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Investor sentiment and the holiday effect in the cryptocurrency market: evidence from China

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Abstract

This study employs a fixed-effects model to investigate the holiday effect in the cryptocurrency market, using trading data for the top 100 cryptocurrencies by market capitalization on Coinmarketcap.com from January 1, 2017 to July 1, 2022. The results indicate that returns on cryptocurrencies increase significantly during Chinese holiday periods. Additionally, we use textual analysis to construct an investor sentiment indicator and find that positive investor sentiment boosts cryptocurrency market returns. However, when positive investor sentiment prevails in the cryptocurrency market, the holiday effect weakens, implying that positive investor sentiment attenuates the holiday effect. Robustness tests based on the Bitcoin market generate consistent results. Moreover, this study explores the mechanisms underlying the cryptocurrency holiday effect and examines the impact of epidemic transmission risk and heterogeneity characteristics on this phenomenon. These findings offer novel insights into the impact of Chinese statutory holidays on the cryptocurrency market and illuminate the role of investor sentiment in this market.

Keywords: Cryptocurrency, Holiday effect, Investor sentiment, Text analysis

JEL Classification: C58, G12, G14

Introduction

The cryptocurrency market has captured the attention of global investors, governments, and financial institutions since Bitcoin's inception in 2009 (Colon et al. 2021). A characteristic of cryptocurrency is its decentralization and independence from monetary authorities. As cryptocurrencies evolve into a new type of asset with unique features (Corbet et al. 2019), more investors are incorporating them into their investment portfolios. The market capitalization of cryptocurrencies experienced a significant increase after the COVID-19 pandemic, reaching a historical peak of USD 2.97 trillion.[1] Consequently, cryptocurrency trading has recently become a focal point for investors, media, and financial researchers (Ma and Tanizaki 2019).

[1] https://coinmarketcap.com/charts/.

The inefficiency of the cryptocurrency market has garnered significant attention from scholars (Al-Yahyaee et al. 2020; Nadarajah and Chu 2017; Urquhart 2016; Zhang et al. 2018). One particular aspect, the holiday effect, remains underexplored in this context. Characterized by heightened returns during holiday periods, the holiday effect is a pronounced calendar anomaly and a pivotal indicator of market inefficiency (Barone 1990). Holidays are perceived as public information that can induce asset price fluctuations (Kim and Park 1994). The elated mood of investors during holidays may trigger impulsive behaviors, consequently influencing their investment decisions (Lahav et al. 2016; Deldin and Levin 1986). This paper contributes to the literature by examining the presence of the holiday effect in the cryptocurrency market. This study seeks to determine whether the cryptocurrency market exhibits the holiday effect and decipher investor sentiment's pivotal role. In addition, this research explores whether significant public safety incidents, such as the COVID-19 pandemic, impact the holiday effect on the cryptocurrency market and which cryptocurrencies garner heightened attention during holidays. Addressing these questions confirms the inefficiency of the cryptocurrency market but also enriches our understanding of its operations and the decision-making behaviors of market participants. It also provides valuable insights for policymaking by regulatory bodies and investors in their decision-making processes.

While some studies have identified the existence of holiday effects in the cryptocurrency market, most are centered on Western holidays, such as Christmas and Halloween, and the research has predominantly focused on a limited subset of cryptocurrencies such as Bitcoin and Ethereum (Kinateder and Papavassiliou 2021; Qadan et al. 2022). There is a research gap examining the impact of holidays on a broader cryptocurrency sample, and the influence of investor sentiment on these holiday effects remains unexplored. Therefore, this article explores the impact of Chinese statutory holidays on cryptocurrency returns by collecting and organizing data on Chinese statutory holidays from January 1, 2017 to July 1, 2022, using the top 100 cryptocurrencies by market capitalization as the sample. The study also measures the sentiment of cryptocurrency investors using social media data and text analysis methods, such as sentiment lexicons and machine learning. Starting from the perspective of behavioral finance, this article examines the psychological activities of investors, tests the impact of investor sentiment on the cryptocurrency market, and analyzes how it influences holiday effects. Chinese statutory holidays were chosen as the research object because, despite strict regulatory measures by the Chinese government against cryptocurrencies, Chinese investors remain a significant force in cryptocurrency trading. Chinese cryptocurrency investors may have higher confidence in cryptocurrencies despite the government's repeated risk warnings. However, they still face specific barriers to investing in cryptocurrencies, including limited access to overseas network services, which may result in higher transaction costs. Therefore, Chinese cryptocurrency investors might respond more significantly to holiday signals.

We have identified a significant holiday effect on the cryptocurrency market. Specifically, during China's legal holidays, the return rate of the cryptocurrency market has seen a notable rise. While positive investor sentiment can boost the market's return rate, it simultaneously can diminish the holiday effect. A plausible explanation could be the shift in investor attention and the tendency to invest in riskier assets during holiday periods, influencing the holiday effect on the cryptocurrency market. This article also explores the impact of the COVID-19 pandemic on the holiday effect, unearthing evidence of heterogeneity in cryptocurrency characteristics.

This article's contributions are fourfold. First, diverging from existing research that predominantly focuses on Bitcoin's trading volume and abnormal returns during holiday periods (Baur et al. 2019; Ma and Tanizaki 2019), or exploring the differences and commonalities of calendar effects among a limited number of major cryptocurrencies (Kaiser 2019; Qadan et al. 2022), this study adopts a broader scope. It departs from the singular focus on specific cryptocurrencies and instead investigates the comprehensive impact of traditional Chinese holidays on the entire cryptocurrency market. Furthermore, this research uncovers the intricate mechanisms underlying these effects. Second, this study applies the "limited attention theory" from behavioral economics, exploring the interaction between holiday information and emotional cues in investor information processing. This enriches the study of investor attention mechanisms and information transmission. Third, this study investigates the influence of pandemic spread risk on the holiday effect, expanding the application of the limited theoretical attention in financial markets. This underscores that investor attention is not limited solely to financial events but also extends to stock markets and other activities. Finally, while examining the holiday effect on the cryptocurrency market, this study delves into investors' preferences and choices among different cryptocurrencies. We found that investors favor investments in cryptocurrencies with longer life cycles during holiday periods. This enhances our understanding of investor behavior and preferences and provides insights into the performance and characteristics of individual assets within the cryptocurrency market.

As a longstanding anomaly in financial markets, the holiday effect diverges from the risk-pricing thinking of modern financial theory, shaking the theoretical foundation of the efficient market hypothesis. This article's findings enrich research on the holiday effect's theoretical analysis and empirical verification. It helps us understand the operation and participant decision-making in the cryptocurrency market, and further reveals the cryptocurrency market's inefficiency.

The rest of this study is as follows: "Literature review" section reviews the existing literature. "Theoretical analysis and research hypotheses" section proposes verifiable research hypotheses based on theoretical analysis. "Data and methodology" section explains the research methods and data used in this study. "Results" section introduces our main findings and robustness test results and conducts a mechanism analysis. "Extended research" section conducts the extended research, and "Conclusion" section concludes.

Literature review

The earliest literature on the study of holiday effects dates back to 1934, when Fields discovered that stock returns increased before holidays (Fields 1934). However, it was not until the 1980s that the holiday effect received widespread scholarly attention (Lakonishok and Smidt 1988; Pettengill 1989). In the US market, extensive evidence of holiday effects was recorded, such as Merrill's (1966) finding that stocks exhibited higher returns a few days before and after holidays when analyzing stock returns from 1897 to 1965 based on the Dow Jones Industrial Average Index. Lakonishok and Smidt (1988) discovered that the average return rate before holidays was 0.22%. In contrast, the normal daily return rate was less than 0.01%, based on the Dow Jones Industrial Average Index from 1897 to 1986. Brockman and Michayluk (1998) provided empirical evidence of the continued existence of the holiday effect using market index data from the New York Stock Exchange, the American Stock Exchange, and the NASDAQ from 1963 to 1993.

Holiday effects have also received increasing attention outside the United States. Cadsby and Ratner (1992) found that the holiday effect on market indices in Canada, Japan, Hong Kong, and Australia was significant in all sample markets. Kim and Park (1994) provided new evidence of the holiday effect in the UK in their study of the Financial Times Stock Exchange Index and the Nikkei Index, confirming Cadsby and Ratner's (1992) findings for Japan and showing that the holiday effects in the UK and Japan were unrelated to those in the US. Marrett and Worthington (2009) investigated the presence of holiday effects in the Australian market and industry returns between 1996 and 2006. Their evidence showed a holiday effect at the market level, with returns before holidays typically five times higher than those on other days. Yuan and Gupta (2014) investigated the impact of the Chinese Lunar New Year holiday on the daily stock index returns of major Asian stock markets. They found that it significantly positively affected daily stock index returns in mainland China, Japan, Malaysia, Hong Kong, Taiwan, and other countries or regions. Liu et al. (2022) also discovered that during holiday periods without stock market stimuli, investor sentiment in China significantly increased, exhibiting a classic holiday effect. In their study of the holiday effect on the Thai stock market, Chancharat et al. (2020) found significant positive returns in the Thai stock market before and after holiday periods, with the abnormal return rate before holidays being higher than after holidays. Eidinejad and Dahlem (2022) found that the holiday effect positively impacted the Swedish stock market after holiday periods over the entire sample period from 1980 to 2019, based on daily price data for the AFGX stock market index.

While much of the literature zeroes in on traditional stock markets, the burgeoning cryptocurrency market has not escaped scholarly attention. (Caporale and Plastun 2019; Kinateder and Papavassiliou 2021; Baur et al. 2019; Kaiser 2019; Qadan et al. 2022). For example, early research on the calendar anomaly effect focused on popular cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin. Caporale and Plastun (2019) found that Bitcoin's return rate is higher on Mondays than on other weekdays, although this was not the case with other cryptocurrencies. Kaiser (2019) tested various calendar effects on ten cryptocurrencies, including the Halloween effect, with the results supporting the holiday effect hypothesis on the Halloween effect. A study by Lopez-Martin (2022) showed that the Ramadan effect is present in Ether, Ripple, and Stellar. However, Kinateder and Papavassiliou (2021) found no significant difference in Bitcoin returns between the Halloween and nonwinter periods, indicating the absence of the Halloween effect. Qadan et al. (2022) investigated the calendar anomaly effect in the cryptocurrency market using eight popular cryptocurrencies, including Bitcoin. They found that the return rates of Litecoin, Dash, Nem, and Ethereum are significantly lower between May and October than in winter and spring, confirming the Halloween effect in the cryptocurrency market. Their study also reveals that cryptocurrencies exhibit a positive and significant return trend on Valentine's Day.

Research on the holiday effect within the cryptocurrency market remains scarce, primarily concentrating on Western holidays and popular cryptocurrencies, such as Bitcoin and Ethereum (Kinateder and Papavassiliou 2021; Kaiser 2019; Qadan et al. 2022). Thus, this article investigates the impact of China's official holidays on the cryptocurrency market by examining the entire spectrum of digital currencies. Specifically, we explore whether investors increase their cryptocurrency purchases or holdings during these holiday periods, potentially driving up cryptocurrency prices. Moreover, cryptocurrency research has extensively used machine learning (Ren et al. 2022). This study constructs an investor sentiment index for the cryptocurrency market by harnessing textual data from investors' social media interactions. Our primary objective is to elucidate the intricate nexus between investor sentiment, as captured by this index, and the holiday effect observed within the cryptocurrency domain.

