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HERDING BEHAVIOUR UNDER EXTREME MARKET CONDITIONS. NEW EVIDENCE IN DEVELOPED CAPITAL MARKETS

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Abstract: This paper aims at analyzing the presence of gregarious behavior within the main developed equity markets, namely the US, European and Asian markets, taking as proxy the absolute deviation of stock returns from markets' (CSAD) for the companies composing the S&P500, STOXX600 and NIKKEI225 indices. The period used for daily stock prices starts from 12/31/2004 to 06/30/2023. Thus, we proposed several regression versions targeting investors' behavior in relation to market direction in various volatility scenarios starting from Chang's (2000) analysis model. The sentiment specific side was quantified by means of the RSI index, therefore having a complete analysis of this social bias. Furthermore, using the three- and five-factor Fama-French models, we were able to delineate herding behavior as fundamental or non-fundamental depending on the information underlying investors' decisions. In order to better isolate the phenomenon based on the sample, we used the quantile-based QREG method in addition to the OLS method. Following the synthesis of the empirical study, the results obtained emphasize the presence of the herding bias in the analyzed markets under different economic hypostases.

JEL Classification: G14, G15, G40, G41

Keywords: behavioral finance, herding, volatility, market scenarios, risk premia, cross-sectional absolute deviation of returns

1. Introduction

Behavioral finance initially emerged as a response to the shortcomings of traditional financial theory. The latter's main hypothesis is the existence of informational efficiency in capital markets, an idea advocated by Eugene Fama and Paul Samuelson. A stock price must therefore fully incorporate all the information available in that market in order to be considered efficient and leading to rational predictions by investors about

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future prices. However, such an assumption does not capture potential behavioral anomalies and biases in the market that directly influence the transactions concluded and imprint volatility on the price of financial assets in the form of random walk. Thus, the new side of finance, further promoted by De Bondt and Thaler (1985) and Shiller (2003) respectively, proposes to facilitate a more detailed approach to the market mechanism and the decision-making process by the investors concerned, by translating the behavioral factors into classical models, also taking into account the moments when rational behavior is antiquated. With the integration of these factors, new more complex regression-based models are created, which we will detail later.

Mainly determined by the different perception of capital market information, the decision-making process takes the form of herding behavior when inexperienced investors, also known as "noise traders", who are considering that they do not have a sufficiently broad information horizon or the necessary skills, will replicate the strategies of other participants ignoring their own forecasts, unlike experienced investors who rely on their own active, technical or fundamental analysis principles. Indian economist Abhijit Banerjee points out that this gregarious/imitation effect directly affects the informational efficiency of the market by reducing the significance of private information of investors following the strategies of others. Hence, recalling the function of capital markets in valuing financial assets, this is, in turn, impacted by the deviation of asset values from their fundamental values, thereby inducing additional volatility and establishing new equilibrium prices through the random walk phenomenon.

2. Literature review

The causes of herding behavior include imperfectly distributed information, compensation structures, managers' lack of confidence in their own abilities, reputational concerns and the assumption that other market players own more information, such as inside information, or have more optimal investment strategies. In addition, the subjective expectations of return and risk that underlie this bias can lead to destabilization of financial markets and crises by creating speculative bubbles through over-buying or stock market crashes through massive selling, both driven by feelings of greed or fear of the crowd. Such bubbles appeared in the US real estate market in the 1970s and 1980s, or more recently in 2008.

Devenow and Welch (1996) argue for the division of behavior as rational and irrational, the latter being based on the instinct to naively follow the initiative of others, while the former reveals mimetic behavior involving an expected utility maximizing analysis before making the actual decision, similar to passive/indicative management of a portfolio of financial assets replicating a particular index. Researchers Avery and Zemsky (1998) state that the emergence of mimetic behavior and speculative bubbles may be generated by complicated information structures in the financial market.

The concepts of spurious behavior and intentional herd behavior were introduced in the literature by Bikhchandani and Sharma (2000). The first classification refers to the coincidences that occur between investors who encounter a similar set of data, guided by fundamentals, and make decisions in a similar context, thus giving the false appearance of herding behavior. On the other hand, investors who lucidly and intentionally follow the strategy of others also denote a phenomenon that is considered rational, which has 3 major underlying causes. A first source is given by the information asymmetry between individuals and the inevitable imitation of the actions of those who possess a surplus of information. Another cause marks the managers' obsession with reputation and implicitly relieving themselves of the responsibilities of poor performance by copying the decisions of other managers and questioning their own professional skills. The last cause refers to the compensation structures specific to fund managers, who get a reward scheme in addition to their salary against a benchmark and have a habit of replicating it.

