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Investors' behaviour in the Brazilian stock exchange: An examination of herding behaviour using static and dynamic models

Maria Beatriz Rebelo Pinto Freitas da Naia

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Supervised by

Professor Júlio Fernando Seara Sequeira da Mota Lobão, PhD

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Biographic Note

Maria Beatriz Naia was born in Aveiro on May 2nd, 1994. She did her first Bachelor's in Medicinal Chemistry, at *Faculdade de Ciências e Tecnologias*, University of Coimbra, and in 2016, she enrolled in the Biomedical Research Master's, specializing in the field of Oncobiology, at *Faculdade de Medicina*, University of Coimbra.

In 2018, after discussing her master's dissertation, her academic path took a turn. Motivated by her interest in Economy, she decided to take a new Bachelor's degree, having chosen to study Economics at the University of Aveiro. During her degree, she developed a particular interest in Finance and in 2021 she enrolled in the Master's in Finance at the School of Economics and Management of the University of Porto.

Additionally, since 2018, she has been conjugating her studies with a part-time job, in a shop, in Aveiro. In September, she will start her professional career in Deloitte's Financial Advisory department.

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Abstract

Herding Behaviour, a phenomenon known to occur in financial markets, is characterised by the fact that investors, moved by rational or irrational arguments, copy their peers' actions, inducing a behavioural correlation. Consequently, higher price instability and deviations from the fundamental values may arise.

Brazil is an emerging economy whose financial system has been growing in terms of volume and liquidity, starting to attract national and foreign investors. However, this equity market was not immune to crises and macroeconomic shocks. Since investors tend to follow their peers in periods of uncertainty, it is plausible to hypothesise that this bias could have occurred in this market.

The present dissertation aims at understanding if investors herd in Ibovespa, where the highest liquidity shares are traded. Herding behaviour is analysed from January 5, 2010, to December 29, 2022. Through an ordinary least squares regression, no evidence of herding is reported in the whole sample, and in different market microstructures – return, trading volume, and volatility. Indeed, during this period investors rely on their private beliefs, given that herding coefficients are positive and statistically significant. The same conclusion is drawn using a quantile regression. Justified by the dynamic nature of herding behaviour, a rolling window regression is run allowing to conclude that herding occurs, in different subperiods, for the whole sample and during different market states. Lastly, the regression results of herding driven by spurious and non-fundamental factors explain the nature of the negative herding behaviour by Ibovespa investors. Particularly, the adverse herding is mainly driven by non-fundamental factors.

These results support the fact that investors trading in the Ibovespa are not fully rational once negative herding occurs during the whole sample. This behaviour is associated with a higher dispersion of stock returns around market returns when compared to the rational model. In addition, it is recognised that anti-herding is associated with diversifiable risk, thus potentially affecting portfolios' composition.

Keywords: Behavioural Finance; Herding Behaviour; Quantile Regression; Brazilian Stock Market; Cross-sectional deviation of returns.

JEL Codes: G11; G40; G41.

Sumário

O comportamento de manada é um fenómeno que ocorre em mercados financeiros e que se caracteriza pelo facto de os investidores, movidos por argumentos racionais e irracionais, copiarem as ações dos seus pares, traduzindo-se numa correlação comportamental. Consequentemente, uma maior instabilidade de preços emerge, bem como desvios face ao valor fundamental.

O Brasil é uma economia emergente, com um sistema financeiro que tem vindo a crescer em termos de volume e liquidez, fatores que contribuíram para atrair investidores nacionais e internacionais. Todavia, o mercado brasileiro não foi imune a crises e choques macroeconómicos. Dado que os investidores tendem a imitar-se em períodos de incerteza, coloca-se a hipótese de este fenómeno poder ocorrer neste mercado.

A presente dissertação tem como intuito perceber se os investidores apresentam um comportamento de manada no índice Ibovespa, do qual fazem parte as ações com maior liquidez. Esta análise é efetuada entre 5 de janeiro de 2010 e 29 de dezembro de 2022. Através do método dos mínimos quadrados, não se deteta evidência do comportamento de manada durante o período em análise, bem como, para diferentes microestruturas de mercado – retornos, volume e volatilidade. Assim, durante este período os investidores seguem as suas próprias crenças, uma vez que os coeficientes de deteção deste comportamento são positivos e estatisticamente significativos. A mesma conclusão é obtida usando uma regressão por quantis. Dada a natureza dinâmica deste comportamento, uma "*janela rolante*" é usada, permitindo inferir que em diferentes subperíodos e estruturas de mercado, os investidores têm tendência a imitar-se. Adicionalmente, os resultados da regressão em termos de fatores fundamentais e não fundamentais permite explicar a natureza do comportamento de manada reverso. Em particular, este comportamento é impulsionado principalmente por fatores não-fundamentais.

Estes resultados corroboram o facto de os investidores no índice Ibovespa não serem totalmente racionais, suportado pelo facto de neste período um comportamento de manada reverso ter ocorrido. De facto, este comportamento está associado a uma maior dispersão dos retornos das ações em termos do retorno do mercado quando comparada com a dos modelos tradicionais. Além disso, tal comportamento está associado com um maior risco de diversificação, o que potencialmente afeta a composição do portfolio.

Palavras-Chave: Finanças Comportamentais; Comportamento de manada; Regressão por quantis; Mercado Acionista Brasileiro; Desvio Secional dos Retornos

Códigos JEL: G11; G40; G41.

Table of Contents

Biographic Note i

Acknowledgements ii

Abstract iii

Sumário iv

Abbreviations viii

1. Introduction 1

2. Literature Review 5

  2.1. Herding Behaviour 5
  2.2. Herding Behaviour in Equity Markets 7
    2.2.1. Empirical Evidence – Whole Period 8
    2.2.2. Empirical Evidence – Asymmetric Herding 10
    2.2.3. Empirical Evidence – Dynamic Herding Behaviour 11
  2.3. Herding Behaviour – Fundamental and Non-Fundamental Drivers 13

3. Development of Hypotheses 14

4. Methodology 17

  4.1. Data Collection 17
  4.2. Herding Behaviour – Ordinary Least Squares Regression 17
  4.3. Herding Behaviour – Quantile Regression 19
  4.4. Herding Behaviour – Dynamic Characterisation 19
  4.5. Herding Behaviour – Fundamental vs. Non-Fundamental Drivers 20

5. Empirical Results and Discussion 22

  5.1. Sample Characterisation 22
  5.2. Herding Behaviour – Estimation through Ordinary Least Squares Regression 23
    5.2.1. Whole-Period 23
    5.2.1.1. Asymmetric Herding - Return, Trading Volume, and Volatility 26
  5.3. Herding Behaviour - Estimation through Quantile Regression 30
    5.3.1. Whole Period 30
    5.3.2. Asymmetric Herding - Return, Trading Volume, and Volatility 32
  5.4. Dynamic Nature of Herding Behaviour 36
  5.5. Fundamental vs. Non-Fundamental Herding Behaviour 40

6. Conclusions and Further Perspectives 47

References 49

Annexes 59

List of Tables

Table 1. Descriptive Statistics, Normality Test, Augmented Dickey-Fuller test, and Autocorrelation. 22

Table 2. Analysis of herding behaviour in the Ibovespa index for the whole period. 23

Table 3. Analysis of herding behaviour in the Ibovespa index considering days of high and low return. 26

Table 4. Analysis of herding behaviour in the Ibovespa index considering days of high and low trading volume. 28

Table 5. Analysis of herding behaviour in the Ibovespa index considering days of high and low trading volatility. 29

Table 6. Analysis of herding behaviour in the Ibovespa Index for the whole period, using a quantile regression. 31

Table 7. Analysis of herding behaviour in the Ibovespa index using a quantile regression for different market states. 33

Table 8. Analysis of CSAD driven by non-fundamental and fundamental factors for the whole period. 41

Table 9. Analysis of CSAD driven by non-fundamental and fundamental factors for returns asymmetries. 42

Table 10. Analysis of CSAD driven by non-fundamental and fundamental factors for volume asymmetries. 44

Table 11. Analysis of CSAD driven by non-fundamental and fundamental factors for volatility asymmetries. 45

List of Figures

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 blue line, there is evidence of herding behaviour, and above the red line, there is evidence supporting anti-herding. 38

Abbreviations

ADF – Augmented Dickey-Fuller

BRICS – Brazil, Russia, India, China, and South Africa

CEE – Central and East Europe

CSAD – Cross-sectional absolute deviation

CSE – Colombo Stock Exchange

CSSD – Cross-sectional standard deviation

HAC – Heteroskedasticity and autocorrelation-consistent estimator

HML – High minus Low

HNX – Hanoi Stock Exchange

HOSE – Ho Chi Minh City Stock Exchange

IML – Illiquid minus liquid

KOSDAQ – Korean Securities Dealers Automated Quotations

KOSPI – Korea Composite Stock Price Index

MA30 – 30-day previous moving average

OLS – Ordinary Least Squares

QR – Quantile regression

SMB – Small minus Big

SSE – Shanghai Stock Exchange

SZSE – Shenzhen Stock Exchange

US – United States of America

WML – Winners minus Losers

1. Introduction

Behavioural finance assumes less stringent hypotheses when compared to the expected utility theory of von Neumann and Morgenstern (Ritter, 2003). In addition, it is presently recognised that individuals' preferences, as well as their beliefs, have an impact on human decisions, supported by the fact that there are deviations from what is rationally expected (Hirshleifer, 2015; Ritter, 2003).

One important behavioural finance bias that has been extensively examined is herding behaviour, confirmed by the finding that individuals living in society, interact with each other, thereby presenting a potential disposition to mimic (Devenow & Welch, 1996; Shiller, 1995). Indeed, human beings exhibit a clear and natural instinct to belong to and to be accepted by their groups, and these sentiments depend on the social settings, indicating that herding is explained not only by biological but also by sociological and psychological factors (Prechter, 2001). Consequently, it is fundamental to understand the impacts of these behavioural patterns, since agents live in an interconnected world where established connections help to shape their personalities (Raafat et al., 2009).

Currently, it is accepted that herding occurs in financial markets as investors tend to mimic the decisions taken by their peers abandoning their own beliefs (Bikhchandani & Sharma, 2000; Devenow & Welch, 1996). Due to social interactions, this behaviour is described as the correlation among investors' trades (Chiang & Zheng, 2010). In some circumstances, herding can exacerbate market volatility, destabilizing its function and, consequently, deviating prices from their fundamental values (Chiang et al., 2010).

Different authors analysed herding at a market level and concluded that this bias tends to be a short-term phenomenon, arising mainly in emerging countries, where uncertainty and information quality, and its costs, contribute to elucidating why investors discard their private beliefs and follow other market participants (Spyrou, 2013).

Notwithstanding, in some countries, the empirical research is discordant, explained, in part, by the argument that herding is a short-lived event, thereby it might not be present in the whole period, but rather in specific subperiods, normally turbulent ones. Additionally, herding behaviour has a dynamic nature and so static models might not capture its evolution. (Babalos & Stavroyiannis, 2015)

Considering studies performed in Latin American countries, and focusing on Brazil, herding's empirical evidence is not unanimous. Nevertheless, these studies focus on different historical periods, with distinct degrees of uncertainty, which can support the existence or absence of herding in this equity market.

Brazil's financial market entered in an enormous transformation at the beginning of the XXI century, contributing to a value and volume increase of stock transactions (Vartanian et al., 2022). This growth started to catch investors' attention given the market's liquidity (Vartanian et al., 2022). In addition, this country was not been immune to the global financial crisis and other macroeconomic shocks, and these conditions could have contributed to an unstable environment, favouring the tendency to mimic other agents' actions (da Rocha Lima Filho et al., 2017; Montes & Tiberto, 2012; Vartanian et al., 2022)

Attending to the mixed evidence on herding behaviour in Brazil, combined with the fact that this equity market has been growing in value and volume, the present dissertation aims at unveiling how investors behave in the Ibovespa index – the most liquid index – between January 2010 and December 2022. The eventual presence of herding will be detected using the cross-sectional absolute deviation (CSAD) of the returns as defined by Chang et al. (2000). By an ordinary least squares (OLS) regression, this behaviour will be analysed in different market structures. Specifically, the use of dummy variables in the regressions will allow to investigate herding in periods of high and low market return, high and low trading volume, and high and low volatility.

Earlier findings showed that OLS could lead to misleading conclusions, given the potential information loss at the distribution tails (Chiang & Zheng, 2010; Zhou & Anderson, 2011). As a consequence of this argument, a more robust method – a quantile regression (QR) – will be employed to understand if the presence of herding is conditional on distinct quantiles.

The occurrence of external and internal shocks, between January 2010 and December 2022, might have caused structural breaks. Since the CSAD is a static framework that assumes constant regression coefficients, the use of this model may result in biased conclusions since it fails to capture any model's dynamic. Therefore, a rolling window will be applied to characterise how herding evolves.

Furthermore, as described by Bikhchandani and Sharma (2000), fundamental factors and non-fundamental factors were found to be herding's drivers. Following some earlier works, such as Dang and Lin (2016), Fei and Liu (2021), Galariotis et al. (2015), and Indārs et al. (2019) – that used the 3-factor, the 4-factor, and the 5-factor models – the total CSAD will be decomposed into non-fundamental (intentional) and fundamental (spurious) components. Thus, it will be possible to assess this behaviour driving forces.

This dissertation adds new insights to the analysis of herding behaviour in Brazil. The Asian markets, with an emphasis on the emergent ones, tend to be preferred for studying this behavioural correlation since information asymmetries and less transparent rules are assumed to be one of the herding driving forces. The fact of being an emerging market can also promote the instinct to mimic peers. Therefore, it is considered opportune to explore other emerging markets, as those in Latin America, and Brazil was chosen. The present work will consider the period starting in 2010 and ending in 2022, which includes the latest events that occurred in the XXI century – the Covid-19 pandemic and Ukraine's war. In addition to OLS regressions, QRs will be employed, hence allowing to scrutinise information conditional on different quantiles. For Brazil, studies employing a QR are scarce. Shrotryia and Kalra (2020) analysed herding in Brazil, India, Russia, China, and South Africa (BRICS), between January 2011 and May 2019 only with a QR. In this dissertation, both methods – OLS and QR – will be applied, to understand how events that occur in distribution tails affect investors' behaviour. Dynamic models highlight herding's evolution, and the literature considering its dynamic evolution in Brazil is still limited. Cakan et al. (2018) used a rolling window in their research to evaluate how herding evolved in Brazil, Turkey, and Russia, between 2005 and 2015, analysing this bias during turmoil periods. This dissertation will consider a different time frame, and the rolling window analysis will be extended to different market states, offering new insights. Lastly, with CSAD's decomposition, it will be possible to get a clearer picture of this phenomenon. Indeed, studies employing returns' dispersion decomposition into fundamental and non-fundamental components in Latin American countries are scarce. In this sense, the current work will also offer insights into the factors that drive this behavioural bias.

From the performed analysis it is concluded that for the whole sample, investors trading in the Ibovespa market do not mimic their peers as shown by the positive and significant herding coefficient (γ_2), significant at 10%, implying that between January 2010 and December 2022 market participants follow their beliefs. The same pattern is observed when considering market asymmetries, that is, investors do not try to reach the market consensus (γ_3 and γ_4 are positive and statistically significant). Specifically, market participants rely on their private beliefs to decide which securities to trade, and this negative herding is statistically different on up days and down days, according to the Wald test results. The QR's results corroborate the OLS's ones, revealing no evidence of herding conditional on different quantiles. Through a rolling window, herding evolution is assessed, permitting to conclude that herding occurs in small subperiods of the following years, 2012, 2015, 2016, 2019, 2020 and 2022. Also, the dynamic analysis highlights that investors tend to imitate each other when facing different market conditions, namely return asymmetries, volume asymmetries and volatility asymmetries. The decomposition into non-fundamental and fundamental factors highlights that during the whole sample period, negative herding is mainly driven by factors other than the fundamental ones.

This dissertation will be organized as follows: Chapter 2 contains the Literature Review; Chapter 3 presents the Hypothesis Development; Chapter 4 describes the Methodology; Chapter 5 corresponds to the Results and Discussion; Chapter 6 contains the Conclusions and Further Perspectives.

2. Literature Review

The outcomes of individuals' decisions were found to systematically deviate from rational models' expectations and behavioural finance permits the relaxing of some of the more rigid classical model's assumptions (Kahneman & Tversky, 1979). With the emergence of behavioural finance, it is possible to fundament part of these divergences, once psychological and sociological arguments started to be considered important drivers in explaining market participants' attitudes (Hirshleifer, 2015; Subrahmanyam, 2007).

Herding behaviour, a renowned behavioural finance bias, has been extensively studied, given the possible negative impacts on financial markets.

2.1. Herding Behaviour

The idea that in volatile environments individuals suppress their own beliefs and follow the crowd was already argued by John Maynard Keynes, who referred that uncertainty leads speculators to believe in what others see, thus taking similar decisions, as discussed, for example, by Scharfstein and Stein (1990) and Baddeley (2010). Specifically, agents tend to follow the crowd, believing that the others have more and better information (Scharfstein & Stein, 1990). Insights from sociology and psychology emphasise that individuals present an instinct to belong to and to be accepted by their groups, being influenced by the decisions taken in such settings (Prechter, 2001; Shiller, 1995).

