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Original Article

An analysis of the behavior of investors in the Brazilian future market between jan/2018 and aug/2024

Uma análise do comportamento dos investidores no mercado futuro brasileiro entre jan/2018 e ago/2024

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ABSTRACT

Objective: Investigate what were the changes in investor behavior in the Brazilian future market between Jan/2018 and Aug/2024.

Design/methodology/approach: The study investigates the behavior of investors' trading volume in three periods: pre-crisis (2018–2019), Covid-19 crisis (2020–2021) and post-crisis (2022–Aug/2024). For data analysis, multiple linear regression is used.

Results: The results indicate that the behavior of large investors remains unchanged, regardless of the economic scenario or changes in the flow of resources from other financial products, understanding that knowledge reduces the possibility of herd behavior. Small investors' trading volume is not influenced by large investors' trading volume or by fluctuations in financial products in the pre-COVID-19 period. However, since COVID-19, small investors' trading volume has followed large investors' trading volume, characterizing herd behavior. Therefore, there is a diverse response from small investors under different market conditions.

The research limitations/implication: Does not capture the motivations and/or subjective perceptions of investors.

Practical implications: Assists in the development of risk mitigation strategies that promote a more resilient market.

Social implications: By understanding changes in small investor behavior in different economic scenarios and different types of financial products risk mitigation strategies can be developed and a more resilient market can be promoted.

Originality/value: The analysis of financial behavior in different investment sizes, different economic scenarios, different financial assets and different financial markets.

Keywords: Herd effect; Covid-19; Investor category; Financial markets

RESUMO

Objetivo: Investigar quais foram as mudanças de comportamento dos investidores no mercado futuro brasileiro entre jan/2018 a ago/2024.
Desenho/metodologia/abordagem: O estudo investiga o comportamento do volume de negociação dos investidores em três períodos: pré-crise (2018–2019), crise da Covid-19 (2020–2021) e pós-crise (2022–ago/2024). Para a análise dos dados utiliza-se a regressão linear múltipla.
Resultados: Os resultados indicam que o comportamento dos grandes investidores não apresenta alteração, independente do cenário econômico ou mudanças no fluxo de recursos de outros produtos financeiros, entendendo que o conhecimento diminui a possibilidade de comportamento manada. O volume de negociação dos pequenos investidores não apresenta influência do volume de negociação dos grandes investidores ou das flutuações dos produtos financeiros no período pré Covid-19. Entretanto, a partir da Covid-19, o volume de negociação dos pequenos investidores segue o volume de negociação dos grandes investidores, caracterizando um comportamento manada. Portanto, existe uma resposta diversificada dos pequenos investidores em diferentes condições de mercado.
Limitações/implicações da pesquisa: Não captura as motivações e/ou percepções subjetivas dos investidores.
Implicações práticas: Auxilia no desenvolvimento de estratégias de mitigação de riscos que promovam um mercado mais resiliente.
Implicações sociais: Ao compreender as mudanças de comportamento dos pequenos investidores em diferentes cenários da economia e diferentes tipos de produtos financeiros pode desenvolver estratégias de mitigação de riscos e promover um mercado mais resiliente.
Originalidade/valor: A análise do comportamento financeiro em diferentes tamanhos de investimento, diferentes cenários econômicos, diferentes ativos financeiros e diferentes mercados financeiros.

Palavras-chave: Efeito manada; Covid-19; Categoria dos investidores; Mercados financeiros

1 INTRODUCTION

The Covid-19 pandemic, which has spread around the world since 2020, has had severe and unexpected impacts on the global economy and, thus, on the financial market. In Brazil, the first confirmed case of Covid-19 was recorded in February 2020, followed by the official decree of the pandemic by the World Health Organization (WHO) in March of the same year (Courel, 2023).

Scenarios like these demonstrate how a crisis and uncertainty situation influences investor behavior, since events affect their emotions and psychological state, challenging Modern Finance Theory, which is based on the assumption of efficient markets and rational investors (Fama, 1970).

Pioneering studies by Tversky and Kahneman (1974) introduced the importance of heuristics and cognitive biases in financial decisions, leading to the development of Behavioral Finance. One of the main heuristics studied by behavioral finance is the herd effect, a behavioral bias that leads investors to trade the same asset in the same direction as the market, ignoring their information and beliefs about the asset's price, which can lead to decision errors (Silva et al., 2015).

Herd behavior is often observed when the market is experiencing financial turbulence, making market volatility and the flow of information difficult to analyze and predict. As a result, investors follow the market consensus, since this behavior seems to be the most efficient solution (Christie & Huang, 1995).

