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Whether and when did bitcoin sentiment matter for investors? Before and during the COVID-19 pandemic

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Abstract

Using a wavelet coherence approach, this study investigates the relationship between Bitcoin return and Bitcoin-specific sentiment from January 1, 2016 to June 30, 2021, covering the COVID-19 pandemic period. The results reveal that before the pandemic, sentiment positively drove prices, especially for relatively higher frequencies (2–18 weeks). During the pandemic, the relationship was still positive, but interestingly, the lead-lag relationship disappeared. Employing partial wavelet tools, we factor out the number of COVID-19 cases and deaths and the Equity Market Volatility Infectious Disease Tracker index to observe the direct relationship between a change in sentiment and return. Our results robustly reveal that, before the pandemic, sentiment had a positive effect on return. Although positive coherence still existed during the pandemic, the lead-lag relationship disappeared again. Thus, the causal relationship that states that sentiment leads to return can only be integrated into short-term trading strategies (up to six weeks frequency).

Keywords: Bitcoin, Return, COVID-19, Sentiment, TRMI

JEL Classification: C21, C22, G11, G14, G17

Introduction

Market prices may diverge from the fundamentals for a long time that betting against market sentiment may be too costly, i.e., there are limits to arbitrage (Shleifer and Vishny 1997). Hence, as a driver of prices, market sentiment is important for both investors and policymakers. The Bitcoin market is a sensational market for investigating the role of sentiment. No central bank or authority regulates the supply of Bitcoin, implying that investor sentiments may affect the prices more pronouncedly. Moreover, it is difficult to pinpoint the fundamentals of the Bitcoin market as opposed to that of national fiat currencies.

The main driver of Bitcoin prices is a pertinent issue, especially for investors. One of the drivers of asset prices is investor sentiment¹ and psychology (Baker and Wurgler

¹ There may be different mechanisms affecting investor sentiment in the markets. For example, when Elon Musk suddenly added the bitcoin symbol to his Twitter account, this news impacted investor sentiment and pushed the prices upwards significantly (Brown 2021). Similarly, when there is news that the US government will regulate Bitcoin markets in the Biden administration (Reuters 2021), this time, investor sentiment works in the opposite direction repressing prices.

2006, 2007). This sentiment is more pronounced in impacting price fluctuations due to the unregulated nature of the Bitcoin market. Among the significant turmoil in the cryptocurrency markets, the coronavirus (COVID-19) pandemic proved a compelling case ever since the Bitcoin market experienced an influx of new investors (Urquhart 2021). Hence, the Bitcoin market needs to be carefully investigated, while considering the COVID-19 pandemic as a natural experiment opportunity.

Although the literature has investigated the relationship between investor psychology and cryptocurrencies, the changing dynamics due to the pandemic are overlooked as most of the studies (Chen et al. 2020; Goodell and Goutte 2021) focused on the initial phase of the COVID-19 pandemic and used a single time–frequency and a generic sentiment measure. This study employs a news and social media-based Bitcoin-specific sentiment measure provided by Thomson Reuters MarketPsych Indices (TRMI) to investigate the role of sentiment in price discovery before and during the COVID-19 pandemic. A wavelet methodology is conducted to analyze this relationship in different trading frequencies, from one week to 24 weeks. Wavelet transformation reveals the spectral characteristics of time series during different periods by providing information in frequency and time domains simultaneously. The wavelet spectrum visualizes how trends, structural changes, seasonality, predominant business cycles, and short-run dynamics in financial time series evolve throughout the observations (Wen 2002; Merrill et al. 2008). The wavelet methodology can decompose the data in different time frames at a specific frequency so that it does not require stationarity, seasonality, and structural break tests, which are necessary standard tests used in time series analysis to maintain consistent estimations (Masset 2015).

Our results reveal that, regarding the co-movement between Bitcoin sentiment and return, the wavelet coherence spectrum had significant coherency at high frequency (2–3 weeks). The coherency still existed in other frequencies (3–6, 6–9, and 9–18 weeks) for different periods. We employed phase diagrams to check the lead-lag relationship. Phase differences reveal that Bitcoin sentiment led to Bitcoin returns before the COVID-19 pandemic, and the relationship is positive. Interestingly, during the pandemic, although positive coherency existed, the lead-lag relationship became insignificant. This is probably due to the extreme uncertainty during the pandemic and the increasing volatility in Bitcoin prices. We also employed partial wavelet tools to investigate the effects of the COVID-19 pandemic because the pandemic may jointly impact both return and sentiment. We used the number of COVID-19 cases and deaths and the Equity Market Volatility Infectious Disease Tracker (EMVID) index to observe the direct relationship between sentiment and return. Our results reveal that before the pandemic, the sentiment had a positive effect on price, but during the pandemic, the lead-lag relation disappeared. Hence, in the Bitcoin market, sentiment was more pronounced even after considering the impact of the unprecedented COVID-19 pandemic. Regarding the effects of the pandemic, the causal relationship that sentiment leads to return can only be integrated as a short-term trading strategy. However, for longer-term trading strategies, Bitcoin-specific sentiment is uninformative for Bitcoin's return. Moreover, Bitcoin-specific sentiment and its return are positively correlated at all frequencies.

This paper contributes to the literature on several grounds. First, the wavelet methodology allows us to investigate the relationship between sentiment and return for different time frequencies, whereas the literature mainly employs a single frequency. For example, Chen et al. (2020) reported linear vector autoregressive (VAR) estimation results only for daily data. Anamika et al. (2021) employed dynamic linear regression using pre-COVID-19 weekly data. Guler (2021) used monthly data and reported VAR estimation results. The contribution of this study is unique as it covers a wide range of frequency domains from 1 to 18 weeks. Hence, we can draw implications for different investment horizons and trading strategies.

Second, earlier literature either focused on a shorter COVID-19 period (Goodell and Goutte 2021; Chen et al. 2020; Guler 2021) or ignored the pandemic period (Anamika et al. 2021). However, we analyze a more extended observation period from January 1, 2016 to June 30, 2021, that is, both before and during the pandemic. This enables us to examine the effect of sentiment on Bitcoin prices more accurately, considering the unprecedented COVID-19 pandemic. Furthermore, we employ a partial wavelet coherence approach that allows us to investigate the net effect of investor sentiment on Bitcoin return by factoring out the impact of the outbreak.

Third, contrary to recent literature (Chen et al. 2020; Guler 2021), we employ a Bitcoin-specific sentiment index rather than a generic index. Utilizing a tailored sentiment index of TRMI provides a more accurate investor psychology measure. Therefore, our analysis reveals the market-specific dynamics of Bitcoin. In contrast, the generic sentiment measures mainly used in the earlier literature cannot capture market-specific psychology.

This study's empirical findings have important implications for the portfolio configurations of Bitcoin investors and its return discovery dynamics during different periods and trading frequencies. Regarding investors' decision-making process, the time and frequency varying causal relationship between Bitcoin and its sentiment allows investors to adopt dynamic investment strategies and adjust crypto-asset weights in their portfolios more efficiently. News and social media updates affect investors' sentiments regarding the price discovery process, thus impacting Bitcoin prices. When making longer-term investment strategies, investors should consider that the Bitcoin market is still not mature compared with other financial markets, such as the stock and bonds markets. Considering the high volatility in Bitcoin prices, investors may be better off following longer-term trends/cycles rather than focusing on short-run sentiment dynamics.

The rest of the paper is organized as follows. The next session explains the dataset. Sect. "Data" examines the methodology used. Sect. "Methodology" presents the results and discusses them in detail, while the last section concludes.

Related literature

As there are no central authorities directly regulating the supply of Bitcoin, it is relevant and timely to investigate the role of sentiment in Bitcoin markets as it is the main cryptocurrency that directly affects the prices and returns of all other cryptocurrencies. The decentralized feature of the Bitcoin market implies that investor sentiments may affect its prices more pronouncedly. The recent empirical literature generally agrees that the cryptocurrency markets are inefficient, and the returns are driven by sentiment and

news about the crypto market innovations and political decisions. Thus, our theoretical contribution is to reveal the relevancy of the sentiment in the Bitcoin markets.²

While the recent sentiment-crypto asset nexus literature differs in relation to the sentiment index, data frequency, and methodology employed, the literature mainly suggests that investor sentiment is a significant determinant of cryptocurrency prices. Although the role of sentiment is well recognized in the literature, finding a proxy to measure sentiment can be challenging as sentiment is not directly observed. Thus, different measures have been employed in the literature:

i. publicly available market data, such as VIX (Chicago Board Options Exchange Volatility Index), EPU (Economic Policy Uncertainty Index), benchmark market return, and volatility (Jo et al. 2020; Paule-Vianez et al. 2020; Shaikh 2020).

ii. author-estimated composite indices based on market-specific data (Baker and Wurgler 2006, 2007).

iii. social media and news search analytics from traditional media, Twitter, Google Trends, and Yahoo (Tetlock 2007; Zhang et al. 2018; Khan et al. 2020).

