Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

To what extent does COVID-19 drive stock market volatility? A comparison between the U.S. and China

Xue Gao, Yixin Ren & Muhammad Umar

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2022, VOL. 35, NO. 1, 1686–1706
https://doi.org/10.1080/1331677X.2021.1906730

To what extent does COVID-19 drive stock market volatility? A comparison between the U.S. and China

Xue Gao[a], Yixin Ren[a] and Muhammad Umar[b]

[a]College of Economics and Management, Shandong University of Science and Technology, Qingdao, China; [b]School of Economics, Qingdao University, Qingdao, China

ABSTRACT

This paper presents a novel wavelet-based quantile-on-quantile method for comparing the impact of COVID-19 on stock market volatility between the U.S. and China. Wavelet decomposition shows that the impact has stronger regularity in the lower frequency domain. Compared with oil price fluctuations, COVID-19 is the main reason for the sharp fluctuation of the U.S. stock market. Unlike China, however, the strong growth of daily new cases, which continued for months, has made the U.S. stock market insensitive to COVID-19. In addition, the particularly loose interest rate policy has effectively suppressed the volatility of the U.S. stock market. However, in contrast to China, the near zero interest rate applied by the U.S. makes it difficult to generate sufficient monetary policy space to address a new potential crisis. The result of this study presents the differences of the financial market response under different epidemic management modes. Under the background that COVID-19 is not effectively controlled, a loose monetary policy may be an expedient measure to stabilise the market. This is of great practical significance towards achieving epidemic control and financial market stability under the background of the global spread of COVID-19.

ARTICLE HISTORY
Received 2 November 2020
Accepted 17 March 2021

KEYWORDS
stock volatility; COVID-19; quantile-on-quantile; wavelet transform

JEL CLASSIFICATIONS
E44; E66; G18

1. Introduction

Since 2020, the worldwide outbreak of the novel coronavirus (COVID-19) has greatly damaged the economy and finance, which far exceeded the damage by previous major public health events (such as the Spanish flu of 1918). Data from the World Health Organization (WHO) showed that, by December 26, 2020, the number of confirmed cases in the U.S. had reached 28,028,815, further indicating that the inflection point of the epidemic has not yet happened. In contrast, although COVID-19 first emerged in Wuhan, China, because of the immediate implementation of a strict home isolation policy, a number of East Asian countries (e.g., South Korea and China) have basically overcome the grip of COVID-19.

CONTACT Yixin Ren 912393320@qq.com

With the spread of the epidemic since early March 2020, the market's risk aversion increased. In March 2020, the U.S. stock market experienced four fusions in less than two weeks. This represents the second time that a circuit breaker occurred at the U.S. stock market since the establishment of the circuit breaker mechanism in 1987. This also represents the first time that four circuit breakers have occurred within eight trading days. The largest declines of the three major stock indexes (DJ, NASDAQ, and S&P 500) were 37.1%, 30.1%, and 31.9%, respectively. This represents a decrease of more than 10 trillion USD, accounting for more than 45% of the U.S. gross domestic product (GDP) in 2019. It was not until the U.S. Federal Reserve cut the interest rates to zero in May 2020 and announced unlimited quantitative easing monetary policy, that this most severe stock market decline could be stopped.

In this context, this paper focuses on the following issues. First, in March 2020, the global crude oil price also experienced strong fluctuations. The extent to which COVID-19 and crude oil price fluctuations led to a significant increase in the volatility of the U.S. stock market was investigated. Second, assuming that COVID-19 as an innovation shock is related to the stock market setback in March 2020, this study investigated whether COVID-19 imposes a temporary shock or a long-term impact on the stock market. Third, this study investigated whether the U.S. stock market has adapted to the sustained shock with the continuing epidemic. In contrast, it was further assessed whether the sensitivity of China's stock market to COVID-19 differed from that of the U.S. stock market. Fourth, the extent to which significant interest rate cuts and unlimited quantitative easing alleviated stock market volatility was investigated. This study assessed whether the background of low interest rates after May 2020 weakens the effectiveness of future loose monetary policy and the space for monetary policy implementation. Fifth, at different stages of COVID-19 development and stock market volatility, the differences and regularities associated with the impact of COVID-19 on stock market volatility were assessed.

To address the above questions, appropriate empirical strategies need to be designed. Firstly, to investigate the correlation between COVID-19 and stock market volatility in different states, the quantile-on-quantile (QQ) method proposed by Sim and Zhou (2015) was used. The QQ approach represents a combination of quantile regression and nonparametric estimation of local linear regression. This method enables the involvement of regressing the quantile of a variable onto the quantile of another variable. Therefore, the nonlinear impact of COVID-19 on the stock market volatility can be estimated. To further compare the impact of oil volatility shocks and to test the effectiveness of the interest rate policy, the two variable QQ method was expanded and changed into the multivariable QQ method by incorporating a number of control variables. In addition, to investigate the short-, medium-, and long-term impacts of COVID-19 on the stock market, wavelet transform was used to decompose the time series of the main variables into three frequencies. Then, the multivariate QQ method was used to re-examine the impact of COVID-19.

The obtained empirical results generated several meaningful results. First, COVID-19 was found to exert a higher impact on stock market volatility when the latter is in a higher quantile (i.e., the leverage effect). This reflects a kind of asymmetry both in the U.S. and China. This leverage effect can also be found in the impact of oil price volatility on stock market volatility. Second, the U.S. stock market was more sensitive to the earlier stage of COVID-19, the impact of which exceeded the oil price volatility. This identifies COVID-19 as the main factor that caused the U.S. stock market volatility. Subsequently, the U.S. stock market seems to have adapted to the background of the persistently high number of daily new COVID-19 cases. Third, China's stock market was found to be more sensitive to slight fluctuations among daily new cases; however, the impact of COVID-19 on the volatility of China's stock market was lower than that of oil price because of the small scale of infection in China. Fourth, the empirical results show that the monetary policy of unlimited quantitative easing, as implied by the U.S. government, has effectively suppressed fluctuations of the U.S. stock market. However, with the decrease of interest rate, the influence of the interest rate policy on the stock market is low. This implies that it is difficult to have sufficient monetary policy space to deal with a potential financial market crisis in the near future. In contrast, China has maintained a high degree of flexibility in its interest rate policy throughout the COVID-19 epidemic.

The main innovations and contributions of this paper are listed in the following: First, the main causes of the U.S. stock market crash in March 2020 are clarified, and the nonlinear impact of COVID-19 is carefully investigated. Furthermore, the dynamic responses of the financial markets of both China and the U.S. to the impact of COVID-19 is intriguing as these responses can be mapped to different governance models of public health crises. Second, the effectiveness of U.S. monetary policy in translating stock market volatility was confirmed, while a low interest rate policy was identified as unsustainable in dealing with persistent potential crisis. This result in particular has implications for the future governance of COVID-19. Third, at the methodological level, this study innovated the combination of wavelet transform with the QQ method, which has reference significance for investigating the nonlinear correlations of time series in different frequency domains.

The remainder of this paper is organised as follows: Section 2 reviews relevant literature about COVID-19 and the stock market. Section 3 introduces the maximum overlap discrete wavelet transform and the QQ approach. Then, Section 4 introduces the utilised data and explains the corresponding empirical results. Section 5 concludes the paper.

2. Literature review

Since 2020, the number of papers discussing the impact of COVID-19 (Mirza et al., 2020a, 2020b, 2020c; Rizvi et al., 2020; Yarovaya et al., 2021), especially its impact on the stock market has increased (Sharif et al., 2020; Zhang et al., 2020). COVID-19 greatly impacts the U.S. stock market, which has basically become a consensus among academia; however, the specific channel and mechanism of its influence has not been clearly investigated to date. Baker et al. (2020) investigated various potential causes and identified the role of governmentally imposed restrictions on individual mobility and commercial activity combined with voluntary social distancing as an important reason that caused the crash of the U.S. stock market. However, although He et al. (2020), Huo and Qiu (2020), and Xiong et al. (2020) all provided evidence that China has implemented a very strict household segregation policy, which negatively impacted the Chinese stock market, the impact was far less severe than that on the U.S. stock market. This means that the implementation of the prevention and control policy for this epidemic may not be the core factor that led to the observed stock price volatility. Although not quite as intuitive, a number of studies on the impact of COVID-19 proposed different perspectives. For example, Onali (2020) used a GARCH model and provided evidence that changes in the number of cases and deaths associated with COVID-19 in the U.S. (and six other countries that are strongly affected by the COVID-19 crisis) did not impact the U.S. stock market returns.

