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Abstract

This study aims to investigate the effect of fear sentiment with a novel data set on Bitcoin's return, volatility and transaction volume. We divide the sample into two subperiods in order to capture the changing dynamics during the Covid-19 pandemic. We retrieve the novel fear sentiment data from Thomson Reuters MarketPsych Indices (TRMI). We denote the subperiods as pre- and post-COVID19 considering January 13th, 2020, when first Covid-19 confirmed case was reported outside China. We employ bivariate vector autoregressive (VAR) models given below with lag-length k, to investigate the dynamics between Bitcoin variables and fear sentiment.Bitcoin market measures have dissimilar dynamics before and after the Coronavirus outbreak. The results reveal that due to the excessive uncertainty led by the outbreak, an increase in fear sentiment negatively affects the Bitcoin returns more persistently and significantly. For the post-COVID-19 period, an increase in fear also results in more fluctuations in transaction volume while its initial and cumulative effects are both negative. Due to extreme uncertainty caused by the COVID-19 pandemic, investors may trade more aggressively in the initial phases of the shock.

Bitcoin-specific fear sentiment and bitcoin returns in the COVID-19 outbreak

1. Introduction

Bitcoin's price experienced a sharp drop, from 9147 USD on 6th March 2020 to 4959 USD on 12th March 2020 at the beginning of the Covid-19 pandemic, which proves that Bitcoin is affected by global events significantly. Then, later it increased to 61288 USD on 13th March 2021, within a year[1]. Considering this high volatility in Bitcoin prices, it is insightful to analyze the effects of market sentiments on cryptocurrencies. This is even more relevant for Bitcoin since the sentiment drives the Bitcoin market in a laxer regulatory framework. COVID-19 as a natural experiment provides an opportunity to explore the pure effects of market sentiment on return, transaction volume and volatility of Bitcoin considering its decentralized and lightly regulated feature. This study allows us to infer lessons from markets in the absence of strict regulatory responses by the governments. Hence, investigating dynamics in the Bitcoin markets reveal more on the potential responses of markets under lighter government regulations[2].

The behavioral literature focuses on analyzing the effects of the sentiments in markets (Tetlock 2007). However, the literature mostly employs generic sentiment measures that are often too general to capture asset-specific sentiments. For example, Da et al. (2015) and Chen et al. (2020) use generic market sentiment data derived from Google Trends that are not specific to the Bitcoin market. Existing research resorts to the general sentiment measures due to the availability of the data. However, in this paper, we benefit from a novel data set of Bitcoin-

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[1] The price data is obtained from coinmetrics.io

[2] One may see some of the related works of the authors as follows in the references: Aysan, A. F. & Bergigui, F. (2020), Aysan, A. F., Bergigui, F. & Disli, M., (2021a), Aysan, A. F., Bergigui, F., & Disli, M. (2021b), Aysan, A. F., Demirtaş, H. B. & Saraç, M., (2021), Aysan, A. F., Disli, M., Nagayev, R., Rizkiah, S. K. & Salim, K. (2021), Aysan, A. F., Khan, A. I. & Topuz, H., (2021), Aysan, A. F., Khan, A. I., Topuz, H., & Tunalı, A. S., (2021), and Aysan, A. F., Sadriu, B. & Topuz, H., (2020).

specific fear sentiment to capture the effects of market psychology on Bitcoin price, volume and price volatility.

There is a growing literature on Bitcoin market dynamics (Sahoo et al. 2019; Poyser 2019; Dahir et al. 2019; Kristoufek, 2019; Aloosh and Ouzan 2020) and whether Bitcoin acts as a safe haven (Aysan et al. 2019; Bouri et al. 2017, Guesmi et al. 2019; Shahzad et al. 2019) or whether it is a bubble (Cheah and Fry 2015; Geuder et al. 2019; Chaim and Laurini 2019). Previous research focused on the effects of sentiment on different market dynamics of Bitcoin (Karalevicius et al. 2017; Kalyvas et al. 2020). Shen et al. (2019) analyze the relationship between Bitcoin return and investor attention using the number of twitters as a proxy for investor attention. Da et al. (2015) construct a daily Internet search-based fear index and find that the fear index can predict asset prices and volatility.

There is no agreement yet whether BTC and other cryptocurrencies satisfy the three main properties of a money/currency (Bariviera et al. 2017, Baur et al. 2018). Thus, investors mostly treat cryptocurrencies as an asset rather than a currency. Baur et al. (2018) claim that: "Bitcoin is mainly used as a speculative investment" not "as an alternative currency". Corbet et al. (2018) analyze the relationship between the three known cryptocurrencies and conventional assets. They show that cryptocurrencies provide some diversification benefits in the short run. Zeng et al. (2020) investigate the connectedness between Bitcoin and other conventional assets and find that the relationship is limited implying a diversification opportunity. Regarding the regulatory difference between conventional assets and cryptocurrencies, Vandezande (2017) mentions that it is inevitable to understand crypto markets in relation to other conventional assets, in order to provide better insights for policy makers and regulators.

