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BEYOND AVERAGE: A STUDY OF HERDING EFFECT IN THE BRAZILIAN STOCK MARKET DURING COVID-19 PANDEMIC USING A QUANTILE REGRESSION APPROACH

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This is a dissertation submitted to obtain the degree of Master of Accounting in accordance with the requirements for the Graduate Program in Accounting of the Federal University of Paraíba.

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Advisor: Prof. Dr. Wenner Glaucio Lopes Lucena.

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RESUMO

A pesquisa buscou investigar como a pandemia de COVID-19 impactou o mercado de ações brasileiro em termos de efeito manada. As análises foram feitas utilizando os 100 primeiros dias da pandemia, primeira, segunda e terceira onda. O modelo escolhido para essa análise foi o *cross-sectional absolute deviation* (CSAD) proposto por Chang; Cheng; Khorana (2000) pois, diferente do *cross-sectional standard deviation* (CSSD) proposto por Christie e Huang (1995), o CSAD é capaz de detectar o efeito manada em diferentes condições de mercado, seja num cenário de estresse ou em um de estabilidade. As estimações foram feitas por meio da regressão por MQO e pela regressão quantílica. Essa última, além de mais robusta a *outliers* por utilizar a mediana, permite analisar vários pontos ao longo da distribuição. Ao contrário da regressão MQO que faz suas estimativas apenas pela média da distribuição. A pesquisa se caracterizou por ser documental, descritiva e quantitativa. A amostra contou com 144 empresas listadas na B3 no período entre janeiro de 2016 a setembro de 2023. Os resultados apontaram que o efeito manada foi detectado nos primeiros 100 dias da pandemia, se estendendo até o fim da primeira onda. Na segunda e terceira ondas o efeito manada não foi evidenciado. Além disso, o mercado brasileiro também apresentou o comportamento manada tanto para mercados de alta como de baixa, com uma certa tendência para mercados de alta se for considerado o período até o fim da primeira onda da pandemia. Esse último resultado para a primeira onda foi detectado pela regressão quantílica e não por MQO. Na segunda e terceira ondas, não foi evidenciado o efeito manada em condições assimétricas.

Palavras-Chave: Finanças Comportamentais; Efeito Manada; COVID-19; Regressão Quantílica.

ABSTRACT

The research aimed to investigate the impact of the COVID-19 pandemic on the Brazilian stock market in terms of herd behavior. The analysis focused primarily on the first 100 days of the pandemic, and then in the first, second, and third waves. The chosen model for this analysis was the cross-sectional absolute deviation (CSAD) proposed by Chang, Cheng, and Khorana (2000). Unlike the cross-sectional standard deviation (CSSD) proposed by Christie and Huang (1995), CSAD is capable of detecting herd behavior under different market conditions, whether stressed or stable. The estimations were conducted using ordinary least squares (OLS) regression and quantile regression. While OLS regression estimates based on the mean of the distribution, quantile regression uses the median which is more robust to outliers and allows for analyzing various points along the distribution. The research was specified as documentary, descriptive, and quantitative. The sample consisted of 144 companies listed on B3 from January 2016 to September 2023. The results indicated that herd behavior was detected in the first 100 days of the pandemic, persisting until the end of the first wave. However, herd behavior was not evident in the second and third waves. It was also observed that the Brazilian market exhibited herd behavior in both bull and bear markets, with a tendency towards bull markets until the end of the first wave of the pandemic. This last result for the first wave was detected using quantile regression, not OLS. In the second and third waves, herd behavior was not evident under asymmetric conditions.

Keywords: Behavioral Finance; Herding Effect; COVID-19; Quantile Regression.

LIST OF ABREVIATIONS

AMH – Adaptive Market Hypothesis

B3 – Bolsa, Brasil, Balcão

CSSD – Cross-sectional standard deviation

CSAD – Cross-sectional absolute deviation

EMH – Efficient Market Hypothesis

IPO – Initial Public Offering

OLS – Ordinary Least Squares

UK – United Kingdom

US – United States

WHO – World Health Organization

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1 INTRODUCTION

In the past two decades, global financial markets have experienced significant crises. Two notable examples are the credit crisis in the real estate market that originated in the United States (US) in 2008, commonly known as the subprime[1] crisis, and the COVID-19 pandemic that began in Wuhan, China, in 2020. These crises had a widespread impact, not only affecting their countries of origin but also spreading to other financial markets, including the Brazilian market (Dulci, 2009; Fang; Lu; Su, 2013; Hall; Beck; Filho, 2013; Kumar *et al.*, 2021).

COVID-19, a highly contagious respiratory illness caused by the novel coronavirus SARS-CoV-2, was first identified in Wuhan in December 2019, and rapidly spread worldwide causing significant impacts on both people's daily lives and the economy. The measures implemented by countries to mitigate the virus's spread, such as quarantine and social isolation, resulted in the closure of numerous businesses, a rise in unemployment, and ultimately, an economic recession (Nicola *et al.*, 2020; Javier *et al.*, 2021).

On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a global pandemic (UNA-SUS, 2020). This designation was in effect until May 5, 2023, when the WHO declared an end to the state of public health emergency of international concern. As a result, COVID-19 would be managed similarly to other infectious diseases (WHO, 2023).

According to the Brazilian Ministry of Health (2022), the first case of COVID-19 in Brazil was recorded on February 26, 2020. After that, Brazil implemented similar restrictive measures as other countries to control the spread of the virus. These measures included the use of masks in enclosed spaces, social distancing, and the closure or limited operating hours of non-essential businesses and other services.

The implementation of these measures resulted in a notable economic slowdown. To illustrate, in 2020, the Brazilian stock exchange began the year at 115.645 points, following an upward trend since 2016. However, in March 2020, the index reached a low of 61,690 points, marking a decrease of nearly 47%. Moreover, there was a considerable rise in market volatility during this period (Kumar *et al.*, 2021).

[1] A term used in the US real estate sector to refer to a type of mortgage credit aimed at borrowers with higher risk.

The intense movement in the stock market may not be solely explained by the Efficient Market Hypothesis (EMH), which assumes that investors have access to all market-related information and make decisions to maximize their utility (Fama, 1970). While the EMH is a widely accepted theory, it may not fully capture the complexity of investor behavior, especially during times of crisis. In such periods, investors are often driven by a mix of emotions, including euphoria and fear, which can significantly influence their decision-making process. These emotional biases can lead investors to deviate from logical and rational analysis.

This type of behavior is studied by another field of knowledge known as behavioral finance. Behavioral finance combines insights from psychology and sociology to provide a comprehensive understanding of why investors sometimes make financial decisions that are not solely based on analytical or rational factors. By incorporating psychological and sociological perspectives, behavioral finance seeks to shed light on the various cognitive biases, emotions, and social influences that can significantly impact investment decision-making. (Scharfstein; Stein, 1990; Mittal, 2022).

Some psychological factors can influence investment decisions, such as loss aversion, overconfidence, and the tendency to follow collective behavior, also known as the herd effect[2]. The herd effect refers to investors making decisions based on a larger group, disregarding their own assessments and judgments (Scharfstein; Stein, 1990; Banerjee, 1992).

It is important to note that the herd effect can have significant negative consequences for the market. These consequences include distortions in asset pricing, increased volatility, and even the formation of financial bubbles (Bekiros et al., 2017). As such, it is crucial for market participants to have a reliable and effective method for detecting this effect. By being able to identify when a herding behavior is at play, investors can make more informed choices that are not solely driven by the actions of others, thereby reducing the potential risks, and enhancing the overall stability of the market.

In this way, Christie and Huang (1995) introduced the cross-sectional standard deviation (CSSD) model to identify herding behavior in stock markets by measuring

[2] In this study, the terms 'herd effect' and 'herd behavior' are used interchangeably to represent the same concept.

the dispersion between individual assets returns and the stock market return, focusing on extreme periods. In contrast, Chang, Cheng, and Khorana (2000) proposed the cross-sectional absolute deviation (CSAD) model, which also calculates dispersion but is more effective in detecting herding behavior compared to the CSSD method. Additionally, the CSAD model can identify this phenomenon during periods of stability, not just when the market is under stress.

In essence, these two models aim to determine the extent to which individual asset returns deviate from the market return. When there is a high dispersion, it means that investors are making their decisions according to their own interests. In consequence, the herd effect is less pronounced and evident, thus, leading the market to be considered rational.

Conversely, if investors are seen to abandon their personal beliefs and make decisions based on market consensus, a smaller dispersion will be exhibited. Consequently, the difference between asset returns and market returns either decreases or increases at a decreasing rate.

When these methods are applied, a decrease in herding behavior can be empirically observed in more mature financial markets, such as the US and the United Kingdom (UK) (Bensaïda; Jlassi; Litimi, 2015; Ampofo *et al.*, 2023; Yang; Chuang, 2023). However, in emerging economies like Brazil, the herding effect remains quite evident (Silva; Lucena, 2019; Jirasakuldech; Emekter, 2021; Signorelli; Camilo-da-Silva; Barbedo, 2021; Maquieira; Espinosa-Méndez, 2022; Vidya; Ravichandran; Deorukhkar, 2023).

Both CSSD and CSAD models can be estimated using ordinary least squares (OLS) regression. However, quantile regression is also useful method to identify the presence of herd behavior in financial markets (Chiang, Thomas C.; Li; Tan, 2010; Choi; Yoon, 2020; Kok Loang; Ahmad, 2023; Mishra P.; Mishra S., 2023; Nguyen; Bakry; Vuong, 2023; Nouri-Goushki; Hojaji, 2023).

The advantage of using quantile regression is its ability to estimate different points along the dispersion distribution through conditional quantiles. This provides more information about herd behavior. Additionally, by using the median instead of the mean to estimate the models, quantile regression is more robust to the presence of outliers (Hwang; Salmon, 2004).

Considering the information provided, the following research question has been formulated: **How has the COVID-19 pandemic affected the Brazilian stock market in terms of herd behavior?**

1.1 Aim

To investigate how the COVID-19 pandemic has affected the Brazilian stock market in relation to the herd effect.

1.2 Objectives

- ✓ Define the method for detecting the herd effect.
- ✓ Identify the stages of the COVID-19 pandemic in Brazil.
- ✓ Apply the model to different stages of the pandemic.
- ✓ Assess the herd effect in asymmetric market conditions during the pandemic stages.
- ✓ Estimate the models using OLS regression and quantile regression.

1.3 Research significance and contributions

The successive crises that have significantly impacted financial markets in recent decades have been the subject of numerous studies. These studies aim to gain a deeper understanding of the development of these crises and even identify potential signals that could anticipate their occurrence (Boyer; Kumagai; Yuan, 2006). In addition, there is a body of research that focuses on evaluating the extensive impacts caused by these events and examining how investors respond to them (Demyanyk; Hemert, 2011; Keys *et al.*, 2010).

The COVID-19 pandemic has had a profound impact on the global financial markets and has sparked a great deal of anxiety among investors. This anxiety has been driven by a number of factors, such as increased market volatility, heightened risk perception, profit loss, and challenges in asset diversification. Investors have been grappling with the uncertainty and unpredictability that the pandemic has brought, as it has disrupted traditional investment strategies and introduced new risks to consider

(Topcu; Gulal, 2020; Shehzad; Xiaoxing; Kazouz, 2020; Zhang; Hu; Ji, 2020; Lee Y.; Wu; Lee C., 2021; Díaz; Henríquez; Winkelried, 2022; Jabeen *et al.*, 2022; Rakshit; Neog, 2022).

Understanding the reaction to market events and the decision-making processes of market participants is crucial for maintaining a balanced market. It is also important to identify patterns of investor behavior that can impact asset prices. However, during times of crisis, various biases come into play and affect the decision-making process and trading in financial markets. In some cases, investors may not act based on their own information or may disregard their own beliefs, leading to a herding behavior (Scharfstein; Stein, 1990).

Most research on herd behavior focuses on its detection, both in developed markets and emerging economies. This is particularly true in market stress scenarios, where high volatility is observed (Christie; Huang, 1995; Chang; Cheng; Khorana, 2000). This volatility can be influenced by local economic conditions as well as external factors, such as financial crises or, as in the most recent case, a health crisis (Chen; Yang; Lin, 2012; Kumar *et al.*, 2021; Rakshit; Neog, 2022).

Research examining the herd effect in Brazil is still limited compared to other countries, and most of the existing studies focus on the subprime crisis (Silva; Lucena, 2019; Signorelli; Camilo-da-Silva; Barbedo, 2021). Other studies also include Brazil within a group, such as the Latin American market or the BRICS economic bloc also focusing on the subprime (Chiang; Zheng, 2010; Almeida; Costa; Costa Jr., 2012; Humayun Kabir; Shakur, 2018).

It is important to note that in these studies, OLS regression was used to estimate the CSSD and CSAD models. However, Hwang and Salmon (2004) pointed out that studies aimed at detecting the herding effect may overlook this effect by solely focusing on the mean of the distribution and neglecting other points, such as the tails of the distribution.

When conducting a study on the financial market, it is also important to evaluate the extreme points of the distribution. By doing so, researchers can gather valuable insights into investors' behavior and gain a more comprehensive understanding of market dynamics (Mensi *et al.*, 2014; Jareño; Ferrer; Miroslavova, 2015).

This need is addressed by applying quantile regression, which is a technique capable of examining the entire data distribution in a flexible and intuitive manner.

Additionally, compared to the OLS model, quantile regression is a more efficient method for estimating when the residual errors do not follow a normal distribution. (Koenker; Hallock, 2001; Barnes; Hughes, 2011).

Another interest in the study of the herd effect is its occurrence in asymmetrical market conditions. As the market volatility tends to increase during times of crisis, it is possible that investors are inclined to quickly acquire more assets in bullish markets and dispose of them in bearish markets, which can cause distortions in asset pricing (Humayun; Shakur, 2018).

Ampofo *et al.* (2023) analyzed the herding effect in the US and UK markets. The authors used OLS and quantile regression to estimate the CSAD model and compared the results. The findings revealed that the OLS regression overestimated the values for the moments when the herding effect occurred, both in the bull and bear markets during the COVID-19 pandemic.

Jani Saastamoinen (2008) discovered evidence of the herding effect in the Helsinki stock exchange, specifically up to the first quartile (25%) of the stock returns distribution. This suggests that the herding effect is present during periods of financial market decline. However, beyond the median of the distribution, there is no longer statistical evidence to support the existence of herding behavior.

Chiang, Thomas C.; Li; Tan (2010) conducted a study on the herd effect in the Shanghai and Shenzhen stock exchanges. They used OLS regression and found evidence of herding behavior in stocks traded in the local currency, but not in stocks traded in foreign currency. However, when using quantile regression, the evidence of herding behavior was found for both types of stocks in the lower quantiles of the distribution.

Additionally, the herd effect may or may not be observed in certain sectors that make up the stock market of the analyzed country. Jirasakuldech and Emekter (2021) demonstrated that the sectors listed in the Thai stock market exhibited different behaviors among themselves during seven crisis periods, spanning from 1997's Asian financial crisis to 2008's subprime crisis.

In summary, this research aims to investigate the presence of herd behavior in the Brazilian market during the COVID-19 pandemic. It includes evaluating this market under asymmetric conditions and using quantile regression to study more data points along the dispersion distribution of returns.

In terms of contributions, this research sheds light on the dynamics of the herd effect and enhances the academic field by examining the phenomenon in Brazil during the recent and highly impactful period of the COVID-19 pandemic.

In addition to academia, investors, portfolio managers, and other professionals in the financial market can benefit from gaining more information on the existence of herd behavior exhibited by investors. This information can help them to develop more robust investment strategies, ultimately leading to better financial outcomes for both individual and institutional investors (Chen, 2013; Gong; Diao, 2023).

Another contribution is that financial regulators and government institutions can develop more effective policies to manage financial crises. Additionally, these policies should aim to mitigate information asymmetry by promoting greater transparency and imposing stricter disclosure requirements for financial institutions. This will enable market participants to make more informed decisions and reduce the likelihood of market failures. Ultimately, by implementing these measures, regulators and government institutions can play a vital role in fostering a stronger and more resilient economy that can withstand and recover from financial shocks more effectively.

The remainder of this study is structured as follows: Section 2 presents the literature review and develops the research hypotheses. Section 3 describes the methodology adopted. Section 4 presents the results obtained. Section 5 discusses the results, and Section 6 contains the final thoughts of the study, as well as suggestions for future research.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This section introduces two major economic crises of the 21st century: the subprime crisis in 2008 and the COVID-19 pandemic in 2020. Despite the occurrence of other crises before, during, and after this period, both events had a significant impact on the global economy and influenced the decision-making of investors in various financial markets.

To gain a deeper understanding of the factors that impact investors behavior, it is important to consider the field of behavioral finance. One of the biases studied in this field highlights the tendency of investors to abandon their individual beliefs and instead follow the actions of other investors. This phenomenon, commonly referred to as the herd effect, is not only observed in more established and mature markets like the US but also in emerging economies such as Brazil.

2.1 Global crises that have impacted Brazil.

The subprime crisis became apparent in 2007 when there was a significant increase in default rates and foreclosures in the US, particularly in subprime loans, which were categorized as second-tier securities. This sudden rise in default rates caused a chain reaction, leading to severe financial repercussions for both the investors who held these loans and the financial institutions that had issued them.

In August 2007, BNP Paribas bank decided to suspend the redemption of units from three real estate funds. These funds were directly linked to subprime loans in the US, which were known for their high risk and potential for default. In the following year, the consequences of the subprime mortgage crisis began to unfold in full force. Multiple banks and financial institutions, both in the US and around the world, found themselves facing serious liquidity and solvency issues (Maciel *et al.*, 2012). This led to a widespread crisis of confidence in the financial system, as investors and institutions alike started to question the reliability and stability of the market.

As a direct result of this crisis, banks became increasingly hesitant to lend to each other. The fear of potential defaults and the uncertain nature of the financial landscape caused a severe tightening of credit conditions. This lack of liquidity had a ripple effect throughout the economy, making it more difficult for businesses and individuals to access the funds they needed to thrive and grow.

Perhaps one of the most significant and iconic events of this crisis occurred in September 2008, when Lehman Brothers, one of the oldest and largest investment banks in the US, filed for bankruptcy (Martelanc; Ghani, 2008).

In Brazil, the crisis had various effects, including the impact on the real estate market, the slowdown in economic growth, the decrease in commodity prices, the increase in the unemployment rate, and the reduction of foreign investments (Dulci, 2009; Hall; Beck, 2013).

The subprime crisis exposed the vulnerabilities and risks inherent in the financial system, leading to significant changes in regulations and practices in the years that followed. It serves as a stark reminder of the importance of prudent risk management and the need for transparency and accountability in the financial industry.