Both national and international literature have identified studies on herd behavior during Covid-19. Bouri et al. (2021) used a financial uncertainty index, based on newspapers associated with infectious diseases, to analyze the association between uncertainty arising from the pandemic and directional similarity in 49 global stock markets between 2019 and 2020. The authors concluded that herd behavior is a short-lived phenomenon, appearing alternately, and that such behavior is due to the instantaneous and dynamic behavior of investors. Ukpong et al. (2021) analyzed 10 US market sectors (1999-2020) and concluded that in the period of high volatility there is no evidence of the herd effect; however, when the scenario presents low volatility, the herd effect appears in some industries. Aslam et al. (2022) analyzed changes in herd behavior in 2020 (quarterly data) in six stock markets in Asia and Europe and concluded that European investors are more likely to exhibit herd behavior, as high volumes of selling generated by investor panic were recorded. Yang and Chuang (2023) concluded that, during the pandemic (2020), the herd effect was mild in Taiwan, the USA and China due to the fight against the herd effect. Courel (2023) analyzed the Brazilian stock market during Covid-19 (2020-2021) and concluded that the herd effect occurs in less volatile segments, while more volatile segments show divergent behavior.

In addition to research on herd behavior during Covid-19, there is research on herd behavior according to the type of investor. Liu et al. (2023) analyzed the behavior of institutional and individual investors in China between 2014 and 2016 and concluded that more informed investors are less prone to the herd effect; however, the difference between the two groups narrows when the market collapses and uncertainty increases.

As can be observed, research has presented different approaches when analyzing herd behavior, varying according to the period of analysis, the periodicity of the data, the market under study, the group of investors, among other factors. Other ways of analyzing herd behavior open up space for new research.

Therefore, this work seeks to answer the following research problem: What were the changes in investor behavior in the Brazilian futures market between January 2018 and August 2024?

The pandemic scenario is infrequent, and no studies have been identified on the impact of the health crisis on the financial behavior of investors in the Brazilian futures market. This study contributes by providing insights that can be used to develop risk mitigation strategies and foster a more resilient market.

Since the herd effect is not a directly observable variable, it is difficult for researchers to measure it. Studies using several statistical methods can be found in the literature. Some of these studies use the Cross-Sectional Standard Deviation of Returns (CSSD), by Christie and Huang (1995), which measures the average proximity of asset returns to the market average. Other studies use the Cross-Sectional Absolute Deviation of Returns (CSAD), by Chang et al. (2000), whose method indicates that in efficient markets a linear relationship is expected between the dispersion of returns and market returns under normal conditions; however, when there is a herd effect, there is a non-linear relationship. Other studies have also used the CSSD variant proposed by Hwang and Salmon (2001), where the authors use the perception of risk-return, measured by the beta of the Capital Asset Pricing Model (CAPM), to identify the bias of investors following the market.

As can be seen, there are several techniques for trying to measure the herd effect and the different techniques can provide different results, even though the methods are similar. Signorelli et al. (2021) investigated the existence of the herd effect in the Brazilian stock market using the CSAD and CSSD. The CSAD method indicates the presence of the herd effect from 2009 to 2015 and in 2018. The CSSD method does not identify the herd effect.

Furthermore, the methods focus on the changes that occur in asset prices. Seeking new statistical techniques, this paper analyzes the herd effect using the multiple linear regression method to capture the influence of the trading volume of large investors on the trading volume of small investors.

This paper is divided into six sections, beginning with the introduction. The theoretical background is presented below. The research methodology is described below. Next, the changes in investors' focus during the Covid-19 crisis and post-crisis period are also presented. The data is then analyzed and the final considerations are made.

2 THEORETICAL REFERENCE

The field of Behavioral Finance seeks to explain the cognitive and psychological factors that explain investors' forecasting errors, as well as analyzing their impact on investment performance results (Antony, 2019). When analyzing the psychological aspects linked to investor behavior, an attempt is made to identify other factors that influence their decisions, but which are not related to economic aspects (Lucena et al., 2013).

The literature on the topic indicates that one of the mistakes investors make is mentally simplifying their decision-making to reduce complex evaluation tasks (Costa, 2017). This simplification is due to several factors, including the investor's limited ability to process all the information and the cost of identifying the best decision (Yoshinaga & Ramalho, 2014). By simplifying the decision-making process, investors can be misled. When error occurs systematically and predictably in a given scenario, it can lead to systematic anomalies in the financial market (Baker & Ricciardi, 2015). Some adverse effects of investor behavior that determine irrational decision-making are the heuristics of representativeness, overconfidence, anchoring, availability, loss aversion and the herd effect (Tversky & Kahneman, 1974).

