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Time and frequency domain relationship between investor sentiment and sectoral cryptocurrencies

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Abstract
Utilizing blockchain technology is transforming traditional business practices into a new paradigm, giving rise to what we refer to as blockchained models. This paper uses wavelet coherence analysis to identify the connectedness of blockchained sectoral indices with Bitcoin and the Fear and Greed Index that represents investor sentiment in the cryptocurrency market. Results show persistent and positive correlations between sector returns and investor sentiment and sectoral return series lead investor sentiment. The relationship between Bitcoin and sectoral indices is consistent for return series and suggests an in-phase (positive) relationship between these variables at all frequencies. We usually have found negative correlations for the co-movements of investor sentiment and sectoral volatility, where investor sentiment leads to sector return volatilities. The application of blockchain technology across various sectors, coupled with the proliferation of altcoins, appears to drive distinct price developments in these cryptocurrency sectors. These developments are predominantly influenced by sentimental factors, often diverging from the trends of Bitcoin.

Keywords Sectoral cryptocurrency · Investor sentiment · Bitcoin · Fear and greed index · Blockchain technology

1 Introduction

Since its invention by various cultures recognizing its role in simplifying trade, money has evolved in many ways. As a medium of exchange, various objects have been used as money, and their value has always been the interest of finance and economics. As such, money has in many ways shaped human relationships, international relations, commerce, economic stability, taxation, and employment among other things. Today, cryptocurrencies, as a new asset class, represent a milestone in

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reshaping economic activities and business practices through their groundbreaking technology—blockchain. This study aims to generate meaningful insights into the interactions between blockchained sectoral indices, Bitcoin, and the Fear and Greed Index, seeking to determine whether these relationships are driven by broader market trends (Bitcoin) or investor sentiment (Fear and Greed Index).

As stated by Ballve (2020), blockchain technology has already spread across a wave of a substantial number of industries. Blockchain technology protects against fraud and hacks as a decentralized platform, allowing transparent transactions and secure data access. The adoption of this technology by conventional financial institutions is gradually progressing to become part of the mainstream. For example, J.P. Morgan introduced a new model in 2020 that utilizes distributed ledger technology in particular services such as intraday repo trade. Additionally, the bank launched a blockchain-based network called Liink, a scalable system that operates for efficient payments-related information across members (JP Morgan 2021). The emergence of the Metaverse likely will expedite the utilization of blockchain technology in the execution of financial transactions such as purchases of virtual goods and services. In these transactions, smart contracts will have an essential role in automating real-world operations in the digital marketplace without requiring compliance. Since smart contracts are founded on the blockchain, this technology will play a vital role in shaping and leading the financial system in the 3D demonstration of the real world. CBInsights (2021) eported that the funds allocated to blockchain startups increased by 713% and hit 25.2 billion dollars in 2021. The enormous growth of blockchain technology utilization in the digital world enhances optimism regarding its future applications.

In the digital revaluation of the finance sector, the most noteworthy development related to the blockchain utilization can be the initialization of Decentralized Finance (DeFi) projects. DeFi is a unique class of financial operations through blockchain-based decentralized applications (DApps). Its most distinguishing feature is the replacement of conventional intermediaries with smart contracts. Other than DeFi, there are various blockchain facilities applied in several real economy sectors today. Incorporating blockchain technology allows these sectors to switch from conventional operations to contemporary business models and facilitate adoption by more organizations. Thus, the utilization of blockchain has already gained a place in numerous sectors, such as logistics, transportation, education, healthcare, entertainment, and supply chain management. Ballve (2020) reports that 65 different industries, such as supply chain management, may interact with this technology. Gaur and Gaiha (2020) argue the employment of blockchain technology would considerably lessen the coordination and traceability problems faced as each participant has his/her own individual copies of the blockchain. This fact would enable each party to monitor the transaction's status, determine whether they comply with counterparty responsibilities, and identify possible errors. Transformation of industries may accelerate the creation of further value for companies and their shareholders by providing higher operating income and the ability to reduce the role of intermediaries. Unlike its traditional counterparts, the adoption of this new technology suggests better-tailored and more secure platforms for clients, with costs that are significantly reduced through the unique infrastructure of this new model. The increasing number

of sectors incorporating blockchain applications demonstrates that these instruments offer promising opportunities for investors and entrepreneurs both as an investible asset and as a service provider. Applications on financial instruments allow us to perform an empirical investigation to explore connectedness with particular market parameters.

In light of the above arguments, this study seeks to identify the relationship between blockchained sectoral cryptocurrency indices, the general market trend (proxied by Bitcoin), and investor sentiment (represented by the Fear and Greed Index). We analyze 15 sectoral indices specifically constructed for this purpose. The primary objective is to determine whether cryptocurrency sectors exhibit distinctive features in these interactions, both in terms of returns and volatility. This could help investors and policymakers devise tailored strategies for investment and regulatory frameworks across various sectors. To strengthen our arguments, we employ frequency domain analysis using the wavelet coherence and time and frequency domain connectedness approaches in our empirical investigations. These methods provide valuable insights that can inform both short- and long-term investor horizons, which correspond to high- and low-frequency bands, respectively, and align with different investor types, such as day traders and long-term investors. The constructed indices represent the following sectors: Decentralized Finance, Electronic Commerce, Energy, Entertainment, Gambling, Gaming, Healthcare, Lending, Logistics, Marketing, Media, Metaverse, Non-Fungible Tokens, Smart Contracts, and Tourism.

The paper differs significantly from existing literature in several key ways. First, unlike previous research, we provide evidence from a comprehensive analysis of the cryptocurrency market, covering a total of 15 sectors. Earlier studies have focused on standalone sectors within the cryptocurrency space. For example, Ustaoglu (2024) examines renewable energy tokens and their interaction with stock market counterparts, while Yousaf et al. (2023) investigate tourism tokens. Similarly, Aharon et al. (2024) study the relationship between Metaverse tokens and Metaverse stocks, and Gunay et al. (2024) focus solely on tourism tokens and their connection to equity markets, particularly in the context of geopolitical risks. In contrast, our study broadens the scope by including a much larger range of sectors, offering a more comprehensive view of the cryptocurrency market. Additionally, by employing frequency domain analysis, our study provides insights into both short-term and long-term dynamics. Short-term horizons (high-frequency bands) capture rapid price movements driven by market sentiment shifts and external factors, such as geopolitical developments and news impacts. On the other hand, long-term horizons (low-frequency bands) are associated with fundamental economic trends, such as GDP growth and monetary policies. Given the criticism that cryptocurrency often faces due to their volatile price movements, our findings, which explore both short- and long-term relationships, offer valuable insights for developing investment strategies tailored to different investment horizons. Finally, as our findings suggest evidence of an emerging market that offers an alternative to conventional business models, our results can be beneficial for entrepreneurs looking to shift their operations to blockchained counterparts. The existing literature on sectoral interactions and responses to economic developments has largely focused on equity markets (Xiang et al. 2021; Wieczorek-Kosmala 2021; Gunay and Kurtulmus, 2021; Gunay

et al. 2021; Zhang, 2022; Mushafiq 2021; Ardolino et al. 2022). Therefore, the paper provides new insights for those interested in integrating blockchain technology into business operations. Entrepreneurs, in particular, will benefit from understanding both short- and long-term interactions, enabling them to make more informed predictions and more accurate capital budgeting decisions.

The remainder of the paper is organized as follows. Section 2 provides a brief survey of the related literature. Section 3 presents the wavelet coherence methodology that is used in this paper. Empirical results are given in Sect. 4, and a summary of conclusions and implications is presented in Sect. 5.

2 Related literature

There is a well-documented literature that focuses on the relationship between cryptocurrency and stock markets (Bouri et al., 2019; Kristjanpoller et al. 2020; Shahzad et al., 2019; Lahiani et al. 2021; Nguyen 2022; James 2022). On the other hand, there is growing literature on the relationship between investor sentiment and cryptocurrency. For example, Kraaijeveld and De Smedt (2020) examined the predictive power of investor sentiment on the nine biggest cryptocurrencies, namely Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Cardano, Stellar, and TRON. Using the Twitter sentiment index for investor sentiment, they documented causality running from investor sentiment to Bitcoin, Bitcoin Cash, and Litecoin returns. Agosto et al. (2022) used the Google search volume for "Bitcoin," "Ethereum," and "Ripple" in measuring investor sentiment for the cryptocurrency market and found evidence of sentiment predicting speculative bubble occurrences. On the other hand, Monki et al. (2022), Güler (2021), and Bourghelle et al. (2022) examined the relationship between the Fear and Greed Index as a proxy for investor sentiment and Bitcoin price and volatility. While Monki et al. (2022) found a relationship running from the return and volatility of Bitcoin to investor sentiment, Güler (2021) and Bourghelle et al. (2022) confirmed investor sentiment-affected Bitcoin volatility. However, Gunay et al. (2022) investigated the regime-dependent impact of investor sentiment on the Non-Fungible Tokens (NFTs) market using the Markov-Switching VAR model where Google search volume (GSV), Fear and Greed Index (FGI), and Volatility Implied Index (VIX) proxy investor sentiment found evidence of Granger causality from GSV to the NFTs in bearish market episodes and from FGI and VIX to NFTs in bullish markets. Bouteska et al. (2022) constructed an investor sentiment index for Bitcoin using a large data set of messages on social media platforms and found a significant relationship between the investor sentiment index and Bitcoin returns.

