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Research article

Navigating the herd: The dynamics of investor behavior in the Brazilian stock market

Júlio Lobão[1], Luís Pacheco[2,*] and Maria Beatriz Naia[1]

[1] School of Economics and Management, University of Porto, and CEF.UP, Porto, Portugal
[2] Department of Economics and Management, Portucalense University, and REMIT – Research on Economics, Management and Information Technologies, Porto, Portugal

* **Correspondence:** Email: luisp@upt.pt.

Abstract: We investigated under-researched dimensions of market-wide herding behavior in the Brazilian stock market using a sample from January 2010 to December 2022. Employing OLS and quantile regressions, we found no evidence of herding in the sample or across market conditions, including return, trading volume, and volatility. However, dynamic analysis via rolling window regressions revealed intermittent herding behavior during various subperiods, including at the onset of the COVID-19 pandemic and around the beginning of the war in Ukraine. Additionally, regression results differentiate between herding driven by fundamental and non-fundamental factors, elucidating the predominance of negative herding attributable to non-fundamental influences. These findings underscore the presence of irrational behavior among investors, potentially leading to increased price instability and deviations from fundamental values. Moreover, the association of negative herding with diversifiable risk suggests potential implications for portfolio composition. Overall, this study contributes to understanding investor behavior in emerging markets and highlights the impact of herding on market dynamics and portfolio management strategies.

Keywords: herding behavior; quantile regression; Brazilian stock market; cross-sectional deviation of returns

JEL Codes: G11, G40, G41

1. Introduction

Behavioral finance diverges from the stringent assumptions of expected utility theory by recognizing that individuals' preferences and beliefs significantly influence decision-making, leading to deviations from rational expectations (Kahneman & Tversky, 1979; Hirshleifer, 2015; Antony, 2020).

A notable bias within behavioral finance is herding behavior, which has attracted considerable attention from academic scholars over the past few decades (e.g., Hirshleifer & Hong Teoh, 2003; Choi & Sias, 2009; Zhou & Anderson, 2011; Nguyen et al., 2023). Herding behavior occurs when investors ignore their own private information and follow the market consensus, leading to increased uniformity in perspectives on asset values and a closer alignment of asset returns with the overall market return. Conversely, negative herding behavior is characterized by asset returns deviating more from the market consensus than would be justified by rational decision-making. Herding and negative herding represent two contrasting behavioral phenomena that deserve equal attention in academic research (Hwang and Salmon, 2004). Understanding these behavioral patterns is essential as they impact interconnected markets, potentially amplifying volatility, distorting prices from their fundamental values, and creating speculative bubbles (Chiang et al., 2010; Bekiros et al., 2017).

Various authors have analyzed herding at the market level, concluding that this bias tends to be a short-term phenomenon, which is prevalent in emerging markets (e.g., Vo & Phan, 2016; Batmunkh et al., 2020). In these markets, factors such as uncertainty and the quality and costs of information contribute to why investors abandon their private beliefs to follow other market participants (Spyrou, 2013). However, empirical research in some countries remains inconclusive, partly due to the dynamic nature of herding behavior and the limitations of static models (Babalos & Stavroyiannis, 2015).

The Brazilian stock market offers a compelling setting for studying herding behavior, as there are indications that the phenomenon is more likely to occur in developing countries due to higher information asymmetry and uncertainty (Dang & Lin, 2016; Vo & Phan, 2016; Mulki & Rizkianto, 2020). We investigate the prevalence of market-wide herding behavior among the stocks comprising the Ibovespa index from 2010 to 2022, considering the impact of significant events such as the Covid-19 pandemic and the war in Ukraine. We explore several under-researched dimensions of herding behavior in the largest stock market on the South American continent. We employ Ordinary Least Squares (OLS) and Quantile Regressions (QR) to investigate herding across different market conditions. Additionally, we use dynamic models to capture the evolution of herding and decompose herding into fundamental and non-fundamental factors, offering insights into the drivers of the phenomenon.

Several innovative contributions of our study can be highlighted, as they represent approaches never before presented in studies applied to the market under analysis, to the best of our knowledge. First, we are the first to study to examine herding behavior in the Brazilian stock market using quantile regressions. This method offers a more suitable approach than OLS for handling outliers in the data and remains robust against heteroscedasticity and skewness, which are common characteristics of market data under scrutiny. Second, in accordance with the principles of the adaptive market hypothesis proposed by Lo (2004), which suggests that investors may exhibit different behaviors in response to specific market circumstances, we apply the rolling window regression technique for the first time to study the dynamics of herding in the Brazilian market. This technique, applied to recent data, enables us to conclude that there was an intensification of herding dynamics at the onset of the COVID-19 pandemic and around the beginning of the war in Ukraine. Third, we distinguish the drivers of herding between fundamental and non-fundamental factors. This enables us to reveal that non-fundamental factors were the origin of the negative herding dynamics detected.

The article is structured as follows: In Section 2, we review the literature and outline hypotheses; in Section 3, we detail the methodology; In Section 4, we present the results; and in Section 5, we conclude with implications and suggestions for future research.

2. Literature review and development of hypotheses

Studies on developed markets reveal varied findings regarding herding behavior. Caporale et al. (2008) and Economou et al. (2011) detected herding in Greece, Italy, and Portugal over specific periods. However, Mobarek et al. (2014) found no evidence of herding in these countries during a different timeframe. In Greece, Economou et al. (2016) observed herding in upper quantiles using quantile regression. Pochea et al. (2017) analyzed Central and East European (CEE) countries, noting herding in some but not all nations. Litimi (2017) reported the existence of significant sectoral herding in France, while Bogdan et al. (2022) found no traces of herding in five European developed stock markets.

In emerging markets, several researchers have reported herding behavior, including in Latin American countries like Argentina, Brazil, Colombia, and Mexico (Chiang & Zheng, 2010; de Almeida et al., 2012; Vo & Phan, 2016; Nguyen et al., 2023). There is no consensus regarding the prevalence of the phenomenon in the Brazilian stock market. For example, while de Almeida et al. (2012) failed to detect significant herding in the Brazilian stock market, Mulki and Rizkianto (2020) found evidence of negative herding. More recently, Signorelli et al. (2021) observed herding in several of the years covered by their sample period.

The 21st century saw significant changes in the Brazilian stock market, with increased value and volume due to economic improvements and political reforms (Vartanian et al., 2022). Despite this growth, Brazil faced challenges from global financial crises and other macroeconomic events.