Phan and Narayan (2020) argued that COVID-19, as a form of unexpected news, could lead to market over-reactions and with the availability of more information, people would better understand the ramifications and the market would correct itself. This suggests that the re-stabilisation of the U.S. stock market in the second half of 2020 is not only the result of the applied loose monetary policy, but also that of the adaptability of the stock market itself. Theoretically, Daniel et al. (1998) and Hong and Stein (1999) proposed that investor underreactions and overreactions can also explain fluctuations of stocks caused by shocks and their reversion. The present study addressed the extent to which the stabilisation of the U.S. stock market results from its own adaptability, the strength of the role of the applied monetary policy, and whether COVID-19 only represents a short-term impact or whether it is likely that is has a lasting and far-reaching impact.

The currently available literature is insufficient to provide a systematic answer. In light of the possible consequences of specific monetary policies, Zhang et al. (2020) analysed the potential consequences of policy interventions. Examples are the U.S. decision to implement both a zero-percent interest rate and unlimited quantitative easing. Zhang et al. (2020) suggested that these policies may introduce further uncertainties into global financial markets. In addition, with regard to the differences among short- and long-term impacts, Sharif et al. (2020) implemented an empirical investigation using wavelet analysis. Mazur et al. (2021) also investigated the asymmetric relationship between stock price return and volatility in specific companies that were affected by COVID-19; however, no empirical evidence regarding this effect has been presented in the macro financial market.

3. Methodology

3.1. Wavelet analysis

Wavelet analysis has been widely used in the field of economics and finance (Su et al., 2019; 2020). A wavelet is a wave-like oscillation beginning at zero, changing over time, and then reverting to zero (Yahya et al., 2019). By using wavelets of different frequencies to fit the time series of different periods, wavelets can be used both in the frequency and the time domain (Crowley, 2007; Graps, 1995; Torrence & Webster, 1999).

The wavelet requires orthonormal bases, which can be obtained by dyadically dilating and translating a pair of particularly constructed functions φ and ψ such that:

$$\int \varphi(t)dt = 1 \tag{1}$$

$$\int \psi(t)dt = 0 \tag{2}$$

where φ and ψ represent the father wavelet and mother wavelet, respectively.

The father wavelet captures the smooth and low-frequency parts of the series, while the mother wavelet captures the detailed and high-frequency components. The obtained wavelet basis can be given respectively by the following pair of functions:

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t - k) \tag{3}$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \tag{4}$$

where $j = 1, \ldots, J$ represents the scale and $k = 1, \ldots, 2^j$ represents the translation. The maximum number of scales that can be considered by the analysis is limited by the number of observations ($T \geq 2^J$).

One special property of wavelet expansion is the localisation property that the coefficient of $\psi_{j,k}(t)$, which represents the information content of the function at the approximate location $k2^{-j}$ and frequency 2^j. Using wavelets, any function in $L^2(\mathbb{R})$ can be uniquely expanded over the wavelet basis as a linear combination at the arbitrary level $J_0 \in \mathbb{N}$ across different scales of type:

$$X(t) = \sum_k S_{J_0,k}\varphi_{J_0,k}(t) + \sum_{j>J_0}\sum_k d_{j,k}\psi_{j,k}(t),\ \ j = J_0, \ldots, J \tag{5}$$

where $\varphi_{J_0,k}$ represents a scaling function, where the corresponding coarse scale coefficients $S_{J_0,k}$ and $d_{j,k}$ represent the detailed (i.e., fine scale) coefficients given by $S_{J_0,k} = \int X(t)\varphi_{J_0,k}(t)dt$ and $d_{j,k} = \int X(t)\psi_{j,k}(t)dt$, respectively. These coefficients add a measure of the contribution of the corresponding wavelet to the function. The series $S_{J,t} = \sum_k S_{J_0,k}\varphi_{J_0,k}(t)$ provides a smooth version of the original time series $X(t)$, which captures the long-term (i.e., low-frequency) properties, while the series $D_{J,t} = \sum_k d_{j,k}\psi_{j,k}(t)$ captures local fluctuations (i.e., the higher-frequency characteristics) of $X(t)$.

3.2. Maximum overlap discrete wavelet transform

Discrete wavelet transform (DWT) can perform wavelet transform for which the wavelets are discretely sampled, based on two types of filters, the scaling filter (h_l, $l = 0, \ldots, L - 1^2$) and the wavelet filter (g_l, $l = 0, \ldots, L - 1^3$). $L \in \mathbb{N}$ represents the length of the filter (Percival and Mofjeld , 1997). By definition, a real-valued wavelet filter satisfies the following three properties:

$$\sum_{l=0}^{L-1} h_l = 0,\ \sum_{l=0}^{L-1} h_l^2 = 1,\ \textit{and}\ \sum_{l=0}^{L-1} h_l h_{l+2n} = 0\ \forall\ n \in N \tag{6}$$

The low- and high-pass filters are defined as quadrature mirror filters (QMfs), which satisfy:

$$h_l = (-1)^l g_{L-1-l} \ or \ g_l = (-1)^{l+1} h_{L-1-l}, \ \ l = 0, \ldots, L-1 \tag{7}$$

Similar to the wavelet filter, the scaling filter satisfies the following conditions:

$$\sum_{l=0}^{L-1} g_l = \sqrt{2}, \ \sum_{l=0}^{L-1} g_l^2 = 1, \ and \ \sum_{l=0}^{L-1} g_l g_{l+2n} = 0 \ \forall \ n \in N \tag{8}$$

The wavelet and scaling coefficients ($W_{j,t}$ and $V_{j,t}$, respectively) of DWT at the j th level for $j \in \{1, \ldots, J\}$ are defined as:

$$W_{j,t} = \sum_{l=0}^{L-1} h_l X_{t-l} \ and \ V_{j,t} = \sum_{l=0}^{L-1} g_l X_{t-l} \tag{9}$$

In this study, the modified version of DWT was applied, namely maximal overlap discrete wavelet transform (MODWT), as introduced by Percival and Mofjeld (1997). This was used to decompose the underlying returns series. The MODWT is an extension of DWT that overcomes the limitations of DWT. Daubechies least asymmetric wavelet filters in MODWT were chosen to obtain the wavelet and scaling coefficients because of their better ability to capture both the time and scale variations in a time series. Furthermore, Daubechies least asymmetric (LA(8)) wavelet filter is most favoured in the financial literature because of its approximate linear phase and near symmetric properties (Percival & Mofjeld, 1997).

Wavelet transform leads to a decomposition of the time series into different frequency bands via successive low- and high-pass filtering of the signal. More specifically, the original return series is decomposed into a set of wavelet coefficients ($\widetilde{W}_{j,t}$) and low-pass filtered versions ($\widetilde{V}_{j,t}$) of the signal. As the MODWT is incorporated, rescaled scaling and wavelet filters were utilised that were directly obtained from DWT as follows:

$$\widetilde{h}_{j,l} = \frac{h_{j,l}}{2^{j/2}} \ and \ g_{j,l} = \frac{g_{j,l}}{2^{j/2}}, \ \ j = 0, \ldots, J \tag{10}$$

Following Mallat (1989), $\widetilde{W}_{j,t}$ and $\widetilde{V}_{j,t}$ were obtained by applying the pyramid algorithm to the series of each variable. Three inputs for each iteration of the MODWT pyramid algorithm are required. The first iteration begins by convolving (i.e., filtering) data with wavelet and scaling filters and obtains the following wavelet and scaling coefficients:

$$\widetilde{W}_{1,t} = \sum_{l=0}^{L-1} \widetilde{h}_l X_{t-l} \ and \ \widetilde{V}_{1,t} = \sum_{l=0}^{L-1} \widetilde{g}_l X_{t-l} \tag{11}$$

In the second step of the MODWT pyramid algorithm, the scaling coefficients of the first iteration become input data vectors and filtering operations are applied to obtain the second-level wavelet and scaling coefficients as follows:

$$\tilde{W}_{2,t} = \sum_{l=0}^{L-1} \tilde{h}_l \tilde{V}_{1,t-l \bmod N} \; and \; \tilde{V}_{2,t} = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{V}_{1,t-l \bmod N} \tag{12}$$

Similarly, the j th level MODWT wavelet and scaling coefficients of the time series X_t are defined as:

$$\tilde{W}_{j,t} = \sum_{l=0}^{L-1} \tilde{h}_l X_{t-l \bmod N} \; and \; \tilde{V}_{j,t} = \sum_{l=0}^{L-1} \tilde{g}_l X_{t-l \bmod N} \tag{13}$$

3.3. The quantile-on-quantile approach

This section briefly describes the key features of the QQ approach (Sim & Zhou, 2015) as well as the model specification used in this study to examine the impact of COVID-19 on stock market volatility. This method has been widely applied to various fields of finance and economics, such as energy consumption (Shahbaz et al., 2018), tourism economics (Shahzad et al., 2017), and stock volatility (Gupta et al., 2018; Mishra et al., 2019).