In financial markets, it is currently recognised that investors are affected by other agents' actions, which may lead to a behavioural correlation once individuals follow the crowd instead of their private beliefs (Camara, 2017; Devenow & Welch, 1996). In fact, these markets are inhabited by arbitrageurs and rationally bounded investors and the correlation that appears when there is an instinct to mimic, in some circumstances, results in prices deviating from their fundamental values (Bikhchandani & Sharma, 2000; Hirshleifer & Hong Teoh, 2003; Nofsinger & Sias, 1999).

Bikchandani and Sharma (2000) distinguished herding driven by fundamentals (spurious) and non-fundamentals (intentional). On one hand, spurious herding occurs when individuals take similar actions, not by deliberately imitating each other, but because they decide to use the same information (Bikhchandani & Sharma, 2000).

On the other hand, intentional herding arises when market participants deliberately deny their convictions to follow the crowd, and this imitation intent can result in a higher utility (Bikhchandani & Sharma, 2000; Kremer & Nautz, 2013). Though spurious herding is viewed as an efficient outcome, the same may not be true for the intentional form, where the outputs might be inefficient (Bikhchandani & Sharma, 2000).

Additionally, herding can be classified as rational or irrational (Baddeley, 2010; Bikhchandani & Sharma, 2000; Devenow & Welch, 1996; Hirshleifer & Hong Teoh, 2003). In turn, rational herding can be explained based on arguments such as information, reputation, or even compensation (Bikhchandani & Sharma, 2000; Devenow & Welch, 1996).

Concerning information-based herding, the empirical findings show that this bias can be justified by informational cascades (Banerjee, 1992; Bikhchandani et al., 1992). According to these authors, an informational cascade emerges when individuals find it optimal to follow the decisions of their predecessors since they can observe their actions, without knowing anything about their signals' quality (Banerjee, 1992; Bikhchandani et al., 1992). Additionally, Banerjee (1992) argued that by entering in cascades, agents would be less responsive to their beliefs, and their decisions would be less informative to their succeeders.

Herding is also driven by reputational and remuneration aspects (Banerjee, 1992; Bikhchandani et al., 1992). In this context, Scharfstein and Stein (1990) demonstrated that managers, in certain circumstances, ignore their private signals and adopt their peers' decisions. In their model, managers, whose focus is reputation, follow each other, and the so-called sharing of the blame contributes to explaining this observation (Scharfstein & Stein, 1990). From a social standpoint, this can be inefficient, nonetheless, considering only reputational issues, it can be rational (Scharfstein & Stein, 1990). Graham (1999) unveiled that herding among investment newsletters tends to occur when the reputation is high, the ability is low and when signals are correlated. Maug and Naik (2011) found that professional investors also reject their own beliefs, converging to the benchmark and the incentive's design can affect asset allocation.

In the literature, several papers report herding behaviour among professional investors and managers, as highlighted, for instance, by Choi and Sias (2009), Lakonishok et al. (1992), Lobão and Serra (2007), Sias (2004), and Wermers (1999).

Lakonishok et al. (1992) evaluated changes in bought and sold proportions using quarterly data of United States (US) equity funds, sorting the data according to size. This framework led the authors to conclude that herding, although weak, was more intense among small-size companies (Lakonishok et al., 1992). Applying this method, Wermers (1999) investigated herding among mutual funds managers evaluating the impact on stock prices. Similar to Lakonishok et al. (1992), smaller stocks and oriented growth mutual funds presented higher levels of herding (Wermers, 1999). In Portugal, Lobão and Serra (2007), using quarterly data, assessed herding behaviour among Portuguese mutual funds. Employing the framework of Lakonishok et al. (1992), the authors documented herding, and the magnitude of this behaviour was stronger for buying orders (Lobão & Serra, 2007).

Sias (2004) analysed herding among institutional investors with a different method. Particularly, in each quarter, an investor's position was defined – as a buyer if his position increased or as a seller if his position decreased. The author concluded that investors' demand over adjacent quarters was not only driven by agents following their lag trades but also by the fact that they mimicked their peers' decisions, and the current quarter's demand was positively correlated with the demand of the last quarter (Sias, 2004). Later, through the framework of Sias (2004), Choi and Sias (2009) unveiled sectoral herding given that, within the same industry, investors followed their peers in their buying and selling decisions.

Herding behaviour is not restricted to the equity market, occurring, for example in the bond market. For instance, this bias was found in European Government bonds being triggered by macroeconomic announcements (Galariotis et al., 2016a). Also, this tendency to mimic was uncovered among Dutch pension funds, in the market of sovereign bonds, being stronger among sell orders (Koetsier & Bikker, 2022). In the US, institutional investors herded in the corporate bonds market (Cai et al., 2019). Moreover, there is evidence of this behavioural correlation in the derivatives market, where herding was studied in the Indian futures market (Banerjee & Padhan, 2017), and also in the US options market (Bernales et al., 2020). Lastly, in China and Indonesia, investors were found to herd in the commodities market (Kumar et al., 2021) and also in the US explained, in part, by monetary policies (Apergis et al., 2020).

2.2. Herding Behaviour in Equity Markets

In financial markets, a pioneering method to detect herding was proposed by Christie and Huang (1995), focused on the cross-sectional standard deviation (CSSD) of the returns. According to the authors, uncertainty could explain why investors discarded their beliefs to reach the market consensus, resulting in lower return dispersions (Christie & Huang, 1995). Chang et al. (2000) developed the CSAD's framework to characterise herding behaviour. Since then, the CSAD method has been extensively employed in different studies.

Herding has been investigated in developed and emerging markets and research points out that this bias is more likely to occur in developing countries, once this phenomenon prevails in scenarios of higher information asymmetry and uncertainty (Dang & Lin, 2016; Mulki & Rizkianto, 2020; Vo & Phan, 2016). Another empirical finding is that this behaviour is a short-lived phenomenon (Caporale et al., 2008; Cont & Bouchaud, 2000; Vo & Phan, 2016).

When driven by irrational factors, herding can lead to inefficient outcomes and considering its hypothetical impact on financial markets, it becomes important to characterise this bias (Bikhchandani & Sharma, 2000; Hirshleifer & Hong Teoh, 2003; Nofsinger & Sias, 1999).

2.2.1. Empirical Evidence – Whole Period

Considering developed markets, Caporale et al. (2008) found out that herding occurred in Greece between January 1998 and December 2007. Economou et al. (2011) corroborated those results, where, for an equally and a value-weighted portfolio, herding was detected, from January 1998 to December 2008. Furthermore, the same authors identified this behavioural pattern in Italy, and Portugal, using an equally weighted and a value-weighted portfolio, respectively (Economou et al., 2011). These results contrast with the ones obtained by Mobarek et al. (2014) who, for these three countries and considering the period between January 2001 to February 2012, did not obtain any evidence of herding behaviour. Focusing also on Greece, Economou et al. (2016), through a QR, a method known to be more robust than the OLS, reported the occurrence of herding in the upper quantiles, based on an equally weighted portfolio, for the period between January 2007 to May 2015. Pochea et al. (2017) conducted a QR analysis, from January 2003 to December 2013, considering a panel of ten Central and East European (CEE) countries, and they concluded that herding was conditional on different quantiles, except in Poland and Romania, countries in which no evidence of herding was found. One different research carried out in France by Litimi (2017) highlighted sectoral herding between 2000 and 2016.

Regarding emerging markets, Tan et al. (2008), for the period between July 1994 and December 2003, characterised herding in China using data from the Shanghai stock exchange

(SSE) and Shenzhen stock exchange (SZSE) for both A- and B-shares, and herding was observed for both markets and both share types. Another important study employing data from these two stock exchanges was designed by Chiang et al. (2010), who considered data between January 1996 and April 2007. In part, their findings confirm the ones of Tan et al. (2008), nonetheless, Chiang et al. (2010) did not obtain any evidence of herding for SSE-B and SZSE-B shares. Still, Chiang et al. (2010) noted that the OLS model could result in information losses at the level of the distribution tails, and to surpass OLS's problems, a QR was used permitting to conclude that herding was conditional to the lower quantiles. In Vietnam, Vo and Phan (2016), using an OLS regression, studied herding in the Ho Chi Minh Stock Exchange (HOSE) and they reported the occurrence of this phenomenon from January 2005 to April 2015, using an OLS regression. For the same country, although using the period between January 2016 and May 2022, Nguyen et al. (2023) assessed the Covid-19 pandemic effects on herding through a QR. For the HOSE, this bias was found in all quantiles, except in τ=75% and τ=90%, whereas for the Hanoi Stock Exchange (HNX), this phenomenon was present in all quantiles, except in τ=90% (Nguyen et al., 2023). Demirer et al. (2010) performed a study in Taiwan between January 1995 and December 2006 and they concluded for the existence of sectoral herding. Batmunkh et al. (2020), considering the Mongolian stock exchange found that investors mimicked their peers between December 1999 and June 2019.

Considering Latin American countries, Chiang and Zheng (2010) carried out a study to detect herding among eighteen countries, and in Argentina, Brazil, Colombia, and Mexico no evidence was documented. When the role of the US market was investigated, these authors found that in Brazil, Colombia, and Mexico, investors herded around that market (Chiang & Zheng, 2010). de Almeida et al. (2012) also studied herding in different Latin American countries between January 3, 2000, and September 15, 2010, and, for the whole period, only in Chile investors tended to follow their peers. For Argentina, Brazil, and Mexico no evidence was found and these results are aligned with the ones of Chiang and Zheng (2010) (de Almeida et al., 2012). When the influence of the US market on Brazil was tested, the corresponding herding coefficient, was negative although not statistically significant, which is inconsistent with Chiang and Zheng (2010) (de Almeida et al., 2012). Mulki and Rizkianto (2020) assessed herding in the BRICS, and, particularly for Brazil, between December 31, 1996, and December 29, 2017, and contrary to other authors, they obtained a negative and statistically significant herding coefficient for the equally weighted portfolio, implying that investors mimicked each other. Signorelli et al. (2021) designed a study focused on the Brazilian stock exchange between January 2008 and May 2019. The CSAD's regression outputs showed that herding was present in this stock exchange in all years, except in 2008, 2016, and 2017 (Signorelli et al., 2021).

2.2.2. Empirical Evidence – Asymmetric Herding

The asymmetric nature of herding behaviour has been confirmed by different studies, based on the argument that this bias is more pronounced during turmoil periods, as suggested by Chang et al. (2000).

In Europe, for instance, herding was found during days of high and low market return, high and low trading volume, and high and low volatility. Specifically, the presence of asymmetric herding was noticed in Greece (Caporale et al., 2008; Economou et al., 2016; Economou et al., 2011), in Portugal (Curto et al., 2017; Economou et al., 2011; Santos & Lagoa, 2017), and in Italy (Caparrelli et al., 2004; Economou et al., 2011). Pochea et al. (2017) took into consideration a panel of ten CEE countries and using a QR herding was present in nearly all countries and all quantiles. Furthermore, when the market conditions deteriorated, investors followed their peers' actions and for days of high trading volume and volatility, herding was found in lower quantiles, once this bias was believed to be stronger for smaller capitalization stocks (Pochea et al., 2017).

In Asia, herding tends to present an asymmetric nature too. In China, investors were found to mirror their peers' decisions during days of high and low return (Chiang et al., 2010; Tan et al., 2008), high and low trading volume (Tan et al., 2008), and high and low volatility (Tan et al., 2008). Tan et al. (2008) reported herding for SSE-A, SSE-B, SZSE-A, and SZSE-B, while Chiang et al. (2010) found no evidence of herding in SSE-B and SZSE-B during days of up and low return. In Vietnam, Vo and Phan (2016) analysed herding in the HOSE, and they determined that investors, significantly, imitated their peers when facing returns' asymmetries, and this bias was more intense during downing conditions. Additionally, for days of low return, a QR permitted to conclude that herding occurred in all quantiles (Vo & Phan, 2016). Also in Vietnam, Nguyen et al. (2023) detected this bias in the HOSE and HNX in all quantiles, on bear days, for the period between January 2016 and May 2022. Also, HOSE's investors tended to mimic their peers during days of high trading volume in all quantiles, except in τ=90% (Nguyen et al., 2023). In South Korea, Choi and Yoon (2020) evaluated investors' sentiment and herding in Korea Composite Stock Price Index (KOSPI) and Korean Securities Dealers Automated Quotations (KOSDAQ) from January 2003 and December 2018. For the former, during days of low market return, herding was conditional to the upper (τ=90%) and the lower (τ=10%) extreme quantiles, while for the latter, this bias was detected in all quantiles except in τ=70% (Choi & Yoon, 2020). In their paper, Choi and Yoon (2020) concluded that for both markets, investors tended to reach the market consensus considering days of high volume, conditional on different quantiles. In the Mongolian stock market, Batmunkh et al. (2020) showed that the participants also mimicked their peers, when they faced different market microstructures, and this bias was stronger for days of low return and days of higher turbulence.

In Latin America, de Almeida et al. (2012) obtained evidence supporting the occurrence of herding in Chile for different market microstructures, while in Argentina and Mexico, investors only mirrored their peers' trades on days of low volatility. In Brazil, they highlighted that market participants tended to follow their own beliefs, given that herding's coefficients were positive and statistically significant (de Almeida et al., 2012). Different results from those were obtained by Mulki and Rizkianto (2020) and Signorelli et al. (2021). Mulki and Rizkianto (2020), using an equally weighted portfolio, observed herding during days of high volatility, which could be a natural consequence of uncertainty faced by investors. Nevertheless, for days of low volatility and employing a value-weighted portfolio, investors trading in Brazil's stock market were found to mimic their peers (Mulki & Rizkianto, 2020). Signorelli et al. (2021) unveiled significant herding during days of high trading volume, high volatility, poor market performance, and a higher number of sell orders.

2.2.3. Empirical Evidence – Dynamic Herding Behaviour

Empirical research revealed that herding has a dynamic nature and the use of a regression, with constant coefficients, does not capture such characteristics (Babalos & Stavroyiannis, 2015). Financial markets are affected by micro- and macroeconomic shocks which, usually, introduce structural breaks in the models, thus it started to be questioned whether static frameworks, such as the CSSD and CSAD, could, undoubtedly, detect any evidence of herding behaviour (Babalos & Stavroyiannis, 2015). Motivated by these arguments, different authors tried to capture herding's time-varying nature.

Focusing on the commodities market, an important study was conducted by Babalos and Stavroyiannis (2015), who investigated herding in the metal market through a time-varying model, between January 1995 and December 2013. Through a dynamic analysis, they concluded that before the financial crisis, investors followed their own beliefs, consistent with anti-herding, while for the post-crisis period, market participants did not display herding or anti-herding behaviour (Babalos & Stavroyiannis, 2015).

In the stock market, Sharma et al. (2015) characterised herding in China, from May 2007 to January 2010, using data from the SHSE and the SSZE and by employing a 100-day rolling window, they unveiled how herding evolved observing that this bias was time- and sector-dependent. Stavroyiannis and Babalos (2017) evaluated if, market participants following Shariah-based ethical investments, imitated their peers. The rolling window regressions indicated that between January 2007 and December 2014, the traders on US Islamic Dow Jones presented anti-herding behaviour, which was stronger during turbulent periods (Stavroyiannis & Babalos, 2017). Cakan et al. (2018) analysed the speculation's role in the oil commodity market on herding for Brazil, Russia, and Turkey's stock markets, from October 2005 to October 2015. With a rolling window, it was highlighted that for Brazil and Russia, investors imitated their peers during periods of intense speculative activities in the oil market, with speculation being used as a proxy of the volatility (Cakan et al., 2018). Recently, Bogdan et al. (2022) explored a European countries' panel to investigate the nature of herding during the Covid-19 pandemic, a shock that potentially increased uncertainty, and thereby could have led to a mimicking instinct among less informed investors. Also with a rolling window, the authors detected herding in all markets – developed, emerging, and frontier – and this phenomenon was stronger in less developed countries. These results allowed to accept the hypothesis that in less developed markets, the lower quality information, favoured herding's occurrence (Bogdan et al., 2022).

As for the cryptocurrency market, Bouri et al. (2019), employing a static model, did not obtain any evidence of herding in the whole period, from April 2013 to May 2018. With the Bai-Perron test, structural breaks were detected, and driven by these findings, a rolling window was applied allowing to conclude that investors imitated their peers, which was not surprising given the high volatility and the information quality of the cryptocurrency market (Bouri et al., 2019). In this line of thought, Amirat et al. (2020) used a static and a dynamic model to also characterise herding in the cryptocurrency market, between January 2015 and January 2019. With a static method, no evidence of herding was reported, whereas with a rolling window, this bias was detected and its magnitude differed over the sample period, and investors were prone to mimic their peers when they felt less comfortable (Amirat et al., 2020). Lobão (2022) analysed the market of green cryptocurrencies, between January 2017 and June 2022, where through CSSD and CSAD no evidence of herding was observed in the whole sample. The application of a rolling window allowed the author to conclude that herding had a dynamic and variable nature over the analysed period and that during the Covid-19 pandemic, herding was more intense (Lobão, 2022).