In 2020, the COVID-19 pandemic has not only created a health crisis but has also sparked a global financial crisis, leading to substantial losses for many investors and companies. According to Goodell (2020), the impact of the COVID-19 crisis has been more extensive than that of the 2008 subprime crisis, affecting not only the financial system but also supply chains, trade relationships, and the daily lives of people around the world.

The first human case of COVID-19 was confirmed in China in December 2019. Initially identified as viral pneumonia, it quickly spread and was declared a pandemic on March 11, 2020, affecting 213 countries (UNA-SUS, 2020). Moreover, the COVID-19 pandemic rapidly transitioned from a public health concern to a factor with significant impact on the global macroeconomic scenario.

According to the Brazilian Ministry of Health (2022), the first case of COVID-19 was recorded in Brazil on February 26, 2020, and the first wave of virus infections totalized 37 weeks, extending from February to November of the same year (Moura *et al.*, 2021).

In an effort to curb the rapid transmission of the virus, authorities have implemented a series of measures. These included the mandatory use of masks in enclosed spaces, social isolation, and, depending on the profession, testing to determine whether individuals were carrying the virus.

These initiatives have had various consequences on economic activity. This includes disruption in the supply chain and commerce, closure of businesses, and employee layoffs. As a result, there has been a shift in consumption patterns across all sectors of the economy (Fernandes, 2020).

To mitigate the effects of the crisis, governments and banks have implemented several measures. These included injecting liquidity into financial markets, reducing interest rates, and implementing fiscal stimulus programs (Bouri *et al.*, 2021).

When comparing the impact of two global crises on the financial market, it is observed that the benchmark index for the Brazilian stock market, IBOVESPA, experienced significant drops. In 2008, it opened at 63,886 points and reached a low of 29,435 points in October of the same year, representing a decrease of approximately 54%.

In 2020, the Brazilian stock exchange started the year at 115,645 points, following a bullish cycle that began in 2016. However, in March, it recorded a low of 61,690 points, resulting in a drop of nearly 47%. These periods also witnessed a notable increase in market volatility (Kumar *et al.*, 2021).

Figure 1 illustrates the IBOVESPA scores during the subprime crisis and the COVID-19 pandemic, highlighting the most significant downward movements.

Figure 1: Performance of the IBOVESPA Index, from January 2007 until April 2023, with a focus on the periods of the subprime crisis and the COVID-19 pandemic.

Source: Elaborated by the author (2023).

It is possible to observe that, during these moments of intense market movements, investors may not exhibit a rational behavior in their decisions. This "irrational behavior" often occurs without any observed fundamentals to justify these movements. It is interesting to note that the field of behavioral finance seeks to understand the underlying reasons behind these phenomena, exploring the various psychological and emotional factors that influence investor behavior.

2.2 The (ir)rationality of the market

Since the subprime crisis in 2008, numerous studies have been conducted to understand the development of these crises and to quantify their impact on financial markets (Demyanyk; Hemert, 2011; Maciel *et al.*, 2012; Hall; Beck, 2013; Huang; Yan; Deng 2017).

Since the behavior of investors plays a crucial role in these markets, particularly in terms of asset pricing, the traditional economic theory, known as the Efficient Market Hypothesis (EMH), argues that investor behavior is always rational. By considering all available information, investors can assess the risks and rewards associated with different assets, ultimately making informed choices that align with their investment goals and objectives. This is why, according to this hypothesis, that asset prices adjust quickly to incorporate new information, allowing investors to make optimal investment decisions (Fama, 1970).

However, this theory has faced challenges in the past few decades. It is a known fact that not all market participants possess the same information. Ching, Firth, and Rui (2006) demonstrated that insiders, individuals with privileged access to internal company information, achieved significantly higher returns compared to external investors prior to the announcement of the initial public offering (IPO) of these companies' stocks.

Furthermore, there are other factors that equally impact the financial market as a whole, leading to further doubts about the presumed market rationality. External events such as financial crises, health crises, and conflicts between countries instigate certain behaviors in investors, causing them to not always make decisions solely aimed at maximizing their utility (Shiller, 2005).

These decisions can be influenced by factors like emotions, asymmetric information, and herd behavior. As a result, the financial market experiences a range of inefficiencies that can give rise to speculative bubbles, crashes, and other phenomena that appear inconsistent with traditional economic theory (De Long *et al.*, 1991).

In order to study these phenomena, economists, psychologists, and sociologists have delved into the field of behavioral economics. They have demonstrated that investment decisions are often not based on impartial and rational analysis of facts, but rather on how people feel about the economy in general (Keynes, 1937).

As a derivative of behavioral economics, behavioral finance emerges. It is an area that seeks insights from psychology and sociology to explain why investors behave the way they do, since, as seen, they will not always make their choices purely rationally (Scharfstein; Stein, 1990; Mittal, 2022).

In this sense, the greater the uncertainty and risk of financial operations, the more investors tend to deviate from their rational analyses. When faced with a market presenting high levels of volatility, for example, some investors are unable to process certain phenomena purely logically.

These investors are led to abandon their personal beliefs and end up following the behavior of other market participants, a phenomenon known as herd behavior (Banerjee, 1992).

2.3 The herd effect

Nofsinger and Sias (1999) define the herd effect as the tendency of a group of investors to engage in similar trading activities in the same direction over a certain period. This suggests that investors, in certain situations, tend to imitate the behavior of other investors, particularly larger ones, when making investment decisions (Hwang; Salmon, 2004; Parker; Prechter, 2005; Yousaf; Ali; Shah, 2018).

These investors exhibit herd behavior because they often find themselves in a situation where they don't have access to enough information to make well-informed choices about trading their assets. Consequently, they tend to overlook their own knowledge and perspectives, and instead, they get swayed by the collective behavior of other investors. It's worth noting that even if following the majority may seem like a reasonable approach, it can sometimes lead these investors astray and result in suboptimal outcomes (Scharfstein; Stein, 1990; Spyrou, 2013).

Bikhchandani and Sharma (2001) further argue that investors imitate the actions of their peers in order to protect their investments against market risks and uncertainties. By doing so, investors believe that they can optimize their investment returns. The rationale behind this behavior is that individuals assume that their peers possess better information or insights for making investment decisions in a particular context.

However, one consequence of this behavior is that individual investment returns tend to move in the same direction as the market portfolio, making diversification more difficult (Chang; Cheng; Khorana, 2000; Hwang; Salmon, 2004).

Herd behavior also leads to errors or inefficiencies in asset pricing, increased stock price fluctuations, higher volatility, imbalances in the risk-return relationship, speculative bubbles, and market collapses (Bikhchandani; Sharma, 2001; Natividad Blasco; Ferreruela, 2012; Javaira; Hassan, 2015; Bekiros *et al.*, 2017; Humayun; Shakur, 2018; Chang; McAleer; Wang, 2020; Fei; Liu, 2021; Sihombing; Sadalia; Wibowo, 2021).

It is important to note that this phenomenon is frequently observed when certain signals are widely disseminated, which leads to investors questioning the accuracy of the information they possess and subsequently making decisions based on the actions of their peers (Devenow; Welch, 1996).

Herd behavior can result from various factors, such as abnormal price movements, financial crises (Banerjee, 1992), feelings of fear, uncertainty, or overconfidence (Kukacka; Barunik, 2013; Sabir; Mohammad; Shahar, 2019; Herlina *et al.*, 2020), information asymmetry (Hirshleifer; Hong; Teoh, 2003; Alhaj-Yaseen; Rao, 2019), political decisions and government interventions (Galariotis; Rong; Spyrou, 2015; Kok Loang; Ahmad, 2023; Nouri-Goushki; Hojaji, 2023), and even market-related news (Graham, 1999; Veronesi, 1999; Da; Engelberg; Gao, 2011; Silva; Lucena, 2019).

In this regard, Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) not only provide more extensive and comprehensive explanations about the herding effect, but they also present and discuss different methodologies and approaches to identify and assess the presence of the herding effect in certain market conditions.

These methods utilize dispersion calculations to identify the presence of the herding effect in financial markets. The underlying idea behind these calculations is that in a market where herding behavior is absent, market participants have diverse interests when making investment decisions. For instance, while one investor aims for profit in a transaction, another may have implemented a hedge[3] strategy. As a result, the asset prices should reflect this range of investor interpretations, leading to a significant dispersion between individual asset returns and market returns.

To summarize, if the herding effect is not detected, the dispersion between individual asset returns and market returns is likely to increase. Thus, it is suggested that investors adhere to their own convictions, supporting the possibility of the market behaving rationally.

However, when the occurrence of herding behavior is confirmed, it indicates that individual asset returns are converging towards the market return. In other words, investors are forsaking their own decisions to follow the decisions of their peers, reducing the dispersion between returns. Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) aimed to capture this relationship by employing these methods.

Further discussion on these methods will be provided in Section 3.3. It is important to note that various studies have utilized these methods to investigate the presence of herding behavior in different countries, time periods, and market perspectives. This includes scenarios of stress and/or stability.

2.4 The presence of the herding effect in financial markets

There is a vast literature that seeks to identify the presence of herd behavior in financial markets in various countries. Some of these countries include the US and UK (Christie; Huang, 1995; Economou; Hassapis; Philippas, 2018; Chang; Cheng; Khorana, 2000; Galariotis, Rong and Spyrou, 2015; Ampofo *et al.*, 2023), other European countries (Mobarek; Mollah; Keasey, 2014; Economou *et al.*, 2015; Pochea; Filip; Pece, 2017; Gavrilakis; Floros, 2023), China (Tan *et al.*, 2008; Chiang, Thomas

[3] An operation aimed at protecting investments against market fluctuation risks.

C; Li; Tan, 2010; Fei; Zhang, 2023), South Korea (Choi; Yoon, 2020), India (Dhall; Singh, 2020; Mishra P.; Mishra S., 2023), other Asian countries (Jirasakuldech; Emekter, 2021; Wen; Yang; Jiang, 2022; Kok Loang; Ahmad, 2023; Nouri-Goushki; Hojaji, 2023), Australia (Henker J.; Henker T.; Mitsios, 2006; Espinosa-Méndez; Arias, 2021).

Some of these studies are not limited to a single country. Additionally, these studies work with different periods and market conditions, including situations of stability and/or crises.

Table 1 provides a summary of these studies, including the evaluated sample, the period used, and the main findings. Research on herd behavior in Brazil will be discussed in Section 2.5.

Table 1: Previous studies have examined the herding effect in different markets.

Referência	Amostra	Período	Principais Resultados
Christie and Huang (1995)	Sectors of the US stock market	1963 – 1988	No herding effect was found in the 12 sectors studied in the American stock market.
Chang, Cheng, and Khorana (2000)	US, Hong Kong, Japan, South Korea and Taiwan	1963 – 1997	The effect of herd behavior was detected in South Korea, Taiwan, and partially in Japan, but it was not evident in the US and Hong Kong.
Henker J., Henker T. and Mitsios (2006)	Australia	2001 – 2002	The herd effect was not found in the Australian market.
Tan *et al.* (2008)	China	1994 – 2003	Herd effect was detected in the Shanghai and Shenzhen markets for type A and B stocks.
Chiang, Li, and Tan (2010)	China	1996 – 2007	Herd effect was detected in the Shanghai and Shenzhen markets for type A stocks, but not for type B stocks.
Chiang and Zheng (2010)	Australia, France, Germany, Hong Kong, Japan, United Kingdom, US, Argentina, Brazil, Chile, Mexico, China, South Korea, Indonesia, Malaysia, Singapore, Thailand, and Taiwan	1988 – 2009	Apart from the period of the subprime crisis, the herd effect was evident in mature markets (except the US) and in Asian markets. No evidence was found in Latin American markets. However, during the crisis period, there is evidence of the herd effect in the US and Latin American markets.
Almeida, Costa, and Costa Jr. (2012)	US, Argentina, Brazil, Chile, and Mexico	2000 – 2010	The herd effect was only evident in Chile.
Mobarek, Mollah, and Keasey (2014)	Portugal, Ireland, Italy, Spain, Greece, Denmark, Norway, Finland, Germany, France, and Sweden	2001 – 2012	The herd effect was detected during market downturns in Portugal, Greece, Sweden, and Germany.

Economou, Hassapis, and Philippas (2018)	US, UK, and Germany	2004 – 2014	The presence of the herd effect was detected in the United Kingdom during the subprime crisis. This behavior was not evident in the United States and Germany.
Economou *et al.* (2015)	Belgium, France, Portugal, and the Netherlands	1989 – 2009	Evidence of the herd effect was found in Belgium, the Netherlands, and Portugal after the emergence of the Eurozone debt crisis.
Galariotis, Rong, and Spyrou (2015)	US and UK	1989 – 2011	Evidence of herd behavior was observed on days of important announcements related to the macroeconomic scenario in the US and the UK.
Pochea, Filip, and Pece (2017)	Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Poland, Lithuania, Romania, Slovenia, and Latvia	2003 – 2013	Except for Poland and Romania, the other countries exhibited herd behavior.
Choi and Yoon (2020)	South Korea	2003 – 2018	Herd behavior was detected during market downturns in the South Korean stock markets KOSPI[4] and KOSDAQ[5].
Dhall and Singh (2020)	India	2015 – 2020	Herd behavior was observed in both bull and bear markets during the pandemic.
Espinosa-Méndez and Arias (2021)	Australia	2008 – 2020	Herd behavior was detected during the pandemic.
Jirasakuldech and Emekter (2021)	Thailand	1988 – 2015	It was detected the herd effect in Thailand during 4 periods of market stress.
Wen, Yang, and Jiang (2022)	Hong Kong	2019 – 2020	The herd effect was detected before the pandemic period but was not evidenced during the pandemic.
Ampofo *et al.* (2023)	US and UK	2017 – 2022	The herd effect was evidenced for the US stock market during the pandemic period but not for the UK stock market.
Fei and Zhang (2023)	China	2019 - 2021	There was an occurrence of the herd effect before and during the pandemic for type B stocks.
Gavrilakis and Floros (2023)	Portugal, Italy, Greece, Spain, France, and Germany	2010 – 2020	The herd effect was detected during the pandemic for companies in Portugal, Italy, and Greece.
Kok Loang, and Ahmad (2023)	Gulf Cooperation Council	2016 – 2021	The herd effect was observed for Shariah and Conventional stocks during the COVID-19 pandemic.
Mishra P. and Mishra S., (2023)	India	2019 – 2020	The herd effect was detected for bull markets during the pandemic.
Nguyen *et al.* (2023)	Vietnam	2016 – 2021	The herd effect was observed during the pandemic period, but in the fourth wave of COVID-19 in Vietnam, this effect was reduced.

[4] South Korean stock market that trades shares of large companies.
[5] South Korean stock market that trades shares of small and medium-sized companies, as well as information technology, biotechnology, and cultural technology companies.

Nouri-Goushki and Hojaji (2023)	Iran	2012 – 2022	The herd effect was observed during the pandemic period.

Source: Elaborated by the author (2023).

It is important to note that the results of these studies have certain nuances. Despite some of these studies focusing on the same countries as the objects of study, the use of different time periods, data frequency, methods, and samples can lead to divergent conclusions (Henker J.; Henker T; Mitsios, 2006; Chiang, Thomas C; Li; Tan, 2010).

For instance, Chang, Cheng, and Khorana (2000) did not observe herd behavior in the Hong Kong market from January 1981 to December 1995. In contrast, Chiang and Zheng (2010) found evidence of herd behavior in the Hong Kong market during their study period from May 1988 to April 2009, which included the subprime crisis. This suggests that a crisis scenario can promote the presence of herd behavior.

According to Christie and Huang (1995), there is a tendency for the existence of a herd effect during market stress scenarios. This encourages investors to follow the majority in their investment decisions. Even in economies considered more mature in these studies, such as the US, UK, and other European countries, the herd effect has been detected during periods of financial crises (Chiang; Zheng, 2010; Economou *et al.*, 2015; Ampofo *et al.*, 2023; Gavrilakis; Floros, 2023).

Tan *et al.* (2008) conducted their research on the Chinese stock market to examine the occurrence of herd effect in two stock exchanges, Shanghai and Shenzhen, from 1994 to 2003. Both markets have stocks traded in local currency, known as type A, and in foreign currency, known as type B. The authors found evidence of herd effect for both types of stocks in both markets.

In contrast, Chiang, Thomas C. Li, and Tan (2010) studied the same two Chinese stock exchanges from January 1996 to April 2007 and found evidence of herd effect only for type A stocks, not for type B stocks.

The authors justify this behavior by pointing out that, apart from the variations in sample size, type B actions are traded by international investors who have greater access to global information resources. As a result, these investors can carry out more comprehensive market analysis and make more rational decisions. On the other hand, type A actions, which represent the majority, are subject to greater influence from the

Chinese government. This influence can prompt these investors to swiftly divest their stock assets in order to evade potential government interventions.

This demonstrates that the characteristics of countries themselves can influence the presence or absence of herd behavior. Nouri-Goushki and Hojaji (2023) examined whether interventions by the Iranian government during the pandemic contributed to reducing herd behavior in the financial market.

The results not only showed that these actions were ineffective in reducing herd behavior, but also stimulated the phenomenon. Galariotis, Rong, and Spyrou (2015) found evidence of herd behavior on days when important announcements related to the macroeconomic scenario were made in the US and the UK. The analysis period for this study was from October 1989 to April 2011.

Some of these studies also conducted tests under asymmetric market conditions to determine whether herd behavior tends to occur more frequently in bull or bear markets. Choi and Yoon (2020) did not find evidence of herd behavior in the South Korean stock market from January 2003 to December 2018. However, when conducting tests under asymmetric conditions, the authors found evidence of herd behavior during market downturns. This suggests that as investor fears increase during stock market declines, they tend to follow the decisions of their peers. This behavior was not observed during market upturns.

Similarly, in the study by Mobarek, Mollah, and Keasey (2014), the authors did not find evidence to support the existence of herd behavior in almost all selected European countries in the sample. However, when examining the markets under asymmetric conditions, Portugal, Greece, Sweden, and Germany exhibited herd behavior when the markets experienced negative returns.

It is evident that numerous studies have been conducted to investigate the relationship between herd behavior in stock markets. One such study by Gleason *et al.* (2003) aimed to assess whether herd behavior occurs in futures contracts traded on European exchanges. Thirteen futures contracts related to the food, grains, oilseeds, and livestock sectors were selected for analysis. However, the authors did not observe any herd behavior in this market.

In contrast, Bernales *et al.* (2020) found evidence of herd behavior when examining the US options market between January 1996 and December 2012. The authors confirmed the presence of herd behavior, influenced by various systemic factors such as periods of high volatility risk, macroeconomic announcements, and the subprime crisis in 2008.

There are also studies on herd behavior in more recent markets, such as cryptocurrencies. Wanidwaranan and Termprasertsakul (2023) conducted tests from 2017 to 2022 using daily prices of the top 100 cryptocurrencies in 2022, representing 96% of the market that year. The authors did not find evidence of herd behavior when analyzing the entire period. However, when the period was divided into before and during the COVID-19 pandemic, evidence of herd behavior was observed before the pandemic but not during it.