Earlier literature focuses on the effect of investor psychology and sentiment in the Bitcoin market (Kaminski 2014; Bukovina and Marticek 2016; Oad Rajput et al. 2020) and on the Covid-19 period (Demir et al. 2020; Conlon and McGee 2020; Chen et al. 2020), yet there are

no studies investigating the impact of changing fear sentiment during Covid-19 outbreak on Bitcoin market dynamics. This study aims to analyze whether the Covid-19 pandemic, as an extreme shock, changed the dynamics in the Bitcoin market. More specifically, we check how fear sentiment affects Bitcoin variables before and after the pandemic and whether the effect of sentiment is more pronounced after the pandemic considering the unprecedented uncertainty during the Covid-19 period. We employ bivariate VAR models to investigate the relationship between the fear sentiment and Bitcoin's return, transaction volume and 30-day return volatility. Fear sentiment data provided by TRMI is a novel sentiment measure since it is unique to the Bitcoin market, not a generic sentiment measure.

The results reveal that due to the excessive uncertainty led by the COVID-19 outbreak, an increase in fear sentiment negatively affects the Bitcoin returns more persistently and significantly. For the post-COVID-19 period, an increase in fear also results in more fluctuations in transaction volume while its initial and cumulative effects are both negative. Due to extreme uncertainty caused by the COVID-19 pandemic, investors may trade more aggressively in the initial phases of the shock.

The paper has several main contributions. First, Chen et al. (2020) focus on the effects of the COVID-19 pandemic and report only VAR estimation results. Their analysis is not very informative since they cannot capture the dynamic relationship between variables due to not analyzing impulse response functions (IRFs). However, we analyze IRFs to understand the dynamic relationship between fear and our Bitcoin variables. Second, we use Bitcoin-specific fear sentiment data set of Thomson Reuters MarketPsych instead of more general market sentiment measures used in the literature and show that fear merges to have more permanent and volatile effects after the outbreak. This enables us to investigate the impact of investor psychology on Bitcoin market dynamics more accurately, since generic sentiment measures, as employed by the earlier literature, cannot capture market specific psychology. Next, this is the

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first study to examine the association between fear and Bitcoin before and after COVID-19, considering the changing dynamics with the outbreak. Thus, we can investigate the effect of the pandemic on the Bitcoin market, through investor psychology, since the pandemic created an unprecedented shock on financial markets.

The paper is organized as follows: Section 2 describes the data and the methodology. Section 3 presents and discusses the results. Section 4 concludes and provides policy implications.

2. Data and methodology

We retrieve fear sentiment data from Thomson Reuters MarketPsych Indices (TRMI). Bitcoin price and total transaction volume[3] in its Blockchain in terms of US dollars, and daily volatility[4] of Bitcoin return are obtained from *coinmetrics.io* for the period between January 1st, 2019 and January 31th, 2021. We denote the subperiods as pre- and post-COVID19 considering January 13th, 2020, when first Covid-19 confirmed case was reported outside China. With the pandemic, fear sentiment increased sharply to 0.012 by mid-March, which is unprecedentedly high (see Fig. 1) considering its mean and standard deviation (see Table 1).

[Figure 1 is about here]

[Table 1 is about here]

TRMI data is unique in capturing market sentiment in multiple ways. First, it is based on advanced linguistic machine learning techniques accounting for variation in sources and correlations among words. Contrary to the most of the methods used in the sentiment literature TRMI is sensitive to grammatical structures. Second, the sentiment data is highly dimensional including more than fifty sentiments and topics. Third, it has a very broad range of coverage compared to other sentiment data used in the literature. Fourth, TRMI is updated minutely and

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[3] The sum USD value of all native units transferred (i.e., the aggregate size in USD of all transfers) that day.
[4] Computed as the standard deviation of the daily natural log returns over 30 days

includes tens of thousands of social media and news sources (Peterson 2013; Audrino and Tetereva 2019; Griffith et al. 2020). Fifth, TRMI releases different types of sentiment data specific to each cryptocurrency.

Peterson (2016) explains how TRMIs are constructed as follows. A TRMI is formed by a combination of variables (Vars). Initially, the absolute values of all TRMI-contributing Vars are determined by the algorithm, for all asset components, over the past 24 hours. Next, "Buzz" is calculated which is the summation of these absolute values for all components. "Buzz" index is also published along with TRMIs of each asset. Namely, let V be the set of all Vars underlying any TRMI of the asset class, where a denotes an asset, and $C(a)$ is the set of all components of a. Then, Buzz is defined as follows:

$$Buzz(a) = \sum_{c \epsilon C(a), v \epsilon V} |Var_{c,v}|$$

Having the Buzz, a TRMI is computed as the ratio of the sum of all Vars related to a specific asset to the Buzz. $V(t)$ is defined as the set of all Vars relevant to a particular TRMI$_t$. After that, a binary function is introduced to determine whether a Var $v \in V(t)$ is additive or subtractive:

$$I(t,v) = \begin{cases} +1 \ if \ additive \\ -1 \ if \ subtractive \end{cases}$$

Finally, TRMI$_t$ of an asset a is computed as follows:

$$TRMI_t(a) = \frac{\sum_{c \in C(a), v \in V(t)} (I(t,v) \times PyschVar_v(c))}{Buzz(Asset)}$$

In this study, we employ Bitcoin specific "fear" index as the $PyschVar$ which measures the fear and anxiety and takes values between 0 and 1 (Peterson 2016).

