Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The Case of COVID-19

Conghui Chen,[a] Lanlan Liu,[b] and Ningru Zhao[c]

[a] *Faculty of Business and Law, University of Northampton, Northampton NN1 5HP, UK*
[b] *Dongwu Business School, Soochow University, Suzhou 215012, China*
[c] *Institute of Economics and Finance, Nanjing Audit University, Nanjing 211815, China.*

Corresponding author:
Dr Ningru Zhao
Institute of Economics and Finance
Nanjing Audit University
86 West Yushan Road
Pukou District
Nanjing 211815
China
Telephone: +86 025 5831 8791
Email: zhaoningru@nau.edu.cn.

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ABSTRACT

This paper studies the impact of fear sentiment caused by the coronavirus pandemic on Bitcoin price dynamics. We construct a new proxy for coronavirus fear sentiment using hourly Google search queries on coronavirus-related words. The results show that market volatility has been exacerbated by fear sentiment as the result of an increase in search interest in coronavirus. Moreover, we find that negative Bitcoin returns and high trading volume can be explained by fear sentiment regarding the coronavirus. Our results also show that Bitcoin fails to act as a safe haven during the pandemic.

Keywords: *Coronavirus, Google search volume, fear sentiment, Bitcoin price dynamics*

JEL Classification: G12, G14, G15

1. Introduction

Bitcoin, the first and most well-known cryptocurrency, has attracted great attention in recent years. Due to its extreme volatility, Bitcoin has been classified as a speculative investment rather than a currency (Yermack 2015; Cheah and Fry 2015). Previous studies have extensively examined the main drivers of changes in Bitcoin prices. It is widely acknowledged that a fundamental supply and demand factor (Kristoufek 2015); investors' interest (Ciaian, Rajcaniova, and Kancs 2016); macroeconomic and financial developments (Panagiotidis, Stengos, and Vravosinos 2019); and technological factors (Adjei 2019) are the main determinants of bitcoin prices. In relation to macroeconomic and financial developments, the expanding literature has examined the relationship between some macroeconomic indicators and Bitcoin prices. Panagiotidis, Stengos, and Vravosinos (2019) find that external shocks, such as changes in interest rates or exchange rates, seem to have an impact on Bitcoin's price. Moreover, Bitcoin is found to be uncorrelated or negatively correlated with other financial asset classes, such as gold, the US dollar, and major stock market indices, so it can be viewed as a hedge to reduce portfolio risk (Dyhrberg 2016; Guesmi et al. 2019) or hailed as "digital gold" with safe-haven properties against extreme downside risks of global stock markets (Shahzad et al. 2019).

During the coronavirus outbreak, Bitcoin was hit hard and lost half its value within days, decreasing from $9,000 on March 7 to around $4,000 on March 13.[1] However, the plunge in Bitcoin price may not be explained by the literature. The purpose of our study is to investigate how Bitcoin's price reacts in the wake of the coronavirus pandemic,

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

since it is the first significant global turmoil to occur while Bitcoin is actively being traded. In particular, we examine how fear sentiment affects Bitcoin price dynamics. Our research is inspired by one strand of the literature on behavioural finance that analyses the impact of investor sentiment on asset price dynamics (Baker and Wugler 2006; Tetlock 2007; Da, Engelberg, and Gao 2015), and demonstrates that low asset returns can be explained by high sentiment. Da, Engelberg, and Gao (2015) construct a fear index by aggregating the Google search volume of words with negative tones and suggest that negative sentiment is associated with return reversals. Because the number of new confirmed cases and mortality rates are increasing dramatically, negative sentiment induced by the coronavirus crisis is the dominant emotion in financial markets. Recent empirical studies intensively discuss the impact of COVID-19 on the financial markets and suggest that it is associated with a decrease in asset prices and an increase in market volatility (Ali, Alam and Rizvi 2020; Apergis and Apergis 2020; Gil-Alana and Monge 2020). Moreover, several studies highlight the impact of negative sentiment and find that it leads to liquidity dry-ups and higher market volatility (Baig et al. 2020; Zaremba et al. 2020). Mamaysky (2020) show that sentiment related to coronavirus news drives changes in asset prices in the markets.

