Journal of Behavioral and Experimental Finance 38 (2023) 100810

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Intentional and spurious herding behavior: A sentiment driven analysis☆

Angela Maria Filip, Maria Miruna Pochea *

Department of Finance, Babeş-Bolyai University, Cluj-Napoca, Romania

ARTICLE INFO

Article history:
Received 10 August 2022
Received in revised form 4 April 2023
Accepted 12 April 2023
Available online 18 April 2023

JEL classification:
G40
G41
G15
G14

Keywords:
Herding behavior
Thomson Reuters MarketPsych Indices (TRMI)
Investors' sentiments
Cross-sectional standard deviation of betas
Cross-sectional absolute deviation of returns

ABSTRACT

By using several Thomson Reuters MarketPsych Indices, this paper explores the nexus between investors' sentiments and herding behavior in the U.S. and Europe stock markets from January 2005 to June 2021. We apply the state–space model approach of Hwang and Salmon (2004), controlling for changes in investors' emotionality, and document that herding is a persistent phenomenon in both markets. These effects remain robust when using the alternative methodology of Chang et al. (2004). Moreover, we find evidence of herding behavior under both extreme positive and negative sentiments, with a conspicuous effect on euphoria days, particularly in the U.S. market.

1. Introduction

The influence of investors' emotionality on market dynamics and investment decisions has increased during recent decades (Gan et al., 2020; Siganos et al., 2014; Sun et al., 2016; Tetlock, 2007). Additionally, the pandemic has boosted the use of digital technologies in investment decision-making. Moreover, given the abundance of information provided by various news outlets, investors are more sensitive to news and social media. The importance of sentiments for assets pricing and financial markets dynamics is well documented in the literature. For instance, Brown and Cliff (2005) and Baker and Wurgler (2006) pave the way for new asset pricing models designed to accommodate the role of investors' sentiment. In terms of market dynamics, most empirical papers provide evidence that sentiments increase the linkages between markets (e.g., Fang et al., 2018; Niţoi and Pochea, 2020).

In this paper, we contribute to the literature by studying the incidence of sentiments on herding behavior in two of the most important stock markets in the world, the U.S. and European market, by using a valuable dataset for investor sentiment i.e., Thomson Reuters MarketPsych Indices (TRMI),[1] derived from news and social media. An important benefit of TRMI indices is that they cover a large variety of assets, countries, and they are available in high frequency. In contrast, the more popular index of Baker and Wurgler is available only for the U.S. market with monthly frequency.

Considering the importance of herding in driving prices further and further from their intrinsic value, many researchers turned their attention to studying it. With respect to stock markets, most of the studies are focused on investigating herding under extreme market conditions such as crisis periods, bullish/bearish markets, high/low volatility or high/low trading volume (e.g., Mobarek et al., 2014; Pochea et al., 2017; Espinosa-Méndez and Arias, 2020; Duygun et al., 2021; Ferreruela and Mallor, 2021; Rubesam and Raimundo Júnior, 2022). However, the relationship between herding behavior and market sentiment is still scarcely explored (Bekiros et al., 2017; Jia et al., 2022).

☆ This paper was supported by a grant of the Ministry of Research, Innovation and Digitization, CNCS - UEFISCDI, project number PN- III-P1-1.1-TE-2019-1702, within PNCDI III. M.M. Pochea acknowledges past financial support from Babeş-Bolyai University, project number GTC-31376/1.04.2020.

* Corresponding author.
E-mail addresses: angela.filip@econ.ubbcluj.ro (A.M. Filip), miruna.pochea@econ.ubbcluj.ro (M.M. Pochea).

[1] We are grateful to Refinitiv Eikon for providing the data.

https://doi.org/10.1016/j.jbef.2023.100810

Our empirical analysis consists in testing herding behavior towards the market consensus by using daily and monthly market data. Next, we offer an overview of the studies that use a similar methodology and are related to the presence of herding in the U.S. and European markets. In their pioneering work in studying herding behavior, Christie and Huang (1995) test for the presence of this bias on the U.S. equity market by examining the relationship between the cross-sectional standard deviation of returns (CSSD) and the market return, finding that periods of extreme market stress do not induce herding among investors. Further, Chang et al. (2000) propose the cross-sectional absolute deviation of returns (CSAD) methodology and examine the incidence of herding behavior on various international markets. Their results confirm the findings of Christie and Huang (1995), providing evidence against the presence of herding behavior in the U.S., Hong Kong, and Japan.

Concerning the European landscape, there are several studies focused both on developed markets (Economou et al., 2011; Mobarek et al., 2014; Espinosa-Méndez and Arias, 2020) and developing and emerging markets (Pochea et al., 2017). The empirical findings are mixed, with a conspicuous presence of herding during the global financial crisis. However, the CSAD methodology unveils some limitations. First, it is a static model that renders a verdict on the existence of herding behavior in a certain market, for a specific period of time. Second, as Bohl et al. (2017) demonstrate, Chang et al. (2000) methodology is biased against detecting evidence in favor of herding. Finally, even if there are some attempts to capture investors' reaction to the fundamental information (Galariotis et al., 2015; Duygun et al., 2021), the CSAD methodology does not accurately control for changes in fundamentals, making it difficult to differentiate spurious herding from movements triggered by sentiment news that influence fundamentals (Rubesam and Raimundo Júnior, 2022). Therefore, to mitigate these drawbacks, in this paper we will examine the impact of investors' sentiments on herding behavior by using the beta herding approach and state–space methodology proposed by Hwang and Salmon (2004). In their view, herding refers to abandoning private information and mimicking the decisions of other investors without reference to fundamental information. This form of herding is termed in the literature as intentional herding (Bikhchandani and Sharma, 2000). The beta herding methodology is based on the assumption that the time variability of betas is the effect of changes in market sentiment, rather than changes in fundamental information (which is unlikely to occur over short periods of time). This methodology allows us to control for the effects of fundamentals, such as market and macroeconomic variables. Moreover, Hwang and Salmon (2004) state–space model succeeds in capturing the dynamic nature of herding behavior.

Our empirical framework is designed as follows. First, we investigate the presence of herding behavior in the U.S. and Europe stock markets by using the state–space model approach and including in our signal equation the most significant market variables (the market excess return and the volatility of the market portfolio), Fama and French (1995, 1996) and Carhart (1997) factors, the Amihud (2002) illiquidity ratio, and two macroeconomic variables i.e., term spread and credit spread. Our empirical findings confirm the presence of the latent herding measure in both markets, regardless of the control variables added. Second, we construct several state–space models by also considering the TRMI sentiment indicators as behavioral variables. By doing so, we aim to test whether the latent herding coefficient remains significant when investors' emotions change. The results reveal that herding behavior is persistent irrespective of the sentiment indicator included in the model. In Europe the coefficients of the sentiment indicators are not statistically significant in any of the models, while in the U.S. all models exhibit significant sentiment coefficients. Third, we follow the approach of Hwang et al. (2021) and estimate the cross-sectional variance of standardized betas which we further regress with market state variables, as well as the TRMI sentiment measures. This new measure of beta herding solves the drawback of heteroscedasticity in the estimation errors. By performing OLS regressions, we find that the behavioral variables play a significant role on the herding behavior phenomenon. Fourth, to compare the results obtained with the beta herding model, we also use the CSAD methodology of Chang et al. (2000). Motivated by the approach of Galariotis et al. (2015) who differentiate spurious from intentional herding, we isolate the CSAD driven by sentiment. Our empirical evidence proves that European and American investors are influenced by sentiments in following the market consensus. Finally, we investigate the impact of euphoria and dysphoria i.e., extreme positive and extreme negative sentiments on herding behavior. We document the presence of herding behavior under extreme sentiments in both markets.

Our paper contributes to the flourishing literature on herding behavior in stock markets by examining the relationship between sentiment indicators and herding behavior. For reaching our goal, we use a unique dataset of textual sentiment indicators for estimating herding i.e., TRMI sentiment indices. Another important contribution is the analysis of the asymmetric effects of extreme sentiments on herding behavior.

The rest of the paper is organized as follows: Section 2 presents the testing methodologies; in Section 3 we describe the dataset; Section 4 reports and discusses the results; Section 5 provides the concluding remarks.

2. Methodology

In this paper, we investigate the impact of investors' sentiment on intentional herding behavior based on two of the most prominent methodologies intended to capture this phenomenon: the beta herding methodology proposed by Hwang and Salmon (2004) and, for comparison reasons, the CSAD methodology developed by Chang et al. (2000).

2.1. Investors' sentiments and beta herding

In Hwang and Salmon (2004) approach, the sentiment-driven herding is reflected by biased betas and a cross-sectional variance of individual betas lower than its equilibrium value. At equilibrium, the CAPM has the following relation, with beta coefficients stable over time:

$$E_t(R_{it}) = \beta_{it} \cdot E_t(R_{mt}) \tag{1}$$

where R_{it}, R_{mt} are the excess return of security i and the excess return of the market portfolio m at time t.

Given the vast empirical evidence on the time variability of the beta coefficients, Hwang and Salmon (2004) argue that a significant proportion of this variation is driven by investors' sentiments. Under this assumption, herding occurs when investors' decisions concentrate on matching individual assets' return with the return of the market portfolio, further than it would be expected at equilibrium. When herding towards the market occurs, the following model is expected to hold:

$$\frac{E_t^b(R_{it})}{E_t(R_{mt})} = \beta_{it}^b = \beta_{it} - h_t(\beta_{it} - 1) \tag{2}$$

where $E_t^b(R_{it})$ and β_{it}^b are the biased conditional expectations on the excess return on security i and on its beta coefficient at time t and $h_t \leq 1$ is a latent time varying parameter which captures the magnitude of herding.

$$When \begin{cases} h_t < 0, \text{there is adverse herding in the market;} \\ h_t = 0, \\ \text{ there is no evidence of herding towards the market;} \\ 0 < h_t < 1, \text{there is a certain level of herding;} \\ h_t = 1, \\ \text{ there is perfect herding towards the market portfolio.} \end{cases}$$

As the cross-sectional mean of betas (β_{it} and β_{it}^b) is constantly 1, the cross-sectional variance and standard deviation of betas are as follows:

$$V_{\beta_{it}^b}^{CS} = E^{CS}(\beta_{it} - h_t\,(\beta_{it} - 1) - 1)^2 = V_{\beta_{it}}^{CS}(1 - h_t)^2 \tag{3}$$

$$\sigma_{\beta_{it}^b}^{CS} = \sigma_{\beta_{it}}^{CS}(1 - h_t) \tag{4}$$

where E^{CS}, V^{CS}, and σ^{CS} represent the cross-sectional expectation, variance, and standard deviation, respectively.

As $\sigma_{\beta_{it}}^{CS}$ is not expected to fluctuate significantly over short periods of time, changes in the $\sigma_{\beta_{it}^b}^{CS}$ are assumed to be the consequence of herding behavior towards the market portfolio.

With a logarithmic transformation, Eq. (4) becomes:

$$\log(\sigma_{\beta_{it}^b}^{CS}) = \log\left(\sigma_{\beta_{it}}^{CS}\right) + \log(1 - h_t) \tag{5}$$

Under the assumption that $\sigma_{\beta_{it}}^{CS}$ is not affected by systematic change, $\log\left(\sigma_{\beta_{it}}^{CS}\right) = \mu + \varepsilon_{1t}$, where $\mu = E(\log\left(\sigma_{\beta_{it}}^{CS}\right))$ and $\varepsilon_{1t} \sim iid(0, \sigma_{\epsilon 1}^2)$. By denoting a latency herding variable $H_t = \log(1-h_t)$, and allowing it to follow a dynamic process $AR(-1)$, the following standard state–space model can be specified:

$$\text{Model (1)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{6}$$

where $\varepsilon_{2t} \sim iid(0, \sigma_{\epsilon 1}^2)$.

