Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Modelling economic policy issues

Contagion and portfolio management in times of COVID-19

Olfa Belhassine\textsuperscript{a,b,∗}, Chiraz Karamti\textsuperscript{c}

\textsuperscript{a} Department of Finance and Accountancy, Univ. Manouba, ESCT, Tunisia
\textsuperscript{b} Univ. Manouba, ESCT, RIM RAAF UR13ES56, Campus Universitaire Manouba, 2010, Tunisia
\textsuperscript{c} Department of Quantitative Methods and Computer, High Institute of Business Administration of Sfax (ISAAS), Sfax University, Tunisia

\textbf{ARTICLE INFO}

\textbf{Article history:}
Received 26 April 2021
Received in revised form 28 July 2021
Accepted 28 July 2021
Available online 5 August 2021

\textbf{JEL classification:}
G15
G11

\textbf{Keywords:}
COVID-19
China
Dynamic conditional correlations
Hedge ratios
Volatility
Break dates

\textbf{ABSTRACT}

This paper aims to investigate the COVID-19 pandemic impacts on the interconnectedness between the Chinese stock market and major financial and commodity markets—gold, silver, Bitcoin, WTI, S&P 500, and Euro STOXX 50—and analyze the portfolio design implications. Using daily data from 2018 to 2021, we first apply the wavelet power spectrum (WPS) to visualize volatility shifts. In contrast to previous research, we empirically identify the precise COVID-19 outbreak dates for each market using the Perron (1997) breakpoint test. Finally, we employ the bivariate DCC-GARCH model to analyze the connectedness between markets. The findings reveal that the COVID-19 pandemic caused volatility shifts of different intensities for all of the studied markets. Moreover, each return series exhibits one break date, which is specific to each market and corresponds to a distinct COVID-19-related event. Correlations, hedge ratios, and optimal portfolio weights changed significantly after the COVID-19 outbreak. There is evidence of contagion effects between the Chinese stock market and S&P 500, Euro STOXX 50, gold, and silver. Interestingly, the latter two assets lost their safe haven property with SSE. However, WTI and Bitcoin act as safe havens against SSE risks.

© 2021 Economic Society of Australia, Queensland. Published by Elsevier B.V. All rights reserved.

1. Introduction

Catastrophes, terrorist events, wars, and crises are turbulences that severely hit economies as well as financial markets. There is a plethora of research on the effect of such major events and financial crises on financial markets. For instance, Kollia et al. (2013) showed that war significantly affects the oil–stock market relationship. Nasir and Du (2018) found that the global financial crisis (GFC) changed the interrelation among the global financial markets. Belhassine and Ben Bouzid (2019) found evidence that both the subprime and Euro debt crises altered the relationship between the oil market and the Eurozone sectors. COVID-19 (also referred to as coronavirus disease) is this century’s first major global pandemic. An unseen, microscopic virus termed SARS-CoV-2 has led to tremendous costs for all people worldwide and at all levels. Being so devastating, this virus has also resulted in plummetts and changes in the financial markets. The worldwide spread of COVID-19 has heightened market risk aversion to levels not seen since the GFC. Around the world, low economic growth and considerable financial instability are caused by this dramatic increase in uncertainty. Such issues first affected China’s stock markets, one of the largest economies in the world, and then the remaining stock markets around the globe. Lyócsa et al. (2020) showed that during the COVID-19 period, fear of the virus, proxied by the excess Google search volume,
explained significant worldwide stock price movements. The circuit-breakers on the US stock market were triggered for the first time since 1997 on March 9, 2020. COVID-19 also caused an unprecedented increase in global financial market risks (Zhang et al., 2020).

A fast-growing body of research on the pandemic effects on financial markets has emerged. Matos et al. (2021) demonstrated that the US stock market was negatively correlated to the cycles of deaths in Italy and the world at the beginning of the pandemic. Albuescu (2020) showed that COVID-19 caused a significant increase in the US stock market volatility. Baig et al. (2020) found that the increase in confirmed cases and deaths due to COVID-19 significantly deteriorated US market liquidity and stability. Corbet et al. (2020a) results indicated the existence of volatility spillovers from coronavirus to other financial assets. Moreover, the pandemic caused a severe recession across all countries and a high contagion level (Chevallier, 2020). Karamti and Belhassine (2021) showed that fear of COVID-19 on the US market spilled over into the international financial markets, particularly at the beginning of the infection waves in the US.

Clearly, COVID-19 has amplified financial market risks, causing new challenges for financial risk managers. To define their portfolio strategies and adequately hedge their risks, investors and portfolio managers need to distinguish between three types of assets: diversifier, hedge, and safe haven (Baur and Lucey, 2010; Bouri et al., 2017). In normal market conditions, an asset is a hedge against the risks of another asset if the correlation is negative or next to nil. Thus, it is recommended to invest in such assets to decrease portfolio risks. During a crisis period, there is evidence of contagion between two markets when the correlation increases (Forbes and Rigobon, 2002). In such circumstances, investors must hold safe haven assets, which are negatively correlated, to reduce the portfolio risks.

Given the importance of this issue, there is a rapidly growing body of research focusing on the impact of the COVID-19 pandemic on the interconnectedness between financial markets. Adekoya and Oliyide (2020) showed that COVID-19 caused strong volatility spillovers across several commodity and financial markets and that gold and USD are net receivers of shocks. Bissoondoyal-Bheenick et al. (2020) documented a significant relationship between COVID–19 stages and deaths, and return and volatility connectedness between the G20 countries. Le et al. (2021) investigated the spillover effects between financial technology stocks and other financial assets. Their results showed an increase in volatility transmission caused by the COVID-19 outbreak. Dutta et al. (2020) and Salisu et al. (2020) found evidence that gold acted as a safe haven for oil risks after the onset of this current pandemic. Conlon and Mcgee (2020) found that the most popular cryptocurrency, Bitcoin, did not act as a safe haven against S&P 500 risks during the COVID-19 crisis. Dutta et al. (2020) studied the Bitcoin/oil pair and also confirmed that Bitcoin lost its safe haven property against oil risks during this crisis. Conlon et al. (2020) results showed that Bitcoin and Ethereum are no longer safe havens for most international equity markets, except for the Chinese index, which achieved modest downside risk reduction with these assets. However, Mariana et al. (2020) findings indicated that Bitcoin and Ethereum both acted as safe havens for stocks in the COVID-19 period. Lin and Su (2021) showed that COVID-19 caused a significant change in the connectedness structure in energy commodity markets over the two months following the pandemic’s onset.