Yarovaya *et al.* (2021) discovered evidence of herd behavior in cryptocurrencies traded in dollars, euros, and yen from January 2019 to March 2020, covering the onset of the COVID-19 pandemic. However, the authors noted that only the euro-traded market was affected by the pandemic. Another study by Bouri *et al.* (2019) examined herd behavior among 14 major cryptocurrencies from April 2013 to May 2018, but did not find any evidence of herd behavior. However, when using a time-varying approach based on a rolling window of 250 observations, herd behavior was detected between 2016 and 2017.

Regarding the Brazilian stock market, there are relatively few studies investigating the presence of herd behavior compared to other countries. However, some evidence of this bias has been found in the Brazilian context under certain circumstances.

2.5 The herd effect in Brazil

The occurrence of herd behavior in the Brazilian stock market was studied by Silva and Lucena (2019). They aimed to determine whether the subprime crisis, the publication of news, and the size of the company influenced herd behavior among the top 100 companies with the highest trading volumes listed on B3.

The results indicated a positive relationship between herd behavior and the subprime crisis period and positive news. However, no statistically significant relationship was found between herd behavior and the publication of negative news.

Another study by Signorelli, Camilo-da-Silva, and Barbedo (2021) analyzed the returns of 173 stocks in the Brazilian stock market from January 2008 to May 2019.

They conducted the analysis on a yearly basis and identified herd behavior in the years 2009 to 2015 and 2018. Additionally, the authors found that herd behavior was influenced by high trading volume, high return volatility, market slowdown, and an imbalance between buy and sell transactions, primarily on the sell side.

Chiang and Zheng (2010) did not find evidence of herd behavior in the Latin American market, including Argentina, Brazil, Mexico, and Chile, from May 1988 to April 2009. However, when analyzing the period from January 2008 to March 2009, which includes the subprime crisis, the authors detected herd behavior specifically in the Brazilian stock market.

In contrast, Almeida, Costa, and Costa Jr. (2012) did not find evidence of herd behavior in the Latin American market from 2000 to 2010, except for Chile. Even when examining the period from May 2008 to October 2008, representative of the subprime crisis, no herd behavior was observed.

These divergences in the studies may be attributed to various factors, such as the selected sample, the evaluated period, the methodology used, the data accessibility, and even the distribution of data points, whether all points or only extreme values, for instance.

It is important to highlight that there are studies that focus on local aspects. For instance, Silva and Lucena (2020) investigated the impact of corruption allegations against the then-president of Brazil, Michel Temer, on the financial market and explored whether it constitutes herd behavior. This allegation occurred on June 26, 2017. The study identified the presence of herd behavior, indicating that local aspects can serve as motivating factors for the occurrence of this phenomenon.

In a study conducted by Araujo Neto *et al.* (2016), managers of public banks in the Federal District were examined. The purpose was to determine if the opinion of financial market analysts could influence the decision-making of these managers, who are qualified professionals in the financial field.

The results showed that the analysts' opinion did not affect how managers evaluated companies in terms of liquidity, indebtedness, and management. However, when comparing the proportions of stock purchases in groups with and without the opinion of a market analyst, it was found that the opinion of the analyst did influence the decision-making of these managers.

Other studies, such as Zulian, Kimura and Basso (2012) and Tariki (2014), have also investigated the herding effect in equity mutual funds in the Brazilian market. Both studies found evidence of the herding effect. Tariki (2014) observed that the intensity of this behavior varied depending on the size and capitalization of the fund. Zulian, Kimura and Basso (2012) found that the occurrence of the effect had a similar intensity to countries like the US, UK, and Germany.

Considering the above, this study aims to contribute to the existing literature by examining the presence of the herding effect in the Brazilian market during the COVID-19 pandemic. Additionally, it seeks to determine whether the market exhibits asymmetric behaviors regarding the herding effect during the same period.

To achieve these objectives, the following research hypotheses were formulated:

H1 - The herding effect occurs in the Brazilian stock market during the COVID-19 pandemic.

H2 - The herding effect occurs in the Brazilian stock market under asymmetric market conditions during the COVID-19 pandemic.

3 METHODOLOGY

In this section, it is defined the characteristics of the research, sample, and methodological procedures used.

3.1 Research classification

The research utilized the closing prices of stocks in the IBOVESPA index to calculate returns. Therefore, the research was conducted in a documentary manner.

In terms of objectives, the research is classified as descriptive as it aims to investigate the impact of the COVID-19 pandemic on the Brazilian stock market and its contribution to the existence of the herd effect.

The data were analyzed using statistical procedures and econometric models, making it a quantitative study.

3.2 Research universe and sample

The sample consists of the companies listed in B3[6] that had a certain percentage of trading days between January 2016 and September 2023, totaling 1,922 trading days. The initial date marks a turning point in the stock market's performance, as it breaks the downward trend that had been prevalent since 2011. The final date indicates the most recent available data until the production of this work. This period encompasses three distinct cycles, often referred to as waves, of the pandemic in Brazil (Moura *et al.*, 2022).

To evaluate the impact of this pandemic on the Brazilian stock market, four time windows were used, starting from the first recorded case of COVID-19 in Brazil, which occurred on February 26, 2020, according to the Brazilian Ministry of Health (2022). The purpose of these time windows is to evaluate herding behavior in the stock market at various stages of the pandemic in Brazil.

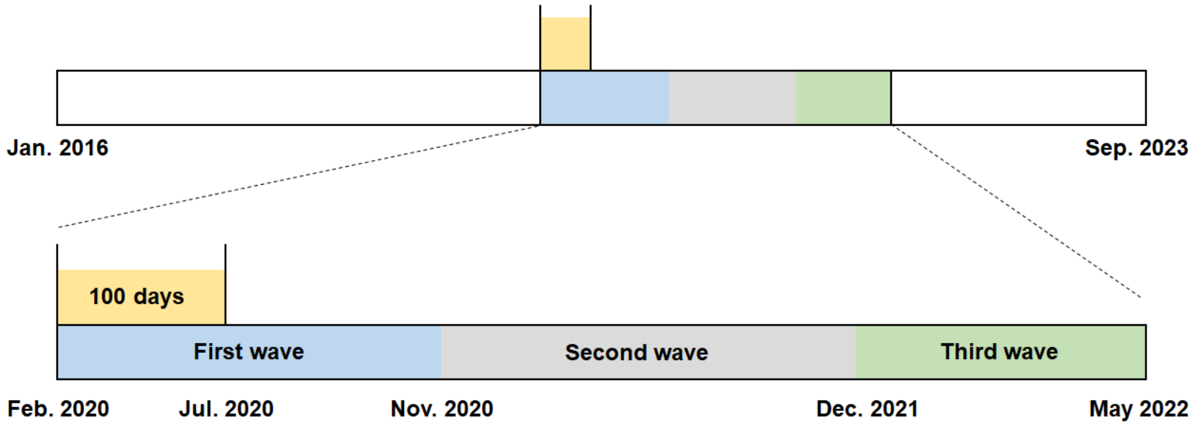
The first time window covers the first 100 trading days after February 26, 2020. This period was adopted to consider the initial impact of the pandemic on the financial market. The next time window extends from February 26, 2020, until the end of the

[6] Formerly known as BM&F Bovespa, is the main stock exchange in Brazil.

first wave of the pandemic in Brazil. The following window covers the period of the second wave, and the last window covers the period of the third wave. The definition of these waves is based on the increase or decrease in the number of registered COVID-19 cases (Moura *et al.*, 2021), and the chosen dates are listed below[7]. The period is illustrated by Figure 2.

- ✓ February 26, 2020 to July 20, 2020 (first 100 trading days).
- ✓ February 26, 2020 to November 9, 2020 (first wave).
- ✓ November 10, 2020 to December 27, 2021 (second wave).
- ✓ December 28, 2021 to May 23, 2022 (third wave).

Figure 2: Period of study in different stages of the COVID-19 pandemic in Brazil.



Source: Elaborated by the author (2023).

Regarding the sample, there are 375 companies listed in B3 until 2023. for the purpose of this analysis, 158 companies that had closed capital on the stock market in January 2016 were excluded. From the 217 companies remained, 73 of them had less than 99%[8] of trading days in relation to the period under study, and thus, they were also excluded from the analysis. As a result, the final sample for analysis were 144[9] companies.

[7] For dates that fall on weekends, the next trading day on the stock exchange was chosen.
[8] 99% indicates that companies that had more than 19 days (1% of 1,922) without trading were excluded.
[9] It was counted 120 companies that had price data for all 1,922 days. 24 companies had less than 19 days without trading and were included in the sample. To prevent panel data from becoming unbalanced, on days when there was no trading for these 24 companies, the previous day's price was replicated. This prevented the need to input the number zero for the closing price, which could distort the data on which the model is based.

Table 2 presents a summary of the sample's condition, and the Appendix presents the list with the names of the companies.

Table 2: Sample composition from January 2016 to September 2023.

Composição da amostra	
Companies listed on B3 until 2023	**375**
(-) Companies without any trading data during the period	158
(-) Companies with insufficient data during the period	73
= Total number of companies in the sample	**144**

Source: Elaborated by the author (2023).

The closing price data of these companies' stocks was collected from the Refinitiv Eikon® platform.

3.3 Methods for detecting the Herd Effect

One of the most common methods for identifying herding behavior in stock markets is by examining the measures of dispersion of asset returns in relation to market returns. These measures provide insights into the extent to which investors are following the crowd or making independent investment decisions.

3.3.1 The method proposed by Christie and Huang (1995)

Christie and Huang (1995) proposed the use of the cross-sectional standard deviation (CSSD) model to detect herd behavior in stock markets. Equation 1 defines this measure.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{N-1}} \qquad (1)$$

Where $R_{i,t}$ represents the return of an asset i at a specific moment t, $R_{m,t}$ refers to the market return[10] at that moment t and N indicates the number of assets.

[10] Most of the literature uses the average of the equally weighted asset returns to calculate $R_{m,t}$.

According to Christie and Huang (1995), the rational asset pricing models predict that there is an increase in CSSD with the absolute value of the market return. This is because individual assets may differ in their sensitivity to the overall market performance. In simpler terms, investors and institutions may choose to make decisions based on their own beliefs rather than blindly following the direction of the market.

However, in the presence of herd behavior, individual asset returns may not deviate much from the overall market return. This is because decision-makers, influenced by the actions of others, suppress their own beliefs and conform to the collective decision-making process. This behavior may not necessarily reflect the fundamental conditions of the economy, market, and companies themselves, but rather the collective behavior of investors (Banerjee, 1992).

In this scenario, the herd effect leads to an increase in CSSD, but at a decreasing rate. If herd behavior becomes even more intense, it can result in a decrease in dispersion, bringing stock returns closer to market returns, as shown in Figure 3.

In Figure 3, presented by Yao *et al.* (2014), it illustrates the magnitude of CSSD in relation to the market return of Chinese type B stocks from January 1999 to December 2008.

Figure 3: Relationship between market returns of Chinese stocks traded in foreign currencies and their $CSSD_t$

Source: Yao *et al.* (2014).

As the average market returns increase in absolute terms, return dispersions also increase, but at a decreasing rate. It is important to note that Chang, Cheng, and

Khorana (2000) identified a non-linear relationship between dispersion and market returns. This non-linear characteristic will be further explored in Section 3.3.2.

Christie and Huang (1995) also suggest that individuals are more likely to suppress their own beliefs in favor of market consensus during periods of extreme movements, such as in crisis scenarios. In this case, when the market return exceeds a certain threshold, CSSD tends to become narrower.

To determine this, an estimation is performed using Equation 2, which empirically examines whether stock return dispersions are significantly lower than average during periods of extreme market movements.

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (2)$$

Where α represents the intercept of the regression, D_t^L and D_t^U are dummy variables that capture the differences in investor behavior in extreme market moments, both in a bearish and bullish scenario. The coefficients β^L and β^U negative and statistically significant indicate the presence of herd behavior. To define periods of extreme price movement, Christie and Huang (1995) used 1% or 5%, both in the upper and lower tail of the market return distribution.

This model has been widely employed in various studies to detect herd behavior in financial markets. However, the model becomes biased when datasets contain outliers (Chang; Cheng; Khorana, 2000; Jirasakuldech; Emekter, 2021).

In addition, the selection of the extreme market return points, either 1% or 5%, in the distribution can be seen as somewhat arbitrary, leading to varying opinions among researchers who utilize this methodology in their studies. Additionally, the characteristics of the return distribution can change over time (Henker J.; Henker T.; Mitsios, 2006).

Furthermore, this model ignores the possibility of herding behavior occurring in typical market conditions, not just during abnormal and stressful periods (Nouri-Goushki; Hojaji, 2023).

Lastly, the model proposed by Christie and Huang (1995) does not account for the non-linear relationship between dispersion and market returns that may result from observed herding behavior in the market. Taking these factors into consideration, Chang, Cheng, and Khorana (2000) proposed an alternative approach to detect herding behavior using a slightly different interpretation and measurement approach compared to the CSSD model, that aimed to provide a more comprehensive analysis of this phenomenon.

3.3.2 The method proposed by Chang, Cheng, and Khorana (2000)

In the search for solving the limitations of the CSSD model, Chang, Cheng, and Khorana (2000) proposed the cross-sectional absolute deviation (CSAD) model, which also make a calculation of the dispersion. The calculation of CSAD is shown in Equation 3.

$$CSAD_t = \sqrt{\frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N}} \quad (3)$$

Similar to Christie and Huang's approach, Chang, Cheng, and Khorana (2000) explain that rational asset pricing models predict a linear and positive relationship between market returns and CSAD. However, when market participants ignore their own beliefs to follow market consensus, the dispersion between individual returns and the market return will decrease or increase at a decreasing rate. In this situation, the linear relationship between market return and dispersion will not hold (Pochea; Filip; Pece, 2017).

Therefore, Chang, Cheng, and Khorana (2000) proposed an alternative model that included a new parameter to capture this potential nonlinearity between asset returns and the market return, which is the squared market return term ($R^2_{m,t}$) in the model.

Thus, in the occurrence of herd behavior, there would be a disproportionate decrease or increase in CSAD as absolute market returns increase. Equation 4 shows how this nonlinear relationship between market return and CSAD is captured:

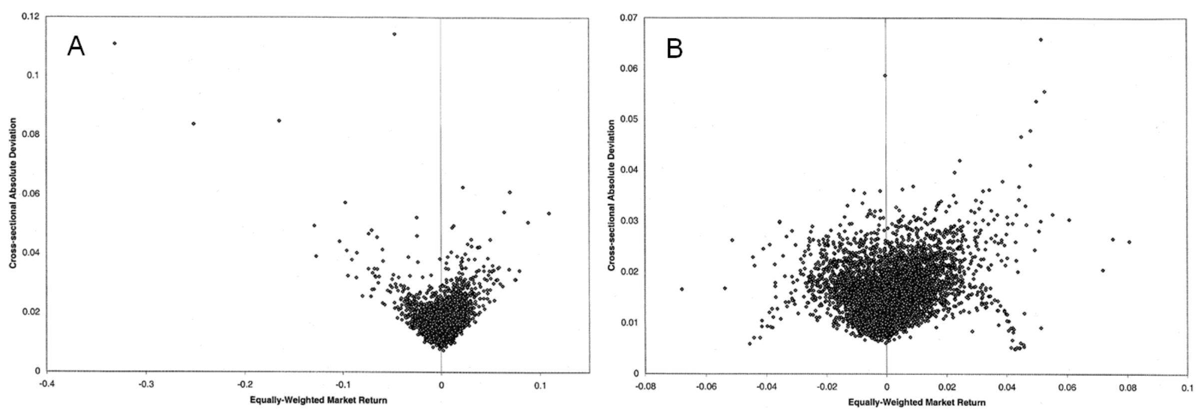
$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \epsilon_t \quad (4)$$

Where α and γ_i represent the intercept and coefficients of the CSAD model, respectively, and ϵ_t represents the error term. $|R_{m,t}|$ represents the absolute market return and $R_{m,t}^2$ is the squared market return, which is responsible for detecting the herding effect. A negative and statistically significant γ_2 indicates evidence of herding behavior.

If both γ_1 and γ_2 are negative, it means that the dispersion between individual asset returns, and the market return is decreasing. If γ_2 is negative and γ_1 is positive, the dispersion between returns increases but at a decreasing rate. This still indicates the occurrence of herding behavior because despite the increase, asset returns are still exerting some pressure that reduces the dispersion relative to the market. If γ_1 and γ_2 are positive, this indicates a movement contrary to the herding effect, in which case the market would be behaving rationally.

Figure 4, extracted from the study of Chang, Cheng, and Khorana (2000), illustrates the behavior of a market exhibiting the herding effect and another that is not. In the period evaluated for the Hong Kong stock exchange (Figure 4A), the greater the market returns move towards extreme values of the distribution, the greater the dispersion between asset returns and the market return. In contrast, in the South Korea market (Figure 4B), it can be observed that the dispersion grows disproportionately along the market return distribution.

Figure 4: (A) Relationship between market returns and CSAD for the Hong Kong market (January 1981 to December 1995); (B) Relationship between market returns and CSAD for the South Korean market (January 1978 to December 1995).



Source: Chang, Cheng, and Khorana (2000).

Some studies still use the term "severe herding effect" to describe a significant decrease in the CSAD. This refers to a situation where there is a high level of similarity or correlation in the investment decisions of market participants, leading to a reduction in the overall dispersion of stock returns. On the other hand, when the CSAD increases at a decreasing rate, it is referred to as a "moderate" herding effect. This implies that there is still some level of similarity or correlation among investors' decisions, but it is not as pronounced as in the case of severe herding (Bernales; Verousis; Voukelatos, 2020).

Chiang, Li and Tan (2010) contribute to this discussion by stating that herding behavior may be present throughout the return distribution, but it tends to become more evident during periods of market stress, such as a crisis. Unlike Christie and Huang (1995), who only recognized herding behavior when market returns exhibited extreme values.

In summary, the CSAD itself is not a measure that determines the herding effect. However, the relationship between CSAD and market returns can indicate the presence of this phenomenon.

Studies investigating the herding effect using both CSSD and CSAD may yield contrasting results. Signorelli, Camilo-da-Silva, and Barbedo (2021) did not detect the herding effect in Brazil between 2009 and 2018 using CSSD method. On the other hand, when using CSAD and extreme points (10% and 90%) of the market returns distribution, the herding effect was observed in the years 2009 to 2015 and in 2018.