Generally, recent literature has investigated the relationship between sentiment and Bitcoin returns with social media sentiment measures. Some researchers measured only positive sentiment; for instance, Bouri et al. (2020) analyzed the role of happiness in dynamic volatility correlation among major cryptocurrencies. Others, including Burggraf et al. (2020) and Chen et al. (2020), constructed the FEARS index as a proxy for negative sentiment and other net sentiment measures by incorporating bearish, bullish, and neutral investor behavior from social media data or surveys (Guegan and Renault 2021). Twitter feed data and Google trend analytics are commonly used social media-based sentiment measurement resources (Lamon et al. 2017; Eom et al. 2019; Lopez et al. 2019; Smuts 2019; Burggraf et al. 2020; Chen et al. 2020; Rajput et al. 2020; Subramaniam and Chakraborty 2020; Guegan and Renault 2021). Karavevicius et al. (2017), Lamon et al. (2017), Entrop et al. (2020), and Rognone et al. (2020) also included news data in their sentiment-cryptocurrency market nexus research.

Among studies that have investigated the relationship between sentiment and Bitcoin returns in the pre-COVID-19 era, Lopez et al. (2019), Valencia et al. (2019), Guegan and Entrop et al. (2020), Eom et al. (2019), Keskin and Aste (2020), Khan et al. (2020), and Renault (2021) justified the existing causality between return and sentiment, in which sentiment has predictive power for Bitcoin returns. Moreover, Karavevicius et al. (2017), Smuts (2019), Jo et al. (2020), and Rajput et al. (2020) concluded that this relationship is positive. However, comparing the impact of Bitcoin news on main currencies and Bitcoin returns, Rognone et al. (2020) indicated that Bitcoin return is irresponsive but positively related to news sentiment. In contrast, major currencies react positively and negatively to positive and negative news, respectively. Regarding negative sentiment, Burggraf et al. (2020) stated that the FEAR index has a negative impact on Bitcoin returns. Similarly, Jo et al. (2020) found that VIX and Bitcoin returns are negatively related.

² We choose Bitcoin (BTC) as our focus due to the following. First, Bitcoin is the main cryptocurrency as being the first and the largest in asset value in the cryptocurrency market. If sentiment affects the bitcoin market, it will also spread to other cryptocurrencies. Hence, we restrict our focus on BTC. Also, the Bitcoin market is deep enough that our sentiment analysis would not be biased by the noise trading compared to analyzing the other cryptocurrencies. The Bitcoin market is also interconnected with conventional financial markets, which helps us to draw policy implications.

Chen et al. (2020), an early study of the pandemic period, examined the relationship between Bitcoin returns, trading volume, and a new FEAR sentiment structured by the authors from search queries of Google Trends that contain “COVID-19” and “Coronavirus.” The study analyzed the relationship by employing the VAR and Granger causality methodology. The findings revealed that pandemic-related words were included. Fear sentiment can explain negative Bitcoin returns and its high trading volume during the early stages of the pandemic. Regarding this outcome, Chen et al. (2020) argued that Bitcoin should be treated as a traditional asset as it behaves like conventional assets during downturn periods. In another recent study, Guler (2021) investigated the impact of investor sentiment on Bitcoin returns and their conditional volatility by employing asymmetric conditional heteroscedasticity models. She also focused on the COVID-19 period by utilizing monthly data. She used the fear and greed index as a proxy for investor sentiment. She concluded that investor sentiment, Bitcoin returns, and volatility are positively related, and this relationship becomes more robust with the pandemic.

Anamika et al. (2021) used the Sentix index, a survey-based sentiment measure, to investigate how sentiment is connected to major cryptocurrency returns, including Bitcoin. They analyzed weekly data from September 2017 to the start of the outbreak in February 2020 and revealed that Bitcoin returns respond positively to the changes in Sentix sentiment.

Contrary to the studies mentioned above, which mainly employed a single frequency, our methodology allows us to investigate the relationship between sentiment and return for different time frequencies (Chen et al. 2020; Anamika et al. 2021; Guler 2021). Our contribution is unique in the literature as our study covers a wide range of frequency domains from 1 to 18 weeks. Hence, we can draw implications for different investment horizons and trading strategies.

Trading and hedging strategies might change concerning the investment horizon. However, few studies have assessed and compared the interrelation between sentiment and Bitcoin returns in different frequencies. For instance, Entrop et al. (2020) and Guegan and Reanult (2021) reported comparative linear model estimations for 1–15-min and 1-min to 24-h frequencies, respectively. The latter stated that the relationship between social media and Bitcoin returns tends to disappear in relatively low frequencies (not more than one-day trading).

Goodell and Goutte (2021) analyzed the co-movement between daily COVID-19-related deaths and Bitcoin prices by conducting a wavelet coherence analysis. Their data spanned from 31st December 2019 to 29th April 2020, that is, just the beginning of the pandemic. In contrast, our study covers a pandemic period much longer than a year (the unprecedented COVID-19 pandemic), enabling us to evaluate investor psychology of Bitcoin prices more accurately. Moreover, the daily death numbers used in their study are a generic proxy, whereas we employ a Bitcoin-specific sentiment measure. We also cover both before and during the pandemic periods to isolate the effect of the pandemic. Furthermore, we use a partial wavelet coherence approach, which enables us to investigate the net effect of investor sentiment on Bitcoin return by factoring out the impact of the outbreak.³

Studies related to the pandemic mostly focus on a shorter COVID-19 period (Goodell and Goutte 2021; Chen et al. 2020; Guler 2021) or ignore the pandemic period at

³ Please see Polyzos et al. (2021), Polat et al. (2022), and Samitas et al. (2022a, b) as the studies investigating the relationship between the COVID-19 pandemic and financial markets.

Table 1 Summary of literature review

Paper	Data Source	Data Period	Method	Findings
Eom et al. (2019)	Google trend analytics	Oct2011-May2017	VAR	Investor sentiment on Bitcoin can predict Bitcoin volatility
Burggraf et al. (2020)	Google trend analytics	Apr2013-Feb2019	OLS VAR	The FEAR index negatively related to Bitcoin returns
Bouri et al. (2020)	Twitter feed data	7Aug2015-11Mar2020	GARCH	Investor happiness explains the volatility connectedness
Chen et al. (2020)	Google trend analytics	15Jan2020-24Apr2020	VAR	Fear sentiment can explain negative Bitcoin returns
Jo et al. (2020)	Google trend analytics	18Jul2010-26Feb2018	VAR	VIX and Bitcoin returns are negatively related
Oad Rajput et al. (2020)	Google trend analytics	2013–2018	OLS GARCH	Bitcoin sentiment positively related to Bitcoin returns
Subramaniam and Chakraborty (2020)	Google trend analytics	Jan2013-Mar2018	VAR	Investors pay attention to the frequent news making and ranked cryptos at all phases
Anamika et al. (2021)	Sentix index	Sep2017-Feb2020	OLS VAR	Bitcoin returns positively react to the changes in Sentix
Goodell and Goutte (2021)	Bitcoin prices	31Dec2019-29Apr2020	Wavelet	Levels of COVID-19 caused a rise in Bitcoin prices
Guegan and Renault (2021)	Twitter feed data	Aug2017-Dec2019	OLS VAR	Justify an existing causality between return and sentiment
Guler (2021)	Google trend analytics	Feb2018-Aug2020	GARCH VAR	Investor sentiment positively related to Bitcoin returns

This table summarizes the selected papers discussed in the Related Literature section

all (Anamika et al. 2021). However, we analyze a more extended observation period from January 1, 2016 to June 30, 2021. This enables us to examine the effect of sentiment on Bitcoin prices more accurately while considering the impact of the COVID-19 pandemic. Furthermore, we employ a partial wavelet coherence approach to investigate the net effect of investor sentiment on Bitcoin return by factoring out the impact of the outbreak. More importantly, contrary to recent literature (Chen et al. 2020; Guler 2021), we employ a Bitcoin-specific sentiment index rather than a generic index. Utilizing a tailored sentiment index of TRMI provides a more accurate investor psychology measure as generic sentiment measures cannot capture market-specific psychology. Table 1 summarizes the methods and findings of recent studies.