The representativeness heuristic occurs when an investor tends to categorize an event as typical of a class, overestimating its importance when making a probability estimate, disregarding the evidence (Tversky & Kahneman, 1974). Mokoteli et al. (2006) checked whether investment analysts are prone to behavioral bias when making their stock projections and recommendations and concluded that doubts arise about the credibility and objectivity of recommendations to buy, sell or hold stocks, given the number of subjective and poorly standardized variables, as well as excessive optimism within the context in which these recommendations are made. Carvalho (2023) believes that analyzing the characteristics of the report issued by the investment analyst is necessary, since investment analysts have to address conflicts of interest, such as pressure from the contracting company to demand optimistic recommendations to please clients, the remuneration they receive according to the work they do, among others.

Aldrighi and Milanez (2005) add that the representativeness heuristic leads to an incorrect assessment of future events when analyzing information from past situations. This occurs in the financial market when the investor analyzes the price behavior of a share in the past without analyzing the financial performance of the company itself, i.e. they do not analyze all the data available to make the decision (Bazerman & Moore, 2010).

The overconfidence heuristic induces investors to feel very secure in their actions, given the analysis of accessible information that indicates that their decision will bring positive results (Waweru et al., 2008; Abdin et al., 2017). This bias may be an explanatory factor for the fact that investment analysts believe they have a superior perception of investments (Mokoteli et al., 2006). Moreover, overconfidence can be intensified by the experience and/or performance of the investment analyst, by the interests of the company in which the investment analyst provides services and by the investment analyst's own interests (Carvalho, 2023). However, this over-optimism can lead both the investment analyst and the investor to underestimate the risks, as they fail to see the contrary information (Waweru et al., 2008; Abdin et al., 2017).

The anchoring heuristic occurs when the investor is indecisive and is influenced by initial information generated by analysts, neglecting the up-to-date information around them, making systematic errors in decision-making (Tversky & Kahneman, 1974; Silva, 2010). Anchoring bias can limit the flexibility and adaptability of projections at a time of change, ignoring the reliability of the information, hindering the investor's ability to respond effectively to new challenges. One example is buying a share based on the target price. For the investor, it is difficult to sell the share at a lower price than was paid (Ferreira et al., 2024), ignoring the moment of change.

The availability heuristic consists of deciding using information or events from the past. This partly explains why investors prefer companies that are known and recommended by financial investors, as they believe they have less chance of making mistakes, given past events (Lobão, 2015). However, the analysis of past data can lead to errors in the decision-making process, due to the analysis of information that is often of little relevance in assessing the probability of the future event, unduly influencing the result (Moraes & Tabak, 2018). Ferreira et al. (2024) states that the investor's most recent memory influences their decision-making process. For example, when bad news about a company is released, it leads investors to not analyze the company, preferring not to buy the stock (Ferreira et al., 2024).

The loss aversion heuristic interprets gains and losses differently, generating fear of loss and accepting any gain, even if that gain is smaller than it should be (Tversky & Kahneman, 1974). The psychological effect of loss is greater than the psychological effect of gain (Costa, 2025). According to Merkle (2020), anticipating a potential loss has a greater effect on aversion than in a situation actually experienced.

Analyzing the ability of investors in a UK bank to cope with financial losses between 2008 and 2010, Merkle (2020) concludes that investors are twice as sensitive to negative expected returns compared to positive expected returns. However, when analyzing the returns obtained, the effect decreases by more than half.

The loss aversion heuristic occurs on the stock market. When the Ibovespa is on the rise, investors take more risks, given the feeling of gain. However, when the Ibovespa falls, the investor exits their position so as not to incur the risk of loss, seeking a certain gain (Melo et al. 2018).

According to Liang (2017), the herd effect heuristic occurs when investors follow the actions of many others, without considering their own analysis or information. According to Medeiros et al. (2024), Covid-19 can generate a herd effect, since the lack of knowledge and future unpredictability generate panic, especially among investors who have little knowledge of the stock market, promoting the sale of securities with the aim of losing as little as possible of the amount invested.

Hwang and Salmon (2001) and Christie and Huang (1995) understand that the herd effect can be caused by both fear and greed, resulting in price fluctuations that are not justified by economic fundamentals and can generate speculative bubbles or liquidity crises (Blasco et al. 2011). Araújo et al. (2015) show that investors often compare their performance to that of the market, and this can motivate them to adopt herd behavior, especially if they perceive that others are succeeding with certain strategies.

