasons, we analyze in this subsection the impact of upward and downward trends on herding behavior in the Nordic countries. We create a dummy variable, D^{up}, that takes the value 1, if the market is up, and 0, if the market is down.

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{up} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{up}) \cdot |R_{m,t}| + \beta_3 \cdot D^{up} \cdot R_{m,t}^2 + \\ + \beta_4 \cdot (1 - D^{up}) \cdot R_{m,t}^2 + \varepsilon_t \quad (6)$$

We consider that market is up, if the market return in that day is greater than the average of market returns in previous 30 days, and is down, otherwise. We also performed a quantile regression to estimate the herding behavior under up and down market, using the following empirical specification:

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_{1,\tau} \cdot D^{up} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot (1 - D^{up}) \cdot |R_{m,t}| + \beta_{3,\tau} \cdot D^{up} \cdot R_{m,t}^2 + \\ + \beta_{4,\tau} \cdot (1 - D^{up}) \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (7)$$

If there is herding behavior, then the coefficients β_3 and β_4 are negative and statistically significant.

Asymmetric Effects of Market Volatility on Herding Behavior

Another subject of interest is the market volatility, which is a statistical measure of the tendency of a market or security to rise or fall sharply within a short period of time. According to Pochea et al. (2017), the tendency of investors to herd is more remarkable when there is an increased volatility, which is determined usually by wide and rapid price fluctuations along with heavy trading.

In order to assess the asymmetric effects of market volatility on herding behavior, we created a dummy variable D^{vol}, that takes the value 1, if the volatility is high, and the value 0, if the volatility is low. According to Pochea et al. (2017), we assumed that market volatility is high when the volatility in that day is higher than the average volatility of market over the previous thirty days. We use the regressions presented below. Regression (8) was used in case of OLS estimation and regression (9) in case of quantile regression.

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{vol} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{vol}) \cdot |R_{m,t}| + \beta_3 \cdot D^{vol} \cdot R_{m,t}^2 + \\ + \beta_4 \cdot (1 - D^{vol}) \cdot R_{m,t}^2 + \varepsilon_t \quad (8)$$

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_{1,\tau} \cdot D^{vol} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot (1 - D^{vol}) \cdot |R_{m,t}| + \\ + \beta_{3,\tau} \cdot D^{vol} \cdot R_{m,t}^2 + \beta_{4,\tau} \cdot (1 - D^{vol}) \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (9)$$

The negative and statistically significant coefficients β_3 and β_4 suggest the presence of herding behavior in the examined market.

The Impact of Crises on Herding Behavior

At the same time, according to Christie and Huang (1995), the phenomenon of herding behavior is expected to be more prominent during periods of extreme market conditions, because of significant market fluctuations and increasing uncertainty, which induce agents to mimic other agents' choices. These extreme market conditions are usually associated or determined by the period of crises. Due to this reason, we also investigated the impact of crises on herding behavior in Nordic countries during July 1, 2002 – July 30, 2021. We have considered 3 crises that occurred during the analyzed period, specifically the Global Financial Crisis, the European Sovereign Debt crisis, and the Covid-19 pandemic crisis.

The Impact of Global Financial Crisis on Herding Behavior

In accordance with Economou et al. (2018), we considered as a timespan of Global Financial Crisis the timespan starting with January 1, 2007 until December 31, 2009. We create a dummy variable, D^{GFC}, that takes value 1 during this period, and 0, otherwise.

In case of analyzing the impact of crises on herding behavior, we also performed both OLS and quantile regressions, using the following empirical specifications:

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{GFC} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{GFC}) \cdot |R_{m,t}| + \beta_3 \cdot D^{GFC} \cdot R_{m,t}^2 + \\ + \beta_4 \cdot (1 - D^{GFC}) \cdot R_{m,t}^2 + \varepsilon_t \quad (10)$$

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_{1,\tau} \cdot D^{GFC} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot (1 - D^{GFC}) \cdot |R_{m,t}| + \\ + \beta_{3,\tau} \cdot D^{GFC} \cdot R_{m,t}^2 + \beta_{4,\tau} \cdot (1 - D^{GFC}) \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (11)$$

The same rule as previously is applied in the interpretation of the regressions' output: herding behavior occurs in the market if coefficients β_3 and β_4 are negative and statistically significant.

The Impact of European Sovereign Debt Crisis on Herding Behavior

In case of setting the start date and ending date of European Sovereign Debt crisis used in our analysis, we follow Duygun et al. (2021), in accordance with which the considered interval is May 2, 2010 until December 31, 2012. The dates correspond to the following events: the bailout package received by Greece from European Union and the International Monetary Fund; and the purchase of the issued earlier sovereign bonds by Greece, which lead to the debt ratio decrease by 21.1 billion euro, as stated by Duygun et al. (2021). We used the same estimation models as in case of measuring the impact of Global Financial Crisis, but the dummy variable D^{GFC} was substituted by D^{ESD} and takes value 1 during European Sovereign Debt crisis and 0, otherwise:

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{ESD} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{ESD}) \cdot |R_{m,t}| + \beta_3 \cdot D^{ESD} \cdot R_{m,t}^2 + \\ + \beta_4 \cdot (1 - D^{ESD}) \cdot R_{m,t}^2 + \varepsilon_t \quad (12)$$

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_{1,\tau} \cdot D^{ESD} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot (1 - D^{ESD}) \cdot |R_{m,t}| + \\ + \beta_{3,\tau} \cdot D^{ESD} \cdot R_{m,t}^2 + \beta_{4,\tau} \cdot (1 - D^{ESD}) \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (13)$$