Following Da, Engelberg, and Gao (2015), we adopt internet search-based measures of investors' sentiment, since the frequency of sentiment measure is available on an hourly basis. In addition, people who search for information on the coronavirus are more concerned about the pandemic, so the search volume of coronavirus-related keywords can well represent a fearful attitude toward the virus. Therefore, we aggregate hourly search volume of terms such as "Coronavirus" and "COVID-19" from Google Trends to construct a proxy for fear sentiment. First, we explore the relationship between coronavirus fear sentiment and market uncertainty. Our results show that fear sentiment driven by coronavirus is positively correlated with uncertainty, as measured by the VIX. This indicates that the degree of market uncertainty is higher when fear sentiment is strong. We then examine the lead-lag relationship between fear sentiment, Bitcoin returns, and Bitcoin trading volume during the outbreak period using vector autoregressive (VAR) models. Our findings show that an increase in fear sentiment will lead to lower Bitcoin returns and higher Bitcoin trading volume.

The paper's contributions are twofold. First, we construct a new proxy of fear sentiment induced by the coronavirus using high-frequency Google search data. The results imply that our fear sentiment measure is appropriate by exploiting its comovement with the VIX, which is widely used as an investor fear gauge (Whaley 2000; Mele, Obayashi, and Shalen 2015). Second, our paper extends the literature by examining Bitcoin price dynamics in the case of extreme events. In line with Ali, Alam and Rizvi (2020) and Gil-Alana and Monge (2020), our research provides evidence that negative Bitcoin returns can be explained by fear sentiment during the coronavirus crisis. In addition, our study shows that Bitcoin returns are adversely affected by market downturn, in contrast to earlier empirical studies (Bouri et al. 2017; Corbet et al. 2018; Shahzad et al. 2019). Based on our results, Bitcoin exhibits patterns similar to traditional financial assets, and its safe-haven properties are highly questionable. Our results suggest that Bitcoin may not be suitable for portfolio management or risk management, because it cannot be viewed as a safe haven during times of extreme crisis.

The rest of the paper is organised as follows. Section 2 describes the data and presents a preliminary analysis. Section 3 outlines the econometric model used to analyse the dynamic linkages between investor sentiment, uncertainty, and Bitcoin price dynamics during the coronavirus pandemic. Section 4 presents the results and our discussion. Section 5 performs robustness checks to validate our findings, and Section 6 concludes.

2. Data and preliminary analysis

2.1 Data and Variables

The data used in this paper are sourced from CryptoCompare, Bloomberg, and Google Trends. We first obtain hourly data on Bitcoin prices in US dollars (BTC/USD) and Bitcoin trading volume from the CryptoCompare website through the application programming interface (API).[2] Specifically, hourly Bitcoin prices are the Bitcoin trading volume-weighted average prices across more than 250 cryptocurrency exchanges. Bitcoin hourly trading volume is the total number of Bitcoins (BTC) traded on those exchanges.

Next, we obtain hourly data on the Cboe Volatility Index (VIX) from Bloomberg to measure investors' expectations on short-term market volatility. The VIX is calculated based on real-time S&P 500 Index call and put options, which reflect the short-term expected volatility of the US equity market. It is widely followed by a variety of global investors as an indicator of financial market uncertainty (Mele, Obayashi, and Shalen 2015).

For the measurement of investors' fear sentiment regarding the coronavirus pandemic, we employ internet search–based data from Google Trends, in line with prior studies (Da, Engelberg, and Gao 2015). Google provides hourly search volume for search

[2] See https://www.cryptocompare.com.

queries through Google Trends, which are scaled by the time-series maximum during the specific period.[3] In order to develop an accurate measure of fear sentiment, it is paramount to identify the proper search terms in Google Trends. The term 'Coronavirus' has experienced the biggest increase in search frequency of all search queries since 15 January 2020.[4] To capture the variation of households' search interest over time, we include the term 'COVID-19', which became the leading search term in Google after the WHO announced on 11 February that would be the official name for the virus. Finally, we download hourly search volume data on the two terms — 'Coronavirus' and 'COVID-19'—using the Python 'gtrendsR' package and choose worldwide search trends to represent the fear sentiment of households across different countries. We aggregate the hourly search volume of the two items to measure the evolution of fear sentiment related to the coronavirus outbreak.