We employ bivariate vector autoregressive (VAR) models given below with lag-length k, to investigate the dynamics between Bitcoin variables and fear sentiment:

$$Model\ 1: \quad Y_t = c + \sum_{j=1}^{k} \beta_j \, Y_{t-j} + \epsilon_t$$

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where $Y_t = [Return, Fear]'$ is a $2x1$ vector of endogenous variables, c is a vector of constants and ϵ_t is a vector of error terms. Model 1 captures the relationship between Bitcoin return and fear sentiment.

$$Model\ 2: \quad X_t = c + \sum_{j=1}^{k} \beta_j X_{t-j} + \epsilon_t$$

where $X_t = [Transaction, Fear]'$ is a $2x1$ vector of endogenous variables, c is a vector of constants and ϵ_t is a vector of error terms. Model 2 captures the relationship between Bitcoin transaction value and fear sentiment.

$$Model\ 3: \quad Z_t = c + \sum_{j=1}^{k} \beta_j Z_{t-j} + \epsilon_t$$

where $Z_t = [Volatility, Fear]'$ is a $2x1$ vector of endogenous variables, c is a vector of constants and ϵ_t is a vector of error terms. Model 3 captures the relationship between Bitcoin volatility and fear sentiment.

We determine the lag-length[5] using HQ Information Criteria (HQIC) criteria and check the stationarity of the variables by performing augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests with and without trends. Diagnostic tests suggest that fear, return, 30-day volatility and Log-transaction volume are stationary at their levels (Table 2).

[Table 2 is about here]

3. Empirical results

In order to capture dynamic relationship between variables we plot impulse response functions (IRF).[6] Fig. 2, 3 and 4 display the orthogonalized impulse response functions (OIRF) of Bitcoin return, transaction volume and Bitcoin volatility respectively to one-unit standard

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[5] The empirical results and IRFs are generated also with different lag-lengths based on other information criteria such as AIC and BIC. We find qualitatively similar results.
[6] See Appendix for the VAR estimation results of both subsamples.

deviation shock on fear, based on the estimated bivariate VAR models. The confidence intervals are for 1 standard error confidence intervals.

Figure 2 shows the IRF for Bitcoin return (Model 1). For the pre-COVID period, the response of return is negative to an increase in fear sentiment and dies out quickly in 6 periods (days). However, after COVID-19, even the response is again negative in the initial periods, later it fluctuates, and the shock persists much longer (more than 15 periods) compared to pre-COVID. Besides, the initial response of return to a fear shock is bigger in magnitude for post-COVID compared to pre-COVID. These results imply that due to the excessive uncertainty caused by the COVID-19 outbreak, an increase in fear negatively affects the Bitcoin returns more persistently. With an increasing fear, investors become more pessimistic which increases the selling pressure (Baker and Wurgler 2006; Chen et al. 2020). The reaction of the Bitcoin fluctuates as fear sentiment leads to return reversals after COVID-19 (Tetlock 2007; Da et al. 2015). This result also implies that Bitcoin prices become exceptionally volatile with coronavirus outbreak. Investors became more sensitive to news after the outbreak. The granger causality test results further support our findings. Fear granger causes Bitcoin return in the post-COVID period more significantly (Table 3).

[Figure 2 is about here]

[Table 3 is about here]

Fig. 3 displays the response of transaction volume based on Model 2. During the pre-COVID period, a positive shock (an increase) in fear decreases transaction volume and the shock starts to die out smoothly after 50 periods. On the other hand, for the post-COVID period, an increase in fear results in more fluctuations in transaction volume even though the initial and cumulative effects are both negative. Interestingly after a few periods, transaction volume increases but reduces later and continues fluctuating

[Figure 3 is about here]

longer. Due to extreme uncertainty caused by the COVID-19 pandemic, investors may trade more aggressively in the initial phases of the shock. However, in the end, due to increasing-bid ask prices, fear probably decreases transaction (Tetlock 2007).

Fig. 4 shows the response of volatility based on Model 3. During the pre-COVID period, an increase in fear decreases the volatility. Conversely, increasing fear has a sharp increasing effect on volatility after COVID-19. The effect is larger in magnitude and is more permanent for the post-COVID period. The increasing severity of the pandemic presumably drives investors to become more uncertain. This may lead to an increase in bid-ask spread and volatility (Lerner and Keltner 2001).