The QQ method can be perceived as a generalisation of the standard quantile regression model, which enables the examination of how the quantiles of a variable affect the conditional quantiles of another variable. The QQ approach is based on a combination of quantile regression and nonparametric estimation of local linear regression.

Within the framework of the present study, the QQ approach is used to investigate the effect of the quantiles of COVID-19 on the quantiles of the stock market volatility of both the U.S. and China. This approach starts with the following nonparametric quantile regression model:

$$VOLT_t = \alpha^\theta + \beta^\theta COVID_{t-1} + \gamma^\theta VOLT_{t-1} + u_t^\theta \tag{14}$$

where $VOLT_t$ represents the market volatility of stock returns; $COVID_t$ represents the number of new cases at day t; θ represents the θ th quantile of the conditional distribution of $VOLT_t$, and u_t^θ represents a quantile error term whose conditional θ th quantile is equal to zero. Parameters, such as $\beta^\theta(\cdot)$, are unknown functions because no prior information was available that linked dependent and independent variables.

Then, to analyse the relationship between the θ th quantile of $VOLT$ and the τ th quantile of $COVID_t$ (denoted by $COVID^\tau$), Equation (15) is examined in the context of $COVID^\tau$ by employing local linear regression. Because $\beta^\theta(\cdot)$ is unknown, this function can be approximated by a first-order Taylor expansion around the quantile $COVID^\tau$, so that

$$\beta^{\theta}(COVID_{t-1}) = \beta^{\theta}(COVID^{\tau}) + \beta^{\theta'}(COVID^{\tau})(COVID_{t-1} - COVID^{\tau}) \tag{15}$$

where $\beta^{\theta'}$ represents the partial derivative of $\beta^{\theta}(COVID_{t-1})$ with respect to $COVID$. This is also called the marginal effect or response, and can be interpreted to be similar to the slope coefficient in a linear regression model.

A prominent feature of Equation (15) is that the parameters $\beta^{\theta}(COVID_{t-1})$ and $\beta^{\theta'}(COVID^{\tau})$ are doubly indexed in θ and τ. Given that $\beta^{\theta}(COVID_{t-1})$ and $\beta^{\theta'}(COVID^{\tau})$ are both functions of θ and $COVID^{\tau}$, and that $COVID^{\tau}$ is a function of τ, it is clear that both $\beta^{\theta}(COVID_{t-1})$ and $\beta^{\theta'}(COVID^{\tau})$ are functions of θ and τ. Additionally, $\beta^{\theta}(COVID_{t-1})$ and $\beta^{\theta'}(COVID^{\tau})$ can be renamed as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$, respectively. Accordingly, Equation (15) can be rewritten as:

$$\beta^{\theta}(COVID_{t-1}) = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(COVID_{t-1} - COVID^{\tau}) \tag{16}$$

Equation (17) is obtained by substituting Equation (16) into Equation (14):

$$VOLT_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(COVID_{t-1} - COVID^{\tau})}_{(*)} + u_t^{\theta} \tag{17}$$

The part $(*)$ of Equation (17) is the θ th conditional quantile of $VOLT$. However, unlike the function of the standard conditional quantile, this expression reflects the relationship between the θ th quantile of $VOLT$ and the τ th quantile of $COVID$ because the parameters β_0 and β_1 are doubly indexed in θ and τ. These parameters may vary across different θ th quantiles of $VOLT$ and the τ th quantile of $COVID$. Moreover, a linear relation is not assumed at any time between the quantiles of the studied variables. Therefore, Equation (17) estimates the overall dependence structure between $VOLT$ and $COVID$ through the dependence between their respective distributions.

Estimating Equation (17) requires replacing $COVID_{t-1}$ and $COVID^{\tau}$ with their estimated counterparts $\widehat{COVID}_{t-1}$ and $\widehat{COVID}^{\tau}$, respectively. The local linear regression estimates of the parameters b_0 and b_1, which are estimates of β_0 and β_1, respectively, are obtained by solving the following minimisation problem:

$$\min_{b_0, b_1} \sum_{i=1}^{n} \rho_{\theta}\left[VOLT_t - b_0 - b_1\left(\widehat{COVID}_{t-1} - \widehat{COVID}^{\tau}\right)\right] \times K\left(\frac{F_n\left(\widehat{COVID}^{\tau}\right) - \tau}{h}\right) \tag{18}$$

where $\rho_{\theta}(u)$ represents the quantile loss function, defined as $\rho_{\theta}(u) = u(\theta - I(u < 0))$, and I represents the usual indicator function. $K(\cdot)$ denotes the Gaussian kernel function and h represents the bandwidth parameter of the kernel. Following Sim and Zhou (2015), $h = 0.05$ was chosen as bandwidth parameter in this paper.

In addition to the core explanatory variable $COVID$, other control variables can be easily added to the above model. In this paper, several important variables are

Table 1. Basic statistical analysis.

	COVID-19		Stock Volatility		Interest Rate		
	China	U.S.	China	U.S.	China	U.S.	Oil Volatility
Minimum	0.000	0.000	0.013	0.007	1.485	0.088	0.023
Maximum	9.626	11.151	0.040	0.090	2.717	1.594	0.275
Mean	3.659	7.885	0.018	0.020	2.088	0.490	0.062
Median	3.584	10.131	0.016	0.015	2.156	0.113	0.037
Stdev	1.944	4.246	0.005	0.015	0.261	0.587	0.054
Skewness	0.322	−1.153	1.681	2.063	−0.341	1.110	1.908
Kurtosis	0.353	−0.517	3.014	4.648	−0.162	−0.551	2.858
ADF	−2.625	−2.192	−9.529	−2.784	−13.229	−11.117	−11.063
Prob.	(0.090)	(0.210)	(0.000)	(0.063)	(0.000)	(0.000)	(0.000)

Note: The size of the sample is 172; COVID-19 shows the natural logarithm of daily new cases; where daily new cases list one, the value of COVID-19 was set to zero. The last two rows present the results of the ADF test and the corresponding p-values.
Source: Authors' calculations.

controlled, including the volatilities of the crude oil price, interest rate, and stock volatility with one period lag.

4. Empirical analysis

4.1. Data

The data of the COVID-19 daily new cases of China and the U.S. were used as the core independent variable (data originated from the WHO). Although literature such as Jeris and Nath (2020) also use daily new deaths to measure shocks of COVID-19, the present study did not consider this indicator since China had zero new cases for most of the time since April 14, 2020. A $GARCH(1,\ 1)$ model with t distribution was used to calculate the volatility of stock returns and oil returns. The returns series are calculated via the logarithmic difference of the corresponding stock price indexes or crude oil prices. Among them, the S&P 500 index and Shanghai Shenzhen 300 (CSI 300) index were used to measure the stock volatilities of China and the U.S., respectively. Moreover, the West Texas Intermediate (WTI, data was obtained from the U.S. Energy Information Administration) price was used to measure crude oil prices. Also, one-week Shibor and Libor were used to measure the interest rate of China and the U.S., respectively. Data of stock prices and interest rates were obtained from the WIND database. All series of prices and daily new cases were presented in the natural logarithm.