Bikhchandani and Sharma (2001) identify two patterns in the herd effect. The first pattern occurs when the investor does this out of difficulty in making their own decisions, resulting in similar choices due to a lack of clear options. Nofsinger and Sias (1999) state that less qualified investors prefer to follow successful investors, as they understand that they will incur greater costs by using their own information and knowledge.

The second pattern identified by Bikhchandani and Sharma (2001) occurs when the investor consciously chooses to follow others. According to the authors, there are three reasons why investors may intentionally follow the herd: the search for security in following the majority, the pressure to conform to what is common and the belief that the majority can know more than the individual alone. Thus, when an investor decides to buy an asset simply because other investors are doing so, it constitutes a herd bias (Ferreira et al., 2024). The investor's thinking is that there is likely to be a good reason for the majority to do what they are doing (Tversky & Kahneman, 1974).

Puckett and Yan (2010), Araújo et al. (2015) and Bikhchandani and Sharma (2001) agree that informational asymmetry fosters the herd effect. Hwang and Salmon (2001) argue that, in certain situations, following the herd can be considered rational. If an investor believes that others have more information, it may make sense to follow these leaders to avoid lower returns, using imitation as a strategy to compensate for the lack of information.

The specialized media can also provoke exaggerated reactions to market events, encouraging investors to act irrationally in response to the news (Tetlock, 2007; Rogers et al., 2016; Galdi & Gonçalves, 2018). Silva and Lucena (2019) analyzed the effects of news during the 2008 crisis and concluded that there is a positive relationship between the presence of the herd effect, the crisis period and good news, i.e. positive reports can generate excessive optimism in investors, causing a bias in their behavior since they consider it to be the best investment option. However, the news may not be the best source of information, as companies may try to influence the market with this resource (Silva & Lucena, 2019).

In summary, as a result of the constant changes in the financial market, the investor's decision-making process is influenced by heuristics, which are ways of addressing the excessive amount of information, the shortage of time to analyze the information and the investor's capacity for analysis.

3 METHODOLOGY

The period of analysis runs from January 2018 to August 2024. The period was chosen due to the Covid-19 pandemic and the availability of the historical series of the volume traded on the futures market on the B3 website (2025d, 2025e).

The sample covers all economically active Brazilians who have accounts registered with financial institutions and invest in savings, investment funds and/or the futures market. Therefore, the sample involves different levels of education and social class, as well as the three investor profiles: conservative, moderate and bold.

According to the seventh edition of Raio X do Investidor Brasileiro (Brazilian Investor's X-Ray), published by the Brazilian Financial and Capital Markets Association (ANBIMA, 2024a), 37% of the Brazilian population has some financial investment, 25% of which is in savings, 4.4% in investment funds, 2.5% in shares and 5.1% in other financial assets. The financial products in the model were selected based on this information, namely savings, investment funds and the futures market.

Savings are the oldest form of fixed-income investment, providing security and simplicity because their return is fixed by law. It is mainly popular with the lower income bracket (Azevedo & Azevedo, 2018).

Investment funds are a way for investors to invest their funds together with other investors, as well as allowing to invest in various financial assets, such as stocks, debentures, government bonds, etc. (Brasil, 2025).

The futures market is an environment where futures contracts are traded. Futures contracts represent a commitment to buy and sell a commodity on a future date at a pre-defined price. It can be a commodity or a financial asset (B3, 2025a). The futures contract allows the market to trade future market expectations and is used for hedging purposes, speculation or leverage (B3, 2024b).

Aiming to analyze investor behavior, the financial volume of the standard Ibovespa futures contract and the financial volume of the Ibovespa mini futures contract were used. The mini futures contract accounts for 20% of the standard futures contract (B3, 2024c). It was created in 2001 and aims to provide individuals and small companies with the possibility of investing in the derivatives market with a minimum trading lot (B3, 2024c). There are mini contracts on different goods and financial assets, allowing small investors to develop investment strategies with different styles (B3, 2024c).

According to Medeiros and Doornik (2008), the financial volume reflects the interest and participation of investors in the market, indicating trends in trading and liquidity of assets, i.e. reflects the amount of relevant information that is perceived by the market. Given a change in investor expectations, there is a variation in market turnover (Medeiros & Doornik, 2008).

The model variables, their composition, calculation formula and data source are shown in Table 1.