Theoretical analysis and research hypotheses

The shift in Chinese investors' investment attention during holiday periods may be one of the reasons for the holiday effect in the cryptocurrency market. Investor attention is an essential factor affecting returns and volatility in the cryptocurrency market (López-Cabarcos et al. 2021; Bashir and Kumar 2023). Traditional holidays have a significant influence in China, where the major financial market, A-shares, is closed during the holiday season, leading to capital outflows. The cryptocurrency market, characterized by continuous, round-the-clock trading and heightened volatility, presents a tempting prospect for investors seeking quick returns. As a result, the holiday season often witnesses a migration of attention, with investors pivoting from conventional financial avenues to the dynamic world of cryptocurrencies. This pivot amplifies liquidity in the cryptocurrency market and boosts its yield. Moreover, an elevated risk appetite among investors during holiday periods could serve as another catalyst for the observed holiday effect in the cryptocurrency realm. Research has shown that traditional festivals in China alter investors' risk perceptions, impacting their trading decisions and spurring a proclivity toward higher-risk assets (Chia et al. 2015). Additionally, holidays' positive sentiment can spur investors' impulsive behaviors, influencing financial markets (Cyders et al. 2007; Wu 2013). Thus, investors' increased risk appetite during holiday seasons may increase investments in riskier assets such as cryptocurrencies, affecting cryptocurrency returns.

In summary, the shift in investors' attention and the change in risk appetite during holiday periods caused a large influx of funds into the cryptocurrency market, increasing cryptocurrency market liquidity and leading to higher returns on cryptocurrencies. Based on the above analysis, this paper proposes the following hypothesis.

H1 There is a holiday effect in the cryptocurrency market, in which cryptocurrency market returns are significantly higher during Chinese holidays.

According to behavioral finance theory, investors are susceptible to cognitive and emotional biases during decision making, leading to asset price fluctuations (Leković 2020). This theoretical perspective offers insights into investor behavioral patterns, especially in the highly unpredictable cryptocurrency market. Given the challenge of pricing cryptocurrencies, investor sentiment is pivotal in driving swift and unforeseen price changes (Akyildirim et al. 2021; Burggraf et al. 2021). Baker and Wurgler (2007) emphasized the significant influence of investor sentiment on financial markets. Emotional factors play a major role in asset price variances, with rising market sentiment fueling stock price appreciation. Narayan et al. (2023) found that the long-term impact of investor sentiment, measured by the U.S. Investor Confidence Index on the portfolio returns of emerging markets, is almost always positively correlated. Jiang et al. (2021) concluded that the predictive power of investor sentiment has led many scholars and institutions to use it as a key indicator for monitoring stock markets. Scholars have found similar evidence in the cryptocurrency market. For instance, sentiment expressed in news articles has been linked to increases in Bitcoin returns (Polasik et al. 2015). Additionally, active investor sentiment, as measured by social media data and online searches, impacts cryptocurrency prices (Phillips and Gorse 2018; Kristoufek 2013; Bouoiyour and Selmi 2015). Naeem et al. (2021) discovered that the sentiment of happiness on Twitter significantly impacts cryptocurrency returns, making it an important cryptocurrency predictor. Valencia et al. (2019) also found that textual sentiment on Twitter contains information about cryptocurrency prices and is thus used to predict cryptocurrency price trends. Therefore, this paper posits that positive sentiment from investors on social media contains bullish information on cryptocurrency market prices, foreshadowing a significant increase in cryptocurrency returns. Based on this analysis, this study proposes the following research hypothesis:

H2 The more positive the investor sentiment, the higher the cryptocurrency returns.

According to cognitive psychology's limited attention theory, attention is a scarce cognitive resource. Furthermore,devoting attention to one thing necessarily is at the expense of attention to another (Kahneman 1973). Investors pay selective attention to different types of information in the market. Those with limited attention tend to prioritize information that easily attracts their attention and overlook useful yet less noticeable information when making investment decisions, resulting in biased decisions (Peng and Xiong 2006; Hirshleifer et al. 2009). During the process of investors' information perception and processing, there is also some enhancement or inhibition between different types of information (Coval and Moskowitz 2001; Cao et al. 2011). Thus, we argue that biases in information perception become more pronounced during holiday periods. External factors, such as market sentiment, might monopolize the limited cognitive resources tied to investors' attention in cryptocurrency. When both investors' sentiment and willingness to invest are low, the market might suffer from an absence of compelling trading information. As a result, investors might shift their focus primarily to readily available holiday information, amplifying the holiday effect. Conversely, when market sentiment is buoyant, investors may be more inclined to trade, thereby increasing market volume and volatility. In this case, the holiday effect may be weakened as investors focus more on short-term market movements than specific periods or holidays.

In a frictionless financial market, the price of a financial asset always adjusts quickly and reflects all new information (Fama 1998). However, cryptocurrency markets are not always efficient, and investors sometimes react to information irrationally (Barberis et al. 1998). As information watchers, investors tend to be overconfident in the accuracy of private information (Brown et al. 2012). When asset prices evolve as anticipated, self-reinforcing psychology prompts investors to become even more confident in their private insights, resulting in overreactions to this type of information (Hong and Stein 1999). Conversely, a tendency toward conservatism may cause investors to underreact to widely disseminated, or public, information (Doukas and McKnight 2005). During heightened market sentiment, self-reinforcing psychology may make investors overly reliant on their private insights, such as sentiment-based judgments. They then struggle to recalibrate their views considering more broadly available information, such as data tied to holidays. Consequently, they may downplay or even disregard the significance of such public data, leading to an underreaction. Based on the above analysis, the following hypothesis is proposed:

H3 The more positive investor sentiment, the weaker the holiday effect in the cryptocurrency market.

Data and methodology

Data collection

Cryptocurrency data

The study is conducted on the 100 cryptocurrencies with the highest market capitalization as of July 2, 2022. The sample period of this study is from January 1, 2017 to July 1, 2022. According to Coinmarketcap.com, the combined market capitalization of these 100 cryptocurrencies as of July 1, 2022, is $844.45 billion, representing 97.51% of the total market capitalization. They represent approximately the entire cryptocurrency market. Daily trading data for cryptocurrencies are obtained from https://coinmarketcap.com/. These data include intraday opening, high and low, closing prices, market capitalization, and trading volume for each cryptocurrency. In addition, we use the CCI30 index to measure cryptocurrency market movements.[2]

Data on official holidays in China

The holidays defined in this study are legal holidays in China. The specific holiday schedule for each year is obtained from the Chinese government website and spans from January 1, 2017 to July 1, 2022.[3]

Investor Twitter text data

Cryptocurrencies differ from traditional financial assets. Regulatory authorities in various countries have successively implemented corresponding regulatory measures regarding cryptocurrency propaganda hype. On September 4, 2017, the People's Bank of China and seven other ministries jointly issued the Announcement on Preventing the Risks of Token Issuance and Financing, which stipulates that the company cannot provide information intermediary services for cryptocurrencies. Therefore, cryptocurrency-related information on Chinese social media does not fully and objectively reflect Chinese investor

[2] https://cci30.com/.

[3] http://www.gov.cn/zhengce/content/2021-10/25/content_5644835.htm.

sentiment. Twitter has several influences among investors as the primary platform for cryptocurrency information distribution. Referring to the existing literature, we selected the Twitter platform as an information source to measure investment sentiment (Zhang and Zhang 2022; Kraaijeveld and De Smedt 2020). Due to government regulations, Chinese investors interested in cryptocurrencies often need Virtual Private Network services. Since such technical tools have a certain threshold and require significant time and cost for users to master, users who postcryptocurrency-related content on Twitter in Chinese are considered more inclined to participate in cryptocurrency trading.

Regarding search terms, we considered "Cryptocurrency" or "Crypto-digital Currency" would be noisier due to the ambiguity of the terms. Conversely, we searched the related terms on the Baidu index and found that the search index of "Bitcoin" is much larger than that of "Cryptocurrency," "Virtual Currency," and "Virtual Coin,"[4] with the difference in search volume often being greater than a hundred times. Moreover, the search terms "Crypto-digital Currency" and "Crypto Coin" are not included due to the low search volume. Meanwhile, the term "Bitcoin" has been repeatedly mentioned in Chinese government regulatory policies and news media reports to refer to the entire cryptocurrency market. Therefore, the discussion under the topic of "Bitcoin" fully reflects Chinese investors' concerns about cryptocurrencies. This study selects the Chinese term "Bitcoin" as the search term.[5] To collect data on the overall sentiment of Chinese cryptocurrency investors, we used the Python tool snscrape library to crawl Twitter text data.[6] Based on the above search terms, we collected 392,882 tweets on Twitter from January 1, 2017 to September 12, 2022 as a source of the overall Chinese cryptocurrency investor sentiment.

Methodology

Indicator construction

Cryptocurrency Return: The daily return of cryptocurrencies is calculated based on the closing price, and the formula is shown below.

$$R_i = \frac{Close_i - Close_{i-1}}{Close_{i-1}} \tag{1}$$

China Holiday Indicators: To study the impact of Chinese holidays on the cryptocurrency market, we construct a dummy variable Holiday_t. If day t falls during a Chinese legal holiday and $\text{Holiday}_t = 1$; otherwise, $\text{Holiday}_t = 0$.

Investor Sentiment Indicators: Because the groups involved in cryptocurrency and traditional financial asset investments are not the same, there are significant differences in information access and the form and content of information dissemination among different investors. Thus, investor sentiment cannot be equated between different financial markets. Thus, we constructed a dataset of Twitter cryptocurrency tweets to address these issues and then used a sentiment dictionary of informal terms common in Chinese

4 https://index.baidu.com/v2/index.html#/.

5 To avoid the difference between Chinese and English contexts, we list the Chinese phrases used in the search and their corresponding English translations. 1. 加密货币—Cryptocurrency 2.加密数字货币—Crypto-digital currency 3.虚拟币—Virtual Currency 4.加密币—Crypto Coin 5.—Bitcoin.

6 https://github.com/JustAnotherArchivist/snscrape.

texts to measure investor sentiment by counting the number of positive and negative words.[7] In this study, we use the simple proportional sum weight method to measure the sentiment of a single social media text, as shown in Eq. (2).

$$Sentiment = \frac{Pos - Neg}{Pos + Neg} \tag{2}$$

Pos indicates the number of positive words in the text, and *Neg* indicates the number of negative words in the text. The calculated text sentiment is between − 1 and 1. When Pos is greater than Neg, the text is positive, and the sentiment value is closer to 1, indicating that the text's tone is more positive.