Some studies particularly focused on the contagion effects of the Chinese stock market amid the COVID-19 period. Indeed, China was the location where the first case of COVID-19 was detected in December 2019 and was considered the first epicenter of the pandemic. Moreover, the Chinese economy is considered globally important (Liu, 2021). Comparing between financial and non-financial Chinese firms, Akhtaruzzaman et al. (2020) found that the correlation of these two groups with G7 countries increased after the COVID-19 outbreak, confirming the existence of contagion between China and the G7 countries. Nguyen et al. (2021) investigated the contagion effects of the Chinese and US stock markets on the G7 and BRICS stock markets. They used daily data from July 2019 to June 2020 and calculated the static correlation between countries. Their results showed the presence of contagion effects from China to most of the studied stock markets. Corbet et al. (2020b) used hourly data from March 11, 2019, to March 10, 2020, to study the contagion effects between the Chinese stock market and other major assets (Bitcoin, gold, WTI, and DJIA). They concluded that these assets do not act as hedges for the Chinese stock market risks. However, their study was limited to the first stage of the disease, when it was considered only an epidemic. Moreover, neither Nguyen et al. (2021) nor Corbet et al. (2020b) analyzed COVID-19’s effects on the portfolio design. The present study intends to fill these gaps.

This paper aims to investigate the effects of the COVID-19 pandemic on the connectedness between the Chinese stock market and major financial and commodity markets, how did this pandemic affect the correlation and hedging effectiveness between the Chinese stock market and other major international markets? The contribution of this paper is twofold. First, to the best of our knowledge, it is the first to examine the effects of COVID-19 in the interdependence between the Chinese market and other major financial markets and to focus on the portfolio design implications of the results. Second, all studies investigating the effects of the COVID-19 pandemic on the relationship between different assets posit the existence of a structural break caused by the onset of the pandemic and arbitrarily choose the break date as one of the most important dates in the COVID-19 timeline. For instance, some studies chose December 31, 2019, when cases of pneumonia detected in Wuhan, China, were first reported to the World Health Organization (WHO) (Akhtaruzzaman et al., 2020; Corbet et al., 2020a; Dutta et al., 2020; Salisu et al., 2021). Other studies opted for January 22, 2020, the date on which John Hopkins University began to publish the daily confirmed and death case statistics for COVID-19 (Adekoya and Oliyide, 2020). Albuescu (2020), Mariana et al. (2020), and Salisu et al. (2020) chose March 11, 2020, when the WHO officially announced COVID-19 to be a global pandemic. As far as we know, our study is the first to empirically demonstrate the existence of a COVID-19-related break date specific to each financial market. The determined break dates for each market should be considered by future research as the start date for the pandemic for each market.
Our dataset covers the period 2018–2021. We collect daily data for the Shanghai Stock Exchange (SSE) Composite Index as a benchmark for the Chinese stock market and major international assets that are commonly used by portfolio managers, namely WTI, gold, silver, Bitcoin, Euro STOXX 50, and S&P 500. We use the wavelet power spectrum (WPS) to visualize volatility shifts and the Perron (1997) breakpoint test to locate the precise COVID-19 break dates. Then, we employ the bivariate DCC-GARCH model of Engle (2002) to estimate the time-varying correlations between SSE and the other assets under study. Our results show that the COVID-19 pandemic unevenly increased the volatility in the studied markets. The pandemic break dates are specific to each market and correspond to distinct COVID-19-related events. Moreover, the dynamic conditional correlations (DCCs), hedge ratios (HRs), and optimal portfolio weights (OPWs) changed significantly after the pandemic’s outbreak. Specifically, there is evidence of contagion effects between the Chinese stock market and S&P 500, Euro STOXX 50, gold, and silver. Interestingly, gold and silver lost their safe haven role in the COVID-19 pandemic. However, WTI and Bitcoin act as safe havens against SSE risks. These results are useful for regulators and policymakers to plan policies that allow them to cope with financial contagion. They are also valuable for portfolio and risk managers, particularly because the pandemic operates in waves.

The remainder of this paper is as follows. Section 2 describes the data. Section 3 outlines the methodology. Section 4 reports and discusses the results. Finally, Section 5 concludes.

2. Data

We collect data on daily frequency from January 2, 2018, to June 7, 2021. To represent the Chinese stock market, we choose the Shanghai Stock Exchange (SSE) Composite Index. Because the disease epicenter moved from China to Europe and then to the US, we consider two stock indices, namely the S&P 500 as a proxy for the US stock market and Euro STOXX 50 representing the Eurozone. We use the West Texas Intermediate (WTI) crude oil price as a proxy for the world oil price level and the London Bullion Market Association (LBMA) gold fixing price as a proxy for gold prices. Finally, we utilize the most important cryptocurrency, which is Bitcoin. The SSE, Euro STOXX 50, and S&P 500 data are sourced from Yahoo Finance, whereas the WTI, gold, silver, and Bitcoin data are collected from the Federal Reserve Economic Database (fred.stlouisfed.org). We have an initial sample of 834 daily observations. All data are synchronized as the SSE index, and the other assets are traded on different stock markets that operate with different holidays. For each data series, daily returns ($r_{it}$) are calculated as $\ln(P_{it}/P_{i,t-1}) \times 100$, where $P_{it}$ is the daily closing price.

Table 1 displays the descriptive statistics for the series under investigation. All standard deviations are relatively high. WTI and Bitcoin have standard deviations that are considerably higher than any of the other financial assets examined. Bitcoin exhibits the highest average return. Moreover, all the kurtosis statistics are higher than 3, suggesting that all the returns are leptokurtic. The skewness statistics show that all return series are negatively skewed, except for gold. Finally, the JB test statistics show that all series are not normally distributed. Unit root tests indicate that all return series are stationary at conventional levels.