Table 1 – Model variables

Variable	Composition	Calculation	Source
Savings	Composed of credit lines for real estate financing using savings and rural credit resources to finance agricultural activities (BCB, 2024a).	The monthly savings balance is the sum of the daily balances for the month. The daily balance is the difference between deposits and withdrawals.	The daily balance of savings deposits (R$ thousand) was obtained from the BCB (2024a).
Investment funds	Composed of fixed income, equities, multimarket, foreign exchange, pension, Exchange Traded Funds, Credit Rights Investment Funds and Equity Investment Funds (ANBIMA, 2024b).	This is the difference between investments and redemptions in investment funds.	The net funding of investment funds (R$ million) was obtained from ANBIMA (2024b).
Trading volume of small investors	Composed of the following segments: interest rates, currencies, commodities, shares and indices (B3, 2025a).	Ratio between the monthly financial volume of the Ibovespa mini futures contract and the number of monthly trading sessions.	Monthly financial volume of the Ibovespa mini futures contract (R$ thousand) was obtained from B3 (2024d). The number of monthly trading sessions was obtained from B3 (2024e).
Trading volume of large investors	Composed of the following segments: interest rates, currencies, commodities, shares and indices (B3, 2025a).	Ratio between the monthly financial volume of the standard Ibovespa futures contract and the number of monthly trading sessions.	Monthly financial volume of the standard Ibovespa futures contract (R$ thousand) was obtained from B3 (2024d). The number of monthly trading sessions was obtained from B3 (2024e).

Source: Research data

Model 1 proposed in this paper verifies whether savings, investment funds and the trading volume of large investors in the futures market influence the trading volume of small investors in the futures market. Equation 1 below shows the calculation formula.

$$VSI = \alpha_1 + \beta_1 * S + \beta_2 * IF + \beta_3 * VLI + \varepsilon_1 \qquad (1)$$

Model 2 checks whether savings and investment funds influence the trading volume of large investors on the futures market. Equation 2 shows the calculation formula.

$$VLI = \alpha_2 + \beta_4 * S + \beta_5 * IF + \varepsilon_2 \qquad (2)$$

Where α is the linear coefficient, VSI is the trading volume of small investors, S is savings, IF are investment funds, VLI is the trading volume of large investors, β is the angular coefficient of the explanatory variable and ε is the error term.

The heuristic to be analyzed in this work is the herd effect. According to Dzielinski (2011), investors behave in line with others in times of crisis, characterizing this herd behavior. However, Sanches (2013) believes that in a period of financial crisis, investors look for economic fundamentals to allocate resources in financial assets, not following the market and therefore reducing the herd effect. This work seeks to verify whether investor behavior in the futures market remains the same in different economic scenarios and whether this behavior can be classified as herd behavior.

Multiple linear regression was used to analyze the relationship between the variables, using the Ordinary Least Squares (OLS) estimation method and the stepwise procedure. For hypothesis testing, the p-value method is used to check whether the null hypothesis is rejected. All hypothesis tests are carried out with a 95% confidence level.

According to Fávero et al. (2009), in order to use the multiple regression technique, some assumptions must be met: a) check that the sample of residuals has a normal distribution (Shapiro-Wilk test); b) verify that there is no multicollinearity (Variance Inflation Factor - VIF statistic), where VIF values greater than 5 indicate the existence of multicollinearity; c) check for homoscedasticity (Breusch-Pagan test).

According to Fávero et al. (2009), in order to analyze the regression model, a number of evaluations are required: a) check that the regression model is statistically significant (F test); b) check whether the explanatory variables are statistically significant (Student's t-test); c) check the model's degree of explanation (R square); d) check the degree of correlation between the variables using Pearson's correlation coefficient (R).

To analyze the intensity of the correlation between the variables, we used the criteria established by Cohen (2013). According to this criterion, a small correlation is considered for a coefficient between 0.10 and 0.29, a medium correlation for a coefficient between 0.30 and 0.49, and a large correlation for a coefficient equal to or greater than 0.50.

The equation is analyzed at three periods: pre Covid-19 period (2018-2019), Covid-19 period (2020-2021) and post Covid-19 (2022-August 2024).

The next section analyzes the data collected, contextualizing it in the Brazilian macroeconomic scenario.

4 THE CHANGING FOCUS OF INVESTORS

According to Baldwin and Di Mauro (2020), the Covid-19 crisis has generated three economic shocks that have led to the disruption of the economy: a) a reduction in company productivity as a result of the absence of contaminated workers; b) the adoption of isolation measures by municipalities, which led to the temporary closure of some establishments; c) the shock to economic agents' expectations. The effects of the crisis were not homogeneous for economic agents, as will be seen below.

Between November and December 2020, ANBIMA surveyed 3,408 people over the age of 16, from Classes A, B and C, in the five regions of Brazil and estimates that this profile corresponds to 103.5 million inhabitants, with a margin of error of 2 percentage points, at a confidence level of 95.0%. According to the ANBIMA survey (2021), 45.0% of the population had a partial loss of income and 10.0% had a total loss of income, with class C having the greatest impact on income, as well as job losses. According to Lameiras et al. (2024), the unemployment rate was 15.0% in the 2nd half of 2020.