There is another strand in the literature that examines the relationship between cryptocurrency and sectoral stock market indices in terms of portfolio diversification. Akhtaruzzaman et al. (2020) analyzed the presence of benefits for portfolio diversification between Bitcoin and the global industry portfolio and bond index. The empirical results showed that the correlations between Bitcoin and sectoral stock market indices and the bond index are generally low and time varying. Specifically, dynamic correlations significantly decrease during financial distress periods,

and hence, Bitcoin proves hedging benefits for sectoral stock markets and bond markets. Damianov and Elsayed (2020) investigated the dynamic relationship between Bitcoin and ten global industry stock markets, namely Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunication Services, and Utilities. The results showed correlations between Bitcoin and sectoral stock market indices are almost zero, and hence, Bitcoin provides diversification opportunities for investors. Umar et al. (2021) examined the interconnectedness between Bitcoin and the technological sector stock market index. They found cryptocurrency can be utilized as a diversifier for technology sector investments, particularly for those aiming to diversify internationally, for investors seeking exposure in the technology industry. Mo et al. (2022) analyzed the connectedness between cryptocurrency and commodity stock markets. Accordingly, total spillovers with different investment horizons differ during the COVID-19 era, and net spillovers vary with time and frequency. After COVID-19, cryptocurrency was found to be the primary transmitter of risk spillovers, with unusually high net spillover effects. The hedging effect of cryptocurrency differs by commodity sectors before and after COVID-19, with cryptocurrency proving to be more effective hedging instruments after the pandemic.

However, there are a limited number of studies that focus on the sectoral analysis of the cryptocurrency market. In this regard, Čuljak et al. (2022) examined the utility of considering cryptocurrencies' sectoral affiliation while developing a portfolio. They suggested that in developing a portfolio, it is critical to analyze the features and capacities of cryptocurrency rather than depending exclusively on their market value. In addition, their empirical results suggested that sectoral allocation can be a beneficial strategy for understanding and taking advantage of investment opportunities in the cryptocurrency market. Zhao et al. (2022) investigated investor herding behavior in the cryptocurrency market. They suggested sectoral analysis for the cryptocurrency market provides more useful in better understanding the price and volatility transmission mechanisms. The study reveals indications of focused herding and reverses herding in the broader market, particularly during the 2020–2022 Covid-19 period. Herding behavior varies between sectors, with larger and more volatile sectors exhibiting higher herding behavior. The study also discovers evidence of reverse herding during bull market periods, implying that categorizing digital assets based on their digital functions could be a valuable technique for future research.

Caferra (2022) explored the interplay between investor sentiment, Bitcoin, and the S&P 500 Index using the wavelet approach. The findings reveal that investor sentiment serves as a mediating factor, influencing the connection between the two markets. Husain et al. (2023) analyzed the dynamic connectedness between green cryptocurrencies, green investments, conventional commodities, and equities from 2018 to 2023 using wavelet coherence. The empirical findings reveal that green cryptocurrencies do not act as hedges or safe havens but function merely as diversifiers and uncertainty in financial markets impacts their interconnectedness with other assets. Hamadou et al. (2024) investigated the relationship between Google investor sentiment and major cryptocurrencies—including Bitcoin, Litecoin, Ethereum, and Tether—using quantile causality and wavelet coherence methods. Their causality

test results indicate that positive investor sentiment is linked to higher returns, while negative sentiment corresponds to lower returns. Meanwhile, the wavelet coherence analysis reveals that all return series, except for Tether, exhibit comovement with investor sentiment across different time scales. Speeckaert and Wang (2024) examined the relationship between investor sentiment and various asset prices, including Bitcoin, Ethereum, the S&P 500 Index, the Nasdaq Composite Index, gold, and oil, using the wavelet approach. Their findings suggest that investor sentiment plays a significant role in shaping market dynamics, whereas the influence of asset returns on investor sentiment appears to be limited. Bossman et al. (2024) examined the impact of media coverage on cryptocurrency-related environmental concerns, as captured by the Index of Cryptocurrency Environmental Attention (ICEA), on Islamic stocks using a bi-wavelet-based time–frequency econometric framework on data from 2014 to July 2022. The results reveal a time-varying relationship between ICEA and Islamic sectoral stocks, suggesting that media attention influences pricing and return dynamics. However, traditional "brick-and-mortar" sectors (e.g., basic materials, consumer goods, industrials, oil and gas) demonstrate strong diversification benefits. These insights have implications for risk management, portfolio allocation, and policy decisions.

3 Econometric framework

In this study, wavelet coherence analysis is employed to examine time and frequency domain relationships between sectoral cryptocurrency prices and investor sentiments. The wavelet coherence approach allows us to examine the relationship between the two sets of variables using the continuous wavelet transform taking account of different scaled levels of localization. Yang et al. (2016) emphasized that the primary advantage of wavelet analysis lies in its ability to decompose a time series into fundamental components that retain intrinsic information about the series. This decomposition enables the examination of different scales within the time series, allowing for a more detailed extraction of insights from raw data. Similarly, Ahmed (2022) described wavelet analysis as a highly versatile and powerful tool that decomposes a signal or time series into a set of basis functions, each corresponding to different frequencies and time locations. Unlike traditional time series methods such as linear regression, vector autoregression, and GARCH models, wavelet analysis facilitates the simultaneous examination of time-varying and frequency-dependent relationships between variables. This capability not only distinguishes between short- and long-term relationships but also captures evolving dependencies over time, making the findings particularly valuable for investors with different investment horizons. Furthermore, wavelet analysis does not require prior knowledge of the functional form of relationships between variables and, unlike conventional time series approaches, does not impose stationarity constraints. Additionally, it remains robust in the presence of structural breaks, providing meaningful insights even when disruptions occur in the data.

The continuous wavelet transform of a time series *x(t)* can be represented as follows:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\tilde{\psi}^*_{\tau,s}(t)dt \tag{1}$$

In Eq. (1), s shows the scaling factor, which determines the length of the wavelet, while τ denotes the translation parameter, which specifies the location of the wavelet in time. The complex conjugate function of $\widetilde{\psi}^*_{\tau,s}(t)$ is denoted as $\psi^*_{\tau,s}(t)$, and $\widetilde{\psi}$ is derived by scaling and shifting the mother wavelet ψ, as described in Eq. (2):

$$\tilde{\psi}^*_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), s, \tau \in \mathbb{R}, s \neq 0 \tag{2}$$

The Morlet wavelet is employed, originally introduced by Goupillaud et al. (1984), as mother wavelet. Equation (3) depicts the cross-wavelet transform applied to the signals $x(t)$ and $y(t)$:

$$W_{xy}(\tau, s) = W_x(\tau, s)W^*_y(\tau, s) \tag{3}$$

The wavelet coherence between $x(t)$ and $y(t)$ is shown as follows:

$$R^2(\tau, s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau, s)\right)\right|^2}{S\left(s^{-1}\left|W_x(\tau, s)\right|^2\right)S\left(s^{-1}\left|W_y(\tau, s)\right|^2\right)} \tag{4}$$

In Eq. (4), the smoothing parameter S is a critical factor influencing the analysis. The coefficient $R^2(\tau, s)$ quantifies the squared correlation between signals x and y, localized in both time and frequency domains with values in the range of 0 to 1. Although wavelet coherence is valuable for identifying co-movements between x and y in these domains, it does not distinguish between positive and negative correlations. To address this limitation, Torrence and Compo (1998) introduced a formula for discriminating between negative and positive correlations within the relationship between x and y as follows:

$$\Phi_{xy}(u, s) = tan^{-1}\left(\frac{\mathcal{I}\left\{S\left(s^{-1}W_{xy}(\tau, s)\right)\right\}}{\mathcal{R}\left\{S\left(s^{-1}W_{xy}(\tau, s)\right)\right\}}\right) \tag{5}$$

In Eq. (5), $\mathcal{I}$ represents the imaginary part, while $\mathcal{R}$ denotes the real part of the smoothed cross-wavelet transform. Equation (5) furnishes the phase difference, a crucial measure employed to delineate the oscillation or cycle delays inherent in a given pair of time series under consideration.

4 Data and empirical results

4.1 Data

The relationship among sectoral cryptocurrency indices, Bitcoin, and the Fear and Greed Index is examined using daily data from July 19, 2019, through July 11, 2022. Thirteen sectoral indices, namely Marketing, E-commerce, Logistics, Tourism, Health, Media, Entertainment, Gaming, Gambling, Smart Contracts, Metaverse, DeFi, and NFTs, are considered in the empirical analysis.

The rise of blockchain technology is intrinsically linked to the introduction of Bitcoin in 2008. Since then, the development of additional cryptocurrencies and tokens has accelerated, offering valuable tools for decentralized applications utilizing blockchain in traditional markets. As a result, numerous new tokens have emerged, allowing for comparisons between the cryptocurrency market and its traditional counterparts. However, despite these advancements, the cryptocurrency market remains in its early stages, facing challenges such as a limited number of tokens within each category and mismatched data lengths across tokens in the same group. These issues present a significant challenge for empirical analysis, limiting our ability to extend the study beyond 2019 while striving to cover as many cryptocurrency sectors as possible. In constructing the sectoral indices, we adhere to two key criteria: (i) Each sector index should comprise at least three cryptocurrencies, and (ii) the weight of each cryptocurrency in the sectoral index is determined by market capitalization. Based on these criteria, we have established thirteen sectoral indices, focusing on the 2019–2022 period to maximize the representation of asset numbers and sectors.

The data for Bitcoin and cryptocurrency used in calculating sectoral indices are obtained from the Refinitiv Eikon database. On the other hand, we consider that the FGI[1] to proxy investor sentiments for Bitcoin and other cryptocurrencies has been widely used in the literature to assess its predictive power for financial markets (e.g., Farrel and O'Connor, 2025). We use logarithmic returns for Bitcoin and sectoral indices in the empirical analysis. To ascertain volatility spillovers between Bitcoin and sectoral indices, we calculate unconditional volatility for each variable using the absolute value of return series except for FGI.

The FGI is presented in Fig. 1 for the sample. Note that the daily FGI is derived from a variety of sources and includes numerous dimensions that encompass diverse and varied types of emotions and attitudes. The index lies between 0 and 100 where index values close to zero indicate "extreme fear" where investor concerns about the cryptocurrency market are quite high. On the other hand, when the index approaches 100, such episodes are dubbed "Extreme Greed" periods with low investor concerns about cryptocurrencies. The result in Fig. 1 shows that the mean FGI within the sample is 45.7 which indicates that the average investor sentiment for the cryptocurrency market is neutral. The minimum and maximum levels for investor sentiment index are between 5 and 95 in the sample, and the index reached its lowest level in

[1] The index is obtained from https://alternative.me/crypto/fear-and-greed-index.