Motivated by previous findings, we hypothesize the following:

H1: There is significant herding behavior in the Brazilian stock market in the whole period, specifically, from January 5, 2010, to December 29, 2022.

Herding behavior often exhibits an asymmetric nature, particularly during turbulent periods, during which investors, faced with increased uncertainty, tend to adhere more closely to market consensus (Chang et al., 2000). Studies show that herding intensity varies across market conditions, such as high/low returns, trading volume, and volatility (Economou et al., 2011; Mobarek et al., 2014; Arjoon et al., 2020; Batmunkh et al., 2020; Signorelli et al., 2021; Costa et al., 2024). In Latin America, de Almeida et al. (2012) found herding in Chile across various market conditions, while in Argentina and Mexico, herding was observed mainly during low volatility days. Contrary to these findings, Mulki and Rizkianto (2020) reported herding in Brazil during high volatility periods. Signorelli et al. (2021) noted significant herding during days of high trading volume, volatility, poor market performance, and increased sell orders.

Based on these findings, our second hypothesis posits the following:

H2: Herding behavior significance depends on market conditions, such as return, trading volume, and volatility.

Regression models for testing hypotheses (H1) and (H2) typically employ Ordinary Least Squares (OLS), which may lose tail distribution information. Quantile Regression (QR) offers more robust results, as evidenced in previous studies (Chiang et al., 2010; Choi & Yoon, 2020; Pochea et al., 2017).

QRs are less sensitive to outliers and more efficient with non-normal data, enabling assessments of investor behavior across quantiles. Herding is more likely to occur in the high quantiles of the distribution, that is, during periods of market instability, than in lower quantiles (Zhou & Anderson, 2011; Aharon, 2021). Thus, our third hypothesis suggests the following:

H3: Herding behavior significance depends on the regression's quantile.

Herding behavior demonstrates a dynamic nature influenced by micro- and macroeconomic shocks, leading to structural breaks in static regression models (Babalos & Stavroyiannis, 2015; Cakan et al., 2018). To capture this dynamic aspect, researchers have explored time-varying models (Sharma et al., 2015; Babalos & Stavroyiannis, 2015; Bouri et al., 2019). Recent studies during the Covid-19 pandemic revealed intensified herding, particularly in less developed markets due to increased uncertainty (Bogdan et al., 2022; Jiang et al., 2022). Investors exhibit a stronger tendency to conform to the consensus during extreme market conditions, and herding has been observed to spill over from advanced markets to emerging markets during times of crisis (Gouta & BenMabrouk, 2024). Considering the lingering effects of the financial crisis and subsequent events like elections, the Covid-19 pandemic, and military conflicts, the fourth hypothesis anticipates the following:

H4: Herding behavior exhibits a dynamic evolution, presenting a higher intensity during adverse market conditions.

Herding behavior can stem from either fundamental (spurious) or non-fundamental (intentional) factors, as delineated by Bikhchandani and Sharma (2000). Spurious herding occurs when individuals use the same information without deliberately imitating each other, while intentional herding arises when participants deliberately follow the crowd (Bikhchandani & Sharma, 2000; Kremer & Nautz, 2013). Galariotis et al. (2015) further dissected these notions using the 3-factor model, decomposing the Cross-Sectional Absolute Deviation (CSAD) into its fundamental and non-fundamental components. They discovered that in the US, investors imitated peers influenced by both fundamental and non-fundamental factors, particularly during crisis periods.

Inspired by Galariotis et al. (2015), various researchers across different markets have analyzed returns' dispersions, splitting them into fundamental and non-fundamental components to understand the drivers of herding behavior (Indārs et al., 2019; Dang & Lin, 2016; Liu et al., 2023). While herding might not always be evident across the entire dataset, decomposition often reveals its presence. For instance, Indārs et al. (2019) initially found no evidence of herding but upon decomposition, discovered intentional herding motives in the Moscow stock exchange. In China, Liu et al. (2023) observed that less informed investors tended to herd more, particularly during turbulent periods. During downturns, less-informed investors followed intentional motifs, while informed investors relied on fundamental information for herding.

Drawing from these studies and recognizing a gap in research on intentional and spurious herding in the Brazilian context, the final hypothesis posits the following:

H5: Herding behavior is driven by fundamental (spurious) and non-fundamental (intentional) factors.

3. Methodology

3.1. Data collection

The daily adjusted closing stock prices of companies comprising the Ibovespa index from January 4th, 2010, to December 29th, 2022, were gathered from the Thomson Reuters Eikon database. The Ibovespa index was created in 1968 and serves as the benchmark index for the Brazilian stock market, accounting for the majority of trading and market capitalization in that market. It is a weighted measurement index that includes a variable number of companies. Companies included in the index must meet a set of liquidity conditions, including the requirement of having been traded for at least 95% of the sessions in the portfolio cycle under consideration. The index composition is reviewed quarterly. At the end of 2022, the index represented a market capitalization of approximately 860 billion US dollars. Given the index's rebalancing on the first Monday of January, May, and September, the final composition for each period was obtained from the Refinitiv database through analysis of leavers and joiners. It is important to note that companies leaving the index between two rebalancing periods were only considered part of the index until the previous period, while those joining in between periods were considered only from the following rebalancing moment. This approach mitigates survivorship bias in the sample. Returns were calculated in logarithmic format.

3.2. Ordinary Least Squares Regression

The Cross-Sectional Absolute Deviation (CSAD) framework is commonly used to detect herding in financial markets, defined as:

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

where $R_{i,t}$ denotes the return of i^{th} security of the market portfolio on day t, $R_{m,t}$ is the return of an equally weighted market portfolio on day t, and N is the number of firms.

Chang et al. (2000) noted that herding manifests as a non-linear relationship between CSAD and market return, captured by the coefficient γ_2, which should be negative and statistically significant. To detect herding across the sample, the following regression is conducted:

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

Newey-West (1987) heteroskedastic and autocorrelation coefficients (HAC) are used to estimate the coefficients in line with prior literature.

Herding is known to occur during asymmetric market conditions. To test the impact of return asymmetries, the following equation is estimated:

$$CSAD_t = \gamma_0 + \gamma_1 D^{Up}\left|R_{m,t}\right| + \gamma_2(1 - D^{Up})\left|R_{m,t}\right| + \gamma_3 D^{Up}(R_{m,t})^2 + \gamma_4(1 - D^{Up})(R_{m,t})^2 + \varepsilon_t \tag{3}$$

where D^{Up} is a dummy variable equal to one on days when $R_{m,t} > 0$ and zero otherwise. The coefficients γ_3 and γ_4 detect herding during bullish and bearish market states, respectively.

