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How does the COVID-19 outbreak affect the causality between gold and the stock market? New evidence from the extreme Granger causality test

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ARTICLE INFO

Keywords:
COVID-19
Extreme Granger causality
Gold market
Stock market
Time and frequency domains

ABSTRACT

The causal relationship between gold and stocks has been widely studied, while their causality and the long- and short-run characteristic of this relationship have not been examined under different shocks. The purpose of this paper is to fill this gap. Meanwhile, considering the impact of the COVID-19 outbreak on gold and stock markets, we also aim to investigate whether the relationship changes after this epidemic. With invoking the time- and frequency-domain extreme Granger causality tests, we find that a significant causality between gold and stock usually comes from extreme shocks, displaying as the long-term causality running from gold shocks to stock shocks while the fickle impact of stock shocks on gold shocks. Besides, empirical results suggest that the causality between gold and stock shocks is greatly promoted after this epidemic. The present study is useful for investors and policymakers, as it has reference significance when dealing with subsequent extreme shocks or events.

1. Introduction

Unpredictability and volatility in financial markets have increased dramatically due to the uncertainty and instability originating from the COVID-19 outbreak (Zhang et al., 2020). This pandemic seems to have a greater negative impact on financial markets than the 2008 Global Financial Crisis (GFC) (Mensi et al., 2020). It is worth noting that the S&P 500 Index prices dropped by 7% in a single day on March 9, 2020. The sharp decline of stock prices prompts an investor “flight to quality” (Jiang and Vo, 2021). The literature on the response of stock markets to the COVID-19 outbreak is growing rapidly. Meanwhile, as one of the most commonly used hedge tools against the sharply increased market risk brought by the COVID-19 outbreak, gold has received more attention during this epidemic (Bhatia et al., 2020; Drake, 2022; Gharib et al., 2021; Salisu et al., 2021). Bouri et al. (2021) confirmed that the relationship among gold and stock markets has been affected by this virus crisis. A large number of documents explored the hedging potential of gold against stock markets during this pandemic (Adekoya et al., 2021; Ji et al., 2020; Mensi et al., 2021). Particularly, detecting the causal relationship among gold and stock markets, is helpful for understanding the process of risk transmission and improving recognition of the connection between them (Adekoya and Oliyide, 2021; Drake, 2022).

However, existing studies mainly focus on detecting their causality during the whole period while ignoring the changes in the relationship before and after this crisis, prompting us to revisit this work. Besides, previous investigations mainly concentrate on the average causality to explain the link between gold and stocks, overlooking the hidden linkage between different components of assets (Bouri et al., 2017; Choudhry et al., 2015; Drake, 2022). Granger and Yoon (2002) first pointed out that some hidden important information can only be detected through testing their components (positive and negative shocks) while not as a whole. Moreover, what makes the situation more complicated is that ignoring the hidden information may misjudge the current state of the market. These relevant judgments will not only affect subsequent investment strategies but may also lead to deeper chaos in the financial system. Many works have confirmed the necessity of studying the relationship between different shocks (Alexakis et al., 2013; Hatemi-J, 2012; Honarvar, 2009). Thus, considering the impact originating from the COVID-19 outbreak, we aim to examine the gold-stocks causality under different shocks during the periods before and after this crisis. Specifically, we begin our research by applying the novel time- and frequency-domain approaches proposed by Wang et al.
(2020, 2021), which can divide gold and stocks into the extremely positive, extremely negative and normal, respectively, and examine the causality among different shocks. In this way, we can observe different risk transmission processes among gold and stocks by their causality and can also focus on the overall difference and time-varying characteristics of these transmissions under different shocks, especially considering the inconsistent responses of gold and stocks on the COVID-19 outbreak.

According to our investigation, our study is the first effort to examine the gold-stocks causality under extreme (positive/negative) and non-extreme (normal) shocks. Sharply dynamic or unstable prices/returns caused by shocks bring about multiple challenges for market participants, who face the question of how to adapt to the dramatic change in future financial markets and stay profitable under different conditions (Baur and Lucey, 2010). Thus, in the era of frequent extreme events, digging more hidden information between gold and stocks becomes increasingly important, particularly given that the case under extreme shocks. However, extensive literature has discussed the relationship among the two markets in many ways but neglected their causal relationship under different shocks (Arouri et al., 2015; Chen and Lin, 2014; Narayan and Sharma, 2011; Tully and Lucey, 2007). In this paper, we find the strong existence of extreme causality across the stocks and gold, with negative/positive stock shocks to negative/positive gold shocks being the most evident. Meanwhile, the causality running from gold to stocks mainly originates from extreme shocks, rather than normal shocks. In summary, the extreme shocks can be considered a more detailed signal for decision-makers understanding the relationship between gold and stocks. Ignoring such important information may lead to the choice of inadequate management policies to control financial risk originating from the extreme fluctuations of stocks and gold prices in financial markets.

Benlagha and El Omari (2021) confirmed the time-varying characteristic of the relation between gold and stocks. Besides, market participants can timely adjust their decision-making to hedge risks, if they can investigate and observe this time-varying characteristic of the relationship among financial fundamentals. Thus, it is necessary to further examine the gold-stocks Granger-causality under different shocks from a frequency-domain perspective, which enables us to uncover the long-run (permanent) and short-run (transient) effect of a certain shock. Obviously, based on the limited attention, investors usually change their current portfolios for chasing higher profits when extreme shocks occur. Market participants have different investment goals, risk tolerance and preferences, and thus they pay attention to market information provided at different frequencies (Li et al., 2021). In fact, active investors, such as bulge bracket banks, mainly focus on short-run changes among markets while passive investors prefer to focus on the long-term dynamics. Strohsal et al. (2019) pointed that the frequency-domain analysis can be better to capture the short-, mid-, and long-run effects of variables. Analyzing the frequency-domain gold-stocks causality can, thus, provide more indispensable insights for different investors over time (Lehkonen and Heimonen, 2014; Yu et al., 2015). Our empirical results suggest that stock shocks often suffer strong and long-run effects of gold shocks while have a fickle (permanent or intermediate or temporary) impact on gold shocks in sample periods. Given that these dynamic responses, detecting the frequency-domain causality under different shocks are becoming increasingly important for long-term investors coping with different gold shocks while investors with short trading cycles are suggested to pay close attention to the shocks of stock risks on gold.