Similarly, in their study, Almeida, Costa, and Costa Jr. (2012) did not find evidence of the herding effect using the CSSD model between 2000 and 2010 for the stock markets of Brazil, Argentina, Chile, Mexico, and the US. However, when using CSAD, the herding effect was detected in Chile. These contrasting results highlight that the method used can lead to find or not the presence of herding behavior. It is possible that CSSD requires a significant magnitude of dispersion to identify the herding effect, which is why this method is more efficient in identifying herding behavior under extreme market conditions (Tan *et al.*, 2008).

It is important to note that both models (CSSD and CSAD) are typically estimated using OLS regression. This method estimates the mean of the distribution but does not capture the full extent of the dispersion distribution, as it disregards what happens in the tails of it.

In a study involving the financial market, it is important to not only examine the central tendency but also evaluate the extreme points of the distribution. By doing so, it is possible to gain a more comprehensive understanding of investor behavior (Mensi *et al.*, 2014; Jareño; Ferrer; Miroslavova, 2015).

Therefore, a complementary approach to estimate these models is through quantile regression. This method is not only more robust but also provides more efficient estimates by allowing the evaluation of the entire dispersion distribution through conditional quantiles. Thus, quantile regression enhances this type of analysis (Chiang and Zheng, 2010; Pochea *et al.*, 2017; Mishra P.; Mishra S., 2021; Kok Loang; Ahmad, 2023; Wen; Yang; Jiang, 2022).

3.3.3 Using Quantile Regression to detect Herding Effect

The quantile regression model, originally proposed by Koenker and Bassett (1978), is a statistical method commonly used in extreme value analysis. It expresses a dependent variable as a function of one or more independent variables (Yu; Lu; Stander, 2003; Schaumburg, 2012). This relationship is estimated through conditional quantiles.

Unlike the OLS model, which focuses on minimizing the sum of squared errors by using the mean of the distribution for calculation, quantile regression is a statistical method that uses the conditional median, as well as other quantiles, to assess the relationship between the dependent variable and the independent variable(s) (Koenker; Hallock, 2001). By using the conditional median, this regression is more robust to the presence of outliers.

Moreover, as it is not restricted to the mean, quantile regression can be used to study all points of a distribution. It provides a more comprehensive framework for understanding the relationship between the dependent variable and the independent variable(s) (Barnes; Hughes, 2002).

There is interest in studies involving the financial market to evaluate behavior in the tails of a distribution, as these regions represent extreme market conditions. These points are not covered by OLS regression (Chiang; Zheng, 2010).

Quantile regression establishes a function for the conditional quantile given by Equation 5:

$$QY_i = (\tau | X = x) = x_i' \gamma \tag{5}$$

Where Y_i is the dependent variable, x_i' is a vector of independent variables, and γ is a vector of coefficients.

To estimate Y_i, a weighted minimization given by Equation 6 is required:

$$\hat{Y}_{(\tau)} = \arg\min \textstyle\sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta) \quad (6)$$

Where $\hat{Y}_{(\tau)}$ is the estimated dependent variable for the quantile τ. ρ_τ is a weighting coefficient, also referred to as a check function. Unlike the quadratic loss function of the OLS model, the check function is an asymmetric loss function (Ashley, 2011).

The asymmetric loss function aims to minimize the sum of absolute errors using the median of the distribution. Thus, for any $\tau \epsilon (0,1)$, a weighting function is defined, as shown in Equation 7:

$$\rho_\tau(u_i) = \begin{cases} \tau \times u_i & se\ u_i \geq 0 \\ (\tau - 1) \times u_i & se\ u_i < 0 \end{cases} \quad (7)$$

Onde $u_i = y_i - x_i'\gamma$.

Equation 8 shows the replacement of this weighting to obtain $\hat{Y}_{(\tau)}$:

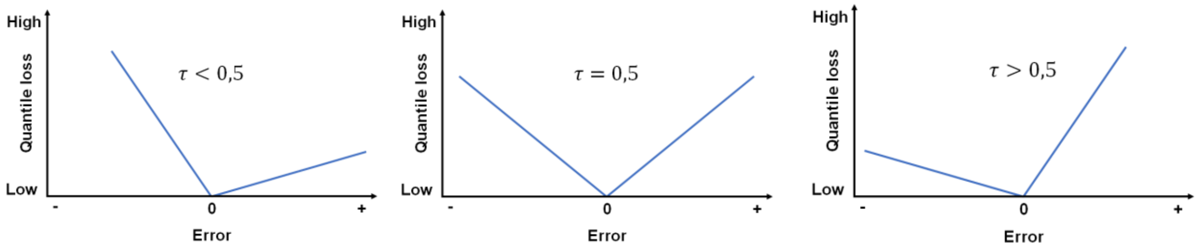
$$\hat{Y}_{(\tau)} = \arg\min \left(\textstyle\sum_{i: y_i > x_i'\gamma} \tau |y_i - x_i'\gamma| + \sum_{i: y_i < x_i'\gamma} (1 - \tau) |y_i - x_i'\gamma| \right) \quad (8)$$

According to Koenker and Bassett (1978), when estimating the coefficients of quantile regression, it is necessary to minimize the weighted sum of absolute errors. The solution for this minimization is to use the conditional quantile at the specific desired point.

For instance, when $\tau = 0.5$, quantile regression becomes median regression, indicating that the loss is equal on both sides of the distribution. For $\tau < 0.5$, the loss for negative deviations increases more rapidly than the loss for positive deviations, resulting in overestimations being penalized more than underestimations.

Conversely, when $\tau > 0.5$, the effect is reversed, and the loss for positive deviations increases more rapidly than the loss for negative deviations. In this case, underestimations are penalized more than overestimations. Figure 5 illustrates these three cases.

Figure 5: Asymmetric loss function for different quantiles.



Source: Elaborated by the author (2023).

Since quantile regression is not restricted to the median level, it provides the flexibility to estimate the relationship between the dependent variable and one or more independent variables at any desired quantile, allowing for a broader examination of the relationship between market returns and CSAD.

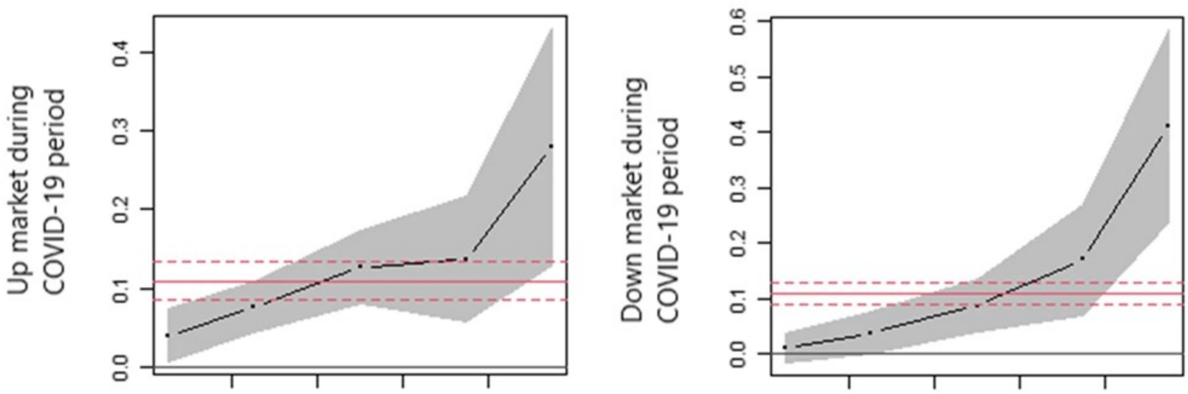
Therefore, quantile regression is capable of verifying the existence of the herding effect in different quantiles (τ) of the return distribution. It is worth noting that the lower quantiles ($\tau \leq 0{,}25$), which represent the smallest values of the distribution, indicate the region where investors would be converging toward the market return.

On the other extreme, the highest values of return dispersion ($\tau \geq 0{,}75$), mean that the asset returns would be deviating from the market consensus. Based on Equation 4, the interpretation remains the same, if γ_2 is negative and statistically significant, the herding effect is present.

Studies that use quantile regression to investigate the herding effect end up finding results that help us understand more about this phenomenon. In a study conducted by Ampofo *et al.* (2023), the authors sought to determine whether the herding effect persisted in asymmetric market conditions, i.e., in scenarios of positive or negative returns, before and during the COVID-19 pandemic in the US.

Estimations were performed using both the OLS method and quantile regression. Figure 6 presents graphs comparing the results for bull and bear markets during the pandemic, with OLS estimation observed through the straight line with confidence intervals represented by dashed parallel lines, and quantile regression estimation observed through lines with certain spaces and confidence intervals in the shaded region.

Figure 6: Plotting of OLS and quantile regression models for CSAD distributions and market returns under asymmetric conditions (bull and bear markets) during the COVID-19 pandemic.



Source: Ampofo *et al.* (2023).

It can be observed that, in this case, OLS regression overestimated the coefficients for the lower regions and underestimated the coefficients for the upper regions of the distribution. Thus, the model estimated by quantile regression is better adjusted to the data reality.

Regarding the detection of herding behavior, both the OLS model and quantile regression identified this phenomenon in both bullish and bearish markets for the US. The difference is that, in addition to the median (50%), herding behavior was identified in the upper quantile (95%) for the bullish market. In this case, quantile regression provided more information about herding behavior in this scenario.

On the other hand, there are studies such as Chiang, Li and Tan (2010) where herding behavior was not observed for Chinese type B stocks in bearish markets using the OLS model. However, using quantile regression, herding behavior was observed in the lower quantiles (10% and 25%) up to the median (50%). This study was conducted from January 1996 to April 2007.

Nguyen et al. (2023) exclusively used quantile regression to investigate whether the Vietnamese stock market exhibited herding behavior during the COVID-19 pandemic. For the two studied stock exchanges, the results showed that the presence of herding behavior was detected from the lower quantiles and extending toward the median.

In addition to the studies mentioned in this section, other researchers have also utilized quantile regression to investigate herding behavior (Pochea; Filip; Pece, 2017;

Choi; Yoon, 2020; Espinosa-Méndez; Arias, 2021; Wen; Yang; Jiang, 2022; Kok Loang; Ahmad, 2023; Mishra P.; Mishra S., 2023; Nouri-Goushki; Hojaji, 2023).

Therefore, this research aligns with the aforementioned studies by using quantile regression to gain a broader understanding of herding behavior in Brazil and provide insights that might not be captured by the conventional OLS model.

3.4 Variables of the research and econometric models.

Due to the limitations of the CSSD mentioned earlier, the model used in this research was the CSAD developed by Chang, Cheng, and Khorana (2000). The CSAD model was chosen because it is capable of capturing the non-linear characteristic that markets tend to exhibit when faced with herd behavior.

As shown in Equation 3, the calculation of CSAD requires the daily returns of assets ($R_{i,t}$) and the market ($R_{m,t}$). Equation 9 demonstrates how these returns are calculated:

$$R_{i,t} = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \tag{9}$$

Where $R_{i,t}$ represents the return of asset i on day t, P_t is the closing price of that asset on day t, and P_{t-1} is the closing price of the previous day. $R_{m,t}$ denotes the market return, which is calculated as the average of the equally weighted asset returns.

In order to ensure comprehensive analysis and comparison, all estimations were conducted using both the OLS model (Equation 10) and quantile regression (Equation 11). The initial estimation was performed using data spanning from January 2016 to September 2023. The objective is to assess the presence of herd behavior throughout the entire study period.

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t \tag{10}$$

$$CSAD_t(\tau|x) = \psi_{0,\tau} + \psi_{1,\tau} |R_{m,t}| + \psi_{2,\tau} \left(R_{m,t}(\tau)\right)^2 + \varepsilon_t \tag{11}$$

Where γ_2 and ψ_2 are the coefficients that indicate the presence of a herd effect if, and only if, they are negative and statistically significant. To obtain a broader picture of this scenario, the estimated conditional quantiles (τ) in Equation 11 were: 10%, 25%, 50%, 75%, and 90%. Thus, the extremes of the distribution are included (Schaumburg, 2012).

3.4.1 Examining the herd effect during the COVID-19 pandemic.

To verify **H1**, a total of ten equations were estimated. These equations were divided into two groups: five were estimated using the OLS model, while the remaining five were estimated using quantile regression.

To investigate whether there was existence of herding behavior prior to the occurrence of the pandemic, the first time window was selected from January 4, 2016, to February 21, 2020, which represents the period before the first recorded case in Brazil. By analyzing this time frame, it is aimed to identify any early signs of herding behavior that may have influenced subsequent events.

The other time windows included the first 100 days of the pandemic, as well as the first, second, and third waves. These periods were segmented using dummy variables (Wanidwaranan; Termprasertsakul, 2023). Equations 12 and 13 provide an overview of how the models were estimated.

$$CSAD_t = \gamma_0 + \gamma_1(1 - D^{PERIOD})\left|R_{m,t}\right| + \gamma_2 D^{PERIOD}\left|R_{m,t}\right| + \gamma_3(1 - D^{PERIOD})\left(R_{m,t}\right)^2 + \gamma_4 D^{PERIOD}\left(R_{m,t}\right)^2 + \varepsilon_t \qquad (12)$$

$$CSAD_t(\tau|x) = \psi_{0,\tau} + \psi_{1,\tau}(1 - D^{PERIOD})\left|R_{m,t}(\tau)\right| + \psi_{2,\tau} D^{PERIOD}\left|R_{m,t}(\tau)\right| + \psi_{3,\tau}(1 - D^{PERIOD})\left(R_{m,t}(\tau)\right)^2 + \psi_{4,\tau} D^{PERIOD}\left(R_{m,t}(\tau)\right)^2 + \varepsilon_t \qquad (13)$$

The dummy variable D^{PERIOD} represents the time window to be analyzed, being 1 for the evaluated period and 0 otherwise. For the occurrence of the herding effect, it is expected that the coefficients γ_3, γ_4, ψ_3 and ψ_4 are negative and statistically significant. The difference is that γ_4 and ψ_4 determine if the herding effect occurred within the time window, and γ_3 and ψ_3 outside of it. The conditional quantiles used were the same as Equation 11.

3.4.2 Assessing the herd effect in asymmetric market conditions during the COVID-19 pandemic

In hypothesis **H2**, the objective is to investigate the occurrence of the herding effect in asymmetric market conditions. This means analyzing whether this behavior tends to manifest more frequently during periods of high or low cycles in the market.

When the herding effect occurs mostly in bull markets, it is implied that investors are driven by euphoria and excitement, leading them to collectively push asset prices upward in an expectation of maximizing their gains, even if there is not necessarily a solid foundation for it.

On the other hand, when this behavior is observed in bear markets, it is assumed that investors are driven by fear and desperation. These prevailing sentiments prompt them to make decisions based on the desire to minimize potential losses. Consequently, they tend to sell their assets creating a strong downward pressure on prices, causing them to drop rapidly (Camara, 2017; Li; Rhee; Wang, 2017; Economou; Hassapis; Philippas, 2018).

$$
\begin{aligned}
CSAD_t = {} & \gamma_0 + \gamma_1 D^{UP}(1 - D^{PERIOD})\left|R_{m,t}\right| + \gamma_2 D^{UP} D^{PERIOD}\left|R_{m,t}\right| + \\
& \gamma_3 D^{DOWN}(1 - D^{PERIOD})\left|R_{m,t}\right| + \gamma_4 D^{DOWN} D^{PERIOD}\left|R_{m,t}\right| + \\
& \gamma_5 D^{UP}(1 - D^{PERIOD})\left(R_{m,t}\right)^2 + \gamma_6 D^{UP} D^{PERIOD}\left(R_{m,t}\right)^2 + \\
& \gamma_7 D^{DOWN}(1 - D^{PERIOD})\left(R_{m,t}\right)^2 + \gamma_8 D^{DOWN} D^{PERIOD}\left(R_{m,t}\right)^2 + \varepsilon_t
\end{aligned}
\tag{14}
$$

$$
\begin{aligned}
CSAD_t = {} & \psi_{0,\tau} + \psi_{1,\tau} D^{UP}(1 - D^{PERIOD})\left|R_{m,t}\right| + \psi_{2,\tau} D^{UP} D^{PERIOD}\left|R_{m,t}\right| + \\
& \psi_{3,\tau} D^{DOWN}(1 - D^{PERIOD})\left|R_{m,t}\right| + \psi_{4,\tau} D^{DOWN} D^{PERIOD}\left|R_{m,t}\right| + \\
& \psi_{5,\tau} D^{UP}(1 - D^{PERIOD})\left(R_{m,t}(\tau)\right)^2 + \psi_{6,\tau} D^{UP} D^{PERIOD}\left(R_{m,t}(\tau)\right)^2 + \\
& \psi_{7,\tau} D^{DOWN}(1 - D^{PERIOD})\left(R_{m,t}(\tau)\right)^2 + \psi_{8,\tau} D^{DOWN} D^{PERIOD}\left(R_{m,t}(\tau)\right)^2 + \varepsilon_t
\end{aligned}
\tag{15}
$$

In order to assess this behavior, Equations 14 and 15 incorporate dummy variables that identify positive or negative returns. These tests were conducted during the stages of the pandemic. Similar to the models of Equations 12 and 13, the evaluated period was segmented again with dummy variables. Those stages include the first 100 days of the pandemic, as well as the first, second, and third waves. Equation 14 was estimated using OLS, while Equation 15 was estimated using quantile regression.

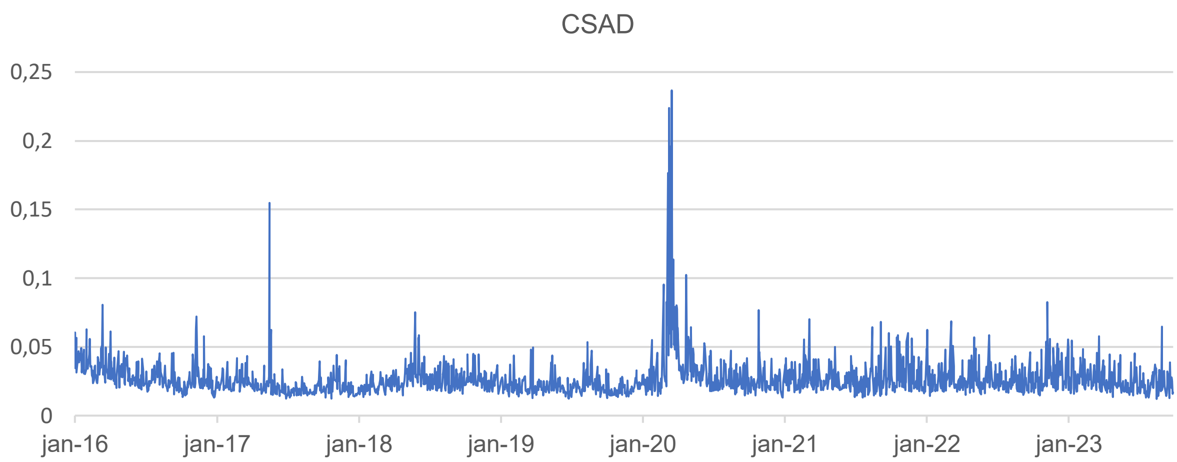
The variable D^{UP} is equal to 1 when $R_{m,t}$ is positive and 0 otherwise. Similarly, D^{DOWN} assumes 1 when $R_{m,t}$ is negative and 0 otherwise. The dummy variables D^{PERIOD} are jointly associated to segment the stages of the pandemic.

