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The COVID-19 pandemic, volatility, and trading behavior in the bitcoin futures market

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ABSTRACT

This paper contributes to the literature on the coronavirus (COVID-19) pandemic impacts on the Bitcoin futures (BTCF) market and to the ongoing consideration of the dynamic relationship between volatility (or returns) and trading behavior variables, such as volume and open interest as a proxy for belief dispersion. This paper focuses on the role of the unprecedented market stress induced by the COVID-19 pandemic in the interrelations among the variables. Accordingly, this paper proposes a structural change (SC)-VAR-MGARCH model and finds the COVID-19 pandemic has initiated a significant regime change. Furthermore, the relationship between the variables in the pre-pandemic regime is notably unclear, whereas an increase in belief dispersion in the pandemic regime due to market stress reduces BTCF returns but raises trading volume and volatility evidently. The outcomes in the pandemic regime are remarkably consistent with the difference of opinions model, though existing evidence on the dynamic relations is ambiguous. Moreover, the outcomes support our hypothesis that, in addition to information flows, market stress causing traders' behavioral biases should be considered as one of the crucial factors of tremendous price variability.

1. Introduction

The current coronavirus (COVID-19) pandemic forces us to live in a socio-economic situation that is rarely experienced in the past. Economic collapse and widespread financial market stress will be featured in the literature in the following years. Market stress is apparent in other financial markets, including the crypto market, though sharp price decline and tremendous equity market volatility have garnered considerable attention. COVID-19 has spread to countries outside of Mainland China. As a result, many investors switched from holding risky assets to perceived safe-haven assets due to mounting worries about the COVID-19 pandemic. Thus, worldwide equity markets that trade representative risky assets reported their largest single-week declines in the final week of February 2020 since the 2008 financial crisis. Moreover, the US equity market lost 12 percent of its value under enormous pressure.

1 I would like to express my appreciation to seminar participants at the Financial Economic Meeting for their valuable comments.

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1 The outbreak of the COVID-19 was first identified in Wuhan, China, in December 2019. The World Health Organization (WHO) declared a Public Health Emergency of International Concern on January 30, 2020, and a pandemic on March 11, 2020. As of July 8, 2020, more than 10.66 million cases of COVID-19 have been reported in more than 188 countries and territories, resulting in more than 539,906 deaths.

2 On March 19, 2020, OFR Financial Stress Index, measuring a systemic financial stress based on disruptions in the normal functioning of financial markets, hit 10.266, which is the highest since the global financial crisis. Note that it is positive when stress levels are above average, and negative when stress levels are below average.

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Certain COVID-19 pandemic impacts on financial markets (e.g., Ashraf, 2020; Shehzad et al., 2020; Harjoto et al., 2021) are concerning from the perspective of investment and risk management. Insights into futures price volatility associated with trading behavior under market stress can adversely impact financial market participants, such as speculators, hedgers, and arbitrageurs, using index futures contracts. Thus, this paper focuses on analyzing how the pandemic-induced market stress has affected the dynamic relationship between volatility and trading behavior variables. These variables include trading volume and open interest as a proxy for dispersion of traders’ beliefs on asset prices following Bessembinder et al. (1996). In the regime of market stress, traders’ biases increase with the belief that updating overreactions to news and traders with relatively different beliefs are more dominant (Basak and Atmaz, 2018). Therefore, market stress leading to the increase in belief dispersion significantly impacts the relationship between volatility and trading behavior.

In financial literature, their relationship has received significant attention from economists and market participants. Among the theoretical studies, Clark (1973) explains the relationship between volatility and trading volume through the mixture of distribution hypothesis (MDH). His findings suggest that volatility and trading volume are positively related due to its dependence on a common latent mixing variable, namely, rate of information arrival (e.g., Epps and Epps, 1976; Tauchen and Pitts, 1983; Fleming et al., 2006). The sequential information arrival model (SIAM) is another theory describing the relationship and generally considered (e.g., Copeland, 1976; Jennings et al., 1981). SIAM assumes that the sequential arrival of new information to the market generates trading volume and price movements. As a result, volatility and volume measured over the period of full response to information arrival exhibit a positive relationship. The primary implication of this model is that volatility can be potentially forecasted for the future price based on trading volume. In addition to trading volume, the information role of open interest has gained much scholarly attention because new information inflow to the market may expand the dispersion of traders’ beliefs, increasing trading volume (Kim and Verrecchia, 1991).

The theory of information-flow paradigm represented by MDH and SIAM illustrates a positive relationship between volatility, trading volume, and open interest. However, the empirical evidence is ambiguous or conflicting. For instance, various studies reveal ambiguous and negative relationships between these variables. Galati (2000); Liesenfeld (2001); Amatyakul (2010), and Park (2011) among others present the evidence of a negative relationship between volatility and trading volume, Bessembinder and Seguin (1993); Diether et al. (2002), and Yu (2011) among others also identify that the relationship of other variables can be negative. Other researchers argue that the relationship changes over time and relies on strategies and certain characteristics (e.g., Admati and Pfleiderer, 1988; Doukas et al., 2006; Avramov et al., 2009; Czudaj, 2019). Admati and Pfleiderer (1988) assert that the relationship of volume and volatility depends on a strategic trading behavior of informed and liquidity traders. Czudaj (2019) emphasizes that the relationship between trading volume, volatility, and open interest in agricultural futures markets varies substantially over time. Volatility is driven by previous periods’ trading volume and open interest, whereas the reversed relationship from lagged volatility to trading volume and open interest is limited to certain periods. In sum, the mixed empirical evidence indicates that information flows are not the only potential factor for price variability but also other crucial factors that should not be overlooked.

