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Economic analysis for the impacts of oil price uncertainty on Chinese and U.S. stock returns before and during the COVID-19 pandemic

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Abstract. The recent outbreak of COVID-19 has increased uncertainty across financial markets; therefore, examining the influences of oil price uncertainly on stock rewards is of considerable significance in this context. This article applies the crude oil volatility index (OVX) as a synthetic, precise measure of oil price uncertainty to explore how Chinese and U.S. stock returns respond differently to OVX changes prior to and during COVID-19. This issue is addressed by adopting a nonparametric causality-in-quantiles method, which can provide a more robust investigation of nonlinear impacts in various market situations. Our results indicate that stock returns in response to OVX changes across China and the U.S. are heterogeneous around the COVID-19 period. Before the epidemic, Chinese stock returns were considerably less responsive to the OVX shocks compared with the U.S. In contrast, China's stock returns responded more strongly to OVX changes during the outbreak, while U.S. stock returns reacted in the opposite way.

Keywords: COVID-19 epidemic; Nonlinear impacts; Nonparametric causality-in-quantiles; OVX changes; Stock rewards

1. Introduction

The global outbreak and spread of COVID-19 has critical implications for public health security and is a serious threat to the global economy and financial markets (Tisdell, 2020; Ji et al., 2020). As of June 29, 2020, the pandemic had affected 215 countries and regions worldwide with a cumulative total of 101,313,376 confirmed cases and 501,794 deaths. In response to the epidemic, many countries imposed strict quarantine measures and shutdown behaviours, which led to large-scale unemployment and business closures (Zhang et al., 2020). The global spread of the epidemic has greatly triggered investor panic and pessimism about economic development. Meanwhile, these effects quickly spread to the oil and stock markets (Narayan et al., 2020; Ashraf, 2020). The IEA (International Energy Agency) reported in April that Brent and WTI crude oil, as the crude oil market bellwether, have been falling since the beginning of 2020. Furthermore, Brent crude oil prices are at a low of $16/BBL, and WTI crude oil futures prices are even trending historically negative. On March 9, 2020, the futures prices of WTI and Brent crude oil fell 22.25% and 23.03%, respectively. Moreover, the WTI contract touched a record low of -$37.63/BBL on April 20, 2020. Suffering the same fate as the oil market, the global stock markets have plummeted since the outbreak of the epidemic (David et al., 2021). From January to May 2020, global equity markets lost 12.35% and accumulated losses of over $9 trillion (Salisu et al., 2020). Affected by the epidemic, China's stock market fell sharply on its first trading day in 2020, with the Shanghai composite closing down more than 7%. A-shares fell by the daily limit of 3,000 shares, which is a rare occurrence in history. As the most developed financial market in the world, the stock market of U.S. also experienced great fluctuations as a result of the COVID-19. In March 2020, the U.S. stock market hit the circuit breaker mechanism four times in 10 days. On March 16, the S&P 500 plunged more than 8% in early trading, directly triggering the circuit breakers mechanism. Although the U.S. government has introduced a series of quantitative easing policies, its stock market is still in the doldrums, and market panic continues to rise.

Oil is hailed as the “blood of the national economy” and plays an essential role in economic activities of countries all over the world (Liu et al., 2020). The stock market, known as the “economic barometer”, reflects the performance and status of a country’s economy. Given that they all have an impact on macroeconomic variables, there has been fierce debate regarding whether oil prices contain predictive ability for stock returns because investors are eager to know the possible impact of volatile oil prices on global financial markets, with special stress being placed on the stock market rewards. The impact of oil prices on equity markets is reasonable based on the impact of oil prices on future cash flows or discount rates that affect gains and dividends and hence equity prices (You et al., 2017). Therefore, numerous studies has been conducted to survey the relationship between oil markets and stock markets (Zhu and Chen, 2019). Nevertheless, these works primarily concentrate on oil price shifts, and the predictions of oil price volatility on the stock market are relatively less thoroughly investigated. Actually, oil price uncertainty is a determining factor in relation to the production and consumption processes, investments decisions, and other aspects on account of the commodity and financial attributes of oil (Dutta, 2017). In this event, the uncertainty in the oil market is inescapably delivered to the economic and financial system and exerts an important impact on asset earning. Moreover, the recent financial crisis and some important events such as economic sanctions, geopolitical tensions, and the financialization of the oil market are exacerbating the uncertainty of the oil market. In particular, the ongoing COVID-19 situation is further increasing uncertainty in the oil market and movement in the financial markets, which has tremendous impact on economic behaviour and financial activity. Therefore, it is of great significance to investigate the causal connection between oil price uncertainty and stock returns in the context of the COVID-19 epidemic.