In this case, to highlight herd behavior, it is expected that the coefficients γ_5, γ_6, γ_7, γ_8, ψ_5, ψ_6, ψ_7, and ψ_8 to be negative and statistically significant. The conditional quantiles used were the same as those in Equation 11.

4 RESULTS

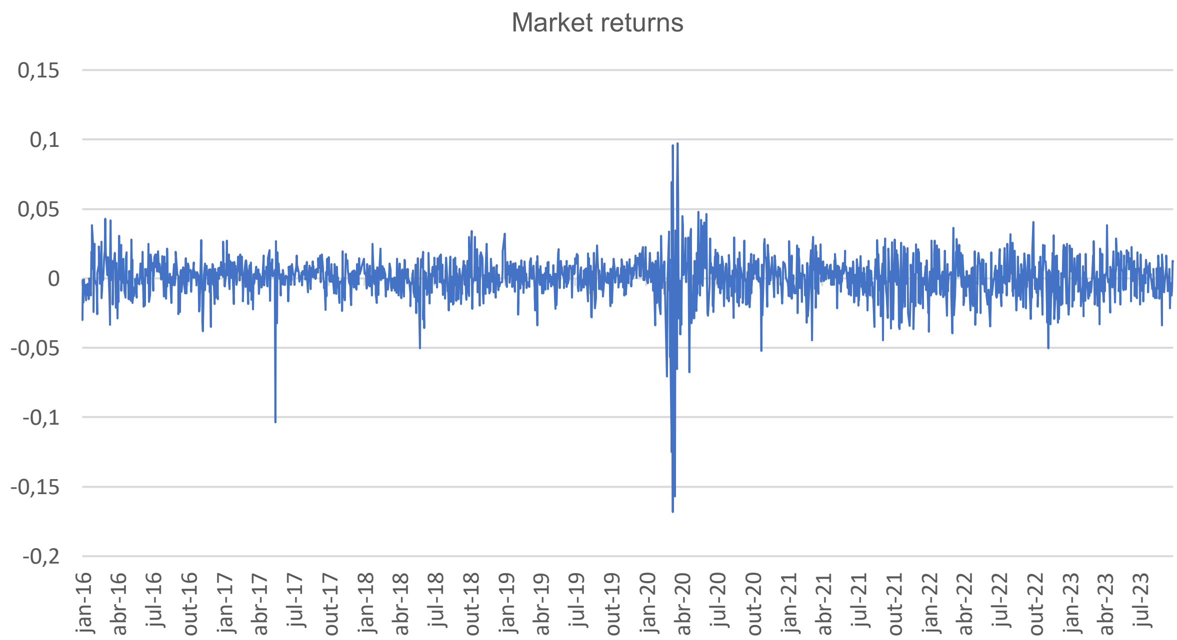
The Figures 7 and 8 show the CSAD and market returns over the entire study period. It is evident that the market exhibited abnormal behavior in the year 2020 due to an unexpected event, leading to increased volatility during this period (Kumar *et al.*, 2021).

Figure 7: CSAD for the period from January 2016 to September 2023.



Source: Elaborated by the author (2023).

Figure 8: Market returns ($R_{m,t}$) for the period from January 2016 to September 2023.



Source: Elaborated by the author (2023).

In order to assess the stationarity property of these two time series (CSAD and market returns), the Dickey-Fuller test was used. The obtained results are displayed in Table 3.

Table 3: Test ADF for market returns and CSAD.

Variable	t-statistics	1%	5%	10%	MacKinnon p-value
Rm	**-44.417**	-3.430	-2.860	-2.570	0.0000
CSAD	**-31.581**	-3.430	-2.860	-2.570	0.0000

Source: Elaborated by the author (2023).

Since the p-value for both variables were 0, it is rejected the null hypothesis that there is at least one unit root in these time series. Therefore, it is implied that both time series are stationary and exhibit no significant deviations from their mean values over time, which could lead to an inaccurate and unreliable model.

Table 4 presents the descriptive statistics of market return and CSAD in different time windows.

Table 4: Descriptive statistics of market return and CSAD.

Variable	Obs.	Mean	Std. Dev	Min	Max
All the period					
Rm	1922	0.0003	0.0160	-0.1734	0.0983
CSAD	1922	0.0184	0.0052	0.0105	0.0769
Before COVID-19					
Rm	1025	0.0009	0.0115	-0.1074	0.0419
CSAD	1025	0.0178	0.0045	0.0105	0.0490
100 first days of COVID-19					
Rm	100	-0.0018	0.0440	-0.1734	0.0983
CSAD	100	0.0280	0.0113	0.0148	0.0769
1st wave (feb.2020 – nov.2020)					
Rm	177	-0.0012	0.0344	-0.1734	0.0983
CSAD	177	0.0234	0.0102	0.0129	0.0769
2nd wave (nov.2020 – dec.2021)					
Rm	279	0.0001	0.0145	-0.0466	0.0297
CSAD	279	0.0182	0.0034	0.0113	0.0314
3rd wave (dec.2021 – may.2022)					
Rm	100	-0.0004	0.0153	-0.0408	0.0361
CSAD	100	0.0186	0.0029	0.0131	0.0266

Source: Elaborated by the author (2023).

Compared to the entire analyzed period, the lowest and highest market returns in the Brazilian stock market (-0.1682 and 0.0973) occurred within the first 100 days of the pandemic.

It is noticeable that the mean of R_m was positive (0.0009) prior to the first case of COVID-19 in Brazil. However, it turned negative (-0.0018) during the first 100 days of the pandemic, persisting until the end of the first wave (-0.0012). In the second wave period, the mean returns to being positive (0.0001), but becomes negative again (-0.0004) in the third wave, although to a lesser value than in the first 100 days and the first wave.

The standard deviation of R_m is higher after the first case (0.0440), indicating an increase in market volatility. However, this deviation decreases in subsequent periods (0.0344, 0.0145, and 0.0153). Similarly, CSAD also exhibits a higher standard deviation (0.0113) after the first case in Brazil, followed by a decrease in subsequent periods (0.0102, 0.0034, and 0.0029).

These observations suggest that the initial phase of the pandemic had a significant impact on the stock market, leading to a decline in stock prices. As the pandemic progressed, the stock market gradually recovered. However, the recovery was not immediate and took place over several phases, with periods of volatility and fluctuations in stock prices, and with investors remaining cautious and vigilant in their investment decisions.

Table 5 presents the initial estimation for the entire period using OLS regression for Equation 10. Variables of interest are color-coded for easy identification. Positive values, with or without statistical significance, are highlighted in yellow, while negative values without statistical significance are also highlighted in yellow. Negative values with statistical significance are highlighted in blue, indicating the presence of the herding behavior.

Table 5: Results for the OLS regression for the period from Jan. 2016 to Sep. 2023.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)	0.2457	0.0131	18.79	0.0001	0.2201	0.2713	***
Rm²	0.3473	0.1267	2.74	0.0062	0.0988	0.5958	***
Constant	0.0157	0.0001	107.02	0.0001	0.0154	0.0160	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4023	Number of obs	1922
F-test	645.7774	Prob > F	0.0000
Akaike crit. (AIC)	-15758.6759	Bayesian crit. (BIC)	-15741.9926

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

According to the model proposed by Chang, Cheng, and Khorana (2000), it is possible to observe an increase in dispersion along with the increase in absolute market returns. Therefore, the premise of rational price behavior is not violated because, although statistically significant, the coefficient for ${R_m}^2$ is positive.

Using quantile regression to estimate Equation 11, as shown in Table 6, the result remains unchanged for any conditional quantile. In other words, throughout the entire period from January 2016 to September 2023 for the adopted sample, herding behavior is not evident.

Table 6: Results for quantile regression for the period from Jan. 2016 to Sep. 2023.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
10%	Abs(Rm)	0.1656	0.0120	13.81	0.0001	0.1421	0.1891	***
	Rm²	0.3665	0.1163	3.15	0.0016	0.1384	0.5945	***
	Constant	0.0123	0.0001	91.60	0.0001	0.0121	0.0126	***
25%	Abs(Rm)	0.1667	0.0127	13.14	0.0001	0.1419	0.1916	***
	Rm²	0.7474	0.1203	6.08	0.0001	0.5063	0.9886	***
	Constant	0.0139	0.0001	97.20	0.0001	0.0136	0.0141	***
50%	Abs(Rm)	0.1792	0.0142	12.58	0.0001	0.1513	0.2071	***
	Rm²	1.2019	0.1381	8.71	0.0001	0.9311	1.4727	***
	Constant	0.0156	0.0002	97.20	0.0001	0.0152	0.0159	***
75%	Abs(Rm)	0.2462	0.0209	11.79	0.0001	0.2052	0.2871	***
	Rm²	0.8696	0.2024	4.30	0.0001	0.4728	1.2665	***
	Constant	0.0175	0.0002	74.51	0.0001	0.0107	0.0179	***
90%	Abs(Rm)	0.3131	0.0354	8.84	0.0001	0.2436	0.3825	***
	Rm²	0.3863	0.3433	1.13	0.2606	-0.2869	1.0595	
	Constant	0.0198	0.0004	49.80	0.0001	0.0190	0.0206	***
Mean dependent var			0.0184	SD dependent var		0.0052		

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The estimates presented in Table 7 were obtained using Equations 12 and 13. These equations utilize dummy variables to segment the period under analysis. The first time window evaluated corresponds to the period prior to the COVID-19 pandemic in Brazil.

Table 7: Results for the OLS regression for the period before COVID-19.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)(1-D)	0.2427	0.0139	17.51	0.0001	0.2155	0.2699	***
Abs(Rm)(D)	0.2266	0.0213	10.61	0.0001	0.1847	0.2685	***
Rm²(1-D)	0.3367	0.1309	2.57	0.0102	0.0799	0.5935	**
Rm²(D)	1.0964	0.4471	2.45	0.0143	0.2195	1.9733	**
Constant	0.0158	0.0002	103.15	0.0001	0.0155	0.0161	***
Mean dependent var		0.0184	SD dependent var			0.0052	
R-squared		0.4033	Number of obs			1922	
F-test		323.9211	Prob > F			0.0000	
Akaike crit. (AIC)		-15757.9546	Bayesian crit. (BIC)			-15730.1490	

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

If the herd effect exists, the term $Rm^2(D)$ indicates its presence during the evaluated period. Since the regression returned a positive coefficient, it suggests no indication of herding behavior. For this estimation, $Rm^2(1-D)$ represents the period outside the analyzed time window, therefore, it covers the period from February 2020 to September 2023, which includes the pandemic period.

The current lack of statistical significance for the coefficient $Rm^2(1-D)$ in this estimation does not necessarily imply that the herd effect did not occur during the pandemic. As the method uses a standard deviation technique, it is possible that the use of a longer period may influence the regression.

Table 8: Results for the quantile regression for the period before COVID-19.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf. interval]		Sig
	Abs(Rm)(1-D)	0.1647	0.0129	12.80	0.0001	0.1395	0.1899	***
	Abs(Rm)(D)	0.0895	0.0198	4.52	0.0001	0.0506	0.1284	***
10%	**Rm^2(1-D)**	0.3636	0.1216	2.99	0.0028	0.1251	0.6020	***
	Rm^2(D)	2.3211	0.4152	5.59	0.0001	1.5068	3.1353	***
	Constant	0.0126	0.0001	88.63	0.0001	0.0123	0.0129	***
	Abs(Rm)(1-D)	0.1894	0.0132	14.33	0.0001	0.1635	0.2154	***
	Abs(Rm)(D)	0.1282	0.0204	6.30	0.0001	0.0883	0.1681	***
25%	**Rm^2(1-D)**	0.1775	0.1249	1.42	0.1553	-0.0674	0.4224	
	Rm^2(D)	1.8482	0.4264	4.33	0.0001	1.0119	2.6844	***
	Constant	0.0139	0.0001	95.23	0.0001	0.0136	0.0142	***
	Abs(Rm)(1-D)	0.1990	0.0151	13.15	0.0001	0.1693	0.2287	***
	Abs(Rm)(D)	0.1491	0.0233	6.40	0.0001	0.1034	0.1948	***
50%	**Rm^2(1-D)**	0.4503	0.1429	3.15	0.0017	0.1700	0.7305	***
	Rm^2(D)	1.5045	0.4880	3.08	0.0021	0.5475	2.4616	***
	Constant	0.0156	0.0002	93.52	0.0001	0.0153	0.0159	***
	Abs(Rm)(1-D)	0.2306	0.0221	10.43	0.0001	0.1872	0.2740	***
	Abs(Rm)(D)	0.2106	0.0341	6.18	0.0001	0.1438	0.2774	***
75%	**Rm^2(1-D)**	0.8113	0.2089	3.88	0.0001	0.4015	1.2210	***
	Rm^2(D)	3.1069	0.7134	4.35	0.0001	1.7077	4.5061	***
	Constant	0.0176	0.0002	72.04	0.0001	0.0171	0.0181	***
	Abs(Rm)(1-D)	0.2260	0.0375	6.02	0.0001	0.1524	0.2996	***
	Abs(Rm)(D)	0.3496	0.0578	6.05	0.0001	0.2363	0.4630	***
90%	**Rm^2(1-D)**	2.2019	0.3544	6.21	0.0001	1.5068	2.8970	***
	Rm^2(D)	2.2582	1.2104	1.87	0.0622	-0.1156	4.6320	*
	Constant	0.0198	0.0004	47.75	0.0001	0.0190	0.0206	***
Mean dependent var			0.0184		SD dependent var	0.0052		

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

Table 8 provides estimates for the same period using quantile regression, and the results do not provide any evidence to support the existence of herd behavior. This suggests that from January 2016 until before the emergence of the pandemic in Brazil, there were no indications of the herd effect in the stock market.

4.1 Results of the herd effect during the COVID-19 pandemic

Table 9 presents the results of the OLS regression for the first 100 days of COVID-19 in Brazil.

Table 9: Results for the OLS regression for the first 100 days of the COVID-19 pandemic.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)(1-D)	0.1458	0.0184	7.91	0.0001	0.1096	0.1819	***
Abs(Rm)(D)	0.4413	0.0203	21.72	0.0001	0.4015	0.4812	***
Rm^2(1-D)	1.7126	0.4143	4.13	0.0001	0.9000	2.5252	***
Rm^2(D)	**-1.0912**	0.1667	-6.55	**0.0001**	-1.4181	-0.7644	***
Constant	0.0163	0.0002	105.16	0.0001	0.0160	0.0166	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4486	Number of obs	1922
F-test	389.9247	Prob > F	0.0000
Akaike crit. (AIC)	-15909.7472	Bayesian crit. (BIC)	-15881.9416

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

There is empirical evidence of herding behavior during the first 100 days of the pandemic. This is indicated by the negative and statistically significant value of the term $Rm^2(D)$. This suggests that individual asset returns closely followed the market return during this period. Table 10 displays the results of Equation 13 using quantile regression.

Table 10: Results for the quantile regression for the first 100 days of the COVID-19 pandemic.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
	Abs(Rm)(1-D)	0.0886	0.0199	4.45	0.0001	0.0495	0.1277	***
	Abs(Rm)(D)	0.3314	0.0220	15.07	0.0001	0.2883	0.3745	***
10%	**Rm^2(1-D)**	2.3161	0.4483	5.17	0.0001	1.4370	3.1953	***
	Rm^2(D)	**-0.6031**	0.1803	-3.34	**0.0008**	-0.9568	-0.2495	***
	Constant	0.0127	0.0002	76.07	0.0001	0.0124	0.0131	***
	Abs(Rm)(1-D)	0.1216	0.0185	6.57	0.0001	0.0853	0.1580	***
	Abs(Rm)(D)	0.3495	0.0204	17.11	0.0001	0.3094	0.3895	***
25%	**Rm^2(1-D)**	1.8966	0.4164	4.55	0.0001	1.0800	2.7132	***
	Rm^2(D)	**-0.7504**	0.1675	-4.48	**0.0001**	-1.0789	-0.4219	***
	Constant	0.0140	0.0002	90.24	0.0001	0.0137	0.0143	***
	Abs(Rm)(1-D)	0.1344	0.0197	6.83	0.0001	0.0958	0.1729	***
	Abs(Rm)(D)	0.4812	0.0217	22.19	0.0001	0.4387	0.5237	***
50%	**Rm^2(1-D)**	1.6283	0.4420	3.68	0.0002	0.7613	2.4952	***
	Rm^2(D)	**-1.5079**	0.1778	-8.48	**0.0001**	-1.8566	-1.1592	***
	Constant	0.0158	0.0002	95.48	0.0001	0.0154	0.0161	***
	Abs(Rm)(1-D)	0.1589	0.0284	5.61	0.0001	0.1033	0.2145	***
	Abs(Rm)(D)	0.4958	0.0313	15.86	0.0001	0.4345	0.5571	***
75%	**Rm^2(1-D)**	1.5677	0.6376	2.46	0.0140	0.3173	2.8182	**
	Rm^2(D)	**-1.1146**	0.2565	-4.35	**0.0001**	-1.6176	-0.6116	***
	Constant	0.0179	0.0002	75.23	0.0001	0.0175	0.0184	***
	Abs(Rm)(1-D)	0.1334	0.0437	3.05	0.0023	0.0478	0.2191	***
90%	Abs(Rm)(D)	0.5631	0.0482	11.69	0.0001	0.4686	0.6576	***
	Rm^2(1-D)	3.7506	0.9824	3.82	0.0001	1.8293	5.6827	***

Rm²(D)	**-1.3340**	0.3952	-3.38	**0.0008**	-2.1091	-0.5589	***
Constant	0.0205	0.0004	55.88	0.0001	0.0198	0.0212	***

Mean dependent var	0.0184	SD dependent var	0.0052

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The herd effect is observed in all adopted conditional quantiles. This behavior is not only evident in the central regions of the distribution, similar to the OLS model, but it also spreads to the extremes of the distribution tails. The largest coefficient was found in the median region (-1.5079), followed by the second largest coefficient in the 90% quantile (-1.3340).

Before the onset of the pandemic and during the period spanning from 2016 to 2023, the presence of the herd effect has not been detected. However, a clear manifestation of this effect emerges upon examining the data for the first 100 days of the pandemic.

Afterwards, estimations are made considering the different stages and impact of the COVID-19 pandemic in Brazil. The analysis in Table 11 provides an overview of the findings for the complete duration of the first wave.

