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Herding or Anti-Herding? Understanding Investor Behavior in the Baltic States

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This paper investigates market-wide herding behavior in the stock markets of Estonia, Latvia, and Lithuania, employing measures that assess the proximity of market returns to market consensus. Using a survivor-bias-free dataset of daily stock returns, we document significant anti-herding behavior among investors in Latvia and Lithuania throughout the sample period. Results for the Estonian market vary based on the herding measure chosen. Herding dynamics fluctuate over time, with the COVID-19 pandemic increasing the intensity of the effect in Estonia and Lithuania. Moreover, the deterioration of investor sentiment and stronger funding restrictions are found to amplify herding in these two markets. Estonia's market displays asymmetric behavior, with herding being more pronounced during negative market performance. Collectively, these findings are relevant to management practice since they suggest that it is difficult to extract the desired benefits of international diversification in the Baltic region, especially during market downturns.

Keywords: *Herding Behavior; COVID-19 Pandemic; International Diversification; Estonia; Latvia; Lithuania.*

Introduction

Financial literature describes herding as investors' tendency to disregard their private informational signals, choosing instead to align their decisions with the market consensus (Chang *et al*., 2000; Hirshleifer & Teoh, 2003). Herding among investors has been attributed to reputational concerns (Scharfstein & Stein, 1990), informational inefficiencies (Froot *et al*., 1992; Hirshleifer *et al*., 1994), or informational cascades (Bikhchandani *et al*., 1992, 1998).

In this paper, we conduct a thorough investigation of market-wide herding behavior among investors operating in the stock markets of Estonia, Latvia, and Lithuania. We use a survivor-bias-free dataset of daily stock returns from January 2001 to June 2022. Our study adopts two herding measures in the empirical analysis. The first measure is based on the cross-sectional standard deviation of stock returns (CSSD) relative to the market consensus, which according to Christie and Huang (1995), is expected to decrease during periods of extreme market returns, signaling the presence of herding behavior among investors. The second measure, developed by Chang *et al*. (2000), uses the cross-sectional absolute deviation of returns (CSAD) in relation to the market consensus to capture the occurrence of herding behavior over the entire distribution of market returns.

Studying herding behavior in frontier markets such as the Baltic stock markets is of significant importance for several reasons. First, although frontier stock markets have been receiving increasing attention from academics and market practitioners, not much is known about the behavior of investors in these markets. At the same time, frontier markets seem to be the ideal setting for herding behavior due to their unique characteristics: they are at an early stage of development, offer limited market capitalizations and trade volumes, suffer from restrictions on information flows, and are often dominated by relatively few institutional investors. Second, herding has important implications for market efficiency as it has been found to contribute to destabilize financial markets, slowing the price-discovery process, and creating systemic risk (Iihara *et al*., 2001; Hsieh, 2013; Gu *et al*., 2022). Herding behavior has also been associated to market contagion, bubbles, and crashes (Lux, 1995; Shiller, 2016; Ghorbel *et al*., 2023). To this extent, studies on this topic are of interest not only to academics but also to policymakers and financial regulators that want to promote the transparency and stability of capital markets. Lastly, studying the phenomenon is valuable from a portfolio management perspective. The correlated trading resulting from herding behavior may produce excessive volatility and lead to sub-optimal diversification, as investing in negatively correlated securities can become significantly more difficult (Chang *et al*., 2000; Chiang & Zheng, 2010). Thus, in the presence of herding, investors would need a more extensive selection of securities to achieve the same degree of diversification than in a herd-free market.

We document that the investors operating in the Latvian and Lithuanian stock markets exhibited a trading pattern away from the market consensus (i.e., anti-herding behavior) during the whole sample period. The results for the investors in the Estonian market depend on the technique used to detect herding effects: while the CSAD approach indicates that herding and anti-herding were absent from the market, the CSSD-based model suggests the occurrence of anti-herding. Moreover, the Estonian market is the only one in which herding has an asymmetric behavior, as the phenomenon tends to be more pronounced when the market performance is negative. Herding dynamics vary substantially over time, with the COVID-19 pandemic strengthening the effect in Estonian and Lithuanian markets in the most recent sample period. Significant cross-country effects were observed in all markets. Finally, the deterioration of investor sentiment and stronger funding restrictions were found to amplify herding in the Estonian and Lithuanian markets.

Our research adds to the behavioral finance literature on herding among investors operating in the Baltic stock markets. Our contribution is relevant given the relative scarcity of information on how investors behave in frontier markets in general, and in the stock markets of the Baltic countries in particular. A second contribution stems from using a sample free from survivorship bias that covers a significantly longer period than that considered in previous studies. This makes it possible to study, for example, the effects of the recent COVID-19 pandemic on herding behavior. Finally, it is worth mentioning that although our study employs methodologies that have been established in the literature for some time, it is the first to analyze some important aspects of herding in the context of the Baltic stock markets. For example, we investigate the dynamic nature of herding behaviors through rolling window regressions. The presence of cross-country effects and the economic determinants of the phenomenon are also investigated for the first time in these markets.

The remainder of the paper is organized as follows. Section 2 provides a review of relevant literature regarding herding behavior. Section 3 describes the data and methodologies employed in the empirical study. Section 4 discusses the results, and Section 5 summarizes the discussion and concludes.

Literature Review

The presence of herding behavior among investors has been scrutinized in different asset classes, including bonds (Galariotis *et al*., 2016a; Cai *et al*., 2019), exchange rates (Pierdzioch *et al*., 2012; Sibande *et al*., 2023), derivatives (Gleason *et al*., 2004; Babalos & Stavroyiannis, 2015), and cryptocurrencies (Yarovaya *et al*., 2021; Lobão, 2022). Regarding stock markets, the empirical literature on herding behavior has been mainly focused on the developed markets of Asia and America, usually with mixed results. For example, Christie and Huang (1995) applied a new test of herding to the US stock market based on the CSSD. They found no significant evidence of herding during periods of large price movements. Chang *et al*. (2000) analyzed the herding on the US, Hong Kong, Japan, South Korea, and Taiwan markets using the CSAD. Similarly to Christie and Huang's (1995) findings, their results refute the presence of herding in the US. Still, they found partial evidence of herding in Japan, and significant evidence in South Korea and Japan. Demirer *et al*. (2010) analyzed the Taiwanese stock market to conclude that models based on the CSSD yield no substantial evidence of herding. However, non-linear models built upon the CSAD indicate strong evidence of herd formation. Choi and Yoon (2020) document that South Korean stock market investors exhibited herding behavior during downward-market periods. More recently, Costa *et al*. (2024) show that herding behavior in Europe is more pronounced during periods of declining returns and rising volatility.