Finally, the remaining contribution is that we care more about analyzing the impact of the COVID-19 on the gold-stocks causality under different shocks. The systemic risk subsequently changes when this epidemic suddenly occurs. A lot of work found that the gold-stocks relationship has undergone significant changes due to the risk caused by this crisis (Adekoya et al., 2021; Akhtaruzzaman et al., 2021; Hung and Vo, 2021; Ji et al., 2020). As one of the effective ways to understand the characteristics of the spread of financial risks, the Granger relationship is widely applied and is helpful for proceeding with follow-up investment and management (Choudhry et al., 2015; Hong et al., 2009; Pradhan et al., 2020). For better preventing and reducing systemic risks, we are committed to studying the influence of this virus crisis by considering their causality before and after this epidemic. Thus, we focus on not only the causality under different shocks but also its time-varying characters before and after this crisis. Our results from the static and dynamic causality tests under the impact of the COVID-19 outbreak suggest that this crisis vastly promotes the gold-stock causality and even changes the direction of some relationships under different shocks, which is first detected by our exploration.

The rest of our research is organized as follows. Section 2 presents a brief literature review of the gold and stock markets during the COVID-19 outbreak. Section 3 introduces the methodology we applied. Section 4 provides a discussion of the data sample. Section 5 presents an analysis of the empirical results and a robustness test. Section 6 concludes the paper.

2. Gold and stock markets, and COVID-19

Fluctuations in the gold and stock markets are easily affected by global market conditions, their dynamic changes are relevant indicators of expectations about the future state of the global economy (Baur and Lucey, 2010; Choudhry et al., 2015; Jaffe, 1989; Liang et al., 2020, 2021). The econometric construction connecting the both markets originate from the long-run linkage between them, and their prices have wide impacts on worldwide macroeconomic fundamentals (Cai et al., 2001). The size of the both markets has also risen due to a rapid development of global economy, and thus they convey more information across the world economy (El-Wassal, 2005; Salisu et al., 2021). However, the negative impact of the recent COVID-19 outbreak has gone beyond the impact of the 2008 financial crisis and cannot be remedied (Mensi et al., 2020; Liang et al., 2022).

The power of gold as a hedge against stocks has received growing concern. The idea that gold is a safe haven for stocks during COVID-19 has received a lot of support. Different studies have analyzed the power of gold hedging stocks in different periods of this crisis (Adekoya et al. (2021) for January 2, 2020–May 15, 2020; Akhtaruzzaman et al. (2021) for December 31, 2019–March 16, 2020, and March 17-April 24, 2020; Benlagha and El Omari (2021) for January 20, 2020–March 24, 2021; Ji et al. (2020) for December 1, 2019–March 31, 2020; Hung and Vo (2021) for January 31, 2020–April 23, 2020; Omana-Adjepong and Alagidede (2021) for December 8, 2019–August 11, 2020; Salisu et al. (2021) for January-July 27, 2020). These studies mainly apply the forecasting models, connectedness methods, risk spillover approach, and causality tests to detect the relationship between gold and stocks. For instance, based on Markov regime-switching model, Adekoya et al. (2021) found the hedging power of gold for stocks during the crisis while Drake (2022) doubted the long-term hedging role of gold by employing a conventional Granger causality test. Buccioli and Kokholm (2021) applied an extended GARCH model based on Hawkes processes to conclude that gold mainly be a short-run hedge against all sectoral stocks that fall. Akhtaruzzaman et al. (2021) pointed that gold does not appear to be a hedge against stock market risks between March 17 and April 24, 2020.

However, they are inconsistent on whether gold can be used as a hedge during the COVID-19 crisis. Actually, due to their close linkage, stock risk will be transferred to the gold market. (Akhtaruzzaman et al., 2021). The average connectedness between both markets is stronger during the epidemic than before (Boari et al., 2021). Meanwhile, the overall causality may not adequately demonstrate the hedging power of gold against stocks. In other words, only studying financial fundamentals as a whole may lead to different results and further have a negative impact on the portfolios of investors and policymakers. Obviously, the existing research on the gold-stocks relationship is incomplete, prompting us to investigate the linkage from multiple perspectives.
Different from the existing works, we apply the approach of Wang et al. (2020) to divide gold and stock returns into three combinations of extremely positive, extremely negative, and normal shocks with the quantiles, and thus detect the causality between shocks in the time domain. We also noticed some quantile-based methods, which can also be applied to examine the causality under different degrees of gold and stock shocks. Although their work has the advantage of being able to explore correlations at different distribution levels, they neglect the connections between the different shocks of variables, which mainly be considered by focusing on extreme conditions in our paper. Further, for the purpose of detecting the dynamic changes in causality under different shocks, we also apply the frequency-domain extreme causality test of Wang et al. (2021). In particular, some analysis methods, such as BK, wavelet, TVP-VAR, time-varying causality test of Rossi and Wang, and also can test the dynamic changes in causality in relationships (Aguiar-Conraria et al., 2008; Li et al., 2015; Lu et al., 2014; Rossi and Wang, 2019). However, they only check the varies of overall causality linkage (one-shot relation) and ignores the changes of hidden relationship under different shocks (multiple relations). The extreme frequency-domain causality test overcomes these shortcomings and can be better to accurately analyze the permanent or temporary causal relationship under different shocks. A deeper understanding of the dynamic dependent relations between gold and stocks could not be obtained without accounting for the extreme causality in the frequency domain. Thus, we invoke the frequency-domain extreme Granger causality test to conduct our research.

3. Methodology

Generally, scholars focus on exploring the overall relationship between time series. However, there may be an asymmetric structure regarding these relationships, which cannot be detected through analyzing the overall data but through their internal shocks. Especially, with the great volatility of financial markets, more accurately detecting the relationship between financial fundamentals is a crucial step for understanding the dynamic changes in financial markets. The idea of exploring the relationship between pair-wise internal components (shocks) comes from Granger and Yoon (2002), who divided the time series into the positive and negative shocks for examining the hidden cointegration. On this basis, Hatemi-J (2012) proposed to detect the causality between pair-wise shocks and defined this method as the asymmetric causality test. Subsequently, a large number of scholars applied and extended this method to test the asymmetric effect (Hatemi-J, 2014; Destek and Aslan, 2017; Ozcán and Ozturk, 2019).