Another important classification of studies emphasizes empirical papers dealing with the herding phenomenon of institutional investors and analysts under the synthesis of Lakonishok, Shleifer and Vishny (1992), which uses the LSV model in identifying the presence of bias, but also papers that use market aggregates and note the collectivism of investors with respect to market direction, e.g. Christie and Huang (1995) - CSSD model, Chang, Cheng and Khorana (2000) - CSAD model, Hwang and Salmon (2004) - state space model.

Christie and Huang analyze the herding phenomenon based on how stock returns cluster around the average market return at times of high volatility. To test this hypothesis, they use the cross-sectional standard deviation (CSSD), reflecting that the value of the CSSD will be lower in high volatility conditions rather than in normal conditions, contrary to classical asset pricing models. Chang, Cheng and Khorana propose a new approach using the cross-sectional absolute standard deviation (CSAD), which represents an improvement of the CSSD. In their study of the US and Asian markets, namely Japan, Hong Kong, South Korea and Taiwan, they find the presence of herding behavior during periods of high volatility only in the emerging markets, South Korea and Taiwan, most likely due to the slower incorporation of existing information into the price. Hwang and Salmon introduce a new model to determine herding behavior, specifically by calculating deviations of asset prices from their long-run equilibrium value, computed using the CAPM valuation relationship. Applied to the US and South Korean markets, it identifies evidence of herding in both countries irrespective of the market trend - bull/bear or macroeconomic coordinates. A particular feature emerges with the Asian and Russian crisis when the herding effect is diminished and prices return to equilibrium.

Another seminal study is the one by Galariotis et al. (2014) dividing investors' response according to fundamental and non-fundamental information under the influence of decomposing dispersion of returns by Fama-French and Carhart factors, respectively. Thus, spurious herding behavior in the US and UK markets was driven by fundamental macroeconomic announcements, while intentional behavior is conditioned on the residuals of the Fama-French multifactor model. Therefore, the results are mixed as they capture spurious herding behavior during the Asian and Russian crisis for both countries, but also intentional behavior only in the US market during the subprime crisis. At the same time Emilios Galariotis (2016) observes the link between highly liquid equities and the herding effect in five main global markets, namely France, Germany, England, the US and Japan,due to low risk diversification potential of a portfolio for highly liquid equities as they have a coefficient of determination R^2 high, therefore the total risk being largely determined by market risk, the share price being in line with the market.

Using the same analytical model, Duygun (2021) investigates the gregarious phenomenon in the Eurozone as well as in the US markets, focusing on the European and global crisis, and infers its emergence to a more significant extent in the higher quantiles under the impact of tumultuous market conditions, financial crises and not least asymmetric volatility. Based on Galariotis's model he identified the characteristics of false and intentional behaviors, isolating them by OLS and QREG method. This investor sentiment leading to the emergence of the two gregarious typologies was defined by Baker and Wurgler in 2007 as beliefs about future cash flows - cash flows and investment risks that are not supported by information available in the market.

Stock market sentiment as a determinant of herding behavior can be measured by various techniques and indicators that are quantified in the form of direct and indirect methods. While direct methods use questionnaires to analyze investors' forecasts of market developments with ESI - Economic Sentiment Indicator, MCSI - Michigan Consumer Sentiment Index or II - Investor Intelligence Index as indices, indirect methods use market variables to reflect liquidity, average returns or the number of initial public offerings (IPOs) through indices such as RSI, ARMS or CCI - Consumer Confidence Index. In the following I will detail a number of empirical studies that analyze the relationship between investor sentiment and different stock market variables – market liquidity, stock returns, trading volume and volatility.

Last but not least, a recent study by Huynh, N., De Mello, L., Li, K. (2025), which targeted 1274 publications from the Web of Science database between 1991-2023, uses bibliographic mapping techniques to confirm the relationship between sentiment, asset returns, volatilities, stock market bubbles and market anomalies. The authors emphasize the need for further refinement in measurement techniques in terms of methodological variations and the limited nature of the data that contributed to inconsistencies and overlaps compared to benchmark sentiment indicators that have considerably improved their explanatory power.

Synthesizing the studies reported above we deduce a certain tendency of transitivity among the factors influencing gregarious behavior. Several analyzed studies expose the relationship between stock returns and market sentiment, while the herding phenomenon is also quantified in relation to returns, thus establishing the direct relationship between market sentiment and perceived behavioral bias.