3. Methodology

3.1. Detecting volatility shifts and break dates

The first step of the study is to detect if the COVID-19 pandemic caused volatility shifts in the variance for the considered return series. To do so, we utilize the wavelet power spectrum (WPS) plots. This technique is used to illustrate the local volatility of the analyzed series $x(t)$ at each scale and at each time (Torrence and Webster, 1999). The WPS is defined as:

$$WPS_x(r, s) = |W_x(r, s)|^2$$

Table 1: Descriptive statistics for the full sample.

|          | SSE       | S&P 500   | Euro STOXX 50 | WTI       | Gold      | Silver    | Bitcoin   |
|----------|-----------|-----------|---------------|-----------|-----------|-----------|-----------|
| Mean     | 0.0090    | 0.0561    | 0.0196        | 0.0172    | 0.0449    | 0.0600    | 0.1003    |
| Median   | 0.0313    | 0.1165    | 0.0719        | 0.1828    | 0.0338    | 0.0282    | 0.1928    |
| Maximum  | 7.5482    | 8.9683    | 8.8343        | 42.5832   | 6.7899    | 10.2088   | 20.9941   |
| Minimum  | −8.0392   | −12.7652  | −13.2405      | −72.0273  | −5.4010   | −19.5856  | −46.8625  |
| Std. Dev. | 1.2431   | 1.4607    | 1.3525        | 5.0277    | 0.9132    | 1.8850    | 4.9929    |
| Skewness | −0.4138   | −1.0193   | −1.2740       | −2.8572   | 0.1168    | −1.0765   | −1.1340   |
| Kurtosis | 10.3161   | 8.5249    | 10.7999       | 155.9300  | 140.62*** | 119.75*** | 441.18*** |
| JB       | 1039.1*** | 8524.9*** | 10799***      | 155930*** | 1406.2*** | 11975***  | 4411.8*** |
| ZA       | −14.51*** | −12.91*** | −11.72***     | −12.05*** | −14.10*** | −12.24*** | −12.76*** |
| Observations | 801 | 801 | 817 | 796 | 803 | 800 | 825 |
with \( W(\tau, s) \) the continuous wavelet transform of the time series for a mother wavelet \( \psi \) given by:

\[
W(\tau, s) = \int_{-\infty}^{\infty} x(t) \psi^*(\frac{t - \tau}{s}) \ dt, \quad s, \tau \in \mathbb{R}, s \neq 0
\]  

(2)

where \( s \) is the scaling factor that determines the length of the wavelet by dilating \(|s| > 1\) and compressing \(|s| < 1\) the series, \( \tau \) the translation parameter that represents its location, and asterisk denotes complex conjugation. The mother wavelet \( \psi(t) \) is used to generate other window functions at a location center \( \tau \). As the window shifts through time, time information is obtained in the transformed domain.

Then, we test each return series for the presence of structural break. We identify the exact break dates by employing the Perron (1997) break date test, applying the mixed IO (innovational outlier) model.\(^1\) The determined break date for each market will be used as the start date for the post-COVID-19 period.

3.2. DCC-GARCH model

We use the bivariate DCC-GARCH model of (Engle, 2002) to estimate the time-varying correlations of SSE-Asset \( (A_i) \) pairs. This methodology is widely used to assess the dynamic correlations between different assets (Akhtaruzzaman et al., 2020; Dutta et al., 2020). It is a two steps estimation technique. Let \( r_t = (r_{1t}, r_{2t}) \) denote the vector of the observed data at time \( t \). First, the GARCH parameters are estimated by an ARMA(0, 0) - GARCH(1, 1)\(^2\) model for the univariate process \( r_{it} \).

\[
r_{it} = \mu_i + \epsilon_{it} \quad \text{with} \quad \epsilon_{it} = \eta_{it} \sqrt{h_{it}}
\]

(3)

\[
h_{it} = \omega_i + \alpha_i \epsilon_{it-1}^2 + \beta_i h_{it-1}
\]

(4)

where \( \mu_i \) is the mean of the process \( r_{it} \), \( h_{it} \) represents the conditional variance of asset \( i \), the parameters \( \alpha \) and \( \beta \) are non-negative (with \( \alpha + \beta < 1 \)) and represent the short- and long-run persistence of shocks to conditional variance, respectively.

Then, the dynamic conditional correlation is estimated through the conditional variance–covariance matrix \( H_t \) of the residuals in the DCC.

\[
H_t = D_t R_t D_t
\]

(5)

\( D_t \) is the \( 2 \times 2 \) diagonal matrix of time-varying standard deviations from the univariate GARCH models. \( R_t \) is the conditional correlation matrix of the standardized residuals.

The multivariate DCC-GARCH models are estimated by quasi-maximum likelihood estimation (QMLE) using the BFGS algorithm.

3.3. Optimal portfolio weights (OPW) and hedge ratios (HR)

We compute \( W_t^{A_i/SSE} \), the OPW of asset \( A_i \) in a one-dollar SSE/\( A_i \) portfolio subject to a no-shorting constraint, where \( A_i \) can be gold, silver, oil, Bitcoin, Euro STOXX 50, or S&P 500. Assuming zero expected returns and a mean–variance utility function, the risk-minimizing OPW proposed by Kroner and Ng (1998) is given by:

\[
W_t^{A_i/SSE} = \frac{h_t^{SSE} - h_t^{SSE/A_i}}{h_t^{SSE} - 2 \times h_t^{SSE/A_i} + h_t^{A_i}}
\]

(6)

and

\[
W_t^{A_i/SSE} = \begin{cases} 
0 & \text{if } W_t^{A_i/SSE} \leq 0 \\
W_t^{A_i/SSE} & \text{if } 0 < W_t^{A_i/SSE} < 1 \\
1 & \text{if } W_t^{A_i/SSE} \geq 1
\end{cases}
\]

(7)

(8)

with \( h_t^{SSE/A_i} \) the conditional covariance between SSE Index and the asset \( A_i \) returns at time \( t \), and \( h_t^{A_i} \) and \( h_t^{SSE} \) are the conditional variances of asset \( A_i \) and the SSE Index at time \( t \), respectively.

We also determine the risk-minimizing HR \( (\beta_{A_i/SSE,t}^{*}) \) for each SSE/\( A_i \) portfolio. A long (buy) position of one USD in the asset \( A_i \) should be hedged with a short (sell) position of \( \beta_{A_i/SSE,t}^{*} \) USD in the SSE Index. Kroner and Sultan (1993) define this ratio as:

\[
\beta_{A_i/SSE,t}^{*} = h_t^{SSE/A_i}/h_t^{SSE}
\]

(9)

\(^1\) See Perron (1997) for more details on test statistics which allow for different forms of structural breaks.