Specification

All-time-related data in this study were converted uniformly based on timestamps to circumvent the effects of time zone issues. The following regression model was established to investigate the impact of Chinese legal holidays on cryptocurrency returns:

$$Return_{i,t} = \alpha_0 + \beta_1 Holiday_t + \beta_3 Control_{t-1} + \lambda_i + u_t + \varepsilon_{i,t} \tag{3}$$

The following regression model is established to investigate investor sentiment's impact on cryptocurrency returns:

$$Return_{i,t} = \alpha_0 + \beta_1 Senti_t + \beta_3 Control_{t-1} + \lambda_i + u_t + \varepsilon\ _{i,t} \tag{4}$$

Furthermore, we employ the following model to investigate the moderating effect of investor sentiment on the relationship between Chinese holidays and cryptocurrency returns:

$$\begin{aligned} Return_{i,t} = {} & \alpha_0 + \beta_1 Holiday_t + \beta_2 Senti_t + \beta_3 Holiday_t \times Senti_t \\ & + \beta_4 Control_{t-1} + \lambda_i + u_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In the above model, $\mathrm{Return}_{i,t}$ represents the return of cryptocurrency i on day t. The core explanatory variable is a dummy variable, $\mathrm{Holiday}_t$. Senti_t is another core explanatory variable that indicates the sentiment of cryptocurrency investors. $\mathrm{Control}_{t\text{-}1}$ is a control variable. To control for the impact of the trading properties on returns, we include each cryptocurrency's market capitalization and trading volume in the control variables (Zhang et al. 2023). Considering the go-live time and Bitcoin dominance, we include the cryptocurrency maturity age and Bitcoin's total capitalization dominance (BTCD) in the model's control variables. We also consider the CCI30 index return to control for the impact of cryptocurrency investors' herding effect.[8] In

[7] The financial sentiment dictionary is a specialized tool used in natural language processing and computational linguistics for analyzing financial news and social media content. It comprises an extensive collection of financial terms, each labeled with a sentiment that denotes whether it is positive or negative. For our study, we employed a sentiment dictionary constructed using Chinese social media text data exclusively for the financial sector. Unlike conventional sentiment dictionaries, this informal dictionary contains a broad range of user-generated sentiment words, such as "半信半疑" (half-trusted, half-doubtful), "暴风雨" (stormy), "被套" (get trapped), and "差强人意" (dissatisfied) for negative words, and "霸主" (domination), "百里挑一" (one in a hundred), "不涨都难" (it's hard not to go up), and "大有作为" (a great deal is at stake) for positive words. The complete dictionary is available on this website: https://gitee.com/arlionn/SentimentDictionaries.

[8] The Cryptocurrency Index 30 (CCI30) selects the 30 largest cryptocurrencies by adjusted market capitalization, excluding stablecoins. It is a rules-based index designed to objectively measure the overall growth and daily and long-term movements of the backchain sector.

Table 1 Brief descriptions of the variables

Variable name	Abbreviation	Description
Cryptocurrency return	Return	$Return_t = \frac{Close_t - Close_{t-1}}{Close_{t-1}}$
Chinese holiday	Holiday	A dummy variable. Take the value of 1 if $Date_t$ is an official Chinese holiday, 0 otherwise
Investor sentiment	Senti	Investor sentiment indicators measured using text analysis methods
Economic policy uncertainty	EPU	EPU is an index of economic policy uncertainty for China. This study takes the natural log of the index
The dominance of bitcoin	BTCD	Bitcoin as a percentage of total cryptocurrency market cap on the t−1 day
Market value	Cap	The natural logarithm of the market value of cryptocurrency i on day t−1
Trading volume	Volume	The natural logarithm of the trading volume of cryptocurrency i on day t−1
Cryptocurrency index	CCI30	CCI30 is a cryptocurrency index based on the top 30 cryptocurrencies in market capitalization. In this study, we take the natural logarithm of this index and lag it by one period, taking day t−1 as a representative
Maturity	Age	The natural logarithm of the number of days that cryptocurrency i is online on day t−1

addition, considering the impact of economic policy uncertainty based on Cheng and Yen (2020), the Chinese EPU index is also included in the model as a control variable. λ_t denotes the time effect of controlling for the effect of time-varying factors, and u_i denotes the individual effect, which represents the influence of factors that do not change over time, and ε_{it} is the residual term. In the first two models, we focus on the coefficients and significance of β_1. In the third model, we focus on the coefficients and significance of the interaction term β_3. The specific definitions of all indicators and the treatment of each control variable are shown in Table 1.

The sample data in this study are panel data. We used the fixed-effects regression model for all hypotheses to mitigate the endogeneity problem. We used a model with clustered robust standard errors at the individual cryptocurrency level to address issues of autocorrelation and heteroskedasticity. The EPU indicator is the same for all cryptocurrencies daily. Multicollinearity may occur when combining macrotime series data (EPU) with microcryptocurrency panel data. Then, the EPU indicator cannot be identified. Therefore, instead of controlling for daily fixed effects, annual fixed effects are included in this study to control for the effect of annual trends. Other methods are used in the robustness tests to further test for omitted variable issues. The statistical software used in this study is Stata16.

Descriptive statistics

Table 2 shows the descriptive statistics of the main variables of mean, median, standard deviation, and other statistical measures for the selected variables: Cryptocurrency Return (Return), Investor Sentiment (Senti), Economic Policy Uncertainty (EPU), Bitcoin Dominance (BTCD), Cryptocurrency Market Value (Cap), Trading Volume (Volume), Cryptocurrency Index (CCI30), and Cryptocurrency Maturity (Age).

Table 2 Descriptive statistics

Variables	N	Mean	Sd	Min	Max	Skewness	Kurtosis	Jarque–Bera test
Return	118,764	0.004	0.0757	− 0.623	4.211	5.190	171.186	140,000,000***
Senti	118,764	0.142	0.250	− 1.000	1.000	0.209	3.688	3207***
EPU	118,764	5.721	0.317	4.873	6.495	− 0.022	3.016	11.24***
BTCD	118,764	0.532	0.106	0.324	0.876	0.285	2.105	5574***
Volume	118,764	18.080	2.684	4.525	27.140	− 0.224	3.231	1255***
Cap	118,764	20.590	2.099	13.640	27.870	0.059	3.414	919***
CCI30	118,764	0.001	0.047	− 0.484	0.196	− 1.365	13.452	580,000***
Age	118,764	6.487	1.001	0.000	8.117	− 1.194	5.231	53,000***

Descriptive statistics for all variables result from preprocessing of the raw data; see Table 1 for descriptions of treatments such as logarithms and lags. The minimum value of Age is 0 because this study takes the logarithm of the age of the cryptocurrency. *** denote significance at 1%

The average cryptocurrency return was 0.004 during the sample period, indicating a positive profitability trend. This return spanned from a low of − 0.623 to a high of 4.211, highlighting cryptocurrencies' inherent high risk and high reward nature. The pronounced skewness and kurtosis in cryptocurrency returns, including the CCI30 index, indicate significant price volatility. Furthermore, Bitcoin's dominance in the market is evident, with a mean value of 0.532 and a peak at 0.876 for the BTCD. Disparities in Volume and Cap metrics emphasize heterogeneity among cryptocurrencies. Analysis of volatility revealed that volume had the highest standard deviation, followed by Cap, with CCI30 being the least volatile.

Skewness and kurtosis evaluations indicated that while four variables (Return, Senti, BTCD, and Cap) displayed positive skewness, the remaining variables (EPU, Volume, Age, and CCI30) were negatively skewed. Only BTCD exhibited a platykurtic distribution, whereas the other variables exhibited leptokurtic tendencies. The Jarque–Bera test results confirmed a nonnormal distribution for all the selected variables at the 1% significance level, indicating that the variables of interest are nonnormally distributed (Batrancea 2021b). The remaining distribution of each variable is similar to the statistical results obtained in existing studies and is within the normal range (Zhang et al. 2023).

Correlation analysis

A correlation analysis was undertaken to assess potential multicollinearity concerns among the independent variables, and Pearson coefficients were calculated, indicating potential multicollinearity issues between predictors (Batrancea et al. 2020). Pearson's correlation coefficients were determined based on the following formula:

$$r = \frac{\sum (x_i - \overline{x})\left(y_i - \overline{y}\right)}{\sqrt{\sum (x_i - \overline{x})^2 \sum \left(y_i - \overline{y}\right)^2}} \tag{6}$$

Within the context of this analysis, the symbols are defined as follows: r represents the Pearson correlation coefficient, which measures the linear relationship between two datasets, x_i is used to represent individual observations of a given variable, while $\overline{x}$ signifies the mean value of those observations. Similarly, y_i denotes individual data points of another variable, and $\overline{y}$ indicates its average value.

Table 3 Matrix of Pearson correlation coefficients for selected variables

Variables	Return	Holiday	Senti	EPU	BTCD	Volume	Cap	Age	CCI30
Return	1								
Holiday	0.020***	1							
Senti	0.083***	0.058***	1						
EPU	− 0.019***	− 0.093***	0.191***	1					
BTCD	0.048***	− 0.005*	0.164***	0.316***	1				
Volume	− 0.018***	− 0.002	− 0.038***	− 0.012***	− 0.200***	1			
Cap	− 0.033***	0.006**	− 0.068***	− 0.120***	− 0.413***	0.824***	1		
Age	− 0.023***	0.007**	− 0.029***	0.061***	− 0.077***	0.427***	0.450***	1	
CCI30	− 0.045***	0.027***	0.272***	− 0.006**	0.084***	− 0.012***	− 0.005*	− 0.010***	1

***, **, and * denote significance at 1%, 5%, and 10%, respectively

As elucidated in the correlation analysis presented in Table 3, the highest correlation among the independent variables was established between Cap and Volume ($r = 0.824$), while the lowest correlation was set between Cap and BTCD ($r = -0.413$). Because none of the Pearson coefficients exceeds 0.9, multicollinearity poses no problem for subsequent econometric estimation (Batrancea 2021a). We conducted variance inflation factor (VIF) tests for the regression models corresponding to H1–H3 to further assess the potential presence of multicollinearity in our regression models. The results show that the VIF values of all variables do not exceed 5, indicating that the multicollinearity problem in this study is not a problem.[9]

Panel unit root test

Panel Unit Root Test: This study first conducts a smoothness analysis of cryptocurrency returns before performing empirical tests to prevent the occurrence of spurious regressions. Due to the unbalanced panel data characteristics in our sample, we chose the Mi-Psarian-Shin (IPS) test for panel unit root, as suggested by Antoniou et al. (2016), to assess the smoothness of cryptocurrency returns. The test results reveal a t-bar statistic of − 35.531, below the critical value of − 1.81 at the 1% significance level. As a result, the null hypothesis of a panel unit root is rejected. Furthermore, the Z-t-tilder-bar statistic corresponds to a p value of 0.000, refuting the null hypothesis; thus, we consider the return series smooth.

Heteroscedasticity test

To ensure the accuracy and reliability of our research, we delved into the potential issue of heteroskedasticity. Following the recommendation of Greene (2000), we employed the modified Wald statistic to detect heteroskedasticity. Upon testing the three primary regression models presented in the main text, the results of the Wald Chi-squared statistic significantly rejected the original hypothesis of homoskedasticity, suggesting a potential heteroskedasticity problem in the paper's models.[10]

[9] Due to space constraints, the results of the VIF test are not published and are available on request.

[10] The Wald Chi-squared statistics for H1, H2, and H3 were 3.10E + 06, 2.00E + 06, and 1.90E + 06, respectively, and the corresponding p values were significantly less than 0.01.

Webel (2011) pointed out that when heteroskedasticity is detected, the OLS regression model can address it, and corrections can be made using standard errors, thereby achieving consistent estimations for regression coefficients and standard errors. To mitigate the potential impact of heteroskedasticity on model parameter estimation and hypothesis testing, we have incorporated robust standard errors in all our model estimations as a corrective measure for heteroskedasticity. To further ensure the robustness of our research, in our robustness check section, we also adopted both FGLS and two-way clustering as alternative parameter estimation methods, aiming to eliminate further the potential influence of heteroskedasticity on our study's conclusions (Reed and Ye 2011; Gu and Yoo 2019).

