Attention allocation and cryptocurrency return co-movement: evidence from the stock market

Attention Allocation and Cryptocurrency Return Co-movement: Evidence from the Stock Market

Abstract

We employ extreme S&P500 returns as an attention-distraction shock event to explore the impact of investor attention allocation on the return co-movement with cryptocurrency markets. We find that the occurrence of extreme S&P500 returns distracts investor attention away from cryptocurrency markets and this shock event increases the return co-movement within cryptocurrency markets. Further, the effect is asymmetric, with a negative return shock having a greater impact on the return co-movement than a positive return shock. Our findings are beneficial to investors, as well as to researchers who are interested in investor attention allocation, return co-movement and cryptocurrencies.

Key words: Attention allocation; Investor attention; Return co-movement; Asymmetric effect; Cryptocurrency market

1. Introduction

The impact of investor attention allocation on return co-movement has recently received much interest in a variety of markets. While extensive studies have been conducted to uncover the impact of investor attention allocation on the stock market or on the cryptocurrency market (Figá-Talamanca and Patacca, 2019; Gargano and Rossi, 2017; Ibikunle, McGroarty, and Rzayev, 2020; Shen, Urquhart, and Wang, 2019), there is scant literature investigating the relationship between the stock market and the cryptocurrency market through the channel of investor attention. Hu, Li, and Shen (2020) employ the extreme Bitcoin returns as an attention shock event and find extreme Bitcoin returns can decrease worldwide stock return co-movement. Motivated by Hu, Li, and Shen (2020), we investigate the contrasting effect where the extreme returns of stock markets influence cryptocurrency market return co-movement through the channel of investor attention allocation.

In the research field of cryptocurrency markets, most researchers focus on the analysis of Bitcoin rather than the entire cryptocurrency market. Kurka (2019) shows that shocks from Bitcoin can be transmitted to stock markets at certain time periods. Matkovskyy and Jalan (2019) discover significant contagion effects from equity market to Bitcoin market in terms of both correlation and co-skewness of market returns. Candelon, Ferrara, and Joëts (2018) find that the largest stock market such as US is the largest shock transmitter to other markets. Ji, Bouri, Lau, and Roubaud (2019) also prove world equities are influential on three digital coins' integration. More recently, Alexander and Heck (2020) show that derivatives products traded on unregulated cryptocurrency exchanges strongly dominate price discovery within the bitcoin market. However, the cryptocurrency market has quickly become a prominent and new investment instrument where it's market capitalization and the number of digital coins is growing exponentially, with a market capitalization of more than $1 trillion since January 2021 and more than 20,000 digital cryptocurrencies listed on coinmarketcap.[1] Thus, the research results obtained for Bitcoin cannot be generalized to the whole cryptocurrency market due to the rapid development of the cryptocurrency market (Zięba, Kokoszczyński, and Śledziewska, 2019). Therefore, studying the entire cryptocurrency market is meaningful and valuable and, in this paper, we employ the top

[1] As of 25th July 2022.

1,000 cryptocurrencies in terms of market capitalization to give us a flavour of the whole cryptocurrency market.[2]

Initially, we explore whether shocks in stock markets can influence the cryptocurrency markets. Our paper is related to a number of strands of literature. Firstly, extant literature shows the existence of contagion. Kodres and Pritsker (2002) construct a contagion model in which investors respond to shocks in one market by optimally readjusting their portfolios in other markets, transmitting the shocks and generating contagion. Candelon, Ferrara, and Joëts (2018) show uncertainty affects investor's behaviors, which leads investors to reallocate their portfolio positions and amplifies financial markets contagion. Matkovskyy and Jalan (2019) show the presence of contagion effect and the manner of shock transmissions from conventional financial markets to cryptocurrency market. Secondly, a number of studies have shown that cryptocurrencies are relatively isolated from popular financial assets and Bitcoin can be an effective diversifier against movements in all the assets (Bouri, Molnár, Azzi, Roubaud, and Hagfors, 2017; Charfeddine, Benlagha, and Maouchi, 2020; Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018; Hussain Shahzad, Bouri, Roubaud, and Kristoufek, 2019; Kurka, 2019). Thirdly, since there are no fundamentals in cryptocurrencies, it can be difficult to measure a "fair" price for cryptocurrencies (Kristoufek, 2013). Thus, the cryptocurrency price is dependent on investors' behavior and driven by investors' faith (Zięba, Kokoszczyński, and Śledziewska, 2019). Ibikunle, McGroarty, and Rzayev (2020) decompose the Bitcoin price into efficient and noise components and show that the noise part of Bitcoin pricing is driven by high levels of attention. Figá-Talamanca and Patacca (2019) confirm that the inclusion of attention measures in model makes the model more accurate in estimating Bitcoin returns and volatility. In summary, given that the cryptocurrency market has a weak correlation with stock market and its price is driven by investor behaviors, we propose an insight that attention shocks in the stock market may impact the cryptocurrency market only indirectly through the channel of investor attention and provide a behavioral explanation of cryptocurrency market return co-movement.

Market shocks can affect the investor attention, with Aharon and Qadan (2020) finding that market shocks attract investors' attention to trading platforms, i.e., market

---

[2] We do not consider cryptocurrencies beyond this as they can be quite small in terms of market capitalization and quite illiquid.

volatility drives investors to pay more attention to their trading platforms. Charfeddine, Benlagha, and Maouchi (2020) find that relationship between cryptocurrency and conventional assets is sensitive to external financial shocks. Given that the S&P500 is a representative and traditional investment tool, the extreme S&P500 returns can serve as a warning to global stock markets and have a great impact on investor attitude toward risk. Thus, we choose the extreme S&P500 returns as an attention shock event and investigate the impact of extreme S&P500 returns on cryptocurrency market through the channel of investor attention allocation.

Investor attention allocation can affect investor behavior and further affect market returns. Many papers have used different measures of investor attention and there is not one ideal measure of investor attention. Yuan (2015) chooses the record levels for the Dow and front-page articles about the stock market as market-wide attention-grabbing events and find they can predict the trading behavior of investors and market returns. Gargano and Rossi (2017) observe a unique brokerage account dataset and find a strong and positive cross-sectional relation between attention and performance. Peress (2016) chooses sensational news as an attention-distraction event and find trading activity, liquidity and volatility all decline among stocks on distraction days. Using the number of Twitter, Shen, Urquhart, and Wang (2019) find that twitter can measure investor attention and can be a driver of next day trading volume and realized volatility. Following the research of Da, Engelberg, and Gao (2011), lots of literature chooses Google Trends data as a proxy for investor attention to investigate the impact of investor attention on Bitcoin market (Dastgir, Demir, Downing, Gozgor, and Lau, 2018; Figá-Talamanca and Patacca, 2019; Ibikunle, McGroarty, and Rzayev, 2020; Kristoufek, 2013; Philippas, Rjiba, Guesmi, and Goutte, 2019). Kristoufek (2013) finds a positive correlation between Bitcoin price and the searched terms measured Google Trend and Wikipedia, and hold the idea that the investor interest can be a good explanatory power of digital currency price. Dastgir, Demir, Downing, Gozgor, and Lau (2018) use the Google search to measure attention and observe that there exists a bidirectional causal relationship between Bitcoin attention and Bitcoin returns under the poor and superior performance. In this paper, we also choose Google Trends as a proxy to measure investor attention allocation.