\(^2\) We estimated several GARCH type specifications (EGARCH, AGARCH, GJR-GARCH etc.) and we used for each returns series the most appropriate one judging by the information criteria.
4. Results

4.1. Volatility analysis and break dates identification

4.1.1. COVID-19-induced volatility

Fig. 1 illustrates the local variance evolution of each return series with respect to the frequency-time domains. The x-axis shows the period under study. The y-axis represents the frequency level, covering short- (high-frequency) to long-term (low-frequency) horizons. The color code represents the volatility spectrum, ranging from blue (low volatility) to red (high volatility)\(^3\) (Grinsted et al., 2004). Fig. 1 shows that for all time scales and the full sample period, there is evidence of low volatility because shades of blue dominate, except for the early 2020s when the virus began to spread. This statistically significant and highly volatile period is common to all return series, but its intensity differs from one asset to the other. When comparing the hot-colored areas, we note that WTI, S&P 500, and Euro STOXX 50 are the most affected markets by the COVID-19 pandemic, particularly in the long run. As for gold, during the same volatile period, red-shaded areas spread only up to 32 days. However, SEE seems the least affected stock market by the COVID-19 outbreak, which is surprising because China was at the forefront of the pandemic exposure. Moreover, the WPS plot suggests that Bitcoin experienced very low volatility over the short-term horizons, denoted by the dark blue shading throughout the sample period, except some moderate volatility at the medium and low frequencies as evident from the yellow and orange islands hanging over the turmoil period.

To summarize, all studied markets experienced higher volatility localized at the beginning of 2020 and coinciding with the COVID-19 outbreak. China and Bitcoin are the markets that seem to be the least affected by the pandemic. It is well documented that China, despite being first to be hit by the virus, was also the first to contain it and limit its consequences, in contrast to other countries. For instance, in August 2021, the Chinese reported that cases were substantially below all the other countries.\(^4\)

4.1.2. Break dates identification

After finding evidence that COVID-19 caused high volatility for all markets under study, we identify the COVID-19 break dates for each series. Table 2 summarizes the precise break date for each financial market and its corresponding event.\(^5\) Interestingly, all the identified structural breaks correspond to a distinct COVID-19-related event. The pandemic triggering event is specific to each return series, suggesting that the onset of COVID-19 is specific to each market. For the Bitcoin market, the break date is March 10, 2020, which is one day before the WHO declared COVID-19 to be a global pandemic, indicating that the Bitcoin market was able to anticipate the WHO announcement. The gold and silver markets were most likely affected by the travel restrictions imposed by the US president, which affected all mining industries because they caused a supply-chain disruption (Corbet et al., 2020b; Jowitt, 2020). Regarding Euro STOXX 50, the break date occurs on the day on which the European Commission (EC) finally announced the first measures and recommendations to face the pandemic. Indeed, on March 17, 2020, EC president Ursula von der Leyen acknowledged that COVID-19 was underestimated and declared the urgent need to unify efforts to face the pandemic. Regarding the oil market, the identified date coincides with the oil market turmoil period. On April 12, 2020, Saudi Arabia and Russia agreed to cut oil supplies because the demand was extremely low and the tanks were full. On April 15, 2020, the Energy Information Administration (EIA) released its monthly report describing and analyzing the devastating effects of the pandemic on oil demands. Consequently, on April 20, 2020, all the world was astonished by the never-seen-before, negative price of WTI closing at -$37.63 per barrel.

We use the identified break dates to divide our full sample for each return series into pre- and post-COVID-19 onset periods. Table 3 displays the descriptive statistics for each series in the two sub-periods. It shows that all the average returns and almost all volatilities increased, whereas the minimum values are lower in the post-COVID-19 period, suggesting higher risks in all markets. The highest volatility in the post-COVID-19 sub-period is detected for WTI. Interestingly, the Chinese stock market is the only market displaying a volatility decrease. All series, except for Euro STOXX 50, are negatively skewed and display higher kurtosis statistics after the break date, indicating that the distributions have heavy tails and that the assets are riskier. Finally, the Jarque–Bera statistic indicates that none of the returns are normally distributed.

---

\(^3\) The null hypothesis of a steady estate is compared with WPS to determine the statistical significance of the volatility. The WPS significance level of 5% is represented by the black contour.

\(^4\) China registered on August 6, 2021, a total of 105 575 of COVID-19-positive cases and 4 848 deaths. These figures have been almost stable since May 2020. In contrast, the global (US) authorities registered on the same date a total of 201 271 096 (35 467 746) COVID-19-positive cases and 4 272 990 (615 438) deaths. [John Hopkins University, https://coronavirus.jhu.edu/map.html].

\(^5\) For the sake of brevity, the Perron (1997) break date test results and graphs are not reported, but they can be obtained upon request from the corresponding author.
4.2. Dynamic conditional correlations

The DCC parameter estimates and the model diagnosis tests for the two sub-periods are presented in Table 4. Fig. 2 displays the DCC conditional correlations for the SSE/Ai pairs. It shows that the COVID-19 pandemic caused a significant
Table 2
Break dates and corresponding events.

| Assets         | Break date   | Event                                                                 |
|----------------|--------------|----------------------------------------------------------------------|
| SSE            | January 23, 2020 | Wuhan was placed under lockdown.                                       |
| Bitcoin        | March 10, 2020   | The WHO declared the COVID-19 a global pandemic on March 11, 2020.    |
| S&P 500        | March 11, 2020   | President Trump suspended travel from Europe to the US effective on March 13, 2020. |
| Silver         | March 13, 2020   | The European Commission announced the first measures and recommendations to face the pandemic. |
| WTI            | April 15, 2020   | Energy Information Administration (EIA) Oil market report released.   |

This table reports the COVID-19 break dates and their corresponding events for each asset returns.

Table 3
Descriptive statistics for the pre- and post-COVID-19 onset sub-samples.

|              | SSE     | S&P 500 | Euro STOXX 50 | WTI     | Gold   | Silver | Bitcoin |
|--------------|---------|---------|---------------|---------|--------|--------|---------|
| Pre-COVID-19 |         |         |               |         |        |        |         |
| Mean         | −0.018  | 0.013   | −0.723        | −0.210  | 0.043  | −0.006 | −0.118  |
| Maximum      | 5.449   | 4.840   | 3.218         | 37.474  | 2.934  | 4.395  | 20.994  |
| Minimum      | −6.007  | −7.901  | −13.241       | −21.138 | −2.471 | −5.756 | −24.106 |
| Std. Dev.    | 1.190   | 1.125   | 1.215         | 4.141   | 0.726  | 0.394  | 0.242   |
| Skewness     | −0.396  | −0.967  | −3.803        | 0.022   | 0.394  | −0.511 | −0.242  |
| Kurtosis     | 6.467   | 10.72   | 35.203        | 29.893  | 6.659  | 6.096  | 214.84  |
| Jarque–Bera  | 262***  | 1340.7***| 23995.7***    | 15919***| 76.92***| 306.66***| 214.84***|
| ADF          | −22.49*** | −24.59***| −9.877***     | −13.93***| −22.29**| −21.03***| −23.37***|
| Spearman A_i/SSE | 1.000 | 0.201***| 0.337***      | 0.214***| −0.0087| 0.071  | −0.075* |
| Observations | 498     | 508     | 526           | 528     | 512    | 510    | 525     |