Results

Model regression results

Table 4 shows the results of the tests of the three main hypotheses. Table 4 Column (1) shows the test results for H1. The coefficient of the core explanatory variable *Holiday* is positive and significant, at least at the 1% level, indicating a significant increase in the return of investing in cryptocurrencies during traditional Chinese holidays; thus, H1

Table 4 Main regression results

Variables	(1) H1 Return	(2) H2 Return	(3) H3 Return
Holiday	0.006***		0.012***
	(9.071)		(12.366)
Senti		0.037***	0.041***
		(20.445)	(20.889)
Holiday × Senti			− 0.045***
			(− 11.655)
EPU	− 0.001	− 0.006***	− 0.006***
	(− 0.720)	(− 8.365)	(− 8.238)
BTCD	0.000***	0.000***	0.000***
	(6.184)	(8.224)	(8.127)
Volume	0.002***	0.002***	0.002***
	(3.444)	(4.254)	(4.375)
Cap	− 0.004***	− 0.005***	− 0.005***
	(− 6.063)	(− 6.957)	(− 7.116)
Age	− 0.002*	− 0.002*	− 0.002*
	(− 1.826)	(− 1.727)	(− 1.692)
CCI30	− 0.087***	− 0.136***	− 0.141***
	(− 14.201)	(− 17.702)	(− 18.056)
Constant	0.063***	0.082***	0.083***
	(6.000)	(7.822)	(7.840)
Observations	118,764	118,764	118,764
R-squared	0.012	0.023	0.025
Coin FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

is verified. Our test results suggest that cryptocurrency investors respond positively to Chinese holidays, as they bring significant positive signals to the cryptocurrency market. During holidays, Chinese investors are more optimistic and tend to believe that investing in cryptocurrencies generates positive investment returns, viewing Chinese holidays as positive trading signals. In addition, the holiday effect indicates the Chinese government's regulatory failure to regulate cryptocurrencies. When China's financial markets are closed during the holiday season, funds seeking short-term gains may turn to cryptocurrencies. The government's regulatory policies have made it difficult to curb the influx of such speculative capital into the cryptocurrency market.

Table 4 Column (2) is the result of the H2 test. The coefficient of *Senti* in the regression result is significantly positive and significant at least at the 1% level, indicating that investor sentiment increases the return on investing in cryptocurrencies; thus, H2 is verified. This agrees with academic findings that when bullish sentiment dominates the market, investing in cryptocurrencies yields positive returns (Anamika et al. 2021; Zhang and Zhang 2022). At the same time, positive changes in investor sentiment lead to investors trading larger amounts (Bowden and Gemayel 2022). Fluctuations in investors' psychological sentiments affect their risk appetite; positive sentiment encourages investors to buy riskier cryptocurrencies, thus increasing the price of cryptocurrencies.

Table 4 Column (3) shows the results of the H3 test. Our test results show that the coefficients of *Holiday* and *Senti* are still positive and significant, at least at the 1% level, after considering investor sentiment. The coefficients of the interaction term $Holiday \times Senti$ are negative and significant, at least at the 1% level, indicating that positive investor sentiment suppresses the holiday effect of cryptocurrencies. The higher the investor sentiment in the cryptocurrency market, the more they ignore the holiday signal. Therefore, the holiday effect of cryptocurrencies is weakened, and H3 is verified.

In summary, our findings indicate that investors are more inclined to invest during holiday periods, causing an increase in cryptocurrency prices. Positive sentiment of investors may also drive up the price of cryptocurrencies. When investors are attracted by the positive investment sentiment in the market, they ignore the holiday message. Our findings further demonstrate the inefficiency of the cryptocurrency market.

Robustness tests

Endogeneity

The empirical results of this study may be affected by endogeneity problems such as omitted variables and reverse causality. We test the following three aspects to mitigate potential endogeneity problems.

First, regarding the method of Li et al. (2016), we use placebo tests to exclude the effect of unobservable omitted variables. To eliminate price fluctuations caused by other random factors and identify causal effects more credibly, we conducted a placebo test for H1 and H3, which entails randomly generating Chinese holiday variables to determine if other random factors cause the cryptocurrency holiday effect. By randomly selecting the pseudoholiday group and repeating it several times, we extracted the placebo results' coefficients or t-values, plotted them in a graph, and observed the actual holiday effects versus the placebo results.

The coefficients of accurate estimates are shown in Figs. 1 and 2 as dashed lines, indicating the actual holiday effect significantly differs from the placebo test results. This implies that legal holidays in China increase cryptocurrency returns and that the holiday effect exists by excluding the time trend and other random factors from the results.

Second, introducing the explanatory variable's lagged term solves the reverse causality problem. In H2, investor sentiment enhances cryptocurrency returns. However, higher returns may also increase investor sentiment; therefore, there may be a reverse causality problem between investor sentiment and cryptocurrency returns. Therefore, we reestimate H2 and H3 using a one-period lag of the investor sentiment variable. The results are shown in Columns (1) and (2) in Table 5. After lagging investor sentiment by one period, the test results remain consistent with the findings in the main text.

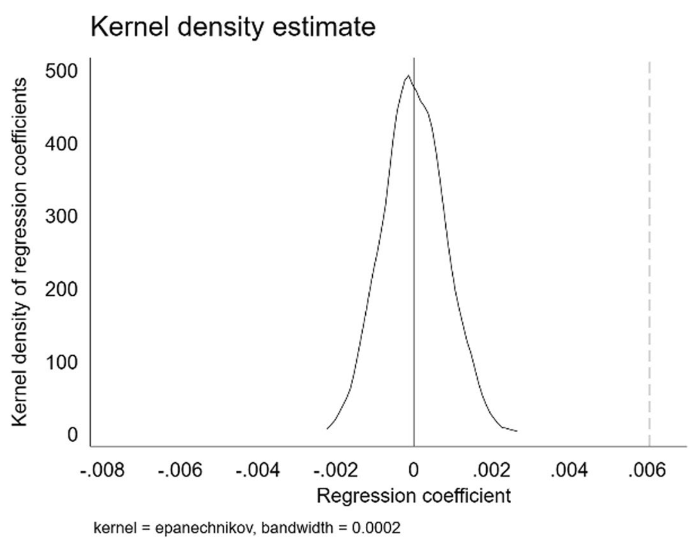

Fig. 1 "Pseudoholiday" regression coefficients for H1

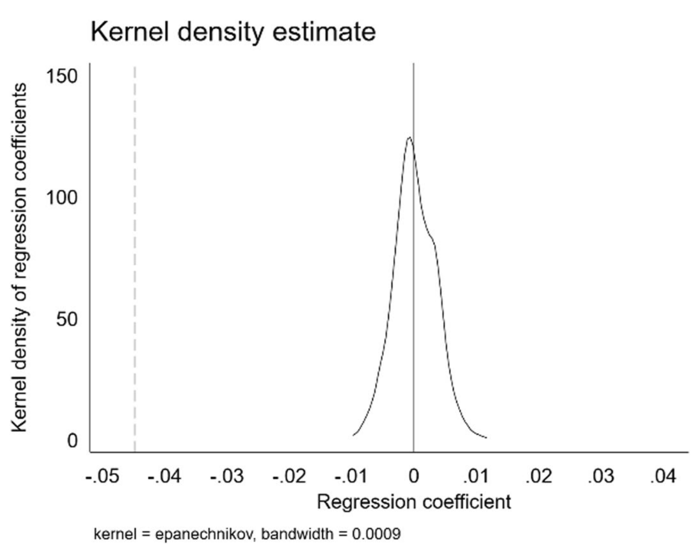

Fig. 2 "Pseudoholiday" regression coefficients for H3

Table 5 Endogeneity test results

Variables	(1)	(2)	(3)	(4)	(5)
	Variable *Senti* lagged		Interaction fixed effects		
	H2	H3	H1	H2	H3
	Return	Return	Return	Return	Return
Holiday		0.010***	0.006***		0.012***
		(11.855)	(7.517)		(11.893)
Senti	0.006***	0.008***		0.038***	0.042***
	(6.279)	(7.938)		(37.436)	(39.591)
Holiday × Senti		− 0.025***			− 0.045***
		(− 10.036)			(− 14.787)
EPU	− 0.002***	− 0.002**	0.000	− 0.005***	− 0.005***
	(− 3.030)	(− 2.097)	(0.454)	(− 5.807)	(− 5.755)
BTCD	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.811)	(6.569)	(8.277)	(13.186)	(13.040)
Volume	0.002***	0.002***	0.002***	0.003***	0.003***
	(3.386)	(3.516)	(7.384)	(10.331)	(10.814)
Cap	− 0.004***	− 0.004***	− 0.005***	− 0.006***	− 0.006***
	(− 6.112)	(− 6.218)	(− 12.713)	(− 15.516)	(− 15.970)
Age	− 0.002*	− 0.002*	− 0.003***	− 0.003***	− 0.003***
	(− 1.940)	(− 1.883)	(− 5.356)	(− 5.603)	(− 5.826)
CCI30	− 0.091***	− 0.095***	− 0.086***	− 0.137***	− 0.141***
	(− 14.681)	(− 15.020)	(− 18.350)	(− 28.043)	(− 28.953)
Constant	0.070***	0.067***	0.071***	0.097***	0.098***
	(6.583)	(6.297)	(9.089)	(12.537)	(12.645)
Observations	118,543	118,543	118,764	118,764	118,764
R-squared	0.012	0.013	–	–	–
Coin FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Interaction FE	NO	NO	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

Third, our model recontrols for individual and year interaction fixed effects. In traditional panel fixed-effects models, both individual and time effects enter the model in an additive form, which controls for individual differences that do not vary over time and time differences that do not vary over individuals in the sample. However, shocks in time may be multidimensional; that is, the same shock may not have the same effect on different cryptocurrencies. Therefore, following Bai (2009), we introduce individual and time interaction effects in the panel model to capture the differences in the impact of common factors on individuals across cryptocurrencies. The results in Columns (3–5) in Table 5 indicate the findings remain robust by fully considering the existence of multidimensional shocks in financial markets and the heterogeneity in the strength of different cryptocurrencies' responses to these shocks.

Autocorrelation and heteroskedasticity

Autocorrelation and heteroskedasticity may bias the results of standard fixed-effects models. In the main text, we use clustering robust standard errors at the individual level of cryptocurrencies to mitigate the impact of these problems. To further rule out the

Table 6 Effect of heteroskedasticity and autocorrelation

Variables	(1) FGLS	(2)	(3)	(4) Two-way clustering	(5)	(6)
	H1	H2	H3	H1	H2	H3
	Return	Return	Return	Return	Return	Return
Holiday	0.006***		0.012***	0.006*		0.012***
	(7.719)		(11.918)	(1.700)		(2.656)
Senti		0.037***	0.041***		0.037***	0.041***
		(36.312)	(38.433)		(6.338)	(6.606)
Holiday × Senti			− 0.045***			− 0.045***
			(− 14.497)			(− 4.131)
EPU	− 0.001	− 0.007***	− 0.007***	− 0.001	− 0.006	− 0.006
	(− 1.179)	(− 7.856)	(− 7.758)	(− 0.119)	(− 1.555)	(− 1.544)
BTCD	0.000***	0.001***	0.001***	0.000**	0.000***	0.000***
	(13.181)	(18.764)	(18.656)	(2.150)	(3.222)	(3.187)
Volume	0.001***	0.001***	0.001***	0.002**	0.002***	0.002***
	(5.246)	(6.777)	(7.074)	(2.464)	(3.278)	(3.405)
Cap	− 0.002***	− 0.002***	− 0.002***	− 0.004***	− 0.005***	− 0.005***
	(− 8.759)	(− 10.385)	(− 10.707)	(− 4.134)	(− 5.010)	(− 5.163)
Age	− 0.000*	− 0.000	− 0.000	− 0.002	− 0.002	− 0.002
	(− 1.854)	(− 1.209)	(− 1.134)	(− 1.477)	(− 1.410)	(− 1.380)
CCI30	− 0.097***	− 0.148***	− 0.152***	− 0.087***	− 0.136***	− 0.141***
	(− 20.879)	(− 30.850)	(− 31.675)	(− 2.938)	(− 4.522)	(− 4.646)
Constant	0.028***	0.044***	0.044***	0.063**	0.082***	0.083***
	(4.916)	(7.894)	(7.784)	(2.320)	(3.257)	(3.269)
Observations	118,764	118,764	118,764	118,764	118,764	118,764
Coin FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Z-statistics are reported in parentheses in Columns (1–3). Robust t-statistics are reported in parentheses in Columns (4–6). ***, **, and * denote significance at the 1%, 5%, and 10%, levels, respectively

confounding effect of the above problems, we used the feasible generalized least squares (FGLS) method to estimate the model parameters more robustly. Based on the characteristics of the unbalanced panel, the FGLS method can accurately solve heteroskedasticity, autocorrelation, and cross-sectional dependence problems (Reed and Ye 2011). The results of the FGLS test are shown in Table 6, Columns (1–3). The findings in the main text remain robust after estimation using the FGLS method. In addition, we apply a two-way cluster adjustment method and time levels to the SE estimates of the empirical model (Gu and Yoo 2019). The results are shown in Table 6, Columns (4–6), indicating that the study's three research hypotheses are still validly tested. Thus, the study's main findings of are not disturbed by autocorrelation or heteroskedasticity factors.