3. Methodology

The econometric model used to highlight the global gregarious behavior on the main developed capital markets is the one of Chang et al. created in 2000, which is based on the relationship between the absolute deviations of security returns from market returns (CSAD):

$$\mathrm{CSAD_t} = \frac{1}{\mathrm{N}}\sum_{1}^{\mathrm{N}}\left|\mathrm{R_{i,t}} - \mathrm{M_t}\right| \quad (1)$$

3.1. Empirical study of the herding phenomenon

Chang et al. (2000) proposed the following nonlinear regression model to assess herding behavior:

$$\mathrm{CSAD_t} = \beta_o + \beta_1 * |\mathrm{M_t}| + \beta_2 * \mathrm{M_t^2} + \varepsilon_t \quad (2)$$

The above model is developed from the CAPM (Capital Asset Pricing Model) hypothesis, which argues that CSAD is in a linear relationship with market returns if investors would act according to decision rationality. Therefore, an increase in the size of market movements leads to a rise in the mean squared deviation under the classical theory, the regression coefficient β_2 is positive and statistically significant in the absence of the gregarious phenomenon, when it has negative values.

For a better explanation of the CSAD we have added to the econometric regression several variables that will isolate the synthesis carried out according to different market hypostases/trends, implicitly improving the model. The newly constructed regressions based on the literature are initially guided by Yao's model, previously mentioned, in order to reduce multicollinearity by introducing the variable $\overline{\mathrm{M}}$ - arithmetic mean of the market, the creation of a centered variable, and at the same time, in order to increase the significance and correct the autocorrelation of the residuals, by using the past moment CSAD_{t-1}.Thus, the obtained model becomes autoregressive and the explanatory power of the variables is also given by the positive change in the coefficient of determination R^2 - price synchronicity. The estimated regression is also based on the Newey West (1997) model for handling heteroskedasticity.

$$\mathrm{CSAD}_t = \beta_o + \beta_1 * |\mathrm{M}_t| + \beta_2 * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_3 * \mathrm{CSAD}_{t-1} + \varepsilon_t \quad (3)$$

3.2. Influence of market trends

The quantification of the upward or downward trends was performed by introducing in the regression dummy – dichotomous variables, calculated in relation to the moving average of the market returns over the last 31 days, as follows:

$$\mathrm{CSAD}_t = \beta_o + \beta_1 * |\mathrm{M}_t| + \beta_2 * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_3 * \mathrm{D}^{\mathrm{UP}} * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_4 * \mathrm{CSAD}_{t-1} + \varepsilon_t \quad (4)$$

$$\mathrm{CSAD}_t = \beta_o + \beta_1 * |\mathrm{M}_t| + \beta_2 * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_3 * \mathrm{D}^{\mathrm{DOWN}} * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_4 * \mathrm{CSAD}_{t-1} + \varepsilon_t \quad (5)$$

3.3. Influence of market volatility

Two other dummies will summarize the effect of market volatility, by referring to the arithmetic moving average of the arithmetic mean squared deviations of the market returns over the last month, as follows:

$$\mathrm{CSAD}_t = \beta_o + \beta_1 * |\mathrm{M}_t| + \beta_2 * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_3 * \mathrm{D}^{\mathrm{HVOL}} * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_4 * \mathrm{CSAD}_{t-1} + \varepsilon_t \quad (6)$$

$$\mathrm{CSAD}_t = \beta_o + \beta_1 * |\mathrm{M}_t| + \beta_2 * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_3 * \mathrm{D}^{\mathrm{LVOL}} * (\mathrm{M}_t - \overline{\mathrm{M}})^2 + \beta_4 * \mathrm{CSAD}_{t-1} + \varepsilon_t \quad (7)$$

3.4. Influence of extreme investors' sentiment

Taking as a proxy Baker and Wugler's study suggesting the psychological influence of sentiment on the herding phenomenon, we evaluate this impact by using the Relative Strength Index (RSI) sentiment index. Developed by former American engineer J.W. Wilder Jr. in 1978, the RSI is a technical gut instinct indicator that captures the amplitude of recent price changes. In addition, the interpretation of this index is segmented into two percentage thresholds, a value above 70% indicates strong demand for the security, leading to optimism and an overvaluation of the stock, while below 30% indicates an increase in supply and, therefore, pessimism and an undervaluation of the financial asset.