Data

We used data on daily Bitcoin returns,⁴ Bitcoin-specific sentiment data from TRMI, the daily number of COVID-19 cases and deaths,⁵ and the daily EMVID constructed by Baker et al. (2020) in this study. As a newspaper-based index, EMVID is built by

⁴ The data is available on different websites, including the <https://www.investing.com/>

⁵ See the data set at: <https://covid.ourworldindata.org/data/owid-covid-data.csv?v=2021-02-24>

Table 2 Descriptive statistics

	Bitcoin	Sentiment	#newcases	#newdeaths	EMVID
Observation Period	1.01.2016–30.06.2021	1.01.2016–30.06.2021	22.01.2020–30.06.2021	22.01.2020–30.06.2021	22.01.2020–30.06.2021
Mean	0.23%	0.00%	346,585	7482	21.40
Std. Dev	4.10%	3.07%	244,264	4250	14.97
Minimum	– 49.73%	– 24.27%	0.0	0.0	0.0
Maximum	22.76%	17.41%	905,378	18,057	112.93
Skewness	– 0.93	– 0.53	0.29	0.15	1.84
Kurtosis	13.70	5.15	– 0.94	– 0.50	5.44
Jarque–Bera	16,041***	2326***	26.96***	7.59**	957***

This table presents descriptive statistics for daily return on Bitcoin price and change in sentiment for the period between 1st January 2016 and 30th June 2021; and daily COVID-19 new cases, COVID-19 new deaths and EMVID index from 22nd January 2020 to 30th June 2021. Jarque–Bera null of normality test returns Chi-squared test statistics and asymptotic p-values. ***indicates $p < 0.01$

searching through a wide range of US newspapers. It focuses on disease-related keywords such as “coronavirus” and “pandemic.” Table 2 summarizes the descriptive statistics of the data. Figure 1 presents seven days moving average number of COVID-19 new cases, new deaths due to COVID-19, and the EMVID index from January 22, 2020 to June 30, 2021.

Our primary variable of interest is the Bitcoin-specific sentiment index produced by Thomson Reuters MarketPsych. TRMI covers multiple sentiment measures, from general sentiment to specific psychological variables, such as fear, stress, and urgency, specific to an asset (Peterson 2013). TRMI is published as two separate contents—news-based and social media-based sentiments. This distinction helps differentiate between professional news from the content produced by retail investors. More than 50,000 news websites regarding news-based sentiments are scanned, including leading sites such as The New York Times, The Wall Street Journal, Financial Times, and Seeking Alpha (Peterson 2013). Social media-based sentiments are produced by scanning millions of social media sites. Using advanced linguistic machine learning algorithms, TRMI is updated every minute, providing a timely measure of investor psychology. These advanced linguistic techniques enable TRMI to present multi-dimensional novel sentiment measures that cannot be captured by bipolar sentiment variables employed by earlier studies (Tetlock 2007; Da et al. 2015; Chen et al. 2020). In this study, we employ the “sentiment” index for Bitcoin to capture the generic sentiment. The sentiment index is defined as the overall positive references, net of negative references, and then normalized to take values between the range of -1 to 1 (Peterson 2016). Following earlier studies, we employ both news-based and social media-based sentiments to capture professional and retail investor sentiments (Nooijen and Broda 2016; Entrop et al. 2019). Figure 2a depicts the time series plot of 30 days moving average of TRMI investor sentiment and Bitcoin price from January 1, 2016 to June 30, 2021.

Figure 2b depicts time-varying correlations between Bitcoin returns and the Bitcoin-specific sentiment index (TRMI) from January 1, 2016 to June 30, 2021. We structure a specific multivariate generalized autoregressive conditional heteroskedasticity that decomposes the conditional covariance matrix into conditional standard deviations and

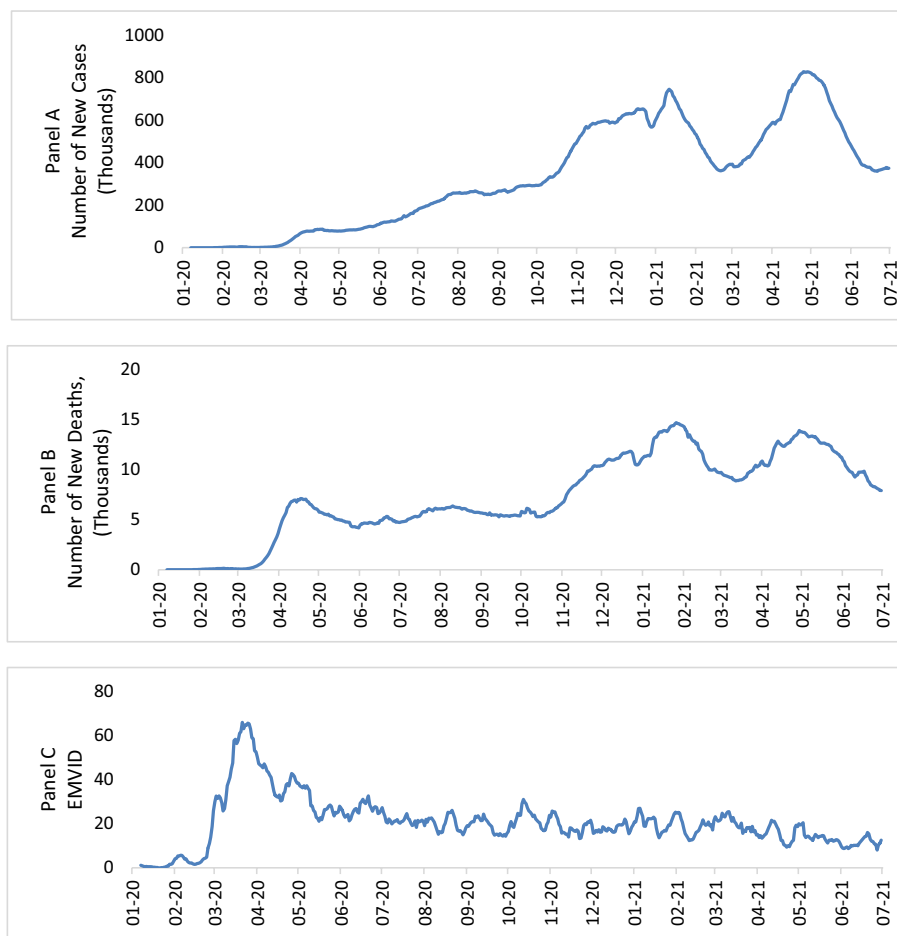


Fig. 1 Panel **A** plots 7 days moving average number of COVID-19 new cases. Panel **B** shows 7 days moving average number of new deaths due to COVID-19 pandemic. Panel **C** shows EMVID index. All panels cover the period from 1st January 2020 to 30th June 2021

correlations, called dynamic conditional correlation (DCC) (Engle 2002; Tse and Tsui 2002). According to Fig. 2b, daily Bitcoin returns and investor sentiment (TRMI) were positively correlated during the observation period, and their DCC varied from 15 and 35%. In Fig. 2b, a structural shift occurred in DCC just after the COVID-19 pandemic began in 2020q1. This structural change in conditional correlation implies that the correlation between Bitcoin return and investor sentiment shifted to a higher correlated state by the start of the pandemic.

Methodology

Wavelet transformation, which was initially used as a signal processing and visualization method in engineering fields, enables finance specialists and economists to analyze the spectral characteristics of time series during different observation periods. Superior to Fourier transformation, which reveals the frequency distribution without indicating where these frequencies occur in time, wavelet transformation simultaneously provides