[Figure 4 is about here]

4. Conclusions

We investigate the relationship between Bitcoin-specific fear sentiment and Bitcoin's return, volatility and transaction volume considering the COVID-19 pandemic driven crisis. The results show that the relationship between fear and our bitcoin variables become more volatile while the shocks have more persistent effects after the COVID-19 outbreak. For conventional currencies, governments, regulators and central banks intervene in the market to stabilize their economies when faced with a crisis like the COVID-19 outbreak. However, the Bitcoin market in nature came out as a reaction to these policies. In this sense, we are convinced that our results in this paper have more far-reaching implications for other markets regulated by the states. Bitcoin provides a natural benchmark to understand how fear sentiment drives and impacts the markets isolated from any interventions. Focusing on Bitcoin-as a decentralized and unregulated market-gives us clues about how the market would have behaved in the absence of

policy responses and trust provided by any central authority. Hence, our results show that in the absence of regulatory frameworks, market dynamics are likely to be more volatile, and the fear sentiment has more persistent impacts. This implies that smart regulation and timely interventions in the markets, such as monetary and fiscal policy responses conducted during the early stage of the outbreak, are relevant and may mitigate the sentiment driven extreme volatility in the markets. Also, considering the expectation management role of central banks, the timely response may help investors to gain confidence in markets. We also highlight the importance of using micro, asset-specific sentiment measures to capture market dynamics better.

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APPENDIX

Table A.1. VAR estimation results for Model 1

	Pre-COVID		Post-COVID	
	$Return_t$	$Fear_t$	$Return_t$	$Fear_t$
R_{t-1}	-0.0736	-0.0017*	-0.1112**	-0.0045***
R_{t-2}			0.0475	-0.0010
R_{t-3}			-0.7550	-0.0017
R_{t-4}			0.1178**	0.0008
R_{t-5}			0.0196	0.0023**
F_{t-1}	-3.9695*	0.4504***	-1.4986	0.4624***
F_{t-2}			0.1898	0.1443**
F_{t-3}			-2.2520	0.0832
F_{t-4}			6.8282**	-0.0465
F_{t-5}			-1.7410	0.2041***

Notes: *pre- and post- Covid periods cover the dates from 1 January, 2019 to 14 March, 2020 and from 15 March, 2020 to 31 January, 2021, respectively.*

**Table A.2.** VAR estimation results for Model 2

	Pre-COVID		Post-COVID	
	$Transaction_t$	$Fear_t$	$Transaction_t$	$Fear_t$
T_{t-1}	0.4918***	0.0000	0.4227***	0.0002
T_{t-2}	0.0860	0.0002	0.0338	-0.0000
T_{t-3}	0.0145	0.0002	0.1564***	0.0001
T_{t-4}	0.0690	-0.0001	-0.0004	-0.0000
T_{t-5}	-0.0491	-0.0001	-0.0722	-0.0000
T_{t-6}	0.1813***	0.0000	0.2217***	-0.0000
T_{t-7}	0.3506***	0.0001	0.4598***	0.0001
T_{t-8}	-0.0653	0.0001	-0.020	-0.0003*
T_{t-9}	-0.1596***	-0.0002	-0.2095***	0.0001
F_{t-1}	-9.3317	0.4291***	-11.735	0.5180***
F_{t-2}	-25.5661	0.0322	-9.2434	0.1315**
F_{t-3}	-2.4945	0.0253	23.921	0.0692
F_{t-4}	6.7491	-0.0172	-1.9842	-0.0763
F_{t-5}	-56.1848***	0.0139	-29.607**	0.1874***
F_{t-6}	-21.2933	-0.0051	-29.6931**	-0.0283
F_{t-7}	34.3180	-0.0030	18.8800	-0.0291
F_{t-8}	-2.5259	0.0731	21.7719	0.0351
F_{t-9}	-42.1709**	0.0063	14.0921	0.0233

Notes: *pre- and post- Covid periods cover the dates from 1 January, 2019 to 14 March, 2020 and from 15 March, 2020 to 31 January, 2021, respectively.*

Table A.3. VAR estimation results for Model 3

	Pre-COVID		Post-COVID	
	Volatility$_t$	Fear$_t$	Volatility$_t$	Fear$_t$
V$_{t-1}$	1.0048***	-0.0084	1.0254***	0.0314514***
V$_{t-2}$	0.1051	0.0195	-0.0591	-0.0232347
V$_{t-3}$	-0.1340***	-0.0085	-0.0527	0.024437
V$_{t-4}$			0.0445	-0.0306693***
F$_{t-1}$	0.1488	0.4349***	0.1639	0.4908896***
F$_{t-2}$	-0.0757	0.0338	0.080	0.1413264**
F$_{t-3}$	-0.2457	0.0140	1.000***	0.095465*
F$_{t-4}$			-0.380	0.0101118

