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Emotions and investments: the influence of investor sentiment on cryptocurrencies during the Covid-19 pandemic

Emociones e inversiones: la influencia del sentimiento de los inversores sobre las criptomonedas durante la pandemia de Covid-19

Emoções e investimentos: a influência do sentimento do investidor nas criptomoedas durante a pandemia de Covid-19

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Abstract

Purpose: The study analyzed the relationship between investor sentiment and the return and trading volume of the main cryptocurrencies in Brazil during the COVID-19 pandemic.

Methodology: Two metrics were used to capture investor sentiment: the Happiness Index (HFI) and the Fear Index (FEARS), collected through Twitter and Google tools. Data related to cryptocurrencies were collected from the Cryptocompare website. Quantile regressions were used to analyze variations in the impact of investor sentiment on different types of currencies.

Results: The results indicated that happiness and fear affect cryptocurrencies heterogeneously, with HFI causing negative and positive impacts on the return of assets such as BTC, USDC, and USDT. FEARS had a predominantly negative impact on the return of cryptocurrencies such as BTC and BRZ but was positive on ETH. Regarding trading volume, IFH had an ambiguous influence on BRZ, while FEARS reduced the volume of BTC, USDT, and USDC. The distinct patterns of impact identified suggest that investor sentiment may be a key indicator for formulating strategies in a highly volatile and emotionally reactive market.

Contributions of the Study: It contributes significantly to the literature by focusing on the Brazilian cryptocurrency market, which has been little explored in international research. It uses a quantile approach to examine how investor sentiment impacts multiple cryptocurrencies, offering a more detailed and non-linear analysis, something rare in the literature. Furthermore, investigating the behavior of cryptocurrencies in Brazil during COVID-19 provides critical insights into how collective emotions, such as fear and euphoria, affect market movements, especially in an environment dominated by individual investors, making the study relevant for emerging markets.

Keywords: Investor Sentiment; Cryptocurrencies; Return; Trading Volume.

Resumen

Objetivo: El estudio analizó la relación entre el sentimiento de los inversores y el rendimiento y el volumen de operaciones de las principales criptomonedas en Brasil, durante el período de la pandemia de Covid-19.

Metodología: Se utilizaron dos métricas para capturar el sentimiento de los inversores, los índices de Felicidad (IFH) y Miedo (FEARS), capturados utilizando las herramientas de Twitter y Google respectivamente. Los datos sobre las criptomonedas se recopilaron en el sitio web Cryptocompare. Utilizando regresiones cuantiles, se analizaron las variaciones en el impacto del sentimiento de los inversores sobre diferentes tipos de monedas.

Resultados: Los resultados indicaron que la felicidad y el miedo afectan de manera heterogénea a las criptomonedas, y que IFH causa impactos tanto negativos como positivos en los rendimientos de activos como BTC, USDC y USDT. Y FEARS tiene un impacto predominantemente negativo en el retorno de criptomonedas como BTC y BRZ, pero positivo en ETH. En términos de volumen de operaciones, IFH influyó de manera ambigua en BRZ, mientras que FEARS redujo el volumen de monedas BTC, USDT y USDC. Los distintos patrones de impacto identificados sugieren que el sentimiento de los inversores puede ser un indicador clave para formular estrategias en un mercado altamente volátil y emocionalmente reactivo.

Contribuciones del estudio: Contribuye significativamente a la literatura, al centrarse en el mercado brasileño de criptomonedas, que ha sido poco explorado en la investigación internacional. Utiliza un enfoque cuantil para examinar cómo el sentimiento de los inversores afecta a múltiples criptomonedas, ofreciendo un análisis más detallado y no lineal, algo poco común en la literatura. Además, al investigar el comportamiento de las criptomonedas en Brasil durante el Covid-19, se proporciona información fundamental sobre cómo las emociones colectivas como el miedo y la euforia afectan los movimientos del mercado, especialmente en un entorno dominado por inversores individuales, lo que hace que el estudio sea relevante para los mercados emergentes.

Palabras clave: Sentimiento de los Inversionistas; Criptomonedas; Devolver; Volumen de negociación.

Resumo

Objetivo: O estudo analisou a relação entre o sentimento do investidor e o retorno e volume de negociação das principais criptomoedas no Brasil, durante o período da pandemia de Covid-19.

Metodologia: Foram utilizadas duas métricas para capturar o sentimento do investidor, os índices de Felicidade (IFH) e Medo (FEARS), captados por meio das ferramentas *Twitter* e *Google* respectivamente. Os dados referentes as criptomoedas foram coletados no *site* Cryptocompare. Por meio de regressões quantílicas foram analisadas as variações no impacto do sentimento dos investidores nos diferentes tipos de moedas.

Resultados: Os resultados indicaram que a felicidade e o medo afetam de forma heterogênea as criptomoedas, com o IFH causando tanto impactos negativos quanto positivos no retorno de ativos como o BTC, USDC e USDT. E o FEARS um impacto predominantemente negativo no retorno de criptomoedas como o BTC e BRZ, mas positivo no ETH. Em termos de volume de negociação, o IFH influenciou de maneira ambígua o BRZ, enquanto o FEARS reduziu o volume das moedas BTC, USDT e USDC. Os padrões distintos de impacto identificados sugerem que o sentimento do investidor pode ser um indicador chave para a formulação de estratégias em um mercado altamente volátil e emocionalmente reativo.

Contribuições do Estudo: Contribui de maneira significativa para a literatura, ao focar no mercado brasileiro de criptomoedas, que tem sido pouco explorado em pesquisas internacionais. Utiliza uma abordagem quantílica para examinar como o sentimento dos investidores impacta múltiplas criptomoedas, oferecendo uma análise mais detalhada e não linear, algo raro na literatura. Além disso, ao investigar o comportamento das criptomoedas no Brasil durante o Covid-19, fornece *insights* críticos sobre como emoções coletivas, como medo e alegria, afetam os movimentos de mercado, especialmente em um ambiente dominado por investidores individuais, tornando o estudo relevante para mercados emergentes.

Palavras-chave: Sentimento do Investidor; Criptomoedas; Retorno; Volume de Negociação.

1 Introduction

The ubiquity of Internet access has triggered the emergence of currencies distinct from those used in the prevailing monetary system. The advent of cryptocurrencies based on a unique method called mining has brought significant changes to the online economic activities of investors (Kim et al., 2016). Several cryptocurrencies have emerged since 2008, when Bitcoin was first introduced (Nakamoto, 2008).

Cryptocurrencies are frequently used in online transactions, which has increased yearly since their introduction (Böhme, Christin, Edelman, & Moore, 2015). They are considered forms of decentralized digital currency that use cryptography to ensure secure transactions and to control the creation of new units (Kraaijeveld, & Smedt, 2020). In addition, they operate on a distributed network of computers, known as blockchain, which records and verifies all transactions in a public and immutable way (Böhme et al., 2015). Cryptocurrencies eliminate the need for financial intermediaries, such as banks, by allowing direct transactions between the involved parties (Kraaijeveld, & Smedt, 2020).