Substitution variables

The different methods of calculating returns are first considered. In the main text, we use the formula of a simple return to calculate the return of cryptocurrencies. To further retest the conclusion's robustness, we recalculate the logarithmic return of

Table 7 Regression results for the alternative variables

Variables	(1)	(2)	(3)	(4)	(5)
	Logarithmic rate of return			ML method of sentiment	
	H1	H2	H3	H2	H3
	Return	Return	Return	Return	Return
Holiday	0.007***		0.013***		0.035***
	(10.926)		(14.709)		(11.905)
Senti		0.040***	0.044***	0.055***	0.059***
		(20.445)	(21.015)	(20.346)	(20.822)
Holiday × Senti			− 0.048***		− 0.057***
			(− 15.175)		(− 10.374)
EPU	0.000	− 0.006***	− 0.006***	− 0.009***	− 0.009***
	(0.205)	(− 9.770)	(− 9.540)	(− 10.784)	(− 10.541)
BTCD	0.000***	0.001***	0.001***	0.000***	0.000***
	(7.529)	(9.519)	(9.414)	(6.398)	(6.282)
Volume	0.001*	0.001***	0.001***	0.002***	0.002***
	(1.812)	(3.156)	(3.336)	(3.409)	(3.568)
Cap	− 0.003***	− 0.004***	− 0.004***	− 0.004***	− 0.004***
	(− 5.434)	(− 6.635)	(− 6.831)	(− 6.595)	(− 6.697)
Age	− 0.000	0.000	0.000	− 0.002*	− 0.002
	(− 0.058)	(0.048)	(0.092)	(− 1.721)	(− 1.651)
CCI30	− 0.084***	− 0.137***	− 0.142***	− 0.108***	− 0.111***
	(− 15.107)	(− 18.528)	(− 18.933)	(− 16.419)	(− 16.586)
Constant	0.038***	0.060***	0.060***	0.085***	0.082***
	(4.356)	(6.720)	(6.768)	(8.084)	(7.781)
Observations	118,764	118,764	118,764	118,764	118,764
R-squared	0.011	0.026	0.028	0.018	0.019
Coin FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

cryptocurrencies as a proxy variable for H1–H3. As shown in Table 7, Columns (1–3), the hypotheses in the main text are still valid.

Second, proxy indicators of investor sentiment are used. To measure text sentiment, we used a machine-learning approach that treats sentiment measurement as a text classification problem that captures valid information at the utterance level and avoids possible information loss of the lexical approach. We approach investor sentiment as a text classification problem and employ machine-learning techniques to predict whether a given text exhibits positive or negative sentiment.

Machine-learning methods use training and test sets to classify samples. Like Smailović et al. (2014) and Renault (2017), we transform unstructured text into machine-recognizable structured feature vectors based on the frequency of vocabulary occurrence. In addition, we collected labeled financial text data, with 4607 predictions, each labeled as "positive" or "negative." Using the above-labeled dataset, we selected eight commonly used machine-learning methods to build classification models for in-sample learning: Linear Support Vector Classification (SVM), Logistic Regression, Stochastic Gradient Descent, Naive Bayes classifier (N.B.), K-Nearest Neighbors, Decision Tree, Random Forest, and Integrated Learning Ada Boost (AB). The trained models match the input text with the corresponding category labels. This study selects 80% of the corpus as the training set and the remaining 20% as the test set. The accuracy of the trained model classification is shown in the "Appendix", Table 12. We found that the LinearSVC model has the highest prediction accuracy; thus, we used this model to predict the text sentiment of the Twitter cryptocurrency tweets dataset. After obtaining the sentiment of individual texts within the dataset, we use simple weighting to measure investor sentiment on a single day. The number $_{\text{bull}}$ and number $_{\text{bear}}$ are the single-day sums of positive and negative sentiment texts, respectively. Columns (4–5) of Table 7 show the results of the tests of H2 and H3 using the above alternative variables, and the main hypothesis is still validated.

$$MLsenti = \frac{number_{bull}}{number_{bull} + number_{\text{bear}}} \tag{7}$$

In addition, we calculated the Pearson correlation coefficient for the sentiment sequences using the lexicon and machine-learning methods, and the result was 0.564. This indicates that the sentiment sequences have good robustness on theme differences between the sentiment sequences measured using the two methods. The lexicon method extracts information at the word level. Moroever, the machine-learning algorithm considers contextual features, such as the order of words and colinear relationships, enabling effective information extraction at the utterance level. There are natural differences in investor sentiment measured based on different levels. However, Columns (4–5) of Table 7 indicate that positive sentiment suppresses the holiday effect in the cryptocurrency market, further supporting the notion that investors pay selective attention to different information while on holiday.

Other robustness tests

First, we recrawled the cryptocurrency price data from another well-known trading platform in the cryptocurrency space, Binance.com. Although only 84 out of the 100 cryptocurrencies examined in this study are available on Binance.com, it still offers a closer representation of the paper's subject in general terms. We tested the study's hypotheses using cryptocurrency data from Binance.com, and the outcomes align with the results presented in this paper. The relevant results are shown in "Appendix B" and Table 13. Thus, we believe this study's results will not change because of the difference in liquidity and trading platforms.

Second, we consider the impact of other calendar effects on the robustness of the conclusions. Some calendar abnormalities, such as the weekend and Western holiday effects, have already been found. To remove the influence of weekend effects, this study reconstructs a dummy variable, $\text{Holiday}_{\text{t}}$, which excludes weekends. If day t is a legal holiday in China and not a weekend, then $Holiday_t = 1$; otherwise $Holiday_t = 0$. On this basis, this paper reconstructs a holiday variable without weekends and Western holidays. We use it as a proxy in the regression model to remove the possible effects of weekends and U.S. holidays on cryptocurrency returns. The H1 and H3 regression results are presented in "Appendix B" and Table 14. The results show that the coefficient of the dummy variable *Holiday* representing the Chinese holiday effect is still significantly positive, and the coefficient of the interaction term between the *Senti* and *Holiday* variables is still significantly negative.

Third, we consider the impact of traditional financial markets, which are inextricably linked to the cryptocurrency market represented by Bitcoin (BTC) (Kong et al. 2023). Studies have shown a link between cryptocurrency and traditional financial markets (Erdas and Caglar 2018). During the 2019 Coronavirus pandemic (COVID-19), Bitcoin, Ethereum, and SP500 index returns were significantly correlated (Mariana et al. 2021), suggesting that when a specific event affects investor sentiment, the correlation between cryptocurrencies and traditional financial assets increases sharply. Meanwhile, the influences that impact financial markets, such as the U.S. and A-shares, propagate to the cryptocurrency market. To avoid the impact of traditional financial markets on regression bias, we consider adding VIX, SP500, and CSI 300 index returns as additional control variables to our model and then retest the hypotheses. Table 15 of "Appendix B" shows that the hypotheses in our main text are still validly tested after controlling for the effects of traditional financial markets.[11]

Fourth, we consider the impact of Bitcoin halving, which entails the halving of Bitcoin, the cornerstone of the digital asset industry and the vane of the cryptocurrency market, every four years. For every 210,000 increase in block height, the Bitcoin reward for a single block is reduced to half its original value (Nakamoto and Bitcoin 2008). This means that producing Bitcoin for mining rewards is cut in half, with less supply and more demand, causing a readjustment in the supply–demand balance. Miners obtain fewer rewards for the exact cost, and Bitcoin costs more per unit mined. Every time a halving occurs, Bitcoin hits a new all-time high and causes a bubble in the cryptocurrency market (Xiong et al. 2020; Meynkhard 2019).[12] To mitigate the regression bias caused by the impact of Bitcoin halving, we exclude the sample for the year of Bitcoin halving, i.e., 2020. The results in Table 16, Columns (1–3), show that the conclusions in the main text remain significant. In addition, we winsorize all continuous variables in the model at 1% to shrink the tails. The findings remain robust, as shown in Table 16, Columns (4–6).

Mechanism analysis

The above empirical analysis verifies the validity and robustness of the main regression results. Returns of the cryptocurrency market are significantly higher during the Chinese holidays. To deepen our study, we build on previous findings and aim to find explanations of the holiday effect. The possible mechanisms proposed in our theoretical analysis are as follows:

(1) During holiday periods, A-shares are closed, but the cryptocurrency market is available for 7*24-h trading. Investors seeking short-term returns shift their attention from A-shares to the cryptocurrency market, increasing its liquidity.

[11] We filled in traditional financial market variables that were missing during the holiday season on the basis of values from the day before the market closed.

[12] Before the November 2012 halving, the price of Bitcoin was $11; following the halving, it soared to a record high of $1,200 in November 2013. In July 2016, Bitcoin's' price was $740 before the halving; after the halving, it reached an all-time high of $19,891 in December 2017. In May 2020, the price of Bitcoin stood at $8,982 before halving; posthalving, it achieved a record high of $69,000 in November 2021.

(2) Investors are more risk-seeking during holiday periods. They prefer high-return, high-risk assets such as cryptocurrencies, exhibiting increased avarice for cryptocurrencies.

In this regard, this paper first examines the effect of festivals on cryptocurrency liquidity. It then examines the effect of festivals on investors' greed and fear of cryptocurrencies. If we find the liquidity of cryptocurrencies is higher and investors are greedier during holiday periods, the proposed holiday effect mechanism is validated.

Holiday effect on cryptocurrency market liquidity

Liquidity is significant for any tradable financial asset. In the cryptocurrency market, greater liquidity means more investors are involved (Corbet et al. 2021). We follow Leirvik (2022) and Corwin and Schultz (2012) to verify the holiday effect on cryptocurrency liquidity. The higher the spread estimate, the less liquid the cryptocurrency.

Based on Corwin and Schultz (2012), the spread estimator S_t is calculated as follows:

$$S_t = \frac{2(\exp(\alpha_t) - 1)}{\exp(\alpha_t) + 1} \tag{8}$$

$$\alpha_t = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{9}$$

where variable β is the sum of the squares of the natural logarithms of the ratio of the highest and lowest prices for each day on days $t-1$ and t:

$$\beta_t = \mathrm{E}\left[\sum_{j=t-1}^{t} \left(\ln\left(\frac{H_j}{L_j}\right)\right)^2\right] \tag{10}$$

where H_j (L_j) denotes the cryptocurrency's highest (lowest) price on day j, and γ is given by the square of the natural logarithm of the ratio of the highest and lowest prices over the two days.

$$\gamma_t = \left(\ln\left(\frac{H_{t,t-1}}{L_{t,t-1}}\right)\right)^2 \tag{11}$$

where $H_{t,\,t-1}$ ($L_{t,\,t-1}$) is the highest (lowest) price on day $t-1$ and two days on day t. After obtaining the spread S_t, we follow Corwin and Schultz (2012), whose recommendation is to set the negative value of S_t to 0.