2.3. Herding Behaviour – Fundamental and Non-Fundamental Drivers

In their seminal paper, Bikchandani and Sharma (2000) asserted that herding could be driven by fundamental (spurious) or non-fundamental factors (intentional).

Having this definition in mind, Galariotis et al. (2015), using the 3-factor model, decomposed the CSAD into a fundamental and a non-fundamental part. By analysing different crisis periods, they found out that in the US, investors imitated their peers, a behaviour driven by fundamental and non-fundamental factors (Galariotis et al., 2015).

Subsequently, different authors published studies trying to justify herding's driving factors. Dang and Lin (2016), deepened Galariotis et al. (2015) analysis and for the HOSE they concluded that investors copied their peers based on fundamentals, as well as non-fundamental information. Indārs et al. (2019) stated that the use of the total CSAD without decomposing on spurious and intentional drivers may mask the presence of herding. Indeed, no evidence of herding was observed in the Moscow stock exchange using the Chang et al. (2000) model. When the total CSAD was split into a fundamental and a non-fundamental component, investors' herding was found to be driven by intentional arguments, whereas fundamentals contributed to an anti-herding behaviour, for the period between April 2008 and December 2015 (Indārs et al., 2019). Furthermore, during days of low return herding was driven by non-fundamental factors, while for days of high liquidity, herding was explained by fundamentals (Indārs et al., 2019). Liu et al. (2023), in a study conducted in China, and for the period between June 2014 and May 2016, pointed out that less informed investors herded more when in comparison with sophisticated investors, nonetheless, this magnitude's difference decreased during turbulent periods (Liu et al., 2023). For example, during down days, less-informed investors herded mainly due to intentional motifs, whereas informed investors herded based on fundamental information (Liu et al., 2023).

3. Development of Hypotheses

The beginning of the XXI century led to a tremendous transformation of the Brazilian stock market which grew in value and volume (Vartanian et al., 2022). The improvement of economic conditions and the implementation of different political reforms attracted investors to the financial market, which improved liquidity (da Rocha Lima Filho et al., 2017; Montes & Tiberto, 2012; Vartanian et al., 2022). Nonetheless, as discussed by Vartanian et al. (2022), Brazil was not immune to the global financial crisis and was also affected by other macroeconomic events.

The empirical evidence suggests that herding tends to occur in emerging economies, since these markets are characterised by a higher degree of information asymmetry, favouring the occurrence of this behaviour (Dang & Lin, 2016; Vo & Phan, 2016).

As previously discussed, Brazil's herding evidence is not unanimous. For example, while Chiang and Zheng (2010) and de Almeida et al. (2012) did not detect herding behaviour in their samples, Mulki and Rizkianto (2020) and Signorelli et al. (2021) documented this behavioural bias. This ambiguity is not restricted to Brazil. For China, Tan et al. (2008) found evidence of herding among B-shares, whilst Chiang et al. (2010) concluded that investors trading B-shares did not mimic their peers, although the time period used in these studies was not the same. In Greece, Economou et al. (2011) reported evidence of herding, while Mobarek et al. (2014) found no herding for the whole period. This behaviour is a short-lived event, implying that the period of analysis may affect the results.

As herding and negative herding have already been reported in Brazil and motivated by the arguments that this behaviour is likely to occur in emerging markets, and also that this equity market has been raising investors' attention, the first hypothesis of this dissertation is:

(H1) *There is significant herding behaviour in the Brazilian stock market in the whole period, specifically, from January 5, 2010, to December 29, 2022.*

The empirical evidence point out that during different market microstructures, namely days of high and low return, high and low trading volume, and high and low volatility, the herding's magnitude can be different (Arjoon et al., 2020; Batmunkh et al., 2020; de Almeida et al., 2012; Economou et al., 2011; Mobarek et al., 2014; Signorelli et al., 2021). Specifically, in periods of extreme market conditions, investors tend to reach the market consensus. Thus, the second hypothesis is related to the occurrence of herding behaviour during distinct market conditions, specifically, return, trading volume, and volatility, that is:

(H2) *There is significant herding behaviour in the Brazilian stock exchange, considering different market structures, for the whole period, that is, from January 5, 2010, to December 29, 2022.*

The regressions to validate hypotheses (H1) and (H2) are usually tested through an OLS method, which has some drawbacks since information on the distribution tails might be lost. In this sense, a QR had already been employed in earlier studies, namely by Chiang et al. (2010), Choi and Yoon (2020), and Pochea et al. (2017), allowing to obtain robust results. Zhou and Anderson (2011) argued that QRs can surpass some OLS's problems, such as the sensitivity to outliers, and in the presence of non-normal data, QR estimators are more efficient. These authors concluded that herding is likely to occur in the upper quantiles, that is, during turbulent periods (Zhou & Anderson, 2011). In fact, with this type of regression, it is possible to assess investors' behaviour conditional on different quantiles (Zhou & Anderson, 2011). In financial markets, low quantiles, the ones below the median, correspond to tranquil times, while high quantiles correspond to periods of greater instability (Adrian & Brunnermeier, 2016; Duygun et al., 2021). Therefore, to evaluate herding conditional on different quantiles, the following hypothesis will be tested through QR:

(H3) *Herding behaviour has a different profile depending on the regression's quantile.*

It is also plausible to argue that between January 2010 and December 2022, herding presents a dynamic evolution. The magnitude of this behaviour tends to increase during crisis periods. For instance, Cakan et al. (2018) and Sharma et al. (2015) analysed the dynamic nature of herding behaviour with a rolling-window regression that allows capturing how the regression coefficients vary over time, as well as its statistical significance. Hence, since the period under analysis starts after the financial crisis and its consequences can still be present in the market, and given also the occurrence of different events, such as presidential elections, the Covid-19 pandemic and the military conflict, factors that might have induced herding behaviour, the following hypothesis will be evaluated:

(H4) *In Ibovespa, herding behaviour presents a dynamic evolution being expected that during adverse market conditions, this bias will be more intense.*

Focusing on the insights provided by the study of Galariotis et al. (2015), distinct authors, considering different markets, analysed and decomposed returns' dispersions into fundamental and non-fundamental factors, to analyse what factors drive herding behaviour.

In the whole sample, herding might not be detected, while its decomposition may support the evidence of this behaviour. For instance, Indārs et al. (2019) did not report evidence of herding for the period between April 2008 and December 2015, applying the total CSAD. When the CSAD was split into a fundamental and a non-fundamental part, the authors concluded that, in the Moscow stock exchange, investors herded during the whole period, being this behaviour driven by intentional motifs. Focusing on fundamental-driven CSAD, market participants followed their personal beliefs, which is consistent with negative herding. In sum, in the Moscow stock exchange, despite no evidence of herding was detected using the total CSAD, its decomposition clarified that investors' intent to mimic was driven by intentional motifs. Based on different authors' research that used the framework initially developed by Galariotis et al. (2015), and on the fact that for Brazil studies analysing intentional and spurious herding are scarce, the last hypothesis to evaluate is:

(H5) *In Ibovespa, herding behaviour is driven by fundamental (spurious) and non-fundamental (intentional) arguments.*

A table resuming the fundamental studies regarding herding behaviour evidence in Brazil is presented in the Annexes Section (Annex A).

4. Methodology

4.1. Data Collection

The daily adjusted closing stock prices of Ibovespa index companies, from 4th January 2010 to 29th December 2022, were retrieved from the Thomson Reuters Eikon database.

An important point to note is that the index is rebalanced on the first Monday of January, May, and September. Therefore, it was necessary to obtain the final composition of each period from the *leavers and joiners* analysis, retrieved from the Refinitiv database.

Additionally, the companies that left the Ibovespa index between two rebalancing periods will only be considered as part of the index until the previous period. In the same way, companies that entered in the index in the middle of two rebalancing periods will only be considered in the following rebalancing moment. Therefore, the sample does not suffer from survivorship bias given its characteristics.

Returns are calculated, as usual, in the logarithmic format (4.1),

$$R_{i,t} = log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{4.1}$$

To perform the statistical and the regression analysis the EViews (Version 12) software was used.

4.2. Herding Behaviour – Ordinary Least Squares Regression

The CSAD framework is widely used to detect herding in financial markets, being defined according to (4.2),

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{4.2}$$

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

Chang et al. (2000) stated that the presence of herding results in a non-linear relationship between the CSAD and the market return, being this relation captured by the coefficient γ_2

which should be negative and statistically significant. In this sense, to detect herding in the whole sample from January 5, 2010, to December 29, 2022, regression (4.3) is run,

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t}^2) + \varepsilon_t \tag{4.3}$$

The coefficients of the previous regression are estimated using the Newey-West (1987) heteroskedastic and autocorrelation coefficients (HAC), in line with previous literature.

Herding is known to be found during asymmetric market conditions.

To test the impact of return asymmetries in the Ibovespa Index, equation (4.4) is estimated according to Economou et al. (2011),

$$\begin{aligned} CSAD_t = \gamma_0 + \gamma_1 D^{Up} |R_{m,t}| + \gamma_2 (1 - D^{Up}) |R_{m,t}| + \gamma_3 D^{Up} (R_{m,t})^2 \\ + \gamma_4 (1 - D^{Up}) (R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.4}$$

In (4.4), D^{Up} is a dummy variable that assumes the value of one on days in which $R_{m,t}>0$ and zero otherwise. The coefficients γ_3 and γ_4 allow detecting herding during bullish and bearish market states, respectively. A Wald test is run to understand whether this bias differs during up and down return conditions.

To examine herding during days of high and low trading volume, equation (4.5) is considered,

$$\begin{aligned} CSAD_t = \gamma_0 + \gamma_1 D^{Vol-High} |R_{m,t}| + \gamma_2 (1 - D^{Vol-High}) |R_{m,t}| \\ + \gamma_3 D^{Vol-High} (R_{m,t})^2 + \gamma_4 (1 - D^{Vol-High}) (R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.5}$$

In (4.5), $D^{Vol\text{-}High}$ is a dummy variable set 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). Again, to assess if herding during high and low trading volume days is statistically different, a Wald test is run.

Lastly, to evaluate the impact of market volatility, regression (4.6) is used,

$$\begin{aligned} CSAD_t = \gamma_0 + \gamma_1 D^{\sigma^2-High} |R_{m,t}| + \gamma_2 (1 - D^{\sigma^2-High}) |R_{m,t}| \\ + \gamma_3 D^{\sigma^2-High} (R_{m,t})^2 + \gamma_4 (1 - D^{\sigma^2-High}) (R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.6}$$

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. Once more, the Wald test is used to evaluate if herding is statistically different during high and low volatility days.

4.3. Herding Behaviour – Quantile Regression

The OLS regression has some drawbacks since it focuses on the mean as a location's measure. With the purpose of not losing the information in the tails of the distribution, a QR is defined (4.7), and the regression coefficients are obtained through the minimization of the weighted sum of the absolute errors,

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau}(R_{m,t})^2 + \varepsilon_{\tau,t} \tag{4.7}$$

In (4.7), X_t represents the vector of the right-hand-side variables. The QR is also applied to evaluate herding during days of high and low return (4.8), high and low trading volume (4.9), and high and low volatility (4.10),

$$\begin{aligned} Q_r(\tau|X_t) = {} & \gamma_{0,\tau} + \gamma_{1,\tau}D^{up}R_{m,t} + \gamma_{2,\tau}(1 - D^{up}) \\ & + \gamma_{3,\tau}D^{up}R_{m,t}^2 + \gamma_{4,\tau}(1 - D^{up})R_{m,t}^2 + \varepsilon_{\tau,t} \end{aligned} \tag{4.8}$$

$$\begin{aligned} Q_r(\tau|X_t) = {} & \gamma_{0,\tau} + \gamma_{1,\tau}D^{Vol-High}R_{m,t} + \gamma_{2,\tau}(1 - D^{Vol-High}) \\ & + \gamma_{3,\tau}D^{Vol-High}R_{m,t}^2 + \gamma_{4,\tau}(1 - D^{Vol-High})R_{m,t}^2 + \varepsilon_{\tau,t} \end{aligned} \tag{4.9}$$

$$\begin{aligned} Q_r(\tau|X_t) = {} & \gamma_{0,\tau} + \gamma_{1,\tau}D^{\sigma^2-High}R_{m,t} + \gamma_{2,\tau}(1 - D^{\sigma^2-High}) \\ & + \gamma_{3,\tau}D^{\sigma^2-High}R_{m,t}^2 + \gamma_{4,\tau}(1 - D^{\sigma^2-High})R_{m,t}^2 + \varepsilon_{\tau,t} \end{aligned} \tag{4.10}$$

In regressions (4.8), (4.9), and (4.10) the dummy variables are defined in the same way as in (4.4), (4.5), and (4.6), respectively.

4.4. Herding Behaviour – Dynamic Characterisation

To characterise herding's dynamic evolution, a rolling window is employed, motivated by the argument that a static model can induce biased conclusions. Specifically, these models assume constant regression coefficients. A dynamic model, particularly, a rolling window of one-day step and 100-days size is considered to evaluate herding's evolution.

The rolling coefficients for regressions (4.3), (4.4), (4.5), and (4.6) and the *t-statistic* graphics for each coefficient are obtained. If investors tended to imitate each other, this would be captured by a negative and statistically significant coefficient. When the *t-statistic* for herding's coefficients has a value lower than -1.96 it is consistent with the presence of herding.

4.5. Herding Behaviour – Fundamental vs. Non-Fundamental Drivers

Different studies to evaluate herding's drivers, such as the ones of Dang and Lin (2016) and Galariotis et al. (2015), decomposed the total CSAD into a fundamental and non-fundamental part, and in these investigations, they used the common risk-factors described in the literature (Carhart, 1997; Fama & French, 1993, 2015). In this line, regression (4.11) is used as a starting point to characterise fundamental and intentional herding,

$$\begin{aligned} CSAD_{TOTAL,t} = \delta_0 + \delta_1 \left| R_{m,t} - R_f \right| + \delta_2 |SMB_t| + \delta_3 |HML_t| \\ + \delta_4 |WML_t| + \delta_5 |IML_t| + \varepsilon_t \end{aligned} \tag{4.11}$$

In (4.11), $|R_{m,t}\text{-}R_f|$ represents the difference between the daily return of the value-weighted portfolio and the risk-free asset, in this case, the 30-day DI Swap. 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. Lastly, 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. In the literature, different authors have already used this database to obtain information on those factors for Brazil (Cavalcante-Filho et al., 2022; Flores et al., 2021; Gea et al., 2023).

As in Galariotis et al. (2015), the total CSAD (4.11) is split into $CSAD_{NON\text{-}FUND,t}$ (4.12) and $CSAD_{FUND,t}$ (4.13).

$$CSAD_{NON-FUND,t} = \varepsilon_t \tag{4.12}$$

$$CSAD_{FUND,t} = CSAD_{TOTAL,t} - CSAD_{NON-FUND,t} \tag{4.13}$$

To identify if herding is driven by non-fundamental or fundamental factors, $CSAD_{NON\text{-}FUND,t}$ and $CSAD_{FUND,t}$ are regressed using the framework of Chang et al. (2000), distinguishing between intentional (4.14) and spurious (4.15) herding,

$$CSAD_{NON-FUND,t} = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4.14}$$

$$CSAD_{FUND,t} = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4.15}$$

Following Dang and Lin (2016), non-fundamental and fundamental herding during different market structures are tested. For returns as in (4.16) and (4.17), for trading volume as in (4.18) and (4.19), and for volatility as in (4.20) and (4.21).

$$\begin{aligned} CSAD_{NON-FUND,t} &= \gamma_0 \\ &+ \gamma_1 D^{Up}|R_{m,t}| + \gamma_2(1 - D^{Up})|R_{m,t}| + \gamma_3 D^{Up}(R_{m,t})^2 \\ &+ \gamma_4(1 - D^{Up})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.16}$$

$$\begin{aligned} CSAD_{FUND,t} = \gamma_0 &+ \gamma_1 D^{Up}|R_{m,t}| + \gamma_2(1 - D^{Up})|R_{m,t}| + \gamma_3 D^{Up}(R_{m,t})^2 \\ &+ \gamma_4(1 - D^{Up})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.17}$$

$$\begin{aligned} CSAD_{NON-FUNDt} &= \gamma_0 \\ &+ \gamma_1 D^{Vol-High}|R_{m,t}| + \gamma_2\left(1 - D^{Vol-High}\right)|R_{m,t}| \\ &+ \gamma_3 D^{Vol-High}(R_{m,t})^2 + \gamma_4(1 - D^{Vol-High})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.18}$$

$$\begin{aligned} CSAD_{FUNDt} = \gamma_0 &+ \gamma_1 D^{Vol-High}|R_{m,t}| + \gamma_2\left(1 - D^{Vol-High}\right)|R_{m,t}| \\ &+ \gamma_3 D^{Vol-High}(R_{m,t})^2 + \gamma_4(1 - D^{Vol-High})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.19}$$

$$\begin{aligned} CSAD_{NON-FUND,t} &= \gamma_0 \\ &+ \gamma_1 D^{\sigma^2-High}|R_{m,t}| + \gamma_2\left(1 - D^{\sigma^2-High}\right)|R_{m,t}| \\ &+ \gamma_3 D^{\sigma^2-High}(R_{m,t})^2 + \gamma_4(1 - D^{\sigma^2-High})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.20}$$

$$\begin{aligned} CSAD_{FUND,t} = \gamma_0 &+ \gamma_1 D^{\sigma^2-High}|R_{m,t}| + \gamma_2\left(1 - D^{\sigma^2-High}\right)|R_{m,t}| \\ &+ \gamma_3 D^{\sigma^2-High}(R_{m,t})^2 + \gamma_4(1 - D^{\sigma^2-High})(R_{m,t})^2 + \varepsilon_t \end{aligned} \tag{4.21}$$

5. Empirical Results and Discussion

5.1. Sample Characterisation

The summary of the descriptive statistics for $CSAD_t$ and $R_{m,t}$ is provided in Table 1 – Panel A. From January 5, 2010, to December 29, 2022, $CSAD_t$ ranges between 0.4833% and 6.9274%, with a mean value of 1.5167%. $R_{m,t}$ presents an average of -0.0028% with the values varying between -18.4531% and 12.0825%. Focusing on the kurtosis, both variables present leptokurtosis (kurtosis higher than three), indicating potential heavy tails. Regarding skewness, $CSAD_t$ has a positive value implying a longer right tail. For $R_{m,t}$ the opposite occurred, where skewness has a negative value, consistent with a longer left tail.