| Post-COVID-19|         |         |               |         |        |        |         |
| Mean         | 0.050   | 0.131   | 0.186         | 0.460   | 0.048  | 0.177  | 0.483   |
| Maximum      | 5.554   | 8.968   | 8.834         | 42.583  | 6.790  | 10.209 | 19.574  |
| Minimum      | −8.039  | −12.765 | −4.634        | −72.027 | −5.401 | −19.586| −46.862 |
| Std. Dev.    | 1.125   | 1.907   | 1.560         | 6.415   | 1.173  | 2.754  | 5.426   |
| Skewness     | −0.895  | −0.987  | 0.786         | −4.238  | −0.017 | −1.001 | −2.210  |
| Kurtosis     | 9.508   | 15.661  | 8.220         | 71.315  | 8.414  | 13.113 | 22.338  |
| Jarque–Bera  | 620.74***| 2004.67***| 360.38***     | 52916.3***| 355.43***| 1284.2***| 4918.68***|
| ADF          | −17.22***| −23.51***| −17.60***     | −18.32***| −15.19***| −15.31***| −19.18***|
| Spearman A_i/SSE | 1.000 | 0.227***| 0.169***      | 0.015** | 0.301***| 0.337***| 0.019   |
| Observations | 327     | 293     | 291           | 268     | 291    | 290    | 300     |

This table reports descriptive statistics of asset returns for the pre- and post-pandemic periods. ADF denotes the Augmented Dickey-Fuller unit root test. Std. Dev. is the standard deviation. Spearman A_i/SSE is the Spearman correlation coefficient for each asset A_i with SSE.

* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

Change in the correlation patterns for all pairs. Table 5, Panel A presents the mean and standard deviations of the SSE/A_i correlations for the two sub-periods and the mean and variance equality tests. It indicates that S&P 500 and Euro STOXX 50 correlations decreased significantly, although remaining positive, indicating that these assets are diversifiers for SSE risks. The same table shows that gold and silver average correlations increased significantly after the COVID-19 onset, suggesting significant financial contagion effects between the Chinese financial market and these markets. Moreover, gold and silver had near-to-zero average correlations with SSE before the COVID-19 onset, meaning that they were weak hedges for SSE. After the crisis, these assets changed to become diversifiers for SSE and lost their hedging property. It is worth noting that our results for gold are specific to the COVID-19 crisis because gold has always been considered a universal safe haven (Baur and Lucey, 2010; Dutta et al., 2020). This result agrees with Będowska-Sójka and Kliber (2021), who found that the COVID-19 pandemic made gold lose its safe haven property against US and European indices’ risks. One possible explanation for this conflicting finding is that, in contrast to previous turmoil, COVID-19 deeply affected the mining industry by restricting travel across countries causing stock, gold, and silver markets to move in the same path. Moreover, China was the first gold producer and the third silver producer in 2019.

Table 5 Panel A shows that for WTI, the average correlation with SSE decreased significantly to become negative. WTI, which was positively correlated with the COVID-19 onset, became a strong safe haven for SSE after the crisis. A tentative explanation for this correlation shift could be that China is the first crude oil-importer; hence, it likely profited

---

6 https://www.gold.org/goldhub/data/historical-mine-production (accessed on March 22, 2021).
7 https://www.statista.com/statistics/264640/silver-production-by-country/#:~:text=Mexico%27s%20silver%20mines%20produced%20some,ranked%20second%20and%20third%2C%20respectivel.
from the unprecedented oil price plummet after the COVID-19 onset. Indeed, the Chinese domestic oil products pricing mechanism sets the refined petroleum products’ retail prices to a minimum of 40$ per barrel if the international crude oil prices are equal to or lower than that level. Therefore, China has kept its retail petrol prices unchanged from March 18, 2020 to June 29, 2020,\(^8\) reducing the uncertainty of its domestic oil products, while the international crude oil prices were lower than 40$/b. Oil product producers were asked to pay their additional earnings to the Chinese government “Price Adjustment Risk Fund”, and the government has no more subsidies to pay to the refining firms. Therefore, the international crude oil price plunge after the COVID-19 outbreak helped the Chinese economy. This was not the case before the pandemic when oil prices were higher than 40$ per barrel, and the Chinese government had to adjust domestic retail oil prices and pay subsidies to refined product companies to compensate for their losses.

\(^8\) https://www.argusmedia.com/en/news/2118562-china-raises-retail-fuel-prices-as-crude-strengthens (visited on March 21, 2021).
Table 4
DCC-GARCH model estimation results for the pre- and post-COVID-19 onset periods.

|                | S&P 500 | Euro STOXX 50 | WTI | Gold | Silver | Bitcoin |
|----------------|---------|---------------|-----|------|--------|---------|
|                | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 |
| \( \rho_\text{SSE/IA} \)  | 0.2793*** | 0.2303*** | 0.2523*** | 0.1628*** | 0.4276 | 0.0297 | -0.0012 | 0.2805*** | 0.0490 | 0.3095*** | 0.1102** | 0.0256 |
| \( \alpha_\text{DCC} \)  | 0.0000 | 0.0112 | 0.0103 | 0.0098 | 0.0134* | 0.0506 | 0.0138 | 0.0066 | 0.0101 | 0.0256 | 0.0171 | 0.0000 |
| \( \beta_\text{DCC} \)  | 0.9919*** | 0.91042*** | 0.9033*** | 0.9866*** | 0.9069*** | 0.9661*** | 0.9167*** | 0.9731*** | 0.8386*** | 0.9183*** | 0.7405 |

**Diagnostics tests**

|                  | McLeod-Li (30) | McLeod-Li² (30) |
|------------------|----------------|-----------------|
|                  | 163.481*       | 128.861         |
|                  | 118.802        | 141.880         |
|                  | 144.674*       | 90.7650         |
|                  | 110.251        | 132.466         |
|                  | 138.209        | 135.586         |
|                  | 115.477        | 57.222          |
|                  | 130.305        | 121.211         |
|                  | 126.513        | 90.6774         |
|                  | 115.374        | 98.9467         |
|                  | 129.575        | 151.960         |
|                  | 114.060        | 122.496         |
|                  | 120.972        | 62.4936         |

This table reports the results for the DCC-GARCH estimations for each A/SSE pair over the pre- and post-COVID-19 periods. McLeod and Li (1983) test for a lag of 30 on both standardized and squared standardized residuals.