With their growing popularity, cryptocurrencies have not only attracted the attention of investors but have also become an active and growing field of academic research. What drives this market has been one of the most investigated questions by academic researchers over the past few years (Burggraf, Huynh, Rudolf, & Wang, 2021). Both academic researchers and practitioners have shown great interest in understanding the behavior of these newly emerging assets (Naeem, Mbarki, & Shahzad, 2021).

Decision theory, especially in the economic and financial context, seeks to understand how agents make decisions under conditions of risk and uncertainty (Biais, Bisière, Bouvard, Casamatta & Menkveld, 2020). In the case of cryptocurrencies, the volatility and uncertainty associated with these assets are amplified, making investment decisions more complex and sensitive to psychological and emotional factors (Liu, Tsyvinski, & Wu, 2022); this means that during times of great uncertainty, such as the COVID-19 pandemic, which has profoundly impacted global financial markets, investor sentiment can lead to impulsive and irrational decisions, resulting in extreme price and trading volume movements (Salisu & Akanni, 2020).

The role of investor sentiment, especially in crises, is significant in the cryptocurrency market, where the dominant presence of individual investors amplifies the influence of emotional factors. As suggested by Liu et al. (2022), cryptocurrency investors are often more susceptible to emotional and behavioral changes, which tend to generate disproportionate reactions to global events. This characteristic became evident during the pandemic as fear, uncertainty, and euphoria shaped trading patterns more pronouncedly (Naeem et al., 2021). This context highlighted the importance of sentiment analysis tools in understanding market behavior better.

Twitter and Google search volume have emerged as crucial sentiment analysis tools in the cryptocurrency market, especially during the pandemic, given the increased use of search and social media platforms to obtain and share information (Naeem et al., 2021). The study by Salisu and Akanni (2020) highlighted that social media played a central role during the pandemic, amplifying feelings of fear and uncertainty that quickly translated into sharp movements in cryptocurrency prices. Naeem et al. (2021) used Google's tool to examine the predictive ability of online investor sentiment for cryptocurrencies and found significant predictability of returns.

The intrinsic volatility of cryptocurrencies makes them particularly sensitive to investor sentiment, where tweets, forum posts, and news articles can trigger abrupt and significant movements (Chen, Li, & Sun, 2020). Furthermore, the cryptocurrency market is dominated by individual investors, and this investor profile tends to be more susceptible to emotional and behavioral influences (Liu et al., 2022). Research shows that events such as regulatory announcements or rumors can cause disproportionate reactions in investor sentiment, leading to sharp fluctuations in cryptocurrency prices (Eom, Kaizoji, Kang, & Pichl, 2019).

Whether cryptocurrencies represent an investment or a speculative activity has been widely debated in the academic literature (Chen et al., 2020). On the one hand, many scholars consider them a new asset class with investment potential, mainly due to their increasing use as a store of value and means of digital transactions (Baur & Dimpfl, 2018). The extreme volatility of cryptocurrencies, however, makes the argument complex. Studies such as those by Liu et al. (2022) suggest that, although cryptocurrencies such as Bitcoin present characteristics of financial assets, their high volatility and unpredictability are clear signs that many investors treat them more as a speculative asset, seeking quick returns rather than a long-term strategy.

As Böhme et al. (2015) argue, the growing institutional interest and integration of cryptocurrencies into traditional financial strategies suggests that they may eventually transcend this speculative phase and evolve into legitimate financial assets. Therefore, although the speculative nature may prevail, the future of cryptocurrencies depends on greater market maturity and stability. Thus, ample research opportunities exist to understand better this market's drivers (Chen et al., 2020).

In this context, the research problem arises: **What is the relationship between investor sentiment and the return and trading volume of the main cryptocurrencies in Brazil during the COVID-19 pandemic?** Therefore, the study aims to analyze the relationship between investor sentiment and Brazil's main cryptocurrencies' return and trading volume during the COVID-19 pandemic.

Two proxies of online investor sentiment were used to achieve this objective. The first is the feeling of happiness on Twitter, and the second is the Financial and Economic Attitudes Revealed by the American Household Survey – later called FEARS. Some international empirical studies have used the Twitter happiness index as a proxy for online investor sentiment and have documented its significant link with stock markets (Chen, De, Hu, & Hwang, 2014; Shen, Urquhart, & Wang, 2019).).

More specifically, in the area of cryptocurrencies, few studies, mostly international, such as those by Shen et al. (2019) and Kraaijeveld and Smedt (2020), found significant relationships between Twitter sentiment and the returns of some cryptocurrencies, such as Litecoin, Bitcoin and Bitcoin Cash. The studies by Eom et al. (2019) and Burggraf et al. (2021) also analyzed the FEARS proxy but only focused on Bitcoin.

This study becomes relevant because the field of cryptocurrencies, although widely studied in the last decade, lacks in-depth research on the impact of investor sentiment on altcoins, as pointed out by Kraaijeveld and Smedt (2020). Much of the existing literature, as noted by Burggraf et al. (2021), focuses on Bitcoin, which limits the understanding of the behavior of other digital currencies that have distinct characteristics. Therefore, this study seeks to bring insights into different cryptocurrencies, observing the behavior of the currencies that grew the most in Brazil, according to data from the Federal Revenue Service (2023).

Cryptocurrencies have become increasingly popular as an alternative asset class. As such, it is in the interest of both investors and researchers to have scientific evidence on the underlying drivers of cryptocurrency prices (Burggraf et al., 2021). Therefore, this study becomes relevant in shedding new light on investor rationality by bringing cryptocurrencies into question.

Recent studies, such as that of Liu et al. (2022), also emphasize that the emotional profile of investors, especially in a market dominated by individual investors, is one of the main factors contributing to abrupt fluctuations in cryptocurrency prices. The literature highlights the need to expand the focus to currencies that have experienced significant growth in emerging markets, such as Brazil.

The Brazilian economic scenario, marked by monetary instability and relatively high inflation, creates a different environment for using cryptocurrencies than countries with more stable economies. Ojo (2023) points out that, in emerging markets, cryptocurrencies can be seen not only as speculative assets but also as viable alternatives to the traditional financial system, especially in times of crisis.

In Brazil, this dual function of cryptocurrencies, as a form of investment and a hedge against currency devaluation, makes the local market unique (Ojo, 2023). In addition, the

Brazilian Federal Revenue Service has implemented regulations that differ from other countries, affecting how investors trade and view cryptocurrencies. This combination of factors reinforces the relevance of a study focused on cryptocurrencies in the Brazilian context since the particularities of the local market can generate valuable insights into how these emerging assets behave in developing economies.

2 Literature review

2.1 Cryptocurrencies

In late 2008, a new decentralized cryptographic money system was published anonymously by the pseudonymous Satoshi Nakamoto, which formed the basis of blockchain technology. Simultaneously, the most well-known application of blockchain technology was launched in the form of a cryptocurrency called Bitcoin (Nakamoto, 2008).

Initially, cryptocurrencies had a questionable reputation as they were often labeled as dubious currencies for criminals (Eenmaa-Dimitrieva, & Schmidt-Kessen, 2019). However, this changed when interest in the cryptocurrency market exploded throughout 2017 and early 2018, leading to hype and an extreme bull market fueled by fear of missing out (Kraaijeveld, & Smedt, 2020).