This study aims to gain further insights into the feasible reasons for the drastic increase in volatility in financial markets during the COVID-19 pandemic. This paper concentrates on pandemic-induced market stress, its impact on trading behavior variables, such as volume and open interest, and the relationships of these variables with return volatility. Accordingly, this paper considers the Bitcoin futures (BTCF) market for empirical analysis, proposes a SC-VAR-MGARCH model incorporating a structural changing vector autoregressive (Sims, 1980) with multivariate GARCH effects (Bollerslev, 1986) and introduces a two-step estimation method. The multivariate model is set up to consider certain properties of the BTCF market. Risks of the COVID-19 pandemic prevail in this market, i.e., volatility clustering in trading behavior variables and returns, dynamic relations, and expected structural break.

Hence, this paper contributes to the literature in several ways. First, to the best of the author’s knowledge, this study is the first to explore the impacts of pandemic-induced market stress on the dynamic relationship between the variables in futures markets. This study is significant in the literature as the ongoing COVID-19 pandemic raises concerns about future market stress under greater economic costs and uncertainty. Second, this study discovers volatility dynamics in BTCF returns relative to trading behavior under extreme market stress. Expanding the understanding of volatility sources in the BTCF market could lead to superior trading and portfolio management strategies. Third, previous studies (e.g., Thies and Molnár, 2018; Ardia et al., 2019; Koutmos, 2020) have found that Bitcoin exhibits regime-switching behavior and pointed out that ignoring regime changes in volatility dynamics can lead to biased estimation results in volatility models. Similarly, this study investigates whether the COVID-19 pandemic resulted in further regime changes. For this investigation, this paper suggests a suitable test method, proposed by Ross (2015), as it considers the model

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3 Open interest is sometimes confused with trading volume, but the two terms refer to different measures. That is, trading volume is widely known to represent the number of contracts traded in a specific period, whereas open interest is the number of outstanding traded contracts at a time point.

4 For our empirical analysis on the effects of the COVID-19, the BTCF market is well suited because of several reasons. First, despite the short COVID-19 period, it has a relatively sufficient accumulation of data compared to other asset markets due to the nature of trading worldwide around the clock (24 hours/7 days) in multiple online exchanges. Second, trading behavior such as volume and open interest are closely linked to demand for speculation and hedging of futures contracts (Bessembinder and Seguin, 1993; Lucia and Pardo, 2010) that are well represented in the BTCF market (Jena et al., 2018). Third, empirical studies (e.g., Fassas et al., 2020) show that the BTCF market has a greater influence on the value of the Bitcoin than the BTC market, implying the futures dominance in the case of Bitcoin. Fourth, crypto markets including the BTCF market do not involve financial institution intermediaries and are linked to the peer-to-peer transactions which reduce transaction costs (Fang et al., 2021). This means that crypto markets are liable to attract speculative interest and reveal traders’ behavioral biases (e.g., Kallinterakis and Wang, 2019). Fifth, crypto markets have gained both market value and academic attention.
Table 1
Descriptive statistics of daily returns ($r_t$), volatility ($\theta_t$), log-volume ($LV_t$) and log-open interest ($LO_t$) for Bitcoin Futures (BTCF).

| Statistics         | Returns ($r_t$) | Volatility ($\theta_t$) | Log-volume ($LV_t$) | Log-open interest ($LO_t$) |
|--------------------|-----------------|--------------------------|---------------------|-----------------------------|
| Minimum            | $-50.1851$      | 0.0107                   | 1.9459              | 4.4921                      |
| Maximum            | 15.5183         | 62.8833                  | 9.1586              | 8.2533                      |
| Mean               | $-0.0115$       | 3.2149                   | 5.0824              | 6.9734                      |
| Median             | $-0.0905$       | 1.9272                   | 5.1445              | 7.6158                      |
| Variance           | 21.9485         | 24.0996                  | 1.5977              | 1.3879                      |
| Skewness           | $-4.5534$       | 7.6675                   | $-0.0895$           | $-0.7315$                   |
| Kurtosis           | 51.5940         | 85.8995                  | $-0.0335$           | $-1.1177$                   |
| JB                 | 28,963***       | 80,309***                | 0.3387              | $-35.2260$***               |
| Q(5)               | 29.18***        | 18.74***                 | 516.84***           | 1174.9***                   |
| Q(10)              | 32.48***        | 28.16***                 | 908.62***           | 2258.3***                   |

Notes: Skewness and Kurtosis are coefficients of skewness and kurtosis, respectively. JB is the Jarque-Bera normality test, Q(M) is the Ljung-Box Q statistics at lag M. Significance levels ($p$-values) are in parentheses, and asterisks *** denote statistical significance at the 1% level.

The rest of this paper is outlined as follows. Section 2 describes data set and preliminary statistics. Section 3 introduces an empirical methodology, including the SC-VAR-MGARCH model and a two-step estimation method. Section 4 runs a test for detecting a structural change caused by the COVID-19 pandemic and provides empirical evidence of the interrelations among volatility, trading volume, and belief dispersion. Then, the feasibility of the econometric model is derived. Finally, Section 5 provides conclusions and suggestions for further work.

2. Data and preliminary statistics

This paper collected data from the Bitfinex exchange using the exchange API from October 29, 2019 to July 5, 2020. The Bitfinex exchange records individual trades for BTCF contracts in real time. Thus, trade-level data match our research purpose to analyze the impact of pandemic-induced market stress on trading behavior and dynamic volatility. In addition, the exchange has the largest volumes of BTC/BTCF–USD exchanges during the selected period and provides data of continuous futures price and trade series. The variables in the daily data are closing BTCF price, trading volume, and open interest.

To avoid problems arising from the non-stationary state usually observed in asset prices, we take the natural logarithmic differences between two successive trading days. Let $p_t$ be the price at time $t$, then the log differences of prices are defined as BTCF returns, $r_t = \ln (p_t/p_{t-1}) \cdot 100$. Following Schwert (1990) and Cao and Tsay (1993), the volatility of the BTCF returns ($\theta_t$) is estimated by the absolute value of returns minus its mean ($\mu_r$), pre-multiplied by $\sqrt{\pi/2}$: $\theta_t = \sqrt{\pi/2} |r_t - \mu_r|$.