*Denotes significance at 10% level.
**Denotes significance at 5% level.
***Denotes significance at 1% level.
Table 5
Dynamic conditional correlations, optimal portfolio weights, and hedge ratios with SSE.

|                    | S&P 500 | Euro STOXX 50 | WTI | Gold | Silver | Bitcoin |
|--------------------|---------|----------------|-----|------|--------|---------|
|                    | Pre-COVID19 | Post-COVID19 | Pre-COVID19 | Post-COVID19 | Pre-COVID19 | Post-COVID19 | Pre-COVID19 | Post-COVID19 | Pre-COVID19 | Post-COVID19 |
| **Panel A: Dynamic conditional correlations with SSE** |         |                |     |      |        |         |                |     |      |        |         |
| Mean               | 0.238   | 0.232          | 0.258 | 0.169 | 0.136  | −0.009  | −0.010    | 0.281 | 0.067 | 0.310  | 0.090   | 0.026   |
| Std. Dev.          | 0.046   | 0.027          | 0.023 | 0.026 | 0.173  | 0.135   | 0.074     | 0.015 | 0.056 | 0.043  | 0.053   | 1.091E−8 |
| **Tests for equality of variances between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Siegel-Tukey       | 7.116***| 10.13***       | 6.22***| 10.18***| 10.10***| 3.36*** |
| Bartlett           | 93.21***| 5.856***       | 19.61***| 597.5***| 23.52***| 862.93***|
| **Tests for equality of means between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Satterthwaite-Welch t-test | 1.20***| 48.30***       | 12.99***| −85.62***| −67.87***| 27.45*** |
| Welch F-test        | 3.99**  | 2332.8***      | 168.69***| 7330.8***| 4606***   | 753.52***|
| **Panel B: Optimal portfolio weights** |         |                |     |      |        |         |                |     |      |        |         |         |
| Mean               | 69.5%   | 42.87%         | 59.42%| 40.38%| 19.4%  | 15.81%  | 74.81%    | 44.7% | 56.98%| 15.20% | 7.20%   | 16.51% |
| Std. Dev.          | 0.207   | 0.248          | 0.211 | 0.254 | 0.129  | 0.129   | 0.111     | 0.175 | 0.152 | 0.082  | 0.138   | 0.073  |
| **Tests for equality of variances between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Siegel-Tukey       | 0.92    | 4.52***        | 2.03** | 8.083***| 9.70***  | 2.85*** |
| Bartlett           | 12.57***| 13.20***       | 0.0001| 80.32***| 121.59***| 133.01***|
| **Tests for equality of means between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Satterthwaite-Welch t-test | 14.95***| 10.86***       | 3.73***| 23.85***| 60.46***| −12.68***|
| Welch F-test        | 233.52***| 117.84***      | 13.88***| 568.85***| 3655***   | 160.71***|
| **Panel C: Hedge ratios** |         |                |     |      |        |         |                |     |      |        |         |         |
| Mean               | 0.175   | 0.317          | 0.240 | 0.259 | 0.225  | −0.032  | −0.007    | 0.302 | 0.058 | 0.758  | 0.337   | 0.115  |
| Std. Dev.          | 0.072   | 0.226          | 0.118 | 0.207 | 0.389  | 0.438   | 0.040     | 0.088 | 0.046 | 0.208  | 0.201   | 0.026  |
| **Tests for equality of variances between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Siegel-Tukey       | 1.60    | 8.04***        | 0.91  | 10.15***| 10.15***| 3.36*** |
| Bartlett           | 84.08***| 124.37***      | 4.89** | 241*** | 785.52***| 862.93***|
| **Tests for equality of means between pre- and post-COVID-19 series** |         |                |     |      |        |         |                |     |      |        |         |         |
| Satterthwaite-Welch t-test | −10.44***| −1.473         | 8.10***| −56.77***| −56.57***| −24.93***|
| Welch F-test        | 109.03***| 2.170          | 65.83***| 3222***| 3199***   | 621.39***|

This table reports the mean and the standard deviation (Std. Dev.) of the dynamic conditional correlations, optimal portfolio weights and hedge ratios for each A/SSE pair over the pre- and post-COVID-19 periods. It also displays mean and variance equality tests between the two sub-periods. Satterthwaite-Welch t-test and Welch F-test are tests for equality of means used to test series that have statistically different variances.

**Denotes significance at 5% level.

***Denotes significance at 1% level.
Regarding Bitcoin, Table 5 Panel A shows that the average correlation with SSE decreased significantly, and Fig. 2 shows that it became almost flat after the pandemic onset. Bitcoin was a weak hedge for SSE during the normal market conditions and is a weak safe heaven after the COVID-19 onset. These results are consistent with those of Conlon et al. (2020) and Bouri et al. (2017), both of whom found that Bitcoin has safe heaven properties for China and Asia Pacific stocks, respectively.

Finally, we conclude that investors should avoid holding portfolios containing S&P 500, Euro STOXX 50, gold, or silver with SSE during the post-COVID-19 outbreak period. However, they can minimize SSE risks if they hold Bitcoin or oil assets.

4.3. Portfolio design implications

The OPW (Eq. (6)) and HR (Eq. (8)) were estimated using the time-varying variances and covariances obtained through the DCC-GARCH model. Panel B of Table 5 displays the average OPW of assets (Ai) in the pre- and post-COVID-19 onset periods and their standard deviations. We also perform mean and variance equality tests for the pre- and post-event series. We can see that the OPW of S&P 500, Euro STOXX 50, gold, and silver are higher than 50% before the COVID-19 onset, meaning that the risk-minimizing portfolio should hold more of these assets than SSE. These average OPWs decreased significantly in the post-COVID-19 onset period to be less than 50%. The lowest average value is recorded for silver, which shifted from 56.58% to 15.20%. These findings indicate that investors should rebalance their risk minimizing portfolio by decreasing these asset holdings after the crisis. Regarding the average OPW of Bitcoin, it was 7.20% in the stable period and increased significantly in the post-COVID-19 period to 16.51%. However, we can observe a drastic and significant decrease in the Bitcoin OPW standard deviation, meaning that Bitcoin is the cheapest safe haven for SEE because it does not require frequent portfolio rebalancing that could be expensive (Belhassine, 2020; Junntila et al., 2018; Olson et al., 2017).