To confirm the presence of herding three conditions should be simultaneously satisfied: the herding process H_t should be stationary, while θ and $\sigma_{\epsilon 2}^2$ should be statistically significant.

To test for the robustness of the beta herd measure extracted from $\sigma_{\beta_{it}^b}^{CS}$ when controlling for various market and macroeconomic variables, we estimate the following state–space models[2]:

$$\text{Model (2)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{7}$$

where $\log(\sigma_{mt})$ and R_{mt} are the monthly excess returns and log-standard deviation of the market portfolio, both being introduced in order to control for the state of the market.

Model (3) adds three market factors to Model (2): the size factor and the book-to market factor of Fama and French (1995, 1996) three factor model and the momentum factor of Carhart (1997).

$$\text{Model (3)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \beta_3 \cdot SMB_t + \beta_4 \cdot HML_t + \beta_5 \cdot MOM_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{8}$$

where SMB_t is the small minus big factor (the size premium), HML_t the high-minus-low factor (the value premium), and MOM_t is the momentum factor.

$$\text{Model (4)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \beta_3 \cdot TS_t + \beta_4 \cdot CS_t + \beta_5 \cdot ILL_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{9}$$

where TS_t is the change in term spread, CS_t is the credit spread and ILL_t is the illiquidity measure. This specification allows us to control whether H_t remains significant when macroeconomic variables are added in the model.

The following state–space models include the TRMI indicators as control variables. By introducing these behavioral variables, we want to test whether the herd measure is still robust when controlling for investors' sentiments. The hypothesis of the model is that short-term changes in the cross-sectional deviation of betas are induced by sentiments and herding rather than fundamentals.

$$\text{Model (5)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \beta_3 \cdot SI_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{10}$$

Model (5) is an extension of Model (2) which adds the sentiment indicator SI_t to the market state variables, $\log(\sigma_{mt})$ and R_{mt}.

$$\text{Model (6)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \beta_3 \cdot SMB_t + \beta_4 \cdot HML_t + \beta_5 \cdot SI_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{11}$$

Model (6) is a state–space model with exogenous market state variables including the Fama and French (1995, 1996) three factors, the volatility of the market portfolio and the sentiment indicator SI_t.

$$\text{Model (7)}: \log(\sigma_{\beta_{it}^b}^{CS}) = \mu + H_t + \beta_1 \cdot R_{mt} + \beta_2 \cdot \log(\sigma_{mt}) + \beta_3 \cdot TS_t + \beta_4 \cdot CS_t + \beta_5 \cdot ILL_t + \beta_3 \cdot SI_t + \varepsilon_{1t} \qquad H_t = \theta \cdot H_{t-1} + \varepsilon_{2t} \tag{12}$$

Model (7) is an extension of Model (4) which adds a sentiment indicator SI_t to the market state variables and the macroeconomic control variables.

In a recent paper, Hwang et al. (2021) show that investors' overconfidence (under-confidence) about market perspectives drives expected returns and betas of individual securities towards (away from) their cross-sectional means. The authors use the cross-sectional variance of standardized betas as a herding measure and explain co-movements in assets returns and risk through overconfidence. By standardizing betas, the heteroscedasticity of idiosyncratic estimation errors is eliminated. To minimize the impact of nonsynchronous price movements, the authors follow Lewellen and Nagel (2006) and estimate beta based on the regression:

$$R_{it} = \alpha_i + \beta_{i0} \cdot R_{mt} + \beta_{i1} \cdot R_{mt-1} + \beta_{i2} \cdot [(R_{mt-2} + R_{mt-3} + R_{mt-4})/3] + \epsilon_{it} \tag{13a}$$

The estimated beta is computed as the sum of the estimated coefficients of level and lagged returns:

$$\hat{\beta}_i = \hat{\beta}_{i1} + \hat{\beta}_{i2} + \hat{\beta}_{i3} \tag{13b}$$

[2] This approach is in line with Hwang and Salmon (2004), Raimundo Júnior et al. (2022), and Rubesam and Raimundo Júnior (2022).

The cross-sectional variance of standardized betas is computed as follows:

$$V_{norm}^{CS}(\beta_{it}^{b}) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\hat{\beta}_{it}^{b} - \overline{\hat{\beta}_{it}^{b}}}{\hat{\sigma}_{\widehat{\beta_{it}^{b}}}}\right)^2 \tag{14}$$

The new measure allows for the dynamic of beta herding to be compared over different periods of time.[3] To analyze the relationship between investors sentiment and herding we regress the cross-sectional variance of standardized betas on our sentiment indicators and market state control variables.

$$\text{Model (8)}: V_{norm}^{CS}\left(\beta_{it}^{b}\right) = \alpha + \beta_1 \cdot V_{norm}^{CS}\left(\beta_{it-1}^{b}\right) + \beta_2 \cdot R_{mt} + \beta_3 \cdot \log\left(\sigma_{mt}\right) + \beta_4 \cdot SI_t + \varepsilon_t \tag{15}$$

where $V_{norm}^{CS}\left(\beta_{it-1}^{b}\right)$ is a lag variable added in order to control for the persistence of the herding measure.

2.2. The CSAD methodology

An alternative methodology for detecting herding behavior toward the market consensus is the CSAD model proposed by Chang et al. (2000). The CSAD variable measures the returns' dispersion and it is calculated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \tag{16}$$

where R_{it} is the return of company i at time t and R_{mt} is the return of the market at time t.

For computing the CSAD, we first calculate the daily logarithmic rates of returns for all companies and equity market indices by using the relationship $R_{i,t} = ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ represents the closing price of day t for stock/index i. Next, for detecting herding behavior, we run the following regression proposed by Chang et al. (2000):

$$CSAD_t = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \varepsilon_t \tag{17}$$

The financial reasoning of this model lies in the CAPM, which assumes that if investors act as rational homo economicus men i.e., they are fully rational, the stocks return dispersion is linearly related to the market return. We can expect that CSAD will decrease or increase at a lower rate than the market return during periods of high fluctuations. In this case, herding behavior is detected and the coefficient β_2 is negative and statistically significant.

Further, we aim to see if there is herding behavior due to fundamental information (spurious) or to sentiment. Spurious herding occurs when a group of investors make analogous decisions because they face a similar informational context (Bikhchandani and Sharma, 2000), while sentiment herding arises when investors mimic the decisions of others driven by their sentiments. Inspired by Galariotis et al. (2015), we decompose the CSAD into the CSAD driven by fundamental information and the CSAD driven by sentiment. For capturing the reaction to fundamental information, we use the Fama and French (1995, 1996) and Carhart (1997) factors, while for the reaction to sentiment, we use the TRMI sentiment index. In this line, we estimate the following regression model:

$$CSAD_t = \beta_0 + \beta_1 \cdot \left(R_{mt} - R_{ft}\right) + \beta_2 \cdot HML_t + \beta_3 \cdot SMB_t + \beta_4 \cdot MOM_t + \beta_5 \cdot SI_t + \varepsilon_t \tag{18}$$

where R_{mt} is the total return of market portfolio at time t, R_{ft} is the risk-free rate at time t, $\left(R_{mt} - R_{ft}\right)$ is the equity market premium, HML_t is the high-minus-low factor, SMB_t is the small minus big factor, MOM_t is the momentum factor, and SI_t is the sentiment index.

Further, we compute the cross-sectional absolute deviation of returns driven by sentiment information as:

$$CSAD_{sentiment,t} = \widehat{\beta_5} \cdot SI_t \tag{19}$$

Therefore, the investors' reaction due to fundamental information is:

$$CSAD_{fundamental,t} = CSAD_t - CSAD_{sentiment,t} - \varepsilon_t \tag{20}$$

Finally, for detecting spurious and intentional herding behavior, we estimate the following regressions:

$$CSAD_{fundamental,t} = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \varepsilon_t \tag{21}$$

$$CSAD_{sentiment,t} = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \varepsilon_t \tag{22}$$

To study the nexus between extreme sentiment conditions and herding behavior, we follow Jia et al. (2022) and we specify the following model:

$$CSAD_t = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \beta_3 \cdot D_{ESt} + \beta_4 \cdot {R_{mt}}^2 \cdot D_{ESt} + \varepsilon_t \tag{23}$$

For the filtered TRMI sentiments, we define a dummy variable to capture the effects of extreme positive sentiment (euphoria) and extreme negative sentiment (dysphoria) on herding behavior. Specifically, when the market is characterized by euphoria, D_{ES} takes the value *1* if the sentiment index value from one day is placed in the highest 5% of the sentiment index distribution and *0* otherwise. On the other hand, for dysphoria on the market, D_{ES} takes the value *1* if the sentiment index value from one day is placed in the lowest 5% of the sentiment index distribution and *0* otherwise. To avoid the look-ahead bias, we define dummy variables for extreme sentiment conditions by considering only the information available prior to each day. If $\beta_3 + \beta_4 < 0$ is negative and statistically significant, then extreme sentiments enhance herding behavior.

In addition to the standard OLS estimation method, we use the quantile regression method for a more insightful analysis. This approach is more appropriate than the OLS in scrutinizing the dispersion of the returns in the distribution tails. The quantile regression model for estimating herding behavior through the CSAD methodology is expressed as follows:

$$Q_\tau\left(\tau|CSADt\right) = \beta_{0\tau} + \beta_{1\tau} \cdot |R_{mt}| + \beta_{2\tau} \cdot {R_{mt}}^2 + \varepsilon_{t,\tau} \tag{24}$$

$CSAD_t$ represents the cross-sectional absolute deviation of returns of quantile τ, where $\tau \in (0, 1)$. The linear parameters are estimated by minimizing the weighted sum of absolute errors and the weights are attributed according to each quantile.

3. Data

Table 1 presents the variables used in this paper.

The dataset for estimating herding behavior comprises the daily and monthly closing price of the equity market indices, S&P 500 and Stoxx 600, and for the constituent companies from January 3, 2005 to June 30, 2021. The S&P 500 includes 500 large companies traded in the American stock exchanges and it captures, according to Bloomberg, approximately 80% of the free-float market capitalization of the American markets. Stoxx 600 comprises 600 companies among 17 European countries and it covers approximately 90% of the available market capitalization of the European markets. However, we construct a survivorship-bias-free dataset by searching the joiners and leavers between January 2005 and June 2021. Therefore, our sample accounts

[3] The same measure has been adopted by Raimundo Júnior et al. (2020), Raimundo Júnior et al. (2022), and Rubesam and Raimundo Júnior (2022).

Table 1
Variables description.