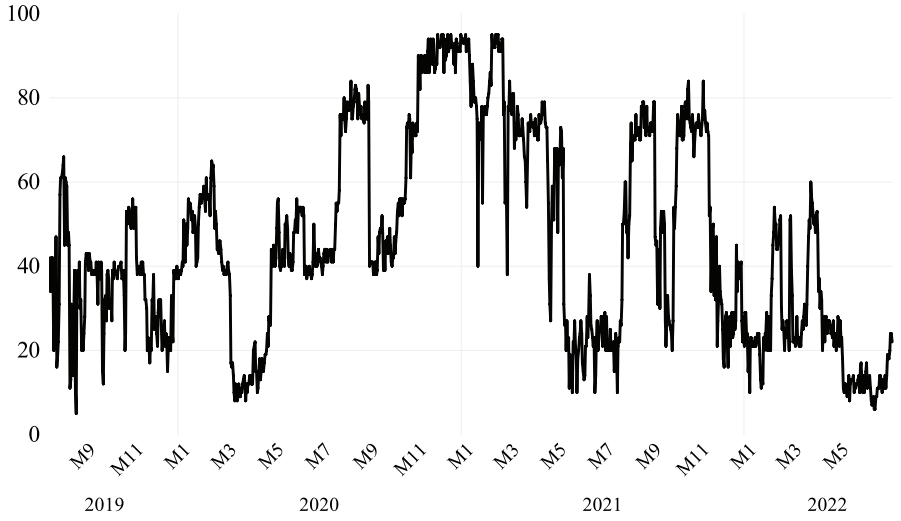

Fig. 1 Fear and Greed Index for Cryptocurrency Market

August 2019. On the other hand, the highest level for the index was reached at the end of 2020/the beginning of 2021.

The descriptive statistics for returns and volatilities are given in Table 1. The results indicate that mean returns are positive for Bitcoin and all sectoral indices except for Gambling, Health, and Logistics sectors. While the Gaming sector yields a higher mean return during the sample, the Logistics sector has the lowest mean return. The Gambling sector has the highest volatility as measured by standard deviations. Skewness statistics show all return series are left-skewed except for DeFi, E-commerce, Entertainment, Gambling, Gaming, and Health. We also confirm all return series are fat-tailed according to kurtosis statistics. We can reject the null hypothesis of normality for all returns and volatility series according to the Jarque–Bera statistics. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test results show both return and volatility series are stationary in levels.

4.2 Wavelet analysis results for sectoral index returns

The empirical analysis starts by implementing wavelet coherence analysis to examine the relationship between investor sentiments, sectoral index returns, and volatilities. The results are given in Figs. 2, 3, 4 and 5. Note that the black contours in the figures represent statistically significant correlations at a 5% significance level and the Monte Carlo simulations with 1000 repetitions are used to estimate the standard deviation of the correlations. The influence cone is presented by the white line. As in it is typical in the finance literature, we consider the ranges 0–32, 32–128, and 128–256 as the short-, medium-, and long-term horizons, respectively, in the figures. Note that since the cryptocurrencies are traded on 7/24, as the 32-day horizon corresponds to approximately a month, and 128 days represent four months. Also, in

Table 1 Descriptive Statistics for Returns and Volatility

Return	Bitcoin	DeFi	E-commerce	Entertainment	Gambling	Gaming	Health	Logistics	Marketing	Media	Metaverse	NFTs	Smart Contract	Tourism
Mean	0.0007	0.0002	0.0018	0.0005	−0.0013	0.0023	−0.0014	−0.0018	0.0008	0.0017	0.0003	0.0004	0.0016	0.0011
Median	0.0015	−0.0056	−0.0024	0.0002	−0.0038	0.0014	−0.0014	−0.0026	0.0006	0.0002	0.0007	0.0025	0.0006	−0.0004
Maximum	0.1760	0.6154	0.5419	0.5233	1.1808	0.5716	1.6680	0.6102	0.3215	0.4447	0.4784	0.3065	0.2373	0.4168
Minimum	−0.4337	−1.0654	−0.4432	−0.2863	−0.9533	−0.6452	−0.6994	−0.7449	−0.5937	−0.6564	−0.5898	−0.6190	−0.5682	−0.5537
Std. Dev	0.0385	0.0930	0.0900	0.0602	0.1079	0.0753	0.1016	0.0781	0.0605	0.0881	0.0702	0.0668	0.0525	0.0660
Skewness	−1.2951	0.2623	0.8915	0.9987	1.0752	0.2514	3.7060	−0.3032	−0.5593	−0.3611	−0.5333	−1.0692	−1.2730	−0.2477
Kurtosis	19.2450	27.2988	8.6907	12.8111	31.2749	15.0294	74.5064	15.1993	15.1180	9.6375	12.9129	13.2844	17.6932	12.9670
J-B	12,278.87 [0.000]	26,803.27 [0.000]	1613.677 [0.000]	4548.751 [0.000]	36,485.76 [0.000]	6577.506 [0.000]	234,502.8 [0.000]	6769.561 [0.000]	6719.947 [0.000]	2022.707 [0.000]	4510.43 [0.000]	5006.716 [0.000]	10,090.1 [0.000]	4518.762 [0.000]
ADF	−15.035***	−14.979***	−14.9***	−35.728***	−23.611***	−34.202***	−32.453***	−14.671***	−8.892***	−15.393***	−14.629***	−10.561***	−14.987***	−22.118***
PP	−34.382***	−37.06***	−36.782***	−35.814***	−42.328***	−34.186***	−32.455***	−35.024***	−36.418***	−34.917***	−35.814***	−36.545***	−35.126***	−34.16***
Volatility	Bitcoin	DeFi	E-commerce	Entertainment	Gambling	Gaming	Health	Logistics	Marketing	Media	Metaverse	NFTs	Smart Contract	Tourism
Mean	0.0259	0.0569	0.0594	0.0407	0.0622	0.0493	0.0584	0.0541	0.0412	0.0603	0.0487	0.0473	0.0362	0.0439
Median	0.0178	0.0365	0.0381	0.0279	0.0393	0.0331	0.0377	0.0398	0.0298	0.0403	0.0349	0.0340	0.0262	0.0292
Maximum	0.4337	1.0654	0.5419	0.5233	1.1808	0.6452	1.6680	0.7449	0.5937	0.6564	0.5898	0.6190	0.5682	0.5537
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001
Std. Dev	0.0285	0.0736	0.0676	0.0444	0.0881	0.0569	0.0831	0.0563	0.0443	0.0642	0.0506	0.0472	0.0381	0.0493

Table 1 (continued)

Volatility	Bitcoin	DeFi	E-commerce	Entertainment	Gambling	Gaming	Health	Logistics	Marketing	Media	Metaverse	NFTs	Smart Contract	Tourism
Skewness	4.0581	5.2079	2.6701	3.4527	5.6151	3.8094	8.4892	3.8911	3.8290	2.8743	3.6037	3.6283	4.0605	3.4126
Kurtosis	43.7100	49.6272	12.9331	25.1465	51.0019	27.8683	138.7939	34.8978	32.2524	17.1468	27.5263	31.6334	41.9213	24.1120
J-B	78,188.97 [0.000]	103,572.3 [0.000]	5771.048 [0.000]	24,418.74 [0.000]	110,274.8 [0.000]	30,695.31 [0.000]	849,793.8 [0.000]	48,915.71 [0.000]	41,488.51 [0.000]	10,580.42 [0.000]	29,651.8 [0.000]	39,591 [0.000]	71,729.46 [0.000]	22,338 [0.000]
ADF	−9.167***	−6.494***	−5.422***	−11.942***	−13.996***	−8.601***	−8.901***	−13.209***	−8.400***	−7.479***	−12.496***	−13.268***	−6.863***	−10.666***
PP	−33.557***	−29.408***	−30.335***	−29.105***	−24.357***	−29.957***	−30.088***	−31.049***	−28.694***	−29.524***	−30.427***	−28.449***	−33.052***	−30.26***

The numbers in square brackets are *p*-values. *** indicates stationary at the 1% level