The ANBIMA survey (2021) indicated that, in 2020, 12.0% of the population withdrew money from financial investments or used emergency reserves in order to meet their financial commitments. Another part of the population (11.0%) used overdrafts, revolving credit cards or borrowed money. A smaller part of the population (5.0%) sold some goods.

Despite this scenario, the population continued to save money. Around 70.0% of Class A and 47.0% of Class B saved money in 2020 (ANBIMA, 2021). The money saved came from the reduction in spending caused by the lockdown. They had nowhere to spend the money, so they saved. Families have also stopped making unnecessary purchases, as well as controlling spending more and setting aside part of their salary (ANBIMA, 2021).

The main destination for the money saved was financial products (53.0%). Keeping the money invested would make it easier to use in an emergency situation (ANBIMA, 2021). According to data from the Central Bank of Brazil (BCB, 2024a), savings were positive from March 2020 to December 2020, with a monthly average of R$ 18.2 billion and an accumulated R$ 182.2 billion. There were three drivers for allocating the amount saved to financial products: return (38.0%), security/confidence (28.0%) and ease/comfort (21.0%) (ANBIMA, 2021).

Part of the funds were allocated to riskier financial products. One of the reasons that encouraged the migration to riskier financial products was the fall in interest rates. The Selic rate opened 2020 at 4.5% and closed at 2.0%, with an average annual rate of 2.8% (BCB, 2024b). As the Selic rate fell, funds migrated to financial products with more attractive returns. From March 2020 to May 2020, investment funds were negative by -R$ 34.9 billion, while from June 2020 to September 2020, they were positive by R$ 66.0 billion (ANBIMA, 2024b). Another factor that may explain this migration of resources is the increased knowledge of Brazilians regarding financial market products (ANBIMA, 2021).

The Brazilian stock market reacted with sharp falls. Seven and Yilmaz (2021) report that between 02/19/2020 and 03/23/2020, the Ibovespa dropped by almost 50%, triggering the Circuit Breaker, a protection mechanism against high market volatility. The sessions were interrupted and investors' buy and sell orders were rebalanced to protect the market from volatility. In all, there were seven circuit breakers in March 2020 (Courel, 2023).

At the end of 2020, the Brazilian futures market began to show signs of recovery. The volume traded on the futures market from January 2020 to September 2020 was R$ 761.0 billion, rising to R$ 55,341.0 billion in the period from October 2020 to November 2020 (B3, 2024d). At the beginning of 2021, despite the continuing economic and health adversities, there were two other peaks in the volume traded. In February the futures market volume reached R$ 35,193.8 billion and in April it reached R$ 57,051.6 billion, according to B3 (2024d). The introduction of economic stimulus measures, such as emergency aid, and the adaptation of companies to the new market conditions helped to initiate a partial recovery of stock indices (Courel, 2023).

In 2021, GDP grew by 4.8%, recovering from the -3.3% drop in 2020 (Agência Gov, 2023). The recovery that began in 2021 was mainly driven by mass vaccinations and the resumption of economic activity. However, the economic recovery has not been uniform across sectors (ANBIMA, 2021). The need for financing by non-financial companies was a record high (R$ 321.8 billion at current prices) and said increase was due to the rise in gross fixed capital formation (R$ 940.9 billion) (Agência Gov, 2023).

The IPCA increased from 4.52% in 2020 to 10.06% in 2021 (IBGE, 2024) and the Selic rate went from 2.0% in December 2020 to 9.25% in December 2021 (BCB, 2024b). Rising inflation and interest rates have imposed additional challenges for both companies and investors, especially in sectors such as consumer goods and services, which have found it more difficult to get back on their feet. Investors who focused on safer assets, such as fixed income, benefited from the rise in the Selic rate (ANBIMA, 2021). Investment funds rose from R$ 178.8 billion in 2020 to R$ 369.0 billion in 2021, accounting for an increase of 106.4% (ANBIMA, 2024b). On the other hand, savings went from R$ 166.3 billion in 2020 to -R$ 35.5 billion in 2021, a drop of -121.3% (BCB, 2024a).

In 2022, the war between Russia and Ukraine brought new obstacles to the financial market, boosting commodity prices and intensifying global inflationary pressure. According to Bastos and Leite (2024), world inflation went from 5.7% (October 2021) to 10.3% (October 2022) while the commodities index reached almost 230 points between June and September 2022. The increase in domestic inflation in 2021 led the Central Bank of Brazil to maintain a tight monetary policy between 2022 and 2023 (Pinheiro & Matos, 2023), which led to a drop in inflation from 10.06% in 2021 to 5.79% in 2022 and 4.62% in 2023 (IBGE, 2024). The Selic rate went from 9.25% in January 2022 to 13.75% in August 2022 and remained there until July 2023, when it began to fall (BCB, 2024b).