Variable	Description	Source
Daily and monthly returns of stock market indices	$R_{m,t} = ln(P_t/P_{t-1})$ for market m on day/month t. The stock market indices are S&P 500 and Stoxx 600.	Refinitiv Eikon
Daily and monthly returns of companies	$R_{i,t} = ln(P_t/P_{t-1})$ for company i on day t. The companies are the constituents of S&P 500 and Stoxx 600.	Refinitiv Eikon
$\log(\sigma_m)$	The log of the monthly standard deviation of the market portfolio.	Authors' estimates
TS	The monthly term spread is the difference between the U.S. (European) 10-year Treasury bond rate and the U.S. (European) 1-year Treasury bond rate.	FRED and ECB websites
CS	The monthly credit spread is the difference between the rate on the U.S. (European) Moody's AAA and BAA rated corporate bonds.	FRED and ECB websites
ILL	The monthly illiquidity measure computed based on Amihud (2002).	Authors' estimates based on Refinitiv Eikon data
$\sigma^{CS}_{1\beta^b_{it}}$	The cross-sectional standard deviation of the betas computed as: $\widehat{\sigma_1}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\hat{\beta}^b_{it} - \overline{\hat{\beta}^b_{it}}\right)^2\right]^{\left(\frac{1}{2}\right)}$, based on the OLS beta coefficients from the market model using daily data within each month.	Authors' estimates
$\sigma^{CS}_{2\beta^b_{it}}$	The cross-sectional standard deviation of the betas computed as: $\widehat{\sigma_2}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\hat{\beta}^b_{it} - \overline{\hat{\beta}^b_{it}}\right)^2\right]^{\left(\frac{1}{2}\right)}$, where betas are obtained by estimating the following regression: $R_{it} = \alpha_i + \beta_{i0}\cdot R_{mt} + \beta_{i1}\cdot R_{mt-1} + \beta_{i2}\cdot[(R_{mt-2} + R_{mt-3} + R_{mt-4})/3] + \epsilon_{it}$. The estimated beta is computed as follows: $\hat{\beta}_i = \hat{\beta}_{i1} + \hat{\beta}_{i2} + \hat{\beta}_{i3}$.	Authors' estimates
$\sigma^{CS}_{3\beta^b_{it}}$	The cross-sectional standard deviation of the standardized betas computed as: $\widehat{\sigma_3}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\frac{\hat{\beta}^b_{it} - \overline{\hat{\beta}^b_{it}}}{\hat{\sigma}_{\widehat{\beta^b_{it}}}}\right)^2\right]^{\left(\frac{1}{2}\right)}$.	Authors' estimates
$V^{CS}_{norm}\left(\beta^b_{it}\right)$	The variance of the standardized betas computed as: $V^{CS}_{norm}(\beta^b_{it}) = \frac{1}{N_t}\sum_{i=1}^{N}\left(\frac{\hat{\beta}^b_{it} - \overline{\hat{\beta}^b_{it}}}{\hat{\sigma}_{\widehat{\beta^b_{it}}}}\right)^2$	Authors' estimates
$CSAD_t$	The cross-sectional absolute deviation of returns at time t computed as: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\lvert R_{it} - R_{mt}\rvert$.	Authors' estimates
$R_{mt} - R_{ft}$	The equity market premium factor.	Kenneth French's online data library
HML	The high-minus-low factor.	Kenneth French's online data library
SMB	The small minus big factor.	Kenneth French's online data library
MOM	The momentum factor.	Kenneth French's online data library
$CSAD_{sentiment,t}$	The cross-sectional absolute deviation of returns due to nonfundamental information at time t computed as: $CSAD_{sentiment,t} = \widehat{\beta_5}\cdot SI_t$ estimated from $CSAD_t = \beta_0 + \beta_1\cdot\left(R_{mt} - R_{ft}\right) + \beta_2.HML_t + \beta_3\cdot SMB_t + \beta_4\cdot MOM_t + \beta_5\cdot SI_t + \varepsilon_t$.	Authors' estimates
$CSAD_{fundamental,t}$	The cross-sectional absolute deviation of returns due to fundamental information at time t computed as: $CSAD_{fundamental,t} = CSAD_t - CSAD_{sentiment,t} - \varepsilon_t$	Authors' estimates
Sent	*Sentiment* score for MPTRXUS500/ MPTRXEU50 company group indices measures the overall positive references, net of negative references. It ranges between −1 and 1.	Authors' estimates based on Refinitiv Eikon data
Bubble	*Market risk* score for MPTRXUS500/ MPTRXEU50 company group indices measures the positive emotionality and positive expectations net of negative emotionality and negative expectations. It includes factors from social media found characteristic of speculative bubbles — higher values indicate greater bubble risk. It ranges between −1 and 1.	Authors' estimates based on Refinitiv Eikon data
Fear	Fear score for MPTRXUS500/ MPTRXEU50 company group indices measures the fear and anxiety. It ranges between 0 and 1.	Authors' estimates based on Refinitiv Eikon data

860 companies for the U.S. and 1416 companies for Europe. The data were extracted from Refinitiv Datastream and Eikon and are denominated in USD.

The data for the equity market premium, value premium, size premium, and momentum factor were extracted from Kenneth R. French's online data library. For computing the illiquidity

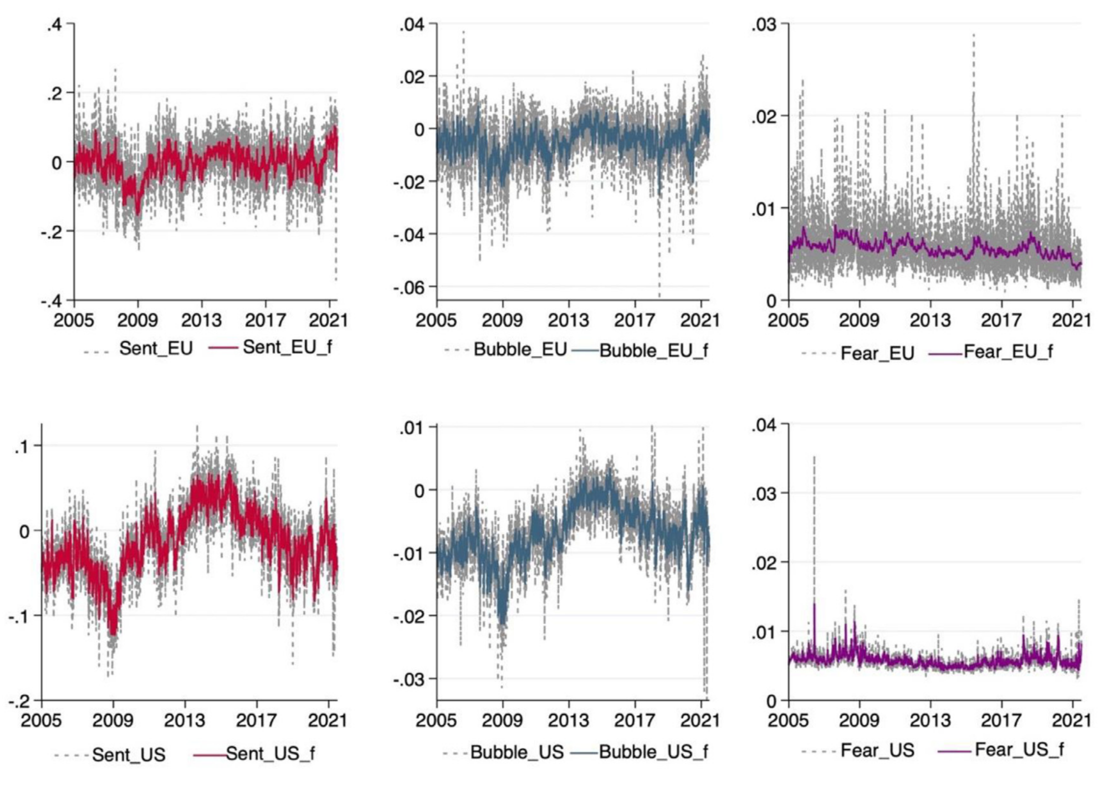

Fig. 1. News and social media sentiment scores for MPTRXEU50 and MPTRXUS500 and the filtered sentiment scores.

measure, we extracted the daily trading volumes and market capitalization for each company from Refinitiv Eikon. The term spread is calculated as the difference between the 10-year Treasury bond rate and the 1-year Treasury bond rate. The monthly data were obtained from the Federal Reserve Economic Data (FRED) and European Central Bank (ECB) websites. The monthly credit spread is computed as the difference between Moody's AAA and BAA rated corporate bonds' yields, based on the data downloaded from FRED website.

Market sentiment is quantified through various approaches in financial literature. For example, Brown and Cliff (2005) built a sentiment measure based on a survey. A popular index in the literature is the one proposed by Baker and Wurgler (2006) who define sentiment as the first principal component of six market variables: closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, equity share in new issues, and dividend premium. Other proxies for market sentiment are the CBOE Volatility Index (VIX) or technical analysis indices such as Relative Strength Indicator, Relative Volatility Indicator, Fear and Greed, Psychological Line Index etc.

The outbreak of online text data and the growing computational power that have started during the last decade fueled a new research branch in the market sentiment literature i.e., indicators based on textual analysis (see Kearney and Liu, 2014). In this paper, we use the TRMI indices as measures of sentiments. The sentiment indices were obtained from Refinitiv Eikon. We collected daily data for MPTRXUS500 and MPTRXEU50 company group indices. TRMI provides various emotional scores for each asset, of which we choose *Sentiment, Market Risk,* and *Fear*. The *Sentiment* score quantifies the overall positive references, net of negative references related to the constituents of S&P 500 and Stoxx 50, respectively. The *Market risk* score, which is also known as the 'Bubbleometer', captures positive emotionality and expectations net of negative emotionality and expectations. As the *Market risk* score includes factors specific to speculative bubbles, higher values indicate greater bubble risk. Due to its meaning and to avoid any confusion with the standard concept of market risk, hereafter we will call this indicator *Bubble*. Finally, the *Fear* score measures the fear and anxiety of investors. The selection of these scores is driven by their relevance in making investment decisions. Additionally, we aim to cover both positive perceptions of investors, as well as the negative ones.

TRMI scores are generated by extracting information from news and social media about the asset of interest with natural language processing techniques. An important concern when working with textual sentiment measures is that they might be exposed to noise. In order to mitigate this issue, we filter the raw TRMI indices by applying a Kalman filter to daily TRMI series (see Fig. 1). Therefore, we consider the approach of Borovkova et al. (2017) and extract the signal from the noisy data by describing a Local Sentiment Level model, which is a special case of a state–space model. Following Borovkova et al. (2017) and Audrino et al. (2020), we define the following equations:

$$y_t = \mu_t + \varepsilon_t, \varepsilon_t \sim NID(0, \sigma_\varepsilon^2), \tag{25}$$

$$\mu_{t+1} = \mu_t + \eta_t, \eta_t \sim NID(0, \sigma_\eta^2) \tag{26}$$

The first equation is the observation equation, where y_t is the observed (noisy) sentiment index at time t. The second equation represents the state equation and it describes the evolution of unobserved sentiment μ_t, which is assumed to be a random walk. The filtered sentiment is obtained by calculating the conditional mean $E(\mu_t|y_1, \dots, y_t)$ using the Kalman filter. Given the one-step ahead state conditional mean, we obtain the minimum mean square error one-step ahead estimate of y_t.

In this filtering procedure, the unobserved sentiment is updated each time a new observation arises.

Table 2
Descriptive statistics.

		Panel A: Europe			Panel B: U.S.		
Variable	Nb. of obs.	Mean	Std. Dev.	ADF	Mean	Std. Dev.	ADF
$\sigma^{CS}_{1\beta^b_{it}}$	198	0.6131	0.1753	−6.2994***	0.6939	0.2358	−11.2394***
$\sigma^{CS}_{2\beta^b_{it}}$	198	1.0899	0.4898	−8.4325***	1.1801	0.4954	−8.5564***
$\sigma^{CS}_{3\beta^b_{it}}$	198	0.9229	0.3522	−8.0048***	0.9095	0.3637	−8.2111***
$\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$	198	−0.5256	0.2652	−5.8718***	−0.4155	0.3125	−10.4231***
$\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$	198	0.0101	0.3769	−7.4192***	0.0866	0.3946	−7.9399***
$\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$	198	−0.1439	0.3522	−7.5378***	−0.1687	0.3843	−7.5931***
$V^{CS}_{norm}(\beta^b_{it})$	198	0.9753	0.8768	−8.9641***	0.9587	0.8399	−9.0295***
h_t	197	−0.0084	0.0939	−3.7172***	0.0039	0.1373	−2.9979**
Sent	198	−0.0137	0.0341	−4.8104***	−0.0220	0.0412	−3.1210**
Bubble	198	−0.0057	0.0045	−4.2635***	−0.0078	0.0048	−3.8044***
Fear	198	0.0056	0.0009	−3.0441**	0.0059	0.0007	−6.6197***
CSAD	4255	0.0134	0.0051	−6.5270***	0.0125	0.0061	−5.9001***

Notes: *** and ** denote statistical significance at the 1% and 5% level.

4. Empirical results

4.1. Results of the beta herding models

First, we estimate the OLS beta coefficients from the market model using daily data within each month for both markets and we compute the cross-sectional standard deviation of estimated betas (BH1): $\widehat{\sigma_1}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\hat{\beta}^b_{it}-\overline{\hat{\beta}^b_{it}}\right)^2\right]^{\left(\frac{1}{2}\right)}$.