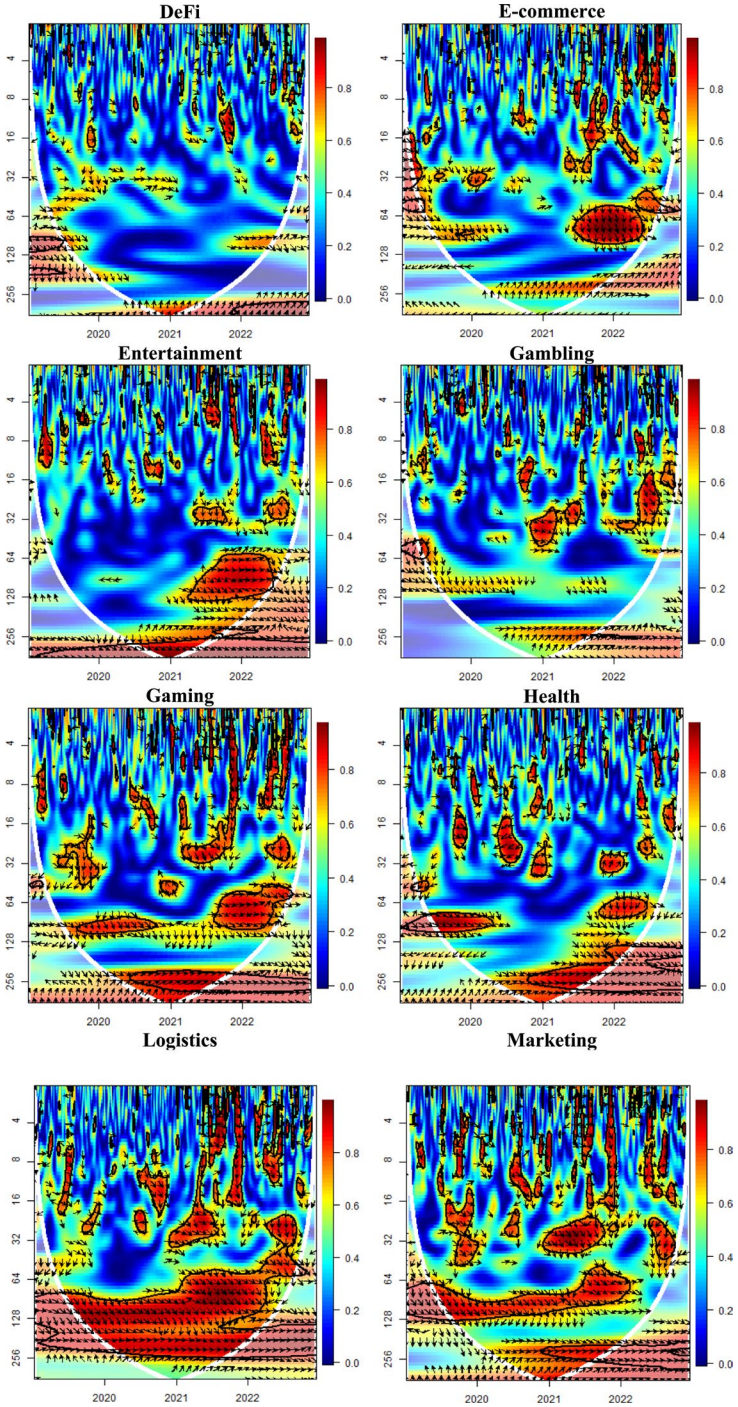

Fig. 2 Wavelet Coherency between FGI and Sectoral Index Returns

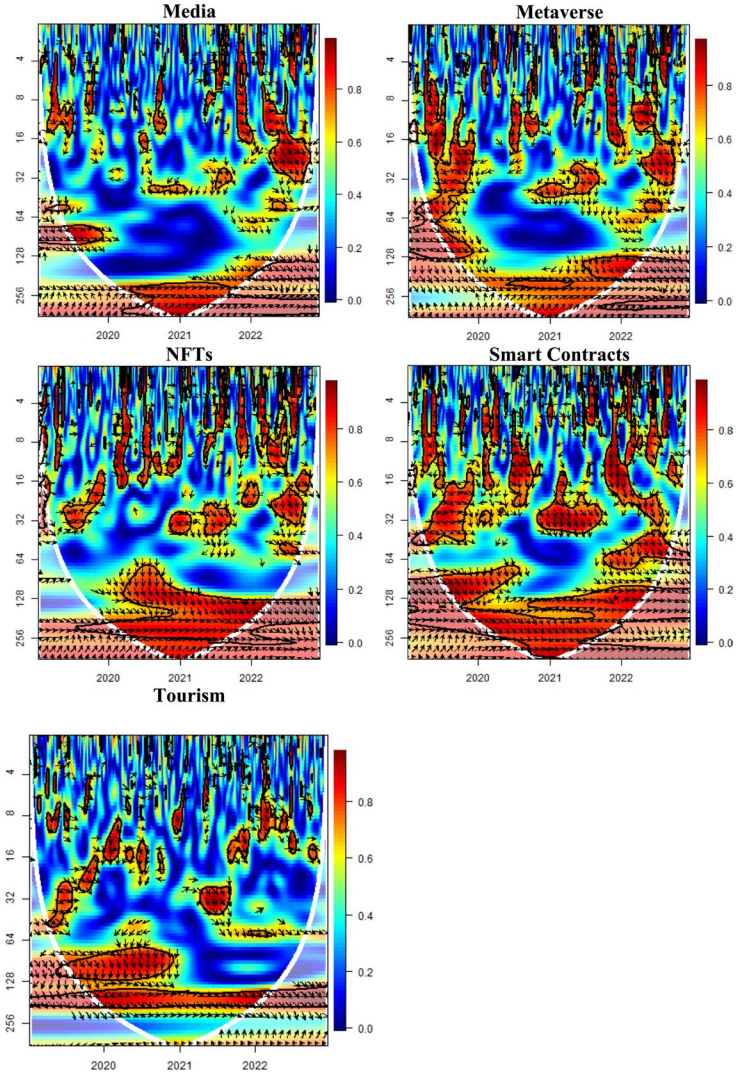

Fig. 2 (continued)

all figures, the vertical and horizontal axes show frequency and time, respectively. Areas with warmer hues imply a high correlation between the variables, while areas in darker blue suggest low correlations between the variables. In this context, the red and blue regions show the highest and lowest correlations between the variables, respectively.

Arrows pointing to the right (→) and left (←), respectively, indicate connections that are in phase (positive co-movements) and out of phase (negative co-movements). Moreover, the arrows pointing up (↑) suggest the FGI (or Bitcoin returns) lead the sectoral index return, whereas the arrows pointing down (↓) imply that the

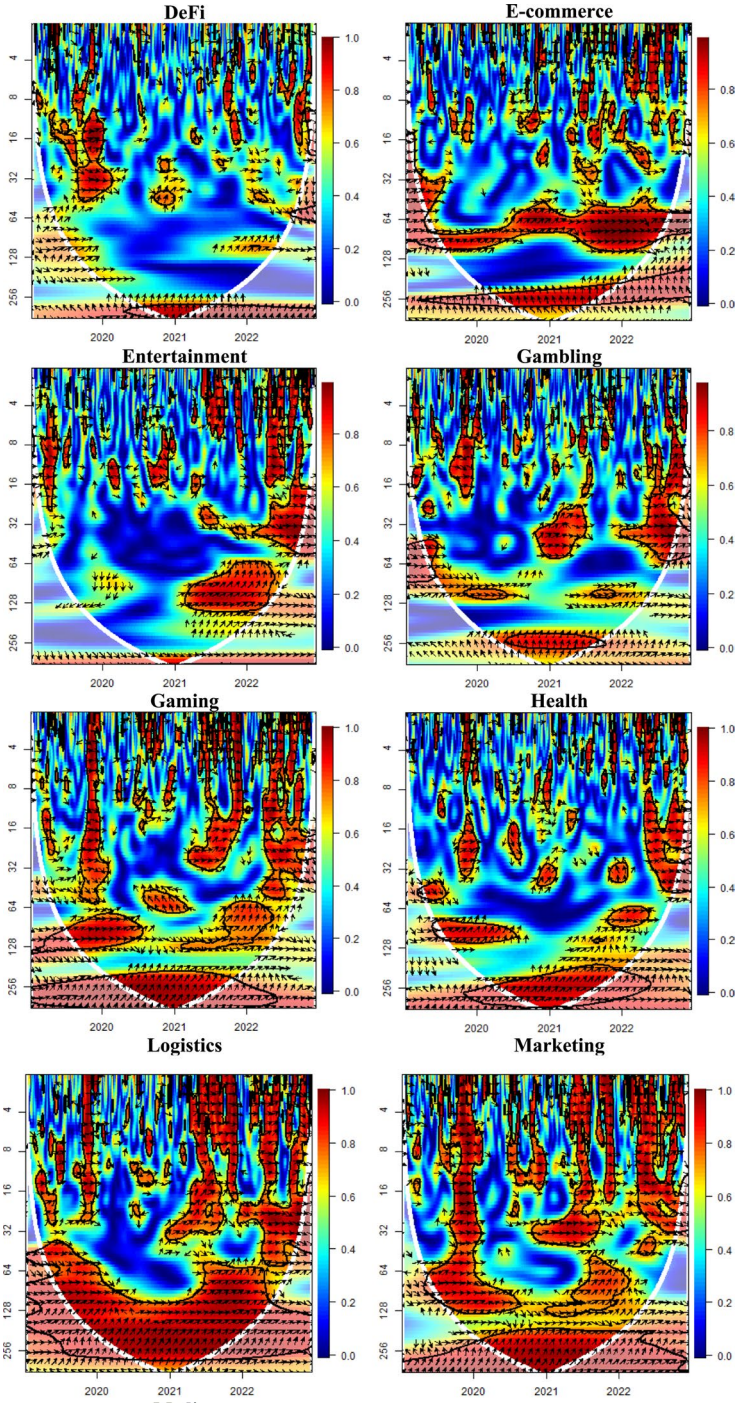

Fig. 3 Wavelet Coherency between Bitcoin Returns and Sectoral Index Returns

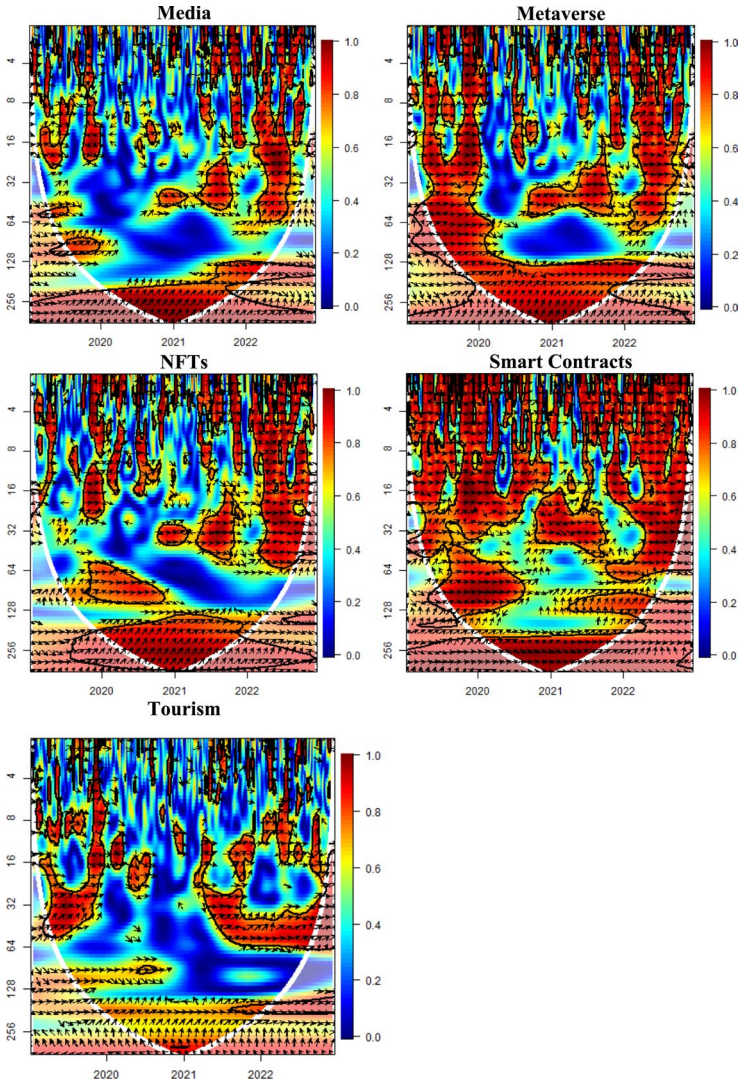

Fig. 3 (continued)

sectoral index return leads the FGI (or Bitcoin returns). It is possible to obtain a combination of the arrows (right and up or left and down, etc.); for example, the "↗" arrow indicates a positive correlation between the FGI (or Bitcoin) and the sectoral index, whereas the FGI (or Bitcoin) leads the sectoral index. The "↘" arrow indicates a positive correlation between the FGI (or Bitcoin) and the sectoral index when the sectoral index leads the FGI (or Bitcoin). Similarly, the "↖" arrow indicates a negative correlation between the FGI (or Bitcoin) and the sectoral index when the FGI (or Bitcoin) leads the sectoral index. Finally, the "↙" arrow indicates