Time-series data on Bitcoin price dynamics, the VIX, and Google Trends cover the period from 15 January 2020 to 24 April 2020, because the first confirmed case of COVID-19 was detected outside of China on 14 January 2020, according to WHO Disease Outbreak News.[5]

2.2 Preliminary analysis

Table 1 reports descriptive statistics for the data used in this study, including the fear sentiment proxy, the VIX, Bitcoin prices, and Bitcoin trading volume. The fear sentiment has a minimum value of zero during the first two hours on 15 January 2020, which indicates that the coronavirus had not attracted attention before that period. The standard deviation of the fear sentiment is 48.070, which suggests a large variation in search

[3] See http://www.google.com/trends.
[4] See https://trends.google.com/trends/explore?date=2020-01-15%202020-04-24.
[5] See https://www.who.int/csr/don/archive/disease/novel_coronavirus/en.

volume data. The mean of the VIX is 35.891, with a historical high of 83.830 on 17 March. The excess skewness and kurtosis of the VIX shows a high degree of market uncertainty during this period. Bitcoin prices have a maximum value of 10,466.600 on 13 February and decrease to a minimum value of 4,240.690 as a result of the continued spread of coronavirus. In addition, Bitcoin's average trading volume is 2309.507 BTC per hour and the kurtosis is 37.842, which reflects the high liquidity of the Bitcoin market.

INSERT TABLE 1

In Figure 1, we plot the dynamics of hourly Bitcoin prices (BTC/USD) and fear sentiment with 2,424 observations for each series. As can be seen, the two series move negatively over the sample period, with a negative correlation of -0.90. As fear sentiment increased to its peak value on 16 March, Bitcoin's price simultaneously plunged. In light of this, we would expect a possible correlation between fear sentiment and Bitcoin price movements.

INSERT FIGURE 1

We employ augmented Dickey-Fuller tests (ADF) to examine the stationarity of time-series data. The results reported in the appendix (Table 1) show that a unit root is present in both the Bitcoin price and fear sentiment. Then we normalize and detrend both series by taking first differences (logarithm difference for Bitcoin prices) and perform additional stationarity tests. As shown in the appendix (Table 2), we can reject the null hypothesis that the series of the fear sentiment (first difference), VIX, Bitcoin returns, and Bitcoin trading volume are not stationary. In Figure 2, we present the dynamics of the sentiment, VIX, Bitcoin returns, and Bitcoin trading volume.

INSERT FIGURE 2

3. Methodology

Following Urquhart (2018), we employ vector autoregressive (VAR) models to investigate the relationship between fear sentiment, uncertainty, and Bitcoin returns and trading volume. VAR is used to capture more complex dynamics of multiple time series. Specifically, it is an appropriate estimation technique to examine the interdependence dynamic relationships among our variables (Tantaopas, Padungsaksawasdi, and Treepongkaruna 2016).

Let X_t be a vector of variables of interest; then a VAR (p) model will have the following structure:

$$X_t = \alpha + \sum_{j=1}^{p} \beta_j X_{t-j} + \varepsilon_t \tag{1}$$

where α is a vector of constants, β_j is a vector of coefficients, and ε_t is a vector of independent white noise innovations. p denotes the number of optimal lags determined by several information criteria, including the Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), Schiwarz-Bayesian information criteria (SBIC), and final prediction error (FPE).

We employ three models to explore the dynamics among fear sentiment, uncertainty, and Bitcoin returns and trading volume. Model 1 study the relationship between fear sentiment and uncertainty (VIX) ($X_t = S_t, V_t$); Model 2 examines the dynamics between fear sentiment and Bitcoin returns ($X_t = S_t, R_t$); and Model 3 investigate the interactions between fear sentiment and Bitcoin trading volume ($X_t = S_t, VOL_t$).

We also employ Granger causality tests (Granger 1969) to further investigate the causal relationships between fear sentiment and the other variables discussed above. We reject the null hypothesis using the statistic of χ^2-test.[6] The lags of each null hypothesis are based on the best optimal lags in VAR models.