Notes: pre- and post- Covid periods cover the dates from 1 January, 2019 to 14 March, 2020 and from 15 March, 2020 to 31 January, 2021, respectively.
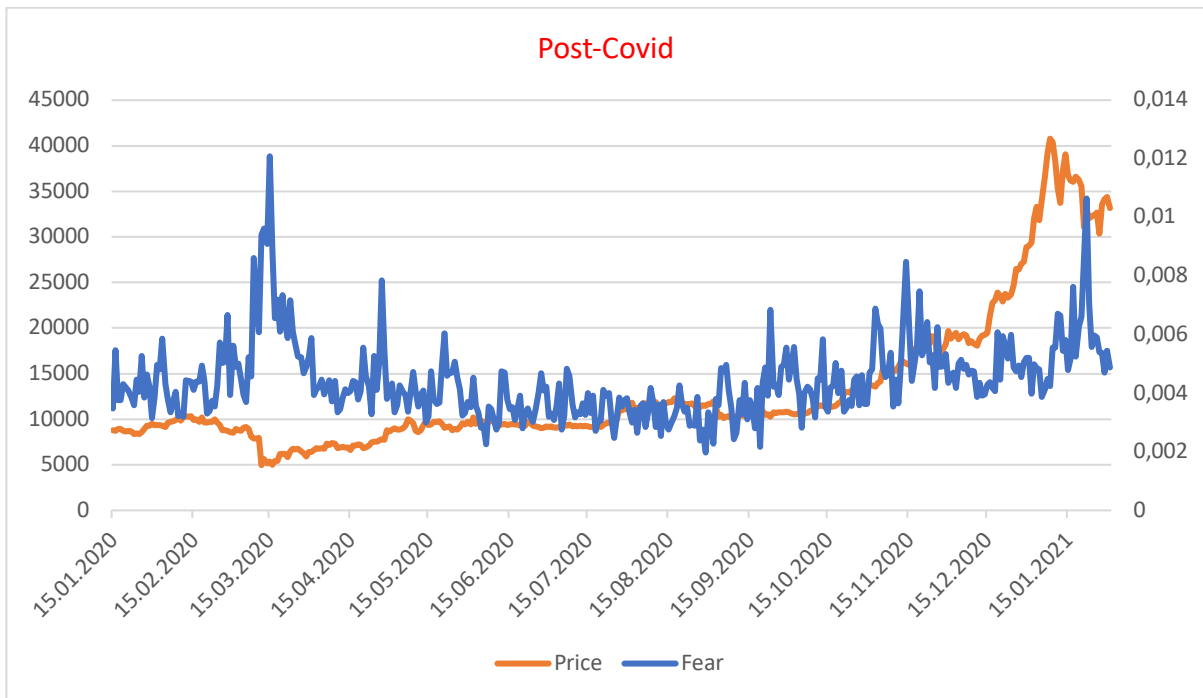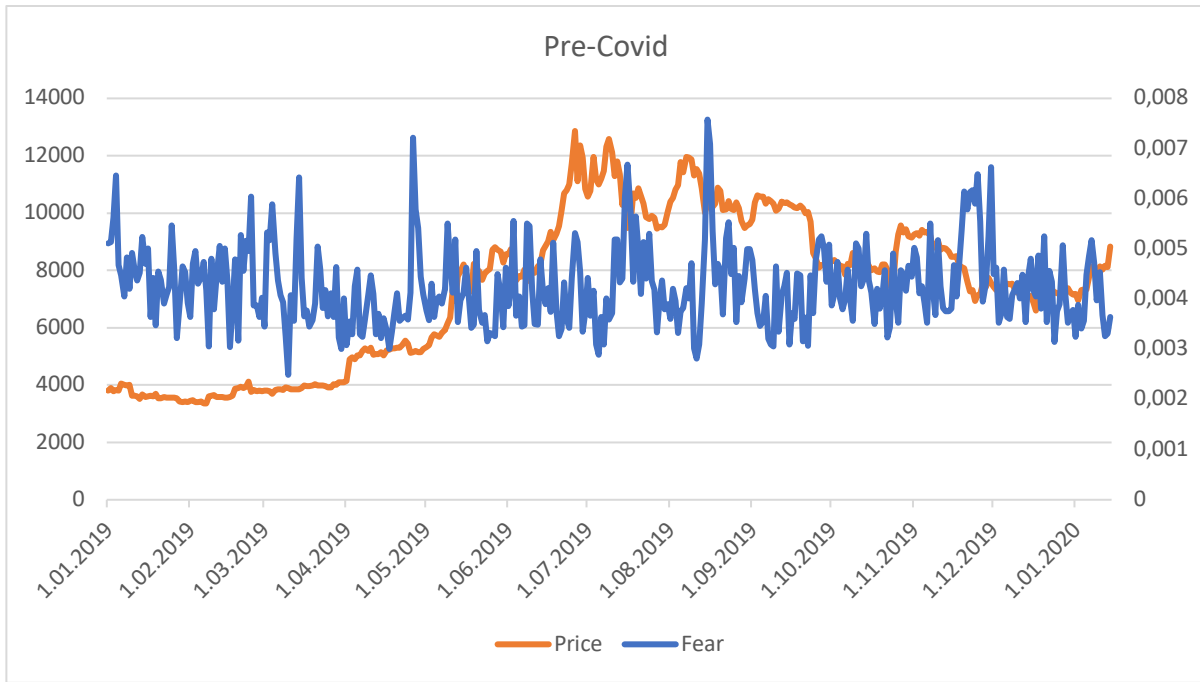
Fig. 1. Fear and BTC price (USD).