Digital currencies have received considerable media and investor attention due to their low transaction costs, peer-to-peer architecture, and government-free nature (Shen et al., 2019). This impact has led to increased trading volume, instability, and the value of cryptocurrencies (Shen et al., 2019).

Trading volume, the amount of cryptocurrencies exchanged in a given period, is often used to indicate market activity and liquidity. Some studies (Chen, Xu, Cheng, & Zhou, 2020; Kyriazis, Papadamou, Tzeremes, & Corbet, 2023) indicate that an increase in trading volume can be driven by changes in investor sentiment, where positive sentiment leads to increased cryptocurrency buying, while negative sentiment results in massive selling. This correlation suggests that investors react quickly to new information and perceptions, amplifying market movements.

Furthermore, specific events, such as regulatory announcements, security breaches on exchanges, or even rumors on social media, can trigger abrupt changes in investor sentiment, immediately reflected in trading volume (Corbet, Larkin, & Lucey, 2020). For example, positive news about the adoption of a cryptocurrency by a large institution can generate a significant increase in buying volume. At the same time, an issue on an exchange can cause a massive sell-off. This herd behavior can amplify market volatility, creating the boom-and-bust cycles characteristic of the cryptocurrency market.

Sentiment analysis tools that monitor social media data, news, and internet searches are often used to predict these movements, allowing investors to identify emerging trends and adjust their trading strategies (Liu et al., 2022). Investor sentiment, measured through social media analysis, internet searches, and media coverage, significantly impacts volume and cryptocurrency returns (Smales, 2019).

Some studies (Smales, 2019; Liu et al., 2022) indicate that positive sentiment, driven by favorable news or a general increase in interest in cryptocurrencies, can lead to positive returns as more investors buy digital assets, driving up their prices. On the other hand, negative sentiment caused by adverse news, such as exchange failures or restrictive regulations, tends to result in negative returns due to massive asset sell-offs (Corbet et al., 2020; Liu et al., 2022).

Research such as (Eom et al., 2019, Burggraf et al., 2021, and Liu et al., 2022) shows that abrupt changes in sentiment, captured by real-time sentiment analysis tools, often precede significant movements in cryptocurrency prices. Shen et al. (2019) studied the relationship between the number of tweets referring to Bitcoin and their utility in predicting realized volatility, volume, or future returns. They found that the number of tweets from the previous day significantly drives Bitcoin's realized volatility and volume but not returns

Eom et al. (2019) investigated the distributional and dynamic properties of Bitcoin's return and volatility. They found that investor sentiment toward this currency has significant informational value in explaining changes in Bitcoin's volatility in future periods. These authors' research results suggest that Bitcoin appears to be an investment asset with high volatility and dependence on investor sentiment rather than a monetary asset.

Kraaijeveld and Smedt (2020), through textual sentiment analysis and using bilateral Granger causality analysis, show that Twitter bots significantly predict the returns of Litecoin, Bitcoin, and Bitcoin Cash. Burggraf et al. (2021) investigated the predictive capacity of investor sentiment on Bitcoin returns and found that this sentiment significantly influences Bitcoin. More specifically, they observed that an increase in pessimistic sentiment negatively impacts Bitcoin, while a decrease has positive effects.

The works mentioned above focus on extracting sentiment from social media and then studying its connection with cryptocurrency returns, mainly Bitcoin, using causality analysis. In turn, this study analyzed two distinct online proxies of investor sentiment and tested their predictability regarding trading volume and returns of five cryptocurrencies, seeking more informative approaches.

2.2 Investor Sentiment

Decision theory is traditionally based on the idea that economic agents are rational and maximize their expected utility when making decisions under conditions of uncertainty (Biais et al., 2020). However, when analyzing the cryptocurrency market, this approach encounters several limitations. Cryptocurrencies are characterized by extreme volatility, a lack of solid fundamentals, and an emerging and highly speculative market, where decisions are often made under strong uncertainty (Eom et al., 2019). Investor behavior tends to be impacted by risk and return assessments and emotions such as fear and greed (Burggraf et al., 2021).

Kahneman and Tversky's (1979) perspective on Behavioral Finance Theory demonstrates that investors make decisions not purely rationally but according to subjective perceptions of gain and loss, distorting risk analysis in uncertain environments such as cryptocurrencies. Behavioral finance challenges the assumption that investors always act rationally in their investment decisions, suggesting that behavioral biases often influence them (Rupande, Muguto, & Muzindutsi, 2019). This perspective has significant implications for the dynamics of financial assets.

The literature on asset pricing and trading volumes has explored variables related to investor mood to elucidate market behavior (Chen et al., 2014; Naeem et al., 2021). It has been observed that trading patterns are closely linked to the prevailing sentiment or mood in the market (Rupande et al., 2019).

Sentiment is the general disposition of investors towards certain assets or financial markets, influenced by the flow of information (Tantaopas, Padungsaksawasdi, & Treepongkaruna, 2016). This sentiment is considered a broad concept encompassing emotions and moods, making it not directly observable and requiring several proxies (Naeem et al., 2021).

To accurately measure investor sentiment, researchers Peter Dodds and Chris Danforth have developed a tool to quantify the happiness of large populations in real time called the Hedonometer Happiness Index (HHI). This tool is available for free on the authors' website (https://hedonometer.org/words/labMT-pt-v2/) and in several languages. It measures happiness through an interactive time series based on Twitter posts.

The Hedonometer can capture the sentiment of potential investors, allowing the analysis of the relationship between investor sentiment and financial market movements (Chen et al., 2014). Twitter provides real-time information about cryptocurrencies and represents a valuable source of emotional intelligence, as investors frequently share their feelings (Kraaijeveld, & Smedt, 2020). The increasing use of this social network as a data source can be attributed to its ability to offer a combination of news and investor sentiment (Kraaijeveld, & Smedt, 2020).

There is a substantial body of research investigating the influence of Twitter on stock markets, exemplified by Chen et al. (2014) and Piñeiro-Chousa, López-Cabarcos, Pérez-Pico, and Ribeiro-Navarrete (2018), who identified significant correlations between this social network and financial markets. Regarding cryptocurrency research, Mai, Bai, Shan, Wang and Chiang (2015), when examining the dynamic relationships between social media and Bitcoin performance, found that more optimistic posts have a positive effect on Bitcoin returns and that the posting of messages has a significant impact on transaction volume, as well as greater disagreement between messages precedes a higher trading volume.

Naeem et al. (2021), examining the predictive ability of online investor sentiment for six significant cryptocurrency returns, found that the happiness sentiment index significantly predicts the returns of Bitcoin and other major cryptocurrencies at both extreme market states and extreme sentiment levels. Thus, the first two hypotheses of the study emerge:

H1: Investor sentiment captured by IFH impacts cryptocurrency trading volume.
H2: Investor sentiment captured by IFH impacts cryptocurrency returns.