Second, to ensure robustness of the results, we follow Abdi and Ranaldo (2017) to estimate the amount of AR spread to recalculate the liquidity indicator.[13]

The test results for the effect of festivals on cryptocurrency liquidity are shown in Table 8, Columns (1–2), indicating that the coefficient of *Holiday* is always significantly negative, regardless of whether the spread estimation method of Corwin and Schultz

[13] Abdi and Ranaldo (2017) proposed a spread estimator based on the natural logarithms of high, low and closing prices in subinterval t, denoted $h_t = \ln(H_t)$, $l_t = \ln(L_t)$ and $c_t = \ln(C_t)$, respectively. further, denote by $\overline{p}_t = (h_t + l_t)/2$. The "two-day corrected version' of the AR estimator is defined as $AR_i = \sqrt{max\{4(c_i - \overline{p}_i)(c_i - \overline{p}_{i+1}), 0\}}$.

Table 8 Mechanism test

Variables	(1) S_t	(2) AR	(3) Greed	(4) Fear
Holiday	−0.002***	−0.002***	0.104***	−0.134***
	(−8.518)	(−5.842)	(5.847)	(−8.698)
EPU	−0.000	0.000	1.306***	−0.992***
	(−0.448)	(0.548)	(67.188)	(−55.716)
BTCD	−0.000***	−0.000***	0.026***	−0.010***
	(−4.191)	(−6.363)	(36.512)	(−15.155)
Volume	0.005***	0.003***	0.013***	−0.016***
	(8.463)	(7.364)	(4.034)	(−5.661)
Cap	−0.005***	−0.003***	0.042***	−0.048***
	(−8.515)	(−6.750)	(9.318)	(−11.693)
Age	−0.005***	−0.004***	−0.087***	0.095***
	(−7.105)	(−6.882)	(−16.620)	(19.334)
CCI30	−0.041***	−0.044***	4.953***	−4.971***
	(−14.185)	(−15.544)	(46.138)	(−48.003)
Constant	0.087***	0.079***	−11.375***	8.014***
	(13.323)	(12.908)	(−84.982)	(67.186)
Observations	118,543	118,324	111,344	111,344
R-squared	0.042	0.021	–	–
Coin FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Columns (1–2) present the test results for the holiday effect on cryptocurrency market liquidity, and Columns (3–4) present the test results for the effect of holidays on investor greed. Robust t-statistics are reported in parentheses in Columns (1–2). Robust z-statistics are reported in parentheses in Columns (3–4). ***, ** and * denote significance at 1%, 5% and 10%, respectively

(2012) or Abdi and Ranaldo (2017) is used. This suggests that liquidity in the cryptocurrency market increases significantly during holiday periods. As we analyzed earlier, investors' attention shifts from traditional financial markets to cryptocurrency markets during holiday periods, increasing crypto liquidity and returns.

Holidays and investor greed

Investors' crisis sentiment can significantly increase the risk of cryptocurrency market volatility and price collapse (Anastasiou et al. 2021; Salisu and Ogbonna 2022). At the risk of a crisis, investor fear can lead to lower cryptocurrency returns (Chen et al. 2020). Therefore, we are particularly interested in whether a happy atmosphere during the holiday increases investor greed and, thus, preference for investing in more volatile cryptocurrencies. To test the above mechanism, we use the Fear–Greed Index of cryptocurrencies created by a professional investment analysis website as a proxy variable for investor greed.[14] The index is calculated based on six main factors: market momentum and trading volume, volatility, trends, dominance, public opinion polls, and social media. The Cryptocurrency Fear–Greed Index is measured on a scale of 0–100, with lower

[14] The Fear–Greed Index is sourced from https://alternative.me/crypto/fear-and-greed-index/. The index is calculated on the basis of six key factors: market momentum and trading volume, volatility, trends, dominance, public opinion polls, and social media. The Cryptocurrency Fear–Greed Index is measured on a scale of 0–100, with lower scores indicating more fearful investors and higher scores indicating more greedy investors.

scores indicating more fearful investors and higher scores indicating more greedy investors. The index also divides investor sentiment into five levels to more intuitively reflect changes in investor sentiment in the cryptocurrency market: Extreme Fear (0–25), Fear (26–46), Neutral (47–54), Greed (55–75), and Extreme Greed (76–100). Based on this, we construct a dummy variable, *Greedy*, to determine whether the investor's sentiment is greedy. Greedy = 1 when the investor is greedy and extremely greedy (value ≥ 55); and 0 otherwise. In addition, we construct a dummy variable, *Fear*, for whether the investor's sentiment is fearful. Fear = 1 when the investor is fearful and extremely fearful (value ≤ 46); and 0 otherwise. As the *Greedy* and *Fear* variables are binary, we employed the Probit binary choice regression model for our empirical study. The results in Table 8, Columns (3–4) show that all coefficients of the variable Holiday are significant, indicating that Chinese festivals increase investors' greed and decrease investors' fear to some extent. This implies that during holiday periods, investors are greedier, more irrational, and more risk-averse in their investment behavior, preferring to invest in more volatile cryptocurrencies.

In summary, the holiday season has increased the liquidity of cryptocurrencies and attracted investors' attention, resulting in an influx of more short-term funds into the market. At the same time, holidays make investors more inclined to be greedy and irrational; thus, this leads to cryptocurrency purchases, which increase their prices. The shift in investor attention and the irrational state affect the cryptocurrency market, making it somewhat ineffective and creating a holiday effect.

Extended research

Impact of COVID-19 pandemic risk

We have considered a range of information that may affect cryptocurrency prices, supporting the holiday effect in the cryptocurrency market. Although the COVID-19 pandemic is a thing of the past internationally, it remains a key factor in investor sentiment for Chinese investors. One study further extends the limited attention model in financial markets and finds that investors' attention is allocated between macro and micro information margins and between financial markets and other activities (Hirshleifer and Sheng 2022). Thus, do pandemics, like investor sentiment, lead investors to pay selective attention to information? In this section, we investigate whether the spread and diffusion of the pandemic risk impact the holiday effect.

First, cryptocurrencies can hedge against the uncertainty risk associated with traditional financial assets, acting as a potential safe haven when the pandemic transmission risk is heightened. When the risk of COVID-19 transmission escalates, investors may be motivated to seek refuge in cryptocurrencies, given the increased uncertainty of conventional financial markets (Corbet et al. 2020; Melki and Nefzi 2022). We argue that in times of greater risk during the pandemic spread, the cryptocurrency market has also been hit. Investors' preference for cryptocurrencies will increase because of higher-risk aversion to traditional financial markets, increasing the return on cryptocurrencies. Following Arroyo-Marioli et al. (2021), we use the effective reproduction rate (*Repro*) of COVID-19 and the daily new confirmed cases (*Cases*) as proxy variables for the transmission risk of the outbreak to verify the cryptocurrency market's safe haven effect. We examine the impact of the transmission risk of COVID-19 on cryptocurrency returns.

Second, because investors' attention is limited, when new information becomes available in the market, investors develop selective preferences for information. In the previous section, we argued that, according to the behavioral finance theory of "Limited Attention," investors focus more on trading signals generated by emotions and less on holiday signals when investor sentiment is high. At the same time, we cannot ignore that pandemic risk is essential information affecting financial market sentiment (Naeem 2021; Apergis 2022). COVID-19 can trigger market panic and risk aversion among investors (Atri et al. 2020). Additionally, investors react more negatively to bad news (Chokor and Alfieri 2021); thus, we believe that pandemic risk, as new market information, will likewise affect investors' attention behavior to holiday information. Therefore, we propose the following hypothesis:

The impact of the cryptocurrency holiday effect will be weakened as investors focus more on pandemic risk and less on holiday information.

Therefore, we also take the same proxy variable of pandemic transmission risk as described above and construct a moderating effect model to verify the effect of COVID-19 transmission risk on the holiday effect.

Table 9 show the results of the effect on the risk of COVID-19 transmission. Column (1–2) results show that the coefficients of *Cases* and *Repro* are both significantly positive, indicating that cryptocurrencies are safe havens when the risk of pandemic transmission is high. Investors' preferences increase when there is a grave risk of pandemic transmission, thus increasing the return. The coefficients of *Cases* × *Holiday* and *Repro* × *Holiday* are both significantly negative, indicating the holiday effect has less impact when the pandemic transmission risk is high, and the pandemic transmission risk weakens the impact of Chinese holidays on cryptocurrency returns. The above findings suggest that the safe haven property of cryptocurrencies itself reflects investors' demand for cryptocurrencies when the risk of pandemic transmission is high. Therefore, they do not react as strongly to holidays. Furthermore, it supports that investors' attention span is limited; when they focus on one piece of information, they ignore the other.

The paper also tests whether the moderating effect of investor sentiment on the holiday effect is related to the effect of the risk in pandemic transmission. The results in Columns (3–4) show that the coefficients of *Senti* × *Holiday* × *Cases* and *Senti* × *Holiday* × *Repro* are both close to zero and insignificant. This suggests that the pandemic spread risk does not change the importance of investor sentiment relative to holiday information. Positive investor sentiment still suppresses the holiday effect in the cryptocurrency market when considering the pandemic spread risk.

Heterogeneity analysis

The individual attributes of cryptocurrencies influence investor decision-making behavior. Cryptocurrencies with higher market capitalization rankings are more popular and mature with longer lifespans. Therefore, do investors' investment preferences for cryptocurrencies with different popularity and maturity levels differ?

To test the heterogeneity of the holiday effect and the inhibitory effect of investor sentiment on individual attributes, we first divide the sample into two groups based on the capitalization of cryptocurrencies. According to the median by daily degree, those below the median are the low-market capitalization group (Lcap), and those above or equal to

Table 9 Impact of pandemic spread risk on cryptocurrency

Variables	(1) Return	(2) Return	(3) Return	(4) Return
Holiday	0.011***	0.009***	0.016***	0.016***
	(5.097)	(5.477)	(12.867)	(12.723)
Cases	0.001***		0.000***	
	(8.185)		(3.753)	
Cases × Holiday	− 0.001**			
	(− 2.448)			
Repro		0.005***		0.002***
		(7.175)		(4.067)
Repro × Holiday		− 0.002*		
		(− 1.922)		
Senti			0.055***	0.055***
			(22.404)	(22.303)
Senti × Holiday			− 0.071***	− 0.066***
			(− 12.551)	(− 13.047)
Senti × Holiday × Cases			0.001	
			(1.642)	
Senti × Holiday × Repro				0.000
				(0.038)
EPU	0.003***	0.005***	− 0.008***	− 0.007***
	(3.663)	(5.329)	(− 8.436)	(− 6.961)
BTCD	0.001***	0.001***	0.001***	0.001***
	(14.545)	(14.242)	(16.330)	(16.196)
Volume	0.001	0.001*	0.002***	0.002***
	(1.367)	(1.868)	(3.178)	(3.372)
Cap	− 0.004***	− 0.005***	− 0.006***	− 0.006***
	(− 5.620)	(− 6.300)	(− 8.435)	(− 8.665)
Age	0.001	0.001	0.002	0.002
	(0.718)	(0.636)	(0.881)	(0.843)
CCI30	− 0.113***	− 0.114***	− 0.176***	− 0.177***
	(− 15.227)	(− 15.274)	(− 19.370)	(− 19.365)
Constant	− 0.015	− 0.020	0.042***	0.039**
	(− 1.003)	(− 1.298)	(2.750)	(2.514)
Observations	76,368	76,368	76,368	76,368
R-squared	0.018	0.019	0.037	0.037
Coin FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Columns (1–2) show the effect of pandemic risk on the holiday effect, and Columns (3–4) show the effect of pandemic risk on the effect of investor sentiment on suppressing the holiday effect. Robust t-statistics are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

the median are the high-market capitalization group (Hcap). Second, this study divides the sample into two groups according to the median duration of cryptocurrencies online in Coinmarketcap: the low-lifetime group (Lage) and the high-lifetime group (Hage). The results of the heterogeneity analysis are presented in Table 10. The coefficients of *Holiday*, *Senti*, and the interaction term of both are significant at the 1% level in both the high and low-market cap and high and low-maturity samples. This further demonstrates the robustness of the above findings that cryptocurrency returns are significantly higher