Table 1.a. Summary statistics for pre-Covid period

	Mean	SD	Min	Max	Skewness	Kurtosis
Fear	0.0042	0.0008	0.0025	0.0075	0.90931	4.2465
Return	0.0022	0.0365	-0.1465	0.1697	0.3302	6.9914
Log-Transaction Volume	23.4472	0.5116	22.1874	24.5322	-0.6643	2.8457
30-day Return Volatility	0.0353	0.0116	0.0119	0.0696	0.8123	3.4139

Notes: pre-Covid covers the period from 1 January, 2019 to 14 March, 2020.

Table 1.b. Summary statistics for post-Covid period

|	Mean	SD	Min	Max	Skewness	Kurtosis
Fear	0.0041	0.0013	0.0019	0.0121	2.2333	10.850
Return	0.0007	0.0442	-0.4705	0.1401	-4.411	51.889
Log-Transaction Volume	24.1253	0.3812	23.229	25.0294	-0.3255	2.3615
30-day Return Volatility	0.0376	0.0242	0.0117	0.1055	2.0116	5.7668

Notes: post-Covid covers the period from 15 March, 2019 to 31 January, 2021.

Table 2. Unit root test results

	Pre-Covid		Post-Covid	
Variables	ADF	Philips-Perron	ADF	Philips-Perron
Fear Sentiment	-11.788 ***	-11.840 ***	-6.409 ***	-6.143***
Bitcoin Return	-20.671 ***	-20.651***	-19.701***	-19.476***
30-day Volatility	-2.079 *	-2.359*	-1.621	-1.786
Log-transaction volume	-3.494 ***	-2.804*	-4.061 ***	-3.400**

*** Indicates significance at 1%. ** Indicates significance at 5%. * Indicates significance at 10%.

Notes: pre- and post- Covid periods cover the dates from 1 January, 2019 to 14 March, 2020 and from 15 March, 2020 to 31 January, 2021, respectively.