European developed markets have also been studied. For example, Caparrelli *et al*. (2004) used CSSD and CSAD approaches to find that herding was present in the Italian stock market in extreme market conditions. However, his results heavily depend on the method employed. Caporale *et al*. (2008) tested for herd behavior in the Greek stock market, concluding that the phenomenon was present for the whole 1998–2007 period. Economou *et al*. (2016) examined the same stock market in the context of the eurozone crisis, finding strong signs of herding under different market conditions. Moreover, four southern European markets (Italy, Portugal, Spain, and Greece) were investigated by Economou *et al*. (2011) for indication of herding during the Global Financial Crisis (GFC). Their findings suggest that herding became more pronounced during the crisis period. Mobarek *et al*. (2014) confirmed that Italia, Portugal, Spain, Greece, and Ireland were intensely affected by both the eurozone crisis and the GFC. Galariotis *et al*. (2016b) found significant evidence of herding behavior in high-liquidity stocks during the GFC in Germany, France, Japan, the UK, and the US. These findings were later corroborated by Bekiros *et al*. (2017). Economou *et al*. (2018) recently concluded that investors' fear significantly influenced the herding behavior observed in the US, the UK, and Germany stock markets.

Evidence of herding behavior among investors in frontier stock markets has attracted increased attention from researchers in recent years. Chen (2013) examined a set of 69 national equity markets, including 26 frontier markets. The Estonian and Lithuanian markets were analyzed for the period 2000–2009, with results from the CSAD model indicating herding behavior only in the latter market. Pochea (2016) investigated the stock markets of the three Baltic states applying a static analysis to data for the period 2003–2013. The results reveal that investors in the Estonian and Lithuanian markets exhibited significant herding behavior. Blasco *et al*. (2016) analyzed nine European frontier stock markets, including the markets of Estonia and Lithuania, during the period 2011–2014. The results obtained were different among the methodologies: while the CSSD approach found herding only in extreme up markets in Ukraine, Romania, and Croatia, the results of the CSAD model signaled the existence of herding only in the Estonian market. Pochea *et al*. (2017) investigated herding behavior in ten Central and East European stock markets, including the three Baltic countries, during 2003–2013. Evidence of herding behavior was found in all countries except Romania and Poland. Arjoon and Bhatnagar (2017) studied the subject in the context of the stocks listed on the Trinidad and Tobago stock exchange. By resorting to a dynamic analysis, the authors found significant evidence of herding across the market, being stronger during periods of rising prices. Bui *et al*. (2018) scrutinized the Vietnamese stock market for indications of herd behavior. They detected pronounced effects of herding behavior both in up and down-market scenarios. Vo and Phan (2019) confirmed the existence of significant herding behavior in the Vietnamese stock market. Batmunkh *et al*. (2020) employed the CSAD approach to conclude that the Mongolian stock market exhibited significant herding behavior in bull and bear market periods. More recently, Nguyen and Vo (2024) confirmed the existence of herding behavior in Vietnam's stock exchanges not only for the whole but also during and post-COVID periods.

The current paper expands the existing literature about herding among investors operating in frontier markets, particularly in the Baltic stock markets, examining several aspects of that behavioral trait for the first time.

Data and Methodology

We examine the patterns of herding behavior in the stock markets of Estonia, Latvia, and Lithuania during the period January 2, 2001 – July 11, 2022. Because herding is considered to be a short-term phenomenon (Christie & Huang, 1995; Caporale *et al*., 2008), we used data with daily frequency. Thus, data on the daily closing prices of all listed stocks in the Baltic stock markets during the sample period were collected from Refinitiv Datastream. We included both active and dead stocks, so our database is free of survivorship bias. The price series were converted into log returns of individual stocks to reduce skewness and kurtosis.

To examine market-wide herding through the study of the evolution of the stock returns concerning the market consensus, it is required to estimate the returns of the market portfolio. Following Caparrelli *et al*. (2004) and Demirer *et al*. (2010), we calculate the market returns by employing an equally-weighted market portfolio for each country,

$$R_{mt} = \frac{\sum_{i=1}^{N} R_{it}}{N} \qquad (1)$$

where R_{it} denotes the return of stock *i* at time t and N is the number of stocks in the given country at time *t*.

We use two models to examine herding toward the market consensus. The first model is based on the cross-sectional standard deviation of returns ($CSSD_t$) proposed by Christie and Huang (1995) as a measure of return dispersion around the market portfolio return:

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

where R_{it} is the return of stock *i* at time t and N is the number of stocks in the portfolio at time *t*.

According to this analysis, it is argued that investors are more likely to suppress their own beliefs and closely follow the market consensus during periods of extreme market movements. As a result, the value of $CSSD_t$ becomes low, which is understood as a signal of herding. The following regression captures the proximity of the return of a particular set of assets to the observed stock market return,

$$CSSD_t = \gamma_0 + \gamma_1 . D_t^U + \gamma_2 . D_t^L + \epsilon_t \qquad (3)$$

where $D_t^U = 1$ if the market returns are at the upper tail of the distribution, and $D_t^U = 0$ otherwise; and $D_t^L = 1$ if the market returns are at the lower tail of the distribution, and $D_t^L = 0$ otherwise. The use of D_t^U and D_t^L enables the identification of differences in investor behavior under extreme market conditions (positive and negative). Therefore, if the dispersion of returns is lower in the presence of large market changes, that is, when the estimated γ_1 and γ_2 are significantly negative, the presence of herding behavior is assumed. However, if γ_1 and γ_2 are found to be significantly positive, that implies that investors exhibited a trading pattern that deviates from the market consensus during periods of large market swings (i.e., anti-herding behavior).

In our empirical estimation of Equation (3), we adopt the criteria of 1 %, 2 %, 5 %, and 10 % for the tails of the distribution of returns.

As argued by Economou *et al*. (2011), $CSSD_t$ has some important shortcomings. The measure is sensitive to outliers, and the herding is analysed under the condition of extreme market movements only, disregarding the herding behavior that might happen in other situations. Considering these criticisms, we also employed the measure proposed by Chang *et al*. (2000), which enables the detection of the effect over the entire distribution of market returns. These authors suggested using the cross-sectional absolute deviation of returns ($CSAD_t$), which assesses the relationship between the cross-sectional returns' dispersion and absolute market returns. $CSAD_t$ may be defined as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \qquad (4)$$

where R_{it} is the return of stock *i* at time *t* and N is the number of stocks in the market portfolio at time *t*.