4. Empirical results

4.1 Fear sentiment and VIX

Table 2 presents the estimates of the impact of fear sentiment on market uncertainty. As expected, we find that an increase in uncertainty can be driven by fear of the coronavirus, as indicated by a significant and positive relationship between fear sentiment and the VIX. Our results are consistent with those of Baig et al. (2020), who suggest that negative sentiment generated by coronavirus news is associated with market volatility. In addition, the results suggest that market uncertainty is attributable to fear sentiment, which indicates that a higher degree of market uncertainty can induce Bitcoin investors to obtain more information regarding the pandemic, leading to increased search volume on the coronavirus. Based on the results of Granger causality tests shown in Panel B of Table 2, we can confirm the existence of a bidirectional causality relationship between the VIX and fear sentiment.

4.2 Fear sentiment and Bitcoin returns

Next, we explore the relationship between fear sentiment and Bitcoin returns. As our results demonstrate in Table 2, there is strong evidence that fear sentiment has a significantly negative impact on Bitcoin returns at lag 3, with a significance level of 1%. In line with Baker and Wugler (2006), negative Bitcoin returns are attributed to mounting fears related to the coronavirus. Investors may put more selling pressure on Bitcoin if they become more pessimistic as a result of increased search activity for coronavirus

[6] The null hypothesis of causality tests is that fear sentiment does not Granger cause a change in VIX, Bitcoin returns and trading volume, respectively

information. We then find a significant and positive relationship between fear sentiment and Bitcoin returns at lag 4. Our findings are consistent with those of Da, Engelberg, and Gao (2015), who argue that fear sentiment leads to return reversal. As Bitcoin can rebound quickly, this indicates that Bitcoin prices are extremely volatile during the outbreak of the coronavirus (Cheah and Fry 2015). Granger causality tests support our findings that fear sentiment has a causal effect on Bitcoin returns. However, the reverse causality from fear sentiment to Bitcoin returns seems to be insignificant, as indicated by the results in Panel B of Table 2. In addition, our results indicate that Bitcoin cannot serve as a safe haven, because Bitcoin returns do not respond independent of the market turmoil caused by the coronavirus. As market conditions deteriorated, Bitcoin returns exhibited the positive correlation with the markets (Conlon and McGee 2020; Corbet, Larkin, and Lucey 2020).

4.3 Fear sentiment and Bitcoin trading volume

We further examine the relationship between fear sentiment and Bitcoin trading volume. As can be seen in Table 2, fear sentiment has a significantly positive effect on Bitcoin trading volume at lag 1. Consistent with Tetlock (2007), our findings suggest that the stronger the fear sentiment, the higher the Bitcoin trading volume. As fear sentiment was amplified through increased search volume for relevant coronavirus terms, Bitcoin investors may trade more frequently and make irrational decisions based on contemporaneous information on the coronavirus. To further justify our results, we performed Granger causality tests on the relationship between fear sentiment and Bitcoin trading volume. Our results are supported by the tests in Panel B of Table 2, since we can reject the null hypothesis that fear sentiment does not Granger cause Bitcoin trading volume at the 1% level.

INSERT TABLE 2

5. Robustness tests

To ensure the reliability of our results, we split our sample into two subsamples to conduct several robustness tests.[7] We select 11 February as the breakpoint, which is when the WHO announced that the new disease had been named COVID-19. Since that day, the search volume of COVID-19 is included to construct our proxy for fear sentiment. Therefore, the first subsample runs from 15 January 2020 to 10 February 2020 while the second subsample covers the period from 11 February 2020 to 24 April 2020.

Table 3 displays the estimation results for the second subsample. Consistent with our main results, we find that fear sentiment is positively correlated with uncertainty. The relationship between fear sentiment and Bitcoin returns remain significant and negative at lag 3 and then return reversal appears at lag 4. We also find that Bitcoin trading volume is positively influenced by fear sentiment. Moreover, the results of Granger causality tests for all pairs of our variables are in favor of our findings, which is consistent with our full sample analysis.

INSERT TABLE 3

6. Conclusion

In this paper, we explore how investors' fear sentiment influences Bitcoin price dynamics during the coronavirus pandemic. We construct a Google search-based fear sentiment measure to proxy investors' fear related to the coronavirus at a high frequency. Our

[7] Another way to conduct a robustness test is to perform the out-of-sample predictions, as described by Sharma, Phan, and Narayan (2019) and Narayan et al. (2020).

results demonstrate that an increase in search interest in the pandemic is correlated with increased financial market uncertainty. We then examine the impact of fear of coronavirus on Bitcoin returns and investors' trading activity. We find that increasing fear of the coronavirus leads to negative Bitcoin returns and high trading volume, which indicates that Bitcoin behaves more like other financial assets rather than traditional safe-haven assets, such as gold, during times of market distress. Our research suggests that it may not be desirable for investors to allocate resources to Bitcoin to reduce their risk exposure, since it may not serve as a safe haven during the coronavirus pandemic.