To examine herding during days of high and low trading volume, equation (4) is considered,

$$CSAD_t = \gamma_0 + \gamma_1 D^{Vol-High}|R_{m,t}| + \gamma_2(1 - D^{Vol-High})|R_{m,t}| + \gamma_3 D^{Vol-High}(R_{m,t})^2 + \gamma_4(1 - D^{Vol-High})(R_{m,t})^2 + \varepsilon_t \quad (4)$$

where $D^{Vol\text{-}High}$ is a dummy variable equal to one on days of high trading volume and zero otherwise. Day t is a day of high volume if the trading volume on day t is higher than the previous 30-day moving average (MA30) (Economou et al., 2011). The presence of herding is detected by coefficients γ_3 (days of high trading volume) and γ_4 (days of low trading volume).

Last, to evaluate the impact of market volatility, regression (5) is used,

$$CSAD_t = \gamma_0 + \gamma_1 D^{\sigma^2-High}|R_{m,t}| + \gamma_2(1 - D^{\sigma^2-High})|R_{m,t}| + \gamma_3 D^{\sigma^2-High}(R_{m,t})^2 + \gamma_4(1 - D^{\sigma^2-High})(R_{m,t})^2 + \varepsilon_t \quad (5)$$

Following Tan et al. (2008), volatility is calculated as the square of the portfolio's return in each day t. D^{σ^2-High} is set equal to one on day t if volatility is higher than the MA30, according to Economou et al. (2011). A negative and statistically significant γ_3 (γ_4) is consistent with investors' herding during high (low) volatility days.

3.3. Quantile regression

Ordinary Least Squares regression has limitations as it focuses on the mean as a location's measure. Quantile Regression (QR) is employed to overcome these limitations by not losing information in the tails of the distribution. QR is defined as:

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau}(R_{m,t})^2 + \varepsilon_{\tau,t} \quad (6)$$

where X_t represents the vector of the right-hand-side variables. QR is applied to evaluate herding during different market conditions, including days of high and low return, trading volume, and volatility. Dummy variables are defined similarly to OLS regressions to capture different market states.

3.4. Dynamic characterization

To understand herding's dynamic evolution, a rolling window approach is adopted. Static models with constant regression coefficients may lead to biased conclusions, assuming unchanging relationships. Utilizing a rolling window of one-day step and 100-day size allows for the assessment of herding's evolution over time.

Rolling coefficients for regressions (2), (3), (4), and (5), along with t-statistic graphics for each coefficient, are generated. A negative and statistically significant coefficient would indicate investors' tendency to imitate each other.

3.5. Fundamental vs. non-fundamental drivers

Studies by Dang and Lin (2016) and Galariotis et al. (2015) decomposed the total CSAD into fundamental and non-fundamental parts using common risk factors from the literature (Carhart, 1997; Fama & French, 1993, 2015). Regression (7) serves as the starting point to characterize fundamental and intentional herding:

$$CSAD_{TOTAL,t} = \delta_0 + \delta_1 |R_{m,t} - R_f| + \delta_2 |SMB_t| + \delta_3 |HML_t| + \delta_4 |WML_t| + \delta_5 |IML_t| + \varepsilon_t \quad (7)$$

Here, $|R_{m,t}\text{-}R_f|$ represents the difference between the daily return of the value-weighted portfolio and the risk-free asset. The other factors represent various risk factors as defined by Fama and French (1993, 2015). The small-minus-big (SMB_t) is the difference between the return of stocks with low market capitalization (small) and stocks with higher market capitalization. The high-minus-low (HML_t) stands for the difference between a portfolio of stocks of high book-to-market equity (BE/ME) and low BE/ME. The winners-minus-losers (WML_t) factor is obtained through the difference between a portfolio of stocks with high past returns and a portfolio of stocks with low past returns. Last, the illiquid-minus-liquid (IML_t) factor is calculated as the difference between a portfolio on liquid stocks and a short position on illiquid stocks, where liquidity is calculated using the Amihud (2002) measure. Information on the factors was retrieved from the Brazilian Center for Research in Financial Economics of the University of São Paulo (NEFIN) website.

As in Galariotis et al. (2015), the total CSAD () is then split into $CSAD_{NON\text{-}FUND,t}$ (8) and $CSAD_{FUND,t}$ (9), distinguishing non-fundamental and fundamental herding:

$$CSAD_{NON-FUND,t} = \varepsilon_t \quad (8)$$

$$CSAD_{FUND,t} = CSAD_{TOTAL,t} - CSAD_{NON-FUND,t} \quad (9)$$

To identify if herding is driven by non-fundamental or fundamental factors, $CSAD_{NON\text{-}FUND,t}$ and $CSAD_{FUND,t}$ are regressed using Chang et al.'s (2000) framework, distinguishing intentional and spurious herding for different market structures, including returns, trading volume, and volatility.

4. Empirical results and discussion

4.1. Sample characterization

Descriptive statistics, normality tests, Augmented Dickey-Fuller tests, and autocorrelation analyses were conducted to characterize the sample. Table 1 summarizes these findings, indicating leptokurtosis and non-Gaussian distributions for $CSAD_t$ and $R_{m,t}$. Both variables are stationary over the analyzed period, with significant autocorrelation at various lags, supporting the use of HAC coefficients.

Table 1. Descriptive Statistics, Normality Test, Augmented Dickey-Fuller test, and Autocorrelation.

Panel A – Descriptive Statistics					
$CSAD_t$			$R_{m,t}$		
Mean		1.5167%	Mean		−0.0028%
Median		1.4224%	Median		0.0351%
Minimum		0.4833%	Minimum		−18.4531%
Maximum		6.9274%	Maximum		12.0825%
Standard Deviation		0.4864%	Standard Deviation		1.5863%
Kurtosis		20.6614	Kurtosis		18.8500
Skewness		2.9298	Skewness		−1.2129
Observations		3217	Observations		3217
Panel B – Normality Test					
$CSAD_t$			$R_{m,t}$		
Jarque−Bera statistic		46412.94***	Jarque−Bera statistic		34463.18***
Panel C – Augmented Dickey−Fuller (ADF) Test					
$CSAD_t$			$R_{m,t}$		
ADF statistic		−9.0922***	ADF statistic		−39.3073***
Panel D – Autocorrelation					
$CSAD_t$			$R_{m,t}$		
Lags	1	0.614***	Lags	1	−0.066***
	2	0.564***		2	0.055***
	3	0.541***		3	−0.004***
	4	0.531***		4	−0.020***
	5	0.504***		5	0.045***
	10	0.390***		10	0.027***

Notes: $CSAD_t$ is calculated according to (1). $R_{m,t}$ is obtained through the procedure described above. The study is conducted from January 5, 2010, to December 29, 2022, resulting in 3217 daily observations. In Panel B, the Jarque-Bera test evaluates if $CSAD_t$ and $R_{m,t}$ conform a normal distribution. In Panel C, the ADF analyses the stationarity and the values in correspond to the *t-statistic*. Panel D contains the values for different serial correlations. *** significant at a 1% level.