Chang *et al*. (2000) argued that in the absence of herding, market returns and $CSAD_t$ should display a positive and linear relationship as implied by the capital asset pricing model (CAPM). However, in the presence of herding, this relation is expected to become non-linear. If, in that period, investors imitate each other, $CSAD_t$ decreases because the securities are expected to cluster around the market portfolio return. In these circumstances, the relation between $CSAD_t$ and the square of market portfolio returns is expected to become negative as the cross-sectional dispersion of asset returns will decrease or increase to a lesser extent than the market return. This negative relation between $CSAD_t$ and the square of market returns is taken as an indication of herding behavior. Therefore, in the following regression equation,

$$CSAD_t = \gamma_0 + \gamma_1 . |R_{mt}| + \gamma_2 . R_{mt}^2 + \epsilon_t \qquad (5)$$

γ_2 is expected to have a significantly negative value if herding is present in the market. However, in the absence of herding, we expect γ_1 to be positive and γ_2 to be statistically no different than zero. If anti-herding exists, then γ_2 should be positive. Economou *et al*. (2015) argue that herding may exhibit an asymmetric behavior during days with positive and negative market returns (up and down markets). According to Tan *et al*. (2008) and Economou *et al*. (2015), down markets may stimulate herding as investors tend to sell their positions to avoid suffering additional losses in case the downturn becomes prolonged. On the other hand, up-markets can also lead to herding since they can motivate investors to ride what they believe to be a positive market trend.

To assess whether herding varies during up and down markets, we follow Economou *et al*. (2011, 2018), employing the following specification:

$$CSAD_t = \gamma_0 + \gamma_1 . D . |R_{mt}| + \gamma_2 . (1 - D) . |R_{mt}| + \gamma_3 . D . R_{mt}^2 + \gamma_4 . (1 - D) . R_{mt}^2 + \epsilon_t \qquad (6)$$

where *D* = 1 on up market ($R_{mt} > 0$), and 0 otherwise. Significantly negative values of γ_3 (γ_4) would signal that herding is significant on days of positive (negative) average stock market performance. On the other hand, significantly positive values of γ_3 (γ_4) would imply that anti-herding is significant on days of positive (negative) average stock returns.

Noise trading models suggest that these agents purchase assets in up markets and sell assets in down markets (De Long *et al*., 1990). In this context, risk-averse arbitrageurs would be reluctant to correct the mispricing because of the unpredictability of the timings of a trend reversal. In consequence, prices will become more volatile, and the cross-sectional correlation of returns will tend to increase in a market with high levels of volatility (Corsetti *et al*., 2005). Because R_{mt}^2 may not properly capture the dynamics of nonlinearity resulting from noise trading, Chiang *et al*. (2013) and Kumar (2021) recommend the introduction of R_{mt}^3 in Equation (5) to examine the asymmetry in herding behavior during up and down-market regimes. Thus, we also estimate the following model:

$$CSAD_t = \gamma_0 + \gamma_1.|R_{mt}| + \gamma_2.R_{mt}^2 + \gamma_3.R_{mt}^3 + \epsilon_t \tag{7}$$

A significantly negative (positive) value of γ_3 indicates that herding increases in an up (down) market.

Balcilar *et al*. (2013) and Stavroyiannis and Babalos (2017) contend that because Equation (5) assumes that the parameters are constant over time, the model may lead to misleading conclusions if the dynamics of herding evolve and are impacted by positive and/or negative shocks. Moreover, Klein (2013) and Clements *et al*. (2017) showed that herding behavior exhibits a significant time-varying nature. To investigate this hypothesis, we implement a time-varying approach based on a rolling window of 250 observations and a step of 10 observations. The window size is the approximate number of trading days in a year. Thus, we re-run Equation (5) under rolling windows. In this case, if γ_2 remains constant over a rolling window, this suggests stability in the relationship between the square term of the market portfolio return and $CSAD_t$; otherwise, our approach is able to capture the time-varying nature of herding.

We also examine the impact of the COVID-19 pandemic on herding behavior. Thus, we run the following regression,

$$CSAD_t = \gamma_0 + \gamma_1.|R_{mt}| + \gamma_2.R_{mt}^2 + \gamma_3.Covid_t.R_{mt}^2 + \epsilon_t \tag{8}$$

where $Covid_t$ is a dummy variable that takes the value 1 on the trading days during the COVID-19 crisis period, and 0 otherwise. A statistically significant and negative (positive) γ_3 means that the dispersion of returns was lower (higher) during the pandemic, thus indicating that herding was stronger (weaker) during that period. There is no consensus as to the exact timing of the COVID-19 crisis. However, as most countries worldwide began to take the new coronavirus seriously only after the World Health Organization (WHO) declared a global public health emergency on January 30, 2020, this is the date that we consider as the commencement of the crisis. We consider that the pandemic period may have had an impact on all observations from that date until the end of the analyzed sample period.

The COVID-19 pandemic has had a profound impact on global economic activity, creating significant levels of uncertainty in financial markets (Lyócsa *et al*., 2020). The pandemic-induced fear triggered a period marked by sharp declines in stock prices and elevated market volatility (Li *et al*., 2022). Under such conditions of heightened fear and anxiety, it might be expected that investors would increasingly suppress their individual beliefs and conform to the prevailing market consensus. However, empirical evidence on this phenomenon remains inconclusive. Several studies, including those by Bouri *et al*. (2021), Jiang *et al*. (2022), and Lobao *et al*. (2024), document a positive relationship between the COVID-19 pandemic and herd behavior in stock markets, particularly in emerging economies. Conversely, Lobão and Almeida (2024) suggest that the pandemic generally amplified anti-herding tendencies. Adding to this debate, Wu *et al*. (2020) and Ferreruela and Mallor (2021) find no significant evidence of increased herding during the pandemic. The lack of consensus in the literature warrants additional studies on this topic.