Other previous research explores the impact of investor sentiment on financial markets through internet searches. For example, studies such as those by Da et al. (2015) used millions of households' daily volume of internet searches to reveal market sentiment. By aggregating the volume of queries related to household concerns – e.g., recession, unemployment, and bankruptcy – they constructed an index of Financial and Economic Attitudes Revealed by Surveys (FEARS) as a new measure of investor sentiment.

This index was, therefore, constructed based on the frequency of searches for terms related to fear and economic concern. Using Google Trends, the authors collected weekly data on the popularity of these searches, which ranged from 0 to 100, reflecting the proportion of searches for terms concerning the total searches in a given period and region (Da et al., 2015).

Thus, constructing the FEARS index involved selecting relevant terms based on the financial literature and consultations with experts, then standardizing the time series of searches for each term by subtracting the mean and dividing by the standard deviation. The final index is a weighted sum of the standardized searches, capturing investors' aggregate economic and financial concern levels. This index was used to analyze the relationship between investor sentiment and asset prices, demonstrating that high levels of FEARS are associated with subsequent negative stock market returns, indicating that an increase in economic concerns precedes a decline in stock prices (Da et al., 2015).

In turn, Naeem et al. (2021), when examining the predictive ability of online investor sentiment for six major cryptocurrency returns, also used the FEARS index and found that it shows significant predictability of returns. However, it is weak predictability, mainly in the short term; this was one of the few studies that used the FEARS index in the cryptocurrency market. Therefore, in the search for new evidence and findings, it is necessary to test this index and the happiness index in a period of crisis, such as the COVID-19 pandemic, and thus hypotheses 3 and 4 arise:

H3: Investor sentiment captured by FEARS impacts cryptocurrency trading volume.
H4: Investor sentiment captured by FEARS impacts cryptocurrency returns.

Based on the hypotheses formed, this study also seeks to expand the Brazilian literature with the analysis of the five currencies with the highest volume of movement in the last five years (2019-2023) in Brazil, as disclosed by the Federal Revenue Service (2023), namely: USDT (Tether), BTC (Bitcoin), USDC (United States Dollar Coin), BRZ (Brazilian Digital Token) and ETH (Ethereum).

Behavioral economics emphasizes that emotions and sentiments have the potential to significantly influence individual behavior, decision-making, and market movements (Kraaijeveld & Smedt, 2020). Irrational investors trade not based on fundamentals but on their emotions and moods, which can influence prices and market movements, leading to their deviation from fundamental value (Rupande et al., 2019).

This deviation can persist because transaction costs and short-selling risks limit arbitrage. Thus, market prices and movements are not determined solely by fundamental factors, as advocated by the Efficient Market Hypothesis, but also by market sentiment, which means how an agent perceives the market and reacts accordingly to investor sentiment (Naeem et al., 2021).

3 Methodology

3.1 Data collection

Daily data for cryptocurrency and sentiment indicators were collected between the second week of March 2020 and the first week of May 2023. The choice of sample space is justified by the fact that, on March 11, 2020, the World Health Organization (WHO) changed the classification of contamination from COVID-19 to pandemic and, on May 5, 2023, the WHO officially announced the end of the Public Health Emergency of International Concern regarding the Covid-19 pandemic, totaling 165 pandemic weeks.

The cryptocurrencies collected were chosen based on the volume of movement over the last five years (2019-2023), as disclosed by the Federal Revenue Service in 2023. Therefore, this study used the following cryptocurrencies: USDT (Tether), BTC (Bitcoin), USDC (United States Dollar Coin), BRZ (Brazilian Digital Token) and ETH (Ethereum). The data related to these currencies was collected from the Cryptocompare website (CryptoCompare.com) in June 2024.

3.2 Investor sentiment

The first sentiment indicator used in the study was the Hedonometer Happiness Index (HHI), a tool recommended by Peter Dodds and Chris Danforth and available at https://hedonometer.org/words/labMT-pt-v2/. The instrument reflects happiness through a time series of posts collected on the social network X – formerly Twitter –, measured based on words associated with feelings and classified on a scale of 1 to 9, in which 1 indicates a highly negative concept, 5 indicates neutrality, and 9 indicates an extremely positive valence.

The use of tools that measure sentiment from social networks is common and is present in the literature through several studies, such as those by Chen et al. (2014), Kyriazis et al. (2023), Yağlı and Haykır (2023), who adopted the Hedonometer Happiness Index to capture investor sentiment. For Chen et al. (2014), this methodology can represent this sentiment, allowing the investigation of a relationship between the sentiment of this investor and the dynamics of the stock market.

The FEARS indicator was the second methodology used in this research to capture investor sentiment. This index was developed by Da et al. (2015) and measures investor sentiment through searches on Google Trends. The authors selected a primitive list of terms related to economic conditions, classifying them as economic, positive, and negative, according to the Harvard IV-4 Dictionary and the Lasswell Values Dictionary.

In this research, to construct the FEARS index, we chose to adapt the methodology applied by Da et al. (2015) since no dictionaries were found in the Portuguese language that provided a classification by categories. Therefore, the thirty most negative terms cataloged by Da et al. (2015) were first translated using the English-Portuguese Cambridge Dictionary, these being the original words of the present study.

Then, terms that did not make sense in the Brazilian context were excluded and entered into Google Trends to collect terms related to these primitive words, resulting in a total of 205 terms. Duplicate terms and those with insufficient data were excluded, totaling 39 terms. After collecting the Search Volume Index (SVI), the daily change of the search term was calculated according to Equation 1.

$$\Delta IVP_{j,t} = log(IVP_{j,t}) - log(IVP_{j,t-1}) \qquad (1)$$

Where $IVP_{j,t}$ is the Search Volume Index for search term j on the current day t, and $IVP_{j,t-1}$ is the Search Volume Index for search term j on the previous day. It is important to note that the logarithmic transformation minimizes non-stationary time series problems (Burggraf et al., 2021).

Subsequently, it was necessary to winsorize $\Delta IVP_{j,t}$ at the 5% level to eliminate outliers. Finally, the Search Volume Index was standardized (IVPP) by scaling it by its standard deviation ($\Delta IVPP_{j,t}$), following Baker and Wurgler (2007) and Da et al. (2015).

The last step was to identify the search terms with negative t-statistics. To do this, $\Delta IVPP$ was regressed against the market return (IBovespa) to determine the relationship between the search terms and the market behavior returns. The t-statistics were ranked, and only the terms with negative values were used to construct the FEARS index since the findings of Da et al. (2015) proved that the relationship between a search term and the market is almost always negative. A total of 11 terms were used, as shown in Table 1.