Second, we estimate betas by running Eq. (13), following the approach of Lewellen and Nagel (2006), Hwang et al. (2021), Raimundo Júnior et al. (2020), Raimundo Júnior et al. (2022), and Rubesam and Raimundo Júnior (2022). Our second beta herding measure (BH2) is the cross-sectional standard deviation of the resulting betas computed as: $\widehat{\sigma_2}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\hat{\beta}^b_{it}-\overline{\hat{\beta}^b_{it}}\right)^2\right]^{\left(\frac{1}{2}\right)}$.

Third, we standardized betas as suggested by Hwang et al. (2021) in order to eliminate the heteroscedasticity of idiosyncratic estimation errors and we compute the cross-sectional standard deviation (BH3) as $\widehat{\sigma_3}^{CS}_{\hat{\beta}^b_{it}} = \left[\frac{1}{N_t}\cdot\sum_{i=1}^{N_t}\left(\frac{\hat{\beta}^b_{it}-\overline{\hat{\beta}^b_{it}}}{\hat{\sigma}_{\hat{\beta}^b_{it}}}\right)^2\right]^{\left(\frac{1}{2}\right)}$ and the variance of the standardized betas as $V^{CS}_{norm}(\beta^b_{it}) = \frac{1}{N_t}\sum_{i=1}^{N}\left(\frac{\hat{\beta}^b_{it}-\overline{\hat{\beta}^b_{it}}}{\hat{\sigma}_{\hat{\beta}^b_{it}}}\right)^2$.

Table 2 summarizes the descriptive statistics of monthly beta herding measures and TRMI sentiment indicators and daily CSAD observations.

The means of beta herding and sentiment measures are quite similar in both panels, with slightly higher standard deviations in the U.S. We used the Augmented Dickey–Fuller (ADF) test to check whether our herding and sentiment measures are stationary. The ADF t-statistic confirms that all series are stationary at 1% and 5% level. The last row reports the statistics for the daily CSAD measure used in the next subsection of this paper.

Fig. 2 presents the evolution of the cross-sectional standard deviations of betas computed by running the market model (BH1), the lagged-returns model (BH2), and the lagged-returns model with standardized betas (BH3).

Table 3 reports the correlation coefficients between our herding measures.[4]

[4] The herding measure h_t derived from Model (2) is not strongly correlated with the logarithmic cross-sectional standard deviation and variance of different beta measures and therefore we report the correlation between similar measures.

Table 3
Correlation matrix of beta herding measures.

Panel A: Europe	$\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$	$\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$	$\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$	$V^{CS}_{norm}(\beta^b_{it})$
$\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$	1.0000			
$\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$	0.7421	1.0000		
$\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$	0.6918	0.9551	1.0000	
$V^{CS}_{norm}(\beta^b_{it})$	0.5973	0.8527	0.8591	1.0000
Panel B: U.S.	$\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$	$\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$	$\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$	$V^{CS}_{norm}(\beta^b_{it})$
$\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$	1.0000			
$\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$	0.7163	1.0000		
$\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$	0.6653	0.9479	1.0000	
$V^{CS}_{norm}(\beta^b_{it})$	0.5765	0.8518	0.8794	1.0000

We notice that $\mathrm{Log}(\sigma^{CS}_{1\beta^b_{it}})$, $\mathrm{Log}(\sigma^{CS}_{2\beta^b_{it}})$, and $\mathrm{Log}(\sigma^{CS}_{3\beta^b_{it}})$ are strongly correlated in both markets, with correlations ranging between 0.6653 and 0.9551.

Table 4 presents the estimation results for models (1) to (4) for the European and U.S. markets. Our main focus is on the estimates $\hat{\theta}$ and $\widehat{\sigma_{\epsilon 2}}$ i.e., the parameter of the latent variable H_t, and the standard deviation of the errors ϵ_2 from the state equation. Model (1) is the standard state–space specification without exogenous variables (see Eq. (6)). The high and significant values of $\hat{\theta}$ and $\widehat{\sigma_{\epsilon 2}}$ confirm the presence of herding behavior in both markets. Model (2) controls for the market state by including two variables: the monthly market excess return and the monthly standard deviation of the market portfolio (see Eq. (7)). The cross-sectional deviation of betas responds directly to changes in the excess return of the market portfolio and inversely to changes in its standard deviation. When the market risk increases, $\hat{\sigma}^{CS}_{\hat{\beta}^b_{it}}$ decreases, which is consistent with the concept of herding towards the market. These relationships are available on both markets, although in Europe the coefficient of the market premium is less significant. Model (3) extends Model (2) and includes the *SMB*, *HML*, and *MOM* factors (see Eq. (8)). The coefficient of the momentum factor is negative and statistically significant in both markets, an increasing momentum leading to a lower $\hat{\sigma}^{CS}_{\hat{\beta}^b_{it}}$. Model (4) includes the Amihud (2002) illiquidity ratio and two macroeconomic variables that were also explored by Hwang and Salmon (2004) i.e, the term spread and the credit spread (see Eq. (9)). The illiquidity ratio is significant for Europe, with a positive coefficient, so the cross-sectional deviation of betas increases when liquidity decreases. The credit spread coefficient is negative and significant in both markets at 1% in Europe and 5% in the U.S.

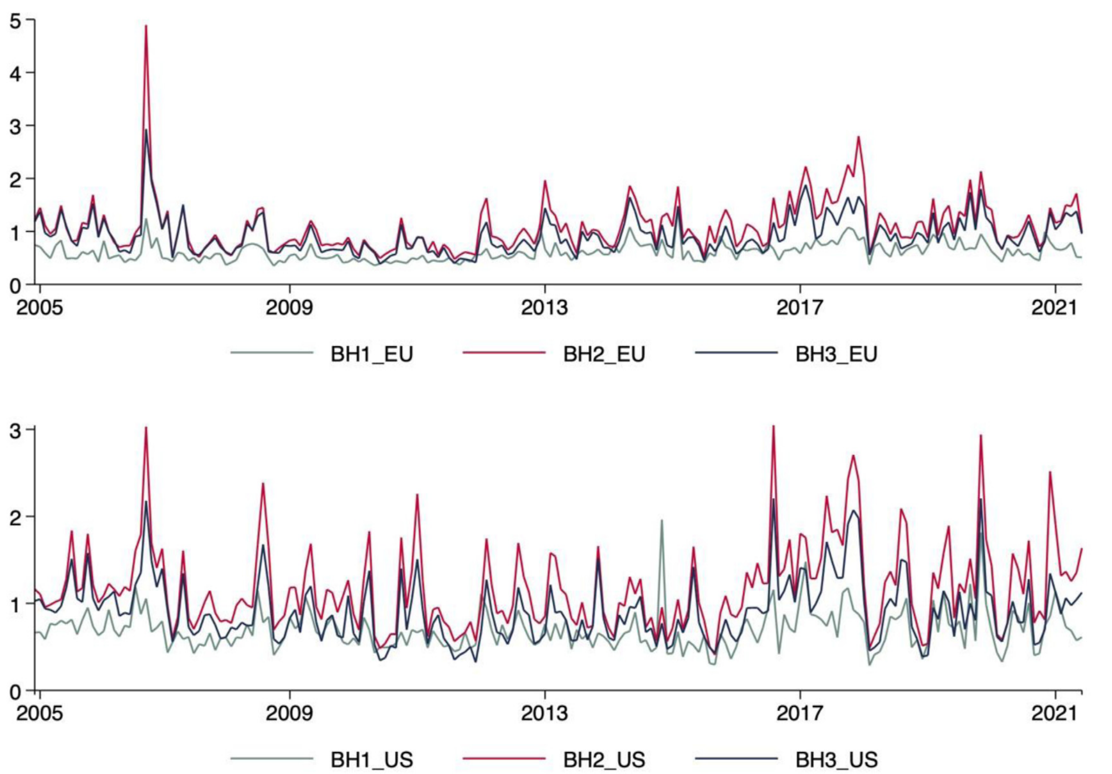

Fig. 2. Beta herding measures in the European and U.S. stock markets.

Table 4
State–space models estimates of herding behavior in Europe and the U.S.

Variables	Herding towards the market portfolio in Europe				Herding towards the market portfolio in the U.S.			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
μ	−0.5207***	−1.7981***	−1.8196***	−2.4401***	−0.4157***	−1.4921***	−1.9411***	−1.5462***
θ	0.9171***	0.8689***	0.8643***	0.8679***	0.4731**	0.9058***	0.8975***	0.9276***
$\sigma_{\epsilon 1}$	0.2004***	0.1382***	0.1367***	0.1371***	0.1964***	0.1953***	0.1648***	0.2014***
$\sigma_{\epsilon 2}$	0.0678***	0.0648***	0.0616***	0.0556***	0.2128***	0.0767***	0.0883***	0.0546***
RP_m		0.3760*	0.1256	0.2828		1.5669***	0.5814	1.4442***
$\mathrm{Log}(\sigma_m)$		−0.4134***	−0.4234***	−0.4931***		−0.3289***	−0.4662***	−0.3494***
SMB			−0.0972				−0.1805	
HML			−0.0569				−0.6663	
MOM			−1.0526**				−1.6243***	
TS				0.0175				0.0451
CS				−0.1693***				−0.1766**
ILL				0.0338**				−0.0661
Loglikelihood	9.6699	73.2622	76.9699	81.4600	−41.3489	10.1851	29.9604	14.8174
AIC	−0.0572	−0.6794	−0.6865	−0.7319	0.4581	−0.0422	−0.2127	−0.0587
SIC	0.0091	−0.5797	−0.5371	−0.5824	0.5245	0.0573	−0.0628	0.0907
Proportionof signal	0.2556	0.2443	0.2323	0.2096	0.6812	0.2455	0.2826	0.1747

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. AIC: Akaike information criterion; SIC: Schwarz information criterion. The beta coefficients are estimated monthly with the market model, by using daily data within each month. Subsequently, we computed 198 monthly cross-sectional standard deviations of betas for each market, representing the signal series in our state–space models. Model (1) is a state–space model with no exogenous variables, while Model (2), Model (3), and Model (4) include potentially explanatory market and macroeconomic variables in the signal equation. The proportion of signal is computed by dividing the $\sigma_{\epsilon 2}$ to the standard deviation of the $\log(\sigma_{\beta}^{CS})$.

Regardless of the control variables included in the signal equation, the latent herding measure is highly persistent in both markets and the standard deviation of the errors ϵ_2 is significant in all our models. In Europe, the estimates of $\hat{\theta}$ vary around 0.9 and the proportion of signal is around 25%. The proportion of signal shows that herding behavior explains around 25% of the total variability of $\hat{\sigma}^{CS}_{\hat{\beta}^{b}_{it}}$. In the U.S., the estimates of $\hat{\theta}$ are statistically significant and vary between 0.5 for Model (1) and 0.9 for models which include control variables. Herding explains between 20% to 70% of the variability of the cross-sectional standard deviation of betas in the U.S. market. The herding phenomenon is confirmed on both markets irrespective of the control variables added in the signal equation.

Models (5) to (7) include three TRMI sentiment indicators i.e., *Sentiment, Bubble,* and *Fear* in the signal equation as behavioral control variables. We add these indicators in models which already include market state and macroeconomic control variables. We are interested in the sign and significance of the sentiment coefficients to capture the influence upon the cross-sectional standard deviation of betas.

The estimation results of models (5) to (7) for the European market are presented in Table 5.

Table 5
State–space models estimates of herding towards the market and exogenous sentiment in Europe.