The Jarque-Bera test the normality and for both variables the null hypothesis is rejected (statistically significant at 1% level), implying that the $CSAD_t$ and $R_{m,t}$ are not conform a Gaussian distribution (Table 1 – Panel B).

The Augmented Dickey-Fuller (ADF) test (Table 1 – Panel C) is performed for both variables. Given the *t-statistic*, the null hypothesis (unit root) for $CSAD_t$ and $R_{m,t}$ is rejected, and so they are stationary over the period under analysis.

Lastly, the values for different autocorrelation lags (Table 1 – Panel D) reveal to be statistically significant (at 1% level), thus $CSAD_t$ and $R_{m,t}$ present serial correlation. Together, the results of Panel C and Panel D support 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	3 217	Observations	3 217
Panel B – Normality Test			
$CSAD_t$		$R_{m,t}$	
Jarque-Bera statistic	46 412.94***	Jarque-Bera statistic	34 463.18***

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 (4.2). $R_{m,t}$ is obtained through the procedure described in the Methodology. The study is conducted from January 5, 2010, to December 29, 2022, resulting in 3 217 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.

5.2. Herding Behaviour – Estimation through Ordinary Least Squares Regression

5.2.1. Whole-Period

Herding behaviour analysis for the whole sample, from January 2010 to December 2022, is performed using (4.3) to test this bias in the Ibovespa index. Results are presented in Table 2.

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

Regression Output – Model (4.3)			
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, which implies that CSAD increases with increasing market returns, in line with the predictions of classical models. Herding's detection coefficient, γ_2, is positive and statistically significant for the whole period, albeit at a 10% level, suggesting that investors trading in Ibovespa have no tendency to mimic their peers. Thereby, no convergence towards the market consensus is reported.

Table 2 results are consistent with previous works, namely Chiang and Zheng (2010)[1] that through a method based on cross-sectional dispersions found no evidence of herding in the Brazilian equity market between July 5, 1994, and April 24, 2009. In the same line, de Almeida et al. (2012), using the model specification as in (4.3), showed that in Brazil's stock exchange, investors did not try to reach the market consensus. These authors found that between January 3, 2000, and September 15, 2010, γ_2 was positive and statistically significant (10% level). Chen (2013) studied herding in a panel of countries including Brazil. This behaviour was assessed between 2000 and 2009, for a sample of 446 companies, and, using the CSAD, they reported, in contrast, a negative and statistically significant γ_2 for the whole period, indicating the occurrence of herding behaviour. Mulki and Rizkianto (2020), for Brazil's stock exchange, found a negative and statistically significant γ_2 coefficient when they considered an equally weighted portfolio, consistent with herding behaviour. In turn, Signorelli et al. (2021) run the CSAD's regression each year, between 2008 and 2018, and detected herding from 2009 to 2015 and 2018.

In the literature, it has been argued that a positive and statistically significant herding's coefficient is associated with reverse herding, a situation, where noise traders ignore market movements, and react based on fundamental values, contributing to a higher return dispersion (Choi & Yoon, 2020; Sheikh et al., 2023).

In this context, Gębka and Wohar (2013) considered the global equity market and they found evidence of negative herding, expressed by a positive and statistically significant γ_2. Indeed, negative herding is related to diversifiable risk, and also to insufficient diversification, if investors only hold in their portfolios assets with excessive return dispersions (Gębka & Wohar, 2013).

For instance, in which concerns low diversification, investors, in the US, were found to hold portfolios with a low level of diversification, which could be explained by some behavioural finance biases such as overconfidence, home bias, or even trend-following (Goetzmann & Kumar, 2008).

In fact, Gębka and Wohar (2013) argued that negative herding could be explained, in part, by overconfidence – investors' gains are attributed to their expertise and skills rather than to favourable market conditions and in future decisions these agents would likely follow their

[1] To detect herd behaviour in their analysis they considered an additional term when to Chang et al. (2000). Indeed, they used the following regression: $CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \varepsilon_t$, where evidence of herd would be detected through γ_3.

beliefs once they had success in the past. Particularly, overconfidence is one important behavioural finance bias, characterised by the fact that agents tend to overvalue their own beliefs and skills, a finding that contributes to support why investors do not mimic their peers and follow their own opinions (Kabir & Shakur, 2018). Shantha (2019) found evidence of negative herding in Sri Lanka during the crash period, March 2011 to July 2012, an observation justified by the argument that investors were more individualistic in their decisions in that period.

The negative herding nature can also be driven by panic selling, as in uncertainty scenarios, investors become more risk-averse and probably they rebalance their portfolios, reducing risky assets (Gębka & Wohar, 2013; Shantha, 2019). Effectively, these adjustments may lead to higher dispersions than those predicted by traditional models (Gębka & Wohar, 2013; Shantha, 2019).

In the presence of heterogeneous beliefs, investors are more prone to decide based on their own beliefs. This hypothesis was already discussed by Chiang and Zheng (2010) who concluded that the presence of heterogeneous opinions could justify why market participants tended to herd in Asian markets and did not present the same behaviour in America.

It is important to mention that Ibovespa is the principal equity index, where the shares of the main Brazil's companies are traded. Hence, the sample under analysis corresponds to shares of the most liquid companies, which might explain why herding is not detected in the present dissertation. Wermers (1999) characterised herding behaviour among fund managers and although this bias tended to have a low expression, this phenomenon was more intense among smaller stocks. Additionally, Arjoon and Bhatnagar (2017) hypothesised that smaller stocks were more susceptible to herding, given the higher levels of information asymmetry. Nevertheless, Galariotis et al. (2016b) examined the relationship between herding and market liquidity in the G5 markets, from January 2000 to January 2015. Focusing on liquidity they observed that the herding was stronger for high liquidity stocks, for all markets except Germany (Galariotis et al., 2016b).

It follows as γ_2 is positive and statistically significant, (H1) is rejected, and consequently, there is no evidence of herding behaviour in the Ibovespa index, during the whole period.

5.2.1.1. Asymmetric Herding - Return, Trading Volume, and Volatility

According to the literature, herding is a short-lived event being more pronounced during turmoil periods, thus this bias might only be detected in distinct market microstructures (Arjoon et al., 2020; Batmunkh et al., 2020; de Almeida et al., 2012; Economou et al., 2011; Mobarek et al., 2014; Signorelli et al., 2021). Motivated by this empirical evidence, herding is assessed during days of high and low return (4.4), days of high and low volume (4.5), and days of high and low volatility (4.6).

The model defined in (4.4) is used to investigate how investors trading in Ibovespa behave in bull and bear markets. The output results for days of high and low return (Panel A) and the Wald test (Panel B) are presented in Table 3.

Table 3. Analysis of herding behaviour in the Ibovespa index considering days of high and low return.

Panel A – Regression Output – Model (4.4)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0128	0.1825	0.1768	2.0870	0.6252	0.3623
(67.2353)***	(5.9924)***	(8.2311)***	(3.0426)**	(2.6112)***	
Panel B – Wald Test					
γ_1-γ_2	0.0056				
χ^2	[0.7675]				
γ_3-γ_4	1.4618				
χ^2	[0.0046]***				

Notes: In Panel A, regression (4.4) is estimated using HAC estimators and the values in parenthesis correspond to the *t-statistic*. In Panel B, 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.

The regression outputs displayed in Table 3, Panel A, do not support the existence of herding either in a bullish or in a bearish market state, since the coefficients of herding detection during days of high (γ_3) and low (γ_4) return are positive and statistically significant. This observation suggests that investors do not have the tendency to mimic their peers towards the market consensus, but rather they rely on their private opinions and beliefs to fundament their decisions.

Moreover, the Wald test (Table 3 – Panel B) leads to the conclusion that negative herding is statistically different (at a 1% significance level) during these two market states. Specifically, the coefficient associated with herding on bull days (γ_3) is higher than the corresponding one during bearish conditions (γ_4)[2].

Compared with other studies performed in Brazil, the evidence provided in Table 3 is in line with de Almeida et al. (2012) who found no herding activity when return asymmetries were considered. Nonetheless, these authors, instead of using a unique regression with dummy variables, they split their sample into days of high return and days of low return as in Chang et al. (2000) paper. Contrarily, Mulki et al. (2020), for the equally weighted portfolio, obtained negative values for these coefficients, although without any statistical significance. Additionally, when the authors used a value-weighted portfolio, a positive and statistically significant γ_3 was observed, implying that investors' opinions, during days of high return diverged from the market consensus (Mulki & Rizkianto, 2020). Signorelli et al. (2021) documented the occurrence of herding during days of low market return in their regressions.

Gębka and Wohar (2013) pointed out that during periods of favourable market movements, investors tend to rely more on their private beliefs, which can be explained, in part, by overconfidence. In Sri Lanka, between March 2011 and July 2012, investors preferred to follow their convictions during days of low market return, explained by individualism and panic selling (Shantha, 2019). In Mongolia, Batmunkh et al. (2020) reported stronger herding on down market days, which could be explained by the pessimism of investors about market conditions. Therefore, investors' sentiment and overconfidence may contribute to explaining why investors avoid imitating their peers and follow their own beliefs.

The results in Table 3 are consistent with the fact that, between January 2010 and December 2022, investors trading in the Ibovespa do not mimic each other when facing return asymmetries.

Trading volume asymmetries are evaluated and the results for the regression output (Panel A) and the Wald test output (Panel B) are presented in Table 4.

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[2] By the unilateral test $\gamma_3 > \gamma_4$ when comparing the *t-critical* value (2.3275) with the *t-statistic* (2.8319) for an $\alpha=1\%$ and for 3 212 degrees of freedom.

Table 4. Analysis of herding behaviour in the Ibovespa index considering days of high and low trading volume.

Panel A – Regression Output – Model (4.5)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0132	0.2200	-0.0011	0.4375	6.0702	0.3749
(70.5136)***	(9.2662)***	(-0.0422)	(1.6704)*	(7.5806)***	
Panel B – Wald Test					
γ_1-γ_2	0.2211				
χ^2	[0.0000]***				
γ_3-γ_4	-5.6327				
χ^2	[0.0000]***				

Notes: In Panel A, regression (4.5) is estimated using HAC estimators and the values in parenthesis correspond to the *t-statistic*. In Panel B, 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 10% level.

The results displayed in Table 4, Panel A, show that there is no evidence of herding behaviour in the Ibovespa index between January 2010 and December 2022. Indeed, and similar to the outputs of Table 3, in Panel A, the coefficients γ_3 and γ_4 are positive and statistically significant, although at different levels, consistent with negative herding.

Results from the Wald test indicate that the anti-herding behaviour is significantly different during days of high (γ_3) and low (γ_4) trading volume once the value of the χ^2 statistic is statistically significant at a 1% level (Table 4 – Panel B). Particularly, negative herding is stronger on days of low trading volume[3].

The outcomes in Table 4 are consistent with the results of de Almeida et al. (2012) who did not find arguments to support herding either on days of intense trading activity or on days of low trading volume. In contrast, Signorelli et al. (2021) only observed herding on high volume days, suggesting that market participants were influenced by their peers on days of high trading activity.

High volume, as a proxy of excess trading activity, does not induce herding among Ibovespa investors, contrasting, for instance, with the conclusions of Economou et al. (2011) for European countries, or the ones presented by Tan et al. (2008) for China. Economou et al. (2011) stated that herding could occur on days of high trading volume given the level of market information. Arjoon et al. (2020) deepened this argument by pointing out that herding

[3] By the unilateral test $\gamma_3 < \gamma_4$, comparing the *t-critical* value (-2.3275) with the *t-statistic* (-7.3792) for an α=1% and for 3 212 degrees of freedom.

on days of low volume could be explained by a slow information flow, promoting herding behaviour.

The results in Table 4 reveal that for Brazil, considering the whole period, investors do not show any tendency to mimic other market participants, and on days of low trading volume, that is, when the information flow is low they strongly follow their opinions.

Lastly, herding during days of higher and lower uncertainty is evaluated using regression (4.6). The outputs and the Wald test results are presented in Panel A and Panel B of Table 5, respectively.

Table 5. Analysis of herding behaviour in the Ibovespa index considering days of high and low trading volatility.

Panel A – Regression Output – Model (4.6)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0124	0.1962	0.2701	0.6475	3.1481	0.3760
(52.8629)***	(9.8412)***	(5.9490)***	(1.6704)**	(2.6854)***	
Panel B – Wald Test					
γ_1-γ_2	-0.0739				
χ^2	[0.0281]**				
γ_3-γ_4	-2.5006				
χ^2	[0.0286]**				

Notes: In Panel A, regression (4.6) is estimated using HAC estimators and the values in parenthesis correspond to the *t-statistic*. In Panel B, 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.

Since the coefficients γ_3 and γ_4 presented in Panel A (Table 5) are positive and statistically significant the results are consistent with reverse herding. Based on a Wald test (Table 5 – Panel B), investors follow their beliefs mainly on days of lower uncertainty[4], when compared to days of higher uncertainty, being that result statistically significant at a 5% level.

de Almeida et al. (2012) divided their sample on days of high volatility and days of low volatility and tested herding's occurrence in different countries, including Brazil. With that analysis, negative herding was observed in both market states, implying that investors tended to trade based on their own beliefs. On the other hand, Mulki et al. (2020) reported that herding was statistically significant during periods of high volatility when they used an equally weighted portfolio. The same authors referred that high volatility was associated with a

[4] By the unilateral test $\gamma_3<\gamma_4$, comparing the *t-critical* value (-1.6453) with the *t-statistic* (-2.1895) for an α=5% and for 3 212 degrees of freedom.

greater level of uncertainty, and investors could be tempted to imitate the actions of other agents. However, when Mulki and Rizkianto (2020) used a value-weighted portfolio, they only detected herding on days of low volatility, which could arise from the fact that in those days, investors easily observed their peers, facilitating mimicry. Additionally, Signorelli et al. (2021) evidenced that this bias occurred in their sample on days of increased uncertainty, whereas on days of low volatility, no evidence of herding was unveiled.

Arjoon et al. (2020) stated that investors' herding could be motivated by the fear of uncertainty, derived from the fact that market participants would overvalue their peers' trades, instead of deciding based on fundamental information.

As opposed to some empirical evidence, investors in Ibovespa, do not follow their peers when uncertainty rises, revealing that market participants can rely on fundamental information to justify their trades.

The results of Table 3, Table 4, and Table 5 lead to the rejection of the (H2) work hypothesis. From January 2010 to December 2022, there is no evidence of herding in asymmetric market conditions.

5.3. Herding Behaviour - Estimation through Quantile Regression

5.3.1. Whole Period

In the literature, different authors analysed the presence of herding using a QR given its advantages compared to the OLS regression (Chiang et al., 2010; Economou et al., 2016; Loang & Ahmad, 2022; Nguyen et al., 2023; Pochea et al., 2017; Shrotryia & Kalra, 2020; Zhou & Anderson, 2011).

In financial markets, information on extreme events occurring at distribution's tails can be lost when using OLS, but a QR can be employed to detect and evaluate herding in different quantiles in line with Chiang et al. (2010). As in Table 1, the leptokurtosis of $CSAD_t$ and $R_{m,t}$ also supports the use of a QR. Hence, the QR regression of model (4.7) is run.

Following Zhou and Anderson (2011), the quantile plot of the γ_2 coefficient representing the values of γ_2 conditional on different quantiles is obtained (Annex B). The output results are presented in Table 6. The choice of the quantiles is supported by previous studies (Chiang et al., 2010; Economou et al., 2016; Loang & Ahmad, 2022; Nguyen et al., 2023; Pochea et al., 2017; Shrotryia & Kalra, 2020; Zhou & Anderson, 2011).

Table 6. Analysis of herding behaviour in the Ibovespa Index for the whole period, using a quantile regression.

Regression Output – Whole Period – Model (4.7)				
	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 behaviour is assessed conditional on the τ value. Values presented in parenthesis represent the *t-statistic*. *** significant at 1%.

From Table 6, it is verifiable that the coefficient γ_2 is positive and statistically significant, so there is any evidence of herding, independently of the quantile. Consequently, investors reveal an anti-herding behaviour between January 2010 and December 2022.