Tan *et al*. (2008) and Economou *et al*. (2011) defend that there may be significant links between the cross-sectional dispersions across markets that are usually classified by the financial press and market analysts into the same category, as is the case of the three Baltic stock markets. To examine whether the cross-sectional returns' dispersions in these markets display a certain degree of co-movement, we test whether the variability in the $CSAD_t$ of one market can be explained by the corresponding return dispersions in the remaining two markets. Thus, we augment the model described in Equation (5) to estimate the following model for each country i:

$$CSAD_{it} = \gamma_0 + \gamma_1.|R_{mt}| + \gamma_2.R_{mt}^2 + \sum_{j=1}^{2} \delta_j CSAD_{jt} + \epsilon_t \tag{9}$$

Significantly positive (or negative) values of δ_j would imply the existence of significant cross-country effects, that is, that the variability in the $CSAD_t$ of country i could be explained by the cross-sectional returns' dispersion observed in countries j.

Finally, we conduct tests to examine whether financial and economic variables determine the evolution of herding behavior. The general form of the regression model we use is as follows:

$$CSAD_t = \gamma_0 + \gamma_1.|R_{mt}| + \gamma_2.R_{mt}^2 + \delta_j X_t + \epsilon_t \tag{10}$$

where X_t is the vector containing the variables by which we augment the benchmark model of Equation (5). We test the statistical significance of three potential determinants of herding behavior. Prior literature suggests that herding effects tend to be more intense during periods of market distress (e.g., Tan *et al*., 2008; Economou *et al*., 2011, 2018). Thus, the first determinant is the sentiment of investors reflected in the logarithmic variation of the Euro Stoxx 50 Volatility Index (VSTOXX). Higher VSTOXX levels indicate a deterioration in investor sentiment. The index is considered to be the "European VIX" and is the most widely followed European volatility index. It measures the implied volatility of near-term EuroStoxx 50 options, which are traded on the Eurex exchange.

Other authors conjecture that funding conditions, reflected in the increase in interest rates, would affect the attractiveness of investing in the stock market and lead to an increase in correlated trading (e.g., Philippas *et al*., 2013). Therefore, the second determinant refers to the macro-shock produced by a variation in interest rates and is captured by the absolute variation in the daily 3-month Euribor rate.

Some financial literature on the subject hypothesizes that herding effects can be a response to extreme price movements in the US stock market, which still is a major influence on the way investors perceive the evolution of international stock markets (e.g., Economou *et al*., 2011; Philippas *et al*., 2013). Consequently, we considered as a potential determinant of herding the lagged squared US market return, proxied by the daily returns of the S&P500 index. The choice of the lagged return was motivated by the fact that the Baltic stock markets close much earlier than the NYSE. All the financial and economic variables included in model (9) were extracted from Refinitiv Datastream.

We apply the Newey-West (1987) estimator in all models included in the empirical analysis to adjust the standard errors of the estimated regressions for autocorrelation and heteroscedasticity.

Table 1 shows the descriptive statistics for $CSSD_t$, $CSAD_t$, and market portfolio return (R_{mt}) for the whole sample period in each of the three countries. The stock markets of the three countries had a positive performance in the sample period, with a daily mean return ranging from 0.02 % (Estonia) to 0.14 % (Latvia). The Latvian market presented the highest volatility, measured by the standard deviation of returns. By definition, $CSSD_t$ and $CSAD_t$ take on a minimum value of zero when all the individual stock returns move in complete unison with the market and increase when the observed returns deviate away from the market consensus. The mean values of $CSSD_t$ and $CSAD_t$ were the lowest in the market of Estonia. Contrary to the market portfolio returns, $CSAD_t$ and $CSSD_t$ exhibited a positive skewness which indicates a longer right tail. All return series showed excessive kurtosis, which means that their distributions are leptokurtic.

Table 1

Descriptive Statistics

	Estonia			**Latvia**			**Lithuania**		
	CSSD	**CSAD**	$\boldsymbol{R_m}$	**CSSD**	**CSAD**	$\boldsymbol{R_m}$	**CSSD**	**CSAD**	$\boldsymbol{R_m}$
Mean	0.0243	0.0164	0.0002	0.0427	0.0283	0.0014	0.0317	0.0191	0.0006
Median	0.0203	0.0140	0.0004	0.0341	0.0230	0.0011	0.0255	0.0161	0.0009
Maximum	0.3629	0.1917	0.1129	0.5015	0.2860	0.1597	0.6362	0.2764	0.1449
Minimum	0.0017	0.0011	-0.0921	0.0011	0.0008	-0.1695	0.0021	0.0008	-0.1463
Std.Dv.	0.0160	0.0101	0.0120	0.0369	0.0225	0.0209	0.0339	0.0157	0.0134
Skewness	4.3428	3.4299	-0.2377	3.8147	3.4018	-0.0737	8.5694	6.6672	-0.5946
Kurtosis	52.6401	31.7082	7.5050	25.6521	20.7912	6.8314	107.4312	75.4022	20.4952
CV	0.65931	0.6084	49.9911	0.8652	0.7965	14.4051	1.0708	0.8222	21.5632
Obs.	5400	5400	5400	5318	5318	5318	5315	5315	5315

Empirical Results and Discussion

Presence of Herding

Table 2 reports the estimation of the coefficients of the CSSD model (Equation (3)). The positive and statistically significant values at the 1 % level of γ_1 and γ_2 indicate that anti-herding behavior was prevalent in the three markets. Our results are similar to those reported by Chen (2013) for the markets of Estonia and Lithuania using a much shorter sample period (2000–2009).

Table 2

Estimated Coefficients of the CSSD Model

$$\boldsymbol{CSSD_t = \gamma_0 + \gamma_1 . D_t^U + \gamma_2 . D_t^L + \epsilon_t}$$

Criteria for 1 % extremes			
Variable	Estonia	Latvia	Lithuania
constant	0.023*** (60. 41)	0.039*** (106.20)	0.028*** (112.80)
D_t^U	0.0398*** (4.07)	0.155*** (12.76)	0.141*** (7.71)
D_t^L	0.033*** (5.77)	0.152*** (10.81)	0.129*** (5.86)
Adjusted R^2	0.100	0.343	0.316
Criteria for 2 % extremes			
Variable	Estonia	Latvia	Lithuania
constant	0.023*** (62.96)	0.038*** (110.60)	0.028*** (120.80)
D_t^U	0.031*** (6.02)	0.115*** (14.62)	0.094*** (8.57)
D_t^L	0.028*** (7.11)	0.106*** (11.87)	0.085*** (6.89)
Adjusted R^2	0.134	0.348	0.270
Criteria for 5 % extremes			
Variable	Estonia	Latvia	Lithuania
constant	0.022***	0.036***	0.027***