4.2. Ordinary least squares regression

4.2.1. Whole period analysis

Herding behavior in the Ibovespa index was analyzed using regression (2) for the sample period. Table 2 presents the results.

Table 2. Analysis of herding behavior in the Ibovespa index for the whole period.

Regression Output – Model (2)			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0127	0.2100	0.5802	0.3487
(64.0362)***	(8.7550)***	(1.8803)*	

Notes: Regression is estimated using HAC estimators and the values in parenthesis correspond to the *t-statistic*. *** significant at 1% level; * significant at 10% level.

The coefficient γ_1 is positive and statistically significant, indicating that CSAD increases with rising market returns, consistent with classical models. However, the herding detection coefficient, γ_2, is positive and statistically significant only at a 10% level, suggesting no tendency for investors to mimic their peers. Thus, no convergence towards the market consensus is observed.

Table 2 results are consistent with previous works (Chiang & Zheng, 2010; de Almeida et al., 2012), but contrast with results from Chen (2013), Mulki and Rizkianto (2020), and Signorelli et al. (2021). Positive and statistically significant herding coefficients have been associated with negative herding. Negative herding can be driven by factors like overconfidence or panic selling, leading to higher return dispersions than predicted by traditional models (Gębka & Wohar, 2013). Regarding overconfidence, Antonelli-Filho et al. (2021) evidence the presence of this bias in Brazilian day traders.

Given that the Ibovespa index comprises shares of the most liquid companies, it is plausible that herding behavior is not detected in this study. The positive and statistically significant γ_2 coefficient rejects hypothesis H1, indicating no evidence of herding behavior in the Ibovespa index over the period analyzed.

4.2.2. Asymmetric herding

Herding is often considered a short-lived event, more pronounced during turmoil periods, and may be detected only in distinct market conditions. Motivated by this empirical evidence, herding is assessed during days of high and low return, trading volume, and volatility. The output results are presented in Table 3.

The regression outputs in Table 3 (Column A) do not support the existence of herding in either a bullish or bearish market state. The coefficients of herding detection during days of high (γ_3) and low (γ_4) return are positive and statistically significant, suggesting that investors rely on their private opinions and beliefs than mimicking peers. The Wald test confirms that negative herding is statistically different during these two market states.

Regarding Column B, the results indicate no evidence of herding behavior. Both γ_3 and γ_4 coefficients are positive and statistically significant, consistent with negative herding. The Wald test confirms significant differences in negative herding during days of high and low trading volume, with stronger negative herding observed on days of low trading volume.

Herding during days of higher and lower uncertainty is evaluated using regression (5). Results in Column C suggest negative herding, with investors following their beliefs mainly on days of lower uncertainty compared to days of higher uncertainty, as indicated by the positive and statistically significant coefficients γ_3 and γ_4.

Table 3. Analysis of herding behavior in the Ibovespa index considering days of high and low return, trading volume, and volatility.

Regression Output			
	A Model (3)	B Model (4)	C Model (4)
γ_0	0.0128 (67.2353)***	0.0132 (70.5136)***	0.0124 (52.8629)***
γ_1	0.1825 (5.9924)***	0.2200 (9.2662)***	0.1962 (9.8412)***
γ_2	0.1768 (8.2311)***	−0.0011 (−0.0422)	0.2701 (5.9490)***
γ_3	2.0870 (3.0426)**	0.4375 (1.6704)*	0.6475 (1.6704)**
γ_4	0.6252 (2.6112)***	6.0702 (7.5806)***	3.1481 (2.6854)***
$\overline{R^2}$	0.3623	0.3749	0.3760
Wald Test			
$\gamma_1-\gamma_2$	0.0056	0.2211	−0.0739
χ^2	[0.7675]	[0.0000]***	[0.0281]**
$\gamma_3-\gamma_4$	1.4618	−5.6327	−2.5006
χ^2	[0.0046]***	[0.0000]***	[0.0286]**

Notes: Regressions (3), (4) and (5) are estimated using HAC estimators and the values in parenthesis correspond to the *t-statistic*. A Wald test evaluates if the coefficients are statistically different. In the first and third rows the values presented represent γ_1-γ_2 and γ_3-γ_4, respectively. The values given in the second and fourth rows represent χ^2 probability (*p-value*). *** significant at 1% level; ** significant at 5% level.

These findings are consistent with some prior studies but diverge from others. For example, de Almeida et al. (2012) observed negative herding in both market states, implying that investors traded based on their own beliefs. However, Mulki and Rizkianto (2020) found herding to be statistically significant during periods of high volatility, while Signorelli et al. (2021) detected herding only on days of increased uncertainty in their sample.

In contrast to some empirical evidence, investors in the Ibovespa do not follow their peers when uncertainty rises, suggesting that market participants may rely on fundamental information to justify their trades. Overall, the results indicate no evidence of herding in asymmetric market conditions from January 2010 to December 2022, leading to the rejection of hypothesis H2.

4.3. Quantile regression

4.3.1. Whole period analysis

In the literature, various authors have analyzed the presence of herding using Quantile Regression (QR), given its advantages over OLS regression. Financial markets often experience extreme events at distribution tails, which may be overlooked by OLS but captured by QR, allowing the evaluation of herding in different quantiles. The positive kurtosis of $CSAD_t$ and $R_{m,t}$ supports the use of QR. The QR regression of model (6) is run, and the output results are presented in Table 4.

Table 4. Analysis of herding behavior in the Ibovespa Index for the whole period, using a quantile regression.