Employing a QR, Shrotryia and Kalra (2020) assessed if from January 2011 to May 2019 investors in the BRICS presented the tendency to mimic their peers. Considering Brazil, the final sample was composed of 44 stocks and, using the same formulation as in (4.7), they found evidence of negative herding for the median and above the median quantiles. For the two quantiles below the median, although the coefficients were positive, they had no statistical significance (Shrotryia & Kalra, 2020). Thus, the results presented in Table 6 are in line with the ones of Shrotryia and Kalra (2020).

Nevertheless, evidence of herding conditional on quantiles was documented by different authors. For instance, Economou et al. (2016) reported herding conditional on the upper quantiles in the Athens stock exchange, for an equally weighted portfolio. In Asia, Shanta (2019) found evidence of herding in the Colombo Stock Exchange (CSE) using an OLS regression for the whole period, from April 2000 to March 2018. Furthermore, for the same period, the use of a more robust method – a QR – permitted to conclude that in CSE herding was conditional on all distribution quantiles, and so this phenomenon was not restricted to the distribution's tails (Shantha, 2019). Important, when the author divided the sample into two subperiods (2000 to 2009 and 2009 to 2018), with the OLS regression, herding behaviour was found to vanish between 2009 and 2018 (Shantha, 2019). Nonetheless, for this period, Shanta (2019) QR's results permitted to highlight that herding was conditional to the lower distribution's tail.

In sum, as γ_2 is positive and statistically significant ,the results documented in Table 6 are consistent with adverse herding.

5.3.2. Asymmetric Herding - Return, Trading Volume, and Volatility

To evaluate investors' behaviour during different market structures, regressions (4.8), (4.9), and (4.10) are run, and the results are presented in Panel A, Panel B, and Panel C of Table 7.

As for the (4.7) model, the quantile plots for the herding coefficients during up (γ_3) and down (γ_4) days are obtained. These plots are shown in Annex C (high and low return), Annex D (high and low trading volume), and Annex E (high and low volatility).

Table 7. Analysis of herding behaviour in the Ibovespa index using a quantile regression for different market states.

Panel A – Regression Output: Return's Asymmetry – Model (4.8)						
	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Quantile (τ=10%)	0.0098	0.0956	0.0881	2.0736	0.8513	0.0899
	(89.0844)***	(7.098)***	(7.5785)***	(18.9134)***	(3.030)***	
Quantile (τ=25%)	0.0110	0.1051	0.10439	2.2326	0.7283	0.0991
	(56.0736)***	(1.6067)***	(5.9775)***	(0.8054)	(7.9123)***	
Quantile (τ=50%)	0.0126	0.1204	0.1546	3.1625	0.55737	0.1298
	(97.8630)***	(5.2014)***	(11.2155)***	(5.3108)***	(3.030)***	
Quantile (τ=75%)	0.0147	0.1787	0.1635	2.7244	1.3660	0.1787
	(98.1750)***	(7.9880)***	(8.7289)***	(7.7000)***	(9.5310)***	
Quantile (τ=90%)	0.0170	0.16014	0.1768	5.5640	2.4172	0.2339
	(51.5979)***	(2.5459)**	(3.9290)***	(3.1726)***	(3.7157)***	
Panel B – Regression Output: Volume's Asymmetry – Model (4.9)						
	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Quantile (τ=10%)	0.0102	0.1034	-0.0656	0.7577	6.6135	0.0996
	(98.3300)***	(10.5894)***	(-3.8777)***	(14.5004)***	(21.3117)***	
Quantile (τ=25%)	0.0113	0.1336	-0.0187	0.6947	5.6452	0.1038
	(96.2439)***	(10.035)***	(-1.0296)	(8.1503)***	(16.5922)***	
Quantile (τ=50%)	0.01294	0.1851	-0.0171	0.5615	6.3932	0.1393
	(93.0213)***	(11.8878)***	(-0.5414)	(2.1467)**	(4.8905)***	
Quantile (τ=75%)	0.0149	0.2218	-0.0094	0.96455	6.8474	0.1883
	(95.3123)***	(12.6100)***	(-0.2292)	(6.9743)***	(4.0556)***	
Quantile (τ=90%)	0.0174	0.2958	-0.1124	1.0365	12.1659	0.2541
	(53.7102)***	(4.6676)***	(-2.1945)**	(1.0192)	(7.2786)***	

[continuation]

Panel C – Regression Output: Volatility's Asymmetry – Model (4.10)						
	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo $\overline{R^2}$
Quantile (τ=10%)	0.0095	0.1123	0.1498	0.7296	2.9915	0.0939
	(66.8219)***	(10.6700)***	(6.7368)***	(13.0735)***	(3.030)***	
Quantile (τ=25%)	0.0107	0.1314	0.1716	0.7308	2.9123	0.1015
	(70.4796)***	(10.7335)***	(6.3409)***	(9.5221)***	(6.3409)***	
Quantile (τ=50%)	0.0123	0.1483	0.1896	1.2456	4.6500	0.1346
	(28.3173)***	(0.3743)	(2.8556)***	(0.2113)	(3.5908)***	
Quantile (τ=75%)	0.0144	0.1574	0.2032	2.1693	6.6928	0.1887
	(67.3982)***	(4.6276)***	(4.2553)***	(2.7721)***	(3.6692)***	
Quantile (τ=90%)	0.0164	0.1972	0.2401	2.2650	7.3482	0.2339
	(42.9493)***	(5.3408)**	(2.3267)**	(4.6667)***	(1.8331)*	

Notes: The outputs for models (4.8), (4.9), and (4.10) are presented in Panel A, B, and C, respectively. 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 behaviour (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 behaviour (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%.

From Table 7, whatever the quantile, no evidence of herding behaviour is observed, once the associated coefficients in up (γ_3) and down-market (γ_4) states are not significantly negative. Although a different regression method (a QR) is employed, the results are in accordance with the ones presented in the previous tables.

Considering the outputs in Panel A (Table 7) the coefficients are positive and significant, consistent with anti-herding, except on bull days, for quantile τ=25%. Shrotryia and Kalra (2020) studied herding in the BRICS from January 2011 to May 2019 and focusing on bull and bear market states they reported adverse herding in all distribution quantiles, at different significance levels, except for the median quantile of γ_4.

Volume asymmetries (Panel B – Table 7) induce investors to follow their personal beliefs in all quantiles, except in quantile τ=90% during high volume days.

The analysis of volatility asymmetries (Panel C – Table 7) emphasises that investors do not try to reach the market consensus in all the quantiles, except in the median quantile for days of high uncertainty once the coefficient is not statistically significant. In their volatility analysis, Shrotryia and Kalra (2020) observed, for the quantile τ=10%, that investors followed the rational predictions, supported by the fact that γ_3 and γ_4 were not statistically significant.

For example, in Slovenia, Pochea et al. (2017) found a negative albeit not statistically significant herding coefficient using an OLS regression. Though, through a QR, this bias was found conditional on the lower quantiles (τ=10%, τ=25%, and τ=50%), thereby confirming the hypothesis that OLS might result in information losses.

In China, focusing on returns' asymmetries, Chiang et al. (2010) reported herding conditional on the lower quantiles for SZSE-A, SZSE-B, SSE-A, and SSE-B shares. The Wald test for the coefficients γ_3 and γ_4 revealed that there were statistical differences in the herding considering market returns (Chiang et al., 2010). In Malaysia herding, during up and down-market states, was detected in the upper distribution tail, between 2016 and 2020 (Loang & Ahmad, 2022). Furthermore, in South Korea, Choi and Yoon (2020) used a QR to characterise herding in the KOSPI and the KOSDAQ stock exchanges. The authors, for the KOSPI and focusing on days of low market return, noted that herding occurred in the upper and lower extreme quantiles (τ=10% and τ=90%), while on days of high market return, herding was conditional only on the upper extreme quantile (τ=90%). During days of low trading activity, investors trading in the KOSPI followed their peers except in the median quantile (Choi & Yoon, 2020). Concerning KOSDAQ, Choi and Yoon (2020) reported herding conditional on all quantiles, except τ=70% for low return days. Contrasting to the KOSPI's results, in KOSDAQ days of high trading volume induced herding in the quantiles above the median (Choi & Yoon, 2020). In fact, the level of information asymmetry and the fear of uncertainty contributed to explaining why herding was only detected in some quantiles. In essence, Choi and Yoon (2020) asserted that in the KOSDAQ, investors' sentiment was an important driver to explain herding. Investors' mood was analysed by Rubbaniy et al. (2022) in the cryptocurrency market using a quantile-on-quantile approach. In this research, the authors mentioned that investors' moods had an effect on herding behaviour, observing that investors' sad moods had a greater impact on herding behaviour when compared to a happy mood (Rubbaniy et al., 2022)

In effect, these papers covered distinct periods and given that herding is more pronounced during turmoil scenarios, this might contribute to explaining why this bias was found to be conditional to the extremes of the distribution's tail.

Noteworthy, from these studies it is possible to infer that markets are inhabited by heterogeneous individuals that take different actions, which in some cases might deviate from the predictions of the classical models. Cultural aspects also have an impact on herding as highlighted by Chang and Lin (2015). Indeed, it was pointed out that herding prevailed in countries following Confucian principles as well as in less sophisticated markets (Chang & Lin, 2015). Lobão and Maio (2019) studied the consequences of cultural aspects in herding behaviour for a sample comprised of 39 countries from 2001 to 2013. With this research, the authors reported that countries characterised by higher masculinity levels were less likely to present herding behaviour. Hence, Lobão and Maio (2019) stated that there were cultural aspects capable of predicting herding behaviour.

In sum, the results shown in Table 6 and Table 7 do not support the work hypothesis (H3), given that no evidence of herding is found in any quantile, for different market states.

5.4. Dynamic Nature of Herding Behaviour

As evidenced by the literature, herding tends to emerge during extreme market conditions, therefore a dynamic analysis can be relevant to highlight its evolution. Actually, the parameters of equations (4.3), (4.4), (4.5), and (4.6) are assumed to be constant, which can lead to erroneous conclusions. Specifically, in an OLS regression, the estimated coefficients are based on an average, and consequently, may not reflect turbulent periods (Babalos & Stavroyiannis, 2015).

Results from the Bai-Perron test show that the models present structural breaks, thus the coefficients are not constant for the entire period. Further details regarding the Bai-Perron test are presented in Annex F, Annex H, Annex J, and Annex L. Prompted by the structural breaks, a regression for each sub-period is run and information on those coefficients is displayed in Annex G, Annex I, Annex K, and Annex M.

Once the models presented structural breaks, as shown by the Bai-Perron test, the herding's dynamic nature is evaluated through a rolling window method, given that this framework captures this evolution. Important to note that during the different model breaks detected by the Bai-Perron test, no evidence of herding is found, using the equations (4.3), (4.4), (4.5), and (4.6).

Thus, to analyse how herding evolved, a rolling window of 100-day size and one-day step is considered for each regression. In Figure 1, the rolling window of the γ_2 is presented, where the x-axis represents the time evolution, and the y-axis the values of γ_2 *t-statistic*.

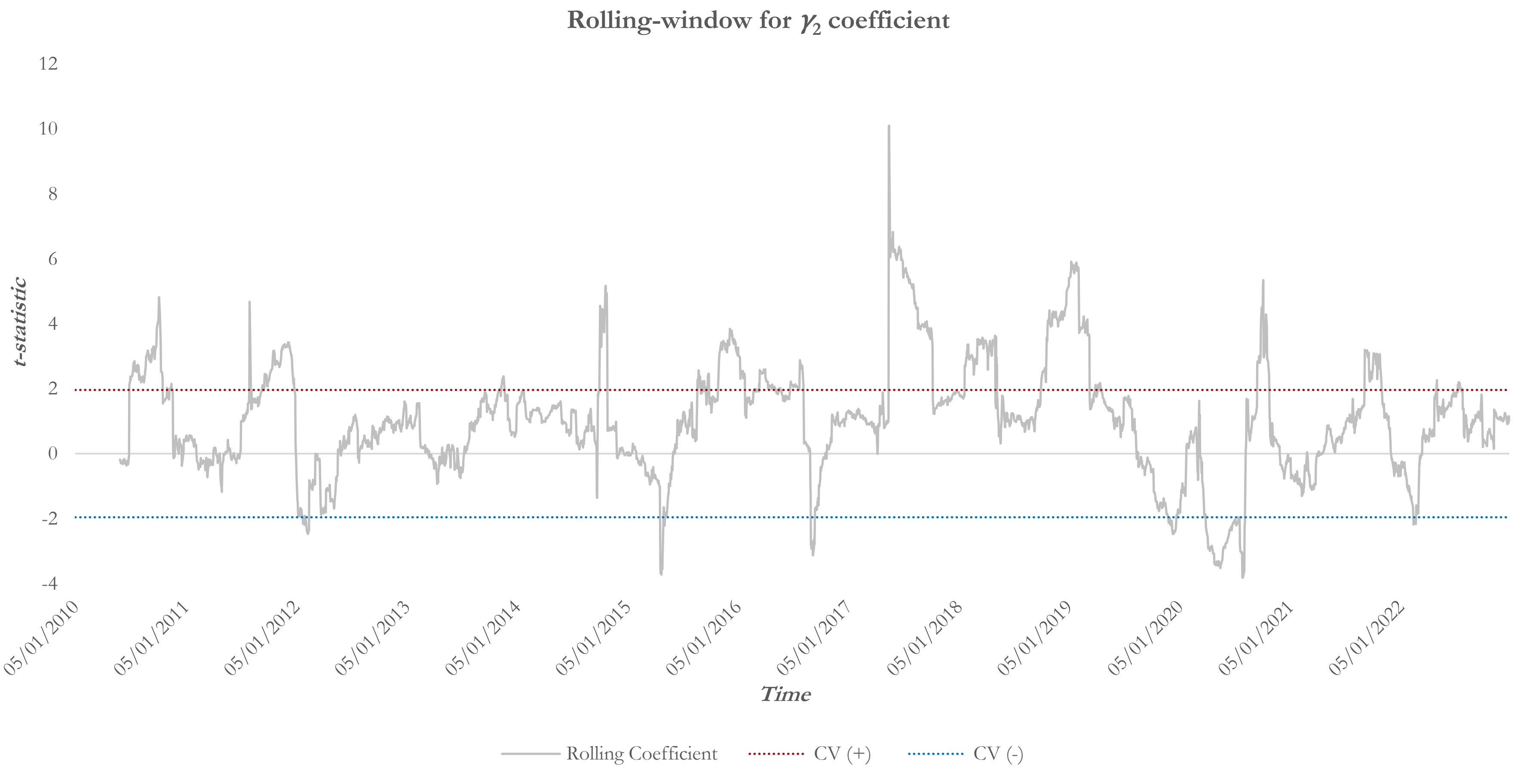

Figure 1. Rolling window *t-statistic* graphic for coefficient γ_2 of regression. CV encodes for confidence value and in this case, CV (+) is +1.96 and CV (-) is -1.96. Below the blue line, there is evidence of herding behaviour, and above the red line, there is evidence supporting anti-herding.

With the OLS and QR frameworks, no evidence of herding is reported as highlighted by the previous results. The Bai-Perron test reveals that the model has structural breaks. Hence, the use of a rolling window permits to conclude that despite of herding is not detected in the whole sample, there are moments in which Ibovespa's investors have the tendency to mimic their peers and try to reach the market consensus. Specifically, as illustrated in Figure 1, between January 27, 2012, and February 16, 2012, with exception of February 2 and February 3, where the *t-statistic* is only statistically significant at a 10% level, investors mimic their peers' trades. Evidence of this bias is revealed, between April 23, 2015, and May 8, 2015, excluding May 4 and May 5. Additionally, herding is evident for the period comprised between September 2, 2016, and September 15, 2016, and also from November 27, 2019, to December 23, 2019. During 2020, with the onset and propagation of the Covid-19 pandemic, investors herd following other agents, being this behaviour statistically significant between March 31, 2020, and August 7, 2020. Lastly, investors are found to mimic their peers just before the onset of the war in Ukraine – from February 16, 2022, to February 24, 2022.

Particularly, the fear and uncertainty about the market prospects might have induced a certain level of panic among investors, and consequently, the emergence of herding. In Taiwan, Huang and Wang (2017) revealed that investors' fear explained herding behaviour since market participants were more affected by negative news, reacting quickly to them when compared to the arrival of good news. In Europe, the Covid-19 pandemic led to an increase in herding among investors, and this behaviour was explained by arguments such as fear and uncertainty (Espinosa-Mendez & Arias, 2021). Particularly, less informed investors tended to mimic the more informed agents (Espinosa-Mendez & Arias, 2021). Recently, the geopolitical instability emerging from Ukraine's war was studied by Bougatef and Nejah (2023) and from the analysis they determined that investors trading in the Moscow stock exchange tried to reach the market consensus, especially during downing conditions.

The tables presented above indicate that, between January 2010 and December 2022, Ibovespa's investors tend to follow their own beliefs given the signal and statistical significance of herding's coefficients. Though, the application of a rolling window permit to detect herding. This fact is in accordance with Bouri et al. (2019), who by employing a static model, observed no evidence of herding in the cryptocurrency market, while through a dynamic framework, investors were found to follow their peers in a sample's subperiod.