The Impact of Covid-19 Pandemic Crisis on Herding Behavior

In case of assessing the impact of Covid-19 pandemic crisis on herding behavior, we have considered 2 cases. Firstly, we consider for all analyzed countries, the time same starting day of Covid-19 pandemic, namely the 11th of March 2020. On this day, the World Health Organization declared the start of Covid-19 pandemic. The created dummy variable D^{CoWHO} takes the value 1 from this date and until de end of the sample, and 0, otherwise. Below are presented the OLS and quantile regression used for estimation:

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{CoWHO} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{CoWHO}) \cdot |R_{m,t}| + \beta_3 \cdot D^{CoWHO} \cdot R_{m,t}^2 + \\ + \beta_4 \cdot (1 - D^{CoWHO}) \cdot R_{m,t}^2 + \varepsilon_t \quad (14)$$

$$Q_\tau(\tau|CSAD_t) = \beta_{0,\tau} + \beta_1 \cdot D^{CoWHO} \cdot |R_{m,t}| + \beta_{2,\tau} \cdot (1 - D^{CoWHO}) \cdot |R_{m,t}| + \\ + \beta_{3,\tau} \cdot D^{CoWHO} \cdot R_{m,t}^2 + \beta_{4,\tau} \cdot (1 - D^{CoWHO}) \cdot R_{m,t}^2 + \varepsilon_{t,\tau} \quad (15)$$

For both regressions presented above, the negative and statistically significant coefficient β_3 point out that there is herding behavior in the market during crisis. In Table 1 are presented all the variable used in our estimations and also their short description.

Table 1. The Description of Variables

Variable	Description	Source
$R_{m,t}$	Daily returns of stock market indices. $R_{m,t} = ln\left(\frac{P_{m,t}}{P_{m,t-1}}\right)$ for market m on day t. The stock market indices are OMXC20, OMXS30, OMXH, OSEAX, OMXRGI, OMXVGI, and OMX Iceland.	Refinitiv Eikon Datastream

Variable	Description	Source
$R_{i,t}$	Daily return of company *i* on day *t*, computed as: $R_{i,t} = ln\ (\frac{P_{i,t}}{P_{i,t-1}})$.	Refinitiv Eikon Datastream
$CSAD_t$	The cross-sectional absolute deviation of returns at time *t*, computed as: $CSAD_t = \frac{1}{n}\sum_{i=1}^{n}\lvert R_{i,t} - R_{m,t}\rvert$.	Author's estimate
D^{up}	Dummy variable that takes the value 1 if the market is up and the value 0, if the market is down.	Pochea et al. (2017)
D^{vol}	Dummy variable that takes the value 1 if the market volatility is high and value 0, if the market volatility is low.	Pochea et al. (2017)
D^{GFC}	Dummy variable that takes the value 1 between January 1, 2007 and December 31, 2009 and 0, otherwise.	Economou et al. (2018)
D^{ESD}	Dummy variable that takes the value 1 between May 2, 2010 and December 31, 2012 and 0, otherwise.	Duygun et al. (2021)
D^{CoWHO}	Dummy variable that takes the value 1 starting with March 11, 2020, when the World Health Organization declared a pandemic, until the end of our sample timespan and 0, otherwise.	World Health Organization

4. Data

This section reveals the data used in the study for assessing herding behavior in three frontier Nordic countries. We have obtained the daily closing stock price from July 1, 2002 to July 30, 2021 of corporations listed in three Nordic countries: Latvia, Lithuania, and Iceland. The dataset also contains the daily closing price of the market indices, namely: OMXRGI, OMXVGI, and OMX Iceland for the same time. The data are expressed in EUR and were extracted from Refinitiv Eikon Datastream database. In Table 2 are highlighted the mean and the standard deviation of the cross-sectional standard deviations and for the market return for each country analyzed in the study. Furthermore, the table contains data regarding the Augmented Dickey-Fuller test, that are statistically significant for both variables, meaning that the series are stationary.

Table 2. Descriptive Statistics of the CSAD and Daily Returns

Country (Market Index)	Observations	Variables	Mean	Std. Dev.	ADF
Iceland (OMX Iceland)	4719	$CSAD$ R_m	0.015 0.000	0.025 0.021	-14.819*** -16.392***
Latvia (OMXRGI)	4790	$CSAD$ R_m	0.018 0.000	0.017 0.011	-14.666*** -76.267***
Lithuania (OMXVGI)	4739	$CSAD$ R_m	0.015 0.001	0.011 0.009	-8.057*** -13.607***

*Note: *** denotes statistical significance at the 1% level.*

5. Empirical Results

Estimates of Herding Behavior in Nordic Countries

In Table 3 are reported the sign and statistical significance of herding coefficients at market level for all three Nordic countries examined. The extended results of both OLS and quantile regression estimates are presented in Appendix 1. A negative and statistically significant coefficient β_2 points out the occurrence of herding behavior in the examined market. As it can be observed in Table 3, most of the coefficients are positive and statistically significant, meaning there is no herding behavior in analyzed markets. We have also performed a quantile regression analysis, which provides a more thorough idea regarding the conditional distributions of the CSAD of returns. Following the results, we detect no herding behavior in frontier Nordic countries analyzed, except for Lithuania for which the coefficient of interest is negative and statistically significant at the 1% level for the quantile 10%.

Table 3. Estimates of Herding Behavior in Nordic Countries

$CSAD_t = \beta_0 + \beta_1 \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot R_{m,t}^2 + \varepsilon_t$						
Methodology	***OLS***	***Q*** $(\tau = 10\%)$	***Q*** $(\tau = 25\%)$	***Q*** $(\tau = 50\%)$	***Q*** $(\tau = 75\%)$	***Q*** $(\tau = 90\%)$
Herd coefficient	β_2	β_2	β_2	β_2	β_2	β_2
Iceland	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***
Latvia	(+)***	(+)	(+)***	(+)***	(+)	(+)***
Lithuania	(+)	(-)***	(+)*	(+)	(+)	(+)***

*Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% level.*

The fact we do not detect herding behavior can be related to the timespan considered and examining the phenomenon as a long-term behavior, while herding behavior is more likely to be a short-term one, as it occurs during extreme market conditions or fluctuations. Consequently, we investigate further this behavioral bias under asymmetric market conditions, namely up or down market, and high or low volatility.