Fig. 3 displays the optimal HR plots over the full sample period. It shows that all HRs are time varying. In addition, there is a noticeable change in all HR patterns after the COVID-19 onset. The optimal HR averages and standard deviations are presented in Panel C of Table 5. We can notice that the average HR for S&P 500, gold, and silver increased significantly after the onset of COVID-19. After the crisis, investors need to short more SSE contracts to hedge a long position of 1 USD of the considered assets, meaning that the pandemic induced higher hedging costs for these assets. This result is consistent with Akhtaruzzaman et al. (2020), who studied the COVID-19 crisis effects on HR of financial and non-financial Chinese firms with G7 countries. Batten et al. (2019) and Belhassine (2020) also found that the GFC increased the studied HRs. Euro STOXX 50 only showed an increase in its HR standard deviation, suggesting that hedging activity has become more expensive after the crisis. However, for WTI, the average HR with SSE decreased significantly and became negative after the COVID-19 onset, meaning that investors should take long positions on SSE contracts to hedge oil risk. The SSE index should be used to hedge oil portfolios. As for Bitcoin, the average HR and its standard deviation decreased significantly to become more stable after the pandemic onset. This result suggests that the relationship between the Chinese stock market and Bitcoin became more stable, and hedges are less responsive because investors are not constrained to rebalance their portfolios constantly, as is the case for the other studied markets. Interestingly, Bitcoin is the only asset that witnessed a significant decrease in its HR standard deviation with SSE, meaning that hedging Bitcoin risk with SSE became more attractive and, less expensive to investors after the COVID-19 onset because the portfolios do not need to be frequently rebalanced.

5. Conclusion

This study provides insights into how the COVID-19 pandemic impacts the interconnectedness between the Chinese stock market and major financial and commodity markets (gold, silver, Bitcoin, WTI, S&P 500, and Euro STOXX 50). Our goal was to model volatility spillovers, explore the dynamics of conditional correlations, and estimate optimal hedge ratios to find the assets with the best hedge efficacy for the Chinese stock market returns (SSE).

Our findings suggest that COVID-19 significantly affected the volatility of the different studied markets. However, the Chinese stock market seems to be the least affected, even though China reported the first viral infections. This result could suggest that the Chinese government was able to contain the pandemic impacts both sanitarily and economically. Indeed, it is of common knowledge that COVID-19 operates in waves. However, in contrast to all the other countries, China was the only one that witnessed only a first wave in the first quarter of 2020. Therefore, it would be interesting to examine the real causes behind the Chinese effectiveness in containing the crisis. Another original result of this study is that the pandemic caused a discernable breakpoint in all the studied return series. Interestingly, we found that there is a unique and specific breakpoint for each asset, coinciding with a specific Covid-19-related event. Therefore, we recommend that future studies consider these specific dates instead of common dates in the COVID-19 timeline when studying the pandemic impacts.

Finally, the findings show the existence of co-movements between the Chinese stock market and the major financial markets. There is evidence of significant contagion effects between the Chinese stock market and S&P 500, Euro STOXX 50, gold, and silver. S&P 500 and Euro STOXX 50 kept their diversifier property with the SSE index. Investors and policymakers should be cautious with the price behavior of these markets after the crisis. Portfolio managers should revise their holding
of these assets downwards and possess more SSE index. However, investors must be aware that gold and silver lost their safe haven property. Holding these assets with SSE in the COVID-19 pandemic could lead to tremendous losses in bearish market conditions. Interestingly, we found that Bitcoin is displacing gold as the most cost-effective hedge against Chinese stock market volatility amid the COVID-19 outbreak. This is a new and interesting finding. It contradicts most recent studies on hedging Chinese equities, which claim that commodity markets, particularly gold, are the strongest risk-hedging assets (Ming et al., 2020; Shahzad et al., 2020). Contrary to these studies, we uncover how the hedging effectiveness of gold against the Chinese stock market is shaped by the COVID-19 outbreak. Moreover, the results show that the pandemic stabilized the co-movements between the Chinese stock market and Bitcoin. In the post-COVID-19 period, WTI and Bitcoin act as safe havens against SSE risk, with Bitcoin being a cheap safe haven for SEE because it does not require frequent portfolio rebalancing that could be expensive. Therefore, we would recommend that investors use these assets to hedge SSE risks in the post-COVID-19 period.

Our findings provide interesting insights for portfolio design in times of the COVID-19 pandemic. They are important to financial market investors, risk managers, and portfolio managers, all of whom should pay increased attention to risk
management during periods of severe risks, such as the COVID-19 crisis, particularly because the pandemic operates in waves.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Funding**

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**References**

Adekoja, O.B., Oliyide, J.A., 2020. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantities techniques. Resour. Policy 101898. http://dx.doi.org/10.1016/j.resourpol.2020.101898.

Akhtaruzzaman, M., Boubaker, S., Sensoy, A., 2020. Financial contagion during COVID-19 crisis. Financ. Res. Lett. 101604. http://dx.doi.org/10.1016/j.frl.2020.101604.

Albulescu, C.T., 2020. COVID-19 and the United States financial markets’ volatility. Financ. Res. Lett. 101699. http://dx.doi.org/10.1016/j.frl.2020.101699.

Baig, A.S., Butt, H.A., Haroon, O., Aun, S., Rizvi, R., 2020. Deaths, panic, lockdowns and US equity markets: the case of COVID-19 pandemic. Financ. Res. Lett. 101701. http://dx.doi.org/10.1016/j.frl.2020.101701.

Batten, J.A., Kinateder, H., Sziilyagi, P.G., Wagner, N.F., 2019. Hedging stocks with oil. Energy Econ. 104422. http://dx.doi.org/10.1016/j.eneco.2019.06.007.

Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ. Rev. 45, 217–229. http://dx.doi.org/10.1016/S0959-8654(06)00082-X.

Będowska-Sójka, B., Kliber, A., 2021. Is there one safe haven for various turbulences? The evidence from gold, Bitcoin and Ether. N. Am. J. Econ. Financ. 101390.

Belhassine, O., 2020. Volatility spillovers and hedging effectiveness between the oil market and eurozone sectors: a tale of two crises. Res. Int. Bus. Financ. 53, 101195. http://dx.doi.org/10.1016/j.ribaf.2020.101195.

Belhassine, O., Ben Bouzid, A., 2019. Further insights into the oil and equity market relationship. Stud. Econ. Financ. 36, 291–310. http://dx.doi.org/10.1016/S1386-265X(19)30054-0.

Bissoondoyal-Bheenick, E., Do, H., Hu, X., Zhong, A., 2020. Learning from SARS: return and volatility connectedness in COVID-19. Financ. Res. Lett. 101796. http://dx.doi.org/10.1016/j.frl.2020.101796.