The contribution of this study is fourfold. (i) Our research extends the inadequate literature exploring the causal linkage between oil price uncertainty and stock earnings by investigating whether the crude oil volatility index (OVX) has predictive power for explaining the Chinese and U.S. stock returns during COVID-19 from a nonlinear perspective. (ii) Different from most oil uncertainty proxies measured only by historical price series, we apply OVX to predict oil uncertainty because OVX includes both historical and future volatility information that provides a more complete and accurate measure of oil market uncertainty. (iii) To our knowledge, this paper is the first to examine causal associations in China and the U.S., the largest developing and developed economies in the world, and compare different responses of these associations based on the effect of COVID-19. The value of this study is that it provides an important reference for China and the U.S., as well as for other countries, in terms of risk management and investment decisions during COVID-19. (iv) Previous studies mainly used linear causality tests, which are insufficient to detect the possible existence of non-linear causality between variables. To overcome these deficits, this research adopts a more flexible nonparametric quantile causality test, and the study demonstrates comprehensive linear or nonlinear nexuses between OVX changes and stock returns.

2. Methodology

This section introduces a new method of nonparametric causality-in-quantiles testing presented by Balcilar et al. (2016) to inspect the nonlinear causality of OVX changes and stock returns at different quantiles. Let X_t and Y_t represent OVX variations and stock returns, respectively. Denote the vectors $X_{t,lag}=(X_{t-1},\ldots,X_{t-p})$, $Y_{t,lag}=(Y_{t-1},\ldots,Y_{t-p})$ and $W_{t,lag}=(X_{t,lag},Y_{t,lag})$, where p represents the lag-order. The null hypothesis that X_t does not Granger cause Y_t at the τ th quantile can be written as

$$P\left(F_{Y_t|W_{t,lag}}\{Q_\tau(Y_t|Y_{t,lag})|W_{t,lag}\}=\tau\right)=1, \tag{1}$$

where $Q_\tau(Y_t|\Omega)$ denotes the τ th quantile of the Y_t conditional on Ω, and $F_{Y_t|W_{t,lag}}(\cdot)$ refers to the conditional distribution functions of Y_t given $W_{t,lag}$. The rejection of the null hypothesis means that X_t can influence Y_t at τ th quantile.

The null hypothesis can be performed by calculating the following statistic:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1;s\neq t}^{T} K\left(\frac{W_{t,lag}-W_{s,lag}}{h}\right)\hat{u}_t^{\tau}\hat{u}_s^{\tau}, \tag{2}$$

where T signifies the sample size, $K(\cdot)$ denotes the kernel function, h stands for the bandwidth and $\hat{u}_t^{\tau}$ is the regression residual at τ th quantile. Furthermore, the quantile residual $\hat{u}_t^{\tau}$ can be estimated by

$$\hat{u}_t^{\tau} = I\{Y_t \leq \hat{Q}_{\tau}(Y_t|Y_{t,lag})\} - \tau, \tag{3}$$

where $\hat{Q}_{\tau}(Y_t|Y_{t,lag})$ is the estimator of the τ th conditional quantile of Y_t given $Y_{t,lag}$. According to the definition of the quantile function, we determine that $\hat{Q}_{\tau}(Y_t|Y_{t,lag})=\hat{F}^{-1}_{Y_t|Y_{t,lag}}(\tau|Y_{t,lag})$, and $\hat{F}^{-1}_{Y_t|Y_{t,lag}}(\tau|Y_{t,lag})$ is computed by using the Nadaraya-Watson kernel method. Moreover, this test method can be generalized to investigate the presence of causality-in-variance, namely,

$$P\left(F_{Y_t^2|W_{t,lag}}\{Q_{\tau}(Y_t|Y_{t,lag})|W_{t,lag}\}=\tau\right)=1. \tag{4}$$

To achieve above examination, it is necessary to determine the bandwidth h, the lag order p, and the kernel type $K(\cdot)$. Similar to research by Shahbaz et al. (2017), we determine the lag order by the Schwarz Information Criterion (SIC) and choose the bandwidth based on the least squares cross-validation technique. Additionally, the Gaussian-type method is employed as the kernel in our research.