Table 10 Cryptocurrency individual heterogeneity test

Variables	(1) Lcap Return	(2) Hcap Return	(3) Lage Return	(4) Hage Return
Holiday	0.011***	0.013***	0.009***	0.014***
	(8.989)	(9.049)	(7.554)	(9.233)
Senti	0.040***	0.044***	0.038***	0.046***
	(13.919)	(17.016)	(12.713)	(17.231)
Holiday × Senti	− 0.044***	− 0.047***	− 0.043***	− 0.048***
	(− 10.631)	(− 7.219)	(− 11.412)	(− 6.695)
EPU	− 0.005***	− 0.007***	− 0.003**	− 0.006***
	(− 3.439)	(− 6.945)	(− 2.430)	(− 8.185)
BTCD	0.000***	0.000***	0.000***	0.001***
	(3.083)	(4.865)	(3.384)	(7.682)
Volume	0.002**	0.004***	0.003***	0.003***
	(2.244)	(5.481)	(3.316)	(3.964)
Cap	− 0.007***	− 0.008***	− 0.007***	− 0.006***
	(− 5.759)	(− 7.657)	(− 6.367)	(− 6.497)
Age	0.000	− 0.004**	− 0.002	− 0.011***
	(0.005)	(− 2.597)	(− 1.482)	(− 2.787)
CCI30	− 0.134***	− 0.145***	− 0.131***	− 0.152***
	(− 10.803)	(− 14.288)	(− 10.910)	(− 17.508)
Constant	0.130***	0.151***	0.109***	0.140***
	(6.526)	(8.297)	(6.033)	(4.982)
Observations	59,918	58,846	59,918	58,846
R-squared	0.021	0.032	0.020	0.034
Coin FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Columns (1) and (2) present the results of the tests for the low and high-market capitalization samples, respectively. Columns (3) and (4) present the results of the tests for the low- and high-maturity samples, respectively. Z-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

during legal holidays in China. Positive investor sentiment has a proxy effect on the holiday effect of cryptocurrencies.

Furthermore, we observe that the coefficients of *Holiday*, *Senti*, and the interaction term *Holiday* **×** *Senti* are higher in the high-market capitalization and high-maturity samples. This implies that the holiday effect is more pronounced for high-market capitalization and high-maturity cryptocurrencies than for low-market capitalization and low-maturity cryptocurrencies. Equally, the impact of investor sentiment and the substitution of positive investor sentiment for the holiday effect is higher. However, note that we used t-testing for the regression results after we grouped the samples differently. Only the coefficients of the *Holiday* variables were significantly different between the high- and low-maturity groups, with a chi-square value of 5.57 and a *p* value of 0.0183. In other cases, the differences in the coefficients of the variables in the different grouped samples were insignificant.[15] This suggests that during the holiday, investors may have preferred

[15] In the two groups of samples with high and low-market cap, the t-test for the coefficient of *Holiday* in both groups had a chi-square value of 1.45 and a *p* value of 0.2287, and the t-test for the coefficient of the *Holiday***Senti* interaction term had a chi-square value of 0.05 and a *p* value of 0.8234. In the two groups of samples with high and low maturity, the t-test for the coefficient of the *Holiday***Senti* interaction term had a chi-square value of 0.25 and a *p* value of 0.6196.

cryptocurrencies that have been online for longer and are more mature. They did not show a significant preference for cryptocurrencies with different market capitalizations.

The bitcoin market

Given the importance of Bitcoin in the overall cryptocurrency market,[16] we analyze it separately in this section to verify the comparability of Bitcoin and other cryptocurrencies. To test whether Chinese festivals significantly affect Bitcoin returns, we estimate autoregressive distributed lag (ARDL) models with the following form:

$$Bitcoin\ return_t = \gamma + \sum_{i=1}^{p} \alpha_i Bitcoin\ return_{t-1} + \beta Holiday_t \sum_{i=0}^{q} \delta_i^T X_{t-1} + EC\ Term + u_t \tag{12}$$

where X_{t-i} contains the first difference of all control variables, δ_i is the corresponding coefficient vector, and u_t is a random error term. Moreover, we also allow for a long-run relationship among the variables by including an error correction term (EC Term) in the spirit of Pesaran et al. (2001). Our control variables are consistent with those in the main body.

Table 11 reports the estimation results for different specifications of the ARDL model. We calculate Bitcoin returns using the simple and logarithmic return methods. Models 1 and 2 account for the lags of Bitcoin return and the error correction terms. In contrast, Models 3 and 4 consider the lags of Bitcoin returns and other control variables.

In all four estimations, the coefficients of the variables of interest are significant and consistent with the hypothesis. This means that Chinese festivals have a significant and positive impact on Bitcoin returns, investor sentiment increases the return of Bitcoin, and positive investor sentiment suppresses the holiday effect of Bitcoin. All test results are consistent with the text.

Conclusion

Key findings

This study examines the impact of Chinese holidays on cryptocurrency returns by collecting data on Chinese official holidays from January 1, 2017, to July 1, 2022. First, the findings indicate that holiday effects exist in the cryptocurrency market. Specifically, cryptocurrency returns increase significantly during Chinese holidays. Second, positive sentiments conveyed on social media also drive significantly higher cryptocurrency returns. However, as positive investor sentiment amplifies, the holiday effect wanes. A time-series analysis of Bitcoin further confirms this observation.

Furthermore, a heightened risk associated with COVID-19 transmission correlates with a muted holiday effect in cryptocurrency. This highlights that both uplifting social media sentiment and the prevailing anxiety around the COVID-19 crisis divert investors' focus from holiday-centric narratives. The empirical results resonate with the seminal Limited Attention Theory from behavioral economics, which posits that investors distribute cognitive resources during information assimilation, leading to attention trade-offs across different information sets.

[16] To compare the results with those of Bitcoin, we also exclude the Bitcoin sample to test our hypothesis, and the results remain consistent. Unreported results are available upon request. We thank an anonymous reviewer for the comment leading to this investigation.

Table 11 Evidence from Bitcoin

Variables	ARDL			
	Model 1	**Model 2**	**Model 3**	**Model 4**
	Return	**LogReturn**	**Return**	**LogReturn**
Holiday	0.011***	0.012***	0.012***	0.013***
	(3.064)	(3.196)	(2.911)	(3.014)
Senti	0.031***	0.032***	0.038***	0.038***
	(9.405)	(9.814)	(9.148)	(9.359)
Holiday × Senti	− 0.031***	− 0.0320***	− 0.038***	− 0.039***
	(− 3.030)	(− 3.141)	(− 3.229)	(− 3.290)
Lag BTC Return	YES[1]	YES[1]	YES[1]	YES[1]
EPU			YES[0]	YES[0]
BTCD			YES[0]	YES[0]
Volume			YES[0]	YES[0]
Cap			YES[0]	YES[0]
Age			YES[0]	YES[0]
CCI30			YES[0]	YES[0]
Constant	YES	YES	YES	YES
Error correction	YES	YES	YES	YES
Observations	1,993	1,993	1,993	1,993
R-squared	0.534	0.536	0.541	0.542

The table displays the estimation results with Bitcoin return as the dependent variable. Square brackets contain the respective number of lags chosen by the Akaike information criterion (AIC) for each of the variables. For example, [1] means that the contemporaneous value and the previous lag of one variable have been included, while [0] means that only the contemporaneous value of the variable has been included. All our control variables are treated with or without lags in line with Table 1—The brief descriptions of the variables. *** indicates significant impact at 1% level, ** at 5% level, and * at 10% level

This study also explores the potential mechanisms of the holiday effect in the cryptocurrency market in terms of both market liquidity and investors' greed–fear sentiment. During the holiday season, investors seeking short-term returns turn to cryptocurrencies, increasing their liquidity. Furthermore, investors in a good mood during the festive season are greedier and prefer to invest in cryptocurrencies. The results of this study also suggest that at the individual level of cryptocurrencies, the holiday effect exhibits heterogeneity, and investors may prefer well-established cryptocurrencies with a longer life cycle.

Policy implications

The findings of this study offer fresh evidence of the cryptocurrency market's inefficiencies, revealing the potential for positive returns when investing in cryptocurrencies during China's official holidays. Moreover, the influence of social media sentiment on investors directly impacts the cryptocurrency market and shapes how investors assimilate other information, highlighting the complex relationship between investor psychology and market anomalies.

These findings have significant implications for policymakers and regulatory bodies. The impact of official holidays on cryptocurrency returns underscores the necessity for flexible and adaptable regulatory frameworks. Policymakers should acknowledge that temporal factors can introduce fluctuations in market behavior, necessitating swift responses to ensure market stability and investor protection. Furthermore, relevant regulatory bodies should consider bolstering market oversight to ensure fairness and transparency, limiting the maneuverability of malicious actors and preventing market manipulation and inappropriate trading behavior.

In addition, the influence of investor sentiment highlights the urgency for policymakers to foster the transparent and accurate dissemination of information. Regulatory bodies should grasp the correlation between emotions and returns, actively promoting informed decision-making while mitigating excessive market volatility resulting from emotion-driven trading. These regulatory bodies should also enhance their oversight of social media platforms, ensuring investors receive authentic and precise information while guarding against false advertising and misleading content.

Given the connection between positive social media sentiment and higher cryptocurrency returns, the government should use various channels to communicate the rational nature of investment decisions to investors and provide education on investment risks. This will help investors manage risks and fluctuations effectively. Additionally, because of the impact of COVID-19 crisis sentiment on the cryptocurrency market, considering external macroeconomic factors within regulatory frameworks is important and highlights the need for a comprehensive approach to better understand cryptocurrency market operations within a broader economic context.

In conclusion, this study's findings contribute to the academic discourse on the inefficiencies of the cryptocurrency market and offer valuable insights for policy formulation. As the cryptocurrency landscape evolves, governments and regulatory bodies should adopt a series of policy measures, ranging from enhanced regulation to improved investor education, guiding the cryptocurrency market toward greater stability and transparency while safeguarding investor interests.[17]

Limitations and scope for further research

This study also has some limitations. Although the study finds that legal holidays in China coincide with heightened cryptocurrency returns, all holidays are categorized together. Nevertheless, different holidays carry unique cultural and emotional nuances. For instance, the Chinese New Year, characterized by family reunions, evokes a joyful, festive aura, potentially making people more risk-averse. In contrast, the Tomb Sweeping Festival, a time of remembrance and mourning, might make individuals more conservative in their financial decisions. Consequently, the financial market's reactions might differ based on these diverse holiday attributes. Moreover, this research focuses on the conseuqnces of official Chinese holidays on cryptocurrency. However, regulatory perspectives on cryptocurrencies are not uniform across nations, and cultures have their own holiday customs that might influence investor tendencies, with distinct effects on the cryptocurrency market. Thus, future studies on the holiday effect on cryptocurreny should consider the intricacies of holiday characteristics and compare the cryptocurrency market's reactions to holidays in various countries. In addition, our analysis does not encompass sentiments conveyed through news articles or other textual mediums. Future research could scrutinize these formal text sources to discern investor responses to textual narratives and better understand the influence of the sentiments expressed in these texts on the holiday effect.