3.1. Time-domain extreme Granger causality test

However, considering the absolute asymmetry of the asymmetric causality test, we prefer to rely on a novel test for extreme causality proposed by Wang et al. (2020), who extended the asymmetric test by dividing a variable into three shocks and further detect the causality between different shocks. Inspired by their work, we can evaluate the effects of different shocks, separately. Specifically, gold (represented by \( G_t \)) and stock (represented by \( S_t \)) are assumed to be integrated variables. Hence, they can be expressed as follows:

\[
G_t = G_{t-1} + \varepsilon_{t1} = G_0 + \sum_{i=1}^{q} \varepsilon_{i1} \\
S_t = S_{t-1} + \varepsilon_{t2} = S_0 + \sum_{i=1}^{q} \varepsilon_{i2}
\]

where \( G_0 \) and \( S_0 \) are the initial values of \( G_t \) and \( S_t \), respectively. \( \varepsilon_{t1} \sim \text{NID}(0, 1) \) and \( \varepsilon_{t2} \sim \text{NID}(0, 1) \). Inspired by Granger and Yoon (2002) and Wang et al. (2020), different shocks can be defined as:

\[
e_{t}^{*} = \begin{cases}
\varepsilon_{t1}, & \text{if } \varepsilon_{t1} > q^* \\
0, & \text{else if } \varepsilon_{t1} < q^*, \\
\varepsilon_{t2}, & \text{if } q^* \leq \varepsilon_{t2} \leq q^*
\end{cases}
\]

where \( \varepsilon_{t1} \), \( \varepsilon_{t2} \), \( \varepsilon_{t}^{*} = (k = 0, l, 1, 2, \ldots, t) \) are extremely positive, extremely negative and normal shocks, respectively. Extremely positive and extremely negative shocks can be called extreme shocks, normal shocks are non-extreme shocks. \( q^1 = \max(q_{01}, q_{21}) \) and \( q^2 = \min(q_{02}, q_{22}) \) are the common thresholds for \( G_t \) and \( F_t \), and \( q_{ik} = Q_k (\delta_j) (j = 1, 2, \delta_1 \geq \delta_2, \delta_1 + \delta_2 = 1) \) is determined with empirical quantiles \( \delta_j \).

An advantage of applying empirical quantiles to define the shocks is that the occurrence of all extreme shocks could compare with the past and future extreme shocks, allowing for a more realistic model (Herrera and Schipp, 2013). In addition, it is proved to be more flexible and ready-to-use in the case of a complicated and volatile financial situation (Sim and Zhou, 2015). However, there is no consensus on how to choose the quantiles. Thus, different quantiles should be used to robustness check.

Then, different shocks of \( G_t \) and \( S_t \) can be expressed by the following cumulative forms,

\[
G_t^* = \sum_{i=1}^{q} \varepsilon_{t1}^{*}, \quad G_t^* = \sum_{i=1}^{q} \varepsilon_{i1}, \quad G_t^* = \sum_{i=1}^{q} \varepsilon_{i2} \\
S_t^* = \sum_{i=1}^{q} \varepsilon_{t1}^{*}, \quad S_t^* = \sum_{i=1}^{q} \varepsilon_{i1}, \quad S_t^* = \sum_{i=1}^{q} \varepsilon_{i2}
\]

Thus,

\[
G_t = G_{t-1} + \varepsilon_{t1} = G_0 + G_t^* + G_t' + G_t'' \\
S_t = S_{t-1} + \varepsilon_{t2} = S_0 + S_t^* + S_t' + S_t''
\]

According to the above-mentioned steps, internal shocks of gold and stocks can be captured and classified in more detail. Then, the response/impact of gold shocks on stock shocks can be grouped into nine different combinations: the response/impact of \( G_t^* \) on \( S_t'/S_t'/S_t' \), the response/impact of \( G_t' \) on \( S_t'/S_t'/S_t' \) and the response/impact of \( G_t'' \) on \( S_t'/S_t'/S_t' \).

For instance, we begin our research by testing the null hypothesis of noncausal form \( G_t' \) to \( S_t'' \). Thus, we construct the following VAR(p)
If $G_i^*$ does not Granger-cause $S_i^*$, then $\gamma_{ik} = 0$ ($k = 1, 2, i = 1, \ldots, p$). Next, $p$ can be selected by the information criterion. Moreover, considering the potential non-asymptoticity of the small sample distribution of the Wald test, we introduce a bootstrap simulation technique to solve this potential problem. Similarly, the other pairs of shocks can also be detected in the time domain.

3.2. Frequency-domain extreme Granger causality test

A stronger relationship between shocks could come from a higher co-movement between the long-run, mid-run, or short-run effects of shocks. A frequency-domain approach can usually examine the strength of this linkage as each frequency is related to a particular effect of the variables: the low-frequency effects last longer than the high-frequency ones (Bodart and Candelon, 2009). Granger (1969, 1980) already pointed that the measure of causality (Geweke, 1982; Hosoya, 1991), and the Granger-causality test.

We also use other stock markets as the robustness tests. We would like to thank anonymous reviewers, who point that this work should consider other U.S. stocks and worldwide stocks. Their valuable suggestion greatly improves the quality of this paper.

model ($p$ is lag order):

$$
\begin{align*}
G_i^* &= \left( a_{i0} + \frac{a_{i1}}{2} \right) \left( S_i^* - \frac{u_i}{2} \right) + \frac{a_{i2}}{2} T_i^* + \ldots + \frac{a_{ip}}{2} T_{ip} + \frac{G_i^*}{2}
\end{align*}
$$

(7)

where $\Theta(L) = I - \sum_{k=1}^{p} \Theta(L^k)$ is a $2 \times 2$ autoregressive polynomial with $L^k x_t$

$= {\ldots}$. The error term $u_t$ is white noise, and $E(\eta_t u_t) = \Sigma$, where $\Sigma$ is a positive definite matrix. Here we assume that $x_t$ is stationary.