Another highlight was the election period in 2022, which caused investors to be more cautious. The political uncertainties surrounding the presidential elections, especially regarding possible changes in fiscal and economic policies, have increased the volatility of the fixed income and savings markets. In 2022, investment funds were negative by -R$ 129.2 billion (ANBIMA, 2024b) and savings were negative by -R$ 103.2 billion (BCB, 2024a).

In 2024, the Brazilian economy continued to show signs of recovery. The Selic rate stabilized at 10.75% from March 2024 to July 2024 (BCB, 2024b) and the annual inflation rate reached 4.83% (IBGE, 2024).

For investors, this period required a cautious approach, with a focus on portfolio diversification and the search for more resilient industries (Courel, 2023). Investors turned to investment funds. Investment funds, which showed negative results in 2022 (-R$ 129.2 billion) and 2023 (-R$ 107.2 billion), reversed the situation in 2024 (+R$ 286.2 billion up to August 2024), according to ANBIMA data (2024b). The volume traded on the futures market also increased, reaching R$ 23,867.3 billion in May 2024 B3 (2024d). Savings remained negative at -R$ 87.8 billion in 2023 and -R$ 4.1 billion in 2024, as a result of high interest rates (BCB, 2024a).

The next section presents the results of the simulations of the two models presented in the methodology section.

5 ASSESSMENT OF THE RESULTS

The simulations were carried out for three periods: pre Covid-19 period (2018-2019), during Covid-19 period (2020-2021) and post Covid-19 period (2022-August 2024) and the results are available in Tables 2, 3 and 4.

Table 2 – R, R square, F test and Breusch-Pagan test

Model	Period	R	R square	F-test p-value	Breusch-Pagan test p-value
Model 1	Pre Covid-19	0.262	0.069	0.691	0.393
Model 1	Covid-19	0.801	0.642	0.000	0.053
Model 1	Post Covid-19	0.980	0.961	0.000	0.867
Model 2	Pre Covid-19	0.081	0.007	0.933	0.920
Model 2	Covid-19	0.222	0.049	0.590	0.403
Model 2	Post Covid-19	0.290	0.084	0.280	0.280

Source: Research data

The regression model for the trading volume of large investors (Model 2) was not statistically significant in any of the periods analyzed (F-test p-value = 0.933, 0.590 and 0.280, Table 2), concluding that savings and investment funds did not influence the trading volume of large investors in the futures market in any economic scenario, regardless of whether there was a crisis or not. Therefore, although there was a migration of funds to savings, the large investors in the futures market did not show a herd effect. As Liu et al. (2023) observed, large investors have greater knowledge and are thus less prone to the herd effect, even when the market collapses and uncertainty increases.

Table 3 – Student's t-test and VIF

Model	Period	Coefficient	Standardized coefficient	Student's t-test p-value	VIF
Model 1	Pre Covid-19	IF	0.125	0.582	1.064
Model 1	Pre Covid-19	S	0.071	0.752	1.070
Model 1	Pre Covid-19	VLI	0.233	0.294	1.007
Model 1	Covid-19	IF	0.163	0.252	1.071
Model 1	Covid-19	S	-0.250	0.083	1.046
Model 1	Covid-19	VLI	0.739	0.000	1.052
Model 1	Post Covid-19	IF	0.061	0.121	1.044
Model 1	Post Covid-19	S	0.013	0.741	1.118
Model 1	Post Covid-19	VLI	0.971	0.000	1.092

Source: Research data

Table 4 – Shapiro-Wilk test on the residuals sample

Model	Period	Statistics	Degrees of Freedom	P-value
Model 1	Pre Covid-19	0.936	24	0.134
Model 1	Covid-19	0.925	24	0.076
Model 1	Post Covid-19	0.944	32	0.097

Source: Research data

In the pre-Covid-19 period, the regression model for the trading volume of small investors (Model 1) was not statistically significant (F-test p-value = 0.691, Table 2), concluding that savings, investment funds and the trading volume of large investors did not affect the trading volume of small investors.