$CSSD_t = \gamma_0 + \gamma_1 . D_t^U + \gamma_2 . D_t^L + \epsilon_t$			
	(64.79)	(110.60)	(123.420)
D_t^U	0.022***	0.072***	0.052***
	(9.49)	(17.17)	(10.56)
D_t^L	0.021***	0.061***	0.050***
	(10.69)	(13.67)	(9.23)
Adjusted R^2	0.169	0.297	0.204
Criteria for 10 % extremes			
Variable	Estonia	Latvia	Lithuania
constant	0.021***	0.032***	0.025***
	(68.30)	(106.70)	(116.70)
D_t^U	0.017***	0.053***	0.034***
	(14.41)	(21.80)	(12.91)
D_t^L	0.017***	0.044***	0.032***
	(14.30)	(17.36)	(11.11)
Adjusted R^2	0.194	0.282	0.153

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. ***: $p < 0.01$*

Table 3 reports the estimated coefficients of the CSAD model (Equation (5)), which considers the entire distribution of market returns. The model's explanatory power, measured by the adjusted R^2, is somewhat higher than those reported in other studies (e.g., Tan *et al*., 2008; Economou *et al*., 2011; Pochea, 2016). Panel A shows that γ_1 is positive and statistically significant at the 1 % level for all sample periods, indicating that the $CSAD_t$ of returns in the three Baltic stock markets is an increasing function of the absolute value of market returns ($|R_{mt}|$). More importantly, γ_2 presents a non-significant value in the stock market of Estonia, implying that investors did not herd on average in this market. This result is at odds with the indication given by the CSSD model (Table 2). The conflicting evidence may stem from the fact that the CSSD analyses the herding toward market consensus under conditions of extreme market movements only, thus disregarding the herding that might happen in other situations. In the cases of the Latvian and Lithuanian stock markets, the coefficient of R_{mt}^2 is shown to have a significantly positive value. This finding confirms the presence of significant anti-herding behavior in these two markets during the observation period.

According to Demirer *et al*. (2010) and Gebka and Wohar (2013), anti-herding behavior is produced when investors attribute excessive importance either to their own views or to the views of a subgroup of other market participants. In these circumstances, there is an increased cross-sectional dispersion of returns over what is implied by rational pricing models. In the opinion of Stavroyiannis and Babalos (2017), this behavior could be due to investors' overconfidence or flight to quality movements.

The existence of anti-herding carries important implications for international investors as it has a deleterious impact on portfolio diversification. As mentioned by Gebka and Wohar (2013, p. 82), "…because the cross-sectional return dispersion is related to idiosyncratic risk (…), evidence of herding within a given set of assets (especially of "negative herding", i.e., excessive return dispersion) signals the existence of diversifiable risk and, for investors only holding these assets, insufficient diversification".

Our results regarding the markets of Latvia and Lithuania are consistent with the studies that report significant anti-herding in frontier markets. For example, Chen (2003) shows that anti-herding was prevalent in Lebanon, Serbia, and Slovenia stock markets, among others. Further, our evidence is at odds with those authors who documented significant levels of herding in frontier stock markets (e.g., Arjoon & Bhatnagar, 2017; Batmunkh *et al*., 2020).

To investigate the impact of having a survivor-bias-free dataset, we re-run the CSAD model considering only the stocks of our sample that were not delisted during the sample period (i.e., surviving stocks). Evidence displayed on Panel B of Table 3 suggests that the results would have been different if the delisted stocks had not been included in the analysis. The adjusted R^2 of the model with the surviving stocks only is lower for the three regressions, and the anti-herding detected in the Lithuanian market would be replaced by the finding of significant herding had we not included the delisted stocks. This suggests that the anti-herding behavior exhibited by investors in that market was mainly concentrated on the stocks that ended up being delisted.

Table 3

Estimated Coefficients of the CSAD Model

$CSAD_t = \gamma_0 + \gamma_1 . \lvert R_{mt} \rvert + \gamma_2 . R_{mt}^2 + \epsilon_t$			
Panel A: all stocks			
Variable	Estonia	Latvia	Lithuania
Constant	0.0107***	0.0145***	0.0118***
	(26.27)	(49.55)	(55.98)
$\lvert R_{mt} \rvert$	0.6658***	0.8101***	0.7450***
	(7.26)	(28.00)	(21.24)
	1.6830	5.1860***	6.8960***

$CSAD_t = \gamma_0 + \gamma_1 . \lvert R_{mt} \rvert + \gamma_2 . R_{mt}^2 + \epsilon_t$			
R_{mt}^2	(0.57)	(12.38)	(10.54)
Adjusted R^2	0.429	0.682	0.706
Panel B: surviving stocks			
Variable	Estonia	Latvia	Lithuania
constant	0.0098*** (25.12)	0.0093*** (27.38)	0.0086*** (41.29)
$\lvert R_{mt} \rvert$	0.6635*** (8.34)	0.8065*** (23.82)	0.9663*** (21.61)
R_{mt}^2	−2.7297 (-1.45)	1.9092*** (4.08)	−2.3241** (-1.967)
Adjusted R^2	0.302	0.624	0.541

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. **: p < 0.05; ***: p < 0.01*

Asymmetric Nature of Herding

In this section, we investigate the nature of herding in different market regimes, that is, in up and down markets. Table 4 displays the estimated coefficients of Equation (6). In the cases of Latvia and Lithuania, the coefficients of $D. R_{mt}^2$ and $(1 - D). R_{mt}^2$ are found to be positive and statistically significant at the 1 % level, denoting that there is a tendency to observe anti-herding, on average, both on days of rising and falling market prices. This conclusion is confirmed by a Wald test for the null hypothesis that the herding coefficients γ_3 and γ_4 are equal.

However, in the case of the Estonian market, the results are distinct: the significantly positive and negative values of γ_3 and γ_4, respectively, indicate that there was a tendency to observe herding (anti-herding) in this market on days of negative (positive) market performance. This asymmetry is confirmed by the result of the Wald test, which allows us to reject the hypothesis that the two coefficients were equal at the statistical significance level of 1 %.