Sentiment indicator	Sent			Bubble			Fear		
Variables	Model (5)	Model (6)	Model (7)	Model (5)	Model (6)	Model (7)	Model (5)	Model (6)	Model (7)
μ	−1.7941***	−1.7921***	−2.3806***	−1.8521***	−1.8493***	−2.3661***	−1.9078***	−1.9031***	−2.4501***
θ	0.8683***	0.8672***	0.8432***	0.8704***	0.8696***	0.8691***	0.8727***	0.8715***	0.8761***
$\sigma_{\epsilon 1}$	0.1377***	0.1372***	0.1328***	0.1389***	0.1385***	0.1374***	0.1364***	0.1359***	0.1361***
$\sigma_{\epsilon 2}$	0.0659***	0.0665***	0.0631***	0.0632***	0.0638***	0.0549***	0.0669***	0.0677***	0.0561***
RP_m	0.3772*	0.3182	0.2808	0.3761*	0.3159	0.2842	0.4235*	0.3684	0.3255
$\text{Log}(\sigma_m)$	−0.4125***	−0.4121***	−0.4925***	−0.4241***	−0.4234***	−0.4941***	−0.4216***	−0.4201***	−0.4979***
SMB		0.0024			0.0048			0.0709	
HML		0.2666			0.2747			0.2669	
TS			0.0215			0.0176			0.0153
CS			−0.1929***			−0.1673***			−0.1694***
ILL			0.0348**			0.0338**			0.0351**
Sent	0.1051	0.0914	0.6944						
Bubble				−3.8087	−3.8251	−0.5863			
Fear							14.9071	14.9755	11.9211
Loglikelihood	73.2784	73.4013	82.2435	73.7625	73.8932	81.4737	73.6948	73.8187	81.7541
AIC	−0.6694	−0.6505	−0.7297	−0.6743	−0.6555	−0.7219	−0.6736	−0.6647	−0.7247
SIC	−0.5532	−0.5011	−0.5636	−0.5581	−0.5061	−0.5559	−0.5574	−0.5053	−0.5587
Proportionof signal	0.2484	0.2507	0.2379	0.2383	0.2406	0.2071	0.2523	0.2553	0.2115

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. AIC: Akaike information criterion; SIC: Schwarz information criterion. The beta coefficients are estimated monthly with the market model, by using daily data within each month. Subsequently, we computed 198 monthly cross-sectional standard deviations of betas, representing the signal series in our state–space models. Model (5) is a state–space model with the market risk-premia, the monthly standard deviation of the market portfolio, and a sentiment indicator as exogenous variables in the signal equation. Model (6) is a state–space model with the Fama and French three factors and a sentiment indicator as exogenous variables in the signal equation. Model (7) is a state–space model with market state variables, macroeconomic control variables, and a sentiment indicator as exogenous variables in the signal equation. The proportion of signal is computed by dividing the $\sigma_{\epsilon 2}$ to the standard deviation of the $\log(\sigma_{\beta}^{CS})$.

Model (5) is a state–space model with the market risk-premia, the monthly standard deviation of the market portfolio, and a sentiment indicator as exogenous variables in the signal equation (see Eq. (10)). While the sign and statistical significance of the market excess return and the standard deviation of the market portfolio are similar to those in Model (2), neither one of the sentiment indicators is significant. Model (6) is a state–space model with the Fama and French three factors and a sentiment indicator as exogenous variables in the signal equation (see Eq. (11)). We do not report significant coefficients for these variables either. Including the sentiment variables in the model does not seem to impact the cross-sectional standard deviation of betas and the herding measure.

The results are similar for Model (7) which controls for illiquidity and macroeconomic fundamentals (see Eq. (12)). Changes in sentiment measures do not induce significant changes to the beta herding in our state–space models for the European market.

For the U.S. stock market, the estimates of models (5) to (7) are displayed in Table 6.

Whereas the standard deviation of ϵ_2 errors remains significant and the latent herding measure continues to be highly persistent, the coefficients of the three TRMI sentiment indicators are statistically significant in all our models. Regardless of the control variables introduced in the model, the sign of the *Sent* is negative. An increase in market sentiment induces a decrease in the cross-sectional standard deviation of betas.

The coefficients of the *Bubble* and *Fear* indicators are positive and significant indicating that $\hat{\sigma}^{CS}_{\hat{\beta}^{b}_{it}}$ responds directly to changes of these emotions.

Finally, we extract the herding measure $h_t = 1 - e^{H_t}$ from Model (2) to control for the most important market state variables[5] (market excess return and volatility). In both markets, the h_t series and the TRMI sentiment series are stationary and show similar evolution as illustrated in Fig. 3.

Fig. 3 displays the herding measure and the TRMI *Sentiment* index for both markets, revealing some noteworthy remarks. First, *h* (left-hand side) and *Sent* (right-hand side) follow similar paths. Second, in times of crisis (i.e., the Global Financial Crisis, the European Sovereign Debt Crisis, the Covid-19 Pandemic) both herding and sentiment measures declined.

Table 7 reports the OLS estimation results of model (8) with robust standard error (Newey–West). The standardized betas series has a homoscedastic distribution, and it is not influenced by the heteroscedasticity in the estimation errors. In our model, the cross-sectional variance of standardized betas is regressed on its lagged value, market excess return, market volatility, and the sentiment indicators (see Eq. (15)). We introduced the lagged variable to control for the highly persistent beta herd measure (see Ang and Chen, 2007). As beta herding is expected to respond to changes in market perspectives, we also added the market excess return and the standard deviation of the market portfolio as control variable. We do not include other macroeconomic control variable, such as term spread, credit spread etc., to avoid multicollinearity in the OLS regression. The market variables, as well as the sentiment indices are already influenced by changes in fundamental information and are highly correlated to these macroeconomic variables.

The autoregressive coefficients of the lagged herding measures are significant at 1% and vary between 0.2 and 0.3 in both markets when investors' sentiment indices are included in the model. The volatility of the market portfolio has a significant indirect effect on beta herding in both markets, suggesting that when the market risk increases, herding towards the market is more likely to occur. The coefficient of the market excess return is not statistically significant in Europe. Two of the TRMI sentiment indices, *Sent* and *Bubble* report negative and statistically significant coefficients. When these indices increase, the cross-sectional variance of standardized beta is expected to decrease, which is associated to herding towards the market. An increased *Sent* is equivalent to more overall positive references with respect to the market outlooks. An increased *Bubble* is a consequence of enhanced positive emotionality net of negative emotionality. For the U.S. market, our results confirm the influence of *Sent* and *Fear*

5 Although the SIC suggests models (4) and (3) as being the best for Europe and the U.S., the estimated results do not differ significantly between the models with control variables. As the coefficient of the latent herding variable, the proportion of signal and even the SIC are quite similar, we extract h_t from Model (2) in both markets.

Table 6
State–space models estimates of herding towards the market and exogenous sentiment in the U.S.

Sentiment indicator	Sent			Bubble			Fear		
Variables	Model (5)	Model (6)	Model (7)	Model (5)	Model (6)	Model (7)	Model (5)	Model (6)	Model (7)
μ	−1.5398***	−1.5551***	−1.5766***	−1.4667***	−1.4843***	−1.6154***	−1.9931***	−2.0117***	−2.0718***
θ	0.8757***	0.8809***	0.9056***	0.9147***	0.9159***	0.9316***	0.8784***	0.8838***	0.9072***
$\sigma_{\epsilon 1}$	0.1961***	0.1946***	0.2003***	0.1868***	0.1863***	0.1927***	0.1908***	0.1895***	0.1983***
$\sigma_{\epsilon 2}$	0.0677***	0.0671***	0.0484***	0.0858***	0.0849***	0.0626***	0.0836***	0.0829***	0.0584***
RP_m	1.7743***	1.9492***	1.6509***	1.3791***	1.5687***	1.1996**	1.7613***	1.9654***	1.6674***
$\text{Log}(\sigma_m)$	−0.3284***	−0.3327***	−0.3498***	−0.3473***	−0.3499***	−0.3803***	−0.3584***	−0.3638***	−0.3816***
SMB		−1.0238			−0.8652			−1.0021	
HML		0.1358			−0.0488			−0.0915	
TS			0.0294			0.0469			0.0269
CS			−0.1487***			−0.2366***			−0.1812**
ILL			−0.0627			−0.0582			−0.0673
Sent	−1.8842***	−1.8871***	−1.7623***						
Bubble				11.2643***	10.2961***	15.3192***			
Fear							68.3014**	68.2267**	70.5534***
Loglikelihood	16.1272	17.3006	20.2312	11.7842	12.6345	17.8806	12.0454	13.1906	16.9285
AIC	−0.0921	−0.0838	−0.1033	−0.0483	−0.0367	−0.0796	−0.0509	−0.0423	−0.0699
SIC	0.0240	0.0656	0.0627	0.0679	0.1127	0.0865	0.0653	0.1072	0.0961
Proportionof signal	0.2167	0.2148	0.1549	0.2746	0.2718	0.2004	0.2676	0.2654	0.1869

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. AIC: Akaike information criterion; SIC: Schwarz information criterion. The beta coefficients are estimated monthly with the market model, by using daily data within each month. Subsequently, we computed 198 monthly cross-sectional standard deviations of betas, representing the signal series in our state–space models. Model (5) is a state–space model with the market excess return, the monthly standard deviation of the market portfolio, and a sentiment indicator as exogenous variables in the signal equation. Model (6) is a state–space model with the Fama and French three factors and a sentiment indicator as exogenous variables in the signal equation. Model (7) is a state–space model with market state variables, macroeconomic control variables, and a sentiment indicator as exogenous variables in the signal equation. The proportion of signal is computed by dividing the $\sigma_{\epsilon 2}$ to the standard deviation of the $\log(\sigma_{\beta}^{CS})$.

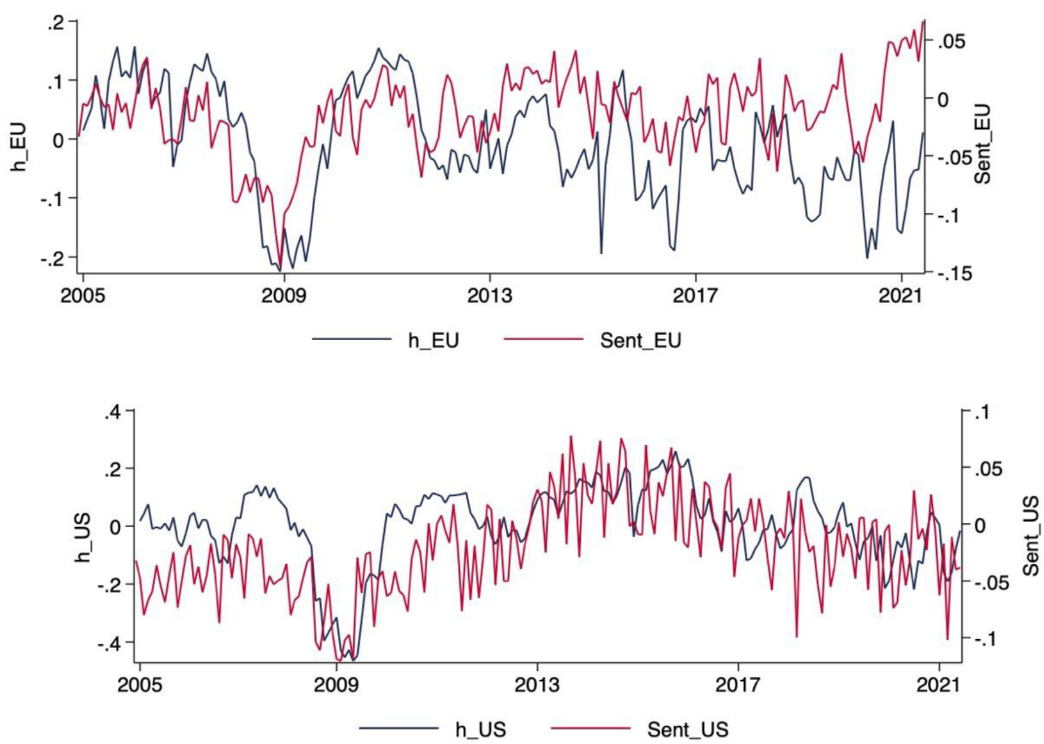

Fig. 3. Monthly herding measure *h* (left-hand side) and *Sentiment* indices (right-hand side) for Europe and the U.S.

on beta herding. Similarly to Europe, the sign of the *Sent* variable is negative suggesting that herding is enhanced by an increase in investors' sentiment. The coefficient of the *Fear* variable is positive, suggesting that decreasing fear is associated to herding behavior.