Table 1 summarises the basic descriptive statistics of the main variables and column 1 of Figure 1 shows their time series. Even after taking the natural logarithm, the average number of new cases per day in the U.S. (7.885) was still much higher than that in China (3.659). In terms of the actual number of new cases, the average number of new cases per day in China was 38.82, while that in the U.S. was 2657.13. In terms of the median, the gap between both countries in terms of daily new cases was even greater (36.01 in China and 25109.46 in the U.S.). This implies that although the epidemic first emerged in China, the U.S. maintained a high number of new cases for a longer period across the sample. Figure 1 (column 1, row 1) shows that in China, the outbreak began in January 2020 and already peaked at the end of

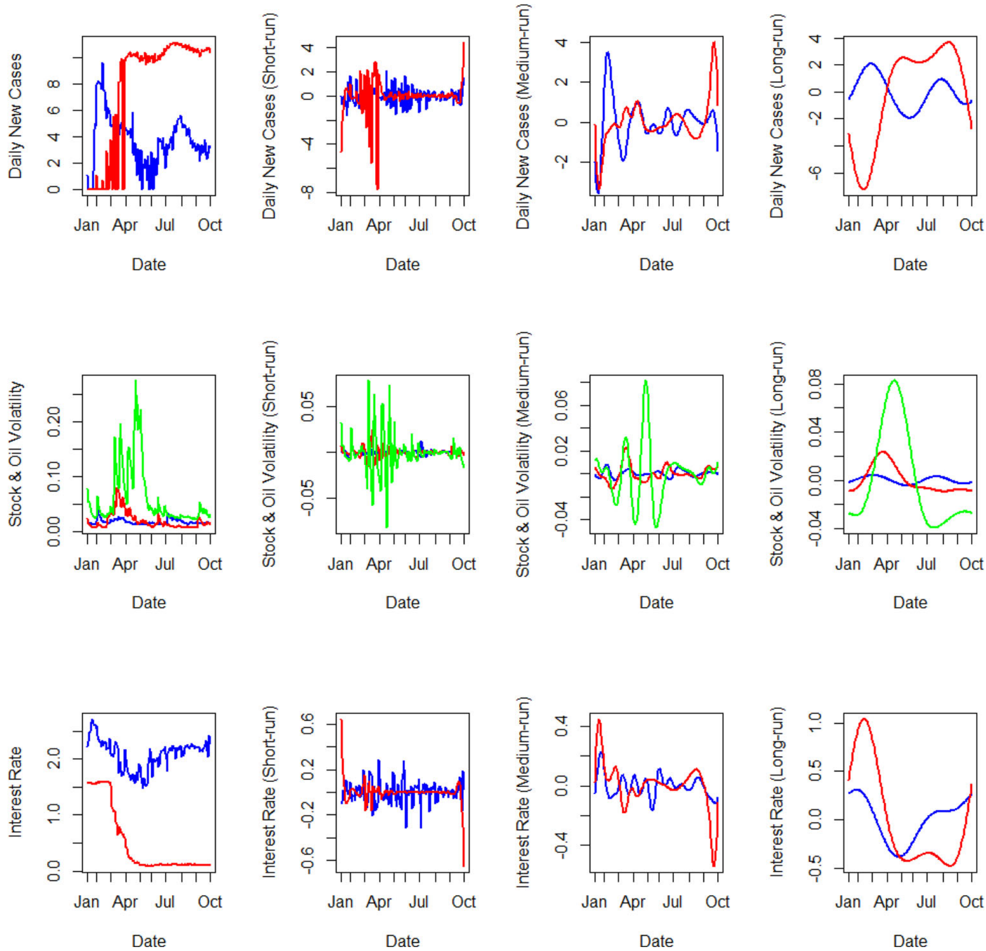

Figure 1. Series of variables and wavelet transforms.
Note: Blue lines denote China, red lines denote the U.S., and green lines denote the oil price volatility; the 1st, 2nd, 3rd, and 4th column show the original, short-, medium-, and long-term series, respectively.
Source: Authors' calculations.

February 2020. In response to the strict isolation policy, the number of new cases decreased rapidly from March and continued to show a low level of fluctuation. In contrast, the number of new cases in the U.S. increased rapidly since March 2020 and maintained at a high level from May 2020 to the end of the sample period.

Whether the outbreak of the epidemic imposed a significant impact on the stock market was investigated next. Figure 1 (column 1, row 2) shows the short-term abnormal fluctuation in China's stock market in January 2020; however, the overall range remained relatively limited. After March 2020, a long-term and large-scale abnormal fluctuation affected the U.S. stock market, which is consistent with the outbreak time of COVID-19. This does not necessarily mean that the outbreak of COVID-19 in the U.S. was the cause of fluctuations in its stock market. Figure 1 shows that the crude oil price also fluctuated significantly in March 2020, which is also consistent with the enormous fluctuation of the U.S. stock market. Therefore, to

Table 2. Decomposed series.

Component	Time-horizon	Definition
Scale 1	2-4 days	Short-term
Scale 2	4-8 days	Short-term
Scale 3	8-16 days	Short-term
Scale 4	16-32 days	Medium-term
Scale 5	32-64 days	Medium-term
Scale 6	64-128 days	Long-term
Scale 7	128-256 days	Long-run

Note: The table provides the definition underlying the applied setup. Scales 1–3 represents the variations over daily, weekly, and fortnightly intervals, respectively, which can then be represented as low scales. Scales 4 and 5 capture the changes between one and two months and can be interpreted as intermediate scales. Scales 6 and 7 represent variations over a half and one-year period and characterise high-scale data.
Source: Authors.

investigate the impact of COVID-19 on the stock market, the crude oil price fluctuation was used as control variable.

In addition, on average, the U.S. interest rate (0.490) was much lower than that of China (2.088) during the sample period. This is closely related to the four stock fusions of the U.S. from March 9 to 18, 2020. Figure 1 (column 1, row 3) shows that the U.S. interest rate sharply declined since March 2020, while China's interest rate remained at a higher level and was more stable. Clearly, the U.S. Federal Reserve quickly released considerable liquidity during the crisis to stabilise the stock market. However, although the volatility of the U.S. stock market reached a lower level after May 2020, the interest rate has remained close to zero since then. In contrast, while China's interest rates also followed an overall decreasing trend during the early stage of the epidemic (i.e., the first half of 2020), the scope of this decline was limited. Gradually, interest rates returned to their original level in the second half of 2020. This suggests that the interest rate policy may play an important role in stabilising the stock market; therefore, the interest rate should also be controlled to investigate the impact of COVID-19.

In addition to the analysis of the original (i.e., undecomposed) series, the multi-scale regression decomposed series was also examined, partitioned into short-, medium-, and long-term trends (Figure 1, columns 2-4). Table 2 presents the applied definition underlying the applied setup. Specifically, the short-term series reflects the variations over the short-term horizon caused by shocks occurring between 2 and 6 succeeding days (i.e., daily and weekly effects); the medium-term series captures the dependence dynamics between 32 and 64 days (i.e., monthly effects); the trend of the long-term series shows variations in the connectedness structure between 64 and 256 succeeding days (i.e., yearly effects).

4.2. The impact of COVID-19

This section presents the primary empirical results of the QQ analysis using both the original series and the series after wavelet decomposition. All regressions had control variables added that included the oil volatility, interest rate, and one period lag of stock market volatility. Figure 2 displays the impact of COVID-19 on China and the volatility of the U.S. stock market. The values in the z-axis capture the effect the τ th quantile of daily new cases exerts on the θ th quantile of stock market volatility.