Then, Eq. (8) can be expressed as

$$
\begin{align*}
\dot{x}_t &= \Phi(L) x_t + \Phi_1(L) \eta_t
\end{align*}
$$

(8)

where $\Phi(L) = \Theta(L)^{-1}$. With the Cholesky decomposition $C C^\top = \Sigma^{-1}$, $\Psi(L) = \Theta(L) C^{-1}$, $\eta_t = C x_t$, and $E(\eta_t \eta_t^\top) = I$. Next, the spectral density of $G_i^*$ and the measure of causality (Geweke, 1982; Hosoya, 1991),

$$
\begin{align*}
f_G(a) &= \frac{1}{2\pi} \left\{ \left| \Psi_{11}(e^{-ia}) \right|^2 + \left| \Psi_{12}(e^{-ia}) \right|^2 \right\}
\end{align*}
$$

(10)

$$
\begin{align*}
M_{G_i^* \rightarrow S_i^*}(a) &= \log \left\{ \frac{2 f_G(a)}{\left| \Psi_{11}(e^{-ia}) \right|^2} \right\} = \log \left\{ 1 + \frac{\left| \Psi_{12}(e^{-ia}) \right|^2}{\left| \Psi_{11}(e^{-ia}) \right|^2} \right\}
\end{align*}
$$

(11)

If $G_i^*$ does not Granger-cause $S_i^*$, then $M_{G_i^* \rightarrow S_i^*}(a) = 0$. This also means that $\left| \Psi_{12}(e^{-ia}) \right|^2 = 0$. The null hypothesis of noncausality was examined by Breitung and Candelon (2006). Moreover, the Wald statistics are also compared with the results of the bootstrap simulation technique to avoid the conclusion error caused by the nonnormal distribution of variables and heteroscedasticity of series (Hatemi-J, 2012). Therefore, we can also detect dynamic changes in the causal relationship between extreme and/or nonextreme shocks.\footnote{See Wang et al. (2021) for more details about the frequency-domain extreme Granger-causality test.}

We conclude the reasons for choosing the time- and frequency-domain extreme Granger-causality tests. First, we want to test whether there is a causal relationship between gold and stocks. If so, which shocks are the main sources of this relationship; if not, whether some hidden relationships can be detected under different shocks. Second, we want to observe the long- and short-run effects of these shocks, so we focus on the relationship not only in the time domain but also in the frequency domain. Third, we are interested in the impact of the COVID-19 outbreak on gold-stocks linkage. Finally, other existing methods seem to cannot test the relationship between extreme and non-extreme shocks. And many works, such as Hung and Vo (2021) and Drake (2022), only examine the average relationship between them but do not consider the case of different shocks. Thus, we are unable to apply other methods to make a comparison. But we will make efforts to propose and extend other methods in our future study. In this paper, the time- and frequency-domain extreme tests can be employed to fill some existing research gaps.

4. Data and preliminary analyses

We analyze the closing price of daily stock and gold prices from January 4, 2010, to March 24, 2021. The sampling starting date is in line with Gharib et al. (2021), and the ending date is determined by the data availability.\footnote{The stock and gold prices are downloaded from Investing.com.} This long analysis period enables us to examine how their causal relationship has progressed. For the stock prices, we choose the S&P 500 index, which play an irreplaceable role in the stock markets and worldwide economy (Sharif et al., 2020).\footnote{We also use other stock markets as the robustness tests. We would like to thank anonymous reviewers, who point that this work should consider other U.S. stocks and worldwide stocks. Their valuable suggestion greatly improves the quality of this paper.} The largest daily trading volume in gold is for the US market (Choudhry et al., 2015). We divide the samples as follows: (i) pre-COVID-19, January 4, 2010–December 11, 2019 (2503 observations); and (ii) post-COVID-19, December 12, 2019–March 28, 2021 (323 observations). The breakpoint is December 12, 2019, which is recognized as the starting point of the COVID-19 outbreak. Meanwhile, investors pay more attention to the returns. Thus, returns are defined as the first difference between the log prices at $t$ and $t - 1$. The following analyses in the present papers are performed by software components in MATLAB.

Table 1 shows the statistical properties of stock and gold returns for pre-COVID-19 and post-COVID-19. We notice that the skewness and kurtosis of stock and gold returns have great changes after the COVID-19 outbreak, revealing their asymmetric and leptokurtic behaviors. According to the Jarque-Bera statistics test, they are not Gaussian distributions, and the ADF test shows that both returns are stationary for the two periods.

Fig. 1 plots all daily returns. Obviously, there is a significant peak in post-COVID-19 period, and S&P 500 is more pronounced. Besides, volatility clustering is more significant in post-COVID-19 than that in pre-COVID-19, revealing that their different dynamic changes for the two subperiods. Boueri et al. (2021) and Mensi et al. (2020) also suggested that co-movement of financial market increased significantly after COVID-19 compared to other periods. Therefore, the gold-stocks causality may be affected by different shocks in different periods.

\footnote{See Wang et al. (2021) for more details about the frequency-domain extreme Granger-causality test.}
5. Discussion of empirical results

Before testing the extreme causality between stock and gold, we first define extreme positive, extreme negative, and normal shocks in our study. In general, extreme events can cause wild fluctuations in futures returns, even reaching the highest or lowest level. Motivated by Herrera and Clements (2018), empirical quantile can be applied to define the extreme returns. Thus, the quantile levels\(^{\text{10}}\) in Eq. (3) are determined by \(\delta_1 = 0.1\) and \(\delta_2 = 0.9\), revealing that the 10% most negative/positive returns are the extreme shocks in our work. Besides, in Table 2, the multivariate diagnostic tests for both returns show that the residuals of VAR are non-normal, suggesting that the necessary of applying the bootstrap method.

5.1. Time-domain extreme Granger causality

In this paper, we firstly aim to detect extreme gold-stocks causality. Second, we focus on the difference in extreme causality before and after COVID-19. Moreover, we also conduct the conventional Granger causality test to examine their average causality. Table 3 shows the time-domain statistical values.

\(^{10}\) Different quantiles are applied as a robustness check to verify the results in this paper; see Section 6.3 for more details.

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**Table 1**
Descriptive statistics for returns.

|                | Gold                      | Stock                      |
|----------------|---------------------------|----------------------------|
|                | Pre-COVID-19 | Post-COVID-19 | Pre-COVID-19 | Post-COVID-19 |
| Max.           | 0.0486       | 0.0210        | 0.0244       | 0.0389        |
| Min.           | -0.0427      | -0.0299       | -0.0222      | -0.0054       |
| Mean           | 0.0001       | 0.0002        | 0.0002       | 0.0003        |
| Std.Dev.       | 0.0045       | 0.0041        | 0.0056       | 0.0086        |
| Skew.          | -0.1400      | -0.4941       | -0.3195      | -0.9277       |
| Kurt.          | 20.0383      | 7.5714        | 6.7214       | 13.3557       |
| Jarque-Bera    | 30272.0000***| 2280.4000***  | 191.2873***  | 1485.0000***  |
| ADF            | -53.3712***  | -52.2649***   | -17.6846***  | -25.3826***   |

Notes: Stock and gold denote the S&P 500 and gold returns, respectively. *, **, and *** denote rejections of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.