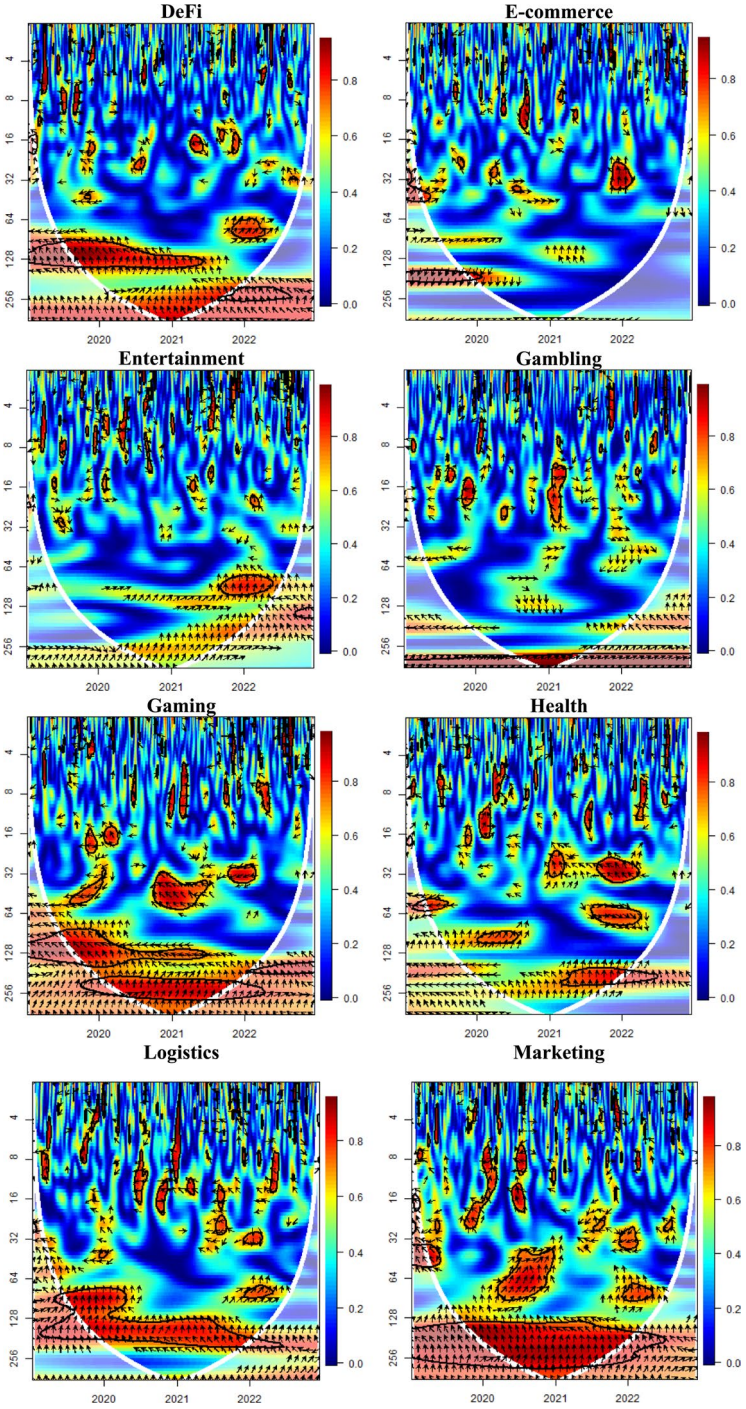

Fig. 4 Wavelet Coherency between FGI and Sectoral Index Volatility

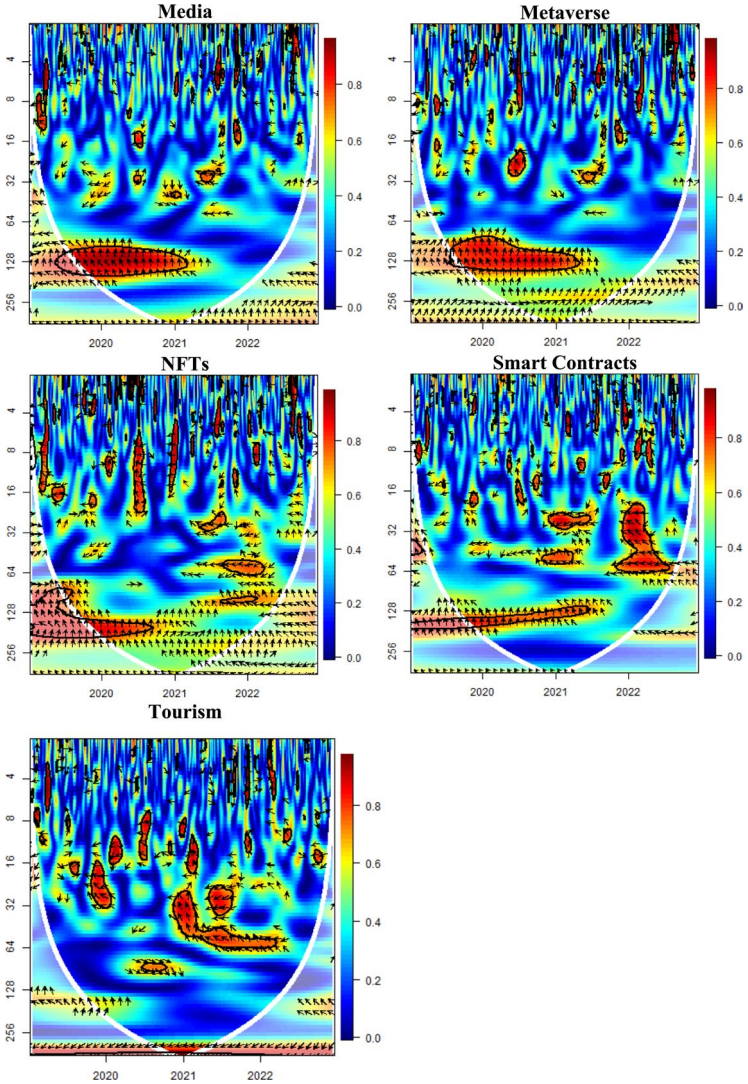

Fig. 4 (continued)

a negative correlation between the FGI (or Bitcoin) and the sectoral index, when the sectoral index leads the FGI (or Bitcoin).

The results for the relationship between investor sentiment and sectoral index returns are presented in Fig. 2. The results in the figure clearly show that the relationship between the FGI and sectoral returns varies over time and frequencies and also the co-movements between the variables are changing according to the sector. For example, there is evidence in favor of a weak relationship between the FGI and DeFi since the wavelet coherence analysis results are generally blue. We just find a significant positive correlation between the FGI and DeFi at the end of

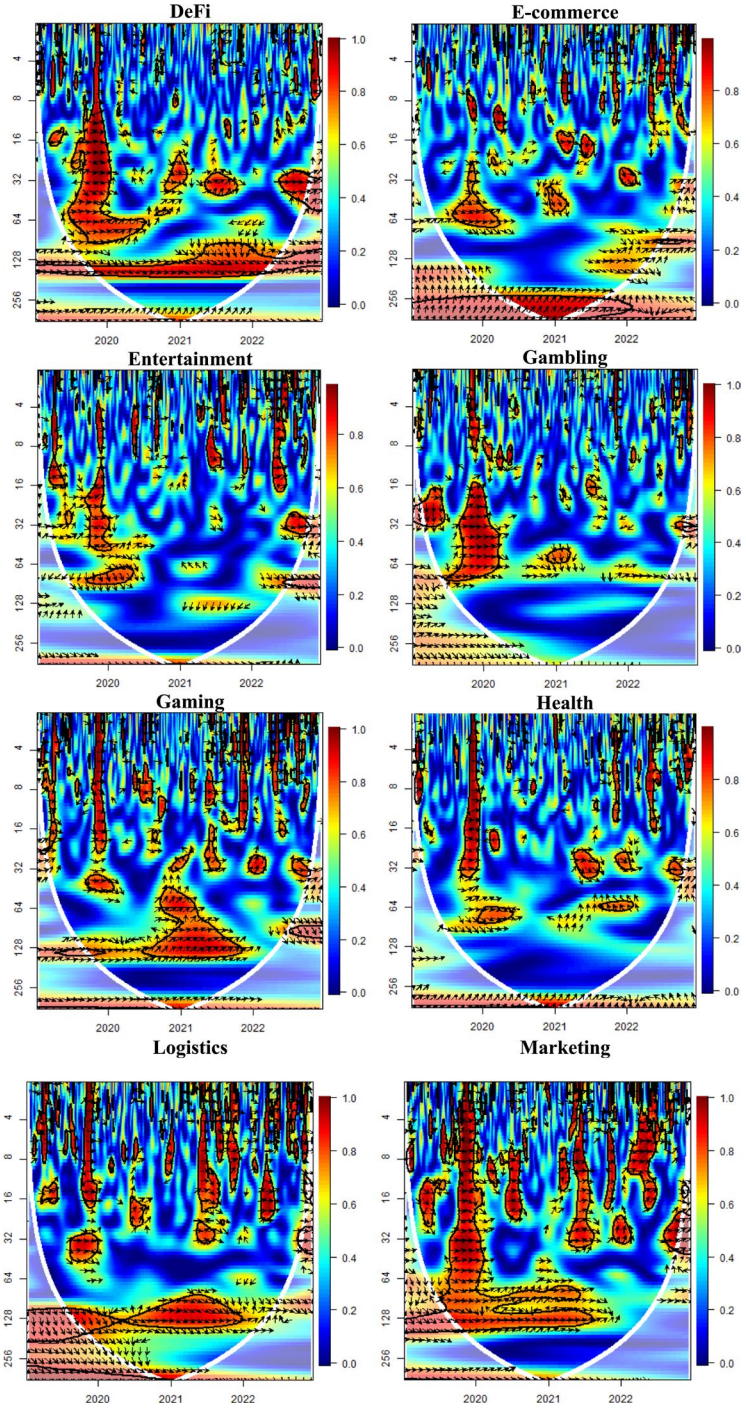

Fig. 5 Wavelet Coherency between Bitcoin Volatility and Sectoral Index Volatility