Table 4

Herding Behavior and Market Performance (Equation (6))

$CSAD_t = \gamma_0 + \gamma_1 . D . \lvert R_{mt} \rvert + \gamma_2 . (1 - D) . \lvert R_{mt} \rvert + \gamma_3 . D . R_{mt}^2 + \gamma_4 . (1 - D) . R_{mt}^2 + \epsilon_t$			
Panel A: Estimates of herding behavior in upward and downward markets			
Variable	Estonia	Latvia	Lithuania
constant	0.0106*** (4014)	0.0145*** (51.88)	0.0118*** (52.44)
$D. \lvert R_{mt} \rvert$	0.6012*** (8.57)	0.8093*** (28.51)	0.7783*** (19.45)
$(1 - D). \lvert R_{mt} \rvert$	0.7790*** (17.11)	0.7908*** (23.72)	0.6796*** (13.40)
$D. R_{mt}^2$	5.6186** (2.06)	5.7168*** (12.52)	7.7966*** (10.58)
$(1 - D). R_{mt}^2$	−2.9248* (-1.84)	4.8772*** (10.15)	6.4907*** (5.60)
Adjusted R^2	0.445	0.682	0.711
Panel B: Wald tests for equality of herding coefficients			
	Estonia	Latvia	Lithuania
γ_1 - γ_2 H0: $\gamma_1 = \gamma_2$	-0.1778*** (7.77)	0.0185 (0.32)	0.0987* (2.73)
γ_3 - γ_4 H0: $\gamma_3 = \gamma_4$	8.5434*** (9.78)	0.8396 (1.75)	1.3059 (1.01)

*Note: Panel A contains the estimated coefficients of Equation (6) using Newey-West consistent standard errors with t-statistics in parentheses. Panel B presents the F-statistics of the Wald test for equity of herding coefficients in parentheses. *: p < 0.10; **: p < 0.05; ***: p < 0.01*

Table 5 shows the results of the estimation of Equation (7). The lack of statistical significance of γ_3 in the case of Lithuania confirms the symmetry in the patterns of herding in this market. Further, the value of γ_3 is found to be positive and statistically significant at the 1% level in the cases of the Estonian and Latvian markets, thus indicating that herding tends to be more pronounced in a downward market in the two countries.

Table 5

Herding Behavior and Market Performance (Equation (7))

$$CSAD_t = \gamma_0 + \gamma_1 . |R_{mt}| + \gamma_2 . R_{mt}^2 + \gamma_3 . R_{mt}^3 + \epsilon_t$$

Variable	Estonia	Latvia	Lithuania
constant	0.0105*** (44.06)	0.01458*** (52.24)	0.0118*** (51.87)
$\lvert R_{mt} \rvert$	0.7037*** (16.94)	0.8005*** (31.09)	0.7402*** (18.78)
R_{mt}^2	0.9137 (0.60)	5.3285*** (15.74)	7.0580*** (9.77)
R_{mt}^3	43.551*** (4.02)	2.6912*** (2.61)	6.2525 (1.43)
Adjusted R^2	0.449	0.683	0.701

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. ***: p < 0.01*

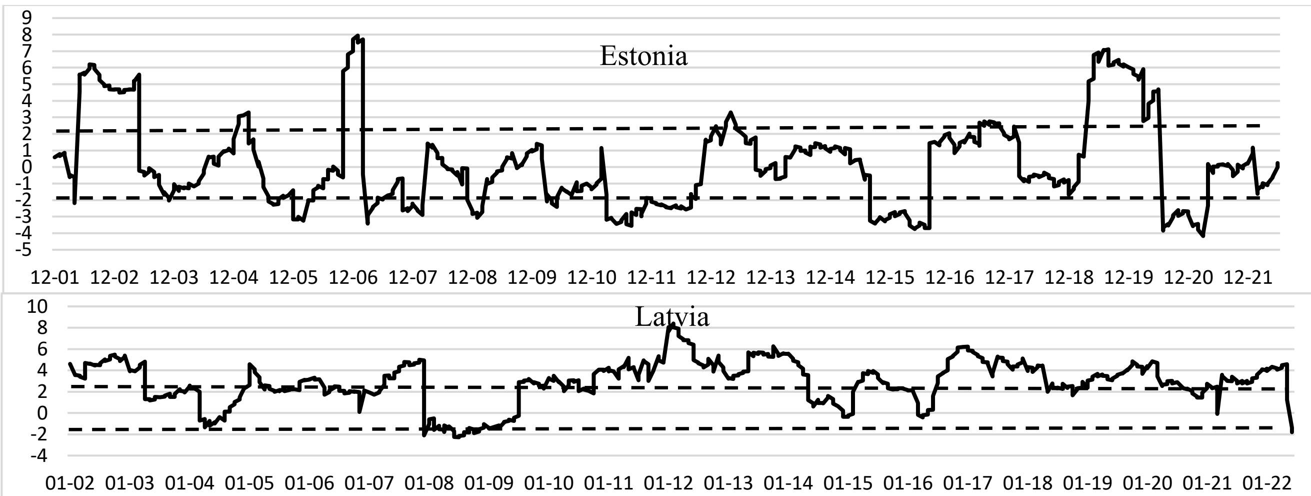
The two models based on Equations (6) and (7) suggest that investors in the Estonian market have a heightened tendency to follow the market consensus when the prices are falling. This situation is consistent with the finding that financial decision-makers in general, and investors in particular, tend to be more sensitive to losses than to gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) and suggests that opportunities for diversification for investors in the Estonian market can become more limited during periods of market losses when diversification is most needed. Thus, our evidence advises Estonian investors to hold a larger number of assets in a downward market to achieve the desired reduction of idiosyncratic risk via diversification.

Time-Varying Nature of Herding Behavior

In this section, we examine the time-varying nature of herding behavior by implementing a rolling window regression of Equation (5) with a rolling window of 250 observations and a step of 10 observations.[1] Figure 1 depicts the rolling *t*-statistics of γ_2.

The figure illustrates the dynamic nature of herding with the *t*-statistics of γ_2 varying substantially throughout the sample period. Despite these variations over time, the figure also shows that the *t*-statistics in the case of the Estonian market fluctuated within the 5 % confidence interval most of the time, implying that herding and anti-herding were usually absent from that market and confirming the results obtained in section 4.1. The periods with herding behavior at statistically significant levels were fairly brief in all markets. On the other hand, anti-herding dynamics were more frequent, especially in the Latvian and Lithuanian stock markets, which is consistent with the results described in section 4.1.

Although the evolution of investor behavior in the three markets is not very synchronized, it is possible to identify some periods in which investors exhibited a similar behavior. For example, there was significant anti-herding behavior in the three Baltic markets in the first half of 2013, the second semester of 2017, and the last months of 2019.