Table 11: Results for the OLS regression for the first wave of the COVID-19 pandemic.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)(1-D)	0.1636	0.0188	8.70	0.0001	0.1267	0.2005	***
Abs(Rm)(D)	0.3656	0.0188	19.42	0.0001	0.3287	0.4025	***
Rm²(1-D)	1.5614	0.4251	3.67	0.0002	0.7278	2.3951	***
Rm²(D)	**-0.5504**	0.1582	-3.48	**0.0005**	-0.8607	-0.2400	***
Constant	0.0161	0.0002	103.23	0.0001	0.0158	0.0164	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4277	Number of obs	1922
F-test	358.2307	Prob > F	0.0000
Akaike crit. (AIC)	-15838.3528	Bayesian crit. (BIC)	-15810.5472

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

Once again, the herd effect is detected. However, the coefficient value (-0.5504) is smaller compared to the first 100 days. This suggests that the impact on the market during the entire duration of the first wave was less pronounced than in the initial 100 days. Table 12 displays the results of the coefficients estimated through quantile regression.

Table 12: Results for the quantile regression for the first wave of the COVID-19 pandemic.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
	Abs(Rm)(1-D)	0.0967	0.0193	5.01	0.0001	0.0588	0.1345	***
	Abs(Rm)(D)	0.1721	0.0193	8.92	0.0001	0.1343	0.2100	***
10%	**Rm²(1-D)**	2.2465	0.4358	5.15	0.0001	1.3917	3.1012	***
	Rm²(D)	0.3176	0.1622	1.96	0.0504	-0.0006	0.6358	*
	Constant	0.0127	0.0002	79.18	0.0001	0.0124	0.0130	***
	Abs(Rm)(1-D)	0.1291	0.0188	6.88	0.0001	0.0923	0.1658	***
	Abs(Rm)(D)	0.2266	0.0188	12.07	0.0001	0.1898	0.2634	***
25%	**Rm²(1-D)**	1.8306	0.4237	4.32	0.0001	0.9996	2.6617	***
	Rm²(D)	-0.0403	0.1577	-0.26	0.7986	-0.3496	0.2691	
	Constant	0.0140	0.0002	89.91	0.0001	0.0137	0.0143	***
	Abs(Rm)(1-D)	0.1534	0.0198	7.74	0.0001	0.1145	0.1923	***
	Abs(Rm)(D)	0.3235	0.0198	16.32	0.0001	0.2846	0.3624	***
50%	**Rm²(1-D)**	1.4627	0.4477	3.27	0.0011	0.5847	2.3407	***
	Rm²(D)	**-0.4160**	0.1667	-2.50	**0.0126**	-0.7428	-0.0891	**
	Constant	0.0156	0.0002	95.02	0.0001	0.0153	0.0160	***
	Abs(Rm)(1-D)	0.1654	0.0304	5.45	0.0001	0.1059	0.2250	***
	Abs(Rm)(D)	0.4311	0.0304	14.19	0.0001	0.3715	0.4907	***
75%	**Rm²(1-D)**	1.7071	0.6859	2.49	0.0129	0.3620	3.0522	**
	Rm²(D)	**-0.4272**	0.2553	-1.67	**0.0944**	-0.9280	0.0735	*
	Constant	0.0179	0.0003	70.93	0.0001	0.0174	0.0184	***
	Abs(Rm)(1-D)	0.1863	0.0450	4.14	0.0001	0.0980	0.2745	***
	Abs(Rm)(D)	0.5351	0.0450	11.89	0.0001	0.4468	0.6233	***
90%	**Rm²(1-D)**	2.4764	1.0165	2.44	0.0149	0.4828	4.4701	**
	Rm²(D)	**-1.1538**	0.3784	-3.05	**0.0023**	-1.8959	-0.4116	***
	Constant	0.0203	0.0004	54.29	0.0001	0.0196	0.0210	***
Mean dependent var		0.0184		SD dependent var		0.0052		

*** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The results indicate that the herding effect was observed from the median level to the upper quantiles. This means that even in regions with greater dispersion values, the term $Rm^2(D)$ still leads to a smaller CSAD, indicating that dispersion increases at a decreasing rate. The herding effect was not observed in the lower quantiles.

Table 13 presents the results obtained from OLS estimation for the second wave of COVID-19 period.

Table 13: Results for the OLS regression for the second wave of the COVID-19 pandemic.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)(1-D)	0.2665	0.0137	19.50	0.0001	0.2397	0.2933	***
Abs(Rm)(D)	0.2286	0.0456	5.02	0.0001	0.1393	0.3180	***
Rm²(1-D)	0.2104	0.1289	1.63	0.1028	-0.0424	0.4633	
Rm²(D)	-1.8022	1.6252	-1.11	0.2676	-4.9896	1.3852	
Constant	0.0157	0.0001	104.61	0.0001	0.0154	0.0160	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4100	Number of obs	1922
F-test	332.9777	Prob > F	0.0000
Akaike crit. (AIC)	-15779.5058	Bayesian crit. (BIC)	-15751.7002

*** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

Although the term $Rm^2(D)$ is negative, no statistical significance was found. Therefore, it is not possible to infer that the herd effect is evident during the second wave of COVID-19. Table 14 displays the results for the same period using quantile regression.

Table 14: Results for the quantile regression for the second wave of the COVID-19 pandemic.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
	Abs(Rm)(1-D)	0.1704	0.0130	13.07	0.0001	0.1448	0.1960	***
	Abs(Rm)(D)	0.1320	0.0434	3.04	0.0024	0.0468	0.2172	***
10%	**Rm²(1-D)**	0.3379	0.1229	2.75	0.0060	0.0968	0.5791	***
	Rm²(D)	0.3080	1.5498	0.20	0.8425	-2.7315	3.3475	
	Constant	0.0124	0.0001	86.66	0.0001	0.0121	0.0127	***
	Abs(Rm)(1-D)	0.1754	0.0135	12.98	0.0001	0.1489	0.2018	***
	Abs(Rm)(D)	0.2229	0.0450	4.95	0.0001	0.1346	0.3112	***
25%	**Rm²(1-D)**	0.6922	0.1274	5.43	0.0001	0.4423	0.9420	***
	Rm²(D)	-1.8714	1.6062	-1.17	0.2441	-5.0214	1.2787	
	Constant	0.0138	0.0001	93.10	0.0001	0.0135	0.0141	***
	Abs(Rm)(1-D)	0.1944	0.0153	12.71	0.0001	0.1644	0.2244	***
	Abs(Rm)(D)	0.2133	0.0510	4.18	0.0001	0.1134	0.3133	***
50%	**Rm²(1-D)**	1.0935	0.1443	7.58	0.0001	0.8105	1.3764	***
	Rm²(D)	-1.3933	1.8189	-0.77	0.4437	-4.9605	2.1738	
	Constant	0.0155	0.0002	92.44	0.0001	0.0152	0.0158	***
	Abs(Rm)(1-D)	0.2735	0.0230	11.89	0.0001	0.2283	0.3186	***
	Abs(Rm)(D)	0.2588	0.0767	3.38	0.0008	0.1084	0.4091	***
75%	**Rm²(1-D)**	0.5554	0.2170	2.56	0.0106	0.1299	0.9810	**
	Rm²(D)	-2.7448	2.7353	-1.00	0.3158	-8.1093	2.6198	
	Constant	0.0174	0.0003	69.10	0.0001	0.0169	0.0179	***
	Abs(Rm)(1-D)	0.3791	0.0353	10.75	0.0001	0.3099	0.4483	***
	Abs(Rm)(D)	0.2333	0.1176	1.98	0.0474	0.0027	0.4639	**
90%	**Rm²(1-D)**	-0.1746	0.3328	-0.52	0.5999	-0.8274	0.4781	
	Rm²(D)	-2.1438	4.1957	-0.51	0.6094	-10.3723	6.0848	
	Constant	0.0196	0.0004	50.79	0.0001	0.0189	0.0204	***
Mean dependent var		0.0184		SD dependent var		0.0052		

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Source: Elaborated by the author (2023).

Despite the negative coefficients, there is no statistical significance for any of the adopted quantiles during the second wave of the pandemic.

Table 15 presents the results of the estimation by OLS for the last time window representing the third wave of the pandemic.

Table 15: Results for the OLS regression for the third wave of the COVID-19 pandemic.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Abs(Rm)(1-D)	0.2502	0.0133	18.77	0.0001	0.2240	0.2763	***
Abs(Rm)(D)	0.2189	0.0722	3.03	0.0025	0.0772	0.3606	***
Rm²(1-D)	0.3173	0.1278	2.48	0.0131	0.0666	0.5680	**
Rm²(D)	-0.3534	2.6892	-0.13	0.8955	-5.6275	4.9207	
Constant	0.0157	0.0001	106.01	0.0001	0.0154	0.0160	***
Mean dependent var		0.0184	SD dependent var			0.0052	
R-squared		0.4033	Number of obs			1922	

F-test	323.8724	Prob > F	0.0000
Akaike crit. (AIC)	-15757.8380	Bayesian crit. (BIC)	-15730.0324

*** p<0.01, ** p<0.05, * p<0.10

Source: Elaborated by the author (2023).

Once again, the herding effect was not detected. To obtain an analysis in other points of the distribution, Table 16 presents the results using quantile regression.

Table 16: Results for the quantile regression for the third wave of the COVID-19 pandemic.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
10%	Abs(Rm)(1-D)	0.1482	0.0125	11.89	0.0001	0.1237	0.1726	***
	Abs(Rm)(D)	0.2355	0.0676	3.49	0.0005	0.1030	0.3680	***
	Rm²(1-D)	0.4638	0.1195	3.88	0.0001	0.2294	0.6982	***
	Rm²(D)	0.8683	2.5144	0.35	0.7299	-4.0630	5.7996	
	Constant	0.0124	0.0001	89.76	0.0001	0.0122	0.0127	***
25%	Abs(Rm)(1-D)	0.1623	0.0126	12.92	0.0001	0.1377	0.1870	***
	Abs(Rm)(D)	0.2322	0.0681	3.41	0.0007	0.0986	0.3657	***
	Rm²(1-D)	0.7783	0.1205	6.46	0.0001	0.5420	1.0146	***
	Rm²(D)	-0.1197	2.5349	-0.05	0.9624	-5.0910	4.8517	
	Constant	0.0139	0.0001	99.14	0.0001	0.0136	0.0141	***
50%	Abs(Rm)(1-D)	0.1820	0.0146	12.44	0.0001	0.1533	0.2107	***
	Abs(Rm)(D)	0.2171	0.0793	2.74	0.0062	0.0616	0.3726	***
	Rm²(1-D)	1.1854	0.1403	8.45	0.0001	0.9103	1.4605	***
	Rm²(D)	-0.5494	2.9511	-0.19	0.8523	-6.3372	5.2383	
	Constant	0.0155	0.0002	95.54	0.0001	0.0152	0.0159	***
75%	Abs(Rm)(1-D)	0.2661	0.0218	12.21	0.0001	0.2234	0.3089	***
	Abs(Rm)(D)	0.1781	0.1181	1.51	0.1319	-0.0536	0.4098	
	Rm²(1-D)	0.6019	0.2090	2.88	0.0040	0.1920	1.0119	***
	Rm²(D)	1.1476	4.3976	0.26	0.7942	-7.4770	9.7722	
	Constant	0.0174	0.0002	71.75	0.0001	0.0169	0.0179	***
90%	Abs(Rm)(1-D)	0.3253	0.0339	9.58	0.0001	0.2587	0.3919	***
	Abs(Rm)(D)	0.0877	0.1840	0.48	0.6336	-0.2731	0.4486	
	Rm²(1-D)	0.1480	0.3256	0.45	0.6495	-0.4905	0.7865	
	Rm²(D)	1.9056	6.8492	0.28	0.7809	-11.527	15.3382	
	Constant	0.0198	0.0004	52.49	0.0001	0.0191	0.0206	***
Mean dependent var		0.0184		SD dependent var		0.0052		

*** p<0.01, ** p<0.05, * p<0.10

Source: Elaborated by the author (2023).

The herd effect was not observed for any of the conditional quantiles during the third wave of COVID-19 in Brazil. The results suggest that the Brazilian stock market was heavily impacted near the beginning of the pandemic, but gradually decreased over time. During the second and third waves, the herd effect was not manifested in the sample used.

The overall findings in this Section indicate that in stress-free scenarios, the Brazilian stock market behaves in accordance with rational asset pricing models. This means that investors make decisions based on their own assessments. However, when faced with disturbances that create uncertainties and lead to a significant increase in market volatility, the behavior of the Brazilian market deviates from rational asset pricing models. In these situations, the herd effect becomes apparent, decreasing over time.

4.2 Results of the herd effect during the COVID-19 pandemic under asymmetric conditions

The following results are related to the tests conducted to verify if there is any asymmetry in the Brazilian stock market regarding the herd effect. The goal is to determine whether herd behavior tends to occur more frequently in bullish or bearish markets. The results from Table 17 refer to the first 100 days of the pandemic and were obtained using OLS regression.

Table 17: Results for the OLS regression for asymmetry in the first 100 days of COVID-19.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Up_Abs(Rm)(1-D)	0.0929	0.0348	2.67	0.0077	0.0247	0.1612	***
Up_Abs(Rm)(D)	0.4992	0.0380	13.14	0.0001	0.4247	0.5738	***
Down_Abs(Rm)(1-D)	0.0873	0.0205	4.26	0.0001	0.0471	0.1274	***
Down_Abs(Rm)(D)	0.3337	0.0291	11.47	0.0001	0.2767	0.3908	***
Up_Rm²(1-D)	5.9520	1.3469	4.42	0.0001	3.3103	8.5936	***
Up_Rm²(D)	**-1.3061**	0.5556	-2.35	**0.0188**	-2.3958	-0.2165	**
Down_Rm²(1-D)	2.1709	0.4245	5.11	0.0001	1.3384	3.0035	***
Down_Rm²(D)	**-0.4330**	0.2113	-2.05	**0.0406**	-0.8474	-0.0186	**
Constant	0.0165	0.0002	99.82	0.0001	0.0161	0.0168	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4669	Number of obs	1922
F-test	209.3363	Prob > F	0.0000
Akaike crit. (AIC)	-15957.5755	Bayesian crit. (BIC)	-15907.5301

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The terms $Up\_Rm^2(D)$ and $Down\_Rm^2(D)$ indicate whether there is a herding effect, during the evaluated period, for the bull and bear markets respectively. $Up\_Rm^2(1-D)$ and $Down\_Rm^2(1-D)$ are the coefficients outside this period. Thus, the herd effect was identified in both bullish and bearish markets for the first 100 days of the pandemic.

Table 18 displays the results for those coefficients using quantile regression.

Table 18: Results for the quantile regression for asymmetry in the first 100 days of COVID-19.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
	Up_Abs(Rm)(1-D)	0.0918	0.0310	2.96	0.0031	0.0310	0.1526	***
	Up_Abs(Rm)(D)	0.3139	0.0339	9.27	0.0001	0.2475	0.3803	***
	Down_Abs(Rm)(1-D)	0.0365	0.0183	2.00	0.0454	0.0007	0.0723	**
	Down_Abs(Rm)(D)	0.1900	0.0259	7.33	0.0001	0.1391	0.2408	***
10%	**Up_Rm²(1-D)**	4.7073	1.2000	3.92	0.0001	2.3538	7.0608	***
	Up_Rm²(D)	0.8527	0.4950	1.72	0.0851	-0.1181	1.8235	*
	Down_Rm²(1-D)	2.7988	0.3782	7.40	0.0001	2.0570	3.5405	***
	Down_Rm²(D)	0.2119	0.1883	1.13	0.2605	-0.1573	0.5811	
	Constant	0.0128	0.0001	86.94	0.0001	0.0125	0.0131	***
	Up_Abs(Rm)(1-D)	0.0950	0.0378	2.52	0.0120	0.0209	0.1690	**
	Up_Abs(Rm)(D)	0.2968	0.0412	7.20	0.0001	0.2160	0.3777	***
	Down_Abs(Rm)(1-D)	0.0650	0.0222	2.92	0.0035	0.0214	0.1085	***
	Down_Abs(Rm)(D)	0.2972	0.0316	9.42	0.0001	0.2353	0.3591	***
25%	**Up_Rm²(1-D)**	5.1179	1.4612	3.50	0.0005	2.2521	7.9836	***
	Up_Rm²(D)	0.8782	0.6027	1.46	0.1453	-0.3038	2.0603	
	Down_Rm²(1-D)	2.4126	0.4605	5.24	0.0001	1.5094	3.3158	***
	Down_Rm²(D)	**-0.4536**	0.2292	-1.98	**0.0480**	-0.9031	-0.0040	**
	Constant	0.0142	0.0002	79.25	0.0001	0.0138	0.0145	***
	Up_Abs(Rm)(1-D)	0.0634	0.0368	1.72	0.0851	-0.0088	0.1356	*
	Up_Abs(Rm)(D)	0.4614	0.0402	11.48	0.0001	0.3826	0.5403	***
	Down_Abs(Rm)(1-D)	0.0824	0.0217	3.80	0.0001	0.0399	0.1249	***
	Down_Abs(Rm)(D)	0.3122	0.0308	10.15	0.0001	0.2519	0.3726	***
50%	**Up_Rm²(1-D)**	6.8752	01.425	4.82	0.0001	4.0805	9.6699	***
	Up_Rm²(D)	**-1.0295**	0.5878	-1.75	**0.0800**	-2.1822	0.1233	*
	Down_Rm²(1-D)	2.0956	0.4491	4.67	0.0001	1.2148	2.9764	***
	Down_Rm²(D)	**-0.4495**	0.2235	-2.01	**0.0445**	-0.8879	-0.0110	**
	Constant	0.0160	0.0002	91.50	0.0001	0.0156	0.0163	***
	Up_Abs(Rm)(1-D)	0.1225	0.0548	2.23	0.0256	0.0149	0.2300	**
	Up_Abs(Rm)(D)	0.5137	0.0599	8.58	0.0001	0.3962	0.6311	***
	Down_Abs(Rm)(1-D)	0.1261	0.0323	3.91	0.0001	0.0628	0.1894	***
	Down_Abs(Rm)(D)	0.4471	0.0458	9.75	0.0001	0.3571	0.5370	***
75%	**Up_Rm²(1-D)**	5.7415	2.1227	2.70	0.0069	1.5785	9.9046	***
	Up_Rm²(D)	**-1.6152**	0.8756	-1.84	**0.0652**	-3.3324	0.1020	*
	Down_Rm²(1-D)	1.5141	0.6690	2.26	0.0237	0.2002	2.8262	**
	Down_Rm²(D)	-0.5285	0.3330	-1.59	0.1127	-1.1816	0.1246	
	Constant	0.0180	0.0003	69.19	0.0001	0.0175	0.0185	***
	Up_Abs(Rm)(1-D)	0.1618	0.0918	1.76	0.0781	-0.0182	0.3418	*
	Up_Abs(Rm)(D)	0.6345	0.1002	6.33	0.0001	0.4380	0.8311	***
	Down_Abs(Rm)(1-D)	0.1402	0.0540	2.59	0.0096	0.0342	0.2461	***
	Down_Abs(Rm)(D)	0.5651	0.0767	7.37	0.0001	0.4147	0.7156	***
90%	**Up_Rm²(1-D)**	3.6478	3.5522	1.03	0.3046	-3.3188	10.6143	
	Up_Rm²(D)	**-2.4851**	1.4652	-1.70	**0.0910**	-5.3587	0.3885	*
	Down_Rm²(1-D)	2.0167	1.1196	1.80	0.0718	-0.1790	4.2124	*
	Down_Rm²(D)	**-1.3441**	0.5573	-2.41	**0.0160**	-2.4370	-0.2512	**
	Constant	0.0204	0.0004	47.04	0.0001	0.0196	0.0213	***
Mean dependent var			0.0184	SD dependent var		0.0052		

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The quantile regression offers a wider range of results. The herding effect was observed not only at the median level but also at the 90% quantile for both bull and bear markets.