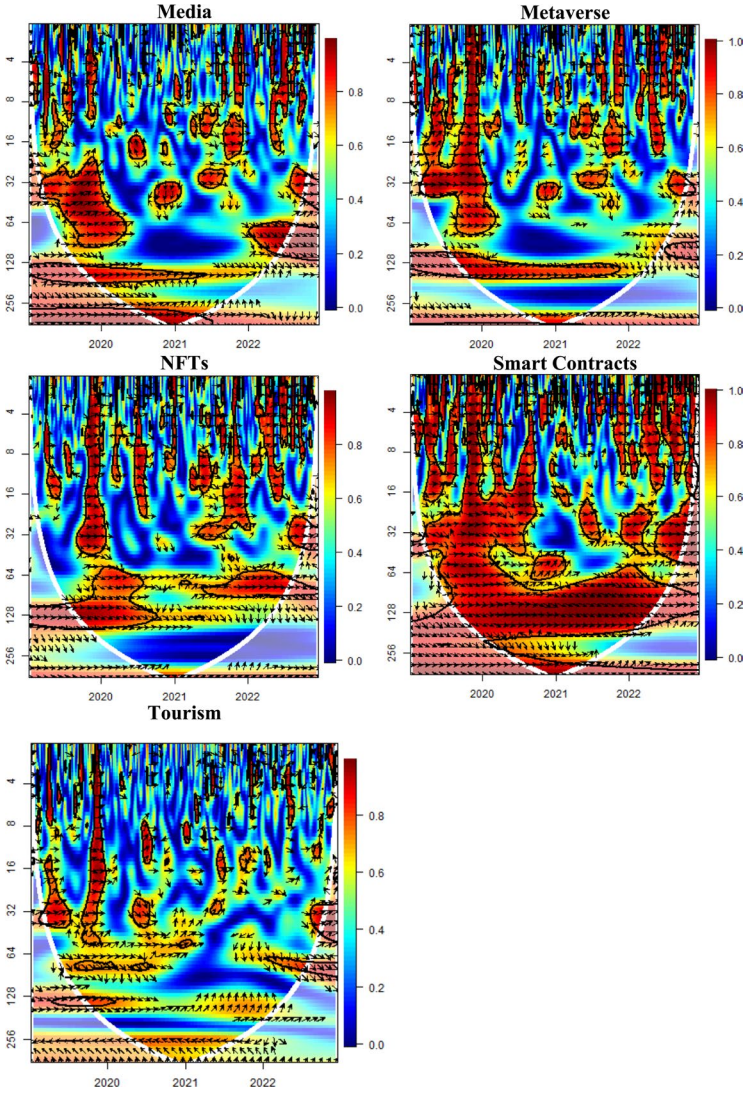

Fig. 5 (continued)

2011 at frequencies of 8–16 days where DeFi leads the FGI. We also find significant co-movements between the FGI and E-commerce at the end of 2011 and at the beginning of 2022 within the 4–128 day frequency range where E-commerce leads the FGI. Entertainment sector return leads the FGI in the short term (at 1–16 day frequencies). Also, there is a positive correlation between the FGI and E-commerce sector returns in 2021 and 2022 at 64–128 day frequencies. Similarly, there is a positive correlation between the FGI and Gambling sector returns at different frequencies (between 4 and 64 days) over some subsamples and the

Gambling sector returns lead the FGI. We find significant co-movements between the FGI and Gaming sector returns that vary over time and frequencies. For example, while we find a positive correlation where Gaming sector returns lead the FGI at 4–128 day frequency ranges, the FGI leads the Gaming sector returns in the same direction in 2020–2021 over long-term horizons. As for the Health sector, we do not find consistent relationships between the variables over short-term horizons as there are positive and negative correlations over subsamples. On the other hand, we find positive correlations between the variables at 64–128 day frequency ranges where sector returns lead the FGI. The empirical results for the Logistics and Marketing sectors are similar. We document positive correlations where sector returns lead the FGI in the short-, medium-, and long-term horizons. However, the relationship is more pronounced in the medium and long term. While the Media sector returns lead the FGI in the same direction in the short and medium terms, the FGI leads the sector returns in the long term in 2020–2021. The relationship between the Metaverse sector returns and the FGI is consistent over the sample, and there is a positive correlation where sector returns lead the FGI. We also document a positive correlation between the FGI and NFT, Smart Contracts, and Tourism sector returns where return lead investor sentiments at all frequencies. Specifically, the relationship between returns in these sectors and investor sentiment is more evident in the long term. This is consistent with Mokni et al. (2022) who found only Bitcoin returns have significant predictive power on the investor sentiment.

Next, the results for the relationship between Bitcoin and sectoral index returns are presented in Fig. 3. The results for DeFi show that generally there is a positive correlation with Bitcoin at low frequencies where DeFi leads Bitcoin returns at the end of the sample. Also, we find a positive correlation at high frequencies in 2021 but where Bitcoin returns lead DeFi. While Bitcoin moves together with the E-commerce sector index in the short term, Bitcoin leads the E-commerce sector at 64–128 frequencies before 2021. After 2021, we document a positive correlation between these variables in the medium term. In the long term, there is a negative correlation where Bitcoin returns lead E-commerce. The results for the Entertainment sector indicate the presence of co-movement between Bitcoin and Entertainment in the short and medium terms, where in some specific periods, Bitcoin leads Entertainment. We find an in-phase relationship for the Gambling sector in the short and medium terms where Bitcoin returns lead the Gambling sector in the long run in 2020–2021. The empirical results for Gaming and Health sectors are similar where there is an in-phase relationship in the short and medium terms, and Bitcoin has leading role for these sectors in the long term. We document very strong co-movements between Bitcoin returns and Logistics, Marketing, Metaverse, NFTs, and Smart Contracts sectors in the short, medium, and long term, and the relationships are generally in phase. However, it seems Bitcoin leads these sectors in the long term. As for the results for the Media sector, we identify a positive correlation where Bitcoin leads in some specific periods. The tourism sector is positively correlated with Bitcoin returns at 4–64 day the frequency ranges and Bitcoin drives the Tourism sector.

4.3 Wavelet analysis results for volatility of sectoral indices

The results for the relationship between investor sentiment and volatility of sectoral indices are given in Fig. 4. Note that since volatility represents uncertainty in the market, the results show the relationship between investor sentiment and uncertainty in the cryptocurrency market and vice versa. The empirical results for the DeFi indicate a negative correlation at 64–128 frequencies between 2020 and 2021 where the FGI leads the DeFi volatility. This suggests that positive investor sentiment leads to decreased volatility. On the other hand, the FGI leads the DeFi in the same direction at a 64 day frequency at the beginning of 2022. The results for E-commerce, Entertainment, and Gambling sectors show the co-movement between investor sentiment and volatility of sectoral indices is weak at best as the graphs for these sectors are generally blue in color. However, we document statistically significant correlations in specific periods for these sectors, which indicate the FGI leads volatility of sector indices. We find a negative correlation between the FGI and the Gaming sector index volatility at 32–128 day frequencies in 2020 and 2021. On the other hand, we observe a positive correlation in the long term in 2020–2021. However, investor sentiment leads the Gaming sector index volatility in all cases. The results for the Health sector are not consistent across time and frequency. While at the beginning of 2020, there is a positive correlation between investor sentiment and Health sector returns at 128 day frequency, a negative correlation can also be detected at 32 day the frequency in 2021. There are significant positive co-movements between the FGI and volatility of Logistics, Marketing, and NFTs sector indices at 32–256 day frequencies in 2020–2021 where the FGI leads the Logistics sector. We find similar results for the Media and Metaverse sectors where the FGI leads volatility of these sectors at 64–256 day frequencies in 2020. While the volatility of the Smart Contracts index was influenced by investor sentiments in the long term in 2020, we find negative correlations in 2020 at 16–64 day frequency ranges. The results for the Tourism sector show that the volatility of the sector index is negatively affected by the sentiment index in the short and medium terms.

Finally, the wavelet coherence analysis results for the relationship between Bitcoin volatility and sectoral indices volatility are given in Fig. 5. Although the results for the sectors in Fig. 5 vary according to frequency ranges and time, there is a positive correlation between Bitcoin volatility and all sector volatilities. While the Smart Contracts sector is the first rank in terms of volatility spillovers with Bitcoin, the Tourism sector is one of the least dependent on Bitcoin in terms of volatility spillovers.

4.4 Robustness analysis results

To assess the robustness of the wavelet coherence analysis results, the time and frequency domain connectedness analysis developed by Barunik and Krehlik (2018) and Chatziantoniou et al. (2023) is employed. This approach leverages the Time-Varying Parameter VAR (TVP-VAR) model to capture the evolving relationship

between variables, while frequency domain analysis distinguishes between short- and long-term dynamics.