For the analysis of herding asymmetries, a rolling window with the same characteristics, size and step, is applied and the results are presented in Annex N, Annex O, Annex P, Annex Q, Annex R, and Annex S.

Comparing days of high (Annex N) and low (Annex O) return, herding is more prevalent on bear market days. In fact, this behavioural correlation is found in 2012, 2015 and 2022. The details of the exact periods are presented in the bottom panels of Annex N and Annex O. Therefore, given the uncertainty underlying stock market evolution, investors might feel more comfortable imitating their peers, thus discarding their private beliefs.

For trading volume differences (Annex P and Annex Q), the evidence for days of low volume is scarce, and during days of high volume herding is detected in 2011, 2012, 2013, 2015, 2016, 2019, 2020, 2021 and 2022. The details of the exact periods are presented in the bottom panels of Annex P (high trading volume) and Annex Q (low trading volume). Economou et al. (2011) pointed out that days of high trading volume corresponded to days when the information flow was high, and thus, investors could feel comfortable in mimic their peers. Important to note that in 2012, 2015, and 2022 herding is observed in states of high trading volume and low market return, conditions that can have promoted this non-rational behaviour.

Lastly, a rolling window for volatility's asymmetries is tested and focusing on days of higher uncertainty (Annex R), investors tend to reach the market consensus in 2012, 2015 and 2020. For days of low volatility (Annex S), herding occurs in 2010, 2013, 2017 and 2020. The evidence of herding during high volatility days coincides, in part, with the results for herding during down market returns and high trading volume, circumstances that contribute to destabilising the market and can induce herding among market participants.

The obtained results lead to accepting the working hypothesis (H4). In Brazil, herding has a dynamic evolution, supported by the fact that in Ibovespa this behaviour is detected in different subperiods.

5.5. Fundamental vs. Non-Fundamental Herding Behaviour

The empirical studies asserted that herding can be driven by intentional (non-fundamental) or spurious (fundamental) reasons (Bikhchandani & Sharma, 2000). In the spirit of Galariotis et al. (2015) and Dang and Lin (2016), herding's driving forces are analysed.

Dang and Lin (2016) referred that the CSAD responded to the absolute value of the factors, thus model (4.11) is estimated in this form. Specifically, when Dang and Lin (2016) compared the results of the absolute regression with the ones obtained through the framework designed by Galariotis et. al (2015), they observed an improvement in the model's explanatory power, and the factors were statistically significant.

In Annex T the output of the model (4.11) is presented. The results of CSAD decomposition for the whole period are in Table 8. In Panel A the output of the model (4.3) is presented once more, Panel B contains the results for non-fundamental herding, and Panel C the estimations for the model driven by fundamental factors.

Table 8. Analysis of CSAD driven by non-fundamental and fundamental factors for the whole period.

Panel A – Total CSAD (4.3)			
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 (4.14)			
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 (4.15)			
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 is decomposed into non-fundamental (4.12) and fundamental (4.13). Both are then regressed using the framework of Chang et al. (2000). Panel B contains the coefficients associated with non-fundamental CSAD. Panel C presents the CSAD considering fundamental factors. *** significant at 1% level; ** significant at 5% level.

From Panel A, of Table 8, it is concluded that investors prefer to follow their private beliefs, consistent with negative herding behaviour. Focusing on CSAD decomposition, particularly in non-fundamental driven CSAD, the results displayed in Panel B highlight that between January 2010 and December 2022, investors trading in Ibovespa, do not mimic their peers once γ_2 is found to be positive and statistically significant. Regarding CSAD driven by fundamentals, Panel C (Table 8), γ_2 is positive and has no statistical significance.

Galariotis et al. (2015) pointed out that herding behaviour is period and country-specific. The CSAD decomposition into fundamental and non-fundamental components permitted Galariotis et al. (2015) to conclude that in the US, investors' herding behaviour was driven by spurious and intentional arguments, considering different crises. In the United Kingdom, investors only followed their peers' trades during the Dotcom bubble (January 2000 to June 2000) and this instinct to mimic was explained by fundamentals. From April 2008 to December 2015, Indārs et al. (2019) investigating the Moscow stock exchange, did not detect evidence of herding in the full period using the total CSAD. Nevertheless, when returns' dispersions were decomposed according to spurious and intentional factors, investors were found to imitate their peers, a behaviour that was driven by non-fundamental arguments (Indārs et al., 2019). This behaviour was expected given the market's transparency levels, which could justify why investors tended to mimic their peers (Indārs et al., 2019).

The results of Panel A (Table 8) support that for the period under analysis, intentional motifs (Table 8 – Panel B) rather than fundamentals (Table 8 – Panel C) contribute to explaining why investors follow their opinions when trading in the Ibovespa equity index.

To assess whether non-fundamental or spurious motifs, during different market states, explain investors' behaviour, regressions (4.14), (4.15), (4.16), (4.17), (4.18), (4.19), (4.20), and (4.21) are run. Results concerning return asymmetries are presented in Table 9.

Table 9. Analysis of CSAD driven by non-fundamental and fundamental factors for return asymmetries.

Panel A – Total CSAD (4.4)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0128 (67.2353)***	0.1825 (5.9924)***	0.1768 (8.2311)***	2.0870 (3.0246)**	0.6252 (2.6112)***	0.3623
Panel B – Non-Fundamental CSAD (4.16)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0002 (1.0332)	-0.0240 (-0.9539)	-0.0430 (-2.6235)***	1.1646 (1.6768)*	0.6204 (4.2773)**	0.024
γ_3-γ_4 χ^2	0.5442 [0.3730]				

Panel C – Fundamental CSAD (4.17)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0127 (146.6505)***	0.2064 (15.6894)***	0.2198 (22.3361)***	0.9225 (3.6478)***	0.0048 (0.0416)	0.5833
γ_3-γ_4 χ^2	0.9177 [0.0003]***				

Notes: In each panel, in the upper part, the model's output is obtained using HAC coefficients. The values in parentheses correspond to the *t-statistic*. Panel A presents the output as in Table 3. In the bottom part, of Panel B and Panel C, 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.

Focusing on days of bear and bull markets, between January 2010 and December 2022, no evidence of herding is detected (Table 9 – Panel A). In Panel B (Table 9), non-fundamentals drive negative herding during days of high (γ_3) and low (γ_4) return, given their signal and statistical significance. From the Wald test anti-herding does not differ between days of high and days of low return, as justified by the *p-value* of the χ^2 statistic. The fundamental's regression results (Table 9 – Panel C) lead to conclude that spurious motifs explain investors' behaviour only in bullish markets γ_3.

During days of low return (γ_4) negative herding is mainly explained by non-fundamental factors since the coefficient is positive and statistically significant only for the model (4.16). On days of high return (γ_3), investors' trades are based on fundamentals and non-fundamentals once the coefficient is positive and statistically significant for models (4.16) and (4.17).

The conclusions obtained for Table 9 contrast with previous literature. In Vietnam, specifically in the HOSE, Dang and Lin (2016) split the total CSAD, and the results showed that herding was driven by spurious and intentional motifs. In Russia, in the Moscow stock exchange, Indārs et al. (2019) observed that, for days of low return, investors relied on their peers' actions, a behaviour driven by non-fundamentals.

Table 10 contains the outputs for the total CSAD decomposition focusing on days of high and days of low trading activity.

Table 10. Analysis of CSAD driven by non-fundamental and fundamental factors for volume asymmetries.

Panel A – Total CSAD (4.5)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0132 (70.5136)***	0.2220 (9.2662)***	-0.0011 (-0.0422)	0.4375 (1.6704)*	6.0702 (7.5806)***	0.3749
Panel B – Non-Fundamental CSAD (4.18)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0004 (2.6854)***	-0.0117 (-0.6999)	-0.1461 (-5.9077)***	0.4499 (2.9589)***	3.6295 (5.4901)***	0.0370
γ_3-γ_4 χ^2	-3.1796 (0.0000)***				
Panel C – Fundamental CSAD (4.19)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0128 (132.2473)***	0.2317 (18.538)***	0.1450 (9.608)***	-0.0124 (-0.0940)	2.4407 (4.3283)***	0.5846
γ_3-γ_4 χ^2	-2.4531 (0.0000)***				

Notes: In each panel, in the upper part, the model's output is obtained using HAC coefficients. The values in parentheses correspond to the *t-statistic*. Panel A presents the output as in Table 4. In the bottom part, of Panel B and Panel C, 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.

From the total CSAD's regression results (Table 10 – Panel A) no evidence of herding is detected, in view of the values and statistical significance of γ_3 and γ_4. In detail, the split of the total CSAD into non-fundamentals (Table 10 – Panel B) and fundamentals (Table 10 – Panel C) permit to conclude that intentional factors justify negative herding during days of high and low volume, γ_3 and γ_4 are positive and statistically significant. Fundamentals only drive this adverse herding on days of low trading volume, as γ_4 is positive and statistically significant. Additionally, in Panel C, the coefficient γ_3 is negative, although not statistically significant. The Wald test in Panel B and Panel C shows that anti-herding is statistically different on days of high and low trading volume, suggesting that negative herding based on non-fundamentals and fundamentals is higher on days of low trading volume.

It can be hypothesised that on days of high market liquidity, negative herding is driven by factors other than fundamentals. On days of low market liquidity, adverse herding is explained by spurious and non-fundamental arguments.

Indārs et al. (2019) also investigated trading volume asymmetries using the total CSAD decomposition. Two volume proxies were used and in both, investors' herding on days of high volume was driven by fundamentals (Indārs et al., 2019).

Lastly, the total CSAD for days of high and low volatility is split into non-fundamental and fundamental components. The results are displayed in Table 11.

Table 11. Analysis of CSAD driven by non-fundamental and fundamental factors for volatility asymmetries.

Panel A – Total CSAD (4.6)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0124	0.1962	0.2701	0.6475	3.1481	0.3760
(52.8629)***	(9.8412)***	(5.9490)***	(1.6704)**	(2.6854)***	
Panel B – Non-Fundamental CSAD (4.20)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
-0.0002	-0.0298	0.0450	0.6025	2.2343	0.0524
(-1.2230)	(-2.2090)**	(1.2017)	(23.6419)***	(2.4322)**	
γ_3-γ_4	-1.6318				
χ^2	(0.0621)*				
Panel C – Fundamental CSAD (4.21)					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0126	0.2260	0.2251	0.0450	0.9138	0.5789
(106.8261)***	(20.0072)***	(10.2250)***	(0.3297)	(1.2204)	
γ_3-γ_4	-0.8688				
χ^2	(0.2455)				

Notes: In each panel, in the upper part, the model's output is obtained using HAC coefficients. The values in parentheses correspond to the *t-statistic*. Panel A presents the output as in Table 5. In the bottom part, of Panel B and Panel C, 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.

In Table 11 the total CSAD (Panel A) decomposition into non-fundamental (Panel B) and fundamental (Panel C) clarify how investors behave during days of high and low volatility.

Indeed, during days of high (γ_3) and low (γ_4) uncertainty, investors' negative herding is motivated by non-fundamental factors, as in Panel B the values of γ_3 and γ_4 are positive and statistically significant. In turn, for CSAD driven by fundamental information, γ_3 and γ_4, although positive are not statistically significant. Furthermore, the alternative hypothesis of the Wald test is only accepted in Panel B, implying that for intentional factors, adverse herding is statistically different during days of high and low uncertainty.

In sum, the results shown in Table 8, Table 9, Table 10, and Table 11 show that negative herding is mainly driven by intentional factors, conducting to the rejection of (H5).

6. Conclusions and Further Perspectives

The present dissertation examined herding behaviour in the Ibovespa Index, which is composed of stocks with the highest liquidity. Specifically, studying this behavioural correlation in Brazil is important not only because this country is still an emerging economy, but also given that the stock market has been growing in terms of value and volume (Vartanian et al., 2022). Although herding behaviour is thought to occur predominantly in emerging countries due to information asymmetries and higher uncertainty, the empirical evidence on Brazil is not unanimous. For instance, Chiang and Zheng (2010) and de Almeida et al. (2012) did not report evidence of herding in their investigations, while other Mulki and Rizkianto (2020) and Signorelli et al. (2021) documented that, in Brazil, investors mimicked each other. Herding behaviour tends to be period-specific, and thus its detection might be period-specific.

This work adds new insights to the analysis and understanding of investors' behaviour in Brazil. In this dissertation, 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 behaviour.

Herding behaviour was analysed between January 5, 2010, and December 29, 2022, thus 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's 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. Given the Bai-Perron test results, 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.

Lastly, 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, according, for example, to Galariotis et al. (2015) and Dang and Lin (2016).

With this division, it was concluded that, for the whole period, the negative herding was explained mainly by non-fundamentals.

In Brazil, studies employing a QR or the CSAD's splitting are scarce, and so, the present dissertation added new insights on investors' behaviour.

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. 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. 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 dissertation.

One important aspect highlighted in this dissertation was the fact that negative herding could be associated with overconfidence. In this sense, it would be important to test the impact of overconfidence on investors' behaviour, as well as to assess the impact of national culture. Another argument explaining negative herding is panic selling, which is characterised 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 analysed too.

To recognise and evaluate the dynamics of the forces that drive investors' behaviour, it would also be interesting to perform a rolling window regression for non-fundamental and fundamental regressions. This analysis would undoubtedly allow a better understanding of how those drivers evolved.

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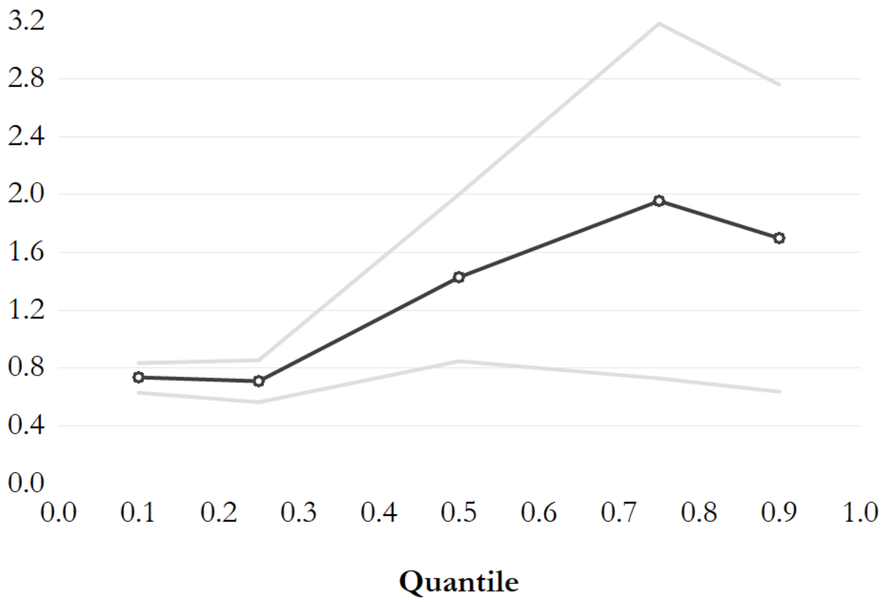
Annexes

Annex A. Fundamental evidence for herding behaviour in Brazil.