The S&P500, as a traditional and representative stock market index, receives extensive investor interest and attention. When an extreme S&P500 return occurs, investors will consider global equity markets to be riskier and more uncertain. Naturally, investors will become more risk averse and try to collect more information to reduce risk. Aharon and Qadan (2020) argue that risk-averse agents will engage in more information gathering when uncertainty occurs, in order to reduce their risk and rebalance their portfolio. Sarwar (2017) provides the notion of flight-to-safety and asserts that risk-averse investors rebalance their portfolios toward less risky assets. The research results of Matkovskyy and Jalan (2019) show that during crisis periods, risk-averse investors tend to move away risky Bitcoin markets towards safer, less volatile, and more established financial markets, especially NASDAQ and NIKKEI. From this perspective, the occurrence of extreme S&P500 returns will amplify investors' risk averse and panic, then, they will rebalance their attention allocation and investment portfolio, i.e., investors will pay more attention on more safety and established market and reduce their attention on risker cryptocurrency markets. Thus, we propose our first hypothesis: *the occurrence of extreme S&P500 returns will reduce investor attention on cryptocurrency market.*

Some research results have shown the existence of cryptocurrency market return co-movement. Ji, Bouri, Lau, and Roubaud (2019) examine the connectedness via return and volatility spillovers across six large cryptocurrencies and find connectedness via negative returns is largely stronger than via positive ones. Tiwari, Adewuyi, Albulescu, and Wohar (2020) observe three digital currencies and find the existence of a contagion phenomenon among the price of cryptocurrencies and there are lower diversification opportunities for cryptocurrencies portfolios. Zięba, Kokoszczyński, and Śledziewska (2019) also discover that there are inter-relationships between other cryptocurrencies, possibly economically connected with each other. The research of Bouri, Roubaud, and Shahzad (2020) shows evidence of co-jumping behavior among the leading twelve cryptocurrencies. Huynh, Nguyen, and Duong (2018) conclude that the spread of contagion risk among three cryptocurrencies exists. However, most studies in the field of cryptocurrency markets just focus on several digital currencies and these conclusions can't be generalized to the entire cryptocurrency market simply. In this paper, we focus on 1000 digital currencies according to market capitalization and we will explore the impact of decreased investor attention on whole cryptocurrency market.

Investor attention is limited and the information processing capacity is also finite. Some researchers explain the investor attention allocation from the channel of information price. L. Veldkamp and Wolfers (2007) discover that the low equilibrium price of aggregate information induces some firms to use aggregate data to make inferences about their sector's productivity. Thus, when many firms' inferences are based on common information, expected productivity is more correlated than true productivity. In terms of investment portfolio, there has the same conclusion in research of Veldkamp (2006) who shows that a profit-maximizing investor will typically not pay for information about every asset and will use a common subset of information to make inferences about the value of all the other assets. As a result, these common shocks to asset prices will generate "excess covariance" or co-movement, which can be evidence of investor irrationality. Gondhi (2018) finds that an aggregate uncertainty shock induces managers to acquire more information about the aggregate economy and hence less information about firm-specific shock. Peng and Xiong (2006) construct a model to study category-learning behavior and find that an attention-constrained investor tends to allocate more attention to market- and sector-level factors than to firm-specific factors.

In summary, given that the aggregate information affects more than firm-specific information, facing aggregate shock events, investors will pay more attention on aggregate information and ignore the idiosyncratic information, in hopes to minimize the portfolio risk. Using large jackpots of Taiwanese lotteries as exogenous attention-distraction shocks, Huang, Huang, and Lin (2019) find that investors will disproportionately reduce more attention allocated to firm-specific shocks than that allocated to market shocks. Thus, the asset price will include more market shock information, which will lead to higher return co-movement with market. Following the spirt of Huang, Huang, and Lin (2019), we develop our idea that when investors decrease their attention on cryptocurrency market due to the occurrence of extreme S&P500 returns, they will disproportionately reduce more attention allocated to idiosyncratic information to minimize the risk. Thus, more information about the market is incorporated into the cryptocurrency price and increase the cryptocurrency market return co-movement. Hence, we postulate the second hypothesis: *decreased investor attention will increase the return co-movement with cryptocurrency market.* Put differently, the return co-movement with cryptocurrency market will increase with the occurrence of extreme S&P500 returns.

In line with the psychology theory, the bad information is stronger than good information. Baumeister, Bratslavsky, Finkenauer, and Vohs (2001) find that negative information receives more processing and contribute more strongly to the final impression than does positive information. Williams (2015) shows that facing shocks that increase macro-uncertainty, investors respond asymmetrically to earnings news, and place greater weight on bad news than on good news. Avanidhar, Subrahmanyam, Barry, Oliver, Shumi, Akhtar, Robert, and Faff (2013) also find a behavior phenomenon that investor favors negative decisions over positive decisions. Soroka (2010) uncovers the evidence of reacting differently to positive and negative economic shifts. Hu, Li, and Shen (2020) also find that there is an asymmetric impact of extreme positive and negative of Bitcoin returns on world indices return co-movement. Thus, in this paper, we explore whether there has an asymmetric impact on return co-movement with cryptocurrency market. Thus, we put forward our third hypothesis: *an extreme negative of S&P500 returns has a greater influence on the increase of the return co-movement between cryptocurrency market than the impact of an extreme positive of S&P500 returns.*

In our empirical setting, we choose the extreme S&P500 returns as an attention-distraction event with 10^{th} percentile of returns as the threshold and choose top 1,000 cryptocurrency daily return as research sample. First, we extract the Google search volume from Google Trend to measure investor attention allocation and calculate the mean and median of Google search volume on days of extreme S&P500 returns and days of non-extreme S&P500 returns. We find that the mean and median of Google search volume on extreme return days are significantly lower than those on non-extreme return days. Then, following the research of Huang, Huang, and Lin (2019), we construct two measures to capture the return co-movement with cryptocurrency market and incorporation of market information. We employ the Pearson correlation coefficient and the adjusted R^2 obtained from market model regression. Both measurements reach the same conclusion that the mean and median of return co-movement with cryptocurrency market are higher on days of extreme S&P500 returns than those on days of non-extreme S&P500 returns. Therefore, the return co-movement with the cryptocurrency market will increase with the occurrence of extreme S&P500 returns. Furthermore, there exists an asymmetric impact of extreme S&P500 returns. The return co-movement with cryptocurrency market will increase more on days of extreme negative in S&P500 returns than those on days of extreme positive in S&P500 returns.