Estimates of Herding Behavior in Nordic Countries Under Asymmetric Market Conditions

In Table 4 are presented the sign and statistical significance of herding coefficients under up or down market, high or low volatility, while in Appendix 2 (up or down market in frontier Nordic countries) and Appendix 3 (high or low volatility in frontier Nordic countries) are revealed the detailed results of our estimates.

According to the OLS estimates, in frontier Nordic countries herding behavior is present under up market in case of Iceland and Lithuania, except for Latvia where no herding behavior is detected. The quantile regression reveals herding behavior under up market both in Lithuania for the quantile of 10% and in Iceland for all quantile levels. The homogenous herding behavior detected in Iceland can be explained by investors' overenthusiasm, meaning they are prone to purchase stocks when the market follows an increasing trend.

In accordance with our results obtained by using the OLS method, volatility does not affect the CSAD in markets under examinations. On the other hand, using quantile regressions, we identify herding behavior, but as an isolated phenomenon. For instance, in Lithuania in case of high volatility for $\tau = 10\%$ and low volatility for $\tau = 90\%$; in Iceland under low volatility for quantile of 10%.

Table 4. Estimates of Herding Behavior Under Different Market Conditions

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{up} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{up}) \cdot |R_{m,t}| + \beta_3 \cdot D^{up} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{up}) \cdot R^2_{m,t} + \varepsilon_t$$

Up/ Down Market	***OLS***		***Q*** $(\tau = 10\%)$		***Q*** $(\tau = 25\%)$		***Q*** $(\tau = 50\%)$		***Q*** $(\tau = 75\%)$		***Q*** $(\tau = 90\%)$	
Herd coefficient	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4
Iceland	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***
Latvia	(+)***	(+)***	(+)	(+)	(+)***	(+)***	(+)***	(+)***	(+)	(+)**	(+)	(+)
Lithuania	(-)**	(+)*	(-)***	(+)***	(-)	(+)***	(+)	(+)	(-)	(+)***	(-)	(+)

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{vol} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{vol}) \cdot |R_{m,t}| + \beta_3 \cdot D^{vol} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{vol}) \cdot R^2_{m,t} + \varepsilon_t$$

High/Low Volatility	***OLS***		***Q*** $(\tau = 10\%)$		***Q*** $(\tau = 25\%)$		***Q*** $(\tau = 50\%)$		***Q*** $(\tau = 75\%)$		***Q*** $(\tau = 90\%)$	
Herd coefficient	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4
Iceland	(+)***	(+)***	(+)***	(-)***	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***
Latvia	(+)***	(-)	(+)	(-)	(+)***	(+)	(+)***	(+)	(+)***	(-)	(+)***	(+)
Lithuania	(+)	(+)	(-)***	(+)***	(-)	(+)***	(+)	(+)	(+)	(+)***	(+)	(-)***

*Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% level.*

Impact of Crises on Herding Behavior in Nordic Countries

Noticing that asymmetric market conditions induce herding behavior in some of the Nordic countries examined, we investigate further how crises affect the herding behavior, as in conformance to Christie and Huang (1995), the phenomenon of herding behavior is expected to be more prominent during periods of extreme market conditions, because of significant market fluctuations and increasing uncertainty, which induce agents to mimic other agents' choices. These extreme market conditions are usually associated or determined by the period of crises.

Table 5 reveals the sign and statistical significance of herding coefficients during crises and during normal market conditions, β_3 and β_4, respectively. In Appendix 4 are presented the detailed results pointing out the impact of Global Financial Crisis on herding behavior in examined markets, in Appendix 5 are reveled the influence of European Sovereign Debt on herding behavior in the same Nordic countries, and the extended results of our estimations regarding the influence of Covid-19 pandemic are reported in Appendix 6.

The OLS estimates detect herding behavior during Global Financial Crisis only in one out of three countries, namely Lithuania. Following the quantile regression results, we identify herding behavior also in Iceland. It must be mentioned that the subprime crisis induces herding behavior in Lithuania on all quantile levels.

Regarding the influence of European Sovereign Debt crisis, conforming to OLS results we do not identify overall herding behavior in any of the examined markets. Analyzing quantile regressions results, we confirm one more time that this is a better method for estimating herding behavior in financial markets, as we detect herding behavior in all countries. For instance, we detect herding behavior during crisis in Latvia ($\tau = 75\%$), Iceland ($\tau = 90\%$). In Lithuania, we identify herding behavior for 10% and 75% quantiles, but this is not induced by the occurrence of crisis.

Another crisis and more recent one that leads to panic in the entire world and also in the financial markets is the one provoked by the Covid-19 pandemic. In Latvia and Lithuania, we do not identify any herding behavior according to OLS estimates. Performing quantile regressions, we identify herding behavior in all countries, excepting Latvia. Only in Lithuania, for the 10% quantile, we identify herding that was not induced by pandemic, while in all Iceland, pandemic explain the occurrence of the behavioral bias.