As in the previous literature, the trading volume and open interest series are converted into logarithms, i.e., log-volume ($LV_t$) and log-open interest ($LO_t$), to stabilize their variability and to reduce the non-normality of their distribution. Table 1 sets out some summary statistics and preliminary test for the BTCF returns, volatility, trading volumes, and open interest. In particular, both return and volatility series exhibit highly dynamic movements and include the extreme values that may be created from the COVID-19 pandemic in terms of their major descriptive statistics such as minimum and maximum values, means and standard deviations.

Sample distributions of return and volatility series are quite skewed and highly leptokurtic, and for all the series the Jarque-Bera test statistics firmly reject the null hypothesis of normality. The Ljung-Box Q test statistics for five and ten lags are also significant suggesting the presence of significant serial correlation in all the series, implying that they tend to be clustered together over time. In particular, the high correlation in the volume and open interest series indicates that the rate of information arrival is serially correlated and supports the validity of the MGARCH-type model proposed in this paper.

The first panel of Fig. 1 shows the dynamic movements of the returns and the second panel exhibits turbulent volatility during the pandemic period. This turbulence was likely caused by market stress that probably formed under high uncertainty in the BTCF market, leading to the more dispersion of traders’ belief and their overreaction to news, when the pandemic crisis introduced a shock to the market. The most conspicuous feature in Fig. 1 is that all series including the trading activity series do show up clear distinction in behavior between the pre-pandemic and the pandemic periods. This distinction implies primarily that we should make inference of a regime change in the BTCF market due to the COVID-19 pandemic.

---

5 For validity of our empirical analysis, the sample spans the period so that the two subperiods before and after the pandemic declaration are similar.

6 For reference, the Chicago Board of Exchange (CBOE) introduced the first financial derivatives tied to Bitcoin on December 10, 2017 and a week later the Chicago Mercantile Exchange (CME) launched its own Bitcoin futures product.
3. Methodology

3.1. Econometric models: SC-VAR-MGARCH models

After Sims’ (1980) pioneering work, the VAR model has become the most popular among multivariate time-series models for correlated series, e.g., returns, volatility, and trading behavior series in the BTCF market. However, the VAR model is useful only for modeling the first-order moment of the series and presupposes the implausible assumption of a constant variance. Thus, the VAR model is extended by employing a class of stochastic process called MGARCH for the inherent conditional heteroscedasticity and correlation structures of its residuals, which may change over time (Ku, 2008; Carnero and Eratalay, 2013).

Hence, the dynamics of the relationship between future returns, open interest, and trading volume can be modeled using the following SC-VAR-MGARCH model. This model combines the VAR model and MGARCH-DCC model (Engle and Sheppard, 2001; Engle, 2002) with structural changes. The concept of the MGARCH-DCC models implies that the conditional covariance matrix, $H_t$, can be decomposed into conditional standard deviations, $D_t$, and correlation matrix, $R_t$, which are time-varying.

![Fig. 1. Daily returns ($r_t$), volatility ($\theta_t$), log-volume ($LV_t$) and log-open interest ($LO_t$) for Bitcoin Futures (BTCF).]
Conditionally on regime $s_t = k$ and information set $\phi_{t-1}$, we specify the SC-VAR-MGARCH model as:

$$Y_t^k(s_t = k, \phi_{t-1}) = C^k + B_k^Y Y_{t-1}^k + \ldots + B_p^k Y_{t-p}^k + e^k_t$$

Where $Y_t^k = (y_{1t}^k, \ldots, y_{nt}^k)'$ is a $n \times 1$ vector at time $t$, $n$ is the number of series, $s_t$ is a state variable with a number of states $K$. $C^k$ is a $n \times 1$ vector of constants, $e_t^k$ is a $n \times 1$ vector of error terms, and $B_p^k$ is a $n \times n$ matrix of autoregressive coefficients as follows:

$$B_p^k = \begin{pmatrix} B_{p,11}^k & B_{p,12}^k & \cdots & B_{p,1n}^k \\ B_{p,21}^k & B_{p,22}^k & \cdots & B_{p,2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ B_{p,n1}^k & B_{p,n2}^k & \cdots & B_{p,nn}^k \end{pmatrix}$$

In regime $k$, the error terms $e_t^k$ is defined as:

$$e_t^k = \sqrt{H_t^k} \epsilon_t^k$$

Where $H_t^k$ is a $n \times n$ matrix of conditional variances of $e_t^k$ at time $t$, $\epsilon_t^k$ is a $n \times 1$ vector of i.i.d. errors such that $E(\epsilon_t^k) = 0$ and $E(\epsilon_t^k \epsilon_t^k') = \sigma^2 I_n$. $\sqrt{H_t^k}$ is a $n \times n$ positive definite matrix at time $t$ and may be obtained by a Cholesky factorization of $H_t^k$. Note that $H_t^k$ can be decomposed as follows:

$$H_t^k = D_t^k R_t^k D_t^k$$

Where $D_t^k$ is a $n \times n$ diagonal matrix of conditional standard deviation and $R_t^k$ is a positive definite correlation matrix that allows to be time-varying with dynamic movement (Engle, 2002). The elements of $H_t^k$ is

$$[H_t^k]_{ij} = \rho^k_{ij} \sqrt{h_{ii}^k h_{jj}^k}$$

And $\rho^k_{ii} = 1$, $i = 1, ..., n$. The elements in the diagonal matrix $D_t^k$ are conditional standard deviations:

$$D_t^k = \begin{pmatrix} \sqrt{h_{11}^k} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22}^k} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{h_{nn}^k} \end{pmatrix}$$

The conditional variance $h_{ii}^k$ is specified as the following GARCH(1,1) model in a vector form:

$$h_{ii}^k = \alpha^k + \beta^k (e_{i,i-1}^k)^2$$

Where $h_t^k = (h_{11}^k, \ldots, h_{nn}^k)'$, $e_{i,i-1}^k = (e_{1,i-1}^k, \ldots, e_{n,i-1}^k)'$, and $d^k$ is a $n \times 1$ vector and $\alpha^k$, $\beta^k$ are $n \times n$ matrices of coefficients.