3. Data description

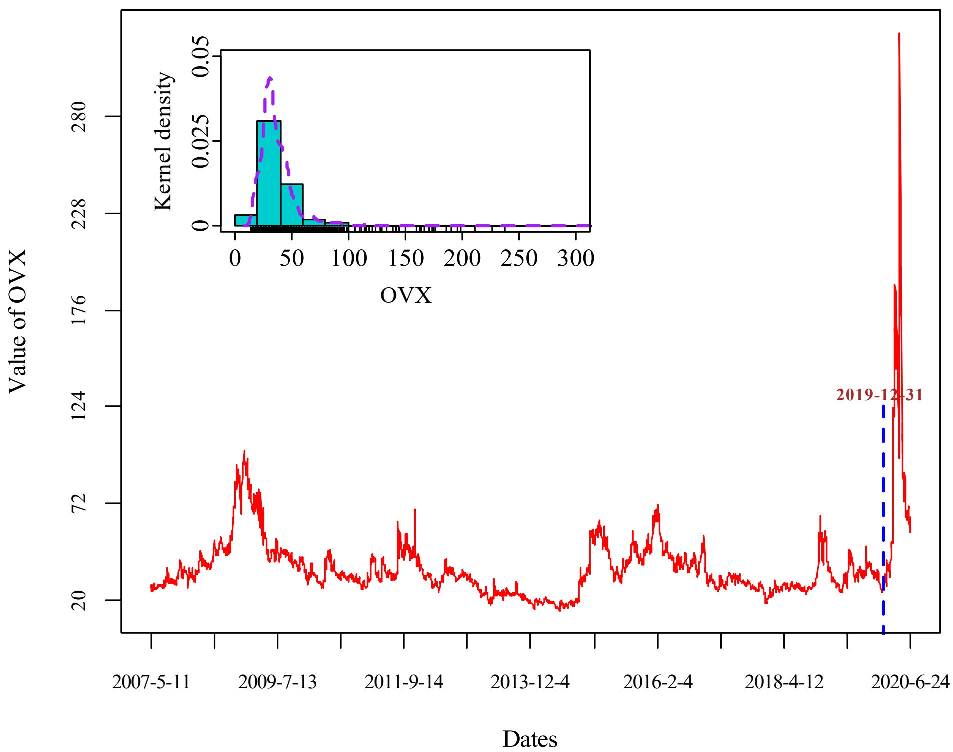

Fig. 1. Dynamic trend of OVX.

This article collects the daily data on the OVX and stock price from May 10, 2007, to June 24, 2020. The OVX data comes from the Chicago Board Options Exchange official website. We selected the closing prices of the Shanghai Composite index (SHCI) and the S&P 500 (S&P500) to represent the overall level of the stock markets in China and the U.S., respectively. The stock price is obtained from the Wind information database. The sequence of stock price is converted to log return: Rt= ln(Pt/Pt−1)×100, where Rt signifies stock return, Pt is the current price and Pt−1 is the price in the previous period. Similarly, the OVX series also fulfil the same transformation. Following Corbet et al. (2020), we split the data into two sub periods of the pre-COVID-19 epidemic and the COVID-19 situation on account of December 31, 2019.

The trend of OVX over the whole sample period is shown in Fig. 1. As presented in the figure, the movement of OVX have many significant spikes. Apparently, the biggest spike appeared during COVID-19. It can be seen from the subplot of Fig. 1 that OVX reveals a right-tailed distribution pattern, indicating an asymmetric variation in OVX.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Skew.	Kurt.	Jarque-Bera	P-value
			Pre-COVID19			
SHCI	-0.001	1.673	-0.639	8.247	3615.619	0.000
S&P500	0.026	1.269	-0.585	16.881	24055.831	0.000
OVX	-0.002	5.042	0.835	11.875	10109.062	0.000
			Dur-COVID19			
SHCI	-0.018	1.413	-1.866	11.590	409.372	0.000
S&P500	-0.049	3.063	-0.583	6.616	67.369	0.000
OVX	0.822	15.066	1.465	14.756	685.001	0.000

Note: P-value denotes the probability of the Jarque-Bera normality test.