To conclude, the beta herding approach provides a comprehensive framework for exploring intentional herding behavior. Our results confirm that investors' sentiments explain the cross-sectional standard deviations and variance of betas, triggering the herding phenomenon.

4.2. Results of the CSAD herding models

In Fig. 4, we notice the mirror symmetry of the CSAD of returns and the filtered *Sent* indices. On the one hand, during turmoil periods, the sentiment indices are negative, while the CSAD of returns increases. This nexus is intuitive given that fear overwhelms investors in such times. On the other hand, during calm periods, the CSAD declines and investors' perceptions become optimistic. This finding is in line with Niţoi and Pochea

Table 7
Impact of investors' sentiment on herding behavior in Europe and the U.S.

Variable	Panel A: Europe results			Panel B: U.S. results		
α	−2.2767***	−2.4367***	−1.7033***	−1.4847***	−1.0882***	−2.1481***
$V^{CS}_{norm}\left(\beta^{b}_{it-1}\right)$	0.2263***	0.2451***	0.2379***	0.3039***	0.3112***	0.2955***
RP_m	0.0317	0.0552	−0.1451	1.6763	2.1615*	2.3038*
$\text{Log}(\sigma_m)$	−0.9720***	−0.9764***	−0.8262***	−0.6202***	−0.5039***	−0.5805***
Sent	−4.2013**			−5.0503***		
Bubble		−32.4354**			−11.1698	
Fear			−14.1931			154.729**
Adj. R^2	0.3699	0.3697	0.3493	0.3475	0.30188	0.3116

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Model (8) regresses the cross-sectional variance of standardized betas on the sentiment indicators and market state control variables (see Eq. 15). The beta herd measure is estimated as the cross-sectional variance of standardized betas. For each market, the beta herd measure is regressed with robust standard error (Newey–West) with its lag value, market excess return and volatility and a sentiment indicator

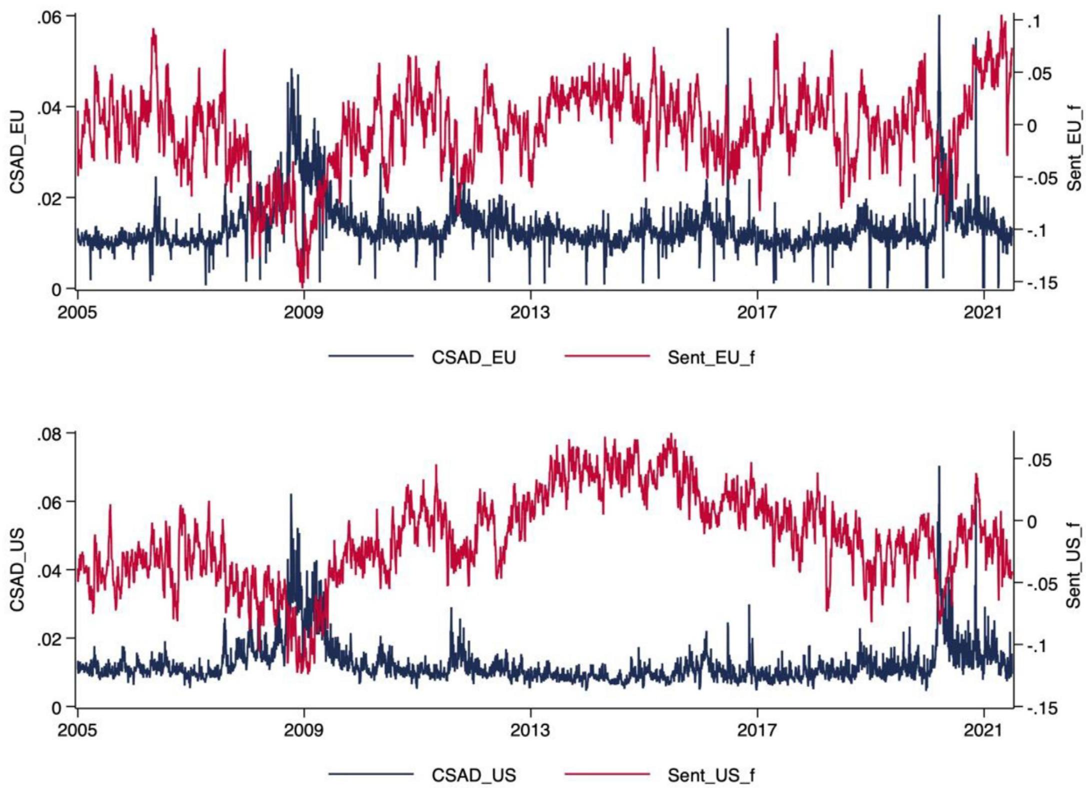

Fig. 4. Daily CSAD (left-hand side) and Sentiment indices (right-hand side) for Europe and the U.S.

(2022) who suggest that TRMI financial indices could be used as a measure for systemic risk.

Table 8 presents the results for the total CSAD, the CSAD driven by fundamental information, and the CSAD driven by sentiment in the U.S. and Europe between January 2005 to June 2021, by using both the OLS and quantile regression analysis as estimation methods. When we estimate the herding regression for the total CSAD, the coefficient of interest, β_2, is positive and statistically significant in most cases, revealing no evidence of overall herding behavior neither for the U.S. nor for the European market. These findings match the ones of previous studies that did not identify the presence of herding in the U.S. (e.g., Chang et al., 2000; Chiang and Zheng, 2010; Galariotis et al., 2015; Ukpong et al., 2021) and Europe (Duygun et al., 2021). In case of spurious herding, we find some sporadic evidence in favor of herding, both for the European and the U.S. upper CSAD quantiles of 90% and 99%. Usually, low quantiles (e.g., up to the 50th percentile) are considered tranquil periods in the market, while high quantiles (e.g., above the 75th percentile) suggest distress in the market (Adrian and Brunnermeier, 2016). Consequently, our results show that the investors in the U.S. stock market are more prone to imitate each other during periods of turbulence.

The findings become more interesting as we isolate the herding component driven by sentiments. We find that the American investors are significantly driven by sentiments when they follow the market consensus as revealed by the OLS and all quantiles' results, except for the 10% quantile. This finding is confirmed also for the European market for the upper quantiles.

For checking the robustness of our results, we use two other alternative measures as proxy for investors' sentiments, *Bubble* and *Fear* scores. The results show that the *Bubble* score is associated with evidence of herding for both markets, while the *Fear* score is relevant only for the European market (Table A.1). To summarize, our results reveal that TRMI indices fuel herding and confirm the assumption that sentiments might drive investors' decisions. In this light, we explore the hypothesis that investors are more prone to follow the crowd under extreme sentiment conditions.

Table 9 reports the results on the effects of extreme sentiments on herding behavior in the U.S. and Europe.

Table 8
Estimates of herding behavior in Europe and the U.S. based on CSAD methodology.

	Panel A: Europe results				Panel B: U.S. results			
Overall herding	β_0	β_1	β_2	Adj. R^2	β_0	β_1	β_2	Adj. R^2
OLS	0.0108***	0.2840***	0.5696	0.3875	0.0096***	0.3568***	0.8449	0.4054
$\tau = 10\%$	0.0086***	0.1670***	0.6139***	0.1225	0.0071***	0.1384***	2.1103***	0.1098
$\tau = 25\%$	0.0097***	0.1348***	1.9699**	0.1524	0.0081***	0.1800***	1.7844***	0.1348
$\tau = 50\%$	0.0107***	0.1917***	1.5946***	0.1873	0.0093***	0.2183***	2.7199***	0.1754
$\tau = 75\%$	0.0121***	0.2391***	2.4100***	0.2332	0.0106***	0.3640***	2.3860***	0.2318
$\tau = 90\%$	0.0136***	0.4321***	0.3572	0.2805	0.0128***	0.6315***	0.1827	0.3066
$\tau = 99\%$	0.0232***	0.5554**	2.7565	0.3038	0.0232***	0.7423**	**−3.6085*** **	0.3409
Spurious herding	β_0	β_1	β_2	Adj. R^2	β_0	β_1	β_2	Adj. R^2
OLS	0.0131***	0.0103**	0.1771*	0.0416	0.0112***	0.0069***	−0.0328	0.0034
$\tau = 10\%$	0.0123***	−0.0230***	0.0757	0.0138	0.0107***	−0.0361***	0.0037	0.0754
$\tau = 25\%$	0.0127***	−0.0156***	0.2587***	0.0029	0.0110***	−0.0211***	−0.0061	0.0228
$\tau = 50\%$	0.0131***	0.0046	0.2138	0.0070	0.0112***	0.0050	0.0480	0.0012
$\tau = 75\%$	0.0135***	0.0283***	0.1882***	0.0486	0.0114***	0.0351***	−0.0582	0.0485
$\tau = 90\%$	0.0138***	0.0629***	**−0.0772** **	0.1219	0.0118***	0.0501***	**−0.0584* **	0.1076
$\tau = 99\%$	0.0148***	0.1073***	**−0.4474*** **	0.2298	0.0129***	0.0679***	**−0.2673*** **	0.1443
Sentiment herding	β_0	β_1	β_2	Adj. R^2	β_0	β_1	β_2	Adj. R^2
OLS	−0.0003***	0.0656***	−0.1661	0.0717	0.0002	0.1371***	**−0.4750** **	0.1046
$\tau = 10\%$	−0.0025***	0.0336***	−0.0322	0.0097	−0.0040***	0.1032***	−0.0878	0.0246
$\tau = 25\%$	−0.0016***	0.0416***	0.0994	0.0177	−0.0020***	0.1288***	**−0.3078* **	0.0334
$\tau = 50\%$	−0.0004***	0.0573***	−0.0318	0.0328	0.0003***	0.1430***	**−0.6175*** **	0.0491
$\tau = 75\%$	0.0008***	0.0929***	**−0.4744*** **	0.0535	0.0024***	0.1554***	**−0.8087*** **	0.0617
$\tau = 90\%$	0.0020***	0.1154***	**−0.6392*** **	0.0717	0.0039***	0.1792***	**−1.0314* **	0.1065
$\tau = 99\%$	0.0052***	0.0793***	**−0.5245** **	0.0567	0.0075***	0.1700***	**−1.3727*** **	0.0807

Notes: The table reports the results for the benchmark model $CSAD_t = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \varepsilon_t$. Overall herding refers to the cross-sectional absolute deviation of returns at time t computed as $CSAD_t = \frac{1}{n}\sum_{i=1}^{n}|R_{it} - R_{mt}|$. Sentiment herding refers to the cross-sectional absolute deviation of returns driven by sentiment information at time t computed as $\widehat{\beta_5} \cdot Sent_t$ estimated from $CSAD_t = \beta_0 + \beta_1 \cdot (R_{mt} - R_{ft}) + \beta_2.HML_t + \beta_3 \cdot SMB_t + \beta_4 \cdot MOM_t + \beta_5 \cdot SI_t + \varepsilon_t$. Spurious herding refers to the cross-sectional absolute deviation of returns due to fundamental information at time t computed as $\mathrm{CSAD_{fundamental,t}} = \mathrm{CSAD_t} - \mathrm{CSAD}_{\mathrm{sentiment,t}} - \varepsilon_t$. Standard errors are estimated by using the Newey–West correction. ***, **, * denote statistical significance at the 1%, 5%, and 10% level.