In case of DCC, the conditional correlation matrix $R_t^k$ is time varying and is denoted as:

$$R_t^k = \begin{pmatrix} 1 & \rho_{12}^k & \cdots & \rho_{1n}^k \\ \rho_{21}^k & 1 & \cdots & \rho_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1}^k & \rho_{n2}^k & \cdots & 1 \end{pmatrix}$$

Where $R_t^k$ is decomposed into:

$$R_t^k = diag(Q_t^k)^{-1/2} Q_t^k diag(Q_t^k)^{-1/2}$$

$$Q_t^k = (1 - d^k - b^k) \overline{Q} + d^k \sqrt{z_{t-1}^k} \epsilon_{t-1}^k + b^k Q_{t-1}^k$$

Where $d^k$ and $b^k$ are scalars including 0 and must be satisfied of $d^k + b^k < 1$ to bound stationarity and $\overline{Q}$ is the unconditional covariance matrix of the standardized errors $\epsilon_t^k = (H_t^k)^{-1/2} \epsilon_t^k$. 



3.2. Estimating the SC-VAR-MGARCH model in two steps

This paper presents SC-VAR-MGARCH models to investigate structural changes and trading behavior in the BTCF market. Under general conditions (Engle and Sheppard, 2001), we conduct estimation methods to allow for two-step estimation. In the first step, a structural change caused by the COVID-19 pandemic is detected. In the second step, the parameters of the SC-VAR-MGARCH model are estimated using the structural break point estimate from the first step.

3.2.1. First step: detection of structural breaks

This paper uses the Ross’s (2015) test method to detect a structural change in the return series caused by the COVID-19 pandemic. The test method accounts for unknown structural changes and thus has important advantages to our analysis. Moreover, the method can not only detect structural changes in the first-order moment but also in the second-order moment of non-Gaussian sequences.

The test method generally assumes a fixed sequence of T observations \( x_1, \ldots, x_T \) from the random variables \( X_1, \ldots, X_T \). These random variables may contain at least one state changes in the probability distribution at the unknown change points \( \delta_1, \delta_2, \ldots, \delta_{K-1} \). Then, \( K \) is a finite number of states. If structural change points do not exist, then the observation sequence is independent and identically distributed according to a distribution, denoted by \( F_0 \). In contrast, if structural changes are present, then the observation sequence after the structural change point is distributed as \( F_1 \).

\[
X_i \sim \begin{cases} 
F_0 & \text{if } i \leq \delta_1 \\
F_1 & \text{if } \delta_1 < i \leq \delta_2 \\
\vdots \\
F_{K-1} & \text{if } \delta_{K-1} < i \leq T 
\end{cases}
\]  
\[(10)\]

Where the \( F_i \) stands for the distribution in each segment.

The following hypotheses can be established to test whether a structural change occurs immediately after a particular observation \( \omega \):

\[
H_0 : X_i \sim F_0(x; \psi_0), \ i = 1, \ldots, T \\
H_1 : X_i \sim \begin{cases} 
F_0(x; \psi_0), & i = 1, \ldots, \omega \\
F_1(x; \psi_1), & i = \omega + 1, \ldots, T 
\end{cases}
\]  
\[(11)\]

Where \( \psi_i \) is the potentially unknown parameters of each distribution. This set-up becomes a standard problem that can be solved by a two-sample hypothesis test with test statistic \( S_{\omega,T} \). In other words, when \( S_{\omega,T} \) is greater than the value of an appropriately chosen threshold \( \pi_{\omega,T} \), we reject the null hypothesis that the two samples have identical distributions. Thus, we can conclude that a structural change point has occurred immediately after observation \( x_{\omega} \). Therefore, for all points \( \omega \ (1 < \omega < T) \), the test statistic \( S_{\omega,T} \) is evaluated, and a point \( \omega \) with a maximum value is considered as the structural break point.

The test statistic is defined as:

\[
S_T = \max_{\omega=2}^{\omega=T-1} S_{\omega,T} = \max_{\omega=2}^{\omega=T-1} \left| \frac{\bar{S}_{\omega,T} - \mu^\prime_{\omega,T}}{\sigma^\prime_{\omega,T}} \right|
\]  
\[(12)\]

Where \( S_{\omega,T} \) are obtained from standardization of \( \bar{S}_{\omega,T} \) that have the means \( \mu^\prime_{\omega,T} \) and the standard deviations \( \sigma^\prime_{\omega,T} \). Since it is assumed that the change point is unknown in advance, Ross (2015) suggests immediately following the value of \( \omega \) that maximizes \( S_T \) as the best estimate of the change point location:

\[
\tilde{\omega} = \arg \max_{\omega} S_{\omega,T}
\]  
\[(13)\]

3.2.2. Second step: estimation of the SC-VAR-MGARCH model

Given the estimates of break points in the first step, the SC-VAR-MGARCH model can be estimated using maximum likelihood. In practice, since there are too many parameters in the model, for compactness let’s define the following vector of the parameters in the model:

\[
(\Psi^k | k = k) = (A^k, \Pi^k, \Phi^k)
\]  
\[(14)\]

Where

\[\text{The threshold is chosen to limit the Type I error rate } \alpha, \text{ like the standard statistical hypothesis test. That is, } \alpha \text{ is the probability of incorrectly deciding that a change has occurred if no change has actually occurred. In this context, } x_{\omega,T} \text{ must be chosen as the upper } \alpha \text{ quantum of the } S_{\omega,T} \text{ distribution in the null hypothesis.}\]
Note: The data of OFR Financial Stress Index (FSI) are obtained from Office of Financial Research, U.S. Department of the Treasury (www.financialresearch.gov/financial-stress-index).