---

**Table 2**
Diagnostic test results.

|                | Pre-COVID-19 | Post-COVID-19 |
|----------------|-------------|---------------|
| \(S, G\)      | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |
| \(S', G'\)    | <0.0001     | <0.0001       |

Notes: \(S\) stands for the S&P 500 and \(G\) is gold. The optimal lag length in the VAR model is set to 1. The Doornik and Hansen (2008) statistic is for testing multivariate normality and Hacker and Hatemi-J (2005) is for the multivariate ARCH effect. The \(p\)-values are presented.

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**Fig. 1.** Daily returns of gold and S&P 500.
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| Table 3 Time-domain results. |
|-----------------------------|
| **Panel A** | **Panel B** |
| Null hypothesis | Pre-COVID-19 | Post-COVID-19 | Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
| $G \rightarrow S$ | 0.2544 | 13.8634*** | $S \rightarrow G$ | 0.7075 | 5.7245 |
| $G \rightarrow S'$ | 2.4579 | 8.4806* | $S' \rightarrow G$ | 2.5894 | 0.1287 |
| $G' \rightarrow S$ | 0.4040 | 1.9218 | $S' \rightarrow G'$ | 0.6764 | 16.7508** |
| $G' \rightarrow S'$ | 0.7521 | 27.5656*** | $S' \rightarrow G'$ | 5.2242 | 3.3138 |
| $G \rightarrow S$ | 2.2810* | 0.679 | $S \rightarrow G'$ | 0.4976 | 0.4033 |
| $G \rightarrow S'$ | 5.1803** | 0.1180 | $S' \rightarrow G$ | 0.2528 | 2.7919 |
| $G' \rightarrow S$ | 1.7446 | 0.4233 | $S \rightarrow G$ | 1.8403 | 1.9446 |
| $G' \rightarrow S'$ | 0.4096 | 10.9811** | $S' \rightarrow G$ | 5.3769 | 7.5230* |
| $G \rightarrow S$ | 0.4198 | 1.0936 | $S \rightarrow G'$ | 13.8634*** | 28.5478*** |
| $G' \rightarrow S'$ | 34.8711*** | 20.5204*** |

Notes: $S$ stands for the S&P 500 and $G$ is gold. *, **, and *** denote rejections of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.

From Fig. 2(a), in the pre-COVID-19 period, we find that the null hypothesis of non-causality of gold to stock is not rejected at 5% level of significance. Interestingly, the results show that the stock does not Granger-cause gold while we find that gold Granger-cause gold while we find that the stock does not Granger-cause gold. The causality from $G'$ to $S'$ and from $G$ to $S'$ can be detected by the extreme causality test. This finding is similar to Jain and Biswal (2016) and Bouri et al. (2021),12 who suggest that gold prices or volatilities have an impact on stock market indices. Besides, negative stock shocks seem to be helpful for forecasting the negative gold shocks. On account of economic globalization and financial market integration, the linkage between gold and stocks has been promoted, which also increases the market risk contagion among them when facing an extreme shock (Berben and Jansen, 2005; Billio and Caporin, 2010; Brière et al., 2012). Thus, gold and stocks may share a similar trend of prices/returns under the same shocks. Particularly, there is a possible reason for the positive relation between gold and stock. When the real rate of interest is lower than zero, risks preferences for investors would be induced under this shock. At this point, investors prefer to choose gold and stocks for better investments (Drake, 2022).

However, these results may be affected by the COVID-19 outbreak. There are some new discoveries in Fig. 2(b). Although the causality from stock to gold is still not apparent in the post-COVID-19 period, the average causality from gold to stock changes. This result is in line with that of Drake (2022), who finds a significant causality from stock to gold during the period of the epidemic outbreak. Furthermore, our analysis reveals that the episodes of causality running from $G'$ to $S'$ and from $G$ to $S'$ are also greatly significant during the post-COVID-19 period. Particularly, gold has traditionally been regarded as a tool to hedge against inflation, especially in crisis periods. Higher gold prices provide protection against the depreciation of the U.S. dollar and the rise in crude oil prices, which directly increase industrial costs and lead to higher inflation rates, further causing lower stock prices (Wen et al., 2020). Meanwhile, the null hypothesis of Granger non-causality from $S' \rightarrow S'$ to $G'$ cannot be rejected with the COVID-19 outbreak. These results seem to be contradictory but reasonable. Negative stock returns are usually considered to be associated with the occurrence of negative gold returns, as negative stock shocks are sometimes closely followed by negative gold shocks (Baumohl and Lyöcza, 2017). Moreover, Baha-ni-Oskooee et al. (2020) indicate that inflation can be procyclical or countercyclical, so gold (as an inflation hedge) can promote a positive or negative linkage with stocks. Meanwhile, the non-existence of these relationships before the outbreak suggests the enormous and timely influence of this crisis. This evidence seems to be similar to the analysis of Hung and Vo (2021), who suggested that the bidirectional relationships across gold and stock markets are stronger in post-COVID-19.

5.2. Frequency-domain extreme Granger causality

The time-domain analysis shows the impact of the COVID-19 outbreak on extreme causality between gold and stock. To further explain how these returns correlated across different frequencies, we extend our work from the time domain to the frequency domain on the basis of Wang et al. (2021). It is worth noting that the frequency $\omega$ on the horizontal axis can be converted into a cycle or periodicity of $T$ by $T = 2\pi/\omega$. Hatemi-J (2012) pointed out that the sample data may not be normally distributed. Thus, a bootstrap technique is applied for 10,000 iterations, and then more accurate critical values for $\omega \in (0, \pi)$ are generated from the empirical distribution. Fig. 2 shows the frequency-domain results. Table 4 shows the frequency-domain statistical values at $\omega = 0.5$ (long-term), 1.5 (mid-term), and 2.5 (short-term).13

Fig. 2(a) shows the frequency-domain conventional and extreme causality in pre-COVID-19. (i) Consistent with time-domain results, the conventional method cannot examine the causality between stock and gold before COVID-19. (ii) $G'$ have medium- and long-term effects on $S'$. This conclusion is similar to Bouri et al. (2021), who pointed out that stocks affect gold at medium and low frequencies for 2011–2017. (iii) $S'$ may usually have an impact on $G' \rightarrow G'$ in the middle and long term of pre-COVID-19. Moreover, causality from $S'$ to $G'$ can be mainly detected in the short term and its strength is strongest in the middle term and then gradually weakens over time. However, it should be noted that causality from $S' \rightarrow G'$ and $S' \rightarrow G$ does not exist in the time domain. This is not surprising. The time-domain test can only examine the average causality over entire sample periods, while the frequency-domain test can detect the dynamic changes in causality over all frequencies.