[1] *In order to assess the adequacy of implementing a time-varying approach when studying herding behavior in the Baltic stock markets, we applied multiple structural breakpoint tests of Bai and Perron (2003) to Equation (5) in the case of the three data series. Following the Schwarz criteria, the tests detected 5, 3, and 5 structural breaks in the markets of Estonia, Latvia, and Lithuania, respectively. Thus, the results support the use of a time-varying approach in the Baltic stock markets. The results of these tests are available from the author upon request.*

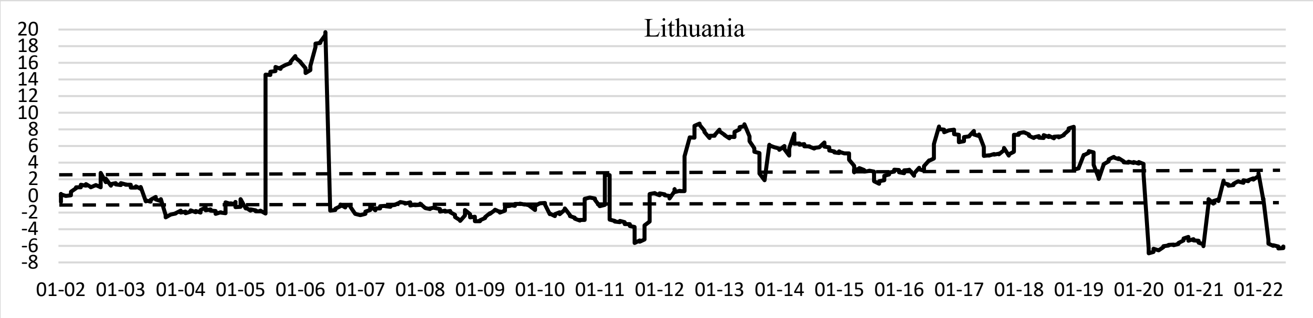


Figure 1. Rolling *t*-Statistics Based on a Rolling-Window Estimation of the CSAD Model (windows of 250 observations with a step of 10 observations)

Impact of the COVID-19 Pandemic on Herding Behavior

Table 6 reports the estimated coefficients of Equation (8), which examines the impact of the COVID-19 pandemic on herding behavior. γ_3 is shown to be negative and statistically significant in Estonia's and Lithuania's stock markets, implying that the level of herding observed during the pandemic in these markets was significantly stronger than that observed in the remaining periods of the sample. These results are similar to those obtained in the Indian and Australian stock markets by Dhall and Singh (2020) and Espinosa-Méndez and Arias (2021), respectively. On the other hand, our findings go against the conclusions of Wu *et al*. (2020), who found that during the COVID-19 pandemic, the herding behavior observed in the Chinese stock market was significantly less pronounced.

Table 6

The Impact of the COVID-19 Pandemic on Herding Behavior

$$\boldsymbol{CSAD_t = \gamma_0 + \gamma_1 . |R_{mt}| + \gamma_2 . R^2_{mt} + \gamma_3 . Covid_t . R^2_{mt} + \epsilon_t}$$

Variable	Estonia	Latvia	Lithuania
constant	0.0108*** (29.57)	0.0145*** (50.58)	0.0117*** (56.48)
$\lvert R_{mt}\rvert$	0.6404*** (8.02)	0.8050*** (28.97)	0.7645*** (22.49)
R^2_{mt}	3.1502 (1.15)	5.3244*** (12.82)	7.0216*** (12.09)
$Covid_t$	−7.1013*** (-3.97)	−0.4262 (-0.57)	−11.6451*** (-4.50)
Adjusted R^2	0.442	0.682	0.718

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. **: p < 0.05; ***: p < 0.01*

Cross-Country Effects on Herding Behavior

Table 7 examines the possibility of links in the cross-sectional dispersions across the three Baltic stock markets. The results strongly suggest significant cross-country effects in the herding behavior among the investors in the three Baltic stock markets. The superior explanatory power of these augmented models is reflected in the higher adjusted R^2 observed in Table 7 compared to the corresponding ones in Table 3. We document a positive and statistically significant relationship between cross-sectional dispersions across the three stock markets, being Estonia and Lithuania the countries with the strongest relationship.

Overall, the results concerning the existence of significant cross-country effects in the herding behavior of investors operating in the three stock markets suggest that it may be difficult to extract the desired benefits of international diversification in the Baltic region.

Table 7

Cross-Country Effects in Herding Behavior

$$\boldsymbol{CSAD_{it} = \gamma_0 + \gamma_1 . |R_{mt}| + \gamma_2 . R^2_{mt} + \sum \delta_j \, CSAD_{jt} + \epsilon_t}$$

Variable	Estonia	Latvia	Lithuania
constant	0.0097*** (20.75)	0.0132*** (29.53)	0.0102*** (29.95)
$\lvert R_{mt}\rvert$	0.6471*** (7.01)	0.7978*** (26.75)	0.7255*** (19.78)
R^2_{mt}	1.8782 (0.67)	5.2761*** (12.23)	6.9997*** (9.93)
$CSAD_{ESTONIA}$	-	0.0667*** (3.39)	0.0855*** (4.93)
	0.0163***	-	0.0114**

$CSAD_{LATVIA}$	(3.41)		(2.19)
$CSAD_{LITHUANIA}$	0.0333*** (3.37)	0.0166 (1.24)	-
Adjusted R^2	0.433	0.685	0.708

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. *: p < 0.10; **: p < 0.05; ***: p < 0.01*

Economic Determinants of Herding Behavior

Table 8 reports the estimation results of the economic determinants of herding behavior.