Table 1
Terms used in the construction of the FEARS index during the Covid-19 period

Gold price	PIS
Direct Treasury	INSS Extract
CPC	Economy

Costs	Employment Record
How much does savings cost?	Benefits
Digital Record	

Source: *Survey data (2024).*

Finally, the FEARS index is defined according to Equation 2. Where, $\Delta IVPP_j$ is the variation of the standardized search volume index of the term j that presented the negative t-statistic.

$$FEARS_j = \sum_{i=1}^{11} (\Delta IVPP_j) \qquad (2)$$

3.3 Econometric Model and Data Analysis

The return and growth in percentage of the trading volume of cryptocurrencies were used to test the research hypotheses. The investor sentiment indices were regressed against the return and volume, according to Equation 3. Where IND represents the indicator of return and growth of the trading volume of the cryptocurrencies listed for the study (BTC, ETH, USDT, USDC, and BRZ) in period t, and SENT is the sentiment indicator represented by the FEARS index and the Hedonometer Happiness Index.

$$IND_t = \alpha + \beta_1 SENT_t + \varepsilon \qquad (3)$$

For data analysis, a quantile regression with fixed effects was applied to panel data, according to Equation 3, based on the observation of non-adequacy to the assumptions of linear regression, and according to Brooks (2019), quantile regressions are more robust to outliers and non-normality. Specific individual effects are controlled in this type of regression, providing a more flexible approach to panel data analysis than that presented by classical fixed and random effects estimators (Galvão Jr., 2011).

The quantiles used were 10, 25, 50, 75, and 90, as they were the ones that best suited the sample of this study after testing with other quantiles. It should be noted that the model was tested according to the assumptions of normality, autocorrelation, and homoscedasticity of the model's residuals.

4 Results and Analysis

4.1 Relationship between IFH and return and trading volume

Table 2 shows the influence of IFH on the return and growth metrics of the trading volume of the cryptocurrencies BTC, ETH, USDT, USDC, and BRZ during the COVID-19 pandemic. It is important to note that IFH during this pandemic period behaved in a neutral (valence 5) to semi-neutral manner (valence 6).

Table 2
IFH behavior during the Covid-19 period

BTC	RETURN					VOLUME				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	0.1373 (0.7873)	0.1505 (0.4288)	0.1987 (0.1435)	0.5299 (0.0113)	0.6851 (0.0766)	-0.1605 (0.7652)	7.5921 (0.4165)	1.5188 (0.5664)	-24.1406 (0.6359)	-2.4357 (0.9609)
IFH	-0.0288 (0.7319)	-0.0274 (0.3840)	-0.0327 (0.1449)	-0.0846*** (0.0144)	-0.1062* (0.0965)	-0.1231 (0.1667)	-1.3248 (0.3922)	-0.2506 (0.5671)	4.1513 (0.6282)	1.8759 (0.8196)
ETH	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0804 (0.6270)	-0.1460 (0.3174)	0.0068 (0.9569)	-0.1105 (0.4148)	0.0539 (0.8714)	-0.6437 (0.2108)	1.3363 (0.7804)	2.9687 (0.3244)	4.4682 (0.7151)	44.0735 (0.4298)
IFH	0.0087 (0.7503)	0.0219 (0.3638)	-0.0012 (0.9527)	0.0204 (0.3625)	-0.0035 (0.9481)	-0.0423 (0.6187)	-0.2746 (0.7296)	-0.4943 (0.3213)	-0.6556 (0.7460)	-5.8214 (0.5283)
USDT	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0011 (0.8017)	-0.0159 (0.0026)	0.0000 (1.0000)	0.0050 (0.4158)	0.0010 (0.6749)	-0.4503 (0.3648)	7.5729 (0.3762)	1.6740 (0.3407)	5.0052 (0.8844)	75.6254 (0.1604)
IFH	0.0000 (0.9758)	0.0025*** (0.0033)	0.0000 (1.0000)	-0.0007 (0.4524)	-0.0000 (0.9748)	-0.0747 (0.3629)	-1.3122 (0.3559)	-0.2769 (0.3407)	-0.7515 (0.8953)	-11.0361 (0.2155)
USDC	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0149 (0.0664)	-0.0001 (0.9310)	0.0000 (1.000)	0.0001 (0.8669)	0.0166 (0.0263)	-0.2648 (0.5538)	4.3663 (0.5682)	-0.4433 (0.7737)	-23.6436 (0.6802)	98.4773 (0.0882)
IFH	0.0023* (0.0786)	0.0000 (0.9997)	0.0000 (1.000)	0.0000 (1.000)	-0.0026** (0.0322)	-0.1054 (0.1548)	-0.8011 (0.5293)	0.0713 (0.7802)	4.0442 (0.6732)	-14.7321 (0.1228)
BRZ	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-1.8028 (0.1381)	-0.8979 (0.1308)	-0.3783 (0.2704)	-0.8815 (0.3070)	1.9719 (0.3498)	-2.6635 (0.0833)	-10.4837 (0.0281)	0.6005 (0.8127)	13.5804 (0.2303)	164.1946 (0.0440)
IFH	0.2900 (0.1462)	0.1449 (0.1395)	0.0611 (0.2820)	0.1487 (0.2964)	-0.3125 (0.3694)	0.2950 (0.2477)	1.6641** (0.0346)	-0.0993 (0.8126)	-2.1422 (0.2503)	-25.9015** (0.0548)

Legend: HFI: Hedonometer Happiness Index; BTC: Bitcoin; ETH: Ethereum; USDT: Tether; UDSC: United States Dollar Coin; BRZ: Brazilian Digital Token. The standard error is in parentheses. P value: *** 1%, ** 5%, * 10%.
Source*: Survey data (2024).*

For the BTC cryptocurrency, the relationship between the IFH and the return was negative and statistically significant for the highest return quantiles (75 and 90), indicating that the greater the investor's happiness, the lower the return of the BTC cryptocurrency; this can be explained by the fact that the Hedonometer, when measuring collective happiness based on Twitter posts, during the Covid-19 pandemic period, captured the decline in general happiness, which can lead to an increase in risk aversion and insecurity among investors; this aligns with Prechter's (2001) analysis of how the widespread decreasing feeling of happiness can lead to massive sales of speculative assets, such as BTC, negatively impacting their returns.

Studies such as that of Garcia, Tessone, Mavrodiev and Perony (2014) show that sentiment expressed on social media, including Twitter, can predict fluctuations in the prices of financial assets, with a more pronounced impact on risky assets. Kim et al. (2016) also found that positive comments from users driven by their positive sentiments significantly affected price fluctuations and returns on bitcoin. Kraaijeveld and Smedt (2020), when analyzing the extent to which public sentiment on Twitter can predict the returns of some cryptocurrencies, found that this sentiment, more specifically optimism, has predictive power for BTC returns.

No significant evidence was found regarding trading volume between investor sentiment and BTC trading volume fluctuations. Tetlock (2007) justifies this finding by pointing out that the impact of media sentiment may be minor compared to other economic and technical factors that influence trading volume. Institutional adoption and technical events, such as protocol upgrades, may significantly impact trading volume more than variations in sentiment captured by the Hedonometer. Kraaijeveld and Smedt (2020) also found no significant relationship between Twitter sentiment and BTC trading volume.

As for ETH, no significant results were obtained between investor happiness and return or trading volume. This result can be explained by the fact that Ethereum – a robust platform for smart contracts and decentralized applications (DApps) – has an underlying value that is not exclusively dependent on short-term market sentiment. Chuen, Lee, Guo and Wang (2017) point out that Ethereum, due to its utility and adoption in various applications, may have an inherent resilience to sentiment fluctuations, such as those measured by the Hedonometer, especially during crises.