Regression Output – Whole Period – Model (6)				
	γ_0	γ_1	γ_2	Pseudo $\overline{R^2}$
Quantile	0.0097	0.1105	0.7324	0.0824
(τ=10%)	(89.4807)***	(11.2723)***	(13.9353)***	
Quantile	0.0108	0.1337	0.7106	0.0928
(τ=25%)	(95.6182)***	(11.8726)***	(9.6061)***	
Quantile	0.0125	0.1513	1.4270	0.1227
(τ=50%)	(96.4691)***	(9.6689)***	(4.8434)***	
Quantile	0.0146	0.1783	1.9545	0.1741
(τ=75%)	(71.9217)***	(5.6698)***	(3.1215)***	
Quantile	0.0165	0.2509	1.6971	0.2298
(τ=90%)	(55.5338)***	(5.9506)***	(3.1297)***	

Notes: For this regression, 5 quantiles are chosen: τ=10%, τ=25%, τ=50%, τ=75%, and τ=90%. Herding behavior is assessed conditional on the τ value. Values presented in parenthesis represent the *t-statistic*. *** significant at 1%.

From Table 4, it is evident that the coefficient γ_2 is positive and statistically significant across all quantiles, indicating negative herding between January 2010 and December 2022. This finding is consistent with Shrotryia and Kalra (2020) , who found negative herding for the median and above the median quantiles.

4.3.2. Asymmetric herding

Regressions based on (6) are run to evaluate investors' behavior during different market structures, and the results are presented in Panels A, B, and C of Table 5. From Table 5, whatever the quantile, no evidence of herding behavior is observed once all the associated coefficients in up (γ_3) and down-market (γ_4) states are not significantly negative.

In Panel A, coefficients are positive and significant, consistent with negative herding, except on bull days for quantile τ=25%. Panel B suggests that volume asymmetries induce investors to follow their beliefs in all quantiles, except during high volume days for quantile τ=90%. Panel C emphasizes that investors do not attempt to reach the market consensus in all quantiles, except for the median quantile during days of high uncertainty.

These findings align with Shrotryia and Kalra (2020), who observed adverse herding in all distribution quantiles for the BRICS, except for the median quantile of γ_4. Similarly, in China, Chiang et al. (2010) reported herding in lower quantiles for certain shares. Herding in Malaysia was detected in the upper distribution tail during up and down-market states (Loang & Ahmad, 2024). In South Korea, Choi and Yoon (2020) found herding in extreme quantiles depending on market conditions.

In sum, the results shown in Table 5 do not support H3, given that no evidence of herding is found in any quantile for different market states.

Table 5. Analysis of herding behavior in the Ibovespa index using a quantile regression for different market states.

	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Panel A – Regression Output: Return's Asymmetry						
Quantile	0.0098	0.0956	0.0881	2.0736	0.8513	0.0899
(τ=10%)	(89.0844)***	(7.098)***	(7.5785)***	(18.9134)***	(3.030)***	
Quantile	0.0110	0.1051	0.10439	2.2326	0.7283	0.0991
(τ=25%)	(56.0736)***	(1.6067)***	(5.9775)***	(0.8054)	(7.9123)***	
Quantile	0.0126	0.1204	0.1546	3.1625	0.55737	0.1298
(τ=50%)	(97.8630)***	(5.2014)***	(11.2155)***	(5.3108)***	(3.030)***	
Quantile	0.0147	0.1787	0.1635	2.7244	1.3660	0.1787
(τ=75%)	(98.1750)***	(7.9880)***	(8.7289)***	(7.7000)***	(9.5310)***	
Quantile	0.0170	0.16014	0.1768	5.5640	2.4172	0.2339
(τ=90%)	(51.5979)***	(2.5459)**	(3.9290)***	(3.1726)***	(3.7157)***	
Panel B – Regression Output: Volume's Asymmetry						
	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Quantile	0.0102	0.1034	-0.0656	0.7577	6.6135	0.0996
(τ=10%)	(98.3300)***	(10.5894)***	(-3.8777)***	(14.5004)***	(21.3117)***	
Quantile	0.0113	0.1336	-0.0187	0.6947	5.6452	0.1038
(τ=25%)	(96.2439)***	(10.035)***	(-1.0296)	(8.1503)***	(16.5922)***	
Quantile	0.01294	0.1851	-0.0171	0.5615	6.3932	0.1393
(τ=50%)	(93.0213)***	(11.8878)***	(-0.5414)	(2.1467)**	(4.8905)***	
Quantile	0.0149	0.2218	-0.0094	0.96455	6.8474	0.1883
(τ=75%)	(95.3123)***	(12.6100)***	(-0.2292)	(6.9743)***	(4.0556)***	
Quantile	0.0174	0.2958	-0.1124	1.0365	12.1659	0.2541
(τ=90%)	(53.7102)***	(4.6676)***	(-2.1945)**	(1.0192)	(7.2786)***	
Panel C – Regression Output: Volatility's Asymmetry						
	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Quantile	0.0095	0.1123	0.1498	0.7296	2.9915	0.0939
(τ=10%)	(66.8219)***	(10.6700)***	(6.7368)***	(13.0735)***	(3.030)***	
Quantile	0.0107	0.1314	0.1716	0.7308	2.9123	0.1015
(τ=25%)	(70.4796)***	(10.7335)***	(6.3409)***	(9.5221)***	(6.3409)***	
Quantile	0.0123	0.1483	0.1896	1.2456	4.6500	0.1346
(τ=50%)	(28.3173)***	(0.3743)	(2.8556)***	(0.2113)	(3.5908)***	
Quantile	0.0144	0.1574	0.2032	2.1693	6.6928	0.1887
(τ=75%)	(67.3982)***	(4.6276)***	(4.2553)***	(2.7721)***	(3.6692)***	
Quantile	0.0164	0.1972	0.2401	2.2650	7.3482	0.2339
(τ=90%)	(42.9493)***	(5.3408)**	(2.3267)**	(4.6667)***	(1.8331)*	

Notes: For each regression 5 quantiles are chosen: τ=10%, τ=25%, τ=50%, τ=75%, and τ=90%. γ_3 allows the detection of herding behavior (if negative and statistically significant) during days of high market return (Panel A), high trading volume (Panel B), and high volatility (Panel C), conditional on the τ value. γ_4 allows the detection of herding behavior (if negative and statistically significant) during days of low market return (Panel A), low trading volume (Panel B), and low volatility (Panel C), conditional on the τ value. Values presented in parenthesis represent the *t-statistic*. *** significant at 1%, ** significant at 5%, * significant at 10%.

4.4. Dynamic nature of herding behavior

As evidenced by the literature, herding tends to emerge during extreme market conditions, making a dynamic analysis relevant to highlight its evolution. Parameters assumed to be constant in equations (2), (3), (4), and (5) might lead to erroneous conclusions. OLS regression coefficients are based on an average and may not reflect turbulent periods accurately (Babalos & Stavroyiannis, 2015).