Table 5. The Impact of Crises on Herding Behavior in Nordic Countries

Global Financial Crisis												
$CSAD_t = \beta_0 + \beta_1 \cdot D^{GFC} \cdot \lvert R_{m,t}\rvert + \beta_2 \cdot (1 - D^{GFC}) \cdot \lvert R_{m,t}\rvert + \beta_3 \cdot D^{GFC} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{GFC}) \cdot R^2_{m,t} + \varepsilon_t$												
	OLS		***Q*** ($\tau = 10\%$)		***Q*** ($\tau = 25\%$)		***Q*** ($\tau = 50\%$)		***Q*** ($\tau = 75\%$)		***Q*** ($\tau = 90\%$)	
Herd coefficient	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4
Iceland	(+)***	(-)	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)	(+)***	(+)
Latvia	(+)	(+)***	(+)	(-)	(+)**	(+)***	(+)	(+)***	(+)	(+)***	(+)***	(+)
Lithuania	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***
European Sovereign Debt Crisis												
$CSAD_t = \beta_0 + \beta_1 \cdot D^{ESD} \cdot \lvert R_{m,t}\rvert + \beta_2 \cdot (1 - D^{ESD}) \cdot \lvert R_{m,t}\rvert + \beta_3 \cdot D^{ESD} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{ESD}) \cdot R^2_{m,t} + \varepsilon_t$												
	OLS		***Q*** ($\tau = 10\%$)		***Q*** ($\tau = 25\%$)		***Q*** ($\tau = 50\%$)		***Q*** ($\tau = 75\%$)		***Q*** ($\tau = 90\%$)	
Herd coefficient	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4
Iceland	(+)***	(+)***	(+)***	(+)***	(+)**	(+)***	(+)***	(+)***	(+)***	(+)***	(-)**	(+)**
Latvia	(-)	(+)***	(-)	(+)	(-)	(+)***	(-)	(+)	(-)***	(+)	(+)	(+)***
Lithuania	(+)***	(-)	(+)	(-)**	(+)*	(+)***	(-)	(+)	(+)***	(-)	(+)	(-)***
Covid-19 Pandemic												
$CSAD_t = \beta_0 + \beta_1 \cdot D^{CoWHO} \cdot \lvert R_{m,t}\rvert + \beta_2 \cdot (1 - D^{CoWHO}) \cdot \lvert R_{m,t}\rvert + \beta_3 \cdot D^{CoWHO} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{CoWHO}) \cdot R^2_{m,t} + \varepsilon_t$												
	OLS		***Q*** ($\tau = 10\%$)		***Q*** ($\tau = 25\%$)		***Q*** ($\tau = 50\%$)		***Q*** ($\tau = 75\%$)		***Q*** ($\tau = 90\%$)	
Herd coefficient	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4	β_3	β_4
Iceland	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)***	(+)***	(-)	(+)***	(-)	(+)**
Latvia	(-)	(+)***	(+)	(+)	(-)	(+)***	(-)	(+)***	(+)	(+)	(+)	(+)
Lithuania	(-)	(-)	(-)	(-)***	(-)	(+)*	(-)	(+)	(+)	(+)	(-)	(-)

*Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% level.*

6. Conclusions

In this paper we approach one of the behavioral biases present in financial markets, namely the herding behavior. We estimate the evidence of this phenomenon in three frontier Nordic countries starting from 1st of July 2002 and ending on 30th of July 2021, employing CSAD as the testing methodology and the OLS and quantile regressions.

We perform comprehensive research of this phenomenon by analyzing how it is manifesting in general circumstances, being influenced by different market conditions, such as up or down market, high or low volatility, and during three crises that occurred in the examined period of time.

We consider this an important study, as from our best knowledge, it is the first one analyzing herding behavior in emerging Nordic countries, so we fill a gap in the existing literature regarding this subject of interest.

Overall, we do not detect herding behavior in the analyzed markets, which is not in conformance with the results obtained by Pochea et. al (2015), where was identified herding behavior in both Latvian and Lithuanian markets. We assume the lack of concordance of the results is due to the timespan implied in the studies, as we used a more extended time period, and according to theoretical background, herding behavior is a short-period phenomenon rather than a long-period one.

The asymmetric market conditions affect the frontier markets, namely Lithuania and Iceland in case of up market. The obtained outcomes are consistent with our a priori expectations, as it is assumed that financial markets from emerging markets are less transparent and efficient, if comparing to developed ones.

Regarding the impact of volatility on herding behavior, we can conclude this does not influence the behavioral bias studied in frontier, if interpreting the OLS estimates results. Following the quantile regressions estimates, we identify herding behavior for at least one quantile in two out of three countries examined.

Herding behavior seems to be more prominent during crises period, as we expected a priori, confirming in this way that in during extreme market conditions, investors tend to herd more than in case of normal market conditions. The only exception in our study is the Latvian market, where we do not identify herding behavior, indifferent of the estimating method used.

At the same time, performing both an OLS and quantile regression estimates, we confirm one more time that the second one is a more appropriate method of testing herding behavior for future studies.

During our research process, we have identified some limitations, specifically, we cannot decompose the CSAD into CSAD driven by fundamental and non-fundamental factors for frontier countries, because the Fama and French factors were only available for the developed countries. Consequently, we consider that it could be analyzed the intentional versus spurious herding behavior in Latvia, Lithuania, and Iceland in following studies regarding the occurrence of this phenomenon in Nordic countries. This subject can also be deepened through analyzing the impact of trading volume, monetary policy, unexpected events, high sentiments, Covid lockdowns, the war from Ukraine on herding behavior in Nordic countries.