We explain the investor attention allocation changes through the channel of investor risk awareness and risk averse. VIX index based on S&P500 refers to the market's expectation of volatility and risk (Candelon, Ferrara, and Joëts, 2018). Thus, the VIX index can be an important market risk indicator which reflects market sentiment and investor expectation (Bouri, Gupta, Tiwari, and Roubaud, 2017). Sarwar (2017) finds that investors will tend to less risky assets with the increases in VIX. Aharon and Qadan (2020) find that a corresponding spike in investors' attention to their online trading websites when there have extreme changes in the VIX. Ji, Bouri, Lau, and Roubaud (2019) claim that the VIX index affects the return spillovers of cryptocurrency. Thus, given that VIX is a risk indicator, we choose VIX index to replicate the main research process in additional tests. We hope to explore the investor attention change resulting from changes in risk perceptions directly. After replication of main research process, we find the extreme positive of VIX index will amplify the risk averse and investors will reduce their attention on risky cryptocurrency market. Thus, the return co-movement with cryptocurrency market will highest on days of extreme positive of VIX.

Our paper mainly contributes to the extant literatures in the following aspects. Firstly, we extend and deepen the branch of the literatures about the investor attention allocation. Unlike Hu, Li, and Shen (2020), we consider the extreme S&P500 returns as an attention-distraction event and return co-movement with cryptocurrency market will increase with the occurrence of extreme S&P500 returns. Second, we connect the cryptocurrency market with the stock market through the channel of investor attention. The extreme S&P500 returns will move investor attention from cryptocurrency markets to stock markets. Further, we provide a new behavior explanation about the cryptocurrency market return co-movement through the changes in attention allocation and risk awareness. Last, to the best of our knowledge, we are the first one to use a large sample to study the return co-movement with cryptocurrency market. Unlike other studies which only focus on several digital currencies, we choose top 1,000 digital currencies as research sample, which can be better to represent the whole cryptocurrency market.

The remainder of this paper is organized as follows. In section 2, we describe the major variables, i.e., the extreme S&P500 returns data, the Google search volume data and the cryptocurrency return data. In section 3, we present our main empirical process and results. Section 4 provides some additional tests, the robustness tests are shown in section 5, and conclusions are in section 6.

2. Data

In this section, we describe the datasets used in our empirical tests with details, i.e., S&P500 trading data, Google search volume index about cryptocurrencies and the cryptocurrencies trading data necessary for capturing cryptocurrency market return co-movements.

2.1 Attention allocation events

In this paper, we choose the extreme returns of S&P500 as an attention shock event to measure the allocation of investor attention on cryptocurrencies. We obtain the historical daily trading data of S&P500 from Datastream. Since cryptocurrency issuance is more intense and concentrated after 2017, to acquire enough cryptocurrencies, our sample period is from January 1st 2017 to September 30th 2021, which covers 1,216 trading days. To obtain the extreme S&P500 returns, we first calculate the daily return change of S&P500 using the equation (1) (Gronwald, 2019):

$$\text{Daily return change}=\frac{\text{Close}_t\text{-Close}_{t\text{-}1}}{\text{Close}_{t\text{-}1}} \tag{1}$$

where Close_t is the closing price of S&P500 at time t, and $\text{Close}_{t\text{-}1}$ is the closing price of S&P500 at time t-1. Then, we divide all S&P500 trading days into extreme trading days and non-extreme trading days with 10th percentile of S&P500 returns as the threshold. Further, we divide the extreme trading days into extreme positive days and extreme negative days. The days in which daily return change of S&P500 is larger than the 90th percentile of S&P500 returns belong to the extreme positive days, and similarly, the days in which daily return change of S&P500 is smaller than the 10th percentile of S&P500 return belong to the extreme negative days. The other days belong to the normal trading days. Overall, there are 243 extreme trading days with 121 days of extreme positive days and 122 days of extreme negative days, separately. We split the extreme return days for S&P500 across different years, months and weeks to see whether our extreme return days are random event. As shown in Table 1, 2020 has the highest number of extreme return days because of COVID-19. In order to avoid the concentration effect of extreme trading data in 2020, we will remove the trading data of 2020 and repeat our empirical tests as a robustness test. As we split the days into months and weeks, we observe that March and Monday tend to have the highest number of extreme return days. However, we do not find clear patterns for calendar effects or weekdays effects for the distribution of extreme return days for S&P500 across our sample period.

[Insert Table 1 Here]

2.2 Google search volume index for cryptocurrencies (SVI)

We extract the Google search volume index from the Google Trends for cryptocurrencies as a measurement of investor attention on cryptocurrencies. We get the corresponding Google search volume index for cryptocurrencies by using the cryptocurrency name list on CoinMarketCap website to measure investor attention on individual cryptocurrency information. We obtained daily data for Google Trends in three-month time intervals and obtained monthly data for the full sample interval. Since the daily data in each interval is not comparable to the daily data in other time periods, we used the monthly data to adjust the daily data to the full sample comparable daily data using the equation (2) (Zhang, Wang, Li, and Shen, 2018):

$$\text{Daily SVI}_i = \text{monthly SVI}_i * \frac{\text{unadjusted daily SVI}_i}{\text{average of unadjusted monthly SVI}_i} \tag{2}$$

Then we sum up the daily SVI_i for each cryptocurrency on the same day to obtain our aggregate investor attention on cryptocurrency on a daily basis. Further, to control the potential seasonal patterns or time trends, we construct abnormal Google search volume index (ASVI) with the equation (3):

$$\text{ASVI}_t = \frac{\text{Daily SVI}_t}{\text{Mean}_t^{30}} \tag{3}$$

where Mean_t^{30} is the 30-day moving average before time t.

2.3 Cryptocurrency trading data

To measure the return co-movement between cryptocurrencies, we download the history price data of the main cryptocurrencies from CoinMarketCap website (https://coinmarketcap.com/all/views/all/). We ranked cryptocurrencies by their market capitalization on July 5th, 2020, and selected the top 1,000 cryptocurrencies by market capitalization as our research sample. In summary, we collect 1,000 cryptocurrencies with 1,066,783 observations with 1,763 trading days. Then, we use the opening price and closing price of each cryptocurrency to calculate the daily return with the equation (1). All cryptocurrency data are winsorized at the 1% and 99% levels. Next, we construct a composite cryptocurrency market index and calculate the daily market return, which is the weighted average of daily return of cryptocurrencies with the trading volume as the weight.

In Table 2, we report the descriptive statistics of daily return change of S&P500 and average cryptocurrency return change. According to Table 2, we can clearly see that the daily return volatility in the cryptocurrency market is greater than that of the S&P500 and has a more pronounced long tail and thick tail characteristics.

[Insert Table 2 Here]

In addition, we download the daily one-year treasury yield rate in the U.S. as the daily risk-free rate, from the website of the U.S Treasury (https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics) to measure the excess return of single digital currency and composite market index.

3. Empirical results

3.1 Extreme S&P500 returns as an attention-distraction events

We put forward our first hypothesis that the occurrence of extreme S&P500 returns, as a risk warning indicator, will draw investor's attention from cryptocurrency market to stock market and extreme S&P500 returns can be considered as an attention-distraction event.

To test this hypothesis, firstly, we divide all S&P500 trading days into extreme return days and non-extreme return days. Further, we divide extreme trading days into extreme positive and extreme negative days referring to the cut-off point illustrated in Section 2.1. Then, we match the result of ASVI for cryptocurrencies and S&P500 trading days. We calculate the mean and median of ASVI for each group according to previously grouping results. The individual t-test is used for testing the mean difference and the Wilcoxon rank sum test is employed for testing the median difference.