The Bai-Perron test revealed structural breaks in the models, indicating that the coefficients are not constant throughout the period being analyzed. Consequently, to explore the dynamic nature of herding, a rolling window approach was employed. Despite no evidence of herding detected across the sample, the rolling window analysis, depicted in Figure 1, uncovered periods where investors exhibited tendencies to mimic their peers and align with market consensus.

The rolling window analysis unveiled several significant periods of herding behavior. Notably, between January 27, 2012, and February 16, 2012, excluding February 2 and February 3, investors mirrored their peers' trades. Similarly, herding behavior was observed between April 23, 2015, and May 8, 2015, except for May 4 and May 5. Additionally, significant instances of herding were identified from September 2, 2016, to September 15, 2016, and from November 27, 2019, to December 23, 2019. The periods in 2012 and 2016 can be associated with strong rallies in the Ibovespa, accompanied by the strengthening of the US dollar. The period in 2015 is closely linked to the "Lava-Jato" scandal and the subsequent crash in Petrobrás, Ibovespa's main company. The onset of the Covid-19 pandemic in 2020 prompted investors to herd, particularly between March 31, 2020, and August 7, 2020. Similarly, investors exhibited herding behavior just before the onset of the war in Ukraine, from February 16, 2022, to February 24, 2022.

The emergence of herding during these periods can be attributed to fear and uncertainty regarding market prospects. For instance, the COVID-19 pandemic in Europe led to increased herding, driven by fear and uncertainty, with less informed investors tending to mimic more informed agents. Similarly, geopolitical instability arising from the war in Ukraine prompted investors to converge toward market consensus, especially during downturns.

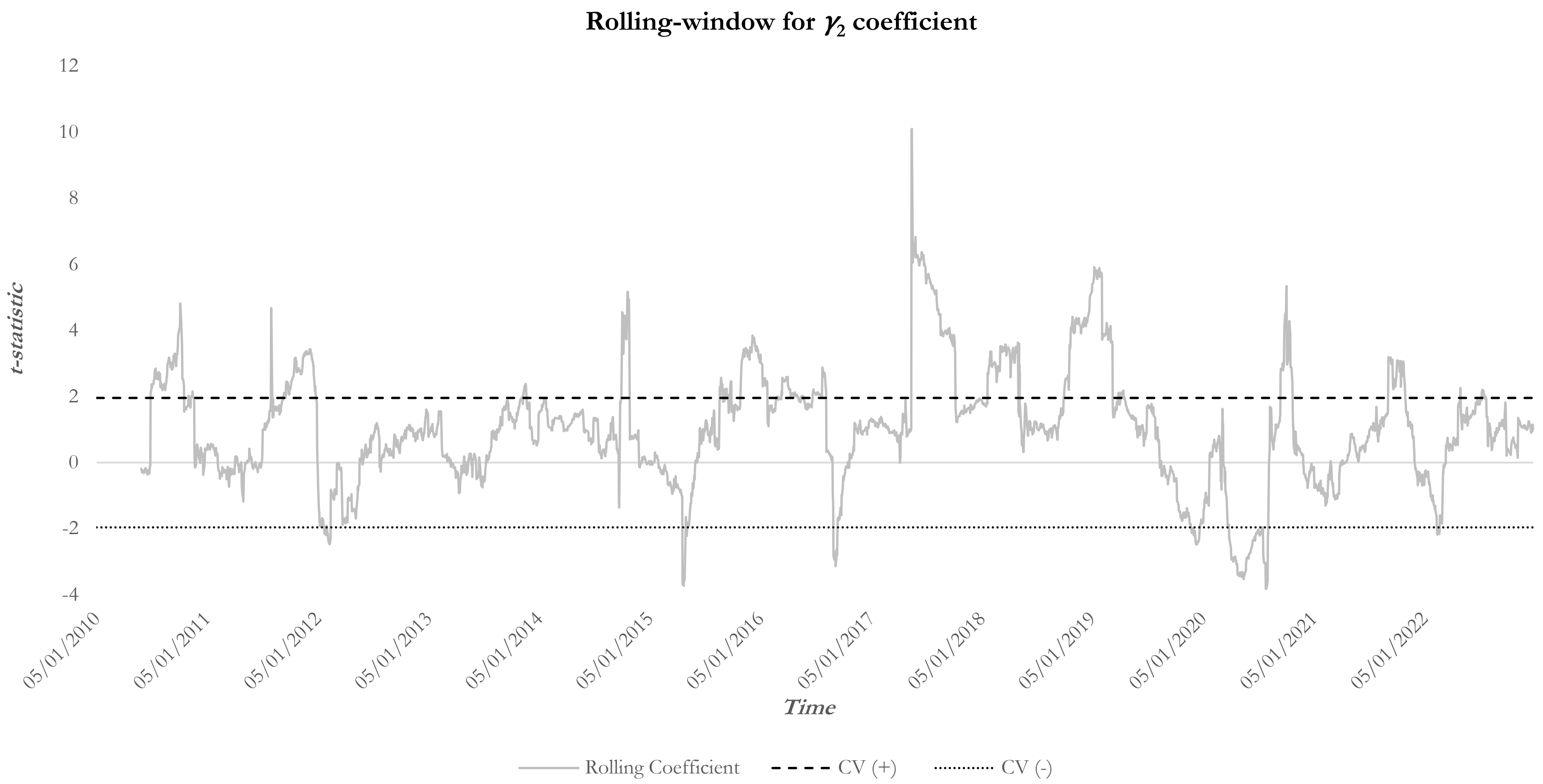

Figure 1. Rolling window t-statistic graphic for coefficient γ_2 of regression. CV encodes for confidence value and in this case, CV (+) is +1.96 and CV (-) is −1.96. Below the dotted line, there is evidence of herding behavior, and above the dashed line, there is evidence supporting negative herding.

The analysis of herding asymmetries during days of high and low return, volume, and volatility further elucidated investor behavior. Herding was found to be more prevalent on bear market days, such as in 2012, 2015, and 2022. During days of high trading volume, herding behavior was observed across multiple years, suggesting that increased information flow during these periods may influence investors to mimic their peers. Notably, herding occurred in high trading volume and low market returns, indicating a potential promotion of non-rational behavior under such circumstances. Last, focusing on days of higher volatility, investors tended to converge toward market consensus in certain years, while herding occurred during low volatility days in others. These results align with findings for herding during down market returns and high trading volume, suggesting that market instability and increased information flow contribute to herding behavior.