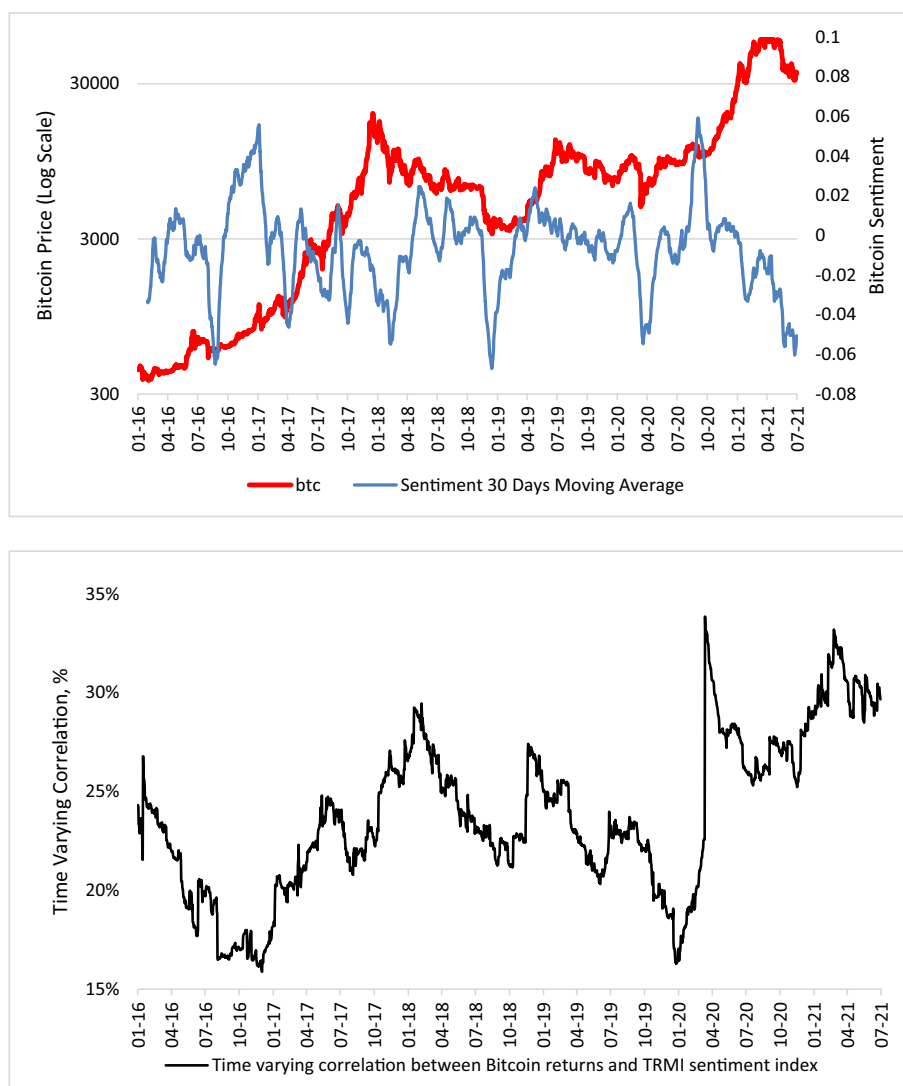


Fig. 2 **a** Investor sentiment (blue line) versus Bitcoin price (red line). Notes: Blue line depicts 30 days moving average Investor sentiment on the right axis. Red line depicts Bitcoin price data in logarithmic scale on the left axis. Observation period is from 1st January 2016 to 30th June 2021. **b** Time varying volatility between Bitcoin returns and TRMI Bitcoin sentiment index. Notes: Results are estimated by a dynamic conditional correlation model of DCC(1,1) model specification. Mean model (ARIMA) and volatility model (GARCH) specification of Bitcoin return and TRMI sentiment are ARIMA(0,1,0) x SGARCH(1,1) and ARIMA(1,1,1) x AVGARCH(1,1), respectively. Both mean and volatility model parameter estimations' results and their estimation diagnostics are available upon request. Data spans from 1st January 2016 to 30th June 2021

information on frequency and time domains. Then, its spectrum visualizes how long-run trends, structural changes, seasonality, predominant business cycles, and short-run dynamics in financial time series would evolve throughout the observation (Wen 2002; Merrill et al. 2008). As wavelet transformation can decompose the data in different time frames at a specific frequency, it does not require stationarity and/or non-trending and/or non-seasonal data assumptions to maintain consistent estimations (Masset 2015). Therefore,

starting with Gençay’s (2002, 2005) introductory studies, wavelet decomposition methodology has spread fast in the financial economics literature. More recent studies that have applied wavelet transformation techniques to various issues, including those of Crowley and Hudgins (2021), Bilgili et al. (2020), Aguiar-Conraria et al. (2020), Hu et al. (2020), Bilgili et al. (2019), and Aguiar-Conraria et al. (2018).

Continuous wavelet transformation (CWT) and wavelet power

A wavelet—the so-called small wave—can be defined as a wave oscillating in a bounded time interval. It is a square differentiable and finite function of time, as described below:

$$\eta_{(a,b)}(t) = \frac{1}{\sqrt{a}}\eta\left(\frac{t-b}{a}\right), b \in \mathbb{R}, a \in \mathbb{R}^+ \text{ and } \eta(t) \in L^2(\mathbb{R}) \tag{1}$$

where $\eta_{(a,b)}(t)$ denotes a wavelet daughter with its mother wavelet $\eta(\cdot)$, which is a function of dilation (a), location (b), and time (t). As the dilation parameter (a) scales $\eta_{(a,b)}(t)$ to capture variations more accurately in different frequencies, the location parameter (b) locates the center of the wavelet in time. $W_x(a, b)$, representing the CWT of a given time series $x(t)$ with respect to a selected wavelet function $\eta_{(a,b)}(t)$, is calculated as follows:

$$W_x(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \overline{\eta\left(\frac{t-b}{a}\right)} dt, x(t) \in L^2(\mathbb{R}) \tag{2}$$

where the bar indicates the complex conjugation of the mother wavelet function $\eta(\cdot)$. The mother wavelet function ($\eta(t)$) must satisfy zero frequency and unit energy conditions stated below:

$$\int_{-\infty}^{\infty} \eta(t) dt = 0 \text{ and } \int_{-\infty}^{\infty} |\eta(t)|^2 dt = 1 \tag{3}$$

These conditions imply that $\eta(t)$ should have no zero-frequency element, and oscillations around the mean are expected to be 0. However, these conditions are not sufficient to analyze the CWTs of different time series (Percival and Walden 2000). Reconstructing the original times series from its CWT requires an admissibility condition for the mother wavelet function $\eta(t)$ of the time series $x(t)$, as presented below:

$$G_\eta = \int_0^\infty \frac{|K(f)|^2}{f} df < \infty \tag{4}$$

where $b \in \mathbb{R}$ and $a > 0$. The wavelet power of $x(t)$ can be defined as $P_x(a, b) = W_x \overline{W_x} = |W_x|^2$. Furthermore, while admissibility and unit energy conditions hold, P_x can be derived as follows:

$$x(t) = \frac{1}{G_\eta} \int_0^\infty \left[\int_{-\infty}^\infty W_x(a, b) \eta_{(a,b)}(t) db \right] \frac{da}{d^2} \tag{5}$$

$$\|x\|^2 = \frac{1}{G_\eta} \int_0^\infty \left[\int_{-\infty}^\infty P_x(a, b) db \right] \frac{da}{d^2} \tag{6}$$

where $\|x\|^2$ measures the preserved energy (). This implies that the wavelet power spectrum $P_x(a, b)$ indicates the energy distribution of $x(t)$ time and frequency domains. This energy can be interpreted as the variance of $x(t)$; hence, the wavelet power spectrum displays the variance distribution of $x(t)$, its time, and frequency domains (Aguiar-Conraria and Soares 2014).

Multivariate wavelet tools

Multivariate wavelet tools can be applied to time series when the interrelation between different time series is examined. They include cross wavelet power (CP), wavelet coherency, and multiple and partial wavelet coherencies. These tools reveal the frequency and time dependency structure between time series. If $x(t)$ and $y(t)$ are random time series, the CP between them ($W_{xy}(a, b)$) can be calculated as follows:

$$W_{xy}(a, b) = W_x(a, b)\overline{W_y(a, b)} \tag{7}$$

W_x and W_y denote individual CWT of $x(t)$ and $y(t)$, respectively. Similarly, a and b denote dilation (scale) and location parameters, respectively. While Hudgins et al. (1993) defined CP as a measurement of the local covariance between two time series, wavelet coherency (R_{xy}) measures the local correlation. Analogous to the linear correlation coefficient, wavelet coherency takes a value from 0 to 1 ($0 \leq R_{xy}(a, b) \leq 1$), and it visualizes this value by coloring areas on its spectrum. Wavelet coherency between time series $x(t)$ and $y(t)$ can be written as follows:

$$R_{xy}(a, b) = \frac{|S(W_{xy}(a, b))|}{\sqrt{S(|W_x|^2)S(|W_y|^2)}} \tag{8}$$

where S is for the smoothing operator. A smoothing process at scale and frequency is required for cross and individual wavelet power spectra because the wavelet coherency spectrum might estimate high coherence spuriously (Liu 1994). When factoring out the possible interaction of some other variables on the interrelation between two time series in time and frequency domains, partial wavelet coherency may occur. When partial wavelet coherency occurs between $x(t)$ and $y(t)$, the effects of $z(t)$ eliminated can be written as follows:

$$R_{xy||z}(a, b) = \frac{R_{xy}(a, b) - R_{xz}(a, b)\overline{R_{yz}(a, b)}}{\sqrt{(1 - R_{xz}^2(a, b))(1 - R_{yz}^2(a, b))}} \tag{9}$$

Complex Morlet wavelet

This study employs a complex Morlet wavelet to detect cycles and variations in Bitcoin return and its sentiment while considering the number of deaths and new cases of COVID-19 to discover co-movement between them in the frequency and time domains.