[Insert Table 3 Here]

We show the results in Table 3. In panel A, we observe that the mean (1.012) and median (0.993) of ASVI on extreme trading days are significantly lower than those on non-extreme trading days. Furthermore, from the panel B, we can conclude that ASVI on extreme negative days and extreme positive days are lower than those on non-extreme trading days. The mean (median) difference between the extreme positive days and non-extreme trading days is -0.024 (-0.030) with significant at 5% (1%) significance level. However, the difference between the extreme negative days and extreme positive days are not significant and the ASVI on extreme positive day is lower than ASVI on extreme negative days. Taken together, the investor attention on cryptocurrencies, measured by abnormal Google search volume index, is distracted by the extreme S&P500 returns. On extreme S&P500 trading days, investor attention on cryptocurrencies decline.

3.2 Return co-movement with cryptocurrency market

Having shown that the extreme S&P500 returns will decline the investor attention on cryptocurrencies market, we further investigate our second and third hypotheses: decreased investor attention on cryptocurrencies will increase the return co-movement with cryptocurrency market and this effect will more significant when the S&P500 return drops. In this part, we follow the measurements used in Huang, Huang, and Lin (2019) to capture the return co-movement with cryptocurrency market. The first measurement is the time series Pearson correlation coefficient, while the second measurement is the adjusted R^2 obtained from market model regression.

Under each measurement, firstly, we investigate our second hypothesis that extreme S&P500 returns will increase the return co-movement between cryptocurrency market by grouping all cryptocurrency trading days into extreme S&P500 trading days and non-extreme S&P500 trading days. Further, given that the extreme change of S&P500 returns have two directions, i.e., extreme positive and extreme negative, we divide all extreme trading days into extreme positive and extreme negative days to examine our third hypothesis that extreme negative of S&P500 returns has a greater impact on the return co-movement with cryptocurrency market than those on days of the extreme positive of

S&P500 returns.

3.2.1 Results on the time series Pearson correlation coefficient

In general, the time series Pearson correlation coefficient can be used to measure the return co-movement. The higher Pearson correlation coefficient means the higher level of return co-movement. In this section, we divide all trading days into different groups according to the extreme S&P500 returns, and calculate the Pearson correlation coefficient between the single cryptocurrency excess return and the composite market excess return under different groups. Then, we calculate the mean, median and difference of Pearson correlation coefficient under different situations. The paired t-test is used for testing the mean difference, and the Wilcoxon signed-rank test is employed for testing the median difference.

The results are reported in Table 4 Panel A. In the left subpanel of Panel A, we find that the mean and median of Pearson correlation coefficient is higher on extreme S&P500 return days than those on non-extreme S&P500 return days. The difference of mean (median) is 0.062 (0.070) with the p-values smaller than 1%. Put differently, the return co-movement with cryptocurrency market is higher on extreme S&P500 return days than those on non-extreme S&P500 return days. Further information shows in right subpanel of panel A that the return co-movement with cryptocurrency market is significantly highest in extreme negative days, while the difference between positive days and normal days is not significant. Notably, the difference of mean and median between negative days and normal days are 0.090 and 0.111. These results show that there exists a positive-negative asymmetric effect and the effect of extreme negative return of S&P500 is greater on return co-movement with cryptocurrency market.

3.2.2 Results on adjusted R^2 obtained from market model regressions

In this section, we use adjusted R^2 to measure the degree of return co-movement of cryptocurrency. Morck, Yeung, and Yu (2000) assert that the R^2 can be used to examine the firm-specific information reflected in stock returns. Migrating their theories to the cryptocurrency market, we argue that higher R^2 also represents the higher level of return co-movement with cryptocurrency market and indicates that more market information is reflected in cryptocurrency price and less specific information is reflected. We calculate adjusted R^2 using equation (4):

$$Ret_{i,t}=\alpha_i+\beta_i mktRet_t+\varepsilon_{i,t} \quad (4)$$

where $Ret_{i,t}$ is the excess return for cryptocurrency i on day t and $mktRet_t$ is the cryptocurrency market excess return on day t. We calculate the adjusted R^2 under different categories, respectively. Then, we calculate the mean and median of the adjusted R^2 for different categories. We use the paired t-test is used to test the difference of means and the Wilcoxon signed-rank test to account for the difference of medians.

The table 4 Panel B illustrates the results about adjusted R^2. These results are in accordance with the results in Panel A. The occurrence of extreme S&P500 returns will increase the return co-movement with cryptocurrency market. The mean (0.246) and median (0.174) of adjusted R^2 on extreme trading days are higher than those on non-extreme trading days shown in left subpanel. From the right subpanel, we can conclude that the mean (0.279) of return co-movement is highest on extreme negative days, followed by the extreme positive days, and both are significant higher than those on non-extreme trading days.

[Insert Table 4 Here]

Taken together, we use the Pearson correlation coefficient and adjusted R^2 obtained from market model regressions to measure the change of return co-movement with cryptocurrency market. Both measurements show the same consequences. The return co-movement of cryptocurrency will increase with the occurrence of extreme S&P500 returns. Further, this impact is asymmetric, which means the impact of extreme negative return of S&P500 on return co-movement with cryptocurrency market is greater than the extreme positive return of S&P500. These observations are consistent with our hypotheses, i.e., the extreme S&P500 returns will distract investor attention from cryptocurrency market, making the return co-movement with cryptocurrency market increase, and this impact will work strongly while the extreme negative return of S&P500 happens.

4. Additional tests

The change of investor attention on cryptocurrency illustrates the change of investor risk awareness. The occurrence of extreme S&P500 returns magnifies investors' fear to risk and make investor decrease their attention on risky asset, i.e., cryptocurrency market. In this section, we use VIX index, which can also illustrate the change of investor risk attitude, as a new attention-distraction event.

In this section, we repeat our empirical process using the extreme VIX returns as an attention-distraction event. Following the process in section 2.1, we divide all trading days into extreme VIX and non-extreme VIX trading days. Further, we also divide all extreme trading days into extreme positive and negative days. First, we observe the changes in investor attention on cryptocurrency, which is shown in Table 5. Then, we use the Pearson correlation coefficient and adjusted R^2 to measure the return co-movement with cryptocurrency market under the occurrence of extreme VIX returns and show the results in Table 6.

[Insert Table 5 Here]

From the panel A in table 5, we observe that the mean (1.009) and median (0.997) of ASVI on extreme trading days is lower than those on non-extreme trading days with a p-value smaller than 1%, which means the extreme VIX returns result in the decrease of investor attention on cryptocurrencies. Further, we find that when the occurrence of extreme positive of VIX returns, the ASVI is lowest, compared with other two subsets. A higher VIX indicates that investors perceive the market to be riskier and more risk-averse. The positive return of VIX means the highest level of investor risk averse and investors tend to move their attention away from risky cryptocurrency market.

[Insert Table 6 Here]

The Panel A and Panel B in table 6 show the similar consequences about the return co-movement with cryptocurrency market, when we choose the extreme VIX returns as an attention-distraction event. We find that the degree of return co-movement with cryptocurrency market is obviously higher on extreme trading days than those on non-extreme trading days. And, the return co-movement is highest on extreme positive days, followed by the extreme negative days, and both are significant higher than those on non-extreme trading days. This results accord with our hypothesis.