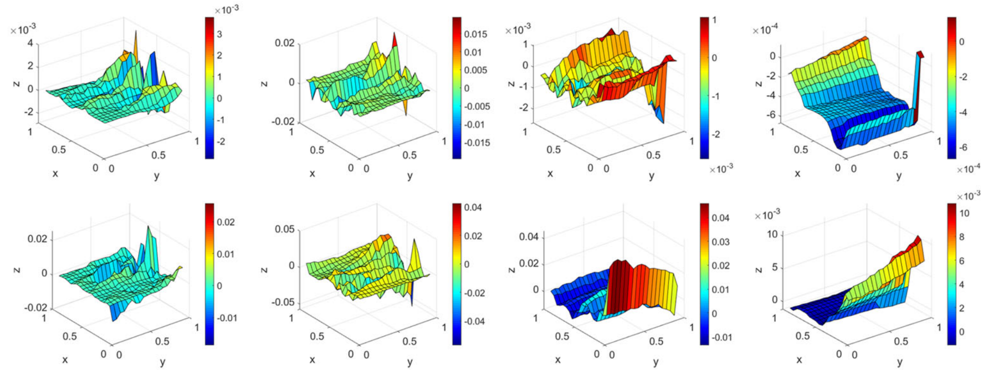

Figure 2. Quantile-on-quantile (QQ) estimates of impacts from COVID-19.
Note: These graphs show the estimates of the slope coefficient of COVID-19 in the *z*-axis against the quantiles of stock volatility in the *y*-axis and the quantiles of daily new cases in the *x*-axis. Rows 1 and 2 show the results for China and the U.S., respectively. Columns 1-4 show the results of original, short-, medium-, and long-term series, respectively.
Source: Authors' calculations.

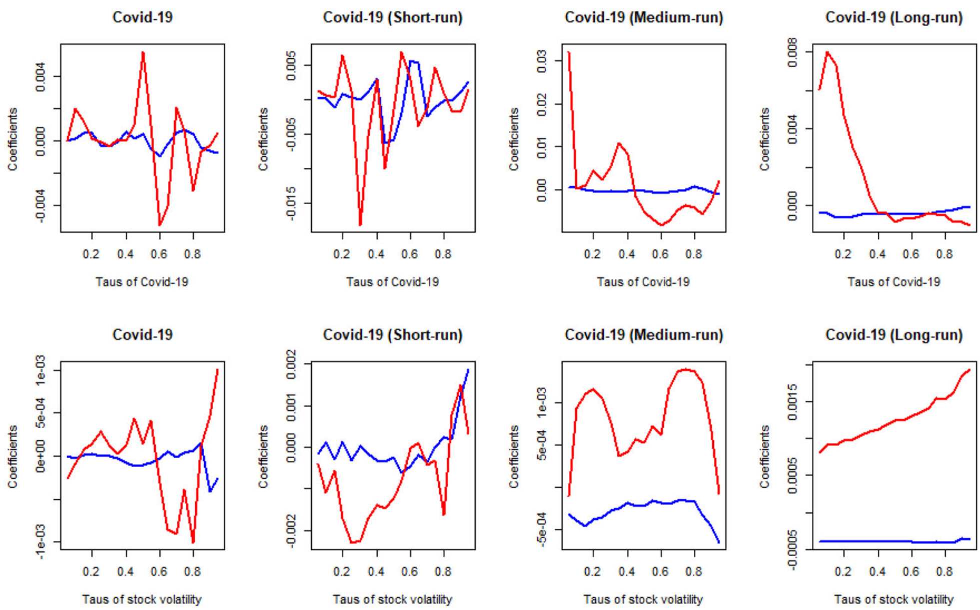

Figure 3. Averaged QQ parameters of COVID-19.
Note: These graphs show the averaged slope coefficients of COVID-19. The blue lines and red lines show the results for China and the U.S., respectively. Rows 1 and 2 are averaged by quantiles of stock volatility and quantiles of daily new cases, respectively. Columns 1-4 show the results of original, short-, medium-, and long-term series, respectively.
Source: Authors' calculations.

Figure 3 shows the averaged QQ regression results to facilitate the study of the impact of different dimensions. Figures 2 and 3 show important results.

The results of the original series (Figures 2 and 3, column 1) show that the impact of daily new cases (in different quantiles) on stock market volatility (in different quantiles) shows many differences. The impact of new cases on the stock volatility in both countries was small when the quantile of stock volatility was low; however, this effect followed an increasing trend with increasing stock volatility quantile. This shows that when the stock market is in a state of extreme volatility, the epidemic situation is more likely to further boost the market panic, thus aggravating the stock volatility. This result is consist with the leverage effect (Christie, 1982 and Schwert,1989), which states that the extreme volatility of a stock is more related to its negative return, and effect that shows strong asymmetry.

Another finding is that COVID-19 had the greatest impact (0.017) on the volatility of China's stock market at the 0.75 quantile of daily new cases and the 0.9 quantile of stock market volatility (Figure 2, row 1, column 1). In case of the U.S., the greatest impact (0.027) was found at the 0.5 quantile of daily new cases and the 0.85 quantile of stock market volatility (Figure 2, row 2, column 1). This result means that when the number of new cases almost reaches the peak, the impact on China's stock market was biggest. In contrast, when the number of new cases is still within the development stage, its impact on the U.S. stock market has already reached the peak. This is clearly depicted in Figure 1 (row 1, column 1): when the number of China's daily new cases peaked at the end of February 2020, it began to decline rapidly, and no sustained period of high new cases was experienced. In contrast, the number of new cases in the U.S. peaked at the end of March 2020 and maintained a high growth rate until the end of the sample period. In this context, it should be noted that the 0.5 quantile of the U.S. daily new case was 25101, while the 0.75 quantile of China's daily new case was only 114.

This result implies that at the beginning of the outbreak, China's stock market was more sensitive to the impact of COVID-19 with regard to the absolute number of new cases. In addition, the enormous difference in the absolute number of daily new cases also partly explains why the U.S. stock market experienced such a large shock in March 2020, while China's stock market remained relatively stable. More importantly, most of the sample data in the 0.5 to 1.0 quantiles of daily new cases in the U.S. are distributed after May 2020. This implies that the U.S. stock market is becoming less sensitive to the COVID-19 shock as the epidemic continued. However, the data suggest that China has always maintained a high sensitivity to COVID-19. For example, three asymptomatic local infections were identified in Qingdao on October 11, 2020, and the Qingdao municipal government immediately imposed large-scale RNA monitoring. As of October 14, more than 8.8 million samples were collected, and a total of 12 confirmed cases were finally identified. These news had a strong impact very quickly. As of October 13, 243 flights to Qingdao had been cancelled.

Although the regression based on the original series has yielded much valuable information, the results shown in Figure 3 (column 1) imply that the influence of COVID-19 still showed strong random fluctuation with the change of quantile. Especially in response to increases of daily new cases, the influence of COVID-19 does not show obvious regularity. One possible explanation is that although the interest rate, oil volatility, and the stock market volatility (which lags one period) have been controlled, many short-term random shocks may still affect the results of the estimation.

The question whether the epidemic had a long-term and far-reaching impact on the stock market, or whether its impact was merely temporary, was investigated next. For this purpose, wavelet transform was used to decompose the time series of variables into three different frequencies, namely short-, medium-, and long-term series. Columns 2-4 of Figures 2 and 3 show the estimation results.

The results imply that with decreasing series volatility frequency, the impact of COVID-19 on the stock market volatility showed more obvious regularity. First, COVID-19 still showed strong randomness in the short-term (daily and weekly, Figures 2 and 3, column 2). However, COVID-19 had a stronger impact on the volatility of the stock market in the two countries at a higher quantile of stock volatility, reflecting a certain degree of asymmetry. Second, the medium- and long-term (Figures 2 and 3, columns 3 and 4) estimates imply that, compared with the U.S., the impact of COVID-19 on China remained relatively stable and close to zero; however, the impact of COVID-19 on the U.S. was more volatile under different quantiles. One reasonable explanation is that the number of new cases in the U.S. far exceeded that of China, which may increase the long-term impact and reach of COVID-19. The data suggest that COVID-19 had a higher impact on the stock market volatility in the medium-term when the daily new cases were in the lower quantile (0.2-0.4) and when the stock market volatility was in the higher quantile (0.6-0.8). In the long-term, when the daily new cases were in the quantile of 0.05-0.4, COVID-19 had a strong impact on the volatility of the U.S. stock market. However, with the further increase of daily new cases, this impact decreased rapidly, even below the impact of COVID-19 on China. At the same time, with increasing volatility of the U.S. stock market, the impact of COVID-19 showed an obvious increasing trend, and the impact on the U.S. stock market was always higher than that on the Chinese stock market. On the one hand, these results further confirm the leverage effect and the dynamic adaptability of the stock market. That is, when an epidemic situation initially breaks out, the market may react violently, but when the epidemic continues, the market begins to adapt to it, thus weakening the influence of the epidemic situation. On the other hand, the medium- and long-term estimates show that COVID-19 had a relatively small impact on China's stock market but may impose a lasting and far-reaching impact on the U.S. stock market.