### Table 2

Descriptive statistics for each regime.

| Statistics | Regime I (pre-pandemic) | Regime II (pandemic) |
|------------|-------------------------|----------------------|
| Minimum    | −5.8947                 | −50.1851             |
| Maximum    | 8.7844                  | 15.5183              |
| Mean       | −0.0299                 | 0.0080               |
| Variance   | 7.3506                  | 37.5802              |
| Skewness   | 0.4627                  | −4.2323              |
| Kurtosis   | 0.7589                  | 6.2074               |

Where $\Psi^k$ is the vector of parameters in the mean equation (Eq. 1), $\Pi^k$ is the vector of parameters in the conditional variance equation (Eq. 7), $P^k$ is the vector of parameters in the conditional correlation equation (Eq. 9), the vec operator is the vectorization of the indicated matrix, and the vech operator is the vectorization of the lower triangular part of the indicated matrix.

Under the assumption of a normal distribution of error terms in the models, the conditional MLE (maximum likelihood estimator) of $\Psi^k$ on $s_t = k$ should be derived by maximizing the multivariate Gaussian log-likelihood function:

$$L(\Psi^k)(s_t = k) = \frac{T_k n}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T_k} \left( \ln |H_t^k| + \epsilon_t^k H_t^{-1} \epsilon_t^k \right)$$

(15)

Where $T_k$ is the number of observations in regime $k$ ($t = 1, 2, \ldots, T_k$). From Eq. 4, the equation can be rewritten as

$$L(\Psi^k)(s_t = k) = \frac{T_k n}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T_k} \left( \ln |D_t^k R_t^k D_t^k| + \epsilon_t^k (D_t^k R_t^k D_t^k)^{-1} \epsilon_t^k \right)$$

$$= \frac{T_k n}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T_k} \ln |R_t^k| - \frac{1}{2} \sum_{t=1}^{T_k} \ln |D_t^k| - \frac{1}{2} \sum_{t=1}^{T_k} w_t^k R_t^{-1} w_t^k$$

(16)

Where $w_t^k = D_t^{-1} \epsilon_t^k$ are the standardized errors.

### 4. Empirical analysis

The COVID-19-induced market stress has created unprecedented volatility that may be closely linked to trading behavior variables, such as open interest as a proxy for belief dispersion. Traders with relatively different beliefs are dominant in the regime of market stress because their biases increase with the belief updating to respond to news (Basak and Atmaz, 2018). Therefore, in the context of the COVID-19-induced market stress, we investigate the dynamic relationships between returns, volatility, and trading behavior variables in the BTCF market using the SC-VAR-MGARCH model and Granger causality tests.

#### 4.1. Detecting a structural break initiated by the COVID-19 pandemic

This subsection focuses on whether the COVID-19 pandemic has initiated a structural change by applying the test method introduced in subsection 3.2.1. to detect a structural change in the returns series of the BTCF. As mentioned above, the test method does not require a known break point and prior distribution parameter information in various regimes. We implement the test and estimate the change point location. The test statistic $S_T$ is 17.2084, which is greater than the value of an appropriately chosen threshold. Thus, we reject the null hypothesis of no structural change. The value of $\omega$ that maximizes $S_T$ is 129, which is the best estimate of the change point location. In other words, the date of the estimated change point is March 5, 2020. This date is a few days ahead of the date when the COVID-19 pandemic was declared, which may be a potential date of structural break.

Table 2 shows summary statistics for each regime. While Regime I can be regarded as a normal situation with volatility up to 11.0240, Regime II is a pandemic situation, which is a very stressful with volatility up to 62.8833. It is worthwhile to note that in...
Table 3
ARCH(M) tests for the residuals obtained from VAR models.

| VAR models                  | Regime I (pre-pandemic) | Regime II (pandemic) |
|-----------------------------|-------------------------|----------------------|
|                             | Test statistics         | p-values             | Test statistics         | p-values             |
| $p_k^D$                      | (18)                    |                      | (17)                    |                      |
| Multivariate ARCH(5)        | 268.86***               | 0.0000               | 367.74***               | 0.0000               |
| Multivariate ARCH(10)       | 424.31**                | 0.0109               | 464.17***               | 0.0001               |
| Av. Log-Likelihood          | -2.98                   |                      | -2.34                   |                      |
| Multivariate ARCH(5)        | 243.94***               | 0.0010               | 375.38***               | 0.0000               |
| Multivariate ARCH(10)       | 417.30**                | 0.0198               | 435.36***               | 0.0039               |
| Av. Log-Likelihood          | -2.72                   |                      | -2.51                   |                      |

Notes: DLO$_t$ = detrended log-open interest, DLV$_t$ = detrended log-volume, ARCH(M) is the LM test statistics for ARCH test at lag M. Significance levels (p-values) are in parentheses. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Regime II the returns distribution has severe non-normality with skewness and kurtosis of -4.2323 and 35.2244, respectively, and despite the higher means of log-volume (LV$_t$) and log-open interest (LO$_t$), their variability is relatively low compared to Regime I. In addition, the OFR Financial Stress Index (FSI) can be used to more objectively identify the differences of market stress between the two regimes and the data of OFR Financial Stress Index (FSI) are obtained from Office of Financial Research, U.S. Department of the Treasury over the same period. The average FSI for Regime I is low at -3.2783, whereas for Regime II is 3.5203 and reached a maximum of 10.266 on March 19. This indicates that the market turmoil of Regime II is closely related to financial stress.