5. Robustness tests

5.1 Alternative threshold of extreme change of S&P500 returns

In our main tests, we use the 10^{th} percentile as the threshold for extreme return of S&P500. In this section, we alter the thresholds to 5^{th} percentile and 15^{th} percentile for our robustness tests. We conduct analysis similar to what have been done in Table 3 and Table 4. We firstly show the results of Abnormal Search Volume Index for cryptocurrency under different thresholds and different categories in Table 7. As table 7 is illustrated, the ASVI is lower on extreme days than non-extreme days under different situations, which is consistent with results in Table 3. This illustrates that the attention shock event does change investor attention allocation. The extreme S&P500 return decrease investor attention. Then, the return co-movement between cryptocurrencies under different thresholds are shown in Table 8. The results are similar with table 4. From the left subpanels, we can see the extreme S&P500 returns will increase the return co-movement between cryptocurrencies. In the right subpanels, the result under the situation of 15^{th} percentile is more significant and better in statistical. The extreme negative change has a greater impact on return co-movement between cryptocurrencies than the extreme positive change does. Such results indicate that though we change the thresholds, our main results are still robust.

[Insert Table 7 Here]

[Insert Table 8 Here]

5.2 Alternative calculation of cryptocurrency market return

Different cryptocurrencies have different trading volumes, and in our previous empirical evidence, we used the trading volume as a weight to calculate the average market return of cryptocurrencies. In order to eliminate the effect of super cryptocurrencies, such as Bitcoin, on the average market return, in this section we use equal weights to calculate the average market return of cryptocurrencies. We repeat our main empirical tests about the calculation of return co-movement between cryptocurrencies and shown the results in Table 9. As illustrated in Table 9, the Pearson correlation coefficient and adjusted R^2 are higher on extreme S&P500 change days than non-extreme days. Such results show that our conclusions are consistent whether we use an equal-weighted approach or a weighted average approach. Our results pass the robustness tests.

[Insert Table 9 Here]

5.3 Alternative subsample analysis

In addition to the two robustness tests mentioned above, we also performed robustness tests across different subsamples. Firstly, considering that the extreme trading days occur more frequently in 2020, we remove the trading data in 2020 and construct the main empirical tests. Overall, the conclusions shown in table 10 and 11 are consistent with our main hypothesis, but somewhat they are different with the previously discussed results. The occurrence of extreme S&P500 return does decrease the investor attention and increase the return co-movement between cryptocurrency market. The different point is that the return co-movement between cryptocurrency is highest on extreme positive days, rather than on extreme negative days.

[Insert Table 10 Here]

[Insert Table 11 Here]

We selected the top 10, 50, 250 and 500 cryptocurrencies in market capitalization to form a sub-sample set to calculate the return co-movement between cryptocurrencies in each sub-sample set. In these four subsample tests, there is partial significant in only top 10 sub-sample test. The results for the other subsamples are significant and consistent with those of the full sample. These results support our previous findings and shows that the cryptocurrency diversification makes sense. Then, we consider that Bitcoin, a super-capitalization cryptocurrency, might have some impact on the results, so we remove the Bitcoin data and conduct a robustness test with the remaining 999 cryptocurrencies as the study sample. After this test, we find the results still hold, which means our conclusion is robust whether Bitcoin is included or not. Given the large overlap in both results and tables, we do not present the detail table here.

6. Conclusions

Motived by Hu, Li, and Shen (2020), we investigate whether the extreme stock returns have an impact on cryptocurrency market. However, the results are partially contrast to the findings of Hu, Li, and Shen (2020), we conclude that the extreme S&P500 is an attention-distraction event. When the extreme S&P500 returns take place, investor will think the market uncertainty increase and be more risk averse. Thus, they will tend to move away from risky cryptocurrency market and lean towards less volatile and safer market. From the perspective of limited attention, investors will disproportionately reduce more idiosyncratic information, which results in high level of return co-movement with cryptocurrency market. Moreover, we find an asymmetric impact of extreme S&P500 on return co-movement with cryptocurrency market. In other words, the impact of extreme negative return of S&P500 will greater than the impact of extreme positive return of S&P500. Our findings are of benefit to investors and academic researchers in portfolio diversification and risk management. Our findings may serve as a reminder for investors using cryptocurrencies for hedging purposes. If there happens a large S&P500 return, especially in the extreme negative S&P500 returns, the return co-movement between cryptocurrencies will increase and the hedging power will reduce. Their hedging and risk management strategies may fail as the return co-movement between cryptocurrencies increases.

References

Aharon, D. Y., and Qadan, M. (2020). When do retail investors pay attention to their trading platforms? *The North American Journal of Economics and Finance, 53*, 101209. doi:https://doi.org/10.1016/j.najef.2020.101209

Avanidhar, Subrahmanyam, Barry, Oliver, Shumi, Akhtar, . . . Faff. (2013). Stock salience and the asymmetric market effect of consumer sentiment news. *Journal of Banking & Finance, 4488-4500.*

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., and Vohs, K. D. (2001). Bad is Stronger than Good. *Review of General Psychology, 5*(4), 323-370. doi:10.1037/1089-2680.5.4.323

Bouri, E., Gupta, R., Tiwari, A. K., and Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters, 23*, 87-95. doi:https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., and Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters, 20*, 192-198. doi:https://doi.org/10.1016/j.frl.2016.09.025

Bouri, E., Roubaud, D., and Shahzad, S. J. H. (2020). Do Bitcoin and other cryptocurrencies jump together? *The Quarterly Review of Economics and Finance, 76*, 396-409. doi:https://doi.org/10.1016/j.qref.2019.09.003

Candelon, B., Ferrara, L., and Joëts, M. (2018). Global Financial Interconnectedness: A nonlinear Assessment of the Uncertainty Channel. *working paper.*

Charfeddine, L., Benlagha, N., and Maouchi, Y. (2020). Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Economic Modelling, 85*, 198-217. doi:https://doi.org/10.1016/j.econmod.2019.05.016

Corbet, S., Meegan, A., Larkin, C., Lucey, B., and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28-34.

Da, Z. H. I., Engelberg, J., and Gao, P. (2011). In Search of Attention. *The Journal of Finance, 66*(5), 1461-1499. doi:10.1111/j.1540-6261.2011.01679.x

Dastgir, S., Demir, E., Downing, G., Gozgor, G., and Lau, C. K. M. (2018). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the

Copula-based Granger causality test. *Finance Research Letters, 28*, 160-164.

Figá-Talamanca, G., and Patacca, M. (2019). Does market attention affect Bitcoin returns and volatility? *Decisions in Economics and Finance, 42*(1), 135-155. doi:10.1007/s10203-019-00258-7

Gargano, A., and Rossi, A. G. (2017). Does It Pay to Pay Attention? *SSRN Electronic Journal*.

Gondhi, N. (2018). Rational inattention, misallocation, and asset prices. *working paper*.