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Appendices

Appendix 1. Estimates of Herding Behavior in Frontier Nordic Countries

$CSAD_t = \beta_0 + \beta_1 \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot R_{m,t}^2 + \varepsilon_t$				
	β_0 *t-stat*	β_1 *t-stat*	β_2 *t-stat*	$Adj.\ R^2$
Latvia				
OLS	0.013***	0.751***	1.466***	0.188
	34.184	21.998	3.971	
$\tau = 10\%$	0.001***	0.869***	0.141	0.254
	4.530	14.773	0.072	
$\tau = 25\%$	0.003***	0.822***	1.241***	0.213
	23.198	54.978	10.514	
$\tau = 50\%$	0.008***	0.771***	1.555***	0.170
	34.314	27.180	3.727	
$\tau = 75\%$	0.017***	0.773***	1.164	0.134
	18.700	3.463	0.169	
$\tau = 90\%$	0.028***	0.649***	2.110***	0.107
	38.104	7.646	2.736	
Lithuania				
OLS	0.010***	0.860***	0.108	0.353
	33.520	15.094	0.096	
$\tau = 10\%$	0.003***	0.789***	-0.596***	0.204
	20.770	40.915	-2.968	
$\tau = 25\%$	0.005***	0.741***	1.220*	0.200
	39.390	29.109	1.828	
$\tau = 50\%$	0.008***	0.787***	1.171	0.204
	45.008	17.247	1.053	
$\tau = 75\%$	0.013***	0.848***	0.885	0.212
	50.348	16.364	1.240	
$\tau = 90\%$	0.028***	0.649***	2.110***	0.107
	37.858	12.122	0.433	
Iceland				
OLS	0.009***	0.667***	0.456***	0.654
	18.973	12.816	10.199	
$\tau = 10\%$	0.001***	0.668***	0.459***	0.273
	13.627	47.313	35.861	
$\tau = 25\%$	0.002***	0.753***	0.381***	0.291
	15.459	49.943	27.916	
$\tau = 50\%$	0.004***	0.761***	0.372***	0.256
	22.133	44.069	23.863	
$\tau = 75\%$	0.010***	0.805***	0.327***	0.194
	22.360	19.172	8.614	
$\tau = 90\%$	0.019***	0.800***	0.324***	0.157
	17.791	5.984	2.681	

Notes: The table reports the OLS and quantile results for the full-period sample for the benchmark model $CSAD_t = \beta_0 + \beta_1 \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot R_{m,t}^2 + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania and Iceland. The market portfolios used are OMXRGI, OMXVGI, and OMX Iceland for Latvia, Lithuania, and Iceland, respectively. A negative and statistically significant coefficient β_2 implies the presence of herding behavior in the examined market. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.

Appendix 2. Evidence of Herding Behavior in
Frontier Nordic Countries Under Up and Down Market

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{up} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{up}) \cdot |R_{m,t}| + \beta_3 \cdot D^{up} \cdot R_{m,t}^2 + \beta_4 \cdot (1 - D^{up}) \cdot R_{m,t}^2 + \varepsilon_t$$

	β_0 *t-stat*	β_1 *t-stat*	β_2 *t-stat*	β_3 *t-stat*	β_4 *t-stat*	$Adj.\ R^2$
Latvia						
OLS	0.013***	0.724***	0.770***	2.004***	1.115***	0.187
	33.940	16.495	19.164	3.298	3.172	
$\tau = 10\%$	0.001***	0.860***	0.868***	0.570	0.147	0.253
	4.708	15.270	12.299	0.285	0.058	
$\tau = 25\%$	0.003***	0.815***	0.819***	1.539***	1.255***	0.212
	23.054	44.350	43.322	6.574	9.622	
$\tau = 50\%$	0.008***	0.765***	0.782***	1.606***	1.295***	0.169
	36.231	26.908	28.709	4.702	6.938	
$\tau = 75\%$	0.017***	0.735***	0.804***	1.787	0.845**	0.133
	30.935	4.557	14.300	0.337	2.517	
$\tau = 90\%$	0.028***	0.585**	0.709***	4.126	1.250	0.106
	28.177	2.498	3.697	0.651	0.334	
Lithuania						
OLS	0.010***	0.917***	0.791***	-1.517**	1.763*	0.354
	35.377	15.683	14.731	-2.001	1.741	
$\tau = 10\%$	0.003***	0.784***	0.7159***	-0.559***	1.829***	0.204
	21.064	34.627	23.934	-2.740	4.021	
$\tau = 25\%$	0.005***	0.762***	0.697***	-0.034	2.615***	0.200
	38.881	32.603	18.630	-0.143	2.893	
$\tau = 50\%$	0.008***	0.794***	0.789***	0.624	1.322	0.203
	46.568	15.665	15.173	0.410	1.422	
$\tau = 75\%$	0.013***	0.890***	0.816***	-1.119	2.633***	0.212
	45.407	11.010	10.970	-0.533	4.469	
$\tau = 90\%$	0.018***	1.272***	1.029***	-4.834	0.502	0.220
	36.685	7.840	11.561	-1.301	0.691	
Iceland						
OLS	0.007***	0.810***	0.703***	-3.706***	0.422***	0.656
	19.058	16.755	11.584	-5.765	7.915	
$\tau = 10\%$	0.001***	0.872***	0.664***	-6.415***	0.462***	0.300
	7.630	46.475	27.028	-12.847	20.718	
$\tau = 25\%$	0.001***	0.906***	0.768***	-4.845***	0.366***	0.303
	10.304	26.693	43.964	-3.375	23.184	
$\tau = 50\%$	0.004***	0.888***	0.763***	-3.760***	0.369***	0.258
	20.531	45.363	32.949	-20.095	17.653	
$\tau = 75\%$	0.009***	0.937***	0.820***	-4.463***	0.312***	0.195
	28.256	20.531	41.727	-12.467	17.551	
$\tau = 90\%$	0.019***	0.956***	0.824***	-5.177***	0.301***	0.157
	26.615	10.047	132.292	-7.058	53.530	

Note: The table reports the OLS and quantile results for the full-period sample for the regression model $CSAD_t = \beta_0 + \beta_1 \cdot D^{up} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{up}) \cdot |R_{m,t}| + \beta_3 \cdot D^{up} \cdot R_{m,t}^2 + \beta_4 \cdot (1 - D^{up}) \cdot R_{m,t}^2 + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania, and Iceland. D^{up} takes value 1, when the market is up and 0, when the market is down. It is assumed that market is up, when the market return in that day is higher than the average market return in previous 30 days. The market portfolios used are OMXRGI, OMXVGI, and OMX Iceland for Latvia, Lithuania, and Iceland, respectively. A negative and statistically significant coefficients β_3, β_4 imply the presence of herding behavior in the examined market in case of up and, respectively, down market. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.