Based on the RSI formula, formed beforehand by determining the RS, and the aforementioned thresholds reflecting opposing sentiments, two dummies will model the regression as follows:

$$CSAD_t = \beta_o + \beta_1 * |M_t| + \beta_2 * (M_t - \bar{M})^2 + \beta_3 * D^O * (M_t - \bar{M})^2 + \beta_4 * CSAD_{t-1} + \varepsilon_t \quad (8)$$

$$CSAD_t = \beta_o + \beta_1 * |M_t| + \beta_2 * (M_t - \bar{M})^2 + \beta_3 * D^P * (M_t - \bar{M})^2 + \beta_4 * CSAD_{t-1} + \varepsilon_t \quad (9)$$

3.5. The Fama-French model as an analysis factor

By examining Galariotis' model, together with the contribution of Bikhchandani and Sharma that the gregarious phenomenon is divided into spurious and intentional, we observe the impact of fundamental information on the spurious herding and non-fundamental sides in determining intentional herding behavior. The three economists have detailed this hypothesis by conditioning the CSAD on the Fama-French and Carhart factors, respectively, to provide superior explanatory power to the original model (Chang) by tracking important fundamental information that may alter investors' investment decisions, while non-fundamental/subjective information is captured in the residuals of the regression. The estimated model based on the Fama-French factors takes the form:

$$CSAD_t = \beta_o + \beta_1 * (M_t - RF_t) + \beta_2 * HML_t + \beta_3 * SMB_t + \varepsilon_t \quad (10)$$

Starting from the above relation, we have divided the CSAD into its two informational forms, namely fundamental and non-fundamental:

$$CSAD_{non-fundamental,t} = \varepsilon_t$$
$$CSAD_{fundamental,t} = \beta_o + \beta_1 * (M_t - RF_t) + \beta_2 * HML_t + \beta_3 * SMB_t$$

By replacing the simple CSAD, in the basic relation, with the above two variations we obtained two regressions that we then used in the construction of the tables:

$$CSAD_{fundamental,t} = \beta_o + \beta_1 * |M_t| + \beta_2 * M_t^2 + \varepsilon_t \quad (11)$$

$$CSAD_{non-fundamental,t} = \beta_o + \beta_1 * |M_t| + \beta_2 * M_t^2 + \varepsilon_t \quad (12)$$

Nonetheless , a coefficient β_2 negative and statistically significant, will give us the certainty of the existence of a false gregarious behavior in the market in question, so that investors adopt decisions according to the classical theory, based on the fundamental analysis, that is, an intentional behavior where decisions are predominantly instinctual.

4. Database and variables

The empirical study was carried out on the main developed stock markets, namely the European, American and Asian-Japanese markets. The computed returns are based on the quotes of the indices S&P500, STOXX600, respectively NIKKEI225 to synthesize the market as a whole, as well as on the share prices of each company in order to determine the deviations from the market average and implicitly their specific herd behavior. The analyzed interval covers almost 19 years, 31.12.2004 - 30.06.2023 and includes a total of 4826 observations. The Fama-French factors used in the models were retrieved from Kenneth French's online data library and synchronized with the returns for the same period.

Table 1 provides the variables used in the empirical analysis and their computation method.

Table 1. Variables overview

Variable	Description
M	Daily log return of the market index used as proxy - $M_t = \ln(P_t/P_{t-1})$
MRP	Market risk premium - $MRP_t = M_t - RF_t$
MC	Centered second-order moment of the (market) index return - $MC_t = (M_t - \bar{M})^2$
RF	Risk-free asset rate
CSADF	CSAD determined by fundamental information $CSADF_t = CSAD_t - \varepsilon_t$, where
CSADNF	CSAD driven by non-fundamental information $CSADNF_t = \varepsilon_t$
RSI	Relative Strength Index $RSI = \frac{RS}{1+RS} * 100$, where $RS = \frac{\sum_1^{16} \max(P_t - P_{t-1}, 0)}{\sum_1^{16} \max(P_{t-1} - P_t, 0)}$
SMB	Small minus big factor
HML	High minus low factor
RMW	Robust minus weak factor
CMA	Conservative minus aggressive factor
MOM	Momentum factor
DO	Dichotomous variable for optimism, takes value 1 when RSI>60% and 0 otherwise
DP	Dichotomous variable for pessimism, takes the value 1 when RSI<40% and 0 otherwise
DUP	Dummy that quantifies the upward trend of the market by taking the value 1 when the market return exceeds the average of the last month and 0 otherwise
DDOWN	Dummy denoting the market's downtrend, taking the value 1 when the index return is below the moving average of the last 31 days
DHVOL	Dummy variable that takes the value 1 in conditions of high volatility and 0 otherwise
DLVOL	Dummy variable that takes the value 1 under low volatility conditions and 0 otherwise

Source: Author's Computation

In addition, table 2 emphasizes the main descriptive statistics related to the variables included in the regressions, such as the mean, the standard deviation and the ADF test that proves the stationarity of the time series.