In the Covid-19 period, the regression model of the trading volume of small investors shows statistical significance (p-value of the F test = 0.000, Table 2). Pearson's correlation coefficient was 0.801 (Table 2), which is considered a high correlation, according to Cohen (2013). The trading volume of small investors is positively influenced (coefficient = 0.739, Table 3) by the trading volume of large investors (t-test p-value = 0.000, Table 3). This movement can be identified as the herd effect, as it confirms a situation where small investors follow the actions of large investors, without considering their own analysis or information, as specified by Liang (2017). Another way of explaining this behavior is the argument put forward by Nofsinger and Sias (1999), which is that small investors feel less qualified, preferring to follow successful investors, in this case large investors, since they understand that they will incur greater costs using their own information and knowledge. The herd effect, which did not exist in the pre-Covid-19 period, appears during the health crisis, confirming the statement made by Dzielinski (2011) that investors behave like others in times of crisis.

The assumptions were confirmed, guaranteeing the reliability of the results obtained in the regression model during the Covid-19 period: a) no multicollinearity (VIF = 1.071, 1.046 and 1.052, Table 3); b) homoscedasticity (p-value of the Breusch-Pagan test = 0.053, Table 2), i.e. homogeneous residual variances; c) normal distribution in the residuals sample (p-value of the Shapiro-Wilk test = 0.076, Table 4).

In the post Covid-19 period, the regression model for the trading volume of small investors shows statistical significance (p-value of the F test = 0.000, Table 2). The degree of correlation is 0.980 (Table 2), which is considered a high degree of correlation according to Cohen (2013). The angular coefficient of the explanatory variable relating to the trading volume of large investors is statistically significant (t-test p-value = 0.000, Table 3), with a positive value (0.971, Table 3), indicating that an increase in the trading volume of large investors leads to an increase in the trading volume of small investors. Again, the herd effect can be identified. One of the explanatory factors is the fact that small investors find it difficult to make their own decisions, resulting in choices similar to those of large investors due to a lack of clear options, as explained by Bikhchandani and Sharma (2001). Hwang and Salmon (2001) argue that following the herd can be considered rational, given that large investors may have more information, using imitation as a strategy to compensate for their lack of information. Bikhchandani and Sharma (2001) also make the argument that investors seek security by following the majority and that the majority may know more than the individual alone.

Aiming to guarantee the results obtained in the regression model in the post Covid-19 period, the assumptions were analyzed, all of which were met: a) There is no multicollinearity between the explanatory variables (VIF = 1.044, 1.118 and 1.092, Table 3); b) The residuals exhibit homoscedasticity (Breusch-Pagan test p-value = 0.867, Table 2); c) the residuals sample has a normal distribution (p-value of the Shapiro-Wilk test = 0.097, Table 4).

6 FINAL CONSIDERATIONS

This paper checked whether investor behavior in the futures market remained the same under different economic scenarios and whether this behavior can be classified as herd behavior. Data analysis used multiple linear regression.

According to the results of the regression model simulations of the trading volume of large investors, they were not influenced by movements in savings and investment funds. Nor did they show herd behavior, regardless of the economic scenario and the movement of other financial products, indicating that having knowledge of the financial market reduces the possibility of the herd effect, even in a scenario of uncertainty. The behavior of large investors did not change during the period in question.

In the pre-Covid-19 period, the trading volume of small investors is not influenced by the trading volume of large investors or other financial products. In the Covid-19 period, the trading volume of small investors follows the trading volume of large investors, characterizing a herd behavior. The same is true in the post Covid-19 period. These results are in line with the statement made by Dzielinski (2011) that investors behave like everyone else in times of crisis. Analyzing the results, we can conclude that during Covid-19 and after the health crisis, small investors began to exhibit herd behavior.

One limitation is that the work focuses on numerical data and statistical analysis. Although effective at identifying behavioral patterns, these techniques do not fully capture investors' subjective motivations or perceptions. A qualitative approach, such as interviews or questionnaires, could complement this analysis.

For future research, we suggest analyzing other emerging markets to compare herd behavior in different economic and social contexts. Furthermore, more in-depth research could consider the impact of financial technologies, such as the use of algorithms and trading robots, on investor behavior. Another approach would be to explore the interaction between herd behavior and other behavioral theories to better understand investment decisions in other scenarios.

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Contribution	[Author 1]	[Author 2]
1. Definition of research problem	√	√
2. Development of hypotheses or research questions (empirical studies)	√	
3. Development of theoretical propositions (theoretical work)	√	√
4. Theoretical foundation / Literature review	√	√
5. Definition of methodological procedures	√	
6. Data collection	√	√
7. Statistical analysis	√	√
8. Analysis and interpretation of data	√	√
9. Critical revision of the manuscript	√	
10. Manuscript writing	√	√
11. Other (please specify)		

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The authors have stated that there is no conflict of interest.

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Data availability statement

Data will be available upon request