In Europe, the results indicate the presence of herding both on euphoria (high level sentiment) for the middle quantiles and dysphoria (low level sentiment) for the upper quantiles. However, we find strong evidence of herding behavior in the U.S. stock market, with a dominance of euphoria. Furthermore, we test the robustness of these results by using alternative measures for sentiments (Table A.2). First, we find sound evidence of herding during the days with extreme values for the *Bubble* score in case of both markets. Similar to the *Sent* score, herding is more pronounced when the market records a high level of the *Bubble* score, this finding being highlighted by the estimates obtained both with the OLS and the quantile regression analysis. Intuitively, we can explain these results by the fact that investors are more prone to abandon their beliefs and analyses when they are irrationally exuberant. Second, the analysis of extreme fear conditions shows evidence of herding in both markets, with a more pronounced effect in the U.S. For the European market, we notice the dominance of low levels of fear over high levels of fear, confirming the previous findings that positive sentiments have a stronger impact on herding than the negative ones.

To summarize, our results on the asymmetric effects of extreme sentiments on herding behavior indicate that investors tend to herd during euphoria days, as well as during dysphoria days.

5. Conclusion

Over time, investors' decisions became significantly sensitive to sentiments driven by information from online news and social media. The main contribution of this paper to the literature consists in studying whether textual sentiment scores are associated to herding behavior. To assess the impact of investors' sentiments on herding toward the market, we adapt the methodology proposed by Hwang and Salmon (2004) and developed by Hwang et al. (2021), Raimundo Júnior et al. (2022), and Rubesam and Raimundo Júnior (2022). The state–space model approach documents significant sentiment indices coefficients for the U.S. market irrespective of the control variables included in the model. For Europe, the coefficients are not significant when using as herding measure the cross-sectional standard deviation of betas estimated with the market model (BH1). Factors such as cultural differences among European countries and investors' reaction to online news and social media information could explain potential dissimilarities in the relationship between investors sentiment and herding behavior in the U.S. versus Europe.

Hwang et al. (2021) proposed the cross-sectional variance of standardized betas as a new herding measure, which eliminates the problem of heteroscedasticity in the estimation errors. When regressing the new measure on our sentiment indices, we find that higher *Sent* and *Bubble* are associated to increasing herding toward the European market. On the U.S. market, our empirical findings reveal a negative (positive) relationship between *Sent* (*Fear*) and the cross-sectional variance of standardized betas i.e., increasing *Sent* and decreasing *Fear* induce intentional herding. For comparison reasons, we also examined the effects of sentiments on the occurrence of herding by employing the Chang et al. (2000) methodology which provides similar results. Additionally, we find evidence of herding behavior under both extreme positive and negative sentiments, with a conspicuous effect on euphoria days.

To summarize, this study enhances the existent literature on herding behavior in the American and European markets by investigating the influence of sentiments on this phenomenon. We find that emotionality among investors, in general, and extreme sentiments, in particular, are driving catalysts of intentional herding. An interesting research direction would be to examine the nexus between investors' sentiments and herding behavior at industry level, and to identify the factors that induce differences in this relationship in the U.S. versus Europe.

Table 9
The impact of investors' extreme sentiments on herding behavior in Europe and the U.S.

Panel A: Europe results						
Low level sentiment	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0107***	0.2735***	0.6441	0.0034***	−0.2591	0.4069
$\tau = 10\%$	0.0086***	0.1638***	0.6182***	0.0004	1.2097***	0.1258
$\tau = 25\%$	0.0096***	0.1500***	1.4273***	0.0013***	0.4026***	0.1561
$\tau = 50\%$	0.0107***	0.1805***	1.6863***	0.0027***	−0.0159	0.1974
$\tau = 75\%$	0.0121***	0.2261***	2.3706	0.0045***	−0.5249	0.2529
$\tau = 90\%$	0.0136***	0.3647***	1.0748***	0.0087***	−2.3173***	0.3103
$\tau = 99\%$	0.0224***	0.5808**	2.5700	0.0059***	−6.3752**	0.3233
High level sentiment	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0108***	0.2851***	0.5578	0.0000	−0.7443	0.3869
$\tau = 10\%$	0.0086***	0.1633***	0.6726	0.0002	0.1759	0.1229
$\tau = 25\%$	0.0097***	0.1333***	2.0536***	0.0003**	−0.5381	0.1527
$\tau = 50\%$	0.0106***	0.1881***	1.8948***	0.0004**	−2.1942***	0.1876
$\tau = 75\%$	0.0120***	0.2469***	2.3067***	0.0005*	−4.2566***	0.2335
$\tau = 90\%$	0.0137***	0.4323***	0.3494	−0.0005*	−2.5324	0.2807
$\tau = 99\%$	0.0237***	0.5131*	3.3986	−0.0071***	13.8042***	0.3208
Panel B: U.S. results						
Low level sentiment	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0095***	0.3167***	0.6596**	0.0085***	−0.0326	0.4917
$\tau = 10\%$	0.0097***	0.2744***	1.3065**	0.0116***	−0.0239	0.1266
$\tau = 25\%$	0.0071***	0.1356***	2.0961***	0.0025***	0.4703	0.1548
$\tau = 50\%$	0.0080***	0.1718***	1.7935***	0.0037***	1.5360***	0.2092
$\tau = 75\%$	0.0092***	0.2282***	1.3173***	0.0069***	−1.3255	0.2891
$\tau = 90\%$	0.0107***	0.3153***	1.7743	0.0136***	−1.4560**	0.3732
$\tau = 99\%$	0.0128***	0.4997***	0.2865	0.0132***	−3.4275***	0.4596
High level sentiment	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0099***	0.3634***	0.7047	−0.0015***	−14.1968***	0.4267
$\tau = 10\%$	0.0073***	0.1484***	2.0255***	−0.0004***	−4.1326***	0.1188
$\tau = 25\%$	0.0082***	0.1865***	1.7092***	−0.0005***	−7.3661***	0.1481
$\tau = 50\%$	0.0094***	0.2410***	2.4483***	−0.0009***	−8.9956***	0.1915
$\tau = 75\%$	0.0111***	0.3655***	2.2642***	−0.0017***	−14.4526***	0.2530
$\tau = 90\%$	0.0134***	0.6186***	0.1647	−0.0032***	−24.6645***	0.3364
$\tau = 99\%$	0.0240***	0.7072***	−3.3821***	−0.0106***	−27.0962***	0.3876

Notes: The table reports the results for the model $CSAD_t = \beta_0 + \beta_1 \cdot |R_{mt}| + \beta_2 \cdot {R_{mt}}^2 + \beta_3 \cdot D_{ESt} + \beta_4 \cdot {R_{mt}}^2 \cdot D_{ESt} + \varepsilon_t$ where D_{ESt} captures the effects of extreme positive sentiment and extreme negative sentiment on herding behavior. If $\beta_3 + \beta_4 < 0$ is negative and statistically significant, then extreme sentiments are a fuel of herding behavior. Standard errors are estimated by using the Newey–West correction. ***, **, * denote statistical significance at the 1%, 5%, and 10% level.

CRediT authorship contribution statement

Angela Maria Filip: Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Visualization. **Maria Miruna Pochea:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Acknowledgments

We are grateful to the editor, Stefan Palan, and the two anonymous referees for their valuable suggestions that noticeably improved the quality of our paper.

Appendix

See Tables A.1 and A.2.

Table A.1
Estimates of bubble and fear herding behavior in Europe and the U.S.

Panel A: Europe results					Panel B: U.S. results			
Bubble herding	β_0	β_1	β_2	Adj. R^2	β_0	β_1	β_2	Adj. R^2
OLS	0.0014***	0.0695***	**−0.2631****	0.0815	0.0047***	0.1528***	**−0.4914****	0.1215
$\tau = 10\%$	−0.0010***	0.0647***	**−0.2689*****	0.0263	0.0008***	0.0519***	0.4882**	0.0184
$\tau = 25\%$	0.0002***	0.0526***	−0.0781	0.0263	0.0024***	0.1424***	−0.2877	0.0350
$\tau = 50\%$	0.0012***	0.0674***	−0.1796	0.0418	0.0048***	0.1554***	**−0.5815*****	0.0580
$\tau = 75\%$	0.0025***	0.0792***	**−0.4009****	0.0513	0.0069***	0.1779***	**−0.9028*****	0.0771
$\tau = 90\%$	0.0036***	0.0976***	**−0.6296*****	0.0604	0.0085***	0.1942***	−0.8545	0.1190
$\tau = 99\%$	0.0063***	0.0852***	**−0.6897*****	0.0428	0.0120***	0.2401***	**−1.8834*****	0.1137
Fear herding	β_0	β_1	β_2	Adj. R^2	β_0	β_1	β_2	Adj. R^2
OLS	0.0065***	0.0249***	**−0.1118****	0.0417	0.0175***	0.0942***	0.0290	0.1124
$\tau = 10\%$	0.0055***	0.0163***	−0.0405	0.0118	0.0150***	0.0551***	0.2217**	0.0319
$\tau = 25\%$	0.0059***	0.0259***	**−0.1308*****	0.0233	0.0159***	0.0519***	0.3989***	0.0342
$\tau = 50\%$	0.0064***	0.0288***	**−0.1507*****	0.0239	0.0173***	0.0699***	0.3129***	0.0391
$\tau = 75\%$	0.0071***	0.0267***	**−0.1142***	0.0211	0.0187***	0.1046***	−0.0155	0.0610
$\tau = 90\%$	0.0077***	0.0244***	−0.1318	0.0230	0.0201***	0.1600***	−0.2658	0.0887
$\tau = 99\%$	0.0089***	0.0120*	−0.0936	0.0070	0.0242***	0.2888	−0.1574	0.1290

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Standard errors are estimated by using the Newey–West correction.

Table A.2
Estimates of herding behavior in Europe and the U.S. under extreme bubble and fear indices.