Table 2. Descriptive statistics

Variable	Average	Mean squared deviation	ADF test
		USA	
CSAD	0,010746	0,005322	-7,831889***
CSADF	0,011138	0,000841	-40,06036***
CSADNF	0,000264*10^{-5}	0,004928	-6,993502***
CSR	55,556975	16,151751	-10,22413***
SMB	0,001016	0,623229	-69,10841***
HML	-0,00448	0,811817	-39,81745***
RMW	0,015532	0,448206	-65,20694***
CMA	0,003203	0,376628	-65,30685***
MOM	0,004129	1,072289	-39,81425***
		Europe	
CSAD	0,011707	0,004752	-6,836676***
CSADF	0,011707	0,000743	-28,30825***
CSADNF	-0,000064*10^{-4}	0,004693	-6,698284***
CSR	52,994813	16,421858	-9,796612***
SMB	0,000655	0,497706	-36,06483***
HML	-0,00205	0,524671	-62,84324***
RMW	0,016292	0,309106	-64,56525***
CMA	-0,00021	0,307312	-64,20259***
MOM	0,032502	0,794383	-47,41177***
		Japan	
CSAD	0,011117	0,004911	-7,830825***
CSADF	0,552953*10^{-8}	0,004901	-59,15998***
CSADNF	0,011117	0,000301	-7,849160***
CSR	52,298121	14,401806	-10,12828***
SMB	0,002833	0,578195	-42,95076***
HML	0,008319	0,617024	-65,23571***
RMW	0,001697	0,354668	-66,29430***
CMA	0,006294	0,400256	-61,79180***
MOM	-0,002275	0,735392	-40,98233***

Note: The Augmented Dickey-Fuller(ADF) test aims to detect the presence of unit root when applied on time series. In our case, we reject the null hypothesis H_0 - the series has a unit root for a confidence threshold of 99%(***).

5. Empirical results and discussions

5.1. Analysis of gregarious behavior in developed markets

We observe that β_2 is positive for both the US and the European markets, which does not provide evidence of herding behavior and confirms previous studies by Chang et al. (2000) - USA and Duygun et al. (2021) - Europe. This may happen due to the periodicity of the herding phenomenon in relation to the extended period of analysis, and its tendency to be present in specific market hypostases. For the Asian market we observe a negative value of the coefficient β_2 in the first quantile but not statistically significant.

Table 3 Model (2) estimation

CSAD	Europe		USA		Japan	
Estimation method	**β_2 (t-stat)**	**R^2 adj.**	**β_2 (t-stat)**	**R^2 adj.**	**β_2 (t-stat)**	**R^2 adj.**
OLS	0,4583*** (2,904)	0,3838	0,4109** (2,202)	0,3979	0,9033*** (4,081)	0,2146
τ = 10%	0,4243*** (6,971)	0,1213	0,1833 (0,076)	0,1152	-1,2684 (-1,292)	0,0675
τ = 25%	1,5660*** (12,083)	0,1417	1,4794*** (17,916)	0,1258	1,0589*** (10,305)	0,0626
τ = 50%	1,9676*** (7,322)	0,1786	1,8471*** (10,041)	0,1641	1,9355*** (9,0861)	0,0767
τ = 75%	2,0455* (1,836)	0,2262	2,6794*** (4,951)	0,2132	1,8379 (1,145)	0,1097
τ = 90%	0,5037 (1,624)	0,2836	0,7893 (0,2906)	0,2878	4,3443*** (4,883)	0,1491

*Note: *** statistical significance at 1% level; **statistical significance at 5% level; *statistical significance at 10% level.*

5.2. Impact of market trends on investors' behavior

The periods of economic growth show a mimetic effect only in the US market, mainly through OLS analysis, which can be explained by the significance of the mean and the absence of outliers, the other two markets recording isolated negative values of the coefficient β_3 and statistically insignificant. On the contrary, the periods of decline reflect the presence of herding behavior particularly in the Japanese market, with the coefficient having a risk threshold of 10%, while the other markets do not provide concrete evidence of herding.

5.3. Impact of volatility on the behavior of the risk-takers

The US market is profoundly affected by asymmetric periods of volatility, thus herding behavior is found in the context of high volatility, with a predilection in the upper quantiles, an effect also confirmed by the literature, Christie and Huang(1995). While the Asian market does not provide significant evidence, in Europe we observe the presence of social bias in the third quantile during periods of high volatility, the coefficient β_3 is negative and has a 90% confidence interval.