In the post-COVID-19 period, Fig. 2(b) shows the dynamic changes in the extreme causality between stock and gold. (i) The impact of gold on stocks is significant in the mid-term COVID-19 outbreak. (ii) In the middle run, $G'$ mainly has an impact on $S'$ while the causality from $G' \rightarrow S'$ is not apparent. Moreover, the strength of causality from $G' \rightarrow S'$ / $S' \rightarrow S$ seems to be strongest. (iii) It is noteworthy that $S'$ mainly affects $G'$ in the long term. However, $S'$ holds the short- and long-term forecasting ability for $G'$. The causality from $S' \rightarrow G'$ is basically not significant in the long term, which possibly accompanied by other causal relationships

13 The complete frequency-domain results are shown in the form of figures (Fig. 3). Meanwhile, for the purpose of quantifying these results (Gorus and Aydin, 2019; Gurdal et al., 2021), we choose three representative frequencies $\omega = 0.5, 1.5, 2.5$ to show the long-, mid-, and short-term linkages (Table 4). Besides, for want of space, results of the following robustness tests are presented in tables.

12 The former collects the data covering 2006–2015 for gold and India stock, and the latter uses the gold and Chinese stock from March 16, 2011, to March 16, 2017.
Fig. 2. Conventional and extreme Granger causality tests in the frequency domain.

Notes: S stands for the S&P 500, and G is gold. The blue line denotes the Wald test statistic value. Yellow, red, and green denote bootstrap CVs of 1%, 5%, and 10%, respectively (Hatemi-J, 2012). For example, if the blue line is higher than the red line, then S is said to significantly “Granger cause” G at frequency ω0.
flight-to-safety) (Hakkio and Keeton, 2009; Soumoites investors to seek more low-risk investments (flight-to-quality or
implement our work. The four statistics can test the time-varying gold-shocks, displaying as the long-term causality running from gold shocks-
show that gold only Granger-cause stocks during the post-COVID-19.

Thus, the severe volatility (especially the fall) of the stock market pro
proving the necessity of our exploration for the extreme shocks.

Besides, we also show the time-varying Granger causality to sup
null hypothesis at significance levels of 10%, 5%, and 1%, respectively.

Notes: S stands for the S&P 500 and G is gold. *, **, and *** denote rejections of the null hypothesis at significance levels of 10%, 5%,
rangeing from a positive stock shock to a positive gold shock in the mid-
term.

Overall, significant gold-stocks causality usually comes from extreme
shocks, displaying as the long-term causality running from gold shocks to stock shocks while the fickle impact of stock shocks on gold shocks.
Empirical results also reveal that their causality is greatly promoted after this epidemic.

Table 4
Frequency-domain results.

| Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
|-----------------|--------------|--------------|
|                 | $\omega = 0.5$ | $\omega = 1.5$ | $\omega = 2.5$ | $\omega = 0.5$ | $\omega = 1.5$ | $\omega = 2.5$ |
| Panel A |
| $G \rightarrow S$ | 2.5126 | 2.5031 | 0.1183 | 8.0237** | 12.9050*** | 4.1713 |
| $G \rightarrow S^*$ | 0.9819 | 2.3428 | 1.8882 | 3.3412 | 6.6752** | 3.7911 |
| $G \rightarrow S$ | 0.4041 | 0.4454 | 0.4517 | 0.6926 | 1.0114 | 1.8597 |
| $G \rightarrow S^*$ | 0.5295 | 0.7651 | 0.4797 | 23.0833*** | 25.3478*** | 2.7613 |
| $G \rightarrow S$ | 1.1217 | 0.6764 | 3.9528 | 3.2192 | 4.0353 | 4.0615 |
| $G \rightarrow S^*$ | 7.4599** | 3.0014 | 1.7518 | 0.6288 | 0.8179 | 2.1688 |
| $G \rightarrow S$ | 1.9225 | 1.5908 | 0.9960 | 0.6710 | 2.0571 | 2.1344 |
| $G \rightarrow S^*$ | 0.5389 | 0.0783 | 0.1781 | 6.4549** | 6.2174** | 11.4051*** |
| $G \rightarrow S$ | 0.5448 | 0.2542 | 0.0913 | 1.0335 | 0.9223 | 0.3808 |
| $G \rightarrow S^*$ | 31.0503*** | 11.7065*** | 3.7229 | 13.5928*** | 17.9185*** | 11.6359*** |
| Panel B |
| $S \rightarrow G$ | 2.3867 | 2.2364 | 2.3170 | 1.5965 | 3.9227 | 4.3965 |
| $S \rightarrow G^*$ | 9.1609** | 12.1253*** | 3.6631 | 23.0711*** | 3.9426 | 4.7087* |
| $S \rightarrow G$ | 4.3907 | 8.5150** | 6.6679** | 8.8107** | 3.0346 | 8.4659** |
| $S \rightarrow G^*$ | 1.9178 | 0.4032 | 0.8836 | 1.9380 | 1.5288 | 1.2563 |
| $S \rightarrow G$ | 4.2788 | 2.6922 | 0.7789 | 4.2573 | 2.1999 | 0.0346 |
| $S \rightarrow G^*$ | 0.3882 | 0.5070 | 0.9700 | 5.2226* | 3.5851 | 2.9223 | 1.0434 |
| $S \rightarrow G$ | 2.0680 | 1.9990 | 0.5222* | 2.1455 | 2.6130 | 1.4471 | 10.7228*** |
| $S \rightarrow G^*$ | 14.8910*** | 14.6058*** | 2.1455 | 2.6130 | 1.4471 | 10.7228*** |
| $S \rightarrow G$ | 0.9114 | 0.4884 | 1.7318 | 2.1799 | 0.8497 | 1.3176 |
| $S \rightarrow G^*$ | 5.2953 | 0.4159 | 0.6528 | 6.2637** | 7.1247** | 2.6723 |

Notes: $S$ stands for the S&P 500 and $G$ is gold. *, **, and *** denote rejections of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.