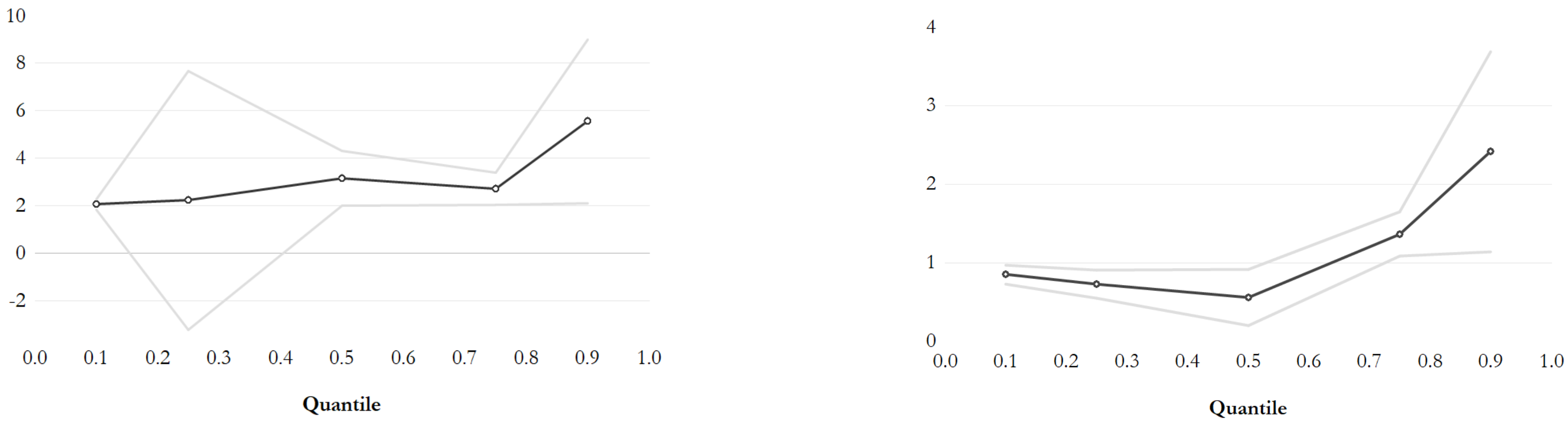
Author	Sample and Period	Methodology	Principal Findings
Chiang and Zheng (2010)	Panel of 18 countries, including Brazil. For Brazil, the sample started on July 5, 1994, and ended on April 24, 2009.	Herding was studied through a CSAD regression, where an additional term, $R_{m,t}$ was considered compared to Chang et. al (2000). Additionally, herding towards the US market was assessed.	No evidence of herding was found for the whole period in Brazil. When evaluating the role of the US stock exchange, in Brazil, investors herded around the US market.
de Almeida et al. (2012)	Panel of Latin American countries, including Brazil. Daily closing prices and trading volumes for the period between January 3, 2000, and September 15, 2010, were considered.	Herding was evaluated through Chang et al. (2000) framework. Asymmetries regarding return, volume and volatility were assessed through two different equations – for up and down-market states. The impact of different crises was evaluated.	For Brazil, evidence of negative herding was found for the whole period and different market conditions. Herd around the US market was found to be non-significant.
Chang and Lin (2015)	Panel of 50 countries, including Brazil. Daily closing prices for the period July 5, 1994, to July 7, 2011, were considered.	Herding behaviour was evaluated using the method proposed by Chiang and Zheng (2010). Besides exploring herding, it explored the effects of culture on herding behaviour.	For the whole period, anti-herding was detected in Brazil, given the positive and statistically significant value of γ_3. Herding was found to occur in nations following Confucian norms.
Cakan et al. (2018)	Panel of 3 countries – Brazil, Russia, and Turkey. The sample included data for the period starting on October 28, 2005, and ending on October 29, 2015.	The relationship between oil speculation and herding behaviour was assessed through CSAD, and herding was then regressed as a function of oil speculation. A rolling window was also used.	For Brazil, herding was detected in the whole sample in some of the subperiod. Rolling window results highlighted herding's dynamic

Shrotryia and Kalra (2020)	BRICS and US markets were considered, and herding was assessed from January 2011 to May 2019.	Using a QR, the presence of herding was tested for the whole period as well as during days of high and low return and volatility. Also, the role of the US market was evaluated.	Through a QR, investors trading in Brazil's stock market were found to follow their opinions, thus indicating the presence of anti-herding, in the whole sample, in asymmetric conditions. There was no evidence supporting herding around the US.
Mulki and Rizkianto (2020)	Analysis of herding behaviour in the BRICS. For Brazil, the sample started on December 31, 1996, and ended on December 29, 2017.	CSAD was calculated using an equally weighted and a value-weighted portfolio and herding was assessed in the whole sample, on days of high/low return and volatility. The impacts of the financial and Asian crises were tested	For the equally weighted portfolio evidence of herding was found for the whole period and during the financial crisis. Also, investors herded on days of high volatility. During days of low uncertainty, anti-herding emerged. For the value-weighted portfolio, investors herded during the two crisis periods and on days of low volatility.
Signorelli et al. (2021)	They used stocks with a liquidity index above 0.01 and their sample started on January 2008 and ended in May 2019.	Herding was tested using the CSSD and the CSAD, and its presence was tested in the whole period, as well as in asymmetric conditions – returns, volume, volatility, imbalance orders and investors' sentiment.	Considering the whole sample, through CSAD herding was found in all years, except in 2008, 2016, and 2017. Evidence of herding was found for days of low market return, high trading volume and a high number of sell orders

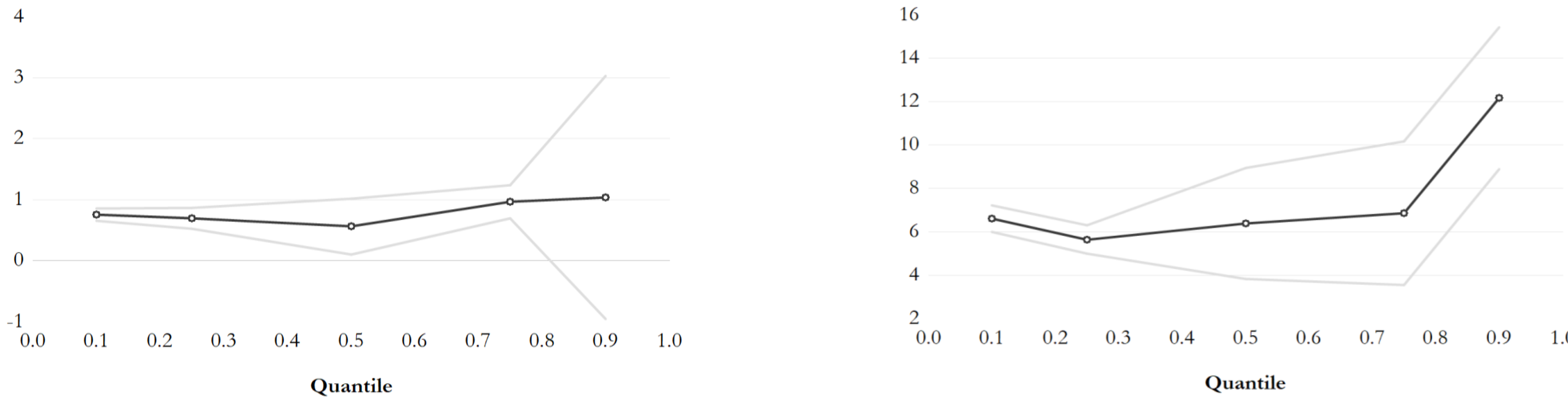
Annex B. Quantile plot for γ_2 coefficient estimated according to equation (4.7). The grey lines delimit the 95% confidence interval and the black line the point estimates of γ_2.



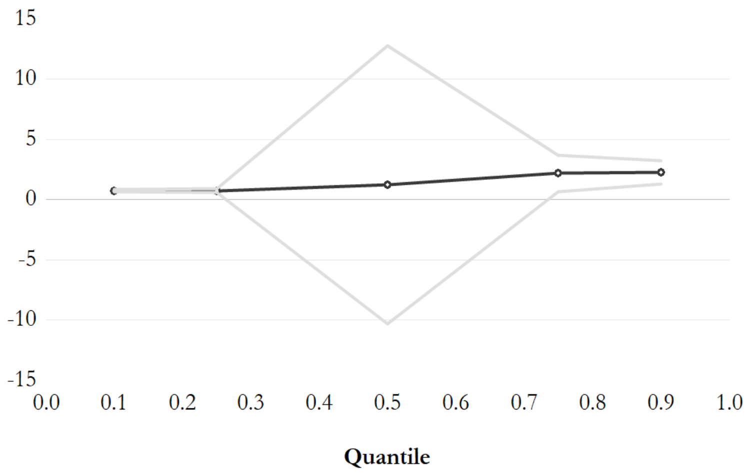
Annex C. Quantile plot for γ_3 (left panel) and for γ_4 (right panel) coefficients, estimated according to equation (4.8). The grey lines delimit the 95% confidence interval and the black line the point estimates of γ_3 or γ_4.

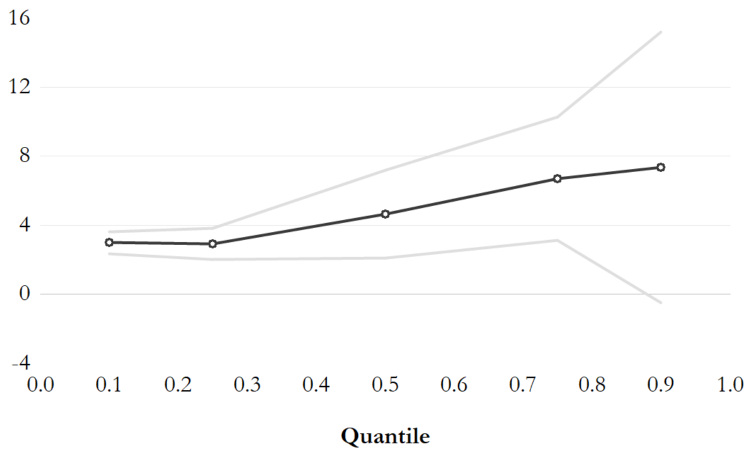


Annex D. Quantile plot for γ_3 (left panel) and for γ_4 (right panel) coefficients, estimated according to equation (4.9). The grey lines delimit the 95% confidence interval and the black line the point estimates of γ_3 or γ_4.



Annex E. Quantile plot for γ_3 (left panel) and for γ_4 (right panel) coefficients, estimated according to equation (4.10). The grey lines delimit the 95% confidence interval and the black line the point estimates of γ_3 or γ_4.





Annex F. Bai-Perron test for the whole period.

Regression Model (4.3)				
Breaks	**F-statistic**	**Scaled F-statistic**	**Weighted F-statistic**	**Critical Value**
1	16.5877	49.7631	49.7631	13.98
2	20.7407	62.2221	72.5492	11.99
3	29.9265	89.7796	120.8006	10.39
4	26.1661	78.7984	121.2605	9.05
5	48.7217	*146.1652*	*273.9127*	7.46
UD Max statistic 146.1652**			UD Max critical value 14.23	
WD Max statistic 273.9127**			WD Max critical value 15.59	
Estimated break dates				
1	21/2/2020			
2	26/5/2017; 17/3/2020			
3	27/8/2017; 9/8/2016; 21/2/2020			
4	30/3/2012; 27/8/2014; 9/8/2016; 21/2/2020			
5	10/4/2012; 12/5/2014; 25/4/2016; 4/4/2018; 17/3/2020			

Notes: The outputs of the Bai-Perron test are obtained using 1 to M globally determined breaks, where the number of maximum breaks is set equal to 5. The critical values for both UD Max and WD Max are in accordance with Bai-Perron (Econometric Journal, 2003). ** significant at 5% level.

Annex G. Regression outputs for model (4.3) estimated according to the structural breaks determined by the Bai-Perron test.

Panel A – 5/1/2010 to 9/4/2012 – 562 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0120	0.0991	1.7581	0.2398
(53.0607)***	(3.8356)***	(3.8315)***	
Panel B – 10/4/2012 to 9/5/2014 – 514 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0138	0.08464	3.4885	0.1679
(41.6279)***	(1.7297)*	(1.9326)	
Panel C – 12/5/2014 to 22/4/2016 – 482 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0151	0.03128	5.2467	0.2327
(27.2399)***	(0.4809)	(2.5495)**	
Panel D – 25/4/2016 to 3/4/2018 – 482 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0121	0.0764	3.9805	0.3902
(46.4405)***	(2.1867)**	(12.9933)***	
Panel E – 4/4/2018 to 16/3/2020 – 482 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.1251	0.1385	0.6920	0.5806
(33.9544)***	(3.3918)***	(2.7738)***	
Panel F – 17/3/2020 to 29/12/2022 – 695 observations			
γ_0	γ_1	γ_2	$\overline{R^2}$
0.0140	0.2061	1.4557	0.4337
(38.3141)***	(4.6454)***	(3.0597)***	

Notes: For each structural break, the model is estimated using the HAC coefficients and the values in parenthesis correspond to the *t-statistic*. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Annex H. Bai-Perron test for return asymmetries.

Regression (4.4)				
Breaks	**F-statistic**	**Scaled F-statistic**	**Weighted F-statistic**	**Critical Value**
1	11.8998	59.4987	59.4988	18.23
2	31.6126	158.0629	184.4742	15.62
3	33.4052	*167.0259*	218.5845	13.93
4	27.8975	139.4877	205.4007	12.38
5	28.0555	140.2773	*243.0851*	10.52
UD Max statistic 167.0259**			UD Max critical value 18.42	
WD Max statistic 243.0851**			WD Max critical value 19.96	
Estimated break dates				
1	21/2/2020			
2	26/5/2017; 17/3/2020			
3	27/8/2017; 9/8/2016; 21/2/2020			
4	30/3/2012; 27/8/2014; 9/8/2016; 21/2/2020			
5	10/4/2012; 12/5/2014; 25/4/2016; 4/4/2018; 17/3/2020			

Notes: The outputs of the Bai-Perron test are obtained using 1 to M globally determined breaks. The determined number of breaks for UD Max is 3 and for WD Max is 5. The critical values for both UD Max and WD Max are in accordance with Bai-Perron (Econometric Journal, 2003). ** significant at 5% level.

Annex I. Regression outputs for model (4.4) estimated according to the structural breaks determined by the Bai-Perron test.

Panel A – 5/1/2010 to 9/4/2012 – 562 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0121	0.0333	0.0715	5.0751	1.8237	0.2503
(48.2582)***	(0.7618)	(2.3868)**	(3.2680)***	(3.9936)***	
Panel B – 10/4/2012 to 9/5/2014 – 514 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0138	0.0724	0.1045	4.3094	2.3924	0.1658
(40.9401)***	(1.1282)	(2.0608)**	(1.5055)	(1.3425)	
Panel C – 12/5/2014 to 22/4/2016 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0151	0.0471	0.0435	5.2480	4.3019	0.2320
(26.6320)***	(0.7372)	(0.4581)	(2.4261)**	(1.1991)	
Panel D – 25/4/2016 to 3/4/2018 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0119	0.1701	0.0954	-0.1639	3.9167	0.3934
(41.8848)	(2.7657)***	(1.6861)*	(-0.0775)	(7.6994)***	
Panel E – 4/4/2018 to 16/3/2020 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0127	0.1287	0.08774	1.8239	0.8945	0.6132
(40.0229)***	(3.3381)***	(2.4788)**	(4.9925)***	(4.4352)***	
Panel F – 17/3/2020 to 29/12/2022 – 695 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0141	0.2268	0.1431	2.0919	1.6750	0.4556
(42.0300)***	(4.9266)***	(3.7307)***	(3.7978)***	(5.4182)***	

Notes: For each structural break, the model is estimated using HAC coefficients and the values in parenthesis correspond to the *t-statistic*. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Annex J. Bai-Perron test output for volume asymmetries.

Regression (4.5)				
Breaks	**F-statistic**	**Scaled F-statistic**	**Weighted F-statistic**	**Critical Value**
1	18.4753	92.3763	92.3763	18.23
2	14.6579	73.2892	85.5354	15.62
3	19.9715	99.8575	130.6822	13.93
4	17.2729	86.3644	127.1747	12.38
5	23.8572	*119.2862*	*206.7099*	10.52
UD Max statistic 119.2862**			UD Max critical value 18.42	
WD Max statistic 206.7099**			WD Max critical value 19.96	
Estimated break dates				
1	17/3/2020			
2	26/5/2017; 17/3/2020			
3	27/8/2017; 9/8/2016; 21/2/2020			
4	30/3/2012; 27/8/2014; 9/8/2016; 21/2/2020			
5	30/3/2012; 12/5/2014; 25/4/2016; 4/4/2018; 17/3/2020			

Notes: The outputs of the Bai-Perron test are obtained using 1 to M globally determined breaks, where the number of maximum breaks is set equal to 5. The critical values for both UD Max and WD Max are in accordance with Bai-Perron (Econometric Journal, 2003). ** significant at 5% level.

Annex K. Regression outputs for model (4.5) according to the structural breaks determined by the Bai-Perron test.

Panel A – 5/1/2010 to 29/3/2012 – 556 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0122	0.1294	-0.0392	1.1280	5.9278	0.2685
(48.2859)***	(4.6100)***	(-0.6997)	(2.6351)***	(2.6800)***	
Panel B – 30/3/2012 to 9/5/2014 – 520 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.01410	0.1646	-0.1243	0.4205	11.4217	0.2100
(40.9996)***	(3.4530)***	(-1.6733)*	(0.2585)	(3.1473)***	
Panel C – 12/5/2014 to 22/4/2016 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0152	0.1110	-0.0464	3.8535	4.775	0.2701
(27.3729)***	(1.6719)*	(-0.5793)	(1.8435)*	(1.5557)	
Panel D – 25/4/2016 to 3/4/2018 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0123	0.1084	-0.0041	3.5735	5.0397	0.4028
(45.4846)***	(2.3668)**	(-0.0720)	(8.7760)***	(2.5955)***	
Panel E – 4/4/2018 to 16/3/2020 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0131	0.1496	-0.0598	0.5920	4.3272	0.6086
(32.4104)***	(3.5555)***	(-0.7635)	(2.3589)**	(1.2571)	
Panel F – 17/3/2020 to 29/12/2022 – 695 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0146	0.2206	-0.0023	1.2076	6.1105	0.4569
(43.3093)***	(4.7102)***	(-0.0419)	(2.9581)***	(5.2078)***	

Notes: For each structural break, the model is estimated using the HAC coefficients and the values in parenthesis correspond to the *t-statistic*. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Annex L. Bai-Perron test output for volatility asymmetries.