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Table 1. Descriptive Statistics

This table reports descriptive statistics of the data, including the fear sentiment proxy, the VIX, Bitcoin prices, and Bitcoin trading volume. The fear sentiment proxy is calculated as the sum of Google search volume for "Coronavirus" and "COVID-19" from 15 January 2020 to 24 April 2020.

	Mean	Std.Dev	Min	Max	Skew	Kurtosis
Sentiment	49.403	48.070	0.000	164.356	0.431	1.702
VIX	35.891	19.803	11.790	83.830	0.402	2.013
Bitcoin prices ($)	8,041.190	1,455.874	4,240.690	10,466.600	-0.243	1.881
Bitcoin trading volume (BTC)	2309.507	2910.273	244.600	38,290.150	4.814	37.842

Table 2. VAR Estimations for Fear Sentiment, Uncertainty (VIX), and Bitcoin Price Dynamics

Panel A shows estimation results for three VAR models. Model 1 reports results for fear sentiment and the VIX; Model 2 for fear sentiment and Bitcoin returns; and Model 3 for fear sentiment and Bitcoin trading volume. Panel B reports test statistics of the Granger causality test for Model 1, Model 2, and Model 3. The sample period is from 15 January 2020 to 24 April 2020.

Panel A: VAR Estimation

	Model 1		Model 2		Model 3	
	V_t	S_t	R_t	S_t	VOL_t	S_t
S_{t-1}	-0.0937*	0.2994***	-0.0001	0.7265***	61.2383***	0.7269***
S_{t-2}	0.1613***	-0.1958	0.00019*	-0.1316***	-33.6227*	-0.1372***
S_{t-3}			-0.00035***	0.0331	7.5371	0.0473**
S_{t-4}			0.00022**	0.0207		
V_{t-1}	0.9421***	0.0159				
V_{t-2}	0.0425	0.0803***				
R_{t-1}			-0.0707***	-3.2772		
R_{t-2}			-0.0538***	0.1919		
R_{t-3}			-0.0122	9.4368**		
R_{t-4}			0.0448**	5.8806		
VOL_{t-1}					0.5853***	0.000015
VOL_{t-2}					0.0444*	0.000048
VOL_{t-3}					0.1637***	-0.000035

Panel B: Granger Causality Test

S_t does not Granger cause V_t	12.090***	V_t does not Granger cause S_t	189.740***
S_t does not Granger cause R_t	12.285**	R_t does not Granger cause S_t	5.901
S_t does not Granger cause VOL_t	17.764***	VOL_t does not Granger Cause S_t	4.829

Notes: *** indicates 1% level significance, ** indicates 5% level significance, and * indicates 10% level significance.

Table 3. VAR Estimations for Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics (Subsample)

Panel A presents estimation results for three VAR models. Model 1 reports results for fear sentiment and the VIX; Model 2 for fear sentiment and Bitcoin returns; and Model 3 for fear sentiment and Bitcoin trading volume. Panel B reports test statistics of the Granger causality test for Model 1, Model 2, and Model 3. The sample period is from 11 February 2020 to 24 April 2020.

Panel A: VAR Estimation

	Model 1		Model 2		Model 3	
	V_t	S_t	R_t	S_t	VOL_t	S_t
S_{t-1}	0.0224	0.2975***	-0.00012	0.7291***	60.4313 ***	0.7294***
S_{t-2}	0.0834***	-0.1990***	0.0002	-0.1328 ***	-33.0992	-0.1385 ***
S_{t-3}			-0.0004 ***	0.0336	7.6242	0.0475 **
S_{t-4}			0.0002 **	0.0203		
V_{t-1}	0.9356***	-0.0916				
V_{t-2}	0.0442	0.1642***				
R_{t-1}			-0.0730***	-3.3721		
R_{t-2}			-0.0569**	0.0853		
R_{t-3}			-0.0150	9.8157 *		
R_{t-4}			0.0451*	6.1212		
VOL_{t-1}					0.5949 ***	0.00002
VOL_{t-2}					0.0345	0.00005
VOL_{t-3}					0.1629***	-0.00004