4.3. Impact of oil volatility and interest rate

From March to May 2020, in addition to the outbreak of COVID-19, the international crude oil price also experienced strong fluctuations. The impact of these crude oil price fluctuations on the stock market were assessed to investigate whether these fluctuations are one of the main factors leading to the four circuit breakers of the U.S. stock market. Figures 4 and 5 show the corresponding estimates. According to the estimation results of the original series (Figures 4 and 5, column 1), only when the oil price volatility is within the low quantile range (0.05-0.2) and when the stock market volatility is within the high quantile range (0.8-0.95), the oil price volatility had a relatively strong impact on the stock market volatility of the U.S. and China. In addition, judging from the absolute size of the coefficient, the impact of oil price volatility on the volatility of China's stock market (Figure 4, column 1, row 2) is higher than that of the U.S. This suggests that the oil price volatility may not be the main factor to have caused the sharp fluctuation of the U.S. stock market.

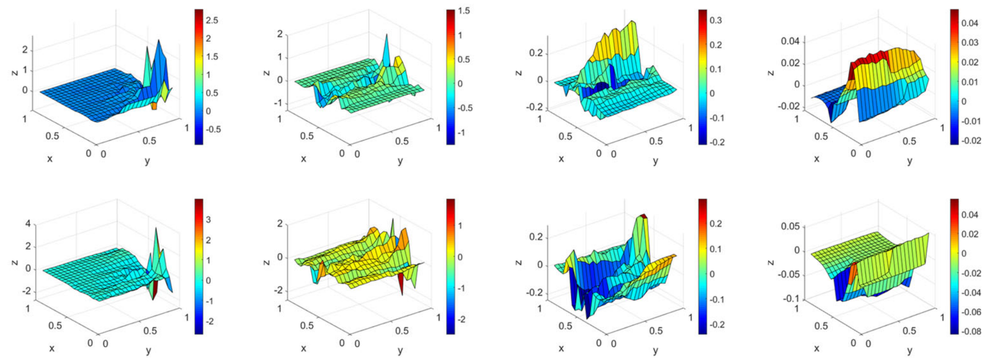

Figure 4. QQ estimates of the impacts of oil volatility.

Note: These graphs show estimates of the slope coefficients of oil volatility on the *z*-axis, plotted against the quantiles of stock volatility on the *y*-axis and the quantiles of oil volatility on the *x*-axis. Rows 1 and 2 show the results for China and the U.S., respectively. Columns 1, 2, 3 and 4 show the results of original, short-, medium-, and long-term series, respectively.

Source: Authors' calculations.

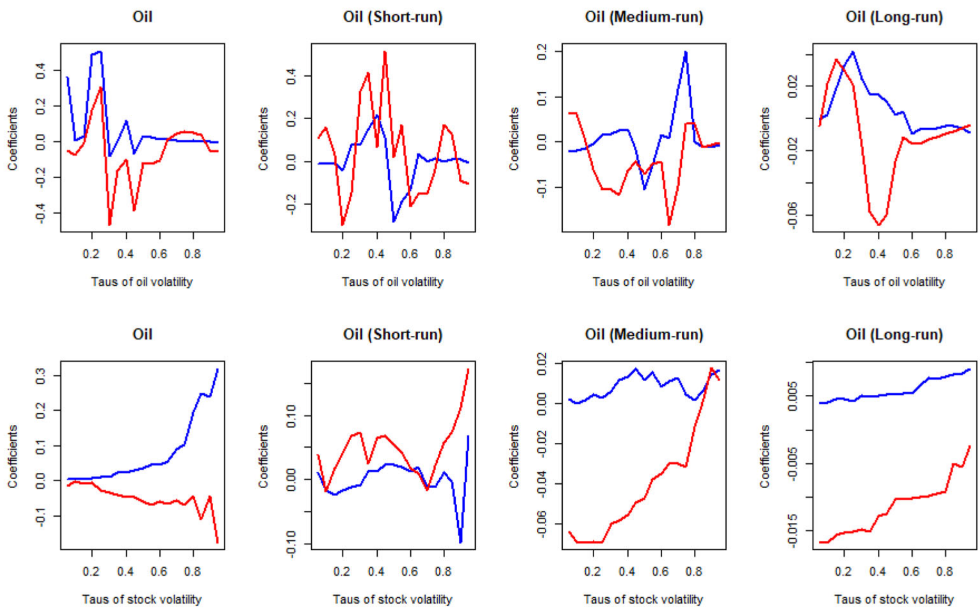

Figure 5. Averaged QQ parameters of oil volatility.

Note: These graphs show averaged slope coefficients of oil volatility. The blue lines and red lines show the results for China and the U.S., respectively. Rows 1 and 2 are averaged by the quantiles of stock volatility and the quantiles of oil volatility, respectively. Columns 1, 2, 3, and 4 show the results of original, short-, medium-, and long-term series, respectively.

Source: Authors' calculations.

Judging from the medium- and long-term regression results (Figures 4 and 5, columns 3 and 3), the impact of oil price volatility on stock price volatility was more regular with the quantile change of the latter. Specifically, oil price volatility more likely imposed a greater impact on high-level stock price volatility. In contrast, oil price volatility imposed a greater impact on China's stock market in the medium-

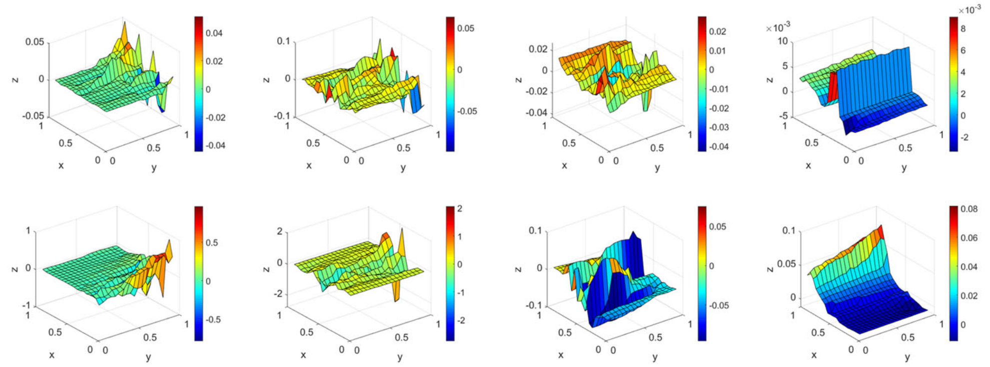

Figure 6. QQ estimates of the impacts of interest rates.
Note: These graphs show estimates of the slope coefficient of interest rates on the *z*-axis against the quantiles of stock volatility on the *y*-axis and the quantiles of interest rates on the *x*-axis. Rows 1 and 2 show the results for China and the U.S., respectively. Columns 1, 2, 3 and 4 show the results of original, short-, medium-, and long-term series, respectively.
Source: Authors' calculations.

and long-term, which is clearer than the regression results of the original series. Overall, the empirical results show that the main inducing factor of the sharp fluctuation of the U.S. stock market since 2020 is most likely COVID-19 rather than the fluctuations of the international crude oil price.

Since March 2020, the U.S. stock market broke down four times in a row, the U.S. Federal Reserve continued to reduce interest rates, and considerable liquidity was released. However, according to the data in Figure 1, after May 2020, the interest rate level in the U.S. almost decreased to zero. In this context, this study focussed on two issues: First, it was investigated whether the continuous interest rate cut since March 2020 had a sufficient effect on restraining the volatility of the U.S. stock market. Second, when the interest rate level was low, the further interest rate reduction space was also low. In this case, it was assessed whether the interest rate policy can continue to play a role in the stock market risk management.