Table 8

Economic Determinants of Herding Behavior

$$CSAD_t = \gamma_0 + \gamma_1 . |R_{mt}| + \gamma_2 . R_{mt}^2 + \delta_j X_t + \epsilon_t$$

Variable	Estonia			Latvia				Lithuania				
constant	0.0107 ***	0.0107 ***	0.0107 ***	0.0107 ***	0.01449 ***	0.0145 ***	0.01456 ***	0.01456 ***	0.0117 ***	0.0117 ***	0.0117 ***	0.0117 ***
	(28.35)	(28.01)	(27.01)	(27.61)	(49.06)	(48.91)	(48.94)	(49.02)	(55.31)	(55.08)	(54.17)	(54.45)
$\|R_{mt}\|$	0.6639 ***	0.6503 ***	0.6583 ***	0.6492 ***	0.8128 ***	0.8119 ***	0.8189 ***	0.8181 ***	0.7619 ***	0.7476 ***	0.7553 ***	0.7473 ***
	(7.37)	(7.11)	(7.15)	(7.19)	(28.15)	(27.90)	(28.02)	(28.14)	(21.68)	(20.96)	(20.94)	(20.96)
R_{mt}^2	1.9272	1.9867	1.8050	2.0255	5.1631 ***	5.1599 ***	5.1198 ***	5.1359 ***	6.7755 ***	6.8404 ***	6.7642 ***	6.8889 ***
	(0.71)	(0.72)	(0.65)	(0.74)	(12.51)	(12.33)	(12.39)	(12.57)	(10.17)	(10.01)	(9.79)	(10.30)
$VSTOXX_t$	−0.0074 ***	-	-	−0.0076 ***	−0.0045	-	-	−0.0042	−0.0092 ***	-	-	−0.0093 ***
	(-3.83)			(-3.98)	(-1.43)			(-1.34)	(-3.83)			(-3.93)
$\Delta Euribor_t$	-	−0.0706 ***	-	−0.0688 ***	-	−0.0084	-	−0.0143	-	−0.0708 ***	-	−0.0702 ***
		(-5.61)		(-5.56)		(-0.39)		(-0.65)		(-3.39)		(-3.49)
$R_{S\&P500_t}^2$	-	-	0.5463*	0.3673	-	-	−0.9058	−0.9279	-	-	0.3486	0.1834
			(1.81)	(1.20)			(-1.39)	(-1.41)			(0.64)	(0.34)
Adjusted R^2	0.433	0.438	0.431	0.441	0.683	0.683	0.684	0.684	0.705	0.706	0.703	0.707

*Note: the table reports Newey-West consistent estimates. t-statistics in parentheses. *: p < 0.10; **: p < 0.05; ***: p < 0.01*

The coefficient of $VSTOXX_t$ is negative for all three markets but it is only statistically significant at the conventional significance levels in the cases of Estonia and Lithuania. These results confirm that as sentiment deteriorates, investors tend to follow the market consensus more closely and consequently, the herding behavior becomes more intense.

The coefficient associated with the 3-month Euribor interest rate variation is negative in the three markets but again only statistically significant for Estonia and Lithuania. These findings confirm that the macro-shock produced by increases in interest rates leads to a reduction in the stock returns' cross-section dispersion.

The coefficient associated with the squared lagged returns of the S&P500 index is shown to be statistically significant only for the Estonian market (statistical significance at the 10 % significance level). Contrary to what was expected, stock returns' cross-sectional dispersion increased on days characterized by extreme market movements in the US stock market. Therefore, we may conclude that this factor did not contribute to the development of herding behavior in the Baltic stock markets.

When all the three financial and economic factors are included in the same regression, the coefficients of $VSTOXX_t$ and $\Delta Euribor_t$ remain statistically significant in the Estonian and Lithuanian markets (statistical significance level of 1 %).

In conclusion, our results indicate that investor sentiment and funding conditions significantly influence the dynamics of herding behavior in the Estonian and Lithuanian stock markets. None of the financial and economic factors considered in our analysis presents a significant explanatory power on the evolution of herding behavior in the Latvian market.

Overall, our findings regarding the impact of the financial and economic variables in the markets of Estonia and Lithuania corroborate the results obtained by Economou *et al.* (2011) for the stock markets of Portugal, Greece, Spain, and Italy.

Conclusions

In this paper, we conducted a thorough investigation of market-wide herding behavior in the stock markets of Estonia, Latvia, and Lithuania. We used a survivor-bias-free dataset of daily stock returns from January 2001 to June 2022, employing the CSSD and CSAD approaches proposed by Christie and Huang (1995) and Chang *et al.* (2000), respectively. The institutional features of the markets in question (limited market capitalizations and trade volumes, restrictions on information flows, small number of institutional investors) provide an interesting setting in which to study behavioral effects.

Our results can be summarized as follows. First, we detected strong signs of anti-herding in the Latvian and Lithuanian stock markets in the whole sample period. The results for the Estonian market are not homogeneous among the methodologies: while the CSAD approach indicates that herding and anti-herding were absent from the market, the CSSD-based model signals the occurrence of anti-herding. Second, our results highlight the importance of including both active and dead stocks in the sample, so that the database is free of survivorship bias. In fact, had we not included the delisted stocks in our analysis, the anti-herding detected in the Lithuanian market would have been replaced by the finding of significant herding. Third, the Estonian market is the only one in which herding has an asymmetric behavior, as the phenomenon tends to be more pronounced when the market performance is negative. Fourth, herding behavior is found to exhibit a distinct time-varying nature, according to the results of the rolling window regressions, with the COVID-19 pandemic significantly increasing the intensity of the effect in the Estonian and Lithuanian markets in the most recent sample period. Fifth, significant cross-country effects were observed in all markets, and in particular between Estonia and Lithuania. Finally, more pessimistic investors in periods of less favorable financing conditions exhibit stronger levels of herding in the Estonian and Lithuanian markets.

Overall, the finding of significant anti-herding in Latvian and Lithuania and the cross-country effects observed in the three stock markets under analysis suggest that extracting the desired benefits of international diversification in the Baltic region may be difficult. This concern is particularly justified in the case of investors operating in the stock market of Estonia, as in this country the dynamics of herding have been found to exhibit an asymmetric nature, with the opportunities for diversification becoming more limited in periods of market losses, that is when diversification is most needed. Thus, our evidence advises investors in the Baltic countries to hold a larger number of assets to achieve the desired reduction of idiosyncratic risk via diversification.

Our results also suggest that financial regulators should maintain their focus on the Baltic stock markets to enhance market efficiency, which is essential for attracting additional investors and strengthening the resilience of the financial system. Policies aimed at increasing market transparency and integrity—such as initiatives to improve investors' financial literacy or encourage greater participation by well-informed market participants, such as institutional investors—appear advisable. Such measures could promote more frequent alignment of investor behavior with the predictions of rational asset pricing models.

In future research on the Baltic stock markets, it would be interesting to compare our findings with those from different methodologies, including tests of herding that use trading data. Additionally, it would be valuable to investigate whether the observed anti-herding behavior persists during periods of high and low trade volumes. Moreover, analyzing the potential impact of geopolitical events, such as the recent Russian aggression on Ukraine, on herding or anti-herding tendencies in these markets could add depth to the understanding of investor behavior under varying external pressures.

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