Table 5
Time-varying Granger causality test of Rossi and Wang (2019).

| Null hypothesis | ExpW | MeanW | Nyblom | SupLR |
|-----------------|------|-------|--------|-------|
| Pre-COVID-19 $G \rightarrow S$ | 0.1280 | 0.2322 | 0.1005 | 0.0341 |
| $S \rightarrow G$ | 1.7420 | 0.7012 | 0.0577 | 0.0015 |
| Post-COVID-19 $G \rightarrow S$ | 0.0120 | 0.0522 | 0.1253 | 0.0003 |
| $S \rightarrow G$ | 0.0130 | 0.0251 | 0.0001 | 0.0000 |

Notes: This table shows the $p$-values at the 5% level of significance. The results show that gold only Granger-causes stocks during the post-COVID-19.

5.3. Discussion

It is well known that gold is usually regarded as a basic safe-haven. Thus, the severe volatility (especially the fall) of the stock market pro-
motes investors to seek more low-risk investments (flight-to-quality or flight-to-safety) (Hakkio and Keeton, 2009; Soucek, 2013). At this point, they choose gold as an alternative asset to hold their profits, thereby pushing up the gold prices. This is the common relative nega-
tion between gold and stocks (Buccioli and Kokholm, 2021). However, does this relationship remains the same in the case of extreme and non-extreme shocks? Our research from detecting the causality under different shocks found this is not the case. The empirical results display that their causality usually exists in extreme shocks rather the normal shocks. Economically, their relationship can be mainly affected by a

behavioral finance channel (Barber and Odean, 2008; Huberman and Regev, 2001).

Based on the limited attention theory, financial prices will quickly respond to new information. For example, investors are likely to pay more attention on new information caused by extreme shocks (Barber and Odean, 2008). Furthermore, as an extreme emotional response to extreme shocks, investors overreacting to new information lead to the stock/gold to become either overbought or oversold. Bartram and Bodnar (2009) confirmed that investors adjusted their portfolios when they questioned the perceptions of market risk during the 2008 global crisis. With this consideration, if an extreme positive shock occurs, such as the successful development of the COVID-19 vaccine, this can create a buying and selling panic for stock and gold, respectively (Rouatbi et al., 2021). Obviously, investors’ behavior greatly drives up the stock price and awfully drives down the gold price. This implies the huge changes in the Granger causal relationship between stock and gold market. On the contrary, when extreme negative shocks occur, gold and stock become excessively overbought and oversold, respectively, due to pessimistic psychological reasons rather than fundamentals. For instance, the COVID-19 crisis suddenly and unexpectedly breaks out, which increases the uncertainty of investors responding to market risks, leading to delayed rebalancing portfolios and further affect the existing relationship between gold and stocks (Salisu et al., 2021).

Moreover, investors are more sensitive to negative shocks and thus have differences in investment decisions when facing extreme negative and positive shocks, respectively. Hence, the Granger causal relationship between stock and gold will change under extreme shocks, investors overreacting to new information lead to the stock/gold to become either overbought or oversold. Bartram and Bodnar (2009) confirmed that investors adjusted their portfolios when they questioned the perceptions of market risk during the 2008 global crisis. With this consideration, if an extreme positive shock occurs, such as the successful development of the COVID-19 vaccine, this can create a buying and selling panic for stock and gold, respectively (Rouatbi et al., 2021). Obviously, investors’ behavior greatly drives up the stock price and awfully drives down the gold price. This implies the huge changes in the Granger causal relationship between stock and gold market. On the contrary, when extreme negative shocks occur, gold and stock become excessively overbought and oversold, respectively, due to pessimistic psychological reasons rather than fundamentals. For instance, the COVID-19 crisis suddenly and unexpectedly breaks out, which increases the uncertainty of investors responding to market risks, leading to delayed rebalancing portfolios and further affect the existing relationship between gold and stocks (Salisu et al., 2021).

6. Robustness tests

6.1. Other US stocks

Considering our findings may vary with the choice for the different

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American stock markets, we apply the Dow Jones Industrial Average (DJIA) and NASDAQ to replace the S&P 500 for robustness testing. S&P 500, DJIA, and NASDAQ are regarded as the most important stock index in the U.S (Huang et al., 2016; Liang et al., 2020). The sample dates of DJIA and NASDAQ are the same as section 4 (with the same number of observations). Fig. 3 plots DJIA and NASDAQ. During the COVID-19 outbreak, fluctuations in DJIA and NASDAQ are as dramatic as those in S&P 500. Tables 6 and 7 show the time-domain results of DJIA and NASDAQ, respectively. The results demonstrate that the response changes with different shocks, showing that the Granger causality between gold and DJIA/NASDAQ exists in extreme shocks. And the tables also present the statistical values at different frequencies. The strength of the causal relationship between DJIA/NASDAQ and gold also varies over time. Meanwhile, empirical results also reveal the huge impact of COVID-19 on their causality. These findings indicate that our main results are efficient.

6.2. Other stock indices in different countries

Since gold is a global commodities index, we consider other stock markets from different countries. In line with Liu et al. (2019), we choose the other two stock indices, HSI (China) and Stoxx 50 (Europe). Another reason we use the Chinese stock market as an alternative stock index is that the COVID-19 outbreak turns into a worldwide pandemic in Wuhan, China (Akhtaruzzaman et al., 2021). Meanwhile, as one of the most liquid futures contracts in the world, the Eurostoxx50 Index plays a leading role in the European stock market (Daly and Vo, 2008). Their sample periods are the same as S&P 500 while the number of

| Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
|-----------------|--------------|---------------|
| Time            | ω = 0.5      | ω = 1.5       | ω = 2.5       |
| Panel A         |              |               |               |
| G↛S             | 0.1947       | 2.1531        | 2.0536        |
| G↛S′            | 1.5986       | 0.0051        | 0.8588        |
| G↛S∗            | 1.4951       | 1.2760        | 1.4778        |
| G↛S             | 1.2707       | 0.6858        | 0.0236        |
| G↛S′            | 2.6176       | 2.7279        | 4.1493        |
| G↛S∗            | 3.2564       | 2.6474        | 0.1046        |
| G↛S             | 0.0153       | 0.0418        | 0.2580        |
| G↛S′            | 0.8410       | 8.0795        | 4.8571        |
| G↛S∗            | 0.4552       | 0.0802        | 0.7371        |
| G↛S             | 34.2723      | 32.1032       | 0.0639        |
| G↛S′            |              |               |               |
| G↛S             | 9.5693       | 6.5850        | 9.0363        |
| G↛S′            | 1.2223       | 8.3779        | 12.1073       |
| G↛S∗            | 1.3951       | 1.7490        | 0.5346        |
| G↛S             | 6.2378       | 6.0873        | 3.6808        |
| G↛S′            | 0.1087       | 0.0645        | 0.3057        |
| G↛S∗            | 0.9095       | 0.7111        | 1.4127        |
| G↛S             | 14.0289      | 13.7167       | 8.3500        |
| G↛S′            | 2.5918       | 4.0799        | 2.7193        |
| G↛S∗            | 7.3198       | 5.8604        | 1.5688        |