At the 25% quantile, the herding effect was asymmetrically detected for bear markets. This behavior suggests that investors converged during market downturns, possibly due to caution and/or fear.

On the other hand, at the 75% quantile it was observed the opposite pattern. The herding effect became evident primarily in bull markets, indicating a significant increase dispersion of CSAD at a disproportionate rate. This phenomenon suggests that investors in bull markets may have been influenced by an optimistic and/or euphoric sentiment toward the market.

Table 19 presents the asymmetry results for the first wave of COVID-19 using OLS regression.

Table 19: Results for the OLS regression for asymmetry in the first wave of COVID-19.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Up_Abs(Rm)(1-D)	0.1091	0.0355	3.07	0.0022	0.0395	0.1788	***
Up_Abs(Rm)(D)	0.4026	0.0339	11.88	0.0001	0.3361	0.4691	***
Down_Abs(Rm)(1-D)	0.1063	0.0210	5.07	0.0001	0.0652	0.1474	***
Down_Abs(Rm)(D)	0.2485	0.0258	9.63	0.0001	0.1979	0.2991	***
Up_Rm²(1-D)	5.6949	1.3830	4.12	0.0001	2.9826	8.4071	***
Up_Rm²(D)	-0.0851	0.5142	-0.17	0.8686	-1.0936	0.9234	
Down_Rm²(1-D)	2.0056	0.4348	4.61	0.0001	1.1529	2.8583	***
Down_Rm²(D)	0.1345	0.1924	0.70	0.4846	-0.2428	0.5117	
Constant	0.0163	0.0002	98.49	0.0001	0.0160	0.0166	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4501	Number of obs	1922
F-test	195.7540	Prob > F	0.0000
Akaike crit. (AIC)	-15907.0514	Bayesian crit. (BIC)	-15857.0013

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The herd effect was not identified with statistical significance for any of the variables of interest. Table 20 provides the estimation of these coefficients using quantile regression.

Table 20: Results for the quantile regression for asymmetry in the first wave of COVID-19.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
10%	Up_Abs(Rm)(1-D)	0.0872	0.0316	2.76	0.0058	0.0252	0.1491	***
	Up_Abs(Rm)(D)	0.2147	0.0301	7.12	0.0001	0.1556	0.2738	***
	Down_Abs(Rm)(1-D)	0.0440	0.0186	2.36	0.0184	0.0074	0.0805	**
	Down_Abs(Rm)(D)	0.1331	0.0229	5.80	0.0001	0.0881	0.1780	***
	Up_Rm²(1-D)	5.6152	1.2298	4.57	0.0001	3.2034	8.0270	***
	Up_Rm²(D)	1.8934	0.4573	4.14	0.0001	0.9966	2.7901	***
	Down_Rm²(1-D)	2.7353	0.3866	7.08	0.0001	1.9771	3.4935	***
	Down_Rm²(D)	0.5424	0.1711	3.17	0.0015	0.2069	0.8778	***
	Constant	0.0127	0.0001	86.23	0.0001	0.0124	0.0130	***
25%	Up_Abs(Rm)(1-D)	0.1005	0.0356	2.82	0.0049	0.0306	0.1704	***
	Up_Abs(Rm)(D)	0.2566	0.0340	7.54	0.0001	0.1899	0.3233	***
	Down_Abs(Rm)(1-D)	0.0901	0.0210	4.29	0.0001	0.0489	0.1314	***
	Down_Abs(Rm)(D)	0.1376	0.0259	5.32	0.0001	0.0868	0.1884	***
	Up_Rm²(1-D)	5.5410	1.3877	3.99	0.0001	2.8195	8.2625	***
	Up_Rm²(D)	1.4019	0.5160	2.72	0.0066	0.3900	2.4138	***
	Down_Rm²(1-D)	2.1869	0.4363	5.01	0.0001	1.3313	3.0425	***
	Down_Rm²(D)	0.4705	0.1930	2.44	0.0149	0.0919	0.8490	**
	Constant	0.0141	0.0002	84.67	0.0001	0.0137	0.0144	***
50%	Up_Abs(Rm)(1-D)	0.0721	0.0385	1.87	0.0614	-0.0034	0.1477	*
	Up_Abs(Rm)(D)	0.3564	0.0368	9.69	0.0001	0.2842	0.4285	***
	Down_Abs(Rm)(1-D)	0.0948	0.0227	4.17	0.0001	0.0502	0.1394	***
	Down_Abs(Rm)(D)	0.2227	0.0280	7.96	0.0001	0.1678	0.2776	***
	Up_Rm²(1-D)	6.7111	1.5006	4.47	0.0001	3.7682	9.6540	***
	Up_Rm²(D)	0.2025	0.5579	0.36	0.7166	-0.8917	1.2968	

	Down_Rm^2(1-D)	1.9884	0.4717	4.21	0.0001	1.0632	2.9136	***
	Down_Rm^2(D)	0.2510	0.2087	1.20	0.2294	-0.1584	0.6603	
	Constant	0.0159	0.0002	88.26	0.0001	0.0155	0.0162	***
75%	Up_Abs(Rm)(1-D)	0.1281	0.0561	2.28	0.0225	0.0181	0.2380	**
	Up_Abs(Rm)(D)	0.4874	0.0535	9.11	0.0001	0.3825	0.5924	***
	Down_Abs(Rm)(1-D)	0.1426	0.0331	4.31	0.0001	0.0777	0.2075	***
	Down_Abs(Rm)(D)	0.3152	0.0407	7.74	0.0001	0.2354	0.3951	***
	Up_Rm^2(1-D)	5.6409	2.1829	2.58	0.0098	1.3598	9.9221	***
	Up_Rm^2(D)	**-1.3423**	0.8117	-1.65	**0.0983**	-2.9341	0.2495	*
	Down_Rm^2(1-D)	1.3656	0.6863	1.99	0.0467	0.0197	2.7115	**
	Down_Rm^2(D)	0.2808	0.3036	0.92	0.3551	-0.3147	0.8763	
	Constant	0.0179	0.0003	68.52	0.0001	0.0174	0.0184	***
90%	Up_Abs(Rm)(1-D)	0.1494	0.0970	1.54	0.1238	-0.0409	0.3396	
	Up_Abs(Rm)(D)	0.5149	0.0926	5.56	0.0001	0.3333	0.6965	***
	Down_Abs(Rm)(1-D)	0.1659	0.0572	2.90	0.0038	0.0536	0.2781	***
	Down_Abs(Rm)(D)	0.4111	0.0705	5.84	0.0001	0.2729	0.5493	***
	Up_Rm^2(1-D)	5.2243	3.7771	1.38	0.1668	-2.1832	12.6319	
	Up_Rm^2(D)	-0.6675	1.4044	-0.48	0.6346	-3.4218	2.0868	
	Down_Rm^2(1-D)	1.3364	1.1874	1.13	0.2605	-0.9924	3.6652	
	Down_Rm^2(D)	-0.3985	0.5254	-0.76	0.4483	-1.4289	0.6319	
	Constant	0.0204	0.0005	45.04	0.0001	0.0195	0.0213	***

Mean dependent var	0.0184	SD dependent var	0.0052

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

The herding effect is evident at the 75% quantile for bull markets when using quantile regression. Which means that investors still exhibited asymmetric behavior when the market presented positive returns. Since this quantile is above the mean of the distribution, the OLS model was not able to detect this behavior.

In the context of the second wave of COVID-19 in Brazil, Table 21 presents the results obtained using the OLS method.

Table 21: Results for the OLS regression for asymmetry in the second wave of COVID-19.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Up_Abs(Rm)(1-D)	0.2477	0.0203	12.22	0.0001	0.2079	0.2874	***
Up_Abs(Rm)(D)	0.2689	0.0801	3.36	0.0008	0.1118	0.4261	***
Down_Abs(Rm)(1-D)	0.2025	0.0158	12.82	0.0001	0.1715	0.2334	***
Down_Abs(Rm)(D)	0.1032	0.0600	1.72	0.0857	-0.0145	0.2210	*
Up_Rm^2(1-D)	2.0288	0.3861	5.25	0.0001	1.2716	2.7861	***
Up_Rm^2(D)	-2.2828	3.8033	-0.60	0.5484	-9.7418	5.1762	
Down_Rm^2(1-D)	0.4988	0.1370	3.64	0.0003	0.2300	0.7676	***
Down_Rm^2(D)	1.2188	1.9301	0.63	0.5278	-2.5665	5.0042	
Constant	0.0158	0.0002	103.77	0.0001	0.0155	0.0161	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4669	Number of obs	1922
F-test	209.3363	Prob > F	0.0000
Akaike crit. (AIC)	-15957.5755	Bayesian crit. (BIC)	-15907.5301

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

Similar to the first wave, herd behavior was not identified during the second wave of the pandemic, both in bull and bear markets. The Table 22 presents the results obtained using quantile regression.

Table 22: Results for the quantile regression for asymmetry in the second wave of COVID-19.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
10%	Up_Abs(Rm)(1-D)	0.1696	0.0207	8.18	0.0001	0.1290	0.2103	***
	Up_Abs(Rm)(D)	0.2464	0.0820	3.01	0.0027	0.0856	0.4072	***
	Down_Abs(Rm)(1-D)	0.1123	0.0162	6.95	0.0001	0.0806	0.1440	***
	Down_Abs(Rm)(D)	0.0030	0.0614	0.05	0.9613	-0.1175	0.1234	
	Up_Rm²(1-D)	2.3864	0.3950	6.04	0.0001	1.6116	3.1612	***
	Up_Rm²(D)	-2.1248	3.8913	-0.55	0.5851	-9.7564	5.5067	
	Down_Rm²(1-D)	0.6691	0.1402	4.77	0.0001	0.3941	0.9441	***
	Down_Rm²(D)	4.2720	1.9747	2.16	0.0306	0.3991	8.1449	**
	Constant	0.0125	0.0002	79.89	0.0001	0.0122	0.0128	***
25%	Up_Abs(Rm)(1-D)	0.1975	0.0198	9.98	0.0001	0.1587	0.2363	***
	Up_Abs(Rm)(D)	0.2706	0.0783	3.46	0.0006	0.1171	0.4241	***
	Down_Abs(Rm)(1-D)	0.1520	0.0154	9.85	0.0001	0.1217	0.1823	***
	Down_Abs(Rm)(D)	0.0777	0.0586	1.32	0.1854	-0.0373	0.1926	
	Up_Rm²(1-D)	2.0391	0.3771	5.41	0.0001	1.2996	2.7786	***
	Up_Rm²(D)	-1.5781	3.7141	-0.42	0.6710	-8.8622	5.7060	
	Down_Rm²(1-D)	0.3991	0.1338	2.98	0.0029	0.1366	0.6616	***
	Down_Rm²(D)	1.9915	1.8848	1.06	0.2908	-1.7051	5.6880	
	Constant	0.0137	0.0001	92.00	0.0001	0.0134	0.0140	***
50%	Up_Abs(Rm)(1-D)	0.2035	0.0212	9.59	0.0001	0.1619	0.2451	***
	Up_Abs(Rm)(D)	0.2132	0.0839	2.54	0.0111	0.0487	0.3777	**
	Down_Abs(Rm)(1-D)	0.1589	0.0165	9.61	0.0001	0.1265	0.1914	***
	Down_Abs(Rm)(D)	0.1048	0.0628	1.67	0.0957	-0.0185	0.2280	*
	Up_Rm²(1-D)	1.8894	0.4042	4.67	0.0001	1.0968	2.6821	***
	Up_Rm²(D)	-0.1066	3.9810	-0.03	0.9786	-7.9141	7.7009	
	Down_Rm²(1-D)	0.7669	0.1434	5.35	0.0001	0.4856	1.0482	***
	Down_Rm²(D)	1.3848	2.0203	0.69	0.4931	-2.5773	5.3470	
	Constant	0.0155	0.0002	97.09	0.0001	0.0152	0.0158	***
75%	Up_Abs(Rm)(1-D)	0.1753	0.0294	5.96	0.0001	0.1177	0.2330	***
	Up_Abs(Rm)(D)	0.3218	0.1162	2.77	0.0057	0.0939	0.5498	***
	Down_Abs(Rm)(1-D)	0.1644	0.0229	7.17	0.0001	0.1194	0.2093	***
	Down_Abs(Rm)(D)	0.1170	0.0871	1.34	0.1791	-0.0538	0.2878	
	Up_Rm²(1-D)	5.0224	0.5601	8.97	0.0001	3.9239	6.1208	***
	Up_Rm²(D)	-6.1325	5.5169	-1.11	0.2665	-16.9523	4.6873	
	Down_Rm²(1-D)	1.2066	0.1988	6.07	0.0001	0.8168	1.5965	***
	Down_Rm²(D)	0.1567	2.7997	0.06	0.9554	-5.3341	5.6476	
	Constant	0.0179	0.0002	80.57	0.0001	0.0174	0.0183	***
90%	Up_Abs(Rm)(1-D)	0.2809	0.0520	5.41	0.0001	0.1790	0.3828	***
	Up_Abs(Rm)(D)	0.0939	0.2054	0.46	0.6476	-0.3090	0.4968	
	Down_Abs(Rm)(1-D)	0.2595	0.0405	6.41	0.0001	0.1801	0.3389	***
	Down_Abs(Rm)(D)	0.0757	0.1539	0.49	0.6228	-0.2261	0.3776	
	Up_Rm²(1-D)	3.8802	0.9899	3.92	0.0001	1.9389	5.8215	***
	Up_Rm²(D)	6.2895	9.7502	0.65	0.5190	-12.8326	25.4117	
	Down_Rm²(1-D)	0.5403	0.3513	1.54	0.1242	-0.1487	1.2294	
	Down_Rm²(D)	1.9960	4.9480	0.40	0.6867	-7.7081	11.7002	
	Constant	0.0201	0.0004	51.31	0.0001	0.0193	0.0209	***
Mean dependent var			0.0184	SD dependent var		0.0052		

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Source: Elaborated by the author (2023).

In this case, the herding effect was not observed in any of the conditional quantiles. Table 23 presents the results for the third wave of COVID-19 using the OLS model.

Table 23: Results for the OLS regression for asymmetry in the third wave of COVID-19.

CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
Up_Abs(Rm)(1-D)	0.2393	0.0197	12.17	0.0001	0.2007	0.2778	***
Up_Abs(Rm)(D)	0.2227	0.1125	1.98	0.0480	0.0020	0.4434	**
Down_Abs(Rm)(1-D)	0.1830	0.0151	12.09	0.0001	0.1533	0.2127	***
Down_Abs(Rm)(D)	0.1913	0.0945	2.02	0.0430	0.0060	0.3766	**
Up_Rm²(1-D)	2.1274	0.3822	5.57	0.0001	1.3779	2.8770	***

Up_Rm²(D)	-0.8460	4.7788	-0.18	0.8595	-10.2183	8.5263	
Down_Rm²(1-D)	0.6253	0.1343	4.65	0.0001	0.3618	0.8887	***
Down_Rm²(D)	0.3768	3.2763	0.11	0.9085	-6.0487	6.8022	
Constant	0.0159	0.0002	105.55	0.0001	0.0156	0.0162	***

Mean dependent var	0.0184	SD dependent var	0.0052
R-squared	0.4313	Number of obs	1922
F-test	181.3546	Prob > F	0.0000
Akaike crit. (AIC)	-15842.3339	Bayesian crit. (BIC)	-15792.2838

*** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

As with the first and second waves using OLS, herd behavior was also not observed in asymmetric conditions during the third wave of the pandemic. Finally, Table 24 displays the results obtained by quantile regression.

Like in the period of the second wave, the herd effect was not detected in any of the conditional quantiles for both the bull and bear markets during the third wave of the pandemic.

Table 24: Results for the quantile regression for asymmetry in the third wave of COVID-19.