5.4. Impact of investors' sentiment

Analyzing the results in Table 4 we deduce a restricted presence of the herd effect impacted by investors' optimism, more precisely it makes its influence felt only on the Asian market in the last quantile with an estimated coefficient of -2.2844. At the same time, the results provide a robust picture of the heavy behavior on the US and European markets in relation to participants' pessimism, which can also be demonstrated by the distinct cultural factor characterizing the Asian market. At the same time, the determination coefficient R^2 higher coefficient of determinacy characterizing Europe and the USA gives a better explanatory power to the variables, and hence to the model in relation to Japan.

Table 4. Models (4),(5),(6),(7),(8),(9) estimation

Europe						
Estimation method	**DUP**	**DDOWN**	**DHVOL**	**DLVOL**	**DO**	**DP**
OLS	0,0136 (0,119)	-0,0136 (-0,119)	-0,1178 (-0,831)	0,1178 (0,831)	0,8161*** (3,209)	-0,8466*** (-6,669)
τ = 10%	0,1124 (0,164)	-0,1124 (-0,164)	-0,1772 (-1,215)	0,1772 (1,215)	0,4905 (0,887)	-0,3969*** (-8,083)
τ = 25%	0,1663 (1,211)	-0,1663 (-1,211)	-0,2676 (-1,301)	0,2676 (1,301)	0,8906*** (3,198)	-0,4693 (-1,432)
τ = 50%	-0,0679 (-0,223)	0,0679 (0,223)	-0,2003* (-1,863)	0,2003* (1,863)	0,5778* (1,705)	-0,7126*** (-2,587)
τ = 75%	0,2033 (0,193)	-0,2033 (-0,193)	-0,2107 (-0,194)	0,2107 (0,194)	1,0023 (1,361)	-1,1657*** (-2,628)
τ = 90%	0,1815 (0,324)	-0,1815 (-0,324)	-0,7105 (-0,723)	0,7105 (0,723)	0,8709 (1,048)	-0,7608 (-0,579)
USA						
Estimation method	**DUP**	**DDOWN**	**DHVOL**	**DLVOL**	**DO**	**DP**
OLS	-0,5332*** (-3,355)	0,5332*** (3,355)	-1,1174*** (-4,607)	1,1174*** (4,607)	0,4863 (1,378)	-0,7695*** (-4,164)
τ = 10%	-0,3031 (-0,397)	0,3031 (0,397)	-0,0817 (-0,122)	0,0817 (0,122)	0,7192 (1,495)	-0,9922 (-1,217)
τ = 25%	-0,6149 (-1,356)	0,6149 (1,356)	-0,6971 (-1,437)	0,6971 (1,437)	0,3907 (1,595)	-0,7337 (-1,599)
τ = 50%	-0,2941 (-0,312)	0,2941 (0,312)	-1,0492*** (-14,775)	1,0492*** (14,775)	1,3802*** (9,324)	-1,0585*** (-18,085)
τ = 75%	-0,4657 (-0,701)	0,4657 (0,701)	-2,4642** (-2,567)	2,4642** (2,567)	2,4596** (2,095)	-1,4011 (-1,418)
τ = 90%	-0,1115 (-0,088)	0,1115 (0,088)	-2,7144*** (-3,542)	2,7144*** (3,542)	1,8448** (2,001)	-0,3212 (-0,303)

Japan						
Estimation method	**DUP**	**DDOWN**	**DHVOL**	**DLVOL**	**DO**	**DP**
OLS	0,3402* (1,695)	-0,3402* (-1,695)	0,0125 (0,044)	-0,0125 (-0,044)	-0,5462 (-1,411)	-0,1283 (-0,557)
τ = 10%	-0,0301 (-0,067)	0,0301 (0,067)	0,0523 (0,127)	-0,0523 (-0,127)	0,0372 (0,074)	0,0446 (0,079)
τ = 25%	0,2363 (0,216)	-0,2363 (-0,216)	-0,2112 (-0,490)	0,2112 (0,490)	-0,1243 (-0,391)	-0,3629 (-0,699)
τ = 50%	0,3311 (0,650)	-0,3311 (-0,650)	-0,1581 (-0,656)	0,1581 (0,656)	-0,201 (-0,602)	-0,0926 (-0,727)
τ = 75%	0,4489 (0,755)	-0,4489 (-0,755)	-0,6066 (-0,743)	0,6066 (0,743)	-0,5017 (-1,105)	-0,7681 (-0,670)
τ = 90%	0,6419 (0,289)	-0,6419 (-0,289)	0,5106 (0,231)	-0,5106 (-0,231)	-2,2844*** (-3,868)	0,1424 (0,159)