In conclusion, the dynamic nature of herding behavior in the Ibovespa index is evident, with significant herding episodes observed in various subperiods. These findings support hypothesis H4, highlighting the evolving nature of herding behavior in the Brazilian stock market.

4.5. Fundamental vs. non-fundamental drivers

Researchers have found that herding behavior in financial markets can stem from non-fundamental (intentional) or fundamental (spurious) reasons (Bikhchandani & Sharma, 2000). Following the approaches outlined by Galariotis et al. (2015) and Dang and Lin (2016), we now delve into the underlying factors driving herding behavior.

Dang and Lin (2016) found that CSAD responded to the absolute value of factors, leading to the estimation of model (7) in this form. Their comparison of the results from absolute regression with those from the framework by Galariotis et. al (2015) showed an enhanced explanatory power and statistically significant factors.

The results of CSAD decomposition for the period are presented in Table 6. Panel A replicates the output of model (2), Panel B displays results for non-fundamental herding, and Panel C shows estimations for the model driven by fundamental factors.

In Panel A, it is observed that investors tend to follow their private beliefs, which is indicative of negative herding behavior. Panel B highlights that investors trading in the Ibovespa index between January 2010 and December 2022 did not mimic their peers, as indicated by the positive and statistically significant γ_2. Conversely, Panel C suggests that fundamental factors did not significantly influence CSAD during this period.

The findings from Table 6 suggest that non-fundamental factors (Panel B) rather than fundamentals (Panel C) play a significant role in explaining why investors adhere to their opinions when trading in the Ibovespa equity index. To further explore whether non-fundamental or fundamental motifs explain investors' behavior across market conditions, regressions based on (8) and (9) are run using Chang et al.'s (2000) framework, and the results are presented in Table 7.

Table 6. Analysis of CSAD driven by non-fundamental and fundamental factors for the whole period.

Panel A – Total CSAD			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0127 (64.0362)***	0.2100 (8.7550)***	0.5802 (1.8803)*	0.3487
Panel B – Non−Fundamental CSAD			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0001 (0.5904)***	−0.0203 (−1.2502)	0.5522 (3.0796)**	0.0154
Panel C – Fundamental CSAD			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0126 (131.4011)***	0.2303 (19.3895)***	0.0280 (0.1898)	0.5772

Notes: In each panel, the coefficients are estimated using HAC estimators and the values in parentheses correspond to the *t-statistic*. Panel A presents the output as in Table 2. The total CSAD (2) is decomposed into non-fundamental (8) and fundamental (9). Both are then regressed using the framework of Chang et al. (2000). Panel B contains the coefficients associated with non-fundamental CSAD, and Panel C presents the CSAD considering fundamental factors. *** significant at 1% level; ** significant at 5% level.

Analyzing days of bear and bull markets between January 2010 and December 2022, Table 7–Column A indicates no evidence of herding. However, Column B reveals that non-fundamentals drive negative herding during days of both high (γ_3) and low (γ_4) returns, supported by their signal and statistical significance. The Wald test indicates no significant difference in negative herding between days of high and low returns. In contrast, the results of the fundamental regression in Column C suggest that fundamental motifs explain investor behavior only in bullish markets (γ_3). During days of low returns (γ_4), negative herding is mainly explained by non-fundamental factors, as the coefficient is positive and statistically significant only in Column B. Conversely, on days of high returns (γ_3), investors' trades are influenced by both fundamentals and non-fundamentals, as indicated by the positive and statistically significant coefficients for models in Columns B and C. These conclusions differ from those of previous literature (e.g., Dang & Lin, 2016; Indārs et al., 2019).

Columns D, E, and F provide the outputs for the total CSAD decomposition focusing on days of high and low trading activity. From the total CSAD's regression results in Column D, no evidence of herding is detected based on the values and statistical significance of γ_3 and γ_4. However, the split of the total CSAD into non-fundamentals (Column E) and fundamentals (Column F) suggests that intentional factors drive negative herding during days of both high and low volume, supported by the positive and statistically significant coefficients for γ_3 and γ_4. Fundamentals contribute only to adverse herding on days of low trading volume, as indicated by the positive and statistically significant coefficient for γ_4. Additionally, in Column F, the coefficient for γ_3 is negative but not statistically significant. The Wald test in Columns E and F suggests that negative herding differs significantly between days of high and low trading volume, indicating that negative herding based on non-fundamentals and fundamentals is more pronounced on days of low trading volume.

Table 7. Analysis of CSAD driven by non-fundamental and fundamental factors for return, volume and volatility asymmetries.

	RETURN ASYMMETRIES			VOLUME ASYMMETRIES			VOLATILITY ASYMMETRIES		
	A	B	C	D	E	F	G	H	I
	Total CSAD (3)	Non-Fundamental CSAD	Fundamental CSAD	Total CSAD (4)	Non-Fundamental CSAD	Fundamental CSAD	Total CSAD (5)	Non-Fundamental CSAD	Fundamental CSAD
γ_0	0.0128	0.0002	0.0127	0.0132	0.0004	0.0128	0.0124	−0.0002	0.0126
	(67.2353)***	(1.0332)	(146.6505)***	(70.5136)***	(2.6854)***	(132.2473)***	(52.8629)***	(−1.2230)	(106.8261)***
γ_1	0.1825	−0.0240	0.2064	0.2220	−0.0117	0.2317	0.1962	−0.0298	0.2260
	(5.9924)***	(−0.9539)	(15.6894)***	(9.2662)***	(−0.6999)	(18.538)***	(9.8412)***	(−2.2090)**	(20.0072)***
γ_2	0.1768	−0.0430	0.2198	−0.0011	−0.1461	0.1450	0.2701	0.0450	0.2251
	(8.2311)***	(−2.6235)***	(22.3361)***	(−0.0422)	(−5.9077)***	(9.608)***	(5.9490)***	(1.2017)	(10.2250)***
γ_3	2.0870	1.1646	0.9225	0.4375	0.4499	−0.0124	0.6475	0.6025	0.0450
	(3.0246)**	(1.6768)*	(3.6478)***	(1.6704)*	(2.9589)***	(−0.0940)	(1.6704)**	(23.6419)***	(0.3297)
γ_4	0.6252	0.6204	0.0048	6.0702	3.6295	2.4407	3.1481	2.2343	0.9138
	(2.6112)***	(4.2773)**	(0.0416)	(7.5806)***	(5.4901)***	(4.3283)***	(2.6854)***	(2.4322)**	(1.2204)
$\overline{R^2}$	0.3623	0.024	0.5833	0.3749	0.0370	0.5846	0.3760	0.0524	0.5789
γ_3–γ_4		0.5442	0.9177		−3.1796	−2.4531		−1.6318	−0.8688
χ^2		[0.3730]	[0.0003]***		(0.0000)***	(0.0000)***		(0.0621)*	(0.2455)

Notes: The model's output is obtained using HAC coefficients. The values in parentheses correspond to the t-statistic. Columns A, D and G present the output as in Table 3. In the bottom part, the results of the Wald test are presented and the values in parentheses represent the probability value (*p-value*). *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

It can be hypothesized that on days of high market liquidity, negative herding is driven by factors other than fundamentals, while on days of low market liquidity, adverse herding is explained by fundamental and non-fundamental arguments. Indārs et al. (2019) also investigated trading volume asymmetries using the total CSAD decomposition and found that investors' herding on days of high volume was primarily driven by fundamentals.