Quantile	CSAD	Coef.	St. Err.	t-value	p-value	[95% Conf.	interval]	Sig
10%	Up_Abs(Rm)(1-D)	0.1630	0.0197	8.26	0.0001	0.1243	0.2017	***
	Up_Abs(Rm)(D)	0.2965	0.1129	2.63	0.0087	0.0750	0.5180	***
	Down_Abs(Rm)(1-D)	0.0954	0.0152	6.28	0.0001	0.0656	0.1252	***
	Down_Abs(Rm)(D)	0.1584	0.0948	1.67	0.0949	-0.0275	0.3444	*
	Up_Rm²(1-D)	2.4517	0.3836	6.39	0.0001	1.6995	3.2039	***
	Up_Rm²(D)	-0.8799	4.7959	-0.18	0.8545	-10.2857	8.5260	
	Down_Rm²(1-D)	0.7656	0.1348	5.68	0.0001	0.5012	1.0300	***
	Down_Rm²(D)	2.7926	3.2880	0.85	0.3958	-3.6559	9.2410	
	Constant	0.0125	0.0002	82.92	0.0001	0.0122	0.0128	***
25%	Up_Abs(Rm)(1-D)	0.1981	0.0184	10.77	0.0001	0.1621	0.2342	***
	Up_Abs(Rm)(D)	0.2851	0.1053	2.71	0.0068	0.0787	0.4916	***
	Down_Abs(Rm)(1-D)	0.1401	0.0142	9.89	0.0001	0.1123	0.1679	***
	Down_Abs(Rm)(D)	0.2043	0.0884	2.31	0.0209	0.0309	0.3776	**
	Up_Rm²(1-D)	2.0330	0.3575	5.69	0.0001	1.3319	2.7342	***
	Up_Rm²(D)	-1.4859	4.4705	-0.33	0.7396	-10.2535	7.2817	
	Down_Rm²(1-D)	0.5546	0.1257	4.41	0.0001	0.3081	0.8011	***
	Down_Rm²(D)	0.7958	3.0649	0.26	0.7952	-5.2151	6.8067	
	Constant	0.0137	0.0001	97.50	0.0001	0.0134	0.0140	***
50%	Up_Abs(Rm)(1-D)	0.2015	0.0198	10.15	0.0001	0.1626	0.2404	***
	Up_Abs(Rm)(D)	0.2212	0.1136	1.95	0.0516	-0.0015	0.4439	*
	Down_Abs(Rm)(1-D)	0.1354	0.0153	8.86	0.0001	0.1055	0.1654	***
	Down_Abs(Rm)(D)	0.3413	0.0954	3.58	0.0004	0.1543	0.5283	***
	Up_Rm²(1-D)	1.9147	0.3857	4.96	0.0001	1.1583	2.6712	***
	Up_Rm²(D)	-1.1087	4.8229	-0.23	0.8182	-10.5674	8.3500	
	Down_Rm²(1-D)	0.9484	0.1356	7.00	0.0001	0.6825	1.2143	***
	Down_Rm²(D)	-3.6473	3.3065	-1.10	0.2701	-10.132	2.8374	
	Constant	0.0155	0.0002	102.35	0.0001	0.0152	0.0158	***
75%	Up_Abs(Rm)(1-D)	0.1734	0.0292	5.94	0.0001	0.1161	0.2307	***
	Up_Abs(Rm)(D)	0.1134	0.1671	0.68	0.4974	-0.2143	0.4411	
	Down_Abs(Rm)(1-D)	0.1553	0.0225	6.91	0.0001	0.1112	0.1994	***
	Down_Abs(Rm)(D)	0.1481	0.1403	1.06	0.2912	-0.1270	0.4232	
	Up_Rm²(1-D)	5.0494	0.5675	8.90	0.0001	3.9365	6.1623	***
	Up_Rm²(D)	2.8073	7.0955	0.40	0.6924	-11.1084	16.7229	
	Down_Rm²(1-D)	1.2616	0.1995	6.33	0.0001	0.8705	1.6528	***
	Down_Rm²(D)	1.5994	4.8645	0.33	0.7424	-7.9409	11.1397	
	Constant	0.0179	0.0002	79.96	0.0001	0.0174	0.0183	***
90%	Up_Abs(Rm)(1-D)	0.2558	0.0490	5.22	0.0001	0.1598	0.3518	***
	Up_Abs(Rm)(D)	0.1030	0.2802	0.37	0.7132	-0.4465	0.6525	
	Down_Abs(Rm)(1-D)	0.2548	0.0377	6.76	0.0001	0.1809	0.3288	***
	Down_Abs(Rm)(D)	0.0504	0.2353	0.21	0.8304	-0.4110	0.5118	

Up_Rm²(1-D)	4.3098	0.9516	4.53	0.0001	2.4435	6.1761	***
Up_Rm²(D)	1.0022	11.8991	0.08	0.9329	-22.3344	24.3388	
Down_Rm²(1-D)	0.5699	0.3345	1.70	0.0886	-0.0861	1.2259	*
Down_Rm²(D)	2.6680	8.1578	0.33	0.7437	-13.3311	18.6671	
Constant	0.0201	0.0004	53.57	0.0001	0.0193	0.0208	***

Mean dependent var	0.0184	SD dependent var	0.0052

**** p<0.01, ** p<0.05, * p<0.10*

Source: Elaborated by the author (2023).

It is important to note that the results indicate that there were more pronounced asymmetric effects in the first 100 days of the pandemic, extending to the first wave as shown in Tables 17, 18 and 20.

The analysis reveals a tendency for a herd effect in the bull markets in regions where CSAD has higher values. This finding was observed by analyzing the conditional quantiles of the return dispersion distribution.

It is worth mentioning that this asymmetry is not identified in the second and third waves of the pandemic. This implies that the herd effect may vary over different stages of the pandemic, with the most significant impact observed in the early stages.

5 DISCUSSION

When examining the entire period from January 2016 to September 2023, the results from Table 5 did not indicate any evidence of herding behavior. This initial analysis did not differentiate any specific periods during the pandemic. This observation implies that, even in the face of the inherent volatility of the stock market, where prices reflect the expectations and strategies of individual investors, it can be inferred that the Brazilian market demonstrates a certain level of rationality when considering a longer time frame.

In Tables 7 and 8, no signs of herding behavior were detected during the pre-pandemic period. The purpose of this analysis was to investigate whether there were any indications of herding behavior prior to the first recorded COVID-19 case in Brazil. The results of this study differ from those obtained by Signorelli, Camilo-da-Silva and Barbedo (2021), who identified herding behavior in 2018. This disparity could be partly attributed to the fact that these authors conducted yearly estimations and the selected sample itself may have had an influence on the outcomes.

What is noteworthy is that, despite being classified as an emerging economy, Brazil demonstrated a behavior similar to that of economies such as the US, UK, Germany, Australia, and other European countries, where herding behavior usually is not observed during periods without crises (Henker; Henker; Mitsios, 2006; Economou *et al.*, 2015; Economou; Hassapis; Philippas, 2018; Gavrilakis; Floros, 2023). This stands in contrast to economies like China, which exhibited this behavior even in the absence of market abnormalities (Tan *et al.*, 2008; Fei; Zhang, 2023).

5.1 The herd effect during pandemic

When the periods corresponding to the stages of the pandemic are segmented, herd behavior is observed to be more pronounced in the first 100 trading days after the first case was registered in Brazil until the end of the first wave of the pandemic, which confirms **H1**.

This suggests that during the initial outbreak of the pandemic, investors experienced a heightened sense of panic, leading to a collective behavior known as herd behavior. This phenomenon is clearly depicted in Figure 1, which shows a significant drop in the stock market. However, as time passed, the market seemed to have absorbed these impacts, and investors gradually returned to making independent decisions based on their own beliefs.

These findings are consistent with the research conducted by Nguyen, Bakry, Vuong, (2023), who also observed the herd effect during the pandemic. However, their study revealed that this behavior was minimized when analyzing the fourth wave of COVID-19 in the Vietnamese stock market.

There is a discussion about the Efficient Market Hypothesis (EMH), which suggests that markets, despite showing evidence of efficiency, may experience periods of inefficiency, known as the Adaptive Market Hypothesis (AMH). According to AMH, markets can be efficient during certain periods and inefficient in others, which aligns with behavioral finance theories (Lo, 2004; Lim; Brooks, 2011).

In the case of Brazil, it appears to exhibit behavior in line with the AMH. When taking a longer-term perspective, as presented in Table 5, the presence of herd behavior is not observed. However, if the analysis is narrowed to extreme periods, like the initial stages of the pandemic, the herd behavior is manifested.

The utilization of quantile regression in this study has provided additional insights by capturing information across the entire distribution of CSAD. The results demonstrate that herd behavior is not limited to the mean of the distribution, but also extends to the tails, indicating its presence across different levels of market performance.

5.2 The herd effect under asymmetric conditions during the pandemic

Tests conducted under asymmetric conditions can provide valuable insights into the emotional state of investors. These tests can help determine whether investors are experiencing extreme feelings of euphoria or fear.

The market volatility tends to increase significantly during times of crisis (Humayun; Shakur, 2018). As a result, investors often exhibit a behavior of rapidly accumulating assets when the market is bullish and divesting them when the market is bearish. This behavior can have significant implications for investment strategies and decision-making processes.

Based on the results from Tables 17, 18, and 20 of this research, it is observed that herd behavior is present in both bullish and bearish markets during the COVID-19 pandemic. In bullish markets there is a distinct tendency towards herd behavior, particularly until the end of the first wave of the pandemic, which confirms **H2**.

This behavior indicates that investors might be deliberately emulating others in an effort to enhance their profits. However, it is important to note that there is no evidence suggesting an asymmetry condition during the period of the second and third waves.

In the study conducted by Mishra P. and Mishra S. (2023), the authors propose an interesting perspective on the herd effect in bull markets. They argue that highlighting this phenomenon could have a beneficial impact by gradually raising investors' expectations. As a result, a sense of overall optimism would be fostered in the market, ultimately contributing to its recovery. It is worth noting that the lack of identification of the asymmetry condition in the second and third waves imply that investors were not influenced by collective behavior and instead remained unwavering in their own convictions.

Almeida, Costa, and Costa Jr. (2012) conducted a study on the Brazilian stock market from 2000 to 2010, which included the period of the subprime crisis. In this case, the authors found no evidence of asymmetry. This finding is aligned with the research conducted by Chiang and Zheng (2010), who also did not observe any asymmetric behavior in Brazil from 1988 to 2009.

However, herd behavior under asymmetric conditions has been identified in international markets in various other studies (Pochea; Filip; Pece, 2017; Choi; Yoon, 2020; Espinosa-Méndez; Arias, 2021; Ampofo *et al.*, 2023; Nouri-Goushki; Hojaji, 2023).

6 CONCLUSION

This study empirically examined the presence of herd behavior in Brazil during the first 100 days of the COVID-19 pandemic, extending to th first, second, and third waves. The model used was the CSAD proposed by Chang, Cheng, and Khorana (2000), which calculates the dispersion of individual asset returns relative to the market return. The models were estimated using OLS and quantile regression to analyze the entire distribution of return dispersion.

The findings of this study indicate that, despite market fluctuations, investors in the Brazilian stock market may observe herd behavior more frequently in extreme market situations, unlike other countries where herd behavior is even observed in stable scenarios.

Herd behavior was detected during the first 100 days of the pandemic and persisted until the first wave. In the second and third waves, herd behavior is no longer evident. It appears that the pandemic outbreak brought uncertainty to the market, initially causing panic among investors which driven them to herding behavior.

Over time, the market seems to have absorbed these impacts, and investors have returned to making decisions based on their own beliefs. It is noteworthy that, despite being considered an emerging economy, Brazil exhibited similar behavior to economies such as the US, UK, Germany, Australia, and other European countries where herd behavior is usually not observed in crisis-free periods.

Therefore, based on the analysis, it can be inferred that the Brazilian stock market exhibits rational behavior over a sustained period. However, it is crucial for investors who are active in the Brazilian stock market to remain cautious of the potential emergence of herd behavior in response to external disruptions or crises. This means that during times of market turbulence or economic downturns, there is a higher likelihood of investors following the actions and decisions of the majority, rather than relying solely on their own independent analysis and judgment.

As far as traditional finance is concerned, investors behave rationally. However, during times of crisis, various biases may affect the decision-making process and trading in financial markets. Behavioral finance uses a set of theories that focus on the irrationality of investors who may not act based on their own information or may disregard their own beliefs. In this way, regulatory bodies have the responsibility to provide transparent and accurate information to ensure that these investors have access to relevant data and are not solely influenced by the behavior of the majority.

Regarding asymmetric conditions, herd behavior was detected in both bullish and bearish markets during the COVID-19 pandemic, with a slight tendency towards bullish markets until the end of the first wave. This behavior may indicate that investors intend to follow others in an attempt to increase their gains.

The use of quantile regression enriched the analysis as it allowed for the observation of more points in the distribution. In the case of the asymmetry test during the first wave of the pandemic, the OLS model did not detect herd behavior. However, the model estimated by quantile regression did evidence this behavior for one of the upper quantiles of the distribution, which highlights the importance of using this method in future research.

It is important to note that this study focused solely on detecting the presence of herd behavior without considering the possible causes for this phenomenon. Therefore, future research could incorporate other variables into the regression model to seek explanations for this behavior, such as macroeconomic issues, government interventions, an increase in the number of cases, and news related to the pandemic that might affect the market.

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APPENDIX – SELECTED COMPANIES FOR THE SAMPLE

The following 144 companies from the B3 were selected:

#	Ticker	Company name
1	TELB4	Telecomunicações Brasileiras SA - Telebras
2	SCAR3	São Carlos Empreendimentos e Participações SA
3	VSTE3	Veste SA Estilo
4	RCSL4	Recrusul SA
5	VULC3	Vulcabras SA
6	PDTC3	Padtec Holding SA
7	FRAS3	Fras Le SA
8	LUPA3	Lupatech S/A
9	EUCA4	Eucatex SA Industria e Comercio
10	LPSB3	LPS Brasil Consultoria de Imóveis SA
11	PINE4	Banco Pine SA
12	ATMP3	ATMA Participações SA
13	CGRA4	Grazziotin SA
14	TECN3	Technos SA
15	COCE5	Companhia Energética do Ceará
16	SLED4	Saraiva Livreiros SA
17	RNEW1	Renova Energia SA
18	RAPT4	Randon SA Implementos e Participações
19	PRIO3	Prio SA
20	NEXP3	Nexpe Participações SA
21	TASA4	Taurus Armas SA
22	GUAR3	Guararapes Confecções SA
23	VIVR3	Viver Incorporadora e Construtora SA
24	AMAR3	Marisa Lojas SA
25	AESB3	AES Brasil Energia SA
26	UCAS3	Unicasa Industria de Móveis S/A
27	ALPA4	Alpargatas SA
28	BRAP4	Bradespar SA
29	CPFE3	CPFL Energia SA
30	GGBR4	Gerdau SA
31	ATOM3	Atom Empreendimentos e Participações SA
32	LOGN3	Log-in Logística Intermodal SA
33	MYPK3	Iochpe Maxion SA
34	SGPS3	Springs Global Participações S A
35	VIVT3	Telefônica Brasil SA
36	WEGE3	WEG SA
37	MILS3	Mills Locação Serviços e Logística SA
38	APER3	Alper Consultoria e Corretora de Seguros SA
39	ARZZ3	Arezzo Industria e Comercio SA
40	ALSO3	Aliansce Sonae Shopping Centers SA

41	ENAT3	Enauta Participações SA
42	MEAL3	International Meal Company Alimentação SA
43	SHOW3	T4F Entretenimento SA
44	MGLU3	Magazine Luiza SA
45	QUAL3	Qualicorp Consultoria e Corretora de Seguros SA
46	OIBR4	Oi SA
47	SQIA3	Sinqia SA
48	ALUP1	Alupar Investimento SA
49	BBSE3	BB Seguridade Participações SA
50	ANIM3	Anima Holding SA
51	SEER3	Ser Educacional SA
52	ABEV3	Ambev SA
53	CVCB3	CVC Brasil Operadora e Agência de Viagens SA
54	RAIL3	Rumo SA
55	WIZC3	Wiz Co Participações e Corretagem de Seguros SA
56	ABCB4	Banco ABC Brasil SA
57	VLID3	Valid Soluções SA
58	AGRO3	Brasilagro Cia Bras Propriedades Agricolas
59	BBAS3	Banco do Brasil SA
60	BBDC4	Banco Bradesco SA
61	BEEF3	Minerva SA
62	BPAN4	Banco Pan SA
63	BRKM5	Braskem SA
64	BRPR3	BR Properties SA
65	BRSR6	Banco do Estado do Rio Grande do Sul SA
66	AMER3	Americanas SA
67	CSUD3	CSU Digital SA
68	CCRO3	CCR SA
69	CMIG4	Cia Energética Minas Gerais SA
70	CPLE6	Companhia Paranaense de Energia
71	CSAN3	Cosan SA
72	CSMG3	Companhia de Saneamento de Minas Gerais COPASA MG
73	CSNA3	Companhia Siderurgica Nacional SA
74	CYRE3	Cyrela SA Empreendimentos e Participações
75	RADL3	Raia Drogasil S/A
76	ELET6	Centrais Eletricas Brasileiras SA
77	EMBR3	Embraer SA
78	EQTL3	Equatorial Energia SA
79	YDUQ3	YDUQS Participações SA
80	ETER3	Eternit SA
81	EVEN3	Even Construtora e Incorporadora S/A
82	EZTC3	EZ TEC Empreendimentos e Participações SA
83	FESA4	Companhia de Ferro Ligas da Bahia Ferbasa
84	FHER3	Fertilizantes Heringer SA
85	GFSA3	Gafisa SA
86	GOAU4	Metalúrgica Gerdau SA

87	GOLL4	Gol Linhas Aéreas Inteligentes SA
88	GRND3	Grendene SA
89	HBOR3	Helbor Empreendimentos SA
90	HYPE3	Hypera SA
91	ITUB4	Itaú Unibanco Holding SA
92	ITSA4	Itausa SA
93	JBSS3	JBS SA
94	JHSF3	JHS F Participações SA
95	KEPL3	Kepler Weber SA
96	KLBN4	Klabin SA
97	COGN3	Cogna Educação SA
98	LEVE3	MAHLE Metal Leve SA
99	LIGT3	Light SA
100	LREN3	Lojas Renner SA
101	MDIA3	M Dias Branco SA Industria e Comercio de Alimentos
102	MRFG3	Marfrig Global Foods SA
103	ENEV3	Eneva SA
104	MRVE3	MRV Engenharia e Participações SA
105	MULT3	Multiplan Empreendimentos Imobiliários SA
106	NTCO3	Natura & Co Holding SA
107	ODPV3	Odontoprev SA
108	PDGR3	PDG Realty SA Empreendimentos e Participações
109	PETR4	Petroleo Brasileiro SA Petrobras
110	PFRM3	Profarma Distribuidora de Produtos Farmacêuticos SA
111	PMAM3	Paranapanema SA
112	POMO4	Marcopolo SA
113	POSI3	Positivo Tecnologia SA
114	PSSA3	Porto Seguro SA
115	RENT3	Localiza Rent a Car SA
116	ROMI3	Romi SA
117	RSID3	Rossi Residencial SA
118	SANB4	Banco Santander Brasil SA
119	SAPR4	Companhia de Saneamento do Paraná Sanepar
120	DXCO3	Dexco SA
121	SBSP3	Companhia de Saneamento Básico do Estado de São Paulo
122	SHUL4	Schulz SA
123	SLCE3	SLC Agrícola SA
124	SMTO3	São Martinho SA
125	EGIE3	ENGIE Brasil Energia SA
126	TCSA3	Tecnisa SA
127	TIMS3	Tim SA
128	TGMA3	Tegma Gestão Logística SA
129	TOTS3	Totvs SA
130	TPIS3	TPI Triunfo Participações e Investimentos SA
131	TAEE1	Transmissora Aliança de Energia Elétrica S/A
132	TRPL4	CTEEP Companhia de Transmissão de Energia Elétrica Paulista

133	TUPY3	Tupy SA
134	UGPA3	Ultrapar Participações SA
135	UNIP6	Unipar Carbocloro SA
136	USIM5	Usinas Siderúrgicas de Minas Gerais SA USIMINAS
137	VALE3	Vale SA
138	B3SA3	B3 SA Brasil Bolsa Balcão
139	DIRR3	Direcional Engenharia SA
140	BRFS3	BRF SA
141	FLRY3	Fleury SA
142	CIEL3	CIELO SA Instituição de Pagamento
143	ECOR3	EcoRodovias Infraestrutura e Logística SA
144	SIMH3	Simpar SA