Panel A: Europe results							Panel B: U.S. results					
Bubble												
Low level	β_0	β_1	β_2	β_3	β_4	Adj. R^2	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0108***	0.2741***	0.6980	0.0026***	−0.4441	0.3960	0.0097***	0.2744***	1.3065**	0.0116***	−0.9708*	0.5235
$\tau = 10\%$	0.0086***	0.1609***	0.6375***	0.0002	0.5657**	0.1238	0.0072***	0.1303***	2.1624***	0.0050***	−0.2939***	0.1367
$\tau = 25\%$	0.0096***	0.1483***	1.4426***	0.0009***	0.3945	0.1541	0.0081***	0.1716***	1.6856***	0.0075***	−0.2376	0.1706
$\tau = 50\%$	0.0107***	0.1761***	2.0090***	0.0018***	−0.5687	0.1901	0.0093***	0.2081***	1.6755	0.0118***	−0.6698	0.2339
$\tau = 75\%$	0.0121***	0.2267***	2.7198***	0.0043***	−1.9482**	0.2428	0.0108***	0.2685***	2.9043***	0.0158***	−2.6687***	0.3121
$\tau = 90\%$	0.0136***	0.3786***	0.9972	0.0081***	−2.3127***	0.2986	0.0130***	0.4194***	2.0492	0.0167***	−3.5252	0.3865
$\tau = 99\%$	0.0227***	0.5798**	2.4659	0.0056***	−6.2617**	0.3171	0.0216***	0.5966***	−2.3602**	0.0341***	−2.1018***	0.4699
High level	β_0	β_1	β_2	β_3	β_4	Adj. R^2	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0108***	0.2868***	0.5297	−0.0004	−5.6494***	0.3897	0.0101***	0.3539***	0.7847	−0.0023***	−12.7319***	0.4400
$\tau = 10\%$	0.0086***	0.1696***	0.5778***	0.0000	−0.6422	0.1225	0.0075***	0.1391***	2.0823***	−0.0010***	−2.9479***	0.1389
$\tau = 25\%$	0.0097***	0.1364***	1.9290**	−0.0001	−1.9780*	0.1530	0.0084***	0.1768***	1.7824***	−0.0012***	−5.9174***	0.1669
$\tau = 50\%$	0.0107***	0.1828***	1.9394	−0.0003*	−4.4610***	0.1886	0.0096***	0.2312***	2.5289***	−0.0015***	−9.0679***	0.2100
$\tau = 75\%$	0.0121***	0.2455***	2.3137***	−0.0004**	−4.3274***	0.2349	0.0113***	0.3372***	2.6347***	−0.0026***	−13.2594***	0.2720
$\tau = 90\%$	0.0137***	0.4281***	0.3854	−0.0008**	−8.0606***	0.2833	0.0137***	0.5878***	0.6670	−0.0044***	−20.6991***	0.3496
$\tau = 99\%$	0.0238***	0.5043*	3.5206	−0.0073***	−15.6660***	0.3238	0.0241***	0.7027***	−3.3499***	−0.0121***	−23.6641***	0.3884
Fear												
Low level	β_0	β_1	β_2	β_3	β_4	Adj. R^2	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0108***	0.2919***	0.4782	−0.0003	−3.3075***	0.3907	0.0098***	0.3597***	0.7874	−0.0013***	−5.5380***	0.4158
$\tau = 10\%$	0.0086***	0.1667***	0.6306	0.0003*	−0.2880	0.1236	0.0072***	0.1375***	2.1121***	−0.0003**	−0.6516	0.1120
$\tau = 25\%$	0.0096***	0.1407***	1.9177**	0.0003***	−1.2661	0.1533	0.0082***	0.1807***	1.7702***	−0.0006***	−2.7572**	0.1399
$\tau = 50\%$	0.0106***	0.1995***	1.7578***	0.0003***	−2.6403***	0.1885	0.0094***	0.2200***	2.6796***	−0.0008***	−3.0819***	0.1824
$\tau = 75\%$	0.0121***	0.2551***	2.1862**	−0.0001	−4.9172***	0.2358	0.0110***	0.3592***	2.3810***	−0.0016***	−6.1018***	0.2442
$\tau = 90\%$	0.0141***	0.4160***	0.4745	−0.0011***	−3.9563***	0.2868	0.0132***	0.6209***	0.2436	−0.0031***	−9.4879***	0.3220
$\tau = 99\%$	0.0240***	0.6094***	1.4603	−0.0081***	−10.9414***	0.3465	0.0233***	0.7738***	−3.8589***	−0.0066***	−10.9132**	0.3561
High level	β_0	β_1	β_2	β_3	β_4	Adj. R^2	β_0	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.0108***	0.2840***	0.5453	0.0002	0.2269	0.3870	0.0095***	0.3301***	1.4279*	0.0035***	−0.8189	0.4182
$\tau = 10\%$	0.0086***	0.1684***	0.5854***	−0.0008*	1.4057***	0.1244	0.0072***	0.1241***	2.4166***	0.0012***	−0.2884***	0.1121
$\tau = 25\%$	0.0097***	0.1404***	1.7791*	−0.0005**	0.3516	0.1530	0.0082***	0.1405***	3.3037***	0.0014***	−1.3551***	0.1395
$\tau = 50\%$	0.0107***	0.1827***	1.9419***	−0.0008***	−0.3166*	0.1876	0.0092***	0.2058***	3.4676***	0.0013***	−1.7145*	0.1794
$\tau = 75\%$	0.0121***	0.2385***	2.4119***	−0.0013	0.3815	0.2333	0.0107***	0.3277***	3.4535***	0.0042***	−1.6652***	0.2371
$\tau = 90\%$	0.0136***	0.4256***	0.4249	0.0008	−0.3820	0.2801	0.0127***	0.5988***	0.6024	0.0079	−2.0195	0.3200
$\tau = 99\%$	0.0236***	0.4602***	4.4160	0.0114***	−8.1640***	0.3170	0.0232***	0.6649***	−3.1128	0.0319***	−1.8391*	0.3940

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Standard errors are estimated by using the Newey–West correction.

References

Adrian, T., Brunnermeier, M., 2016. CoVaR. Am. Econ. Rev. 106 (7), 1705–1741. http://dx.doi.org/10.1257/aer.20120555.

Amihud, Y., 2002. Lliquidity and stock returns: cross-section and time-series effects. J. Financial Mark. 5 (1), 31–56. http://dx.doi.org/10.1016/S1386-4181(01)00024-6.

Ang, A., Chen, J., 2007. CAPM over the long run: 1926–2001. J. Empir. Financ. 14 (1), 1–40. http://dx.doi.org/10.1016/j.jempfin.2005.12.001.

Audrino, F., Sigrist, F., Ballinari, D., 2020. The impact of sentiment and attention measures on stock market volatility. Int. J. Forecast. 36 (2), 334–357. http://dx.doi.org/10.1016/j.ijforecast.2019.05.010.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680. http://dx.doi.org/10.1111/j.1540-6261.2006.00885.x.

Bekiros, S.J., Lucey, B., Naoui, K., Uddin, G.S., 2017. Herding behavior, market sentiment and volatility: will the bubble resume? North Am. J. Econ. Finance 42, 107–131. http://dx.doi.org/10.1016/j.najef.2017.07.005.

Bikhchandani, S., Sharma, S., 2000. Herd behavior in financial markets. IMF Staff Pap. 47 (3), 279–310, link: https://www.jstor.org/stable/3867650.

Bohl, M.T., Branger, N., Trede, M., 2017. The case for herding is stronger than you think. J. Bank. Financ. 85, 30–40. http://dx.doi.org/10.1016/j.jbankfin.2017.08.006.

Borovkova, S., Garmaev, E., Lammers, P., Rustige, J., 2017. SenSR: A Sentiment-Based Systemic Risk Indicator. De Nederlandsche Bank Working Paper No. 553, Netherlands Central Bank, Research Department, link: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2951036.

Brown, G.W., Cliff, M.T., 2005. Investor sentiment and asset valuation. J. Bus. 78 (2), 405–440. http://dx.doi.org/10.1086/427633.

Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82. http://dx.doi.org/10.2307/2329556.

Chang, E., Cheng, J., Khorana, A., 2000. An examination of herd behavior in equity markets: an international perspective. J. Bank. Financ. 24 (10), 1651–1679. http://dx.doi.org/10.1016/S0378-4266(99)00096.

Chiang, C.T., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. Financ. 34 (8), 1911–1921. http://dx.doi.org/10.1016/j.jbankfin.2009.12.014.

Christie, W., Huang, R., 1995. Following the pied piper: Do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37, https://www.jstor.org/stable/4479855.

Duygun, M., Tunaru, R., Vioto, D., 2021. Herding by corporates in the US and the Eurozone through different market conditions. J. Int. Money Finance 110, 102311. http://dx.doi.org/10.1016/j.jimonfin.2020.102311.

Economou, F., Kostakis, A., Philippas, N., 2011. Cross-country effects in herding behaviour: evidence from four South European markets. J. Int. Financial Mark. Inst. Money 21, 443–460. http://dx.doi.org/10.1016/j.intfin.2011.01.005.

Espinosa-Méndez, C., Arias, J., 2020. COVID-19 effect on herding behaviour in European capital markets. Finance Res. Lett. (38), 101787. http://dx.doi.org/10.1016/j.frl.2020.101787.

Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. J. Finance 50 (1), 131–155. http://dx.doi.org/10.2307/2329241.

Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. J. Finance 51 (1), 55–84. http://dx.doi.org/10.2307/2329302.

Fang, L., Yu, H., Huang, Y., 2018. The role of investor sentiment in the long-term correlation between U.S. stock and bond markets. Int. Rev. Econ. Finance 58, 127–139. http://dx.doi.org/10.1016/j.iref.2018.03.005.

Ferreruela, S., Mallor, T., 2021. Herding in the bad times: The 2008 and COVID-19 crises. North Am. J. Econ. Finance 58, 101531. http://dx.doi.org/10.1016/j.najef.2021.101531.

Galariotis, E.C., Rong, W., Spyrou, S.I., 2015. Herding on fundamental information: A comparative study. J. Bank. Financ. 50, 589–598. http://dx.doi.org/10.1016/j.jbankfin.2014.03.014.

Gan, B., Alexeev, V., Bird, R., Yeung, D., 2020. Sensitivity to sentiment: News vs social media. Int. Rev. Financ. Anal. 67, 101390. http://dx.doi.org/10.1016/j.irfa.2019.101390.

Hwang, S., Rubesam, A., Salmon, M., 2021. Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly. J. Int. Money Finance 111, 102318. http://dx.doi.org/10.1016/j.jimonfin.2020.102318.

Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Financ. 11 (4), 585–616. http://dx.doi.org/10.1016/j.jempfin.2004.04.003.

Jia, B., Shen, D., Zhang, W., 2022. Extreme sentiment and herding: Evidence from the cryptocurrency market. Res. Int. Bus. Finance 63, 101770. http://dx.doi.org/10.1016/j.ribaf.2022.101770.

Kearney, C., Liu, S., 2014. Textual sentiment in finance: A survey of methods and models. Int. Rev. Financ. Anal. 33, 171–185. http://dx.doi.org/10.1016/j.irfa.2014.02.006.

Lewellen, J., Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies. J. Financ. Econ. 82, 289–314. http://dx.doi.org/10.1016/j.jfineco.2005.05.012.

Mobarek, A., Mollah, S., Keasey, K., 2014. A cross-country analysis of herd behavior in Europe. J. Int. Financial Mark. Inst. Money 32, 107–127. http://dx.doi.org/10.1016/j.intfin.2014.05.008.

Niţoi, M., Pochea, M.M., 2020. Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. Econ. Model. 86, 133–147. http://dx.doi.org/10.1016/j.econmod.2019.06.007.

Niţoi, M., Pochea, M.M., 2022. The nexus between bank connectedness and investors' sentiment. Finance Res. Lett. 44, 102432. http://dx.doi.org/10.1016/j.frl.2021.102432.

Pochea, M.M., Filip, A.M., Pece, A.M., 2017. Herding behavior in CEE stock markets under asymmetric conditions, A quantile regression analysis. J. Behav. Finance 18 (4), 400–416. http://dx.doi.org/10.1080/15427560.2017.1344677.

Raimundo Júnior, G.d.S., Baptista Palazzi, R., Cabus Klotzle, M., Pinto, A.C.F., 2020. Analyzing herding behavior in commodities markets – an empirical approach. Finance Res. Lett. 35, 101285. http://dx.doi.org/10.1016/j.frl.2019.08.033.

Raimundo Júnior, G.d.S., Baptista Palazzi, R., Souza Tavares, R., Cabus Klotzle, M., 2022. Market stress and herding: A new approach to the cryptocurrency market. J. Behav. Finance 23 (1), 43–57. http://dx.doi.org/10.1080/15427560.2020.1821688.

Rubesam, A., Raimundo Júnior, G.d.S., 2022. Covid-19 and herding in global equity markets. J. Behav. Exp. Finance 35, 100672. http://dx.doi.org/10.1016/j.jbef.2022.100672.

Siganos, A., Vagenas-Nanos, E., Verwijmeren, P., 2014. Facebook's daily sentiment and international stock markets. J. Econ. Behav. Organ. 107 (part B), 730–743. http://dx.doi.org/10.1016/j.jebo.2014.06.004.

Sun, L., Najand, M., Shen, J., 2016. Stock return predictability and investor sentiment: A high-frequency perspective. J. Bank. Financ. 73, 147–164. http://dx.doi.org/10.1016/j.jbankfin.2016.09.01.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. J. Finance 62 (3), 1139–1168. http://dx.doi.org/10.1111/j.1540-6261.2007.01232.x.

Ukpong, I., Tan, H., Yarovaya, L., 2021. Determinants of industry herding in the US stock market. Finance Res. Lett. 43, 101953, doi: https://doi-org.am.e-nformation.ro/10.1016/j.frl.2021.101953.