4.2. Estimation results

We estimate the SC-VAR(1)-MGARCH(1,1) model given the detected break point as follows:

$$Y^X_t(k= 1, 2; \phi_{-1}) = C + B^Y_{t-1} + \epsilon_t$$

(17)

Where $Y^X_t = (r^X_t, DLO^X_t, DLV^X_t)$ or $(\delta^X_t, DLO^X_t, DLV^X_t)$, and $DLO^X_t =$ detrended log-open interest, $DLV^X_t =$ detrended log-volume, the conditional variance of the error terms $\epsilon_t$ is defined as a GJR-GARCH model to consider asymmetric volatility:

$$h^X_t = \alpha + \alpha_i (\epsilon^2_{t-1} \delta^2_{t-1}) + \gamma (\epsilon^2_{t-1} \delta^2_{t-1}) I_{-1}(\epsilon^2_{t-1} < 0) + \beta h^X_{t-1}$$

(18)

Where $I_{-1}$ is an indicator function, i.e., $I_{-1} = 1$ if $\epsilon^2_{t-1} < 0$, $I_{-1} = 0$ otherwise. Orders of the model are determined to minimize the value of SIC criterion and to avoid over-parameterization leading to converging problems.

Multivariate ARCH tests for the residuals obtained from VAR models are performed first to determine the validity of this model. Table 3 shows that the test statistics for 5 and 10 lags are significantly large to indicate the presence of ARCH effects. These results explicitly indicate the need for further use of the MGARCH-type model to expand the understanding of the series relations. In addition, the strong ARCH effects in all specifications of each regime should be closely related to the time series dependence of the trading behavior variables shown in the previous data analysis.

The empirical results for the SC-VAR(1)-MGARCH(1,1) models of $Y^X_t = (r^X_t, DLO^X_t, DLV^X_t)$ and $Y^X_t = (\delta^X_t, DLO^X_t, DLV^X_t)$ are provided in Tables 4 and 5, respectively. This study mainly examines how the time-varying relationship between returns (or volatility), trading volume, and open interest reacts to the COVID-19 pandemic. Therefore, the results of regime I (pre-pandemic) and regime II (pandemic) must be compared. Table 4 indicates that returns and trading behavior in regime I have no significant relationship,

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8 Clear identification of financial market stress is challenging due to the difficulty in measuring sentiment in markets. In that perspective, the use of OFR Financial Stress Index, which measures disruptions in the normal functioning of financial markets as a systemic financial stress, can be an alternative solution to the problem of identifying market stress. The OFR FSI is constructed from 33 financial market variables, such as yield spreads, valuation measures, and interest rates.

9 According to existing studies (e.g., Najand and Yung, 1991), when contemporary relationships are considered in the GARCH-type models, the estimates might suffer from simultaneity bias because the variables are endogenous as in theoretical models based on information flow. Hence, this study does not reflect contemporary relationships.

10 Some empirical studies (e.g., Bessembinder and Seguin, 1993; Galati, 2000) distinguish the variables of volume and open interest into the expected and unexpected parts. As far as the author knows, however, there is no existing theoretical analysis to distinguish the variables into the expected and the unexpected parts. Furthermore, this study focuses on how behavioral biases due to COVID-19 pandemic affect the relationship between volatility and the variables that include all information on trading behavior such as serial correlation. Therefore, in order not to obscure the point, it is not necessary to divide the variables into the expected and the unexpected parts in this paper.

11 As in existing literature (Galati, 2000; Park, 2010; Czudaj, 2019, etc.), it is necessary to filter out trends that are present in the time series of the trading volume and open interest.
whereas one lagged trading volume negatively affects returns and one lagged return negatively affects open interest in regime II. As mentioned above, the relationships are theoretically controversial. When traders have rational expectations and use prices correctly, open interest acting as a proxy for the dispersion of traders’ beliefs and trading volume are positively related to expected returns and volatility. By contrast, when traders do not use the price or have behavioral biases, as in a difference of opinions model (Bessembinder et al., 1996), these relationships are reversed (Diether et al., 2002; Yu, 2011). Therefore, the latter interprets that these relationships are negatively significant in regime II (pandemic) due to behavioral biases, such as overreaction to COVID-19-related news, in contrast to regime I (pre-pandemic) in which the relationships are not significant.

The peculiarity that the relationship between volatility and trading behavior differs in the two regimes is also confirmed in Table 5. Trading behavior variables have no significant relation to volatility in Regime I. However, one lagged open interest and trading volume positively influence volatility, and one lagged volatility positively influences open interest in Regime II. In line with the difference of opinions model, belief dispersion is a crucial factor and may reflect information asymmetry or information uncertainty. Therefore, an increase in belief dispersion reduces BTCF prices but contributes to higher volatility. Despite conflicting claims about the relationship between returns (or volatility) and trading behavior, the increase of belief dispersion is known to mostly raise trading volume (Goetzmann and Massa, 2005), and the estimates of the relevant coefficients are also consistent with this. According to estimates of GARCH parameters (\( \alpha, \beta, \gamma \)), all series for the sample period in Regime II tend to be more clustered over time and to have the greater persistence of shocks as compared with the sample period in Regime I. Overall, it can be assured that pandemic-induced market stress plays a significant role in trading behavior variables and their correlations to returns and volatility on the BTCF market.

As a next step, to clarify the causal relationship between the variables, Granger causality tests are implemented and reported in Table 6. In Regime I, returns do not Granger-cause trading volume/open interest nor does it cause a reverse relationship at conventional levels of significance. Whereas in Regime II, returns Granger-causes trading volume/open interest and trading volume Granger-causes returns at conventional levels of significance. Using volatility instead of returns, their causal relationship becomes more significant. Further, a bi-directional causality relationship between volatility and trading volume/open interest in Regime II presumably support our intuition based on the difference of opinions model that severe market stress caused by the COVID-19 pandemic might generate the trader’s behavioral biases, leading to a drastic change in the causal relations of the variables.