Hu, Y., Li, X., and Shen, D. (2020). Attention allocation and international stock return comovement: Evidence from the Bitcoin market. *Research in International Business and Finance, 54*, 101286. doi:https://doi.org/10.1016/j.ribaf.2020.101286

Huang, S., Huang, Y., and Lin, T.-C. (2019). Attention allocation and return co-movement: Evidence from repeated natural experiments. *Journal of Financial Economics, 132*(2), 369-383. doi:https://doi.org/10.1016/j.jfineco.2018.10.006

Hussain Shahzad, S. J., Bouri, E., Roubaud, D., and Kristoufek, L. (2019). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling*. doi:https://doi.org/10.1016/j.econmod.2019.07.023

Huynh, T. L. D., Nguyen, S. P., and Duong, D. (2018, 2018//). *Contagion Risk Measured by Return Among Cryptocurrencies*. Paper presented at the Econometrics for Financial Applications, Cham.

Ibikunle, G., McGroarty, F., and Rzayev, K. (2020). More heat than light: Investor attention and bitcoin price discovery. *International Review of Financial Analysis, 69*, 101459. doi:https://doi.org/10.1016/j.irfa.2020.101459

Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis, 63*, 257-272. doi:https://doi.org/10.1016/j.irfa.2018.12.002

Kodres, L. E., and Pritsker, M. (2002). A Rational Expectations Model of Financial Contagion. *Journal of Finance, 57*(2), 769-799.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *entific Reports, 3*.

Kurka, J. (2019). Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters, 31*, 38-46. doi:https://doi.org/10.1016/j.frl.2019.04.018

Matkovskyy, R., and Jalan, A. (2019). From Financial Markets to Bitcoin Markets: A Fresh Look at the Contagion Effect. *Finance Research Letters, 31*, 93-97.

Morck, R., Yeung, B., and Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics, 58*(1), 215-260. doi:https://doi.org/10.1016/S0304-405X(00)00071-4

Peng, L., and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics, 80*(3), 563-602. doi:https://doi.org/10.1016/j.jfineco.2005.05.003

Peress, J. (2016). Glued to the TV: Distracted Retail Investors and Stock Market Liquidity. *Social Science Electronic Publishing*.

Philippas, D., Rjiba, H., Guesmi, K., and Goutte, S. (2019). Media attention and Bitcoin prices. *Finance Research Letters, 30*, 37-43. doi:https://doi.org/10.1016/j.frl.2019.03.031

Sarwar, G. (2017). Examining the flight-to-safety with the implied volatilities. *Finance Research Letters, 20*, 118-124. doi:https://doi.org/10.1016/j.frl.2016.09.015

Shen, D., Urquhart, A., and Wang, P. (2019). Does twitter predict Bitcoin? *Economics Letters, 174*, 118-122. doi:https://doi.org/10.1016/j.econlet.2018.11.007

Soroka, S. N. (2010). Good News and Bad News: Asymmetric Responses to Economic Information. *Journal of Politics, 68*(02), 372-385.

Tiwari, A. K., Adewuyi, A. O., Albulescu, C. T., and Wohar, M. E. (2020). Empirical evidence of extreme dependence and contagion risk between main cryptocurrencies. *The North American Journal of Economics and Finance, 51*, 101083. doi:https://doi.org/10.1016/j.najef.2019.101083

Veldkamp. (2006). Information Markets and the Comovement of Asset Prices. *The Review of Economic Studies, 73*(3), 823–845. doi:https://doi.org/10.1111/j.1467-937X.2006.00397.x

Veldkamp, L., and Wolfers, J. (2007). Aggregate shocks or aggregate information? Costly information and business cycle comovement. *Journal of Monetary Economics, 54*, 37-55. doi:https://doi.org/10.1016/j.jmoneco.2007.06.001

Williams, C. D. (2015). Asymmetric Responses to Earnings News: A Case for Ambiguity. *Accounting Review, 90*(2), 785-817. doi:10.2308/accr-50866

Yuan, Y. (2015). Market-wide attention, trading, and stock returns. *Journal of Financial Economics, 116*(3), 548-564. doi:https://doi.org/10.1016/j.jfineco.2015.03.006

Zięba, D., Kokoszczyński, R., and Śledziewska, K. (2019). Shock transmission in the cryptocurrency market. Is Bitcoin the most influential? *International Review of Financial Analysis, 64*, 102-125. doi:https://doi.org/10.1016/j.irfa.2019.04.009

Zhang, W., Wang, P., Li, X., and Shen, D. (2018). The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. Physica A: Statistical Mechanics and its Applications, 510, 658-670. doi: https://doi.org/10.1016/j.physa.2018.07.032

Table 1: Distribution of extreme S&P500 return days

This table shows the number of extreme S&P500 return days for each year (Panel A), for each month (Panel B); as well as the number of extreme S&P500 return days that are on different weekdays: Monday, Tuesday, Wednesday, Thursday and Friday (Panel C).

Panel A: Annual distribution of extreme S&P500 return days

Year	#Days
2017	6
2018	58
2019	33
2020	108
2021	38
Total	243

Panel B: Monthly distribution of extreme S&P500 return days

Month	#Days
January	14
February	24
March	41
April	28
May	23
June	16
July	11
August	15
September	17
October	26
November	17
December	11
Total	243

Panel C: weekly distribution of extreme S&P500 return days

Week	#Days
Monday	55
Tuesday	48
Wednesday	46
Thursday	46
Friday	48
Total	243

Table 2: Descriptive statistic of return change of S&P and cryptocurrency

This table shows descriptive statistics for the daily return change of S&P500 and cryptocurrencies from January 1st, 2017–June 30th, 2020, including the mean, maximum, minimum, standard deviation, skewness and kurtosis.

	Return change of S&P500	Return change of cryptocurrency
Mean	0.001	0.005
Maximum	0.094	0.508
Minimum	-0.120	-0.316
Standard deviation	0.012	0.107
Skewness	-0.748	1.281
Kurtosis	20.578	6.307

Table 3: Justification of extreme S&P500 returns as an attention-distraction event

We extract the Google search volume index from the Google Trends for cryptocurrency by using the cryptocurrency name list on CoinMarketCap website. The sample period is from January 1st, 2017 to September 30th, 2021. We collect the incomparable daily Google search volume index and comparable monthly Google search volume index (SVI) and transfer those to comparable daily Google search volume index using the equation which is monthly SVI * (unadjusted daily SVI / average of unadjusted monthly SVI). Then we sum up the daily SVI for each cryptocurrency on the same day to obtain our aggregate investor attention on cryptocurrencies on a daily basis. Further, to control the potential seasonal patterns or time trends, we construct Abnormal Google search volume index (ASVI) with 30-day moving average. We match the result of Abnormal Google search volume index and S&P500 trading days, and calculate the mean and median of Abnormal Google search volume index for each group according to previously grouping results. The panel A is the result under extreme and non-extreme S&P500 return days and panel B shows the result under positive, negative and normal of S&P500 return days. The individual t-test is used for testing the mean difference, and the Wilcoxon rank sum test is employed for testing the median difference. The value in parentheses is the P-value of the test result. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Panel A: The ASVI of cryptocurrencies under extreme and non-extreme S&P500 return days

	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)
Mean	1.012	1.034	-0.022** (0.015)
Median	0.993	1.014	-0.021*** (0.003)