Appendix 3. Evidence of Herding Behavior in
Frontier Nordic Countries Under High and Low Volatility

$CSAD_t = \beta_0 + \beta_1 \cdot D^{vol} \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot (1 - D^{vol}) \cdot \lvert R_{m,t} \rvert + \beta_3 \cdot D^{vol} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{vol}) \cdot R^2_{m,t} + \varepsilon_t$						
	β_0 ***t-stat***	β_1 ***t-stat***	β_2 ***t-stat***	β_3 ***t-stat***	β_4 ***t-stat***	$Adj.\ R^2$
Latvia						
OLS	0.012***	0.716***	0.834***	1.887***	-0.215	0.188
	33.282	17.768	14.821	4.007	-0.218	
$\tau = 10\%$	0.001***	0.851***	0.871***	1.054	-0.616	0.254
	7.796	22.607	38.498	0.972	-1.269	
$\tau = 25\%$	0.003***	0.826***	0.840***	1.212***	0.491	0.212
	19.772	45.238	19.569	9.325	0.320	
$\tau = 50\%$	0.008***	0.740***	0.819***	1.937***	0.524	0.170
	33.209	22.529	19.081	3.596	0.633	
$\tau = 75\%$	0.016***	0.633***	0.889***	3.063***	-0.767	0.134
	38.308	9.540	15.412	4.498	-1.307	
$\tau = 90\%$	0.027***	0.576***	0.766***	2.739***	0.442	0.107
	38.352	6.726	5.084	3.415	0.186	
Lithuania						
OLS	0.010***	0.815***	0.930***	0.027	1.188	0.356
	35.356	17.615	11.330	0.044	1.089	
$\tau = 10\%$	0.003***	0.783***	0.689***	-0.557***	4.387***	0.205
	23.529	37.687	41.194	-2.781	29.006	
$\tau = 25\%$	0.005***	0.760***	0.675***	-0.022	4.247***	0.200
	42.127	32.902	26.608	-0.092	9.332	
$\tau = 50\%$	0.008***	0.768***	0.774 ***	0.934	2.868	0.203
	28.151	13.845	4.782	0.821	0.394	
$\tau = 75\%$	0.012***	0.817***	0.927***	0.701	1.709***	0.213
	46.730	11.846	11.755	0.378	2.662	
$\tau = 90\%$	0.017***	0.980***	1.403***	0.013	-2.619***	0.226
	36.168	7.538	15.501	0.007	-3.545	
Iceland						
OLS	0.009***	0.644***	0.630***	0.472**	0.826***	0.654
	19.508	9.889	11.994	8.005	6.002	
$\tau = 10\%$	0.001***	0.645***	0.789***	0.479***	-3.860***	0.280
	3.552	21.267	9.901	17.419	-2.125	
$\tau = 25\%$	0.001***	0.735***	0.758***	0.397***	0.599***	0.291
	16.130	38.956	50.226	23.186	14.947	
$\tau = 50\%$	0.004***	0.746***	0.753***	0.384***	0.596***	0.255
	23.417	37.186	44.148	21.161	13.148	
$\tau = 75\%$	0.009***	0.781***	0.751***	0.347***	0.560***	0.194
	21.111	12.036	15.253	5.905	4.349	
$\tau = 90\%$	0.020***	0.754***	0.649***	0.363***	0.759***	0.157
	23.199	59.185	7.129	32.257	3.185	

Note: The table reports the OLS and quantile results for the full-period sample for the regression model $CSAD_t = \beta_0 + \beta_1 \cdot D^{vol} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{vol}) \cdot |R_{m,t}| + \beta_3 \cdot D^{vol} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{vol}) \cdot R^2_{m,t} + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania, and Iceland. D^{vol} takes value 1, when the market volatility is high and 0, otherwise. It is assumed that market volatility is high, when the market standard deviation in that day is higher than the average market standard deviation in previous 30 days. The market portfolios used are OMXRGI, OMXVGI, and OMX Iceland for Latvia, Lithuania, and Iceland, respectively. A negative and statistically significant coefficients β_3, β_4 imply the presence of herding behavior in the examined market in case of high and, respectively, low market volatility. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.

Appendix 4. The Impact of Global Financial Crisis on Herding Behavior in Frontier Nordic Countries