Within this framework, a VAR model is employed using the FGI and sectoral cryptocurrency returns, determining an optimal lag length of one. Next, the TVP-VAR model was estimated at both low- and high-frequency values to derive spillover effects. To maintain consistency with the wavelet coherence analysis, the short-term period was defined as 1–32 days, while the long-term period was set at 128 days or more. Following Chatziantoniou et al. (2023), a 100 day forecast error variance decomposition was employed.

The results in Table 2 indicate that, in the short term, the FGI functions as a net spillover receiver, with the highest return spillovers originating from the Smart Contracts, Metaverse, Marketing, NFTs, and Logistics sectors. This finding aligns with the wavelet coherence analysis results in Fig. 2, which show that FGI exhibits the strongest interactions with these sectors over short time horizons. In the long term, as shown in Table 2, FGI is determined as a net spillover transmitter, with the highest spillovers directed toward the Logistics, Smart Contracts, E-commerce, Metaverse, and Tourism sectors. Furthermore, the Total Connectedness Index (TCI) for the long term (70.01) is higher than that for the short term (65.7), indicating stronger connectedness among variables over extended periods. This result is consistent with the wavelet coherence analysis, which similarly suggests that comovement between variables intensifies over longer time horizons.

Table 3 presents the short- and long-term spillover analysis results between Bitcoin and sectoral cryptocurrency returns. The findings reveal that Bitcoin consistently acts as a spillover transmitter across all sectors in both time horizons. The strongest spillovers from Bitcoin are observed in the Smart Contracts, Logistics, Metaverse, and E-commerce sectors, aligning with the wavelet coherence analysis results in Fig. 3.

Overall, the time–frequency domain spillover analysis closely mirrors the wavelet coherence findings, reinforcing the robustness of the conclusions drawn from the latter.

5 Conclusions

5.1 Empirical findings

This paper uses wavelet coherence analysis to identify the connectedness of sectoral cryptocurrency indices with Bitcoin returns and the Fear and Greed Index that measure investors' risk appetite in the cryptocurrency market. Our objective is to ascertain whether market trends, proxied by Bitcoin, or investor sentiment, represented by the Fear and Greed Index, impact the return and volatility of sectoral indices. The sectoral indices consist of Decentralized Finance, Electronic Commerce, Energy, Entertainment, Gambling, Gaming, Healthcare, Lending, Logistics, Marketing, Media, Metaverse, Non-Fungible Tokens, Smart Contracts, and Tourism. Using daily data from July 19, 2019, through July 11, 2022, we construct the sectoral

Table 2 Average Dynamic Connectedness between FGI and Sectoral Cryptocurrency Returns

Short term	FGI	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
FGI	44.28	1.52	2.7	3.05	4.45	1.64	1.25	4.59	6.17	4.53	7.03	5.12	3.96	9.72	55.72
DeFi	2.45	46.79	2.47	1.89	4.53	2.2	1.95	4.43	5.51	3.18	4.69	3.68	3.57	12.65	53.21
E-commerce	3.64	2.59	56.54	2.35	3.1	1.69	1.79	3.41	3.98	3.36	3.69	4.14	2.59	7.13	43.46
Entertainment	3.4	2.2	2.14	53.62	4.58	2.01	2.23	3.29	4.78	4.15	4.27	3.66	3.82	5.83	46.38
Gaming	3.56	2.73	1.64	3.44	29.36	1.88	3.91	7.49	11.2	7.57	7.68	7.15	4.15	8.24	70.64
Gambling	1.94	2.53	2.03	2.67	3.57	58.42	2.22	3.53	3.93	2.73	4.27	3.46	2.39	6.3	41.58
Health	1.72	2.09	1.81	2.95	5.84	2.31	51.58	3.78	6.23	4.34	3.95	4.85	3.31	5.23	48.42
Logistics	3.64	3.18	1.95	2.57	8.36	1.95	2.75	31.94	8.45	6.08	8.36	7.71	3.55	9.51	68.06
Marketing	4.55	3.44	1.91	3.36	10.32	1.87	3.68	7.08	26.7	6.79	8.25	8.76	4.01	9.28	73.3
Media	3.36	2.38	1.75	2.77	7.23	1.48	2.51	5.51	6.91	28.45	16.31	9.81	3.77	7.75	71.55
Metaverse	4.12	2.97	1.81	2.67	6.66	2.12	2.2	6.48	7.82	13.65	24.93	11.83	3.57	9.17	75.07
NFTs	3.52	2.4	2	2.3	6.45	2	2.75	6.26	8.92	8.56	12.09	29.19	3.99	9.57	70.81
Tourism	4.14	3.88	1.64	2.7	5.18	1.63	2.9	4.66	5.95	5.07	5.77	6.21	40.59	9.68	59.41
Smart Contracts	5.96	6.37	3.5	3.04	6.85	2.87	2.79	7.26	8.58	6.43	8.46	8.81	5.61	23.46	76.54
TO	46	38.28	27.34	35.77	77.12	25.64	32.93	67.78	88.44	76.44	94.82	85.2	48.31	110.08	854.15
Net	−9.72	−14.93	−16.12	−10.61	6.48	−15.94	−15.49	−0.28	15.15	4.89	19.76	14.38	−11.11	33.54	TCI: 65.7
Long term	FGI	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
FGI	45.17	1.3	2.61	3.27	4.17	1.75	1.2	4.58	5.76	4.41	7.17	5.13	3.93	9.54	54.83
DeFi	9.04	43.61	2.16	2.47	3.71	1.55	1.8	4.47	6.08	2.38	4.44	3.3	3.3	11.7	56.39

Table 2 (continued)

Long term	FGI	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
E−commerce	10.18	2.46	50.15	2.56	2.89	1.51	1.36	3.82	3.37	4.16	4.19	3.33	2.91	7.13	49.85
Entertainment	6.89	1.71	2.6	49.27	4.39	1.06	2.95	3.39	4.32	5.09	4.2	3.89	4.41	5.83	50.73
Gaming	7.01	2.56	1.83	2.91	28.3	1.84	3.25	7.44	10.67	8.12	7.5	6.31	3.72	8.53	71.7
Gambling	6.63	2.68	2.33	3.46	4.14	46.16	2.83	4.42	5.64	3.28	4.67	3.95	2.61	7.2	53.84
Health	5.54	1.55	1.94	3.15	6.65	1.96	43.69	4.74	7.11	5.76	4.5	4.92	3.02	5.46	56.31
Logistics	11.72	2.97	2.36	3.05	7.28	1.78	2.02	24.36	8.09	6.37	9.44	6.58	4.06	9.93	75.64
Marketing	7.16	3.31	1.98	3.1	9.94	1.75	3.27	7.16	26.44	6.59	8.32	7.44	4.15	9.41	73.56
Media	8.22	2.41	1.86	2.71	7.34	1.25	3	6.49	7.61	24.84	13.86	8.24	3.86	8.3	75.16
Metaverse	9.19	3.47	2.08	3.28	6.8	2.08	2.65	7.11	8.25	10.7	21.8	9.73	3.41	9.45	78.2
NFTs	6.79	1.95	1.88	2.57	6.58	1.28	2.35	6.36	9.29	7.57	11.36	27.09	4.8	10.13	72.91
Tourism	8.26	3.59	1.7	2.34	4.34	1.44	3.11	4.54	6.42	5.45	5.73	5.44	37.81	9.84	62.19
Smart Contracts	11.3	6.19	3.06	3.49	6.48	2.42	2.79	7.21	8.07	6.29	8.76	7.1	5.69	21.16	78.84
TO	107.93	36.14	28.38	38.37	74.71	21.67	32.57	71.73	90.67	76.16	94.14	75.37	49.88	112.44	910.15
Net	53.1	−20.25	−21.46	−12.36	3.01	−32.18	−23.74	−3.92	17.11	1	15.94	2.46	−12.32	33.61	TCI: 70.01

Table 3 Average Dynamic Connectedness between Bitcoin and Sectoral Cryptocurrency Returns

Short term	Bitcoin	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
Bitcoin	22.31	3.86	3.33	3.29	6.31	3.16	2.35	6.01	8.41	6.48	8.12	8.36	4.19	13.83	77.69
DeFi	7.47	44.38	2.42	1.96	4.12	1.99	1.69	4.18	5.01	2.86	4.45	3.73	3.68	12.06	55.62
E−commerce	7.14	2.46	54.92	2.11	2.95	1.62	1.56	3.32	4.06	3.2	3.35	4.35	1.98	6.96	45.08
Entertainment	6	2.32	1.94	52.69	4.08	2.08	2.11	3.33	4.67	3.98	4.13	3.9	3.19	5.59	47.31
Gaming	7.35	2.47	1.52	3.07	27.98	1.77	3.69	7.44	10.83	7.34	7.46	7.33	3.68	8.08	72.02
Gambling	7	2.28	1.83	2.69	3.27	55.64	2.04	3.33	3.67	2.56	4.06	3.43	2.36	5.84	44.36
Health	4.49	1.98	1.66	2.87	5.72	2.13	50.38	3.87	5.71	4.11	4.06	4.72	3.18	5.12	49.62
Logistics	7.59	2.67	1.88	2.59	8.25	1.78	2.69	29.81	8.39	6.19	7.69	7.7	3.56	9.2	70.19
Marketing	9.15	2.89	2	3.22	9.69	1.8	3.19	7.02	24.24	7.21	7.72	8.9	3.83	9.14	75.76
Media	7.37	2.16	1.63	2.55	6.93	1.34	2.34	5.52	7.29	26.81	15.49	9.93	3.33	7.3	73.19
Metaverse	8.43	2.84	1.56	2.67	6.42	1.97	2.13	6	7.22	13.12	23.41	11.66	3.64	8.91	76.59
NFTs	8.54	2.38	1.79	2.33	6.26	1.81	2.52	6.16	8.01	8.43	11.87	26.87	3.81	9.23	73.13
Tourism	7.09	3.88	1.4	2.75	5.19	1.49	2.86	4.74	5.52	4.52	5.94	6.26	39.36	9.01	60.64
Smart Contracts	13.31	5.86	3.2	3.02	6.44	2.5	2.45	6.78	8.16	5.96	7.89	8.3	4.81	21.32	78.68
TO	100.92	38.03	26.18	35.11	75.63	25.47	31.63	67.7	86.94	75.96	92.23	88.57	45.24	110.26	899.88
Net	23.24	−17.59	−18.9	−12.2	3.61	−18.89	−17.99	−2.49	11.18	2.78	15.64	15.44	−15.4	31.58	TCI: 69.22
Long term	Bitcoin	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
Bitcoin	24.14	3.91	3.38	3.74	5.83	3.2	1.96	5.94	8.11	6.34	8.31	6.44	4.73	13.99	75.86
DeFi	6.4	51.93	1.86	2.29	2.65	1.56	1.75	3.5	4.45	2.41	4.13	2.33	3.27	11.47	48.07
E-commerce	8.19	2.56	56.1	2.03	2.58	1.25	1.22	3.36	3.38	3.67	3.9	3.27	1.84	6.66	43.9