The impacts of the interest rate on the volatilities of the stock markets of China and the U.S. are presented in Figures 6 and 7. The visual layout of the empirical results is consistent with Figures 2 to 5. According to the regression results of the original series, when the interest rate was in the extremely low quantile (0.05), the reduction of the interest rate exerted a strongest inhibitory effect on the stock market volatility (Figure 7, column 1, row 1). However, with increasing interest rate quantile, the impact of the interest rate on stock market volatility showed strong uncertainty. In contrast, China's stock market was less sensitive to different levels of interest rate changes, which may be due to the large changes in the interest rate level of the U.S. during the sample period. This also caused the degree of its impact to undergo great changes. Considering the potential risk from the stock market, the long-term effects of interest rate are more concerning. According to the regression results of Figure 7 (row 2), the interest rate policy imposed a greater impact on the volatility of China's stock market in the short- and medium-term; however, it had a greater impact on the volatility of the U.S. stock market in the long-term. This means that the impact of the sharp interest rate reduction policy, as imposed by the U.S. since 2020, on the

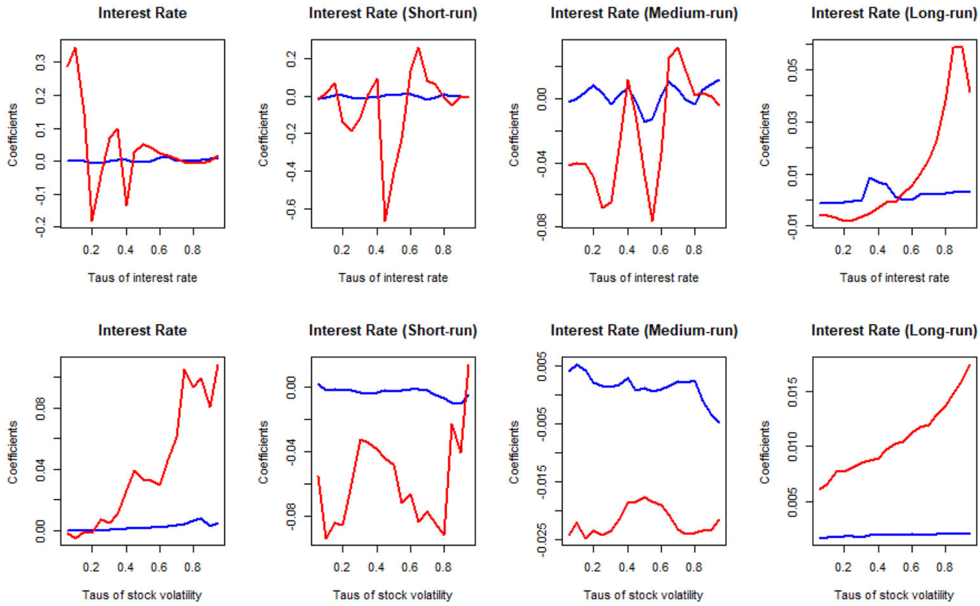

Figure 7. Averaged QQ parameters of interest rates.
Note: These graphs show the averaged slope coefficients of interest rates. The blue lines and red lines depict the results for China and the U.S., respectively. Rows 1 and 2 are averaged by the quantiles of stock volatility and the quantiles of interest rates, respectively. Columns 1, 2, 3 and 4 show the results of original, short-, medium-, and long-term series, respectively.
Source: Authors' calculations.

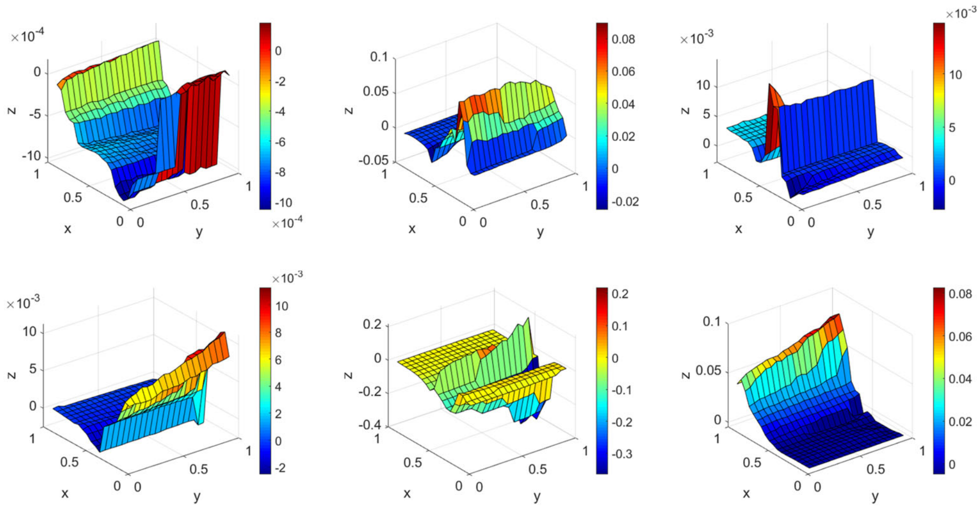

Figure 8. QQ estimates of long-term impacts.
Note: These graphs show the estimates of the slope coefficient of COVID-19 (column 1), oil volatility (column 2) and interest rates (column 3) on the *z*-axis against the quantiles of stock volatility on the *y*-axis and the quantiles of COVID-19, oil volatility, and interest rates on the *x*-axis, respectively. Rows 1 and 2 show the results of China and the U.S., respectively.
Source: Authors' calculations.

U.S. stock market is more likely to result in a long-term impact. However, China's interest rate adjustment range was relatively small and more inclined to be flexible in the short- and medium-terms.

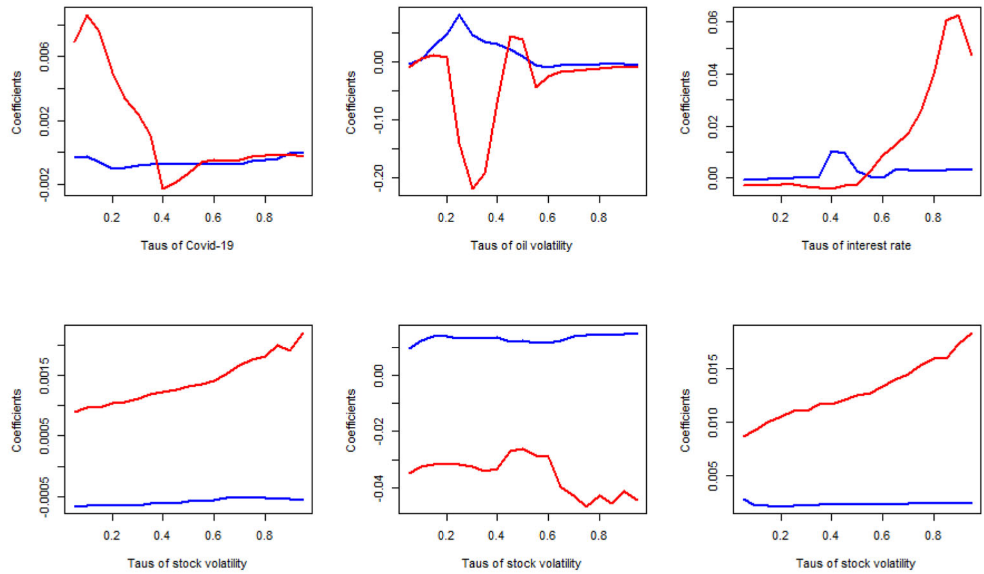

Figure 9. Long-term averaged QQ parameters.
Note: These graphs show the estimates of the slope coefficient of COVID-19 (column 1), oil volatility (column 2) and interest rates (column 3). The blue lines and red lines show results of China and the U.S., respectively. Rows 1 and 2 are averaged by the quantiles of stock volatility and the quantiles of COVID-19, oil volatility, and interest rates on the *x*-axis, respectively.
Source: Authors' calculations.

5. Robustness

The robustness of results of Section 4 were test by changing the measurement method of stock volatility. Specifically, the Shenzhen Index replaced the CSI 300, and the NASDAQ index replaced the S&P 500. Considering that the long-term results from the wavelet decomposition present clearer regularities, the long-term result is used for the robustness check. Figures 8 and 9 show the corresponding results. The overall result does not show much difference with the fourth column of Figures 2–7, which suggests that the results are reliable.