$CSAD_t = \beta_0 + \beta_1 \cdot D^{GFC} \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot (1 - D^{GFC}) \cdot \lvert R_{m,t} \rvert + \beta_3 \cdot D^{GFC} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{GFC}) \cdot R^2_{m,t} + \varepsilon_t$						
	β_0 ***t-stat***	β_1 ***t-stat***	β_2 ***t-stat***	β_3 ***t-stat***	β_4 ***t-stat***	$Adj.\ R^2$
Latvia						
OLS	0.013***	0.744***	0.738***	2.084	1.409***	0.187
	33.919	10.304	18.877	1.643	3.941	
$\tau = 10\%$	0.001***	0.883***	0.873***	0.314	-0.329	0.254
	4.926	18.128	14.877	0.214	-0.147	
$\tau = 25\%$	0.003***	0.869***	0.794***	0.729**	1.405***	0.213
	22.885	35.647	45.557	2.126	11.269	
$\tau = 50\%$	0.008***	0.871***	0.731***	0.224	1.881***	0.170
	34.463	20.372	23.940	0.410	4.315	
$\tau = 75\%$	0.017***	0.806***	0.661***	2.062	1.855***	0.134
	35.499	9.102	8.875	1.064	2.744	
$\tau = 90\%$	0.028***	0.582***	0.620***	4.645***	2.348	0.107
	32.072	7.119	3.491	5.098	1.561	
Lithuania						
OLS	0.010***	1.273***	0.539***	-5.806***	5.098***	0.387
	34.889	13.375	13.192	-4.458	10.148	
$\tau = 10\%$	0.003***	0.861***	0.672***	-1.281***	3.455***	0.207
	21.117	27.910	22.594	-4.670	4.194	
$\tau = 25\%$	0.005***	0.916***	0.605***	-1.465***	4.914***	0.208
	45.299	32.794	32.401	-4.716	28.739	
$\tau = 50\%$	0.008***	1.100***	0.593***	-3.471***	4.782***	0.215
	60.560	19.816	26.273	-6.202	20.273	
$\tau = 75\%$	0.013***	1.572***	0.616***	-8.567***	4.282***	0.241
	60.743	22.656	20.216	-12.490	16.873	
$\tau = 90\%$	0.019***	2.185***	0.507***	-14.555***	4.783***	0.271
	39.690	9.228	7.955	-6.309	9.481	
Iceland						
OLS	0.008***	0.661***	0.775***	0.461***	-2.003	0.654
	16.018	8.982	11.040	7.131	-1.404	
$\tau = 10\%$	0.000	0.512***	0.963***	0.600***	-8.210***	0.317
	1.596	12.841	32.642	16.538	-5.511	
$\tau = 25\%$	0.001***	0.686***	0.906***	0.441***	-3.591***	0.303
	12.221	30.371	70.128	21.529	-20.309	
$\tau = 50\%$	0.003***	0.718***	0.878***	0.410***	-2.751**	0.257
	16.385	22.564	21.372	14.242	-2.056	
$\tau = 75\%$	0.009***	0.718***	0.913***	0.406***	-2.063	0.195
	13.599	14.127	4.782	8.840	-0.245	
$\tau = 90\%$	0.019***	0.822***	0.754***	0.302***	0.402	0.156
	20.960	128.269	4.661	53.242	0.114	

Note: The table reports the OLS and quantile results for the full-period sample for the regression model $CSAD_t = \beta_0 + \beta_1 \cdot D^{GFC} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{GFC}) \cdot |R_{m,t}| + \beta_3 \cdot D^{GFC} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{GFC}) \cdot R^2_{m,t} + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania, and Iceland. D^{GFC} takes value 1, during period of Global Financial Crisis, and 0, otherwise. The considered period of Global Financial Crisis is from January 1, 2007 until December 31, 2009. The market portfolios used are OMXRGI, OMXVGI. and OMX Iceland for Latvia, Lithuania, and Iceland, respectively. A negative and statistically significant coefficient β_3 implies the presence of herding behavior in the examined market during crisis. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.

Appendix 5. The Impact of European Sovereign Debt Crisis on Herding Behavior in Frontier Nordic Countries

$CSAD_t = \beta_0 + \beta_1 \cdot D^{ESD} \cdot \lvert R_{m,t} \rvert + \beta_2 \cdot (1 - D^{ESD}) \cdot \lvert R_{m,t} \rvert + \beta_3 \cdot D^{ESD} \cdot R_{m,t}^2 + \beta_4 \cdot (1 - D^{ESD}) \cdot R_{m,t}^2 + \varepsilon_t$						
	β_0 *t-stat*	β_1 *t-stat*	β_2 *t-stat*	β_3 *t-stat*	β_4 *t-stat*	$Adj.\ R^2$
Latvia						
OLS	0.012***	0.889***	0.749***	-3.404	1.515***	0.187
	33.311	7.165	21.245	-0.936	3.957	
$\tau = 10\%$	0.001***	0.969***	0.851***	-3.730	0.730	0.254
	5.110	14.287	16.608	-1.077	0.456	
$\tau = 25\%$	0.003***	1.043***	0.820***	-5.439	1.253***	0.213
	21.623	8.286	51.712	-0.739	10.295	
$\tau = 50\%$	0.008***	1.011***	0.762***	-6.312	1.639	0.170
	33.501	9.166	26.202	-1.286	3.872	
$\tau = 75\%$	0.016***	1.073***	0.752***	-8.305***	1.563	0.133
	19.418	6.546	3.302	-2.768	0.219	
$\tau = 90\%$	0.028***	0.736**	0.636***	1.390	2.292***	0.106
	37.607	2.502	7.655	0.216	2.907	
Lithuania						
OLS	0.010***	0.814***	0.891***	2.323***	-0.897	0.354
	35.594	11.772	16.958	2.917	-1.321	
$\tau = 10\%$	0.002***	0.722***	0.775***	3.207	-0.481**	0.204
	18.821	4.384	34.801	0.435	-2.261	
$\tau = 25\%$	0.005***	0.751***	0.713***	2.872*	1.541***	0.200
	39.049	10.865	28.989	1.700	2.628	
$\tau = 50\%$	0.008***	0.876***	0.776***	-0.080	0.873	0.203
	45.044	9.143	17.931	-0.035	0.871	
$\tau = 75\%$	0.012***	0.875***	0.866***	2.142***	-0.016	0.212
	47.778	8.868	13.327	2.627	-0.010	
$\tau = 90\%$	0.017***	0.961***	1.211***	1.068	-3.718***	0.220
	38.935	4.378	17.229	0.589	-4.265	
Iceland						
OLS	0.009***	0.582***	0.659***	11.536***	0.462***	0.654
	18.517	3.047	12.447	1.207	10.184	
$\tau = 10\%$	0.001***	0.637***	0.646***	5.779***	0.478***	0.274
	14.340	31.748	41.427	7.166	33.789	
$\tau = 25\%$	0.001***	0.641***	0.745***	6.306**	0.387***	0.292
	15.276	16.001	46.157	2.330	26.492	
$\tau = 50\%$	0.004***	0.216***	0.752***	27.011***	0.378***	0.262
	23.806	3.514	41.100	6.421	22.900	
$\tau = 75\%$	0.009***	-0.326	0.814***	45.453***	0.317***	0.200
	30.739	-1.588	35.810	3.153	15.445	
$\tau = 90\%$	0.018***	1.861***	0.802***	-32.040**	0.321**	0.159
	17.129	3.407	5.678	-2.430	2.509	