Pre-COVID
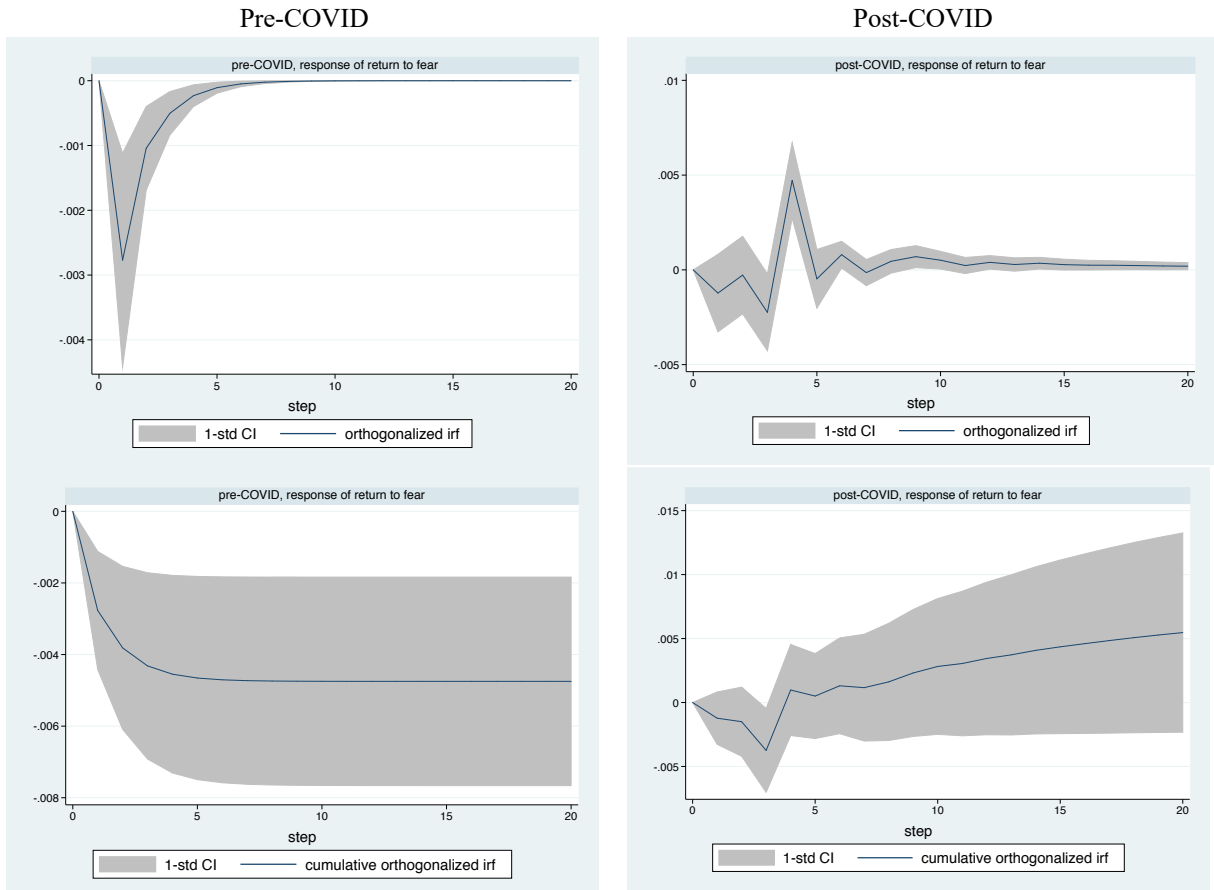
Post-COVID

Fig. 2. Orthogonalized and cumulative IRFs for pre- and post-COVID periods of Bitcoin return (Model 1).
Notes: This figure show the response of BTC return to a shock in fear having 1-standard deviation confidence intervals.

**Table 3.** Granger causality Wald test results.

Pre-COVID		Post-COVID	
Fear does not granger cause Return	2.7952*	Fear does not granger cause Return	16.899***
Fear does not granger cause transaction volume	24.383***	Fear does not granger cause transaction volume	20.624 ***
Fear does not granger cause volatility	3.3468	Fear does not granger cause volatility	33.03***

*** Indicates significance at 1%. * Indicates significance at 10%.

Notes: pre- and post- Covid periods cover the dates from 1 January, 2019 to 14 March, 2020 and from 15 March, 2020 to 31 January, 2021, respectively.