Table 1 reports the descriptive statistics for the relevant variables. There is noticeable heterogeneity before and within COVID-19, as indicated by the distinct difference in the mean values of all variables. Particularly, the OVX variations in the epidemic has a higher standard deviation than before, which implies that the oil market presents enormous volatility and risks during the COVID-19 periods. As observed from the skewness, the SHCI and S&P500 both show left-skewered distribution, while the OVX is opposite. The kurtoses of all series are greater than 3, meaning that they have a leptokurtic distribution. Additionally, the Jarque-Bera normality test shows that all series reject the null of normal distribution. These non-normal distribution series prompt us to employ the quantile-based regression.

4. Empirical results

4.1. Preliminary analysis

Before the regression analysis, we first carry out the unit root test for all variables. In this instance, three unit root test methods of ADF, PP, and Z-A are applied, where the Z-A test allows for the endogenous structural mutations in the time series. As shown in Table 2, both the ADF and PP tests reject the null hypothesis of the presence of unit roots at the 1% significance level for all circumstances. Furthermore, the Z-A test also confirms that all sequences are stationary and do not contain unit roots. Therefore, the regression analysis can be performed.

Table 2. Unit root tests.

Variable	ADF test		PP test		Z-A statistic
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	
			Pre-COVID19		
SHCI	-54.767***	-54.769***	-54.779***	-54.781***	-39.160***
S&P500	-42.660***	-42.696***	-59.686***	-59.842***	-43.229***
OVX	-34.878***	-34.875***	-62.551***	-62.554***	-39.556***
			Dur-COVID19		
SHCI	-10.865***	-10.893***	-10.862***	-10.900***	-8.273**
S&P500	-15.186***	-15.201***	-14.745***	-15.058***	-9.393***
OVX	-10.233***	-10.308***	-10.238***	-10.345***	-9.184**

Note: ** P<0.05 and *** P<0.01.

Table 3 presents the results of the linear causality test. For SHCI and S&P500, the null hypothesis that there is no linear causality from OVX shocks to stock returns is rejected at 1% significant level before the breakout periods. This result indicates that OVX changes have a significant impact on the earnings of stock markets prior to the epidemic. Within the COVID-19 periods, SHCI and S&P500 reject the null hypothesis of no linear causality from OVX to returns at significant levels of 10% and 5%, respectively. This finding reveals that the predictive power of OVX changes of stock returns weakened due to the effect of COVID-19.

Table 3. Linear Granger causality tests.

Null hypothesis	Pre-COVID19		Dur-COVID19	
	SHCI	S&P500	SHCI	S&P500
OVX≠>Returns	5.131*** (0.000)	6.219*** (0.000)	3.273* (0.072)	3.139** (0.016)

Note: * P<0.1, ** P<0.05 and *** P<0.01. The parenthesis is the P-values for the test. ≠> implies does not linearly Granger-cause.

Table 4 reports the nonlinear test results of BDS. It can be seen from the table that there is a remarkable nonlinear linkage between OVX changes and stock rewards before the epidemic. In the epidemic situation, the test results also prove the existence of the non-linear relationship between OVX changes and stock returns as a whole.

Table 4. BDS non-linearity test from VAR residuals.

Test	*m*=2	*m*=3	*m*=4	*m*=5	*m*=6
			Pre-COVID19		
SHCI	7.697***	11.878***	16.087***	20.522***	27.384***
-	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OVX	7.085***	7.610***	10.937***	19.012***	34.661***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SP500	11.560***	18.610***	25.218***	32.040***	40.234***
-	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OVX	7.012***	8.409***	10.508***	12.775***	23.949***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Dur-COVID19		
SHCI	2.950***	3.506***	4.412***	4.320***	3.012***
-	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)
OVX	0.016	2.494**	-3.229***	-2.101**	-1.474
	(0.915)	(0.012)	(0.001)	(0.036)	(0.141)
SP500	4.017***	8.056***	10.251***	18.048***	33.781***
-	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OVX	-3.288***	14.861***	-5.685***	-3.778***	-2.710***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.007)

Note: *** P<0.01. The parenthesis is the P-values for the test.

