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Bitcoin-specific fear sentiment matters in the COVID-19 outbreak

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Abstract

Purpose – This study aims to investigate the effect of fear sentiment with a novel data set on Bitcoin's (BTC) return, volatility and transaction volume. The authors divide the sample into two subperiods to capture the changing dynamics during the COVID-19 pandemic.

Design/methodology/approach – The authors retrieve the novel fear sentiment data from Thomson Reuters MarketPsych Indices (TRMI). The authors denote the subperiods as pre- and post-COVID-19 considering January 13, 2020, when the first COVID-19 confirmed case was reported outside China. The authors use bivariate vector autoregressive models given below with lag-length k, to investigate the dynamics between BTC variables and fear sentiment.

Findings – BTC 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 BTC 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.

Practical implications – The authors are convinced that the results in this paper have more far-reaching implications for other markets regulated by the states. BTC provides a natural benchmark to understand how fear sentiment drives and impacts the markets isolated from any interventions. Hence, the 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. The authors also highlight the importance of using micro, asset-specific sentiment measures to capture market dynamics better.

Originality/value – BTC is not associated with any regulatory authority and is not produced by the governments and central banks. COVID-19 as a natural experiment provides an opportunity to explore the pure effects of market sentiment on BTC considering its decentralized and unregulated features. The paper has two main contributions. First, the authors use BTC-specific fear sentiment novel data set of TRMI instead of more general market sentiments used in the existing studies. Next, this is the first study to examine the association between fear and BTC before and after COVID-19.

Keywords Volatility, TRMI, COVID-19, Fear sentiment, Bitcoin's return, Transaction volume

Paper type Research paper

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1. Introduction

Bitcoin's (BTC) price experienced a sharp drop, from US$9,147 on March 6, 2020 to US$4,959 on March 12, 2020, at the beginning of the COVID-19 pandemic, which proves that BTC is affected by global events significantly. Then, later it increased to US$61,288 on March 13, 2021, within a year [1]. Considering this high volatility in BTC prices, it is insightful to analyze the effects of market sentiments on cryptocurrencies. This is even more relevant for BTC, as the sentiment drives the BTC 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 BTC 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 BTC markets reveal more on the potential responses of markets under lighter government regulations.

The behavioral literature focuses on analyzing the effects of the sentiments in markets (Tetlock, 2007). However, the literature mostly uses 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 BTC 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 BTC-specific fear sentiment to capture the effects of market psychology on BTC price, volume and price volatility.

There is a growing literature on BTC market dynamics (Sahoo *et al.*, 2019; Poyser, 2019; Dahir *et al.*, 2019; Kristoufek, 2019; Aloosh and Ouzan, 2020) and whether BTC 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 BTC (Karalevicius *et al.*, 2018; Kalyvas *et al.*, 2020). Shen *et al.* (2019) analyze the relationship between BTC 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 BTC 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, to provide better insights for policymakers and regulators.

Earlier literature focuses on the effect of investor psychology and sentiment in the BTC 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 BTC market dynamics. This study aims to analyze whether the COVID-19 pandemic, as an extreme shock, changed the dynamics in the BTC market. More specifically, we check how fear sentiment affects BTC 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 use bivariate vector autoregressive (VAR) models to investigate the relationship between the fear sentiment and BTC's return, transaction volume and 30-day return volatility. Fear sentiment data provided by Thomson Reuters MarketPsych Indices (TRMI) is a novel sentiment measure, as it is unique to the BTC 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 BTC 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, as 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 BTC variables. Second, we use the BTC-specific fear sentiment data set of TRMI 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 BTC market dynamics more accurately, as generic sentiment measures, as used by the earlier literature, cannot capture market specific psychology. Next, this is the first study to examine the association between fear and BTC before and after COVID-19, considering the changing dynamics with the outbreak. Thus, we can investigate the effect of the pandemic on the BTC market, through investor psychology, as 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 TRMI. BTC price and total transaction volume [2] in its Blockchain in terms of US dollars, and daily volatility [3] of BTC return are obtained from coinmetrics.io for the period between January 1, 2019 and January 31, 2021. We denote the subperiods as pre- and post-COVID19 considering January 13, 2020, when the 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 (Figure 1) considering its mean and standard deviation (Table 1).