Pre-COVID
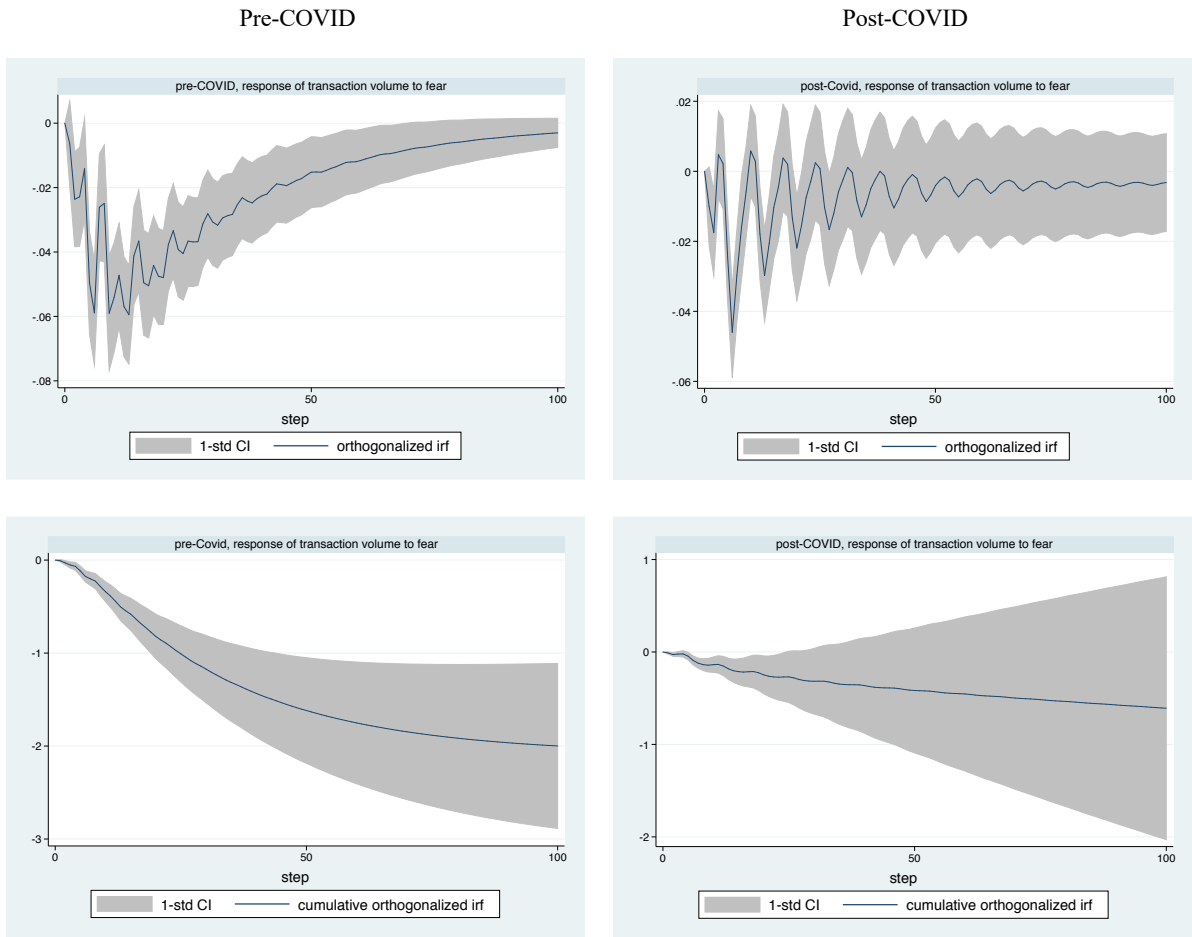
Post-COVID

Fig. 3. Orthogonalized and cumulative IRFs for pre- and post-COVID periods of transaction volume to a shock in fear.

Pre-COVID
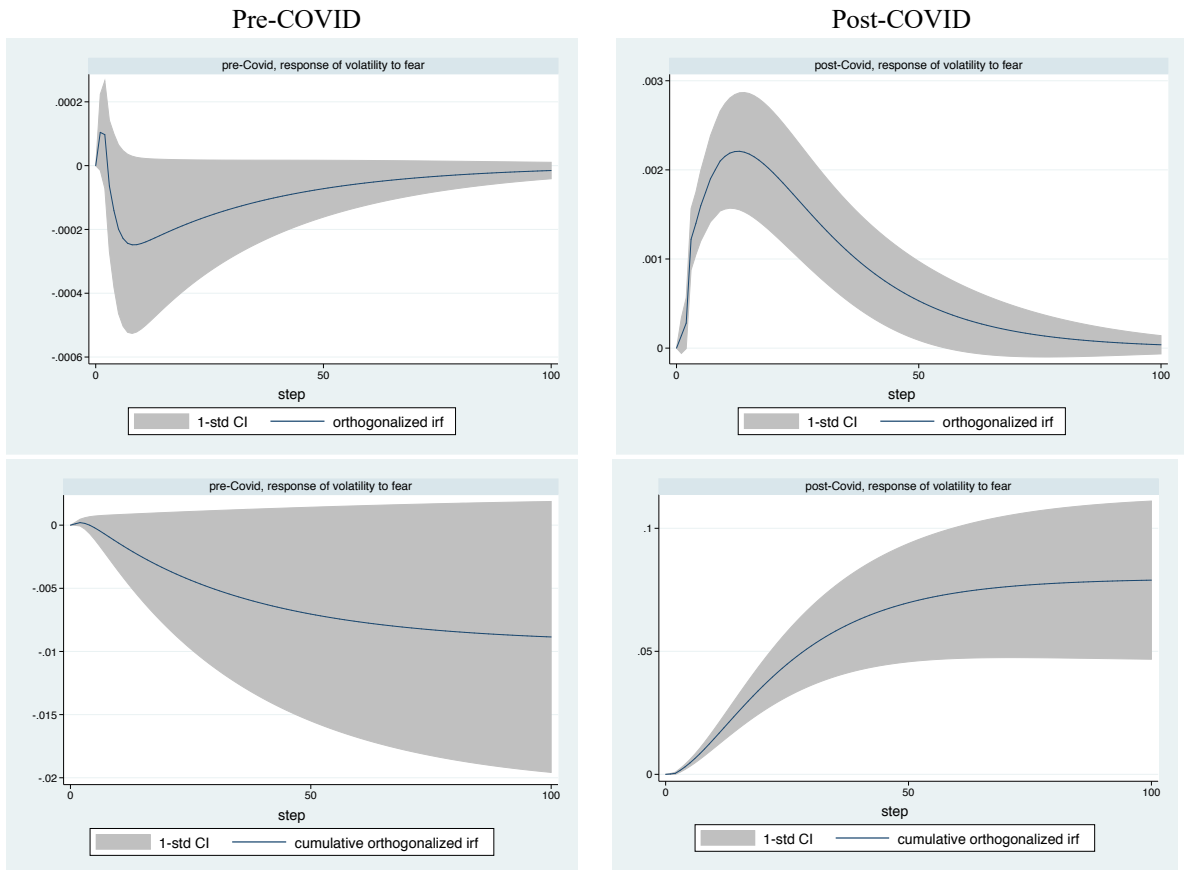
Post-COVID

Fig. 4. Orthogonalized and cumulative IRFs for pre- and post-COVID periods of volatility to a shock in fear.