Panel B: Granger Causality Test

S_t does not Granger cause V_t	9.9472***	V_t does not Granger cause S_t	111.02***
S_t does not Granger cause R_t	9.528**	R_t does not Granger cause S_t	4.469
S_t does not Granger cause VOL_t	13.747***	VOL_t does not Granger cause S_t	3.702

Notes: *** indicates 1% level significance, ** indicates 5% level significance, and * indicates 10% level significance.

Figure 1. Evolution of Fear Sentiment (Level) and Bitcoin Prices

This graph plots hourly data on the fear sentiment proxy (right y-axis) and Bitcoin prices (BTC/USD, left y-axis) from 15 January 2020 to 24 April 2020.

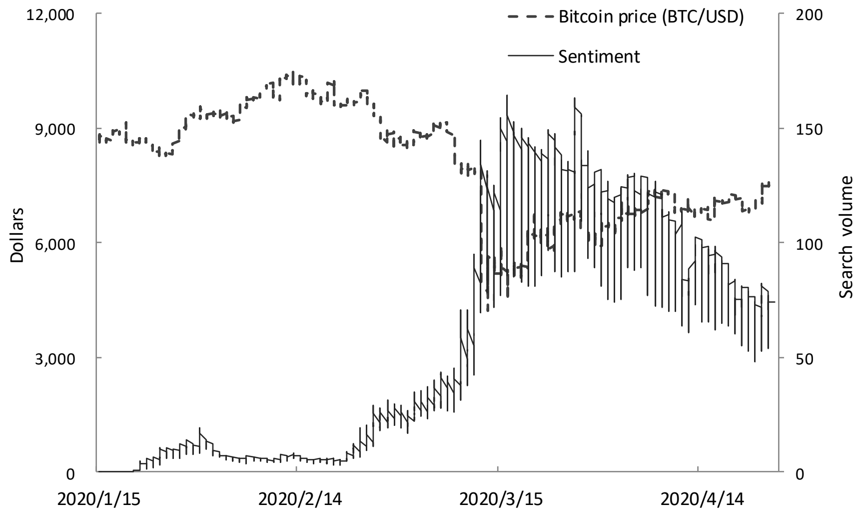
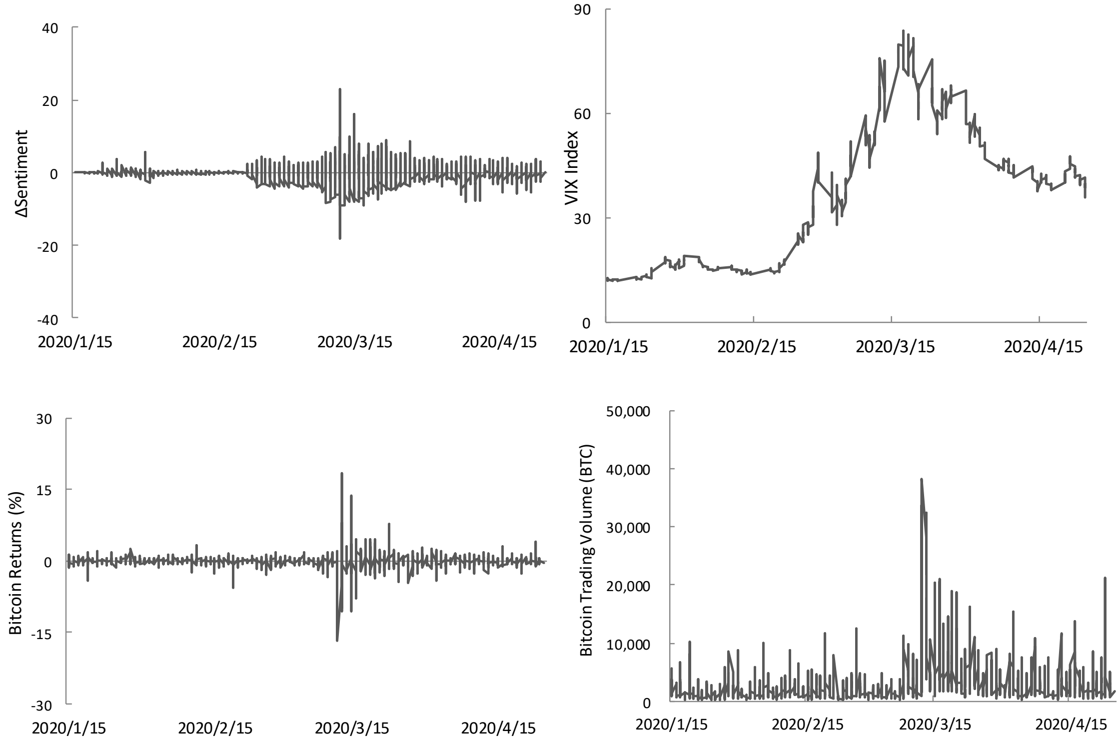