[17] See Table 17 for more detailed regulatory implications.

Appendix A: Classification accuracy of different models

See Table 12.

Table 12 Classification accuracy—investor social lexicons

	CC	CC_{bull}	$Recall_{bull}$	$F1_{bull}$	CC_{bear}	$Recall_{bear}$	$F1_{bear}$
SVM	88.16	88.05	88.25	88.15	88.24	88.01	88.13
LR	88.08	87.90	88.29	88.09	88.26	87.82	88.03
SGD	88.24	88.24	88.17	88.20	88.22	88.22	88.22
NB	87.96	88.21	87.60	87.90	87.67	88.32	87.99
KNN	82.01	80.71	84.04	82.34	83.36	79.91	81.59
DT	79.51	81.34	76.52	78.85	77.83	82.48	80.08
RF	84.75	86.94	81.76	84.27	82.77	87.72	85.17
AB	77.17	79.71	79.86	76.52	82.50	75.92	76.63

This table shows the classification accuracy for classifiers SVM, L.R., SGD, NB, KNN, D.T., R.F., and A.B. We report the percentage of correct classification excluding unclassified messages CC, the percentage of correct classification per class (respectively CCbull and CCbear), the percentage of recall and the F-score per class

Appendix B: Results considering other factors

See Table 13, 14, 15 and 16.

Table 13 Cryptocurrency price data from Binance.com

Variables	(1) Return	(2) Return	(3) Return
Holiday	0.009***		0.017***
	(10.515)		(15.161)
Senti		0.050***	0.055***
		(23.624)	(24.759)
Holiday × Senti			− 0.064***
			(− 19.650)
EPU	0.002**	− 0.007***	− 0.007***
	(2.426)	(− 7.619)	(− 7.722)
BTCD	0.001***	0.001***	0.001***
	(10.338)	(13.771)	(13.798)
Volume	0.002***	0.003***	0.003***
	(6.416)	(8.402)	(8.780)
Cap	− 0.004***	− 0.004***	− 0.004***
	(− 8.681)	(− 8.902)	(− 9.001)
Age	− 0.002**	− 0.001	− 0.001
	(− 2.247)	(− 1.469)	(− 1.475)
CCI30	− 0.125***	− 0.190***	− 0.196***
	(− 18.296)	(− 22.125)	(− 22.519)
Constant	0.019**	0.044***	0.045***
	(2.160)	(4.782)	(5.009)
Observations	70,430	70,430	70,430
R-squared	0.019	0.037	0.041
Number of Coins	84	84	84
Coin FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 14 Regression results considering other calendar effects

Variables	(1)	(2)	(3)	(4)
	Excluding weekends		Excluding weekends and western holidays	
	H1	H3	H1	H3
	Return	Return	Return	Return
Holiday	0.006***	0.013***	0.006***	0.013**
	(7.431)	(11.861)	(7.259)	(2.009)
Senti		0.040***		0.040***
		(20.818)		(6.565)
Holiday × Senti		− 0.050***		− 0.050***
		(− 15.471)		(− 3.554)
EPU	− 0.001	− 0.006***	− 0.001	− 0.006
	(− 1.112)	(− 8.070)	(− 1.183)	(− 1.509)
BTCD	0.000***	0.000***	0.000***	0.000***
	(6.302)	(8.107)	(6.344)	(3.192)
Volume	0.002***	0.002***	0.002***	0.002***
	(3.408)	(4.345)	(3.401)	(3.375)
Cap	− 0.004***	− 0.005***	− 0.004***	− 0.005***
	(− 6.042)	(− 7.077)	(− 6.038)	(− 5.123)
Age	− 0.002*	− 0.002*	− 0.002*	− 0.002
	(− 1.858)	(− 1.703)	(− 1.876)	(− 1.402)
CCI30	− 0.086***	− 0.138***	− 0.086***	− 0.138***
	(− 14.116)	(− 17.878)	(− 14.122)	(− 4.576)
Constant	0.064***	0.082***	0.064***	0.082***
	(6.116)	(7.731)	(6.139)	(3.235)
Observations	118,764	118,764	118,764	118,764
R-squared	0.012	0.024	0.012	0.024
Coin FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 15 Regression results considering traditional financial market

Variables	(1)	(2)	(3)
	Adding the mainstream financial market returns in the control variables		
	H1	H2	H3
	Return	Return	Return
Holiday	0.007***		0.012***
	(9.739)		(14.246)
Senti		0.038***	0.042***
		(20.296)	(20.703)
Holiday × Senti			− 0.041***
			(− 13.528)
EPU	− 0.002***	− 0.007***	− 0.007***
	(− 2.913)	(− 11.797)	(− 11.154)
BTCD	0.000***	0.001***	0.001***
	(6.790)	(10.015)	(9.858)
Volume	0.002***	0.001***	0.001***
	(3.306)	(2.910)	(3.100)
Cap	− 0.004***	− 0.004***	− 0.004***
	(− 5.909)	(− 6.393)	(− 6.592)

Table 15 (continued)

Variables	(1)	(2)	(3)
	Adding the mainstream financial market returns in the control variables		
	H1	H2	H3
	Return	Return	Return
Age	− 0.002	0.000	0.000
	(− 1.619)	(0.303)	(0.359)
CCI30	− 0.092***	− 0.140***	− 0.144***
	(− 14.612)	(− 18.508)	(− 18.832)
SPX	0.651***	0.659***	0.668***
	(17.125)	(16.975)	(17.040)
VIX	− 0.048***	− 0.050***	− 0.047***
	(− 14.950)	(− 17.511)	(− 16.943)
CSI30	0.055***	0.073***	0.051***
	(3.993)	(6.090)	(4.314)
Constant	0.065***	0.062***	0.061***
	(6.345)	(7.123)	(7.018)
Observations	118,764	118,764	118,764
R-squared	0.037	0.055	0.057
Coin FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 16 Regression results considering bitcoin halving event and variable winsorize

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding the 2020 sample			Winsorize		
	H1	H2	H3	H1	H2	H3
	Return	Return	Return	Return	Return	Return
Holiday	0.006***		0.012***	0.008***		0.011***
	(10.272)		(12.824)	(9.261)		(10.040)
Senti		0.033***	0.042***		0.043***	0.046***
		(21.939)	(21.872)		(17.293)	(17.674)
Holiday × Senti			− 0.047***			− 0.043***
			(− 13.093)			(− 6.268)
EPU	− 0.002***	− 0.007***	− 0.007***	− 0.005***	− 0.007***	− 0.006***
	(− 3.157)	(− 12.202)	(− 8.910)	(− 5.223)	(− 7.826)	(− 6.211)
BTCD	0.000***	0.001***	0.001***	0.000***	0.000***	0.000***
	(9.525)	(12.489)	(10.805)	(5.133)	(6.914)	(6.674)
Volume	0.001**	0.001***	0.002***	0.003***	0.003***	0.003***
	(2.411)	(3.537)	(4.447)	(3.977)	(4.749)	(4.817)
Cap	− 0.003***	− 0.003***	− 0.005***	− 0.005***	− 0.006***	− 0.006***
	(− 5.653)	(− 6.577)	(− 7.026)	(− 6.260)	(− 6.755)	(− 6.813)
Age	− 0.000	0.000	− 0.001	− 0.002**	− 0.002**	− 0.002**
	(− 0.006)	(0.098)	(− 1.538)	(− 2.025)	(− 2.144)	(− 2.095)
CCI30	− 0.080***	− 0.127***	− 0.133***	− 0.076***	− 0.135***	− 0.138***
	(− 15.842)	(− 19.786)	(− 17.503)	(− 11.891)	(− 15.921)	(− 16.258)
Constant	0.043***	0.061***	0.078***	0.100***	0.100***	0.094***
	(5.685)	(7.698)	(7.458)	(8.372)	(8.179)	(7.584)
Observations	118,764	118,764	118,764	92,574	92,574	92,574
R-squared	0.013	0.024	0.023	0.014	0.025	0.027
Coin FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics are in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively

Appendix C: Regulatory implications

See Table 17.

Table 17 Regulatory implications

Findings and observations	Regulatory implications	Additional considerations/regulatory actions
1. Holiday Effects in Cryptocurrency Market		
Cryptocurrency returns increase during Chinese holidays	(1) Regulatory authorities should monitor cryptocurrency market activity during holidays for potential manipulation or speculative trading	Consider implementing temporary trading restrictions or enhanced surveillance during holiday periods
Positive sentiments on social media drive higher cryptocurrency returns	(2) Regulators may need to enhance surveillance of social media platforms for cryptocurrency-related activities during holidays to detect and address potential market manipulation	Collaborate with social media platforms to report suspicious activities and enforce guidelines on cryptocurrency-related content
Increased positive investor sentiment can weaken the holiday effect	(3) Regulatory agencies should be vigilant in detecting and addressing any market distortions caused by sudden shifts in investor sentiment during holidays	Develop mechanisms to respond quickly to unexpected sentiment-driven market volatility during the holiday season
2. COVID-19 Impact		
Heightened COVID-19 risk correlates with a muted holiday effect	(4) Regulatory responses to cryptocurrency market dynamics should consider external factors, such as pandemics, and be flexible in adapting to changing market conditions	Assess the impact of external crises on market stability and adjust regulatory measures accordingly
Anxiety around the COVID-19 crisis diverts attention from holiday narratives	(5) Regulators should factor in the potential influence of external events on cryptocurrency market behavior when developing regulatory policies	Establish contingency plans for managing market disruptions during major crises
3. Investors are greedier during the holiday season	(6) Regulatory authorities should focus on investor protection by enforcing stricter risk disclosure requirements. This can help ensure that investors are fully aware of the risks associated with cryptocurrencies' high volatility	Enforce comprehensive risk disclosure—Enhance suitability assessment for retail investors—Issue warnings about speculative behavior during holidays
4. Limited Attention Theory		
Investors distribute cognitive resources during information assimilation	(7) Regulators should encourage transparency in cryptocurrency projects and require clear, accessible information for investors to aid decision-making during holidays and beyond	Promote standardized reporting and disclosure practices among cryptocurrency projects
Attention trade-offs across different information sets	(8) Regulatory agencies should consider providing educational resources to help investors manage their attention and make informed decisions when navigating the cryptocurrency market during holidays	Promote investor education programs—Publish reports on attention allocation strategies—Conduct awareness campaigns on market risk factors

Abbreviations

EMH	Efficient market hypothesis
BTC-USD	Bitcoin-United States dollar
EPU	Economic policy uncertainty
IPS	Im-Pesaran-Shin
FGLS	Feasible generalized least squares
COVID-19	Corona Virus Disease 2019
L.R.	Logistic regression
SGD	Stochastic gradient descent
N.B.	Naive Bayes classifier
KNN	K-nearest neighbors
D.T.	Decision tree
R.F.	Random forest
AB	Integrated learning ada boost

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PZ: conceptualization, writing—review and editing, project administration; KX: writing—data analysis and visualization; JH: writing—review and editing, supervision, project administration; JQ: review and editing, supervision, project administration. All authors reviewed the manuscript. All authors read and approved the final manuscript.

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Declarations

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