Panel B: The ASVI of cryptocurrencies under positive, negative and normal of S&P500 return days

	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	1.010	1.015	1.034	-0.005 (0.752)	-0.024** (0.045)	-0.019 (0.103)
Median	0.984	0.997	1.014	-0.013 (0.228)	-0.030*** (0.007)	-0.017* (0.051)

Table 4: The return co-movement between cryptocurrencies under the extreme S&P500 returns

In this table, we choose three measurements to capture the return co-movement between cryptocurrencies under the extreme change of S&P500 return. Panel A shows the first measurement, that is time series Pearson correlation coefficient. For each cryptocurrency i, we calculate the time series Pearson correlation coefficient between the cryptocurrency i excess return and the composite market excess return under different categories. The second measurement is shown in Panel B. We calculate the adjusted R^2. To measure the adjusted R^2, we run the following regression model for cryptocurrency i on different categories, separately, which is $\text{excess return}_{i,t}=\alpha_i+\beta_i*\text{composite excess return}_t+\varepsilon_{i,t}$, where the $\text{excess return}_{i,t}$ is the daily excess return of cryptocurrency i at time t and the $\text{composite market excess return}_t$ is composite cryptocurrency market index excess return at time t. Then we calculate the mean, median and difference in each subpanel under different categories. The left subpanel in each panel shows the results under extreme and non-extreme S&P500 return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of S&P500 return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** indicates statistical significance at the 1% level.

Panel A: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.449	0.387	0.062*** (0.000)	0.391	0.476	0.386	-0.085*** (0.000)	0.005 (0.365)	0.090*** (0.000)
Median	0.467	0.397	0.070*** (0.000)	0.383	0.507	0.396	-0.124*** (0.000)	-0.013 (0.331)	0.111*** (0.000)

Panel B: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	0.246	0.174	0.072*** (0.000)	0.196	0.279	0.174	-0.083*** (0.000)	0.022*** (0.000)	0.105*** (0.000)
Median	0.219	0.157	0.062*** (0.000)	0.147	0.259	0.157	-0.112*** (0.000)	-0.010 (0.331)	0.102*** (0.000)

Table 5: Justification of extreme VIX returns as an attention-distraction event

We extract the Google search volume index from the Google Trends for cryptocurrency by using the cryptocurrency name list on CoinMarketCap website. The sample period is from January 1st, 2017 to September 30th, 2021. We collect the incomparable daily Google search volume index and comparable monthly Google search volume index (SVI) and transfer those to comparable daily Google search volume index using the equation which is monthly SVI * (unadjusted daily SVI / average of unadjusted monthly SVI). Then we sum up the daily SVI for each cryptocurrency on the same day to obtain our aggregate investor attention on cryptocurrencies on a daily basis. Further, to control the potential seasonal patterns or time trends, we construct Abnormal Google search volume index (ASVI) with 30-day moving average. We match the result of Abnormal Google search volume index and S&P500 trading days, and calculate the mean and median of Abnormal Google search volume index for each group according to previously grouping results. The panel A is the result under extreme and non-extreme VIX return days and panel B shows the result under positive, negative and normal of VIX return days. The individual t-test is used for testing the mean difference, and the Wilcoxon rank sum test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** and * indicate statistical significance at the 1% and 10% level, respectively.

Panel A: The ASVI of cryptocurrencies under extreme and non-extreme VIX return days

	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)
Mean	1.009	1.035	-0.026*** (0.003)
Median	0.997	1.013	-0.016*** (0.002)

Panel B: The ASVI of cryptocurrencies under positive, negative and normal of VIX return days

	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	1.014	1.004	1.035	0.010 (0.520)	-0.021* (0.076)	-0.031*** (0.010)
Median	1.001	0.992	1.013	0.009 (0.167)	-0.012* (0.062)	-0.021*** (0.003)

Table 6: The return co-movement between cryptocurrencies under the extreme VIX returns

In this table, we choose extreme VIX returns as an attention-distraction event and use time series Pearson correlation coefficient and adjusted R^2 to capture the return co-movement between cryptocurrencies under the extreme VIX returns. Panel A shows the result of time series Pearson correlation coefficient. For each cryptocurrency i, we calculate the time series Pearson correlation coefficient between the cryptocurrency i excess return and the composite market excess return under different categories. In Panel B, we calculate the adjusted R^2. To measure the adjusted R^2, we run the following regression model for cryptocurrency i on different categories, separately, which is $\text{excess return}_{i,t}=\alpha_i+\beta_i*\text{composite excess return}_t+\varepsilon_{i,t}$, where the $\text{excess return}_{i,t}$ is the daily excess return of cryptocurrency i at time t and the $\text{composite market excess return}_t$ is composite cryptocurrency market index excess return at time t. Then we calculate the mean, median and difference in each subpanel under different categories. The left subpanel in each panel shows the results under extreme and non-extreme VIX return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of VIX return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** indicates statistical significance at the 1% level.

Panel A: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme VIX return days			Under positive, negative and normal of VIX return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.494	0.366	0.128*** (0.000)	0.499	0.455	0.366	0.044*** (0.000)	0.133*** (0.000)	0.089*** (0.000)
Median	0.520	0.372	0.148*** (0.000)	0.529	0.473	0.373	0.056*** (0.000)	0.156*** (0.000)	0.100*** (0.000)

Panel B: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme VIX return days			Under positive, negative and normal of VIX return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.287	0.158	0.129*** (0.000)	0.304	0.249	0.158	0.055*** (0.000)	0.146*** (0.000)	0.091*** (0.000)
Median	0.270	0.139	0.131*** (0.000)	0.280	0.224	0.139	0.056*** (0.000)	0.141*** (0.000)	0.085*** (0.000)

Table 7: The additional test about the Abnormal Search Volume Index of cryptocurrencies under the extreme S&P500 returns

In this table, we choose 5th percentile and 15th percentile of extreme change of S&P500 return as the new thresholds respectively to make additional tests. We repeat the test in table 3 and calculate Abnormal Search Volume Index (ASVI) of cryptocurrencies. The panel A is the result of ASVI calculated using the 5th percentile of the extreme S&P500 returns as the threshold. And panel B is shown the result about the ASVI by using the 15th percentile of the extreme S&P500 returns as the threshold. Then we calculate the mean, median and difference in each subpanel under different threshold. The left subpanel in each panel shows the results under extreme and non-extreme S&P500 return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of S&P500 return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The ASVI of cryptocurrencies with the threshold of 5th percentile

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	1.002	1.033	-0.031*** (0.010)	0.998	1.006	1.033	-0.008 (0.746)	-0.035** (0.038)	-0.027* (0.099)
Median	0.991	1.012	-0.021*** (0.007)	0.982	0.994	1.012	-0.012 (0.399)	-0.030** (0.025)	-0.018* (0.055)

Panel B: The ASVI of cryptocurrencies with the threshold of 15th percentile

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	1.015	1.036	-0.021*** (0.010)	1.015	1.016	1.036	-0.001 (0.916)	-0.021** (0.045)	-0.020** (0.050)
Median	0.999	1.013	-0.014*** (0.003)	0.996	1.002	1.013	-0.006 (0.302)	-0.017*** (0.009)	-0.011** (0.031)