Last, the total CSAD for days of high and low volatility is divided into non-fundamental and fundamental components, with the results presented in Columns G, H, and I. The decomposition into non-fundamental (Column H) and fundamental factors (Column I) clarifies how investors behave during periods of high and low volatility. Specifically, during days of high (γ_3) and low (γ_4) uncertainty, investors' negative herding is driven by non-fundamental factors, supported by the positive and statistically significant coefficients in Column H. Conversely, for CSAD driven by fundamental information, γ_3 and γ_4 are positive but not statistically significant. Furthermore, the alternative hypothesis of the Wald test is accepted only in Column H, implying that for intentional factors, adverse herding is statistically different during periods of high and low uncertainty.

In conclusion, the results from Tables 6 and 7 indicate that negative herding is primarily driven by intentional factors, leading to the rejection of hypothesis H5.

5. Conclusion

We examined herding behavior in the Ibovespa Index, which is composed of stocks with the highest liquidity. Studying this behavioral correlation in Brazil is important not only because this country is an emerging economy but also since the stock market has been growing in terms of value and volume (Vartanian et al., 2022). Although herding behavior is thought to occur predominantly in emerging countries due to information asymmetries and higher uncertainty, the empirical evidence on Brazil is not unanimous.

This work adds new insights to the analysis and understanding of investors' behavior in Brazil. In this article, a new data set, including the most recent shocks was used in static and dynamic models. Furthermore, and for the first time, a 5-factor model was employed in Brazil to distinguish between spurious and intentional herding behavior.

Herding behavior was analyzed between January 5, 2010, and December 29, 2022, covering two recent major events. This phenomenon was evaluated using a static and a dynamic approach. The results of the static approach, using both an OLS and a QR, revealed that during this period, investors did not copy the actions of their peers. Instead, they followed their private beliefs supported by the positive and statistically significant herding coefficient (γ_2). The hypothesis that herding could occur when investors faced different market structures was also rejected using both static models – OLS and QR – as the coefficients associated with herding during up (γ_3) and down (γ_4) days were positive and statistically significant, suggesting negative herding.

A dynamic model is useful when there are structural breaks. A rolling window with a size of 100 observations and a step of one observation was considered, and investors trading in the Ibovespa were documented to follow their peers in specific subperiods, namely, in 2012, 2015, 2016, 2019, 2020, and 2022.

Last, following the argument that intentional and spurious factors may be important drivers, the total CSAD was decomposed into a non-fundamental and a fundamental component. With this division, it was concluded that, for the whole period, the negative herding was explained mainly by non-fundamental factors.

In terms of implications, this article highlights the consequences of herd behavior on investment policy design, noting that herding leads to suboptimal diversification and security mispricing. Investors would need a broader range of stocks to achieve the desired diversification effect in their portfolio than they would if herding behaviors were not prevalent in the market. Policymakers should enhance market transparency and protect investors' interests to reduce herding and improve price discovery. Our findings also imply that improved information quality, strict sanctions on market manipulation, and investor education can mitigate herding and its adverse effects on market stability and social welfare.

In Brazil, researchers employing a QR or the CSAD's splitting are scarce, and so the present article adds new insights into investors' behavior. Nonetheless, it is important to mention that due to the herding's nature, the choice of the period can explain, in part, the divergent conclusions for that equity market. The differences found between our results and those obtained in previous studies applied to Brazil are, most likely, due to differences in the sample period since the method used is the same (both de Almeida et al. (2012) and Signorelli et al. (2021) also use CSAD as our article). Regarding the sample period, we think it would be interesting to use a longer sample period to refine the study of the relation between herding and the development of the stock market. Additionally, the use of an equally weighted or a value-weighted portfolio might impact the results, as highlighted in the studies of Economou et al. (2016) and Mulki and Rizkianto (2020). Hence, in the future, it could be important to perform a similar analysis using a value-weighted portfolio to compare the results. Our article adopts the indicator proposed by Chang et al. (2000) as a measure of herding. However, Bohl et al. (2017) show that the statistical inference inherent in the approach of Chang et al. (2000) assumes the existence of identically zero idiosyncratic components. Therefore, to test the robustness of our results, it would be interesting to recalculate the herding measure with the data from our article under the condition that the idiosyncratic components are non-vanishing. Furthermore, it would be interesting to explore alternative measures for the trading volume and volatility, such as the illiquidity measure of Amihud (2002), and a GARCH model, respectively. Such analysis would likely give robustness to the findings of this article.

According to Gebka and Wohar (2013), negative herding could be due to overconfidence, localized herding, or excessive "flight to quality" during market stress. Since we did not aim to identify which of these determinants may explain the observed anti-herding behavior, it would be interesting to address this in future research. Another argument explaining negative herding is panic selling, which is characterized by the fact that fear leads investors to shift from risky to safe assets. Thus, the influence of panic selling on negative herding should be analyzed too. Finally, to recognize and evaluate the dynamics of the forces that drive investors' behavior, it would also be interesting to perform a rolling window regression for non-fundamental and fundamental regressions. This analysis would allow a better understanding of how those drivers evolved.

Author contributions

Conceptualization: Maria Beatriz Naia; Júlio Lobão
Data curation: Maria Beatriz Naia
Formal analysis: Maria Beatriz Naia; Júlio Lobão; Luís Pacheco
Investigation: Maria Beatriz Naia
Methodology: Maria Beatriz Naia; Júlio Lobão

Project administration: Júlio Lobão
Supervision: Júlio Lobão; Luís Pacheco
Validation: Júlio Lobão
Writing – original draft: Maria Beatriz Naia
Writing – review & editing: Júlio Lobão; Luís Pacheco

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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