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 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 50 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 includes 10,000s 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

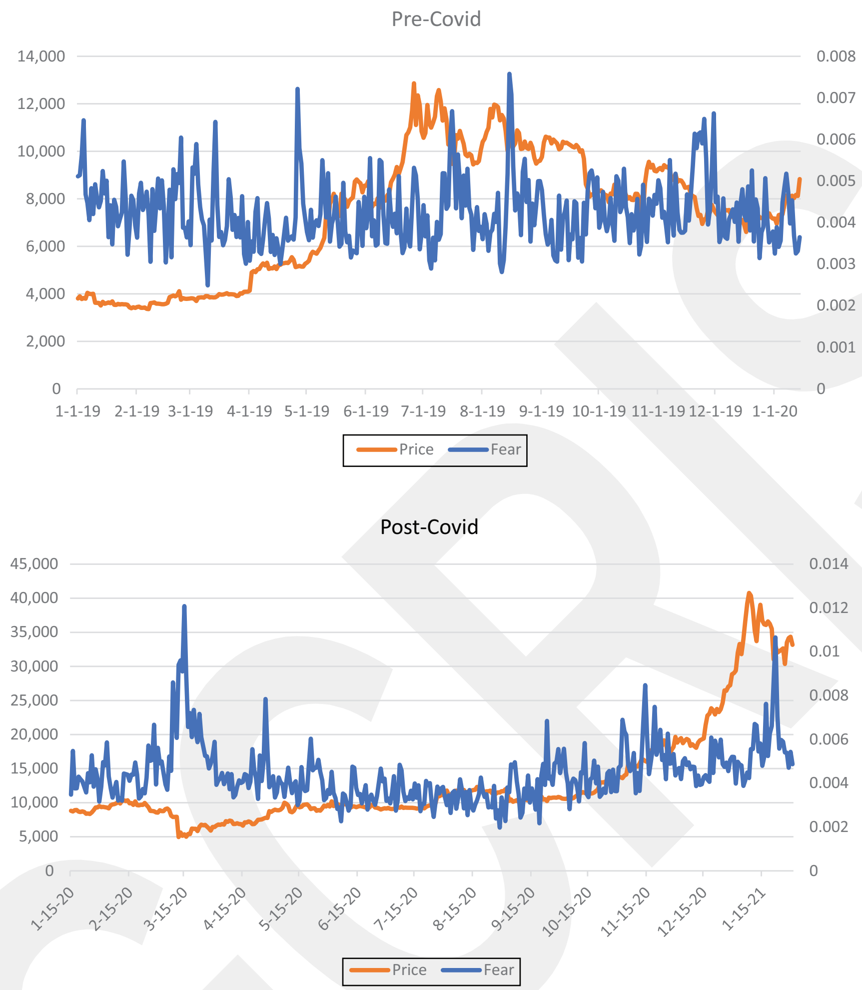

Figure 1.
Fear and BTC price (US$)

are determined by the algorithm, for all asset components, over the past 24 h. 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

Variables	Mean	SD	Min	Max	Skewness	Kurtosis
Panel A. Summary statistics for pre-COVID period						
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
Panel B. Summary statistics for the post-COVID period						
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 0.0242	0.0117	0.1055	2.0116	5.7668

Note: Pre-COVID covers the period from January 1, 2019 to March 14, 2020, post-COVID covers the period from March 15, 2019 to January 31, 2021

Table 1.
Summary statistics

that, a binary function is introduced to determine whether a Var $v \in V(t)$ is additive or subtractive as follows:

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

Finally, TRMI_t of an asset a is computed as follows:

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

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

We use bivariate VAR models given below with lag-length k, to investigate the dynamics between BTC variables and fear sentiment as follows:

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

where $Y_t = [Return, Fear]'$ is a 2×1 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 BTC return and fear sentiment.

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

where $X_t = [Transaction, Fear]'$ is a 2×1 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 BTC transaction value and fear sentiment.

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

where Z_t = [*Volatility*, *Fear*]' is a 2 × 1 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 BTC volatility and fear sentiment.

We determine the lag-length [4] using HQ Information Criteria 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).

3. Empirical results

To capture the dynamic relationship between variables we plot IRF [5]. Figures 2–4 display the orthogonalized impulse response functions of BTC return, transaction volume and BTC volatility, respectively to one-unit standard 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 BTC 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 six 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 BTC 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 BTC fluctuates as fear sentiment leads to return reversals after COVID-19 (Tetlock, 2007; Da *et al.*, 2015). This result also implies that BTC 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 BTC return in the post-COVID period more significantly (Table 3).