Table 3 (continued)

Long term	Bitcoin	DeFi	E-commerce	Entertainment	Gaming	Gambling	Health	Logistics	Marketing	Media	Metaverse	NFTs	Tourism	Smart Contracts	FROM
Entertainment	5.92	1.45	1.99	53.81	4.25	1.03	2.85	2.94	4.6	4.46	3.93	3.89	3.63	5.25	46.19
Gaming	7.94	2.22	1.39	2.78	30.28	1.57	2.77	7.04	11.31	7.71	7.45	6.06	3.47	7.99	69.72
Gambling	7.53	2.34	1.81	3.38	3.6	51.65	2.49	3.69	4.56	3.1	4.32	3.33	2.25	5.96	48.35
Health	4.59	1.45	1.43	2.74	6.24	1.77	51.63	4.12	5.79	5.2	3.98	4.2	2.81	4.05	48.37
Logistics	7.83	2.78	2.09	2.85	7.62	1.44	2.13	29.61	8.28	6.86	8.67	6.56	4.07	9.22	70.39
Marketing	8.87	3.29	1.89	3.33	10.02	1.74	3.28	6.95	25.96	6.43	8	7.18	3.91	9.15	74.04
Media	7.91	1.94	1.44	2.43	6.75	0.95	2.58	5.96	7.43	27.29	16.02	8.83	3.22	7.25	72.71
Metaverse	9.61	2.61	1.72	2.98	6.72	1.79	2.37	6.4	7.28	13.27	22.75	10.44	3.3	8.76	77.25
NFTs	8.2	2.02	1.57	2.47	6.45	1.24	2.29	6.19	8.49	8.19	12.2	26.81	4.5	9.37	73.19
Tourism	5.99	3.25	1.25	2.21	4.71	1.38	3.36	4.46	5.63	5.1	6.31	5.67	41.56	9.11	58.44
Smart Contracts	13.24	6.59	3.16	3.35	6.16	2.17	2.63	7.01	7.49	5.86	8.1	6.7	5.21	22.35	77.65
TO	102.22	36.4	24.97	36.57	73.57	21.09	31.69	67.56	86.82	78.58	95.31	74.9	46.19	108.24	884.13
Net	26.36	−11.67	−18.93	−9.62	3.86	−27.25	−16.67	−2.83	12.78	5.87	18.07	1.71	−12.25	30.58	68.01

indices based on at least three cryptocurrencies, and the weight of each cryptocurrency in the sectoral index is set according to market capitalization.

The empirical results for the relationship between investor sentiment and sectoral index returns show that there is a positive correlation between sector returns and investor sentiment and sectoral return series lead investor sentiment. Moreover, this finding is more pronounced in the medium to long term. Therefore, it can be argued that cryptocurrency prices have an important bearing on investor mood where an increase in the price of cryptocurrency raises investor sentiment. On the other hand, the wavelet coherence regarding the relationship between Bitcoin and sectoral indices generally suggests an in-phase (positive) relationship between these variables at all frequencies where Bitcoin returns lead sectoral returns. The relationship is strongest for Bitcoin returns and Logistics, Marketing, Metaverse, NFTs, and Smart Contracts.

The empirical results for the relationship between investor sentiment and sectoral volatility do not point to a consistent picture. For example, for certain sectors such as E-commerce, Entertainment, and Gambling the co-movement between investor sentiment and volatility of sectoral indices is weak. Yet for other sectors, there is usually a negative relationship between investor sentiment and sector return volatilities where investor sentiment leads to sector return volatilities. Hence, positive investor sentiment for the cryptocurrency market is accompanied by low volatility of sectoral indices, which indicates positive investor sentiment helps to reduce uncertainty in the cryptocurrency market. Finally, we generally document a positive correlation between Bitcoin and all sectoral indices in terms of volatility.

To conclude, our results suggest that the impact of Bitcoin over sectoral indices is limited and possesses an uncertain pattern compared to the investor sentiment proxied by Fear and Greed Index. This finding can be attributed to the exponential growth of blockchain technology applications in various sectors and substantial growth in altcoins. It appears that the solutions offered by blockchain technology and their practices over conventional models allow project-based crypto assets to gain idiosyncratic features in their price developments. It is plausible to assume that based on the market events that occurred, sectoral crypto assets may display distinctive features in their returns and volatilities. For instance, hacks and exploits in the DeFi market might have a limited effect on other sectoral crypto assets depending on their linkage to this market. Our findings have empirically verified this insight.

5.2 Policy implications

The findings of this study provide valuable insights for various market participants, including investors, academia, the public, and policymakers. From an investor's perspective, the extent of connectedness identified between cryptocurrency sectors and Bitcoin can be leveraged in portfolio diversification strategies. For example, as demonstrated by wavelet coherence and time–frequency connectedness analysis, the relationship between Bitcoin and certain sectors (DeFi, Entertainment, Gambling, and Health) is significantly weaker than that observed with other sectoral indices. Consequently, including constituents from these

sectors (DeFi, Entertainment, Gambling, and Health) alongside Bitcoin in a portfolio could enhance diversification outcomes. Furthermore, the evidence derived from both low- and high-frequency bands offers additional insights into determining investment horizons for diversification strategies. As our results show, certain sectors (Smart Contracts) exhibit interactions with Bitcoin at higher frequencies, while others (E-commerce, Logistics, Metaverse, NFTs, and Tourism) maintain this connectedness at lower frequencies, reflecting longer-term dynamics. Therefore, investors with different time horizons can tailor their portfolio diversification strategies according to the insights provided by our findings, utilizing both short-term (high-frequency) and long-term (low-frequency) perspectives. In addition to portfolio managers, entrepreneurs may also find our results beneficial, as the distinction between short- and long-term interactions is particularly valuable for their business strategies. The long-term interactions highlighted in our study can help entrepreneurs make more informed decisions in capital budgeting, providing them with a clearer understanding of how economic trends and market dynamics might impact their planning and predictions.

As highlighted in the finance literature, the cryptocurrency market exhibits significantly higher volatility compared to traditional asset classes. Our results suggest that investor sentiment is closely tied to price movements in various sectoral indices (Logistics, Smart Contracts, and NFTs) within the cryptocurrency market, with sentiment often leads the price developments of sectoral tokens. Therefore, the strong connection between investor sentiment and sectoral indices could serve as an early indicator in the cryptocurrency market. Trading strategies that incorporate investor sentiment indicators may improve the timing of buy and sell decisions. The lack of fundamental analysis tools and concerns surrounding technical analysis may be mitigated by the signals derived from investor sentiment, as proxied by the Fear and Greed Index. More accurate trading decisions based on sentiment indicators could help stabilize prices in the cryptocurrency market, addressing the criticism of extreme volatility in token prices. In the long term, this could foster greater participation from both corporate and individual investors, leading to increased market depth and further maturation of the cryptocurrency market.

As the cryptocurrency market remains in its nascent stage and is built on decentralized infrastructure, policymakers face significant challenges in implementing the necessary regulations. However, it is clear that the increasing adoption of blockchain technology in traditional sectors will eventually require the involvement of policymakers. Blockchain is already operational in a wide range of fields, including tourism, logistics, supply chain management, and even charity activities. To maximize the benefits for society while addressing potential risks, including misuse, policymakers may need to introduce certain regulations. Sector-specific regulations could enhance investor and public confidence in tokens, promoting more stable asset prices, which would benefit both businesses in these sectors and investors in the tokens. This approach mirrors regulated capital markets, which aim to provide advantages for both corporations and investors in their shares. Our findings, which highlight varying results across 15 sectors, can assist policymakers in identifying more vulnerable sectors, particularly those closely linked to investor sentiment and Bitcoin, especially at higher frequencies, where price fluctuations tend to be more

abrupt and severe. Regulatory authorities could prioritize these sectors to better protect investors and entrepreneurs considering investments in these areas.

5.3 Limitations and future research directions

Although this study aims to provide comprehensive insights into the rapidly growing cryptocurrency market, it is subject to certain limitations. For example, sectoral classification within the cryptocurrency market has only recently been established, and the market is still in its early stages. As a result, data are limited for some sectors, which restricts our analysis to just 15 sectors. Future research could expand the scope by examining larger groups, both in terms of the analysis period and the number of constituents in sectoral indices. This would likely lead to more robust findings in empirical investigations. This study uses the Fear and Greed Index as a proxy for investor sentiment, a factor that has been shown to be crucial in the cryptocurrency market, as evidenced by existing literature. Future studies may also explore alternative sentiment indices. Additionally, grouping sentiment factors based on underlying drivers, such as geopolitical events, herd behavior, or seasonality, could offer valuable insights. These factors might serve as early indicators, complementing our empirical findings and providing a more nuanced understanding of sentiment dynamics in the cryptocurrency market.

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Data availability The data sets analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest None, no conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

Consent to participate No human or animal subjects were used in our study, and no questionnaire was conducted.

Consent for publication Our study does not contain individual person's data.

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