Cheah and Fry (2015) argue that the complexity and diversification of factors affecting cryptocurrencies may dilute the impact of specific sentiments on trading volume. Kraaijeveld and Smedt (2020) also found no predictive power of Twitter sentiment on cryptocurrency returns. Bouteska, Hajek, Abedin, and Dong (2023) examined whether Ethereum prices and returns are affected by Twitter engagement at different times following the COVID-19 pandemic and found that no potential impact was identified for ETH.

Regarding the third cryptocurrency analyzed, USDT, the Hedonometer Happiness Index proved to positively influence the currency's return during the Covid-19 period, with this relationship being statistically significant at quantile 25. However, the same significant relationship was verified for the return of the cryptocurrency USDC for quantile 10. These findings indicate that, in periods of crisis, the HFI can positively influence only the groups of low returns for these cryptocurrencies. This result may occur because the period analyzed is one of crisis, so the investor, even if happy – greater feeling – prefers not to risk so much.

However, if the Hedonometer indicates an increase in overall happiness, this could signal a recovery or improvement in the economic outlook, leading to greater investor confidence in the market's stability. This confidence could increase demand for stablecoins such as USDT and USDC, widely used to protect cryptocurrency gains or facilitate transactions in times of optimism. Baker and Wurgler (2007) studied how investor sentiment can influence market behavior, noting that positive sentiment generally translates into greater market activity and willingness to take moderate risks. However, these investors still seek to preserve safety.

With an increase in the happiness index, investors may expand their holdings of stablecoins like USDT and USDC, facilitating greater participation in crypto markets or preparing to reinvest in more volatile assets when conditions improve; this could increase demand for these stablecoins, positively impacting their indirect returns through appreciation relative to volume and usage.

Schär (2021) highlights that the stability and liquidity of stablecoins make them attractive to investors who seek security in times of uncertainty but also want to be prepared for emerging investment opportunities. This increase in demand may indirectly positively impact the returns of USDT and USDC, reflected in the increase in circulation and use in the crypto ecosystem.

On the other hand, at quantile 90, a significant negative relationship was obtained between investor sentiment and the return of the USDC cryptocurrency, indicating that the sign is reversed in the high-return group. Then, investor sentiment begins to impact returns negatively. Suppose the increase in happiness leads investors to reallocate capital to riskier cryptocurrencies, such as BTC or ETH, instead of holding USDC. In that case, it may result in a decrease in the demand for stablecoins. Baur and Dimpfl (2018) highlight that investor behavior is strongly influenced by market sentiment, and, in this case, a positive sentiment may reduce the need to hold stable assets, negatively impacting their returns.

Regarding the trading volume of these two stablecoins, no statistical significance was found related to investor happiness sentiment and the trading volume of USDT and USDC coins. Cheah and Fry (2015) indicate reduced trading activity may occur when investors prefer to maintain liquidity or avoid volatile markets. Smales (2019) suggests that high volatility in times of fear may lead to decreased trading activity, as investors may choose to wait or avoid trading in an uncertain environment.

The Brazilian cryptocurrency (BRZ) did not show a significant relationship between investor happiness and return. It was the only one in which the IFH showed a significant relationship with trading volume growth, being positive for quantile 25 and negative for quantile 90. Kraaijeveld and Smedt (2020) state that niche altcoins, such as BRZ, may have their price and return dynamics more strongly influenced by local market-specific economic factors than global sentiments expressed on social media. Mancini-Griffoli et al. (2018) indicate that stablecoins, such as BRZ, pegged to specific fiat currencies have their value maintained by market mechanisms that are not necessarily reflected by changes in global sentiment.

Regarding trading volume, Liu et al. (2022) discuss how social media sentiment can have a more direct impact on local markets and cryptocurrencies with a specific investor base, explaining the positive effect of the Hedonometer on BRZ trading volume. However, Shiller (2003) suggests that widespread enthusiasm can lead to bubbles and subsequent corrections, causing abrupt price movements and decreased trading due to uncertainty and fear of losses. Chen et al. (2014) discuss how cycles of positive sentiment followed by negative reactions can create uncertainty and reduce trading activity.

Schär (2021) points out that trust in the stability of fiat currency, or lack of trust – which is very common in times of crisis – and regulation of the cryptocurrency market may be predominant factors that negatively affect the trading volume of stablecoins. Therefore, it is possible to understand how much this crypto universe is impacted by numerous variables that, depending on how investors see and perceive, influence each currency's returns and trading volumes separately in different ways.

4.2 Relationship between FEARS and trading volume and return

Table 3 illustrates the relationship between the FEARS sentiment index and five cryptocurrencies' return and trading volume growth during COVID-19. These findings demonstrate the influence of investor sentiment on all the coins studied, whether on return or trading volume.

Table 3
Behavior of the FEARS Index during the Covid-19 period

BTC	RETURN					VOLUME				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0372 (0.0000)	-0.0154 (0.0000)	0.0007 (0.4253)	0.0185 (0.0000)	0.0414 (0.0000)	-0.9046 (0.0000)	-0.3922 (0.0001)	-0.0034 (0.7911)	1.1501 (0.1890)	8.9628 (0.0000)

FEARS	-0.0019	0.0018	-0.0002	-0.0020	-0.0108**	-0.0239***	-0.1904*	-0.0987***	0.0832	-0.8078
	(0.7286)	(0.4138)	(0.9053)	(0.4454)	(0.0258)	(0.0003)	(0.0980)	(0.0084)	(0.2972)	(0.1435)
ETH	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0278	-0.0133	-0.0007	0.0125	0.0319	-0.8966	-0.2930	-0.0255	0.4663	8.9147
	(0.0000)	(0.0000)	(0.2804)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0703)	(0.0001)	(0.0000)
FEARS	0.0063**	0.0013	-0.0018	-0.0028	-0.0021	0.0178	-0.0731	-0.0682	-0.1503	-0.8081
	(0.0469)	(0.4094)	(0.1303)	(0.1642)	(0.6136)	(0.2035)	(0.1570)	(0.1061)	(0.4151)	(0.4093)
USDT	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0010	-0.0004	0.0000	0.0004	0.0010	-0.9033	-0.3319	0.0008	0.4788	8.9846
	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0034)	(0.9406)	(0.5942)	(0.0000)
FEARS	0.0000	0.0000	0.000	0.0000	0.0000	-0.0067	-0.0482	-0.0159	0.2451	-1.3400***
	(0.9598)	(0.9976)	(1.0000)	(0.9946)	(1.0000)	(0.2334)	(0.6836)	(0.6808)	(0.7692)	(0.0064)
USDC	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0006	-0.0001	0.0000	0.0001	0.0006	-0.9023	-0.4546	-0.0219	0.7297	9.4390
	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0886)	(0.5972)	(0.0000)
FEARS	0.0001	0.0000	0.000	0.0000	0.0000	-0.0120	-0.1595	-0.1319***	-0.2970	-2.2657***
	(0.4236)	(1.0000)	(1.0000)	(1.0000)	(0.9957)	(0.2260)	(0.3447)	(0.0009)	(0.8057)	(0.0029)
BRZ	**RETURN**					**VOLUME**				
	P10	**P25**	**P50**	**P75**	**P90**	**P10**	**P25**	**P50**	**P75**	**P90**
α	-0.0609	-0.0208	-0.0085	0.0168	0.0927	-0.8821	-0.4120	-0.0037	0.6231	7.7251
	(0.0009)	(0.0000)	(0.0000)	(0.0707)	(0.0000)	(0.0000)	(0.0000)	(0.7874)	(0.0000)	(0.0000)
FEARS	-0.0286	-0.0047	-0.0059*	-0.0132	-0.0423*	0.0260	0.0747	-0.0365	-0.2455	0.9278
	(0.3196)	(0.3025)	(0.0779)	(0.1214)	(0.0750)	(0.2980)	(0.3077)	(0.3770)	(0.3149)	(0.4713)