Morlet wavelet is widely preferred in wavelet-based financial and economic time series studies. For example, it was used in the following studies: Percival and Walden (2000), Crowley (2005), Rua and Nunes (2009), Galleati et al. (2014), Madaleno and Pinho (2014), Aguiar-Conraria et al. (2018), and Aguiar-Conraria and Soares (2021). Choosing a more appropriate wavelet mother that suits the time series' cyclical properties well is crucial as there are major differences in their structures. Shannon, Meyer, Beta, Mexican hat, Morlet, and dozens of others are wavelet families that are widely used as mother wavelets for CWT. The complex Morlet wavelet has two main advantages. First, its complex-valued structure contains additional information about the phase structure of the signals (time series), which allows analysts to compare the location of the signals of different cycles at a specific frequency interval throughout the observation. This comparison supports the test of causal inference between the series by observing differences between the phases of signals, which reveals signals that lead and how they interact. Second, the complex Morlet mother wavelet satisfies the optimal joint frequency–time concentration (Addo et al. 2014; Gallegati et al. 2014). A complex Morlet mother wavelet, which was first introduced by Grossman and Morlet (1984), can be written as follows:

$$\eta(\varepsilon, t) = \frac{1}{\pi^{1/4}} \left(\exp(i\varepsilon t) - \exp\left(\frac{-\varepsilon^2}{2}\right) \right) \exp\left(\frac{-t^2}{2}\right) \tag{10}$$

where complex Morlet wavelet $\eta(\varepsilon, t)$ is a function of the central frequency parameter ε rather than the frequency itself. However, if the location parameter is $\varepsilon > 5$, the value of $\exp(-\varepsilon^2/2)$ becomes negligibly small; then, Eq. 4 can be rewritten as $\eta(\varepsilon, t) = \frac{1}{\pi^{1/4}} \exp(i\varepsilon t) \exp\left(\frac{-t^2}{2}\right)$. Moreover, Aguiar-Conraria and Soares (2014) stated that the central frequency parameter is commonly chosen to be six, that is, $\varepsilon = 6$, which allows a substitution from scale to the frequency (scale can be written as the reciprocal of the frequency). After this setup, a complex Morlet wavelet can be written as time t and frequency f , which provides the best available information mix in both domains.

Phase difference

Complex CWT can determine the phase of a signal (time series), that is, the location of its cycles in time at a specific frequency band. Once the phase structures of two time series are computed, their difference would provide evidence of a causal relationship. The phase difference $\gamma_{x,y}$ between time series $x(t)$ and $y(t)$ can be denoted as follows:

$$\gamma_{x,y} = \arctan\left(\frac{\Im(W_{xy}(a, b))}{\Re(W_{xy}(a, b))}\right) \tag{11}$$

where $\gamma_{x,y} \in [-\pi, \pi]$, and $\Im(W_{xy})$ and $\Re(W_{xy})$ denote imaginary and real parts of a given complex CWT $W_{xy}(a, b)$, respectively. Phase differences formulate the direction and lead-lag structure of the relationship between $x(t)$ and $y(t)$ as follows: if $\gamma_{x,y} \in [(-\frac{\pi}{2}, 0); (\frac{\pi}{2}, \pi)]$, then $y(t)$ leads $x(t)$ and vice versa if $\gamma_{x,y} \in [(0, \frac{\pi}{2}); (-\pi, -\frac{\pi}{2})]$.

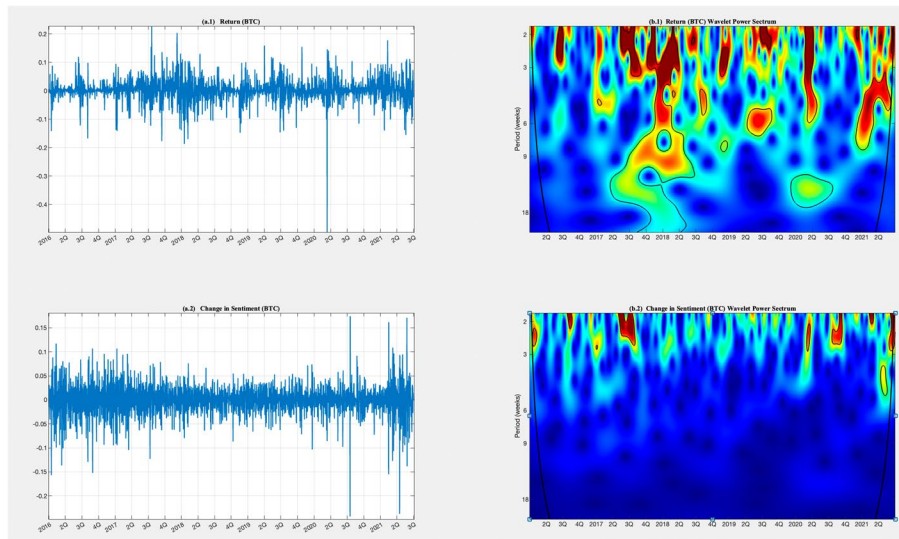


Fig. 3 Left Panel (a) depicts the daily return on Bitcoin prices and change in bitcoin specific sentiment index from 1st January 2016 to 30th June 2021. Right Panel (b) shows the wavelet power spectrum of return and sentiment index data, respectively. Thick black line indicates the boundaries of the cone of influence (COI). Thin black line shades the areas with 10% significant level. These areas have been simulated after 1000 runs. The wavelet power ranges respect to jet color codes from low (blue) to high (red). Periods are depicted as weekly on the vertical axis

If $\gamma_{x,y} \in [(-\frac{\pi}{2}, \frac{\pi}{2})]$, then $x(t)$ and $y(t)$ are in phase, implying a positive relationship. Conversely, if $\gamma_{x,y} \in [(-\frac{\pi}{2}, -\pi); (\frac{\pi}{2}, \pi)]$, then $x(t)$ and $y(t)$ are out of phase, implying a negative relationship. Hence, an exact phase difference of either π or $-\pi$ indicates an exact negative relationship. However, a phase difference of 0 indicates contemporaneous positive co-movement at a specific frequency band.

Results

Figure 3 depicts the individual wavelet power spectra of return on Bitcoin prices and change in Bitcoin-specific investor sentiment (on the right) as well as their daily time plots (on the left). The observation data span from January 1, 2016 to June 30, 2021. Wavelet power spectra separately visualize the relative variance intensities of return and change in sentiment by scaling them in relation to a range of frequency from 2 to 23 weeks. The return has significant wavelet power areas on the upper panel, mostly at a 2–3-week frequency. These areas extended their power to relatively lower frequencies of 3–6 and 6–9 weeks during 2017q3–2018q1, 2020q1–2020q2, and 2021q1–2021q2 time intervals. The latter corresponds to COVID-19 pandemic-related financial outcomes. The first interval coincided with August 2017, its all-time high-price upsurge in December 2017, and its dramatic fall in February 2018.

The wavelet power of change in sentiment on the lower right panel reveals relatively high power in shorter cycles of 2–3 weeks. On the power spectrum, significant high-power areas existed in 2017q3, 2020q1, and 2020q3 time intervals as they did in the

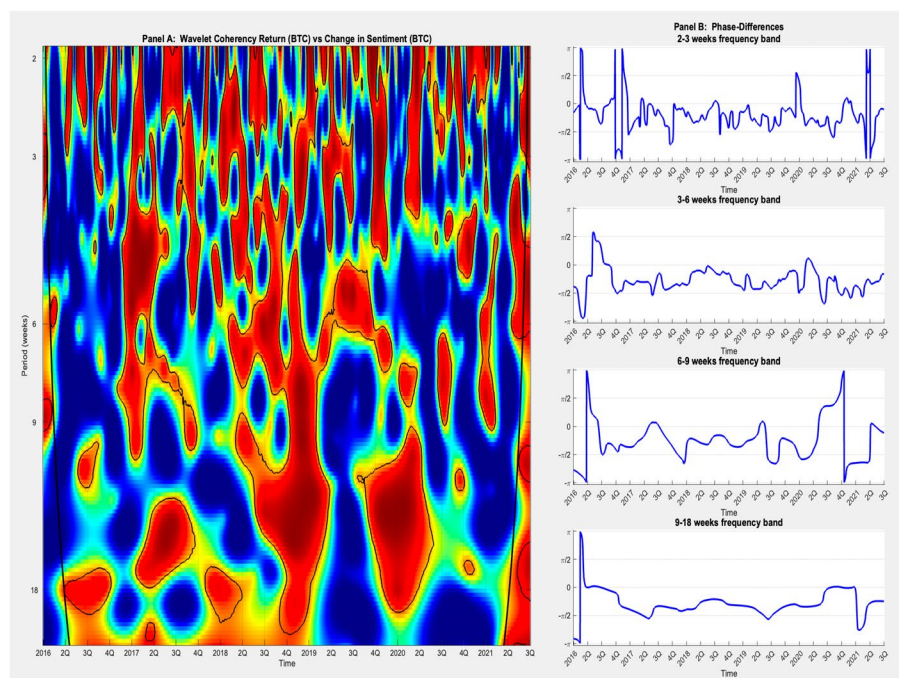


Fig. 4 On the left: wavelet coherency spectrum between return Bitcoin prices and change in Bitcoin specific sentiment index. Periods are depicted as weekly on the vertical axis. Thick black line indicates the boundaries of the cone of influence (COI). Thin black line shades the areas with 10% significant level. These areas have been simulated after 1000 runs. The wavelet coherency ranges from low (blue) to high (red). On the right: phase differences diagrams of 2–3, 3–6, 6–9- and 9–18-weeks frequency, respectively. Blue line indicates mean of phase difference between return and sentiment index throughout particular frequency intervals. Data spans from 1st January 2016 to 30th June 2021

Bitcoin return's power spectrum. These results for Bitcoin-specific sentiment are similar to recent studies that employ CWT techniques for spectral decomposition analysis of different investor sentiment measures and various asset returns. Zhang and Li (2019), Khan et al. (2020), and Aloui et al. (2021) displayed wavelet power spectra of individual, household, and oil investor sentiment indices in the US, respectively. Their results mainly revealed that the wavelet power of sentiment indices becomes significantly high at relatively lower frequencies but during specific dates related to important events, such as the Global Financial Crisis (2008–2009) and the Tapering action (end of 2013 and early 2014).