Figure 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

	Pre-COVID		Post-COVID	
Variables	ADF	Philips-Perron	ADF	Philips-Perron
Fear sentiment	−11.788 ***	−11.840 ***	−6.409 ***	−6.143***
BTC 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**

Notes: ***Indicates significance at 1%. ** Indicates significance at 5%. *Indicates significance at 10%. Pre- and post-COVID periods cover the dates from January 1, 2019 to March 14, 2020 and from March 15, 2020 to January 31, 2021, respectively

Table 2.
Unit root test results

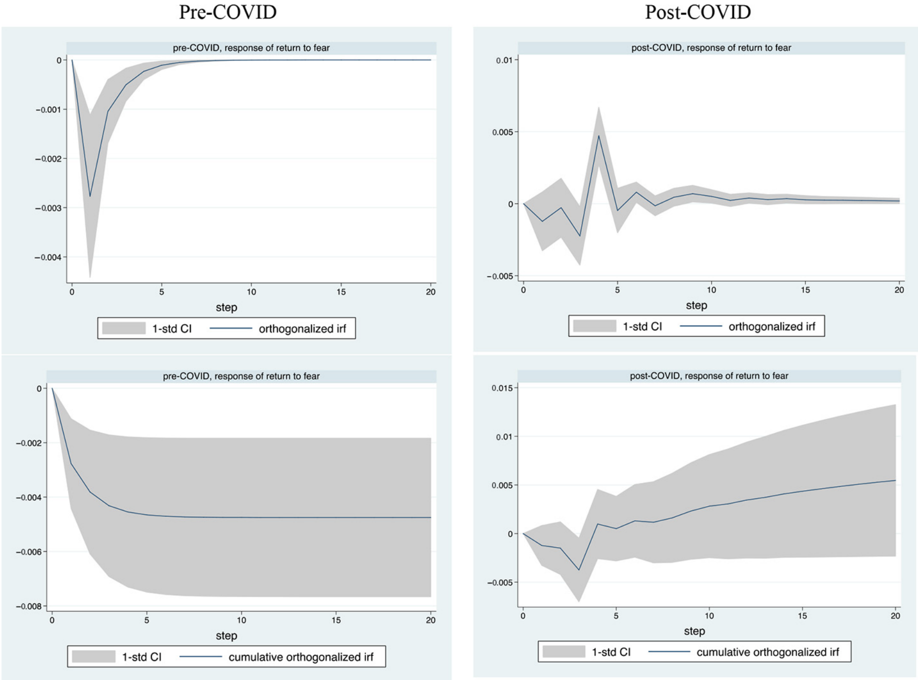

Figure 2.
Orthogonalized and cumulative IRFs for pre- and post-COVID periods of BTC return (Model 1)

Notes: This figure show the response of BTC return to a shock in fear having one-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***

Notes: ***Indicates significance at 1%. *Indicates significance at 10%. pre- and post-COVID periods cover the dates from January 1, 2019 to March 14, 2020 and from March 15, 2020 to January 31, 2021, respectively

the initial and cumulative effects are both negative. Interestingly after a few periods, transaction volume increases but reduces later and continues fluctuating 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).

Figure 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

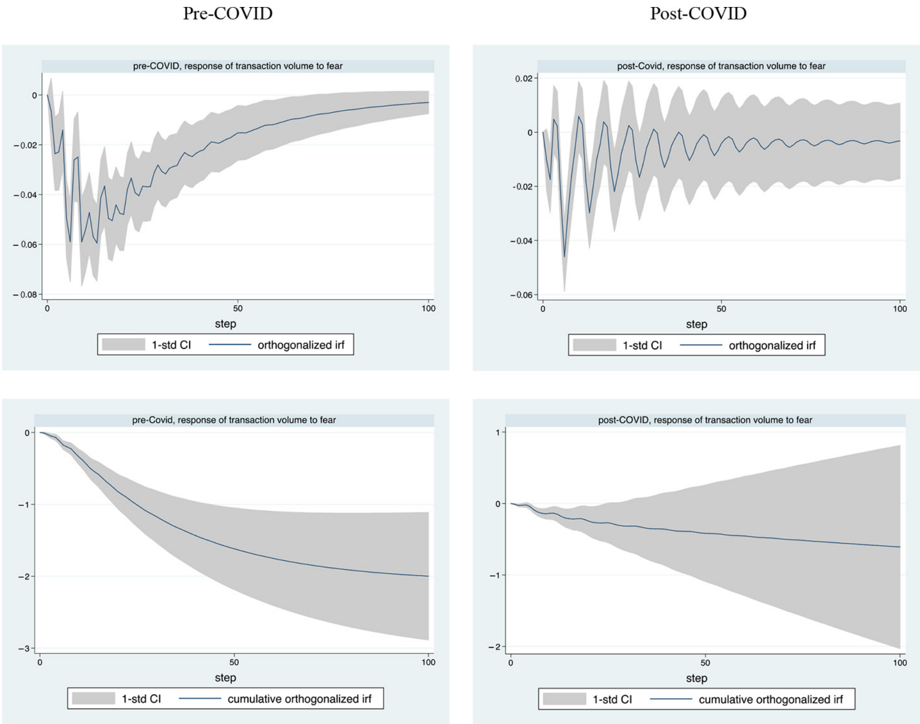

Figure 3.
Orthogonalized and cumulative IRFs for pre- and post-COVID periods of transaction volume to a shock in fear

drives investors to become more uncertain. This may lead to an increase in bid-ask spread and volatility (Lerner and Keltner, 2001).