Figure 2. Evolution of the Fear Sentiment (difference), VIX, Bitcoin Returns, and Bitcoin Trading Volume

This graph plots hourly data on the first difference of fear sentiment proxy (upper left), VIX (upper right), Bitcoin returns (lower left), and Bitcoin dollar trading volume (lower right) from 15 January 2020 to 24 April 2020. In particular, Bitcoin returns are the first differences of log Bitcoin prices.



Appendix

Table 1. Stationarity Tests for Fear Sentiment (Level) and Bitcoin Prices

This table shows the results of stationarity tests for hourly data on fear sentiment and Bitcoin prices using the augmented Dickey-Fuller method. The sample period is from 15 January 2020 to 24 April 2020.

Panel A: Dickey-Fuller Test for Fear Sentiment (Level)				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.007	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.2836				
Panel B: Dickey-Fuller Test for Bitcoin Prices (BTC/USD)				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.245	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.6538				

Notes: Critical values at the 10% level are smaller than corresponding T-statistics. Therefore, the null hypothesis that the two series are not stationary cannot be rejected at the 10% level.

Table 2. Stationarity Tests for Fear Sentiment (difference), VIX, Bitcoin Returns, and Bitcoin Trading Volume

This table shows the results of stationarity tests for hourly data on the first difference of fear sentiment, the VIX, Bitcoin returns, and Bitcoin dollar trading volume using the Dickey-Fuller method. The sample period is from 15 January 2020 to 24 April 2020.

Panel A: Dickey-Fuller Test for Fear Sentiment				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-22.367***	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.0000				
Panel B: Dickey-Fuller Test for VIX				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.913**	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.0438				
Panel C: Dickey-Fuller Test for Bitcoin Returns				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-52.766***	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.0000				
Panel D: Dickey-Fuller Test for Bitcoin Trading Volume				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-21.642***	-3.430	-2.860	-2.570
MacKinnon approximate p-value for Z(t) = 0.0000				

Notes: All critical values at the 5% level are larger than corresponding T-statistics. Therefore, the null hypothesis that the four series are not stationary can be rejected at the 5% level.

Table 3. VAR Estimations for Fear Sentiment and Bitcoin Price Dynamics (Subsample 1)

Panel A shows estimation results for two VAR models. Model 1 reports results for fear sentiment and Bitcoin returns and Model 2 for fear sentiment and Bitcoin trading volume. Panel B shows test statistics of the Granger causality test for Model 1 and Model 2. The sample period is from 15 January 2020 to 10 February 2020.

Panel A: VAR Estimation

	Model 1		Model 2	
	R_t	S_t	VOL_t	S_t
S_{t-1}	0.0007*	0.3872***	166.9879 **	0.3434***
S_{t-2}	0.0003	-0.1243***		
R_{t-1}	-0.0469	2.4606		
R_{t-2}	-0.0256	4.3220		
VOL_{t-1}			0.3795***	0.00001

Panel B: Granger Causality Test

S_t does not Granger Cause R_t	5.230 *	R_t does not Granger Cause S_t	1.584
S_t does not Granger Cause VOL_t	4.249 **	VOL_t does not Granger Cause S_t	0.840

Notes: *** indicates 1% level of significance, ** indicates 5% of level significance, and * indicates 10% of level significance.