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**Table 4**
The dynamic relations between returns \( r_t \) and trading variables such as \( DLO_t \) and \( DLV_t \) in the BTCF market: Parameter estimates of the SC-VAR-MGARCH Model of \( Y^t = (r^t, DLO^t, DLV^t) \)

| Parameters | Regime I (pre-pandemic) | Regime II (pandemic) |
|------------|-------------------------|----------------------|
|            | Estimates | p-values | Estimates | p-values |
| \( r_t \)  |           |          |           |          |
| \( c \)    | \(-0.0438\) | 0.8366   | \(-0.5472\) | 0.2805   |
| \( B_r \)  | \(-0.1468\) | 0.1553   | \(-0.4076^{***}\) | 0.0000   |
| \( B_{DLO} \) | \(0.3935\) | 0.6141   | \(0.6534\) | 0.5438   |
| \( B_{DLV} \) | \(0.0356\) | 0.9372   | \(-1.9260^{***}\) | 0.0014   |
| \( d \)    | \(5.8526\) | 0.1256   | \(1.6157\) | 0.3592   |
| \( \alpha \) | \(0.0000\) | 1.0000   | \(0.6678^{***}\) | 0.0000   |
| \( \beta \) | \(0.0476\) | 0.9358   | \(0.6750^{***}\) | 0.0000   |
| \( \gamma \) | \(0.3096\) | 0.2805   | \(-0.6877^{***}\) | 0.0000   |
| \( c \)    | \(-0.4083^{***}\) | 0.0012   | \(-0.3498\) | 0.1887   |
| \( B_{DLO} \) | \(1.0000^{***}\) | 0.0000   | \(0.9693^{***}\) | 0.0000   |
| \( B_r \)  | \(0.0007\) | 0.6011   | \(-0.0010^{**}\) | 0.0213   |
| \( DLO_t \) |           |          |           |          |
| \( B_{DLV} \) | \(0.0150\) | 0.1262   | \(0.0028\) | 0.3918   |
| \( d \)    | \(0.0030^{***}\) | 0.0049   | \(0.0001^{**}\) | 0.0109   |
| \( \alpha \) | \(0.0602\) | 0.8053   | \(0.0000\) | 1.0000   |
| \( \beta \) | \(0.3556^{**}\) | 0.0279   | \(0.5969^{***}\) | 0.0000   |
| \( \gamma \) | \(1.0000\) | 0.1033   | \(0.8041^{*}\) | 0.0505   |
| \( c \)    | \(-0.0135\) | 0.9041   | \(-0.0160\) | 0.9312   |
| \( B_{DLV} \) | \(0.3509^{***}\) | 0.0005   | \(0.5936^{***}\) | 0.0000   |
| \( B_r \)  | \(-0.0169\) | 0.4675   | \(-0.0020\) | 0.9250   |
| \( DLV_t \) |           |          |           |          |
| \( B_{DLO} \) | \(1.3414^{***}\) | 0.0000   | \(1.1947^{***}\) | 0.0079   |
| \( d \)    | \(0.5568^{***}\) | 0.0092   | \(0.0067\) | 0.4545   |
| \( \alpha \) | \(0.3646\) | 0.1714   | \(0.0011\) | 0.8526   |
| \( \beta \) | \(0.0000\) | 1.0000   | \(1.0000^{***}\) | 0.0000   |
| \( \gamma \) | \(-0.2497\) | 0.3355   | \(-0.0338\) | 0.4394   |
| \( DCC \)  |           |          |           |          |
| \( a \)    | \(0.0560\) | 0.2809   | \(0.0079\) | 0.6294   |
| \( b \)    | \(0.5283^{***}\) | 0.0001   | \(0.7324^{***}\) | 0.0000   |
| \( Av. \lnL \) | \(-2.63\) |          | \(-1.94\) |          |

**Notes:** \( DLO_t \) = detrended log-open interest, \( DLV_t \) = detrended log-volume, \( Av. \lnL \) represents the mean value of the maximized log-likelihood function, asterisks ‘*, **, and ***’ denote statistical significance at the 10 %, 5%, and 1% levels, respectively.
Turning to dynamic conditional correlations (DCC) between returns/volatility and trading behavior variables, we find that since the sum of estimates of DCC parameters $\theta$ and $\phi$ for each specification is less than 1 in Tables 4 and 5, the correlation itself is mean reverting and it fluctuates around the unconditional correlation. That is, $\theta + \phi = 0.5843$ for Regime I and 0.7403 for Regime II in the model of $Y_k = (r_k^*, \ DLO_k, DLV_k^*)$. On the other hand, $\theta + \phi = 0.0592$ for Regime I and 0.0298 for Regime II in the model of $Y_k = (\varphi_k, \ DLO_k, DLV_k^*)$. Since $\theta$ and $\phi$ are the parameters of the news term and the decay term respectively, the closer the sum is to 1, especially the greater $\theta$ is, the more severely the conditional correlation changes over time. Thus, the conditional correlations for the sample period in Regime II are stronger and their movements are more stable than Regime I, which are also visually evident by Figs. 2 and 3. From the figures, we can get insights on the dynamics between returns/volatility, trading volume, and open interest on the BTCF.