4. Conclusions

We investigate the relationship between BTC-specific fear sentiment and BTC's return, volatility and transaction volume considering the COVID-19 pandemic driven crisis. The results show that the relationship between fear and our BTC 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 BTC 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. BTC provides a natural benchmark to understand how fear sentiment drives and impacts the markets isolated from any interventions. Focusing on BTC-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

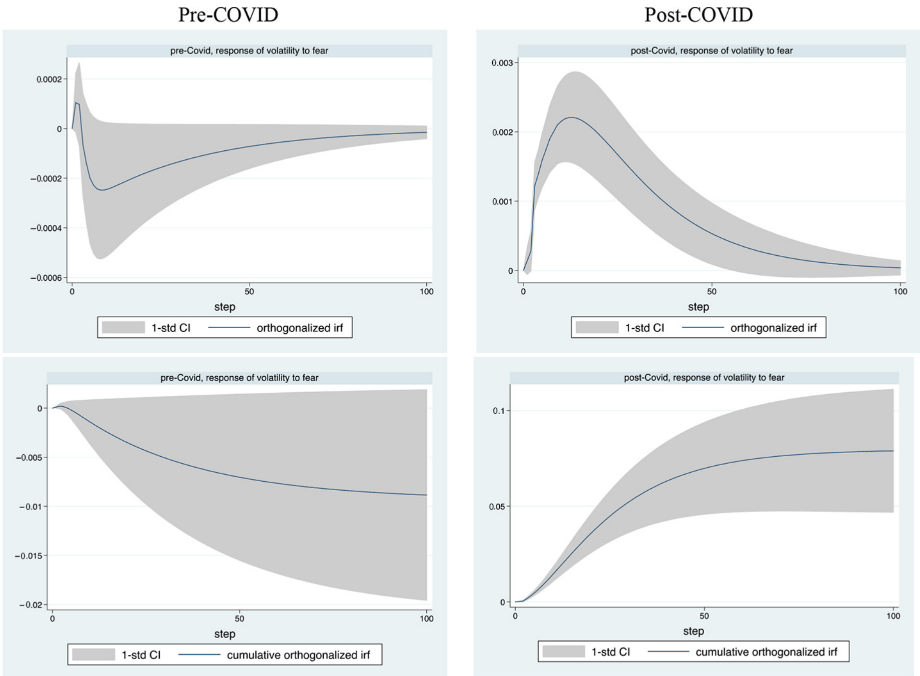

Figure 4.
Orthogonalized and cumulative IRFs for pre- and post-COVID periods of volatility to a shock in fear

confidence in markets. We also highlight the importance of using micro, asset-specific sentiment measures to capture market dynamics better.

Notes

1. The price data is obtained from coinmetrics.io
2. The sum US$ value of all native units transferred (i.e. the aggregate size in US$ of all transfers) that day.
3. Computed as the standard deviation of the daily natural log returns over 30 days.
4. The empirical results and IRFs are generated also with different lag-lengths based on other information criteria such as Akaike Infromation Criterion and Bayesian Infromation Criterion. We find qualitatively similar results.
5. See Appendix for the VAR estimation results of both subsamples.

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Further reading

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GCRS

Appendix

Variables	Pre-COVID Return$_t$	Pre-COVID Fear$_t$	Post-COVID Return$_t$	Post-COVID 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 January 1, 2019 to March 14, 2020 and from March 15, 2020 to January 31, 2021, respectively; ***Indicates significance at 1%. **Indicates significance at 5%. *Indicates significance at 10%

Table A1.
VAR estimation results for Model 1

Variables	Pre-COVID Transaction$_t$	Pre-COVID Fear$_t$	Post-COVID Transaction$_t$	Post-COVID 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 January 1, 2019 to March 14, 2020 and from March 15, 2020 to January 31, 2021, respectively; ***Indicates significance at 1%. **Indicates significance at 5%. *Indicates significance at 10%

Table A2.
VAR estimation results for Model 2

Table A3.
VAR estimation results for Model 3

	Pre-COVID		Post-COVID	
Variables	$Volatility_t$	$Fear_t$	$Volatility_t$	$Fear_t$
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 January 1, 2019 to March 14, 2020 and from March 15, 2020 to January 31, 2021, respectively; ***Indicates significance at 1%. **Indicates significance at 5%. *Indicates significance at 10%

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