Note: The table reports the OLS and quantile results for the full-period sample for the regression model $CSAD_t = \beta_0 + \beta_1 \cdot D^{ESD} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{ESD}) \cdot |R_{m,t}| + \beta_3 \cdot D^{ESD} \cdot R_{m,t}^2 + \beta_4 \cdot (1 - D^{ESD}) \cdot R_{m,t}^2 + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania, and Iceland. D^{ESD} takes value 1, during period of European Sovereign Debt Crisis, and 0, otherwise. The considered period of European Sovereign Debt Crisis is from May 2, 2010 until December 31, 2012. The market portfolios used are OMXRGI, OMXVGI, and OMX Iceland for Latvia, Lithuania, and Iceland, respectively. A negative and statistically significant coefficient β_3 implies the presence of herding behavior in the examined market during crisis. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.

Appendix 6. The Impact of Covid-19 Pandemic on Herding Behavior in Frontier Nordic Countries

$$CSAD_t = \beta_0 + \beta_1 \cdot D^{CoWHO} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{CoWHO}) \cdot |R_{m,t}| + \beta_3 \cdot D^{CoWHO} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{CoWHO}) \cdot R^2_{m,t} + \varepsilon_t$$

	β_0 *t-stat*	β_1 *t-stat*	β_2 *t-stat*	β_3 *t-stat*	β_4 *t-stat*	$Adj.\ R^2$
Latvia						
OLS	0.012***	1.027***	0.750***	-8.432	1.492***	0.187
	33.777	2.781	21.938	-0.763	4.043	
$\tau = 10\%$	0.001***	0.892***	0.864***	0.505	0.320	0.253
	4.753	8.922	15.541	0.085	0.177	
$\tau = 25\%$	0.003***	0.886***	0.821***	-1.997	1.244***	0.212
	22.743	5.640	53.934	-0.199	10.424	
$\tau = 50\%$	0.008***	0.983***	0.770***	-5.278	1.567***	0.170
	33.931	6.919	27.033	-1.200	3.746	
$\tau = 75\%$	0.016***	0.708**	0.773***	3.465	1.163	0.133
	18.950	2.102	3.467	0.374	0.167	
$\tau = 90\%$	0.028***	0.511	0.653***	0.284	2.069	0.106
	37.281	0.642	7.598	0.013	2.655	
Lithuania						
OLS	0.010***	0.620***	0.872***	-4.976	-0.040	0.354
	33.658	3.723	15.092	-0.711	-0.035	
$\tau = 10\%$	0.002***	1.008***	0.795***	-21.208	-0.654***	0.204
	20.115	4.066	40.125	-1.052	-3.209	
$\tau = 25\%$	0.005***	0.808***	0.746***	-10.416	1.166*	0.200
	37.711	3.476	28.411	-0.479	1.730	
$\tau = 50\%$	0.008***	0.583***	0.807***	-0.416	0.722	0.205
	37.402	7.754	12.272	-0.185	0.370	
$\tau = 75\%$	0.012***	0.425***	0.853***	0.692	0.806	0.213
	48.990	3.107	15.910	0.185	1.119	
$\tau = 90\%$	0.018***	0.317***	1.126***	-0.096	-1.722	0.223
	27.311	1.892	6.120	-0.021	-0.327	
Iceland						
OLS	0.009***	0.844***	0.667***	-3.018**	0.454***	0.654
	18.578	8.434	12.207	-2.342	9.663	
$\tau = 10\%$	0.001***	0.910***	0.656***	-3.622***	0.469***	0.281
	14.488	43.493	48.082	-17.444	37.936	
$\tau = 25\%$	0.001***	0.984***	0.737***	-4.404***	0.394***	0.296
	15.887	39.358	48.266	-16.970	28.527	
$\tau = 50\%$	0.003***	1.086***	0.753***	-5.611***	0.378***	0.258
	20.997	16.450	40.282	-8.860	22.439	
$\tau = 75\%$	0.009***	0.967***	0.784***	-1.434	0.345***	0.194
	18.323	8.537	13.392	-0.705	6.513	
$\tau = 90\%$	0.019***	0.884***	0.817***	-2.501	0.307**	0.156
	18.275	4.588	5.886	-0.795	2.445	

Note: The table reports the OLS and quantile results for the full-period sample for the regression model $CSAD_t = \beta_0 + \beta_1 \cdot D^{CoWHO} \cdot |R_{m,t}| + \beta_2 \cdot (1 - D^{CoWHO}) \cdot |R_{m,t}| + \beta_3 \cdot D^{CoWHO} \cdot R^2_{m,t} + \beta_4 \cdot (1 - D^{CoWHO}) \cdot R^2_{m,t} + \varepsilon_t$, for frontier Nordic countries: Latvia, Lithuania, and Iceland. D^{CoWHO} takes value 1, during period of Covid-19 pandemic announced by the World Health Organization, and 0, otherwise. The considered period of Covid-19 pandemic is from March 11, 2020 until the end of the sample. The market portfolios used are OMXRGI, OMXVGI, and OMX Iceland for Latvia, Lithuania and Iceland, respectively. A negative and statistically significant coefficient β_3 implies the presence of herding behavior in the examined market during crisis. Standard errors are estimated by using Newey-West (1987) correction.
***, **, * denote statistical significance at the 1%, 5%, and 10% level.