4.2. Main analysis

Fig. 2 displays the findings of the nonparametric quantile causality examination prior to the COVID-19 pandemic. As shown in the figure, an evident difference exists of the quantile causality from SHCI to S&P500. In terms of SHCI, when examining the quantile causality test in mean, the null hypothesis is accepted for all quantiles at 1% critical value. However, most quantiles represent rejection of the null hypothesis at the 5% critical value, with the exception of 0.05-0.15 and 0.75-0.95 quantiles for acceptance. The quantile causality test in variance illustrates that the null hypothesis is rejected for the quantiles from 0.4 to 0.65 and from 0.2 to 0.7 at 1% and 5% critical levels, respectively. This result is not partly consistent with the strong causality from the OVX shocks to China's stock returns given by the linear causality test. In the case of S&P500, the quantile causality test in mean reveals the rejection of the null hypothesis in the quantiles ranging from 0.15 to 0.85 at 1% critical value, and the quantiles in the range of 0.1-0.9 are also rejected at 5% critical value. Similar to the results of the mean test, the quantile causality test in variance rejects the null hypothesis at the majority of the quantiles, except for the quantile ranges 0.05-0.15 and 0.75-0.95, which shows the acceptance. These findings broadly align with the results of the linear causality test that changes in OVX are able to predict stock returns in the United States.

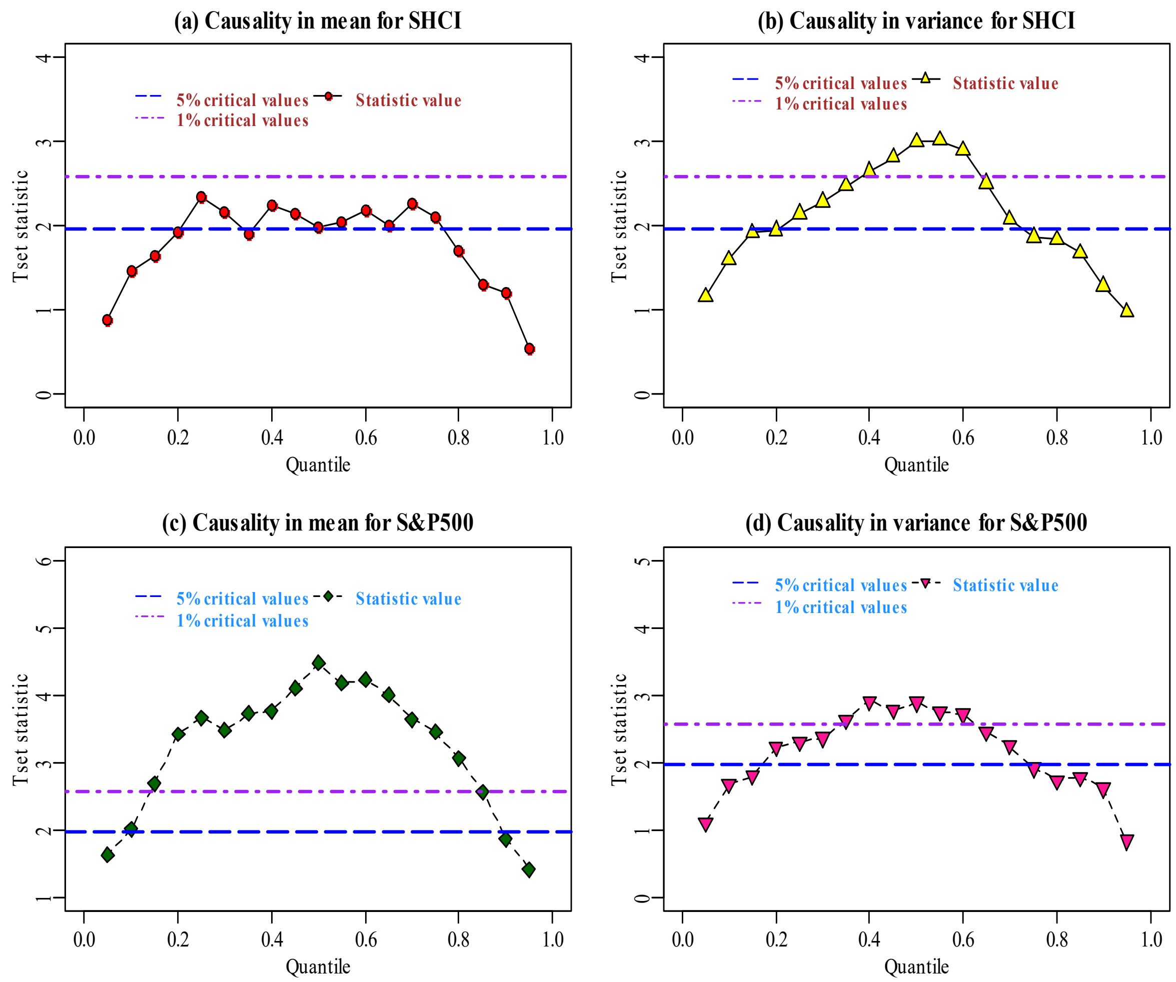

Fig. 2 Quantile causality test before the COVID-19 pandemic.