*Note: *** statistical significance at 1% level; **statistical significance at 5% level; *statistical significance at 10% level.*

5.5. Intentional and false gregarious behavior

Table 5 shows that the spurious herd effect is present only in the USA and Japan in the fourth quantile by estimating a regression coefficient β_3 negative and significant with a 99% confidence interval. As for the manifestation of intentional behavior guided by non-fundamental information, it is not supported by conclusive evidence in the US and European markets, while in Japan the specific coefficient takes a single negative value in the first quantile, but with a risk threshold above 10%. Last but not least, we note that this model is strongly influenced by the adjustment brought by the QREG method which considers the flexibility of herd behavior by reducing the assumptions on the distribution of endogenous variables and the resistance to the impact of extreme values – outliers.

Table 5. Model (11) estimation

CSADF Europe					
Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	0,0116*** (695,481)	0,0071*** (3,729)	0,1081*** (3,496)	0,0323	0,0319
τ = 10%	0,0110*** (278,588)	-0,0167* (-1,873)	0,1717 (0,577)	0,0093	0,0089
τ = 25%	0,0113*** (477,737)	-0,0102* (-1,958)	0,2047 (1,286)	0,0019	0,0015

τ = 50%	0,0116*** (740,163)	0,0007 (0,289)	0,2042*** (3,916)	0,0074	0,0070
τ = 75%	0,0119*** (628,617)	0,0183*** (5,672)	0,1149** (2,415)	0,0379	0,0375
τ = 90%	0,0122*** (492,012)	0,0373*** (9,958)	-0,0628 (-0,829)	0,0940	0,0936

CSADF USA

Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	0,0111*** (592,039)	0,0059** (2,516)	0,0157 (0,411)	0,0059	0,0054
τ = 10%	0,0105*** (280,327)	-0,0377*** (-3,654)	0,0784 (0,226)	0,0595	0,0591
τ = 25%	0,0107*** (533,172)	-0,0151*** (-4,413)	-0,0581 (-1,420)	0,0128	0,0123
τ = 50%	0,0111*** (700,762)	0,0014 (0,423)	0,1542** (2,424)	0,0026	0,0021
τ = 75%	0,0113*** (403,522)	0,0326*** (3,824)	-0,0786*** (-0,278)	0,0435	0,0431
τ = 90%	0,0116*** (403,064)	0,0473*** (10,580)	0,0166 (0,501)	0,0907	0,0903

CSADF Japan

Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	0,0111*** (1521,825)	0,0031*** (3,641)	-0,0416*** (-2,728)	0,0028	0,0024
τ = 10%	0,0108*** (884,111)	-0,0044*** (-3,239)	0,0297** (2,552)	0,0051	0,0047
τ = 25%	0,0109*** (1464,096)	-0,0016* (-1,875)	-0,0059 (-0,665)	0,0023	0,0019
τ = 50%	0,0111*** (2293,978)	0,0006 (0,932)	-0,0185* (-1,775)	0,0002	-0,0001
τ = 75%	0,0112*** (1363,663)	0,0081*** (8,476)	-0,0931*** (-8,549)	0,0127	0,0123
τ = 90%	0,0113*** (656,869)	0,0128*** (3,596)	-0,1356 (-1,282)	0,0238	0,0234

*Note: *** statistical significance at 1% level; **statistical significance at 5% level; *statistical significance at 10% level.*

Table 6 does not provide significant evidence of herding behavior due to the positive β_2 coefficient or its statistical insignificance, a result also confirmed by a recent study, Wang and Zhang (2024), which attests to the presence of herding behavior for a period of only 5 months out of 48 analyzed between 2019-2022, more precisely in 2020, thus there is no relevant evidence at the level of the entire sample on the S&P500 index.