Although the asset returns had high wavelet power again at specific dates, larger frequency bands similar to their sentiment proxies or indices such as the Bitcoin returns' power spectrum appears on the upper right panel. Similarly, Celeste et al. (2020) and Qiao et al. (2020) concluded that the price levels and returns of other main cryptocurrencies have similar wavelet power images.

According to the wavelet power spectra (Fig. 3), Bitcoin's returns and its specific sentiment had common high variability (high wavelet power) in 2017q3 and early 2020, when the pandemic started at higher frequencies (2–3 weeks periods). These

variability measures (wavelet power) still do not provide sufficient information to explain the dynamic interrelation or causality between a single series. The wavelet coherency and phase difference analysis can explain the co-movement between two time series and/or their causality structure in both the frequency and time domains by employing CWT techniques. In Fig. 4, the right panel depicts the co-movement (coherency) between daily return (Bitcoin) and its sentiment data from January 2016 to June 2021 at a 2–23-week frequency band interval. According to the wavelet coherency spectrum (right panel), there were significant coherency areas at high frequency (2–3 weeks). There were also significant coherency areas at 3–9-week frequency bands, predominantly during 2016q4–2017q1, 2018q1–2019q1, and 2020q4. At 9–18-week frequency bands, significant coherence existed throughout 2018q3–2019q1 and 2019q4–2021q1. Significant coherency areas reveal that return and sentiment had high coherency in the short term (2–3 weeks). Co-movement can be observed at lower frequencies (2–3, 6–9, and 9–18 weeks) without disappearing at higher frequencies at specific periods, which lasts at most one year. Finally, the co-movement (coherency) between return and sentiment increased with the COVID-19 pandemic. However, it vanished after 2020q1.

The left panel in Fig. 4 depicts the mean of phase differences between return and sentiment separately at 2–3-, 3–6-, 6–9-, and 9–18-week frequencies from 2016 to 2021. Phase-difference diagrams help us understand the direction of causality (which series lead or lag) and co-movement (in the same direction or inversely) at specific periods. The phase differences reveal that Bitcoin-specific sentiment generally leads to Bitcoin returns and is positively related at any observation frequency ($-\pi/2, 0$). This result is consistent with that of Burggraf et al. (2020), who examined the relationship between investor sentiment and Bitcoin for the pre-COVID-19 period and argued that sentiment has a high predictive power on Bitcoin returns. Guegan and Renault (2021) supported the same causality from Bitcoin sentiment to its return at less than 15 min trading frequency from 2018 to 2019.

Throughout the observation period, return and sentiment are positively coherent (phase difference is $(-\pi/2, \pi/2)$), but the direction of causation becomes uncertain at some points. In particular, the phase difference starts to change its state at lower frequencies (6–9 and 9–18 weeks) in 2020q1. These fluctuations may be due to the COVID-19 pandemic and its probable joint effects on investor sentiment and asset returns. Hence, partial wavelet tools are used to re-examine the interrelation between Bitcoin's return and its specific sentiment, excluding the effects of the outbreak by factoring out the number of new deaths and new cases of COVID-19 as well as the EMVID index. The partial wavelet spectra (on the left) and phase difference diagrams (on the right) are depicted in Fig. 5. After the number of new deaths, the number of new cases, and the EMVID index are factored out from the coherency between sentiment and return, the partial wavelet coherency spectra in Fig. 5 indicate that (i) during the pre-COVID-19 period, the significant high coherency areas in Fig. 5 (1st and 2nd spectra) overlapped with the high coherency areas in Fig. 4 as the number of new deaths and new cases

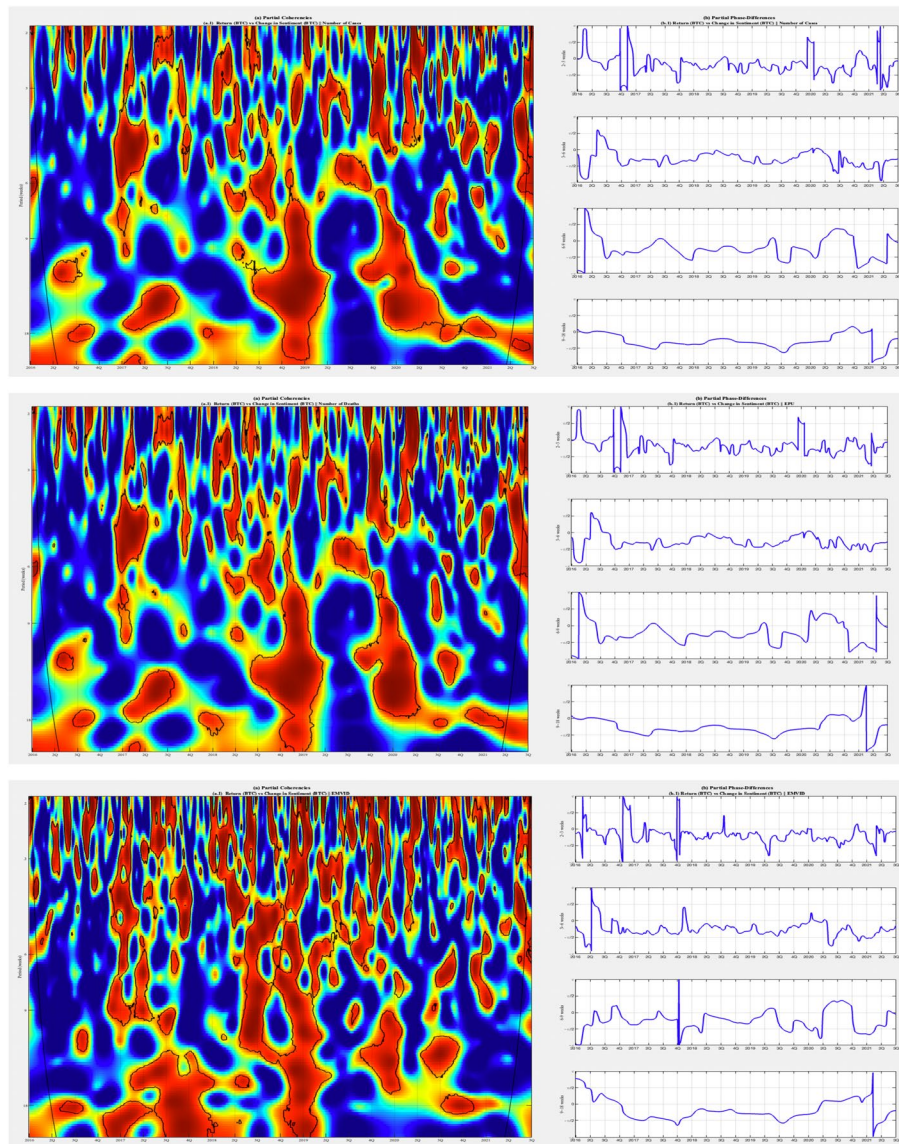


Fig. 5 On the left: partial wavelet coherence between return Bitcoin prices and change in Bitcoin specific sentiment index by factoring out number of new cases (1st row), number of new deaths (2nd row) and EMVID index (3rd row), respectively. Thick black line indicates the boundaries of the cone of influence (COI). Thin black line shades the areas with 10% significant level. These areas have been simulated after 1000 runs. Partial wavelet coherence ranges respect to jet color codes from low (blue) to high (red). On the right: partial phase differences diagrams of 2–3-, 3–6-, 6–9- and 9–18-weeks frequency, respectively. Blue line indicates mean of partial phase difference between return and sentiment index throughout frequency intervals. Data spans from 1st January 2016 to 30th June 2021

data were not available before the COVID-19 pandemic. Although the EMVID index is incorporated into the analysis for the pre-COVID-19 period, there are some minor differences in the third spectrum compared with that in Fig. 4. (ii) During the COVID-19 period, high coherence regions at 9–18 weeks became more extensive and continuous compared with those in Fig. 4.