The results of the nonparametric quantile causality test during the COVID-19 pandemic are presented in Fig. 3. It can be seen from the figure that the results remarkably vary from SHCI to S&P500. For SHCI, the quantile causality test in mean rejects the null hypothesis in the quantiles ranging from 0.05 to 0.6 and 0.05 to 0.7 at 1% and 5% critical values, respectively. The similar patterns are found concerning the quantile causality test in variance, with the causal linkage from the OVX changes to stock returns being significant in quantiles below 0.7. These findings are agreement with the results of the linear causality test that the OVX shocks can affect Chinese stock returns during the COVID-19 pandemic. As far as the S&P500 is concerned, the quantile causality test in mean manifests that the null hypothesis is accepted for all quantiles at 1% critical value and is merely rejected for 0.35 and 0.5 quantiles at 5% critical value. The quantile causality test in variance provides a similar situation, showing the acceptance of the null hypothesis in all quantiles at 1% critical value and rejection of the null hypothesis only in 0.05 and 0.1 quantiles at 5% critical value. These results imply that OVX variations have little impact on U.S. stock returns within the breakout of COVID-19, which roughly contradicts the significant impact of the linear causality test.

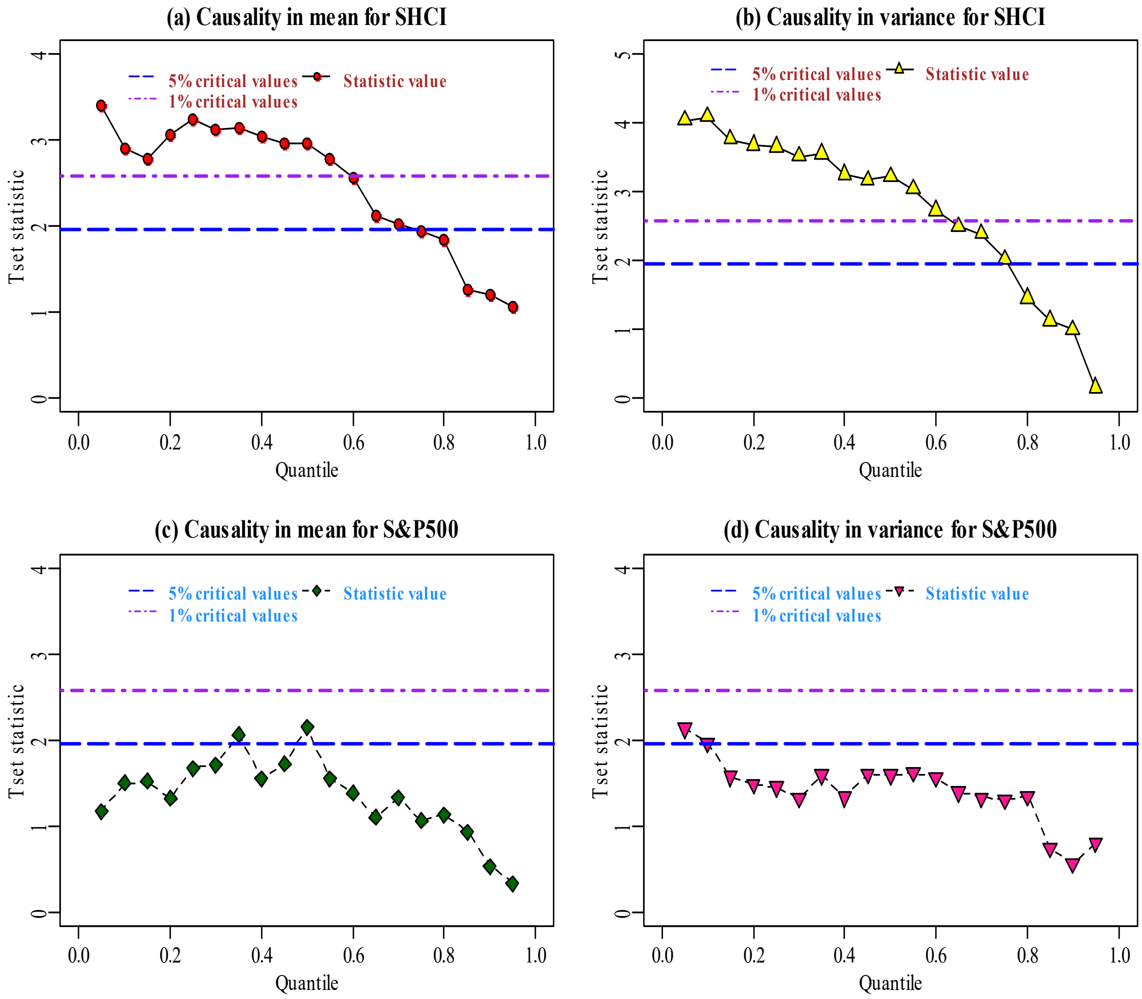

Fig. 3. Quantile causality test during the COVID-19 pandemic.

Thus, we can conclude that there is a causal relationship between OVX shocks to Chinese stock rewards in the normal market, but this relationship was weak or absent in bear or bull markets prior to the COVID-19 pandemic. Such association has been reinforced by the impact of the epidemic, particularly OVX variations can cause stock rewards in a bearish market and can serve as a strong predictor of stock returns in China. A possible explanation is that companies and market investors are more sensitive to uncertainty shocks in the oil market, as investment confidence is restored as a result of the effective control of the epidemic in China. Accordingly, the impacts of oil price uncertainty variations are easily delivered to the stock market. In contrast, the causal nexus running from OVX changes to stock returns is significant for all market cases in U.S. before the outbreak of COVID-19. However, this connection becomes insignificant due to the impact of the pandemic, and OVX shocks cannot act as a predictor of stock returns in U.S. during the period. Our finding might explain that firms and market investors are susceptible to the unpredictability alterations in COVID-19 outbreak, rather than oil prices, in the present market because of the widespread spread and severe intensification of the epidemic in the United States. The largest risk to the U.S. financial markets comes from the uncertainty of COVID-19, in which investors become more risk-averse and sell stocks and other risky assets indiscriminately out of panic. Therefore, the uncertainty caused by the change of oil price hardly affects stock returns in the United States.