### Table 5

| Parameters | Regime I (pre-pandemic) | Regime II (pandemic) |
|------------|-------------------------|----------------------|
|            | Estimates | $p$-values | Estimates | $p$-values |
| $c$        | 2.5012*** | 0.0031    | 3.8274*** | 0.0000    |
| $b$        | 0.0066   | 0.9955    | -0.1752  | 0.3859    |
| $b_{RO}$   | -0.0837  | 0.9702    | 3.3994*** | 0.0004    |
| $b_{RV}$   | 0.0296   | 0.9953    | 0.8607*  | 0.0570    |
| $d$        | 0.0719   | 0.9942    | 2.4983   | 0.7089    |
| $a$        | 0.0000   | 1.0000    | 0.0276   | 0.6634    |
| $\beta$    | 0.9671***| 0.0000    | 0.4714   | 0.5333    |
| $\gamma$   | 0.0637   | 0.9911    | 1.0000   | 0.2689    |
| $c$        | -0.4290  | 0.0000    | 0.6955***| 0.0000    |
| $b_{RO}$   | 0.9999***| 0.0000    | 0.9999***| 0.0000    |
| $b_0$      | 0.0040   | 0.1787    | 0.0013*  | 0.0882    |
| $DLO_i$    | 0.0178   | 0.1320    | 0.0041   | 0.3076    |
| $d$        | 0.0028** | 0.0162    | 0.0001** | 0.0575    |
| $a$        | 0.0889   | 0.6668    | 0.0850   | 0.4379    |
| $\beta$    | 0.3424   | 0.0301    | 0.6358***| 0.0000    |
| $\gamma$   | 1.0000***| 0.0001    | 0.2760   | 0.0505    |
| $c$        | 0.0932   | 0.5717    | 0.1385   | 0.4195    |
| $b_{RO}$   | 0.3906   | 0.0020    | 0.6758***| 0.0000    |
| $b_0$      | -0.0453  | 0.1564    | -0.0297  | 0.2401    |
| $DLV_i$    | 1.3570***| 0.0000    | 1.2561** | 0.0104    |
| $d$        | 0.5666** | 0.0138    | 0.0103   | 0.3498    |
| $a$        | 0.3013   | 0.0000    | 0.0091   | 0.6471    |
| $\beta$    | 0.0000   | 1.0000    | 0.0099***| 0.0000    |
| $\gamma$   | -0.1890  | 0.2186    | -0.0636  | 0.3382    |
| $DCC$      | 0.0592   | 0.9485    | 0.0298   | 0.7341    |
| $b$        | 0.0000   | 1.0000    | 0.0000   | 1.0000    |
| $Av. \lnL$ | -2.46    | -1.76     |          |            |

Notes: $DLO_i$ = detrended log-open interest, $DLV_i$ = detrended log-volume, $Av. \lnL$ represents the mean value of the maximized log-likelihood function, asterisks *, **, and *** denote statistical significance at the 10 %, 5%, and 1% levels, respectively.

### Table 6

Granger causality tests.

| The causality | Regime I (pre-pandemic) | Regime II (pandemic) |
|---------------|-------------------------|----------------------|
|               | Test statistics | $p$-values | Test statistics | $p$-values |
| from returns to open interest | 2.6625 | 0.1040 | 84.509*** | 0.0000 |
| vice versa    | 1.4182 | 0.2348 | 0.6136 | 0.4342 |
| from returns to volume | 1.0261 | 0.3121 | 2.8086* | 0.0951 |
| vice versa    | 1.0059 | 0.3169 | 4.1999** | 0.0415 |
| from open interest to volume | 18.352*** | 0.0000 | 7.1963*** | 0.0078 |
| vice versa    | 0.5592 | 0.4553 | 1.3281 | 0.2503 |
| from volatility to open interest | 3.1993 | 0.0748 | 14.597*** | 0.0001 |
| vice versa    | 0.1687 | 0.6816 | 7.5902*** | 0.0066 |
| from volatility to volume | 22.560*** | 0.0000 | 41.954*** | 0.0000 |
| vice versa    | 0.1048 | 0.7463 | 8.8363*** | 0.0032 |

Notes: Chi-sq test statistics and their p values of the test are reported with the null hypothesis of unconditional Granger, and asterisks *, **, and *** denote statistical significance at the 10 %, 5%, and 1% levels, respectively.
market. In the presence of belief dispersion, the BTCF price and trading volume are more sensitive to news but the variability of their conditional correlations become lower in comparison to relatively normal states. The empirical analyses highlight that it is important to account for regime change initiated by pandemic-induced market stress when modeling the relationship between returns/volatility, trading volume and open interest for the BTCF market.

Fig. 2. Dynamic conditional correlations (DCC) between returns ($r_t$), detrended log-open interest ($DLO_t$) and detrended log-volume ($DLV_t$) for the sample period in each regime.
5. Concluding remarks

This paper explains the dynamic relationship between returns (or volatility) and trading behavior variables, such as trading volume and open interest, as a proxy for dispersion of traders’ beliefs on asset prices. Moreover, this study investigates how the COVID-19 pandemic impacts their interrelations. Accordingly, this paper considers the BTCF market for empirical analysis given its certain advantages and proposes the SC-VAR-MGARCH model.

Fig. 3. Dynamic conditional correlations (DCC) between volatility ($\theta_t$), detrended log-open interest ($DLO_t$) and detrended log-volume ($DLV_t$) for the sample period in each regime.
This study contributes to literature in several ways. First, this study is significant in that it is the first to explore the impact of pandemic-induced market stress on the dynamic relationship between price and trading behavior variables in the futures market. Furthermore, this study also explains that the ongoing COVID-19 pandemic raises concerns about future market stress with greater economic risk. Second, this study finds that the COVID-19 pandemic has initiated a significant regime change. The estimated change point is on March 5, 2020, which is a few days ahead when the COVID-19 pandemic was declared. The declaration date may be a potential date of structural break. Third, this study can help investors, hedgers, and arbitrages understand the implications of returns volatility sources and the dynamics of the relationships under extreme financial market stress beyond the BTCF market, thus establishing excellent trading and portfolio management strategies. The estimates of the SC-VAR-MGARCH models are remarkably consistent with the difference of opinions model during the pandemic-induced market stress, though existing evidence of the relationships are ambiguous. As a result, an increase in belief dispersion due to market stress reduces BTCF returns but significantly raises trading volume and volatility in the pandemic regime in contrast with the pre-pandemic regime. Therefore, our empirical results sufficiently support the SC-VAR-MGARCH model considering the pandemic-induced market stress and emphasize the intrinsic role of market stress causing traders’ behavioral biases, such as overreaction to news.

Our study suggests future research to consider the dynamic relationship between price and trading variables as a more reliable model for reflecting traders’ herd behavior generated from market stress and uncertainty. In addition, when high-frequency time-series data of the COVID-19 pandemic period sufficiently accumulate in the future, the COVID-19 impacts on realized volatility, realized jumps, and trading behavior in asset markets, in addition to the BTCF market, must be closely analyzed.

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