6. Conclusion

Based on the analysis presented in Section 4, the following main empirical results can be summarised: First, the impact of COVID-19 on the stock market showed significant leverage effect in both the U.S. and China. When the stock market volatility was high, COVID-19 imposed a stronger effect on the stock market volatility. This leverage effect was also identified in the impact of oil price volatility on stock market volatility. Second, COVID-19 imposed a stronger impact on the U.S. stock market during the early stage of the outbreak, and its impact exceeded the oil price volatility, implying that COVID-19 was the main factor causing the four U.S. stock market meltdowns in March 2020. However, with the ongoing epidemic, the U.S. stock market became insensitive to the impact of 30000-40000 new cases per day. In contrast, China still remained highly sensitive to relatively small daily increases in new cases;

however, the powerful epidemic control did not cause excessive abnormal volatility on the stock market. Third, instead of a strict segregation policy, the U.S. government has implemented an extreme monetary policy, which effectively suppressed stock market volatility. However, the empirical results imply that only when the interest rate is at a high quantile, such an extreme interest rate policy can achieve a good effect on the stock market volatility in the long-term. Combined with the realistic background that the interest rate of the U.S. may likely continue to be close to zero and that the daily new cases continued to remain high after May 2020, it will be difficult for the U.S. Federal Reserve to have enough monetary policy space to address a new potential financial market crash.

These results are of great significance for the development of emergency management strategies in response to major public health events as well as for the future management of the financial market of the U.S. In response to extreme financial market volatility caused by major public health events, a loose monetary policy may only be a pragmatic measure to stabilise the volatility. Solving the public health problems as early as possible not only reduces the loss caused by the impact of the epidemic and the ensuing governance costs, it can also provide sufficient space for monetary policy to cope with the uncertainty and potential risks that may emerge in the near future.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research is supported by the National Social Science Foundation of China (18BJY229).

References

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, *10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6

Crowley, P. M. (2007). A guide to wavelets for economists. *Journal of Economic Surveys*, *21*(2), 207–267. https://doi.org/10.1111/j.1467-6419.2006.00502.x

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance*, *53*(6), 1839–1886. https://doi.org/10.1111/0022-1082.00077

Graps, A. (1995). An introduction to wavelets. *IEEE Computational Science and Engineering*, *2*(2), 50–61. https://doi.org/10.1109/99.388960

Gupta, R., Pierdzioch, C., Selmi, R., & Wohar, M. E. (2018). Does partisan conflict predict a reduction in US stock market (realized) volatility? Evidence from a quantile-on-quantile regression model. *The North American Journal of Economics and Finance*, *43*, 87–96. https://doi.org/10.1016/j.najef.2017.10.006

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, *56*(10), 2198–2212. https://doi.org/10.1080/1540496X.2020.1785865

Hong, H., & Stein, J. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*(6), 2143–2184. https://doi.org/10.1111/0022-1082.00184

Huo, X., & Qiu, Z. (2020). How does China's stock market react to the announcement of the COVID-19 pandemic lockdown. *Economic and Political Studies*, *8*(4), 426–436. ? https://doi.org/10.1080/20954816.2020.1780695

Jeris, S. S., & Nath, R. D. (2020). COVID-19, oil price and UK economic policy uncertainty: evidence from the ARDL approach. *Quantitative Finance and Economics*, *4*(3), 503. https://doi.org/10.3934/QFE.2020023

Mallat, S. G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *11*(7), 674–693. https://doi.org/10.1109/34.192463

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, *38*, 101690. https://doi.org/10.1016/j.frl.2020.101690

Mirza, N., Hasnaoui, J. A., Naqvi, B., & Rizvi, S. K. A. (2020a). The impact of human capital efficiency on Latin American mutual funds during Covid-19 outbreak. *Swiss Journal of Economics and Statistics*, *156*(1), 1–7. https://doi.org/10.1186/s41937-020-00066-6

Mirza, N., Naqvi, B., Rahat, B., & Rizvi, S. K. A. (2020c). Price reaction, volatility timing and funds' performance during Covid-19. *Finance Research Letters*, *36*, 101657 https://doi.org/10.1016/j.frl.2020.101657

Mirza, N., Rahat, B., Naqvi, B., & Rizvi, S. K. A. (2020b). Impact of Covid-19 on corporate solvency and possible policy responses in the EU. *The Quarterly Review of Economics and Finance*, 1–10. Available online 22 September 2020. https://doi.org/10.1016/j.qref.2020.09.002

Mishra, S., Sharif, A., Khuntia, S., Meo, M. S., & Khan, S. A. R. (2019). Does oil prices impede Islamic stock indices? Fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy*, *62*, 292–304. https://doi.org/10.1016/j.resourpol.2019.04.005

Onali, E. (2020). Covid-19 and stock market volatility. Available at SSRN 3571453, https://doi.org/10.2139/ssrn.3571453

Percival, D. B., & Mofjeld, H. O. (1997). Analysis of subtidal coastal sea level fluctuations using wavelets. *Journal of the American Statistical Association*, *92*(439), 868–880. https://doi.org/10.1080/01621459.1997.10474042

Phan, D. H. B., & Narayan, P. K. (2020). Country responses and the reaction of the stock market to COVID-19—A preliminary exposition. *Emerging Markets Finance and Trade*, *56*(10), 2138–2150. https://doi.org/10.1080/1540496X.2020.1784719

Rizvi, S. K. A., Mirza, N., Naqvi, B., & Rahat, B. (2020). Covid-19 and asset management in EU: A preliminary assessment of performance and investment styles. *Journal of Asset Management*, *21*(4), 281–291. https://doi.org/10.1057/s41260-020-00172-3

Schwert, G. W. (1989). Why does stock market volatility change over time. ? *The Journal of Finance*, *44*(5), 1115–1153. https://doi.org/10.1111/j.1540-6261.1989.tb02647.x

Shahbaz, M., Zakaria, M., Shahzad, S. J. H., & Mahalik, M. K. (2018). The energy consumption and economic growth nexus in top ten energy-consuming countries: Fresh evidence from using the quantile-on-quantile approach. *Energy Economics*, *71*, 282–301. https://doi.org/10.1016/j.eneco.2018.02.023

Shahzad, S. J. H., Shahbaz, M., Ferrer, R., & Kumar, R. R. (2017). Tourism-led growth hypothesis in the top ten tourist destinations: New evidence using the quantile-on-quantile approach. *Tourism Management*, *60*, 223–232. https://doi.org/10.1016/j.tourman.2016.12.006

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, *55*, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Su, C. W., Khan, K., Tao, R., & Nicoleta-Claudia, M. (2019). Does geopolitical risk strengthen or depress oil prices and financial liquidity? Evidence from Saudi Arabia. *Energy*, *187*, 116003. https://doi.org/10.1016/j.energy.2019.116003

Su, C. W., Khan, K., Tao, R., & Umar, M. (2020). A Review of Resource Curse Burden on Inflation in Venezuela. *Energy*, *204*, 117925. https://doi.org/10.1016/j.energy.2020.117925

Torrence, C., & Webster, P. J. (1999). Interdecadal changes in the ENSO–monsoon system. *Journal of Climate*, *12*(8), 2679–2690. https://doi.org/10.1175/1520-0442(1999)012%3C2679:ICITEM%3E2.0.CO;2

Xiong, H., Wu, Z., Hou, F., & Zhang, J. (2020). Which firm-specific characteristics affect the market reaction of Chinese listed companies to the COVID-19 pandemic? *Emerging Markets Finance and Trade*, *56*(10), 2231–2242. https://doi.org/10.1080/1540496X.2020.1787151

Yahya, M., Oglend, A., & Dahl, R. E. (2019). Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach. *Energy Economics*, *80*, 277–296. https://doi.org/10.1016/j.eneco.2019.01.011

Yarovaya, L., Mirza, N., Abaidi, J., & Hasnaoui, A. (2021). Human capital efficiency and equity funds' performance during the COVID-19 pandemic. *International Review of Economics & Finance*, *71*, 584–591. https://doi.org/10.1016/j.iref.2020.09.017

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528