The above conclusion regarding the quantile causality from the OVX shocks to stock returns provides some important implications for risk managers and market investors in the Chinese and U.S. financial markets. According to our conclusion, risk managers and market investors should pay attention to the predictive ability of oil price uncertainly on Chinese stock rewards to improve risk control and investment efficiency within the period of COVID-19. In particular, a bearish market with low expected returns needs to be given more attention in China. Since the U.S financial market cannot be directly affected by oil during the pandemic, related risk managers and market investors should shift their focus from oil prices uncertainty to the uncertainty of COVID-19. It is more important to monitor the risks posed by the epidemic and concentrate on the relevant macroeconomic policies. Additionally, the conclusion provided in this study could be a guiding instrument for portfolio design between stock markets and oil markets. Policy makers, risk managers and investors on one hand need to be careful because the influence of oil price shocks on stock earnings varies by country and period, whether the oil price uncertainly is relevant or irrelevant to stock rewards. On the other hand, they know how to deal with the volatility of stock and oil markets associated with COVID-19 spread. Since the prediction of oil price changes are not constant throughout the distribution of stock returns, the results based on traditional linear causality tests may not be appropriate for drawing policy recommendations. The nonparametric quantile causality test can explore the possible linear or nonlinear relationship between variables as well as depict the examination at different distribution. Therefore, it might be more appropriate and interesting to investigate the causal linkage in other markets by this method.

4.3. Robustness

To illustrate the robustness of the results, we rerun the above nonparametric quantile causality by replacing the Shanghai Composite index and the S&P 500 index with the Shenzhen 300 Composite index and the Dow Jones index, respectively. Generally, these robust tests yield similar results.

5. Conclusions

This article sets out to explore how the Chinese and U.S. stock returns react in different ways to oil price uncertainty in a pre-COVID-19 pandemic and during the pandemic period. To accurately describe the dynamic response, we apply the new measure OVX as the proxy of oil price uncertainty and adopt a recent method of the nonparametric causality-in-quantiles test as the main analysis instrument. Our study finds the following: (1) pre-epidemic, the effects of OVX variations on the Chinese stock market exist only at median quantiles, while OVX shocks can present predictability at all the quantiles for U.S. stock market; (2) within-epidemic, the changes of OVX can affect the Chinese stock market, especially at the low quantiles, but fail to provide predictability over the entire distribution for the U.S stock market.

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