Regression (4.6)				
Breaks	**F-statistic**	**Scaled F-statistic**	**Weighted F-statistic**	**Critical Value**
1	10.8368	54.1842	54.1842	18.23
2	18.4968	92.4840	107.9375	15.62
3	18.0572	90.2862	118.1563	13.93
4	16.0361	80.1806	118.0688	12.38
5	22.9549	*114.7747*	*1198.8919*	10.52
UD MAX STATISTIC 114.7747**			UD MAX CRITICAL VALUE 18.42	
WD MAX STATISTIC 198.8919**			WD MAX CRITICAL VALUE 19.96	
Estimated break dates				
1	21/2/2020			
2	22/6/2017; 20/3/2020			
3	27/8/2017; 9/8/2016; 21/2/2020			
4	10/4/2012; 27/8/2014; 9/8/2016; 21/2/2020			
5	10/4/2012; 15/5/2014; 25/4/2016; 28/4/2018; 20/3/2020			

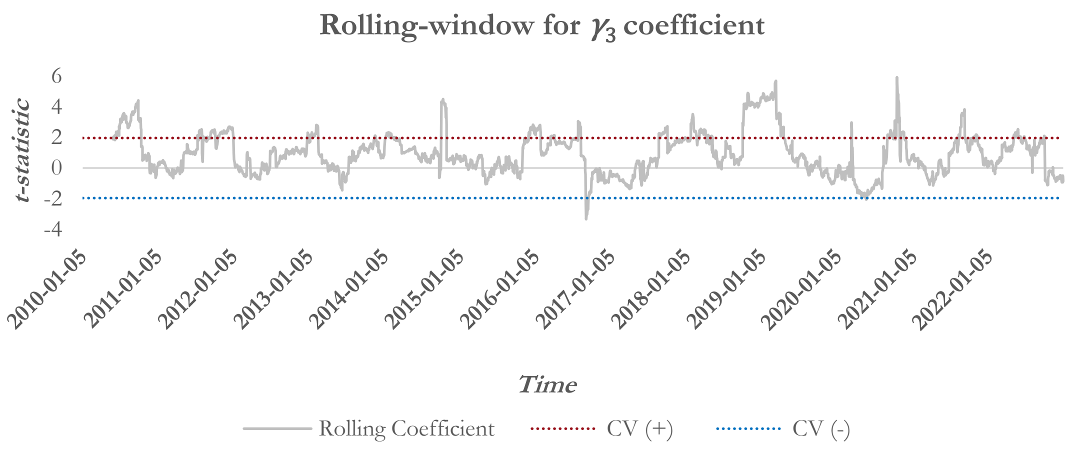
Notes: The outputs of the Bai-Perron test are obtained using 1 to M globally determined breaks, where the number of maximum breaks is set equal to 5. The critical values for both UD Max and WD Max are in accordance with Bai-Perron (Econometric Journal, 2003). ** significant at 5% level.

Annex M. Regression outputs for model (4.6) according to the structural breaks determined by the Bai-Perron test.

Panel A – 5/1/2010 to 9/4/2012 – 562 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0123 (39.0925)***	0.0806 (2.6740)***	-0.0383 (-0.4055)	1.9341 (4.0473)***	10.7325 (1.6360)	0.2410
Panel B – 10/4/2012 to 14/5/2014 – 517 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.01410 (40.9996)***	0.0816 (1.3869)	0.2527 (1.9598)*	4.2318 (1.9479)*	-5.0233 (-0.6040)	0.1711
Panel C – 15/5/2014 to 27/4/2016 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0146 (23.0647)***	0.0035 (0.0488)	0.1771 (1.3369)	6.4141 (2.8169)***	3.1414 (0.4395)	0.2419
Panel D – 28/4/2016 to 6/4/2018 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0114 (28.8326)***	0.0968 (2.2355)**	0.3214 (2.4674)**	3.9072 (10.2014)***	-8.7940 (-1.1771)	0.3980
Panel E – 9/4/2018 to 19/3/2020 – 482 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0128 (22.5757)***	0.1177 (2.2441)**	-0.1391 (-1.0448)	0.9636 (2.4301)**	28.3082 (3.6445)***	0.6553
Panel F – 20/3/2020 to 29/12/2022 – 692 observations					
γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$
0.0138 (35.3314)***	0.1028 (3.7724)***	0.2843 (3.8903)***	3.2202 (8.7418)***	2.0278 (1.3433)	0.4291

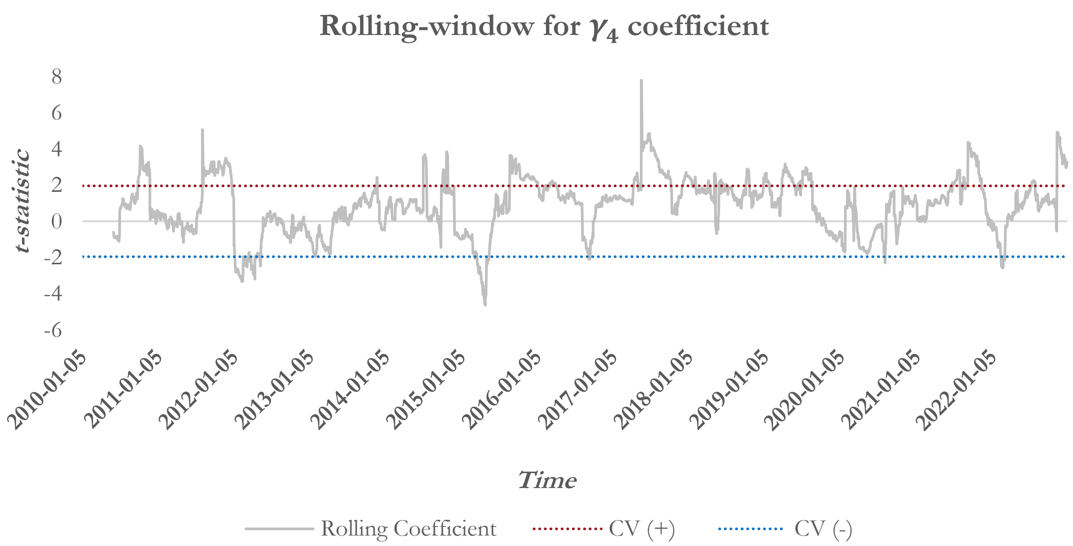
Notes: For each structural break, the model is estimated using the HAC coefficients and the values in parenthesis correspond to the *t-statistic*. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Annex N. Rolling window of γ_3 for regression (4.4) for a window of 100 observations. The red and blue lines represent the value of the *t-statistic*. Below the blue line there is evidence of herding and above the red line of anti-herding.



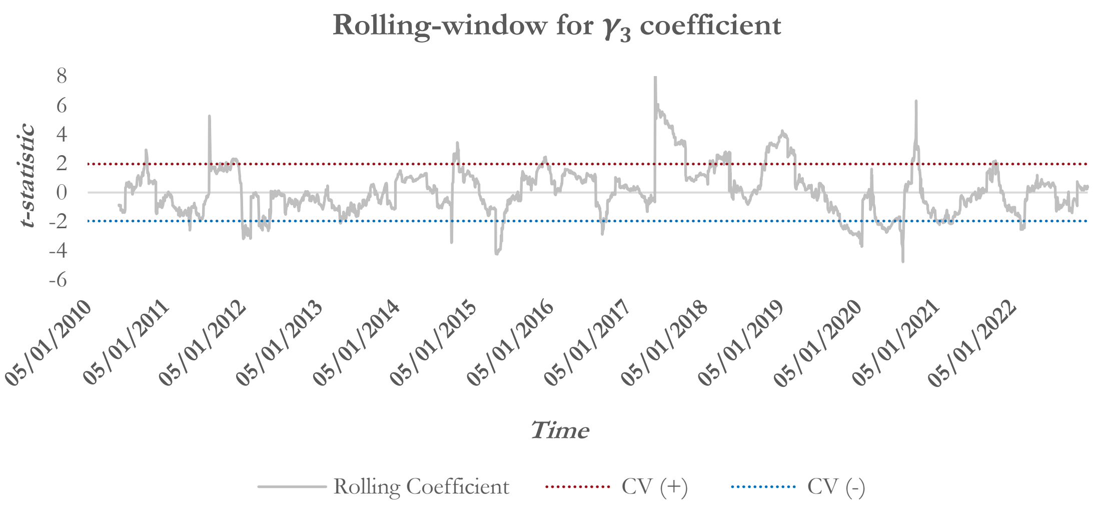
Herding Periods - 5% Confidence Level
2/9/2016-15/9/2016; 21/5/2020-22/5/2020;

Annex O. Rolling window of γ_4 for regression (4.4) for a window of 100 observations. The blue and red lines represent the value of the *t-statistic*. Below the blue line there is evidence of herding and above the red line of anti-herding.



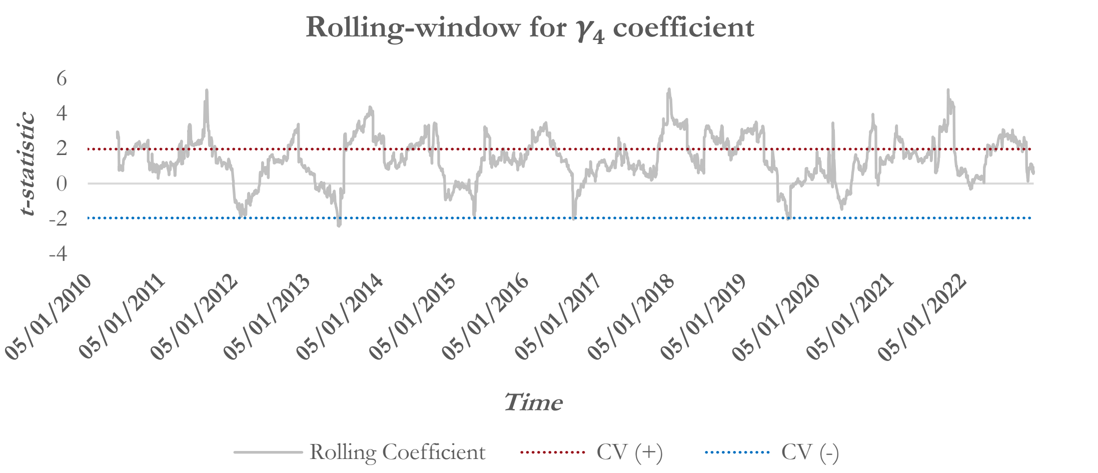
Herding Periods – 5% Confidence Level
9/1/2012-16/2/2012; 22/2/2012-13/3/2012; 16/3/2012-17/4/2012; 7/5/2012-11/5/2012; 9/3/2015-10/3/2015; 19/3/2015-30/4/2015; 5/5/2015-15/5/2015; 9/9/2016-12/9/2016; 14/2/2022-4/3/2022;

Annex P. Rolling window of γ_3 for regression (4.5) for a window of 100 observations. The blue and red lines represent the value of the *t-statistic*. Below the blue line there is evidence of herding and above the red line of anti-herding.



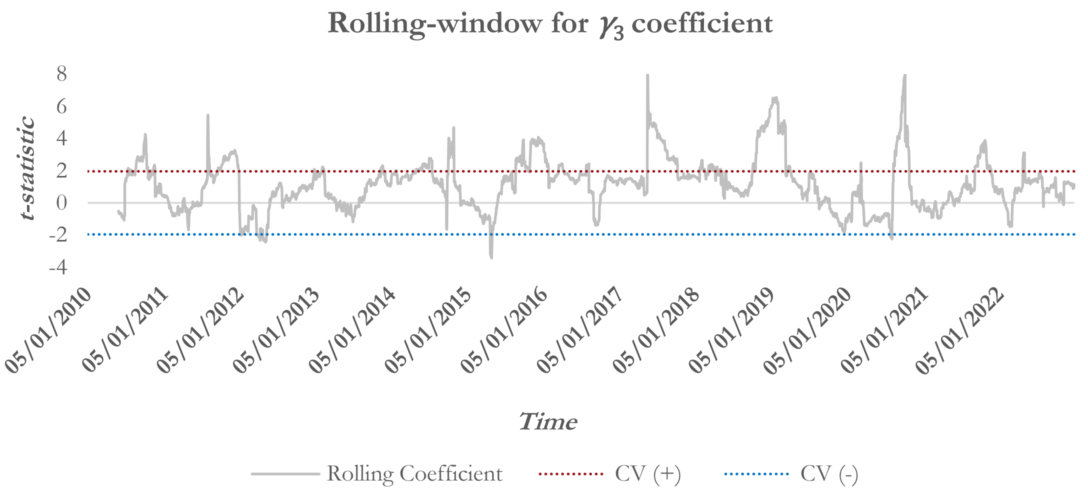
Herding Periods – 5% Confidence Level
2/5/2011-5/5/2011; 9/1/2012-16/2/2012; 27/3/2012-12/4/2012; 26/4/2012-14/5/2012; 15/4/2013-19/4/2013; 25/9/2014-26/9/2014; 23/4/2015-26/5/2015; 28/5/2015-29/5/2015; 2/6/2015; 2/9/2016-5/9/2016; 9/9/2016-15/9/2016; 21/9/2016-22/9/2016;27/9/2016-28/9/2016; 11/10/2019-24/1/2020; 1/4/2020-22/6/2020; 24/6/2020-25/6/2020; 22/7/2020-7/8/2020; 15/1/2021-21/1/2021; 26/1/2021-29/1/2021; 5/2/2021-10/2/2021; 12/2/2021-17/2/2021; 19/2/2021; 11/3/2021-29/3/2021; 15/2/2022-4/3/2022;

Annex Q. Rolling window of γ_4 for regression (4.5) for a window of 100 observations. The blue and red lines represent the value of the *t-statistic*. Below the blue line there is evidence of herding and above the red line of anti-herding.



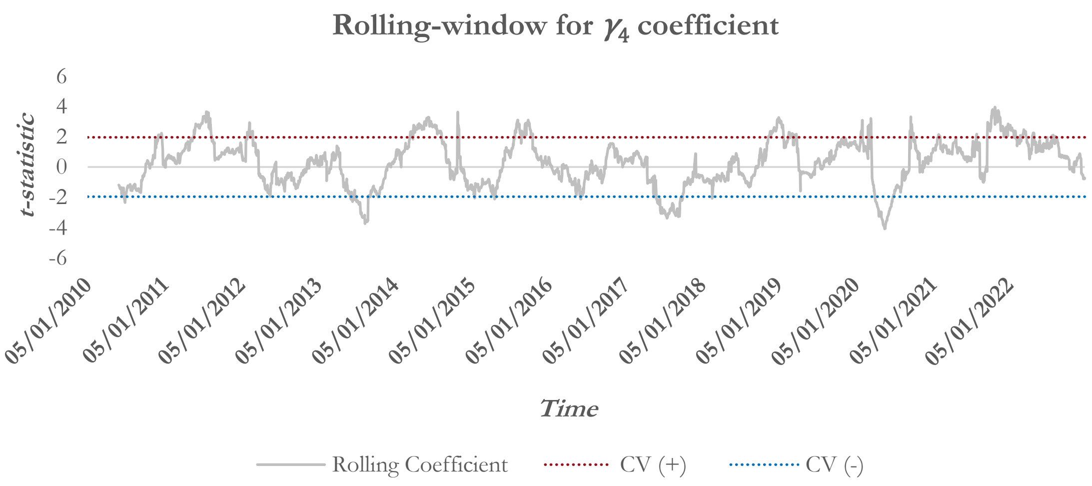
Herding Periods – 5% Confidence Level
12/6/2013-24/6/2013; 13/8/2019; 26/8/2019; 28/8/2019;

Annex R. Rolling window of γ_3 for regression (4.6) for a window of 100 observations. The blue and red lines represent the value of the *t-statistic*. Below the blue line there is evidence of herding and above the red line of anti-herding.



Herding Periods – 5% Confidence Level
12/1/2012-13/1/2012; 26/3/2012-29/3/2012; 2/4/2012-12/4/2012; 26/4/2012-11/5/2012; 23/4/2015-30/4/2015; 30/7/2020-3/8/2020; 5/8/2020;

Annex S. Rolling window of γ_4 for regression (4.6) for a window of 100 observations. The blue and red lines represent the value of the *t-statistic*. Below the blue line, there is evidence of herding and above the red line of anti-herding.



Herding Periods – 5% Confidence Level
18/6/2010; 28/9/2010-2/7/2010; 10/6/2013-11/6/2013; 17/6/2013-25/6/2013; 28/6/2013-3/7/2013; 5/7/2013-2/9/2013; 6/9/2013-9/9/2013; 16/10/2013; 19/1/2015; 24/4/2015-25/4/2015; 6/6/2016-8/6/2016; 22/5/2017; 1/6/2017-5/10/2017; 22/2/2018; 6/4/2020-30/6/2020;

Annex T. Output of the 5-factor model.

Regression (4.11)						
δ_0	δ_1 $\lvert R_{m,t}-R_{f,t}\rvert$	δ_2 $\lvert HML_t\rvert$	δ_3 $\lvert SMB_t\rvert$	δ_4 $\lvert WML_t\rvert$	δ_5 $\lvert IML_t\rvert$	$\overline{R^2}$
0.0099	0.1756	0.1530	0.1608	0.2243	-0.0133	0.5012
(28.8154)***	(10.2922)***	(8.2394)***	(5.9895)***	(14.5727)***	(-0.6359)	

Notes: Regression (4.11) is estimated using information regarding the market, HML, SMB, WML, and IML factors. The error terms are then regressed using the framework of Chang et. al (2000), thereby allowing to characterise intentional herding, while spurious herding was obtained by the difference between the total and the non-fundamental CSAD.