Legend: BTC: Bitcoin; ETH: Ethereum; USDT: Tether; UDSC: United States Dollar Coin; BRZ: Brazilian Digital Token. The standard error is in parentheses. P value: *** 1%, ** 5%, * 10%.
Source: *Survey data (2024).*

Regarding BTC returns, the relationship presented is statistically significant only for the 90th quantile; the highest returns negatively influence the FEARS sentiment indicator. A similar result was found when analyzing the relationship between the IFH and BTC returns, with the difference being that in the IFH result, the influence also occurred in the 75th quantile.

Baur and Dimpfl (2018) show that, although BTC is often seen as an alternative asset, its volatility is significantly higher than that of traditional assets, including stocks and commodities such as gold. In times of crisis, such as the COVID-19 pandemic, this volatility can intensify due to increased uncertainty, causing investors, especially risk-averse investors, to reevaluate their positions in volatile assets, negatively pressuring their returns.

Smales' (2019) research suggests that during negative sentiment, investors tend to reassess their exposures to volatile assets such as cryptocurrencies, which can result in liquidations and negative returns. BTC volatility, combined with a general sense of unhappiness and pessimism, can lead to even steeper price movements and declines in returns. Vasileiou and Koutrakos (2023) examined the performance of cryptocurrencies during COVID-19 from a sentiment analysis perspective using Google Trends indices. They found that negative sentiments of fear generated by the pandemic negatively impacted the returns of BTC and some other coins.

When observing the growth in BTC trading volume, this impact is negative and significant at quantiles 10, 25, and 50, showing that medium and lower trading volumes are more affected than higher ones. Baker and Wurgler (2007) and Bouri, Gupta, and Roubaud (2019) show that, in times of high fear, investors tend to move away from riskier assets and seek safety, which can lead to a reduction in the trading volume of volatile assets such as BTC.

The cryptocurrency ETH showed a statistically significant connection only concerning return and quantile 10; however, the influence was positive. For Naeem et al. (2021), ETH is a cryptocurrency with a history of stability, and in times of crisis, it presents itself as an alternative for investors. Cevik, Kirci Altinkeski, Cevik and Dibooglu (2022) argue that financial crises increase volatility and uncertainty, leading investors to seek assets that they consider safe or even to seek safe havens, such as gold and, more recently, cryptocurrencies.

This perception can be justified by the fact that, in times of crisis, there is a search for assets that are not directly influenced by traditional economic policies, such as interest rates or money printing. The study by Smales (2019) argues that, in crises, decentralized assets that do not depend on central banks can offer protection against the depreciation of fiat currencies.

During the pandemic, the perception that the traditional financial system could be overwhelmed or fail led more investors to see cryptocurrencies as a viable alternative. The increase in institutional adoption and the growing use of smart contracts, as pointed out by Chuen et al. (2017), also reinforced the appreciation of ETH, particularly in a scenario of fear and uncertainty.

According to Güler (2023), the positive impact of investor sentiment can be attributed to the fear of missing out (FOMO) behavior of irrational and speculative investors. The Fear of Missing Out (FOMO) related to investments refers, in particular, to the fear an investor feels of missing out on a potentially profitable investment or trading opportunity in a cryptocurrency.

Regarding ETH trading volume, there was no significant relationship with negative investor sentiment. Baker and Wurgler (2007) argue that risk aversion can lead to changes in investor behavior. However, in the case of ETH, its continued utility and technological innovation can mitigate the negative impact of fear on trading volume.

The USDT cryptocurrency showed a negative and significant relationship with the trading volume growth in the 90th quantile. Therefore, in the group with the highest volumes, the lower the FEARS index, the more significant the increase in volume. Still, concerning the trading growth, the USDC cryptocurrency showed a negative and statistically significant relationship for the 50th and 90th quantiles. Thus, FEARS was influenced by the groups with medium and high trading volume growth. As for the return of both currencies, there was no significance.

Market confidence can be severely shaken during high volatility and uncertainty, such as during the COVID-19 pandemic. Smales (2019) argues that increased volatility can decrease trading volumes as market participants become more cautious, avoiding transactions until uncertainty subsides. Bouri, Gupta, and Roubaud (2019) indicate that in times of extreme fear, investor confidence in the market can be significantly undermined, leading to reduced trading activity in assets typically used as liquidity vehicles, such as USDT and USDC.

Regarding returns, Schär's (2021) research corroborates that, in crises, stablecoins offer a combination of safety due to their parity with the dollar and utility due to their integration into trading and DeFi platforms, making them a natural choice for investors looking to reduce exposure to volatile assets without leaving the crypto ecosystem. For this reason, the increase in fear, as captured by FEARS, does not translate into negative returns for USDT and USDC.

Investor sentiment also influenced the Brazilian cryptocurrency BRZ, but in the 50 and 90 quantiles, this influence is more evident in the highest-return quantile and negatively. This result can be explained by the fact that BRZ is a stablecoin pegged to the Brazilian real (BRL) and is, therefore, directly exposed to fluctuations in the real against the US dollar and other strong currencies. In this sense, during the COVID-19 pandemic, the real suffered a significant depreciation due to economic instability, political uncertainties, and a deterioration in Brazil's macroeconomic outlook.

Studies such as that of Katsiampa, Corbet and Lucey (2019) highlight that the volatility of altcoins tends to increase significantly during periods of crisis and document that the high volatility of currencies, such as the BRL, can negatively impact assets denominated in reais, including the BRZ.

Furthermore, Katsiampa et al. (2019) and Cevik et al. (2022) discuss how global financial crises can heighten investors' risk aversion, which may lead them to avoid emerging market currencies with higher volatility and exchange rate risk. Since BRZ is directly pegged to the Brazilian real, the increased fear, as captured by the FEARS index, may have led investors to avoid this altcoin in search of assets denominated in more stable currencies, such as the US dollar, which contributed to the downward pressure on their returns. As for BRZ's trading volume, it did not prove to be significant to negative investor sentiment.

The results reveal that the IFH and FEARS metrics, used to measure investor sentiment, significantly impact the cryptocurrency market in terms of volume and returns for certain coins and in different ways for each of them. These findings suggest a divergence from the EMH, given that the observed price variations, often driven by collective emotions, indicate that the cryptocurrency market may not operate fully efficiently. This behavior highlights the sensitivity of assets to objective information and emotional and psychological factors, which, according to the EMH, should not substantially influence prices.