The right panel in Fig. 5 presents the mean of partial phase differences between daily sentiment and return series at 2–3-, 3–6-, 6–9-, and 9–18-week frequency

bands. According to partial phase difference diagrams, in the short run (at 2–3-week and 3–6-week frequencies), the mean of partial phase differences varied between $(-\pi/2, 0)$, suggesting that sentiment led to return, and the partial phase differences were in phase. Similarly, the phase difference at the 6–9-week frequency band fluctuated between $(-\pi/2, 0)$ till 2019q4 as it did at former frequency bands. However, during 2020q2 and 2020q3, the phase difference shifted in locating in the interval $(0, \pi/2)$, indicating a change in the lead-lag relation, while return and sentiment continued to co-move in the same direction (in phase). This change in the phase difference structure suggests that Bitcoin price return led the sentiment from March to September 2020, and they co-move positively at the 6–9-week period.

The frequency in partial wavelet coherency diagrams of significant regions from 2020q1 to 2020q3 at 6–9 weeks supports this change. However, they do not provide strong evidence of a determined and persistent structural change in causality. Because these regions are small and discontinuous after 2020q3, at 9–18-week frequency, the partial phase difference diagrams depict a similar but smoother pattern relative to shorter frequency bands. Hence, they indicate a positive co-movement between sentiment and return during the observation period. Moreover, there were phase differences $(-\pi/2, 0)$ until the beginning of 2020, suggesting that sentiment leads to return. However, the phase differences were close to 0 from 2020q2 to 2020q4. Although this does not provide evidence of a significant lead-lag relationship between return and sentiment, it proposes a positive contemporaneous impact on each other, starting from 2020q2.

This study repeats the wavelet methodology using data on daily Bitcoin returns; its specific sentiment; and the VIX index, S&P500, and gold prices during the pandemic period to conduct a robustness test. The partial wavelet coherency and phase difference estimations that factor out the number of new deaths and new cases as well as the EMVID index are robust to the analyses that factor out the VIX index, S&P500, and gold. The spectrum of partial wavelet coherency between sentiment and Bitcoin returns indicates similar significant coherency areas and partial phase differences when VIX, S&P500, and gold are factored out in the analysis.⁶

The wavelet coherency between Bitcoin returns and its sentiment appears to be significantly high on specific dates at lower frequencies (vertically located coherency regions) rather than during an extended period at a particular frequency (horizontally located coherency regions). These dates coincide with specific events, which cause high volatility in Bitcoin returns (as depicted in its wavelet power spectrum). This implies that specific circumstances that increase the volatility of return (wavelet power) allow investors to determine a potential co-movement between return and sentiment. Furthermore, Bitcoin-specific sentiment and its return tend to co-move in the same direction, that is, positively correlated, both in the short and long run, meaning that sentiment and return series are significantly pro-cyclical.⁷ This result indicates that a higher return (sentiment)

⁶ See Fig. 6 in the Appendix for partial wavelet coherency spectrums and partial phase difference diagrams that factor out VIX, S&P500, and gold.

⁷ We have conducted a nonparametric wavelet-based Granger causality test (NWGC), developed by Detto et al. (2012), to test the causal relationship between Bitcoin returns and TRMI sentiment data. The test results suggest that there is unidirectional causality from bitcoin specific sentiment TRMI to Bitcoin returns. This causality exists for a frequency range from 26 to 3 weeks during the observation period. It supports our phase difference and partial phase difference results inferring that TRMI sentiment index leads (on average and during specific time domain) Bitcoin returns at 2–3-, 3–6-, 6–9- and 9–18-week frequencies. The results are available upon request.

is associated with a higher sentiment (return). Hence, investors should consider that Bitcoin-specific sentiment and its return are predicted to have a positive co-movement at all frequencies.

Additionally, Bitcoin-specific sentiment led to Bitcoin returns both in the short and long run from 2016q1 to 2020q1. However, this causal dependence disappeared at lower frequencies (9–18 weeks) after 2020q2 and shifted into the opposite at the 6–9-week frequency, which implies that Bitcoin return was influenced by sentiment from 2020q2 to 2020q3. Nevertheless, the latter state of causality cannot be justified empirically as the significant regions are relatively small and intermittent. The causality between return and sentiment tended to diverge from its $(-\pi/2, 0)$ range, and it was no longer valid that sentiment led to return at relatively more extended frequencies after 2020q2. Hence, during the COVID-19 outbreak, investors should have noted that the causal relationship that states that sentiment indicates return can only be integrated into short-term trading strategies (up to 6-week frequency). However, Bitcoin-specific sentiment would be uninformative to its return discovery in a 9–18-week frequency trading strategy.⁸ Investors should note that Bitcoin-specific sentiment and its return are estimated to have a positive co-movement at all frequencies.

Conclusion

This paper contributes to the literature in several aspects. First, the wavelet methodology reveals the relationship between sentiment and return in different investment horizons. Second, focusing on the unprecedented COVID-19 pandemic period allows us to investigate the changing dynamics in investor psychology. Third, we employ a partial wavelet coherence approach to explore the net effect of investor sentiment on Bitcoin return by factoring out the impact of the outbreak. Last, phase differences help us to check the direction of the causality between Bitcoin return and sentiment.

By employing a wavelet coherence method, we analyze the relationship between Bitcoin price and sentiment. Bitcoin-specific sentiment indicates high volatility at the beginning of the COVID-19 pandemic as it had done when Bitcoin prices started to rise steeply in 2017. We find that Bitcoin sentiment variability increased in the short run (2–3 weeks) during critical events. The pandemic has significantly affected Bitcoin-specific sentiment variability. Using the COVID-19 pandemic as a natural experiment, we check whether the relationship changes. The results reveal that before the pandemic, sentiment had a positive effect on Bitcoin prices. During the pandemic, the relationship was still positive, but sentiment did not affect Bitcoin prices. Then, employing a partial wavelet approach, we factor out new COVID-19 cases and deaths and the EMVID index to observe the direct relationship between Bitcoin sentiment and price. We find

⁸ Based on the suggestion of a notable referee, we also consider Amihud's (2002) illiquidity measure for Bitcoin in partial wavelet coherence analysis. Compared to wavelet coherency, two significant coherency areas appear, which are located from 2020-Q2 to 2021-Q1 (one year long) at lower frequencies of 9–18 weeks. The phase difference at 9–18 weeks frequency interval during the Covid-19 pandemic significantly indicates that sentiment leads to bitcoin returns in the same direction (in-phase). Moreover, factoring out the illiquidity measure does not contradict our results rather, it supports the main finding of this study that sentiment has a price discovery role in the Bitcoin market at lower frequencies (9–18 weeks). As Brauneis et al. (2021) state, Amihud (2002) illiquidity measure outperforms other liquidity measures in cryptocurrency markets, especially at lower frequencies. We include these findings in Appendix Figs. 7 and 8.

robust results—after factoring out, the positive coherence between sentiment and price still existed, but the lead-lag relationship disappeared. These results reveal that positive coherence existed strongly even during the pandemic, which might be due to the effect of the pandemic on markets.

Sentiment-motivated strategies were expected to perform better than the expected market return before the pandemic emerged. However, the influence of sentiment on Bitcoin returns had disappeared by the start of the outbreak at a lower frequency of 9–18 weeks. Although the positive relationship between the change in sentiment and Bitcoin returns persisted during the COVID-19 pandemic, sentiment lost its Bitcoin price discovery role in lower-frequency trading strategies. This is probably due to the excess information revealed during the pandemic, making it harder to extract information from sentiment. Sentiment-driven strategies preserve their importance at relatively higher frequency trading of up to 6 weeks. These results imply that short-term investment decisions should rely more on sentiment measures. Regarding long-term investment strategies, investors should consider that the Bitcoin market is not mature compared with other financial markets, such as the stock and bonds markets. Due to the high volatility in Bitcoin prices, investors may be better off following long-term trends/cycles rather than focusing on short-term sentiment dynamics. In particular, the lead-lag relationship during the COVID-19 pandemic period may differ (or even disappear) compared with normal times due to the unprecedented uncertainty caused by the pandemic.

From the perspective of the efficient market hypothesis, the Bitcoin market is not efficient as sentiment plays a significant price discovery role at an average of up to a one-month investment horizon. In addition, just after the pandemic started, a contemporaneous co-movement between Bitcoin return and its sentiment arose at 9–18-week trading frequency when the impact of the pandemic was excluded. The results suggest that wavelet methodology can be conducted in future research that investigates Bitcoin's causal dependence on other types of disaggregated sentiment measures. Future studies can also perform time–frequency analysis of the relationship between other major cryptocurrencies and their specific sentiments.