Table 8: The additional test about the return co-movement between cryptocurrencies under the extreme S&P500 returns

In this table, we choose 5th percentile and 15th percentile of extreme change of S&P500 return as the new threshold respectively to make additional tests. We repeat the test in table 4 and calculate the return co-movement between cryptocurrencies. We choose the Pearson correlation coefficient and the adjusted R^2 to calculate the return co-movement. The Part 1 is about the result of return co-movement by using the 5th percentile of the extreme change of S&P500 returns as the threshold and Part 2 is about the result by using the 15th percentile of the extreme change of S&P500 returns as the threshold. The panel A is the result of Pearson correlation coefficient under 5th percentile and panel B is the result of adjusted R^2 under 5th percentile. The panel C is the result of Pearson correlation coefficient under 15th percentile and panel D is the result of adjusted R^2 under 15th percentile. Then we calculate the mean, median and difference in each subpanel under different threshold. The left subpanel in each panel shows the results under extreme and non-extreme S&P500 return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of S&P500 return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** indicate statistical significance at the 1% level.

Part 1: The return co-movement between cryptocurrencies with the 5th percentile of extreme S&P500 returns as the threshold

Panel A: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.497	0.386	0.111*** (0.000)	0.381	0.537	0.386	-0.156*** (0.000)	-0.005 (0.388)	0.151*** (0.000)
Median	0.520	0.393	0.127*** (0.000)	0.399	0.580	0.393	-0.181*** (0.000)	0.006 (0.541)	0.187*** (0.000)

Panel B: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.303	0.174	0.129*** (0.000)	0.203	0.354	0.174	-0.151*** (0.000)	0.029*** (0.000)	0.180*** (0.000)
Median	0.271	0.154	0.117*** (0.000)	0.161	0.339	0.154	-0.178*** (0.000)	0.007 (0.119)	0.185*** (0.000)

Part 2: The return co-movement between cryptocurrencies with the 15^{th} percentile of extreme S&P500 returns as the threshold

Panel C: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	0.443	0.379	0.064*** (0.000)	0.406	0.447	0.379	-0.041*** (0.000)	0.027*** (0.000)	0.068*** (0.000)
Median	0.450	0.389	0.061*** (0.000)	0.409	0.471	0.389	-0.062*** (0.000)	0.020*** (0.000)	0.082*** (0.000)

Panel D: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	0.233	0.168	0.065*** (0.000)	0.202	0.246	0.168	-0.044*** (0.000)	0.034*** (0.000)	0.078*** (0.000)
Median	0.203	0.151	0.052*** (0.000)	0.168	0.223	0.151	-0.055*** (0.000)	0.017*** (0.001)	0.072*** (0.000)

Table 9: The additional test about the return co-movement between cryptocurrencies under the extreme S&P500 returns

In this table, we calculate the average market return of cryptocurrencies using an equal weighting method, instead of weighting by trading volume. We repeat the test in table 4 and calculate the return co-movement between cryptocurrencies. We choose the Pearson correlation coefficient and the adjusted R^2 to calculate the return co-movement. The panel A is the result of Pearson correlation coefficient under different categories. The panel B is the result of adjusted R^2 under different categories. Then we calculate the mean, median and difference in each subpanel under different threshold. The left subpanel in each panel shows the results under extreme and non-extreme S&P500 return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of S&P500 return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** indicates statistical significance at the 1% level.

Panel A: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.473	0.421	0.052*** (0.000)	0.416	0.500	0.421	-0.084*** (0.000)	-0.005 (0.287)	0.079*** (0.000)
Median	0.491	0.424	0.067*** (0.000)	0.413	0.537	0.424	-0.124*** (0.000)	-0.011 (0.307)	0.113*** (0.000)

Panel B: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	0.274	0.208	0.066*** (0.000)	0.221	0.309	0.208	-0.088*** (0.000)	0.013*** (0.001)	0.101*** (0.000)
Median	0.242	0.180	0.062*** (0.000)	0.171	0.289	0.180	-0.118*** (0.000)	-0.009 (0.383)	0.109*** (0.000)

Table 10: The additional test about the Abnormal Search Volume Index of cryptocurrencies

In this table, we remove the trading data in 2020 and employ remaining sample to make additional test. We repeat the test in table 3 and calculate Abnormal Search Volume Index (ASVI) of cryptocurrencies. The panel A is the result under extreme and non-extreme S&P500 return days and panel B shows the result under positive, negative and normal of S&P500 return days. The individual t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** and * indicate statistical significance at the 1% and 10% level, respectively.

Panel A: The ASVI of cryptocurrencies under extreme and non-extreme S&P500 return days

	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)
Mean	1.007	1.031	-0.024** (0.048)
Median	0.983	1.012	-0.029*** (0.002)

Panel B: The ASVI of cryptocurrencies under positive, negative and normal of S&P500 return days

	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	1.003	1.011	1.031	-0.008 (0.712)	-0.028* (0.095)	-0.020 (0.207)
Median	0.976	0.994	1.012	-0.018 (0.128)	-0.036*** (0.003)	-0.018* (0.068)

Table 11: The return co-movement between cryptocurrencies under the extreme S&P500 returns

In this table, In this table, we remove the trading data in 2020 and employ remaining sample to make additional test. We repeat the test in table 4 and calculate the return co-movement between cryptocurrencies. We choose the Pearson correlation coefficient and the adjusted R^2 to calculate the return co-movement. The panel A is the result of Pearson correlation coefficient. The panel B is the result of adjusted R^2. Then we calculate the mean, median and difference in each subpanel. The left subpanel in each panel shows the results under extreme and non-extreme S&P500 return days and the right subpanel in each panel shows the results under extreme positive, negative and normal of S&P500 return days. The paired t-test is used for testing the mean difference, and Wilcoxon signed-rank test is employed for testing the median difference. The value in parentheses is the P-value of the test result. *** and * indicate statistical significance at the 1% and 10% level, respectively.

Panel A: The Pearson correlation coefficient between cryptocurrencies

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) – (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) – (2)	Difference (1) – (3)	Difference (2) – (3)
Mean	0.464	0.405	0.059*** (0.000)	0.466	0.454	0.405	0.012* (0.095)	0.061*** (0.000)	0.049*** (0.000)
Median	0.483	0.414	0.069*** (0.000)	0.488	0.487	0.414	0.001 (0.298)	0.074*** (0.000)	0.073*** (0.000)

Panel B: The adjusted R^2 between cryptocurrency and market

	Under extreme and non-extreme S&P500 return days			Under positive, negative and normal of S&P500 return days					
	Extreme days (1)	Non-extreme days (2)	Difference (1) - (2)	Positive days (1)	Negative days (2)	Normal days (3)	Difference (1) - (2)	Difference (1) - (3)	Difference (2) - (3)
Mean	0.264	0.191	0.073*** (0.000)	0.270	0.269	0.191	0.001 (0.827)	0.079*** (0.000)	0.078*** (0.000)
Median	0.233	0.171	0.062*** (0.000)	0.241	0.238	0.171	0.003 (0.447)	0.070 (0.331)	0.067*** (0.000)