5 Sensitivity analysis

Seeking to verify whether the findings of the relationship between investor sentiment and cryptocurrencies during the Covid-19 period are also verified in non-crisis periods, the study also reproduced the analysis from January 1, 2017, to March 7, 2020.

The construction of the FEARS index was done in the same way. However, the terms with negative t-statistics were the following: silver, dollar price, fixed income, direct treasury, unemployment insurance, SELIC, capital, expenses, costs, INSS table, economy, unemployment, and social security. It is essential to highlight that the cryptocurrencies USDC and BRZ were excluded from this analysis because they did not have data for the entire study period.

As represented by FEARS, investor sentiment showed a statistically significant and negative relationship with BTC trading volume growth in the 90th quantile. This finding reveals that investor sentiment impacts the group with the highest growth in BTC trading volume in periods of economic normality, a relationship not found in periods of crisis. Outside of periods of crisis, negative sentiment captured by FEARS tends to be low, which may give investors greater confidence to take risks and increase their trading activities. Chen et al. (2020) discuss how market confidence in regular times can lead to a cycle of high liquidity and increasing trading volumes.

Still, a negative and significant relationship was found between FEARS and the return of the USDT cryptocurrency for quantiles 10 and 90. During the pandemic period, this relationship was not observed. However, the findings for the USDC cryptocurrency were similar for both periods, proving that crises and widespread panic affect assets differently than regular periods.

Regarding the IFH, the results were more convincing in the pre-pandemic period. While the cryptocurrency ETH did not show a significant relationship during the pandemic period, in the pre-COVID period, the return and growth in trading volume were impacted by investor sentiment. Cevik et al. (2022) highlight that fear and panic dominate market behavior in times of crisis, minimizing the influence of positive feelings, such as happiness, on some assets' returns and trading volumes.

As for the other cryptocurrencies, BTC's return was also affected in the pre-COVID period. However, in this analysis, a negative and significant relationship was found in quantiles 10 and 25, which indicates that investor sentiment in periods of lower economic fluctuation impacts BTC in groups with lower returns. As for the cryptocurrency USDT, the results were similar to those found in the COVID period. Finally, USDC did not show statistical significance for this period under analysis.

6 Final Considerations

This study analyzed the relationship between investor sentiment and Brazil's main cryptocurrencies' return and trading volume during the COVID-19 pandemic. The study used the IFH and FEARS as proxies to measure investor sentiment and test the research hypotheses, using the return and growth as a percentage of the trading volume of cryptocurrencies. Data collection covered the pandemic period, as reported by the WHO: from March 11, 2020, to May 5, 2023. The results of this investigation were obtained through the use of quantile regressions.

These results showed that feelings of happiness and fear have different impacts on cryptocurrencies. The happiness index can negatively impact returns, as in the case of Bitcoin and USDC, or positive effects, as in the USDT and USDC currencies. In the case of USDC, whether the impact is positive or negative depends on the quantile analyzed, whether low or high. Regarding the fear index, its negative impact occurs on the return of Bitcoin and the BRZ currency, while, in ETH, this impact becomes positive. As for trading volume, the IFH only ambiguously impacted the BRZ currency, and the FEARS negatively impacted BTC, USDT, and USDC.

The study demonstrated that investor sentiment affects both the trading volume and the return of cryptocurrencies, but in a heterogeneous manner across the assets analyzed; this leads to the partial acceptance of some of the hypotheses. Regarding H1, which postulates that the feeling of happiness impacts the trading volume of cryptocurrencies, the results showed that, for the BRZ currency, this impact did indeed occur, but in an ambiguous way. However, the other currencies did not show a significant effect, which indicates that the hypothesis was partially rejected.

H2, which suggests that IFH impacts cryptocurrency returns, has been shown to be valid in some cases, such as USDT, USDC, and bitcoin, although the impact differs depending on the quantile analyzed; this suggests that positive sentiment may sometimes lead to a euphoria that drives the price, while at other times, it may not be enough to sustain a consistent increase.

H3 and H4, which deal with the impact of the fear index (FEARS) on trading volume and cryptocurrency returns, respectively, were also partially accepted. The negative effects of fear on the trading volume of assets such as BTC, USDT, and USDC were evident, corroborating hypothesis H3. In the case of returns, there was an impact, although varied, on Bitcoin, ETH, and BRZ, partially accepting H4.

The results obtained in this study highlight the complexity and variability of investor sentiment's effects on the cryptocurrency market. The analysis demonstrated that emotions, such as happiness and fear, do not impact different cryptocurrencies uniformly, varying in magnitude and direction. These findings corroborate behavioral theory that emotional biases play a fundamental role in decision-making in contexts of uncertainty and high volatility.

The strong influence of happiness and fear sentiment on cryptocurrency trading volume and returns, as identified using the HIF and FEARS indices, indicates an inconsistency with the

EMH. Cryptocurrency price fluctuations, often driven by collective emotions, as seen in the effects of fear on Bitcoin and happiness on USDC, indicate that cryptocurrency markets may not be completely efficient. These assets appear to be sensitive to objective information and emotional and psychological factors that, according to the EMH, should not significantly impact prices.

This contrast reveals that EMH principles may not explain price movements in emerging and speculative markets like cryptocurrencies. Instead, behavioral finance, which emphasizes investor irrationality and emotional biases, appears to be a more appropriate theoretical framework for understanding the behavior of crypto markets.

The intrinsic volatility of the cryptocurrency market, combined with the emotional sensitivity of investors, reinforces the importance of investment strategies being dynamic and adjustable according to the emotional scenario of investors. The sensitivity analysis showed differences in the results when there is a change from a crisis scenario to a typical scenario. Identifying distinct patterns of impact between different cryptocurrencies suggests that investor sentiment may be a critical indicator to be considered when formulating investment strategies, especially in an environment so sensitive to emotional changes.

The study offers significant contributions to the literature. Firstly, we will focus on the fastest-growing cryptocurrencies in Brazil, an emerging market that has so far been little explored in international cryptocurrency research. Secondly, by adopting a quantile approach to examine the impact of investor sentiment on multiple cryptocurrencies, which is rare in the existing literature. The methodology allows for a more detailed analysis, identifying how different sentiment levels affect specific cryptocurrencies non-linearly.

Third, the cryptocurrency market, dominated by individual investors, is particularly vulnerable to collective sentiments such as fear and happiness. Thus, investigating the relationship between investor sentiment and cryptocurrency behavior in Brazil during one of the most turbulent periods in recent history provides critical insights for understanding how emotions shape market movements.

The study also has some limitations, such as the survey's focus on only a few specific cryptocurrencies, which limits the generalizability of the results to the cryptocurrency market as a whole. Furthermore, the influence of other external factors, such as regulatory policies, global economic events, and technological advances, was not examined, which could complement the understanding of emotional impacts.

The results suggest that future studies should investigate how different sentiment intensities and specific moments affect the market. Such studies could focus on particular periods of high volatility or more excellent stability to determine whether the impact of sentiment varies across the broader economic landscape. In this way, by better understanding the effects of investor sentiment on different cryptocurrencies, investors and analysts can improve their strategies in high-risk markets such as cryptocurrencies.

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