Bouri, E., Molnár, P., Azzi, G., Rouboud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of bitcoin: is it really more than a diversifier? Financ. Res. Lett. 20, 192–198. http://dx.doi.org/10.1016/j.frl.2016.09.025.

Chevallier, J., 2020. COVID-19 pandemic and financial contagion. Risk Financ. Manag. 13 (309). http://dx.doi.org/10.3390/jrfm13120309.

Conlon, T., Corbet, S., Mcgee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. Res. Int. Bus. Financ. 54, 101248. http://dx.doi.org/10.1016/j.ribaf.2020.101248.

Conlon, T., Mcgee, R., 2020. Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. Financ. Res. Lett. 35, 101607. http://dx.doi.org/10.1016/j.frl.2020.101607.

Corbet, S., Hou, Y., Hu, Y., Lucey, B., Oxley, L., 2020a. Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic. Financ. Res. Lett. 101591. http://dx.doi.org/10.1016/j.frl.2020.101591.

Corbet, S., Larkin, C., Lucey, B., 2020b. The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. Financ. Res. Lett. 35, 101554. http://dx.doi.org/10.1016/j.frl.2020.101554.

Dutta, A., Das, D., Jana, R.K., Vinh, X., 2020. COVID-19 and oil market crash: revisiting the safe haven property of gold and Bitcoin. Resour. Policy 69, 101816. http://dx.doi.org/10.1016/j.resourpol.2020.101816.

Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econom. Statist. 20, 339–350. http://dx.doi.org/10.1198/073500102288618487.

Forbes, K.J., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market co-movements. J. Finance 57, 2223–2261. http://dx.doi.org/10.1111/1051-5255.00494.

Grinfeld, A., Moore, J.C., Jevrejeva, S., 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Process. Geophys. 11, 561–566.

Jowitt, S.M., 2020. COVID-19 and the global mining industry. SEG Discov. 3, 3–41. http://dx.doi.org/10.5382/SEGnews.2020-122.fea-02.

Junttila, J., Pesonen, J., Raatikainen, J., 2018. Commodity market based hedging against stock market risk in times of financial crisis: the case of crude oil and gold. J. Int. Financ. Mark. Inst. Money 56, 255–280. http://dx.doi.org/10.1016/j.intfin.2018.01.002.

Karamti, C., Belhassine, O., 2021. COVID-19 pandemic waves and global financial markets: evidence from wavelet coherence analysis. Financ. Res. Lett. 102136. http://dx.doi.org/10.1016/j.frl.2021.102136.

Kollias, C., Kyrtou, C., Papadamou, S., 2013. The effects of terrorism and war on the oil price-stock index relationship. Energy Econ. 40, 743–752. http://dx.doi.org/10.1016/j.eneco.2013.09.006.

Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Rev. Financ. Stud. 11, 817–844. http://dx.doi.org/10.1093/rfs/11.4.817.

Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financ. Quant. Anal. 28, 535–551.

Le, L.T.N., Yarovaya, L., Nasir, M.A., 2021. Did COVID-19 change spillover patterns between Fintech and other asset classes?. Res. Int. Bus. Financ. 58, 101441. http://dx.doi.org/10.1016/j.ribaf.2021.101441.

Lin, B., Su, T., 2021. Does COVID-19 open a Pandora’s box of changing the connectedness in energy commodities?. Res. Int. Bus. Financ. 56, 101360. http://dx.doi.org/10.1016/j.ribaf.2021.101360.

Liu, K., 2021. COVID-19 and the Chinese economy: impacts, policy responses and implications. Int. Rev. Appl. Econ. 35 (2), 308–330. http://dx.doi.org/10.1080/02692171.2021.1876641.

Lýočsa, Š., Baumöhö, E., Výrost, T., Molnár, P., 2020. Fear of the coronavirus and the stock markets. Financ. Res. Lett. 36, 101735. http://dx.doi.org/10.1016/j.frl.2020.101735.
Mariana, C.D., Ekaputra, I.A., Husodo, Z., 2020. Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? Financ. Res. Lett. 101798. http://dx.doi.org/10.1016/j.frll.2020.101798.

Matos, P., Costa, A., da Silva, C., 2021. COVID-19, stock market and sectoral contagion in US: a time-frequency analysis. Res. Int. Bus. Financ. 57, 101400. http://dx.doi.org/10.1016/j.ribaf.2021.101400.

McLeod, A., Li, W., 1983. Diagnostic checking ARMA time series models using squared-residual autocorrelations. J. Time Ser. Anal. 44 (4), 269–273.

Ming, Lei, Zhang, Xinran, Liu, Qianqiu, Yang, Shenggang, 2020. A revisit to the hedge and safe haven properties of gold: New evidence from China. J. Futures Mark. 40, 1442–1456.

Nasir, M.A., Du, M., 2018. Integration of financial markets in post global financial crises and implications for british financial sector : analysis based on a panel VAR model. J. Quant. Econ. 16, 363–388. http://dx.doi.org/10.1007/s40953-017-0087-2.

Nguyen, D.T., Phan, D.H.B., Ming, T.C., Nguyen, V.K.L., 2021. An assessment of how COVID-19 changed the global equity market. Econ. Anal. Policy 69, 480–491. http://dx.doi.org/10.1016/j.eap.2021.01.003.

Olson, E., Vivian, A., Wohar, M.E., 2017. Do commodities make effective hedges for equity investors? Res. Int. Bus. Financ. 42, 1274–1288. http://dx.doi.org/10.1016/j.ribaf.2017.07.064.

Perron, P., 1997. Further evidence on breaking trend functions in macroeconomic variables. J. Econom. 80, 355–385. http://dx.doi.org/10.1016/S0304-4076(97)00049-3.

Salisu, A.A., Ebuh, G.U., Usman, N., 2020. Revisiting oil-stock nexus during COVID-19 pandemic: Some preliminary results. Int. Rev. Econ. Financ. 69, 280–294. http://dx.doi.org/10.1016/j.iref.2020.06.023.

Salisu, A.A., Vo, X.V., Lawal, A., 2021. Hedging oil price risk with gold during COVID-19 pandemic. Resour. Policy 101897.

Shahzad, Syed Jawad Hussain, Bouri, Elie, Roubaud, David, Kristoufek, Ladislav, 2020. Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. Econ. Model. 87, 212–224.

Torrence, C., Webster, P.J., 1999. Interdecadal changes in the ENSO–monsoon system. J. Clim. 12, 2679–2690. http://dx.doi.org/10.1175/1520-0442(1999)012<2679:ICITEM>2.0.CO;2.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Financ. Res. Lett. 36, 101528. http://dx.doi.org/10.1016/j.frll.2020.101528.