Appendix

See Figs. 6, 7, 8.

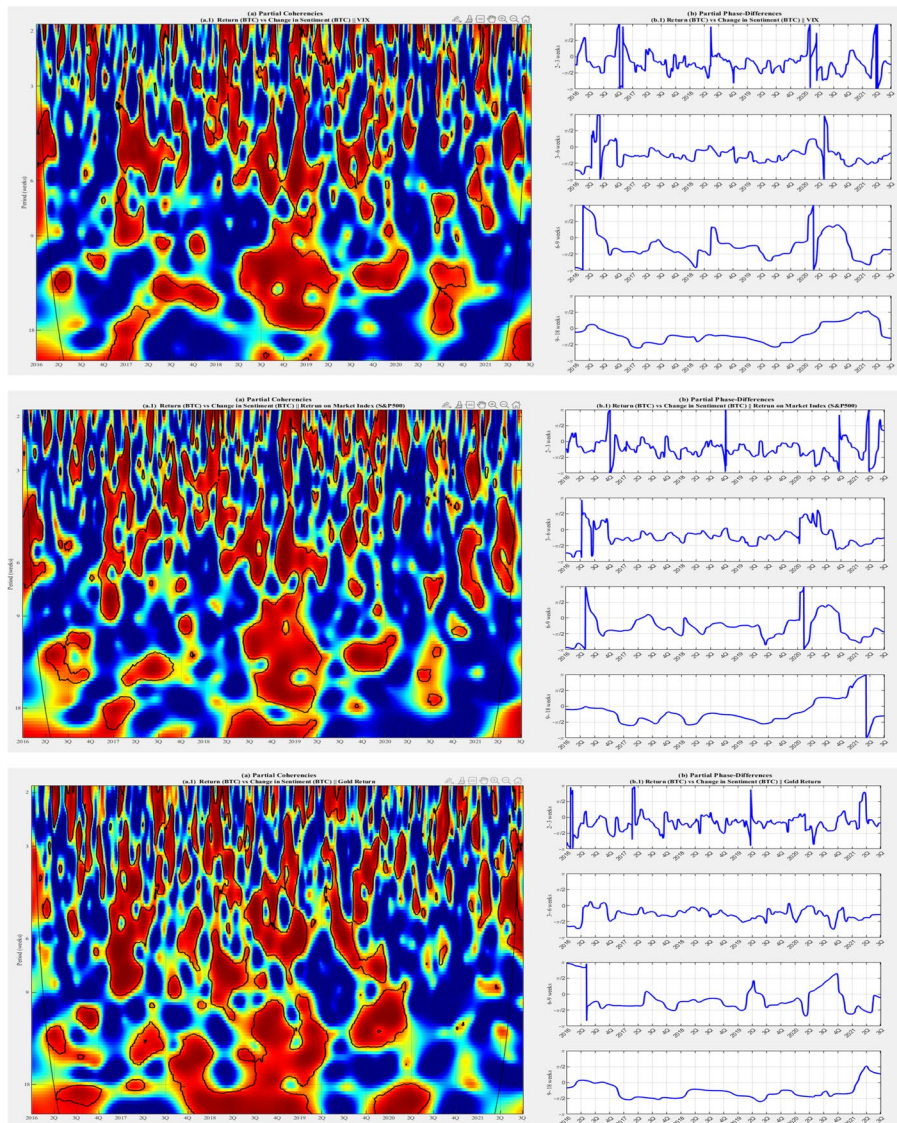


Fig. 6 On the left: partial wavelet coherence between return Bitcoin prices and change in Bitcoin specific sentiment index (TRMI) by factoring out VIX (1st row), S&P500 (2nd row) and gold return (3rd row), respectively. Thick black line indicates the boundaries of the cone of influence (COI). Thin black line shades the areas with 10% significant level. These areas have been simulated after 1000 runs. Partial wavelet coherence ranges respect to jet color codes from low (blue) to high (red). On the right: partial phase differences diagrams of 2–3, 3–6, 6–9- and 9–18-weeks frequency, respectively. Blue line indicates mean of partial phase difference between return and sentiment index throughout frequency intervals. Data spans from 1st January 2016 to 30th June 2021

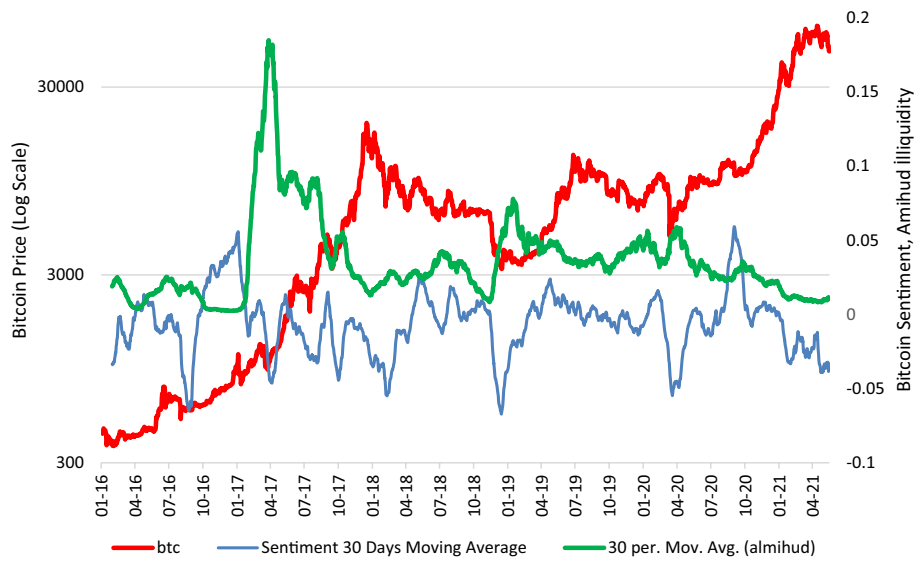


Fig. 7 Investor sentiment (blue line), Bitcoin price (red line), Amihud illiquidity (green line). Notes: Blue and green lines depict 30 days moving average investor sentiment and Amihud illiquidity measure, respectively, on the right axis. Red line depicts Bitcoin price data in logarithmic scale on the left axis. Observation period is from 1st January 2016 to 30th June 2021

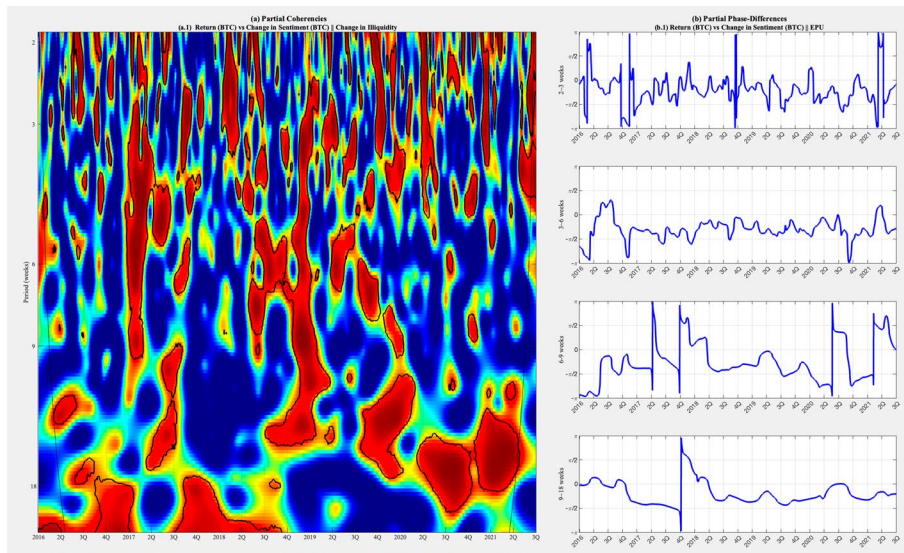


Fig. 8 On the left: partial wavelet coherency between return Bitcoin prices and change in Bitcoin specific sentiment index by factoring out Almihud illiquidity measure. Thick black line indicates the boundaries of the cone of influence (COI). Thin black line shades the areas with 10% significant level. These areas have been simulated after 1000 runs. Partial wavelet coherency ranges respect to jet color codes from low (blue) to high (red). On the right: partial phase differences diagrams of 2–3, 3–6, 6–9- and 9–18-weeks frequency, respectively. Blue line indicates mean of partial phase difference between return and sentiment index throughout frequency intervals

Author contributions

All authors have contributed equally at all stages of the paper.

Declarations**Competing interests**

No potential competing interests was reported by the author(s).

Received: 21 June 2022 Accepted: 6 August 2023

Published online: 21 December 2023

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