Table 6. Model (12) estimation

CSADNF Europe					
Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	-0,0024*** (-28,269)	0,2617*** (26,528)	0,3501** (2,202)	0,3596	0,3593
τ = 10%	-0,0046*** (-48,687)	0,1616*** (18,293)	0,2595*** (4,290)	0,1033	0,1030
τ = 25%	-0,0034*** (-58,260)	0,1346*** (17,661)	1,2222*** (9,115)	0,1264	0,1260
τ = 50%	-0,0023*** (-33,338)	0,1468*** (11,785)	1,9531*** (6,461)	0,1618	0,1615
τ = 75%	-0,0011*** (-8,613)	0,2332*** (7,668)	1,5577* (1,765)	0,2113	0,2110
τ = 90%	0,0003** (2,219)	0,3948*** (17,992)	0,0878 (0,296)	0,2691	0,2688
CSADNF USA					
Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	-0,0022*** (-26,322)	0,2632*** (24,348)	1,1322*** (6,455)	0,3930	0,3927
τ = 10%	-0,0044*** (-63,997)	0,1015*** (10,912)	1,6271*** (22,431)	0,0909	0,0905
τ = 25%	-0,0035*** (-60,780)	0,1251*** (13,351)	1,8046*** (12,118)	0,1141	0,1137
τ = 50%	-0,0025*** (-22,781)	0,1804*** (5,053)	2,0455 (1,325)	0,1603	0,1599
τ = 75%	-0,0010*** (-9,031)	0,2266*** (8,463)	3,5758*** (5,501)	0,2162	0,2158
τ = 90%	0,0006** (2,188)	0,4303*** (4,426)	1,5619 (0,556)	0,2868	0,2865

CSADNF Japan					
Coefficients	**β_0 (t-stat)**	**β_1 (t-stat)**	**β_2 (t-stat)**	**R^2**	**R^2 adj.**
OLS	-0,0020*** (-19,012)	0,1905*** (15,716)	0,9449*** (4,274)	0,2139	0,2136
τ = 10%	-0,0061*** (-9,916)	0,2359*** (4,147)	-1,3700 (-1,196)	0,0671	0,0667
τ = 25%	-0,0032*** (-38,788)	0,1060*** (12,334)	1,0866*** (10,549)	0,0617	0,0613
τ = 50%	-0,0016*** (-18,195)	0,0965*** (7,797)	1,9969*** (9,165)	0,0751	0,0747
τ = 75%	0,0003 (1,585)	0,1494*** (3,354)	1,9828 (1,219)	0,1081	0,1077
τ = 90%	0,0028*** (12,109)	0,1222*** (3,474)	4,5221*** (6,221)	0,1495	0,1492

*Note: *** statistical significance at 1% level; **statistical significance at 5% level; *statistical significance at 10% level.*

6. Conclusions

In the above paper we investigated the emergence of herding behavior in developed stock markets of Europe, the US and Japan starting from the econometric model of Chang, Cheng and Khorana, and then forming various versions based on it according to the hypostases of the markets. Therefore, three key influencing criteria were market trends, volatility fluctuations, and investor sentiment towards the market. In addition to these, we detailed herding behavior according to the underlying information, in fact, the fundamental information that characterizes spurious behavior and the non-fundamental information that drives intentional behavior, using the multifactor model developed by Eugene Fama and Kenneth French in 1992, which was subsequently used in his study and by Galariotis et al. in 2015. The OLS method confirmed the presence of the gregarious effect in all three markets through the estimated results, but under different market circumstances. We also used the QREG method for each case for a better distribution of the dependent variable CSAD and increased robustness of the relationship between the variables, hence the explanatory power.

As its main repercussions, the herd effect gives rise to systematic risk, threatening market stability, and should be a primary responsibility for financial authorities and policy makers. By detailing the process, it increases market volatility and undermines informational efficiency, resulting in so-called informational cascades, whereby investors ignoring their own forecasts diminish the information content embedded in security prices through active portfolio management. Individual investors therefore tend to be vulnerable to specific risk because they do not diversify their portfolio efficiently enough. As time passes, the presence of this behavioral bias shifts the share price away from its fundamental value, causing disruptions to business cycles through speculative bubbles. Among the historical financial events caused by this phenomenon we mention the dot-com speculative bubble in the 1990s - investors stormed the technology stock market and then suffered massive losses in 2000 as a result of the accelerated price increases, the global financial crisis in 2008 - participants massively sold risky assets amid pessimism, increasing panic and causing the market to fall, and the emergence of the cryptocurrency Bitcoin in 2017 - the hurding effect caused its price to soar on the back of investor optimism.

In conclusion, proper regulation and assessment of the anomalies produced, through policies that limit the spread of herding behavior and maintain financial stability in the markets, by financial supervisors with expert academic support, enhance investment decisions towards the superior outcomes proliferated by classical, deeply rational financial theory. Future research can extend the present study towards the detailed relationship between idiosyncratic volatility, herding and liquidity by extending the empirical framework proposed by Lof (2023) which reveals the influence of asymmetric information between investors on the distribution of transaction volume – volume coefficient of variation.

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