Notes: S stands for the DJIA, and G is gold. This table denotes the statistic of the null hypothesis at significance levels of 5% (bold font).
observations is not, as stock trading days differ from these regions. Fig. 4 plots HSI and Stoxx 50. It is obvious that Stoxx 50 shows more violent fluctuations than HSI during this outbreak. But the empirical analysis results of HSI (Table 8) and Stoxx 50 (Table 9) are a little bit different from the U.S stocks. One possible reason is that they are affected by the trading days. Nevertheless, time-domain results also suggest that the gold-stocks causality usually originates from extreme shocks. On the other hand, the strength and direction of these extreme causalities show signs of change by the extreme frequency-domain test. However, the causality between Stoxx 50 and gold is more vulnerable to COVID-19 under different shocks than that between HSI and gold.

6.3. Different thresholds

The selection of the quantile level may affect the type of shocks and further cause analysis error for the interaction between gold and stocks (Herrera et al., 2017). To assess whether the extreme causality findings are also significant in different threshold testing exercises, we apply a series of proxy thresholds to analyze causality in the time and frequency domains. Specifically, we consider the other two thresholds $\delta_1 = 0.05$ ($\delta_2 = 0.95$), $\delta_1 = 0.20$ ($\delta_2 = 0.80$) for determining the empirical quantile levels of extreme positive and negative shocks in Eq. (3).

Table 7

Time-domain and frequency-domain results for NASDAQ.

| Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
|-----------------|--------------|---------------|
| Time            | $\omega = 0.5$ | $\omega = 1.5$ | $\omega = 2.5$ | $\omega = 0.5$ | $\omega = 1.5$ | $\omega = 2.5$ |
| Panel A         |              |               |               |              |               |               |
| $G \rightarrow S$ | 1.3115 | 5.6334 | 3.1067 | 0.1648 | 11.3526 | 5.2309 | 11.0558 | 5.8488 |
| $G \rightarrow S^*$ | 3.6257 | 0.8583 | 2.7982 | 3.4410 | 16.3646 | 12.8485 | 15.0645 | 15.9858 |
| $G^* \rightarrow S$ | 0.0882 | 0.0115 | 0.1019 | 0.1149 | 0.8374 | 1.6039 | 0.0322 | 1.1608 |
| $G^* \rightarrow S^*$ | 0.5426 | 0.0712 | 0.3347 | 0.1599 | 0.6106 | 1.6219 | 1.6479 | 4.7550 |
| $G^* \rightarrow S$ | 0.0072 | 0.0141 | 0.0168 | 0.0030 | 0.3967 | 4.1553 | 1.6950 | 2.7007 |
| $G^* \rightarrow S^*$ | 0.0120 | 0.2448 | 0.2526 | 0.1115 | 24.8711 | 13.2717 | 6.1607 | 12.2822 |
| $G \rightarrow S$ | 2.9474 | 2.8021 | 0.0103 | 3.8402 | 0.5426 | 0.6712 | 0.3347 | 0.1599 |
| $G \rightarrow S^*$ | 6.5353 | 21.6906 | 9.7120 | 1.2833 | 6.5535 | 21.6906 | 9.7120 | 1.2833 |
| $G^* \rightarrow S$ | 0.4647 | 2.6046 | 2.2202 | 2.1750 | 9.4072 | 17.8226 | 9.4276 | 0.6800 |
| $G \rightarrow S^*$ | 0.4647 | 2.6046 | 2.2202 | 2.1750 | 9.4072 | 17.8226 | 9.4276 | 0.6800 |
| $S \rightarrow G$ | 7.6220 | 7.1597 | 6.3330 | 2.9019 | 32.4777 | 18.0595 | 9.4503 | 13.4087 |
| $S \rightarrow G^*$ | 0.0006 | 1.9513 | 1.8051 | 0.6492 | 1.2778 | 3.4902 | 2.9489 | 0.7140 |
| $S \rightarrow G$ | 0.0192 | 0.6212 | 0.3308 | 0.4905 | 29.7386 | 10.9847 | 15.4489 | 15.1107 |
| $S \rightarrow G^*$ | 3.1427 | 2.2634 | 0.1982 | 1.3797 | 4.1561 | 1.8970 | 2.2161 | 2.2107 |
| $S \rightarrow G$ | 1.4987 | 1.2866 | 1.2781 | 1.5472 | 0.7977 | 1.0910 | 0.1712 | 0.6921 |
| $S \rightarrow G^*$ | 0.7124 | 3.0371 | 1.1984 | 2.2888 | 7.6358 | 5.0535 | 4.2971 | 7.3515 |
| $S \rightarrow G$ | 14.7963 | 13.3815 | 11.2325 | 0.6661 | 13.8629 | 1.5345 | 4.1901 | 11.6878 |
| $S \rightarrow G^*$ | 0.9743 | 1.2124 | 1.3355 | 1.0491 | 1.1204 | 0.6563 | 2.2575 | 2.2982 |
| $S \rightarrow G$ | 0.3154 | 1.3672 | 2.3636 | 0.9475 | 3.3341 | 10.7918 | 0.7139 | 0.4569 |
| $S \rightarrow G^*$ | 0.3154 | 1.3672 | 2.3636 | 0.9475 | 3.3341 | 10.7918 | 0.7139 | 0.4569 |

Notes: $S$ stands for the NASDAQ, and $G$ is gold. This table denotes the statistic of the null hypothesis at significance levels of 5% (bold font).

Fig. 4. Daily returns of HSI and Stoxx 50.

The statistics values of these results are not reported in the table for want of space but can be provided upon request.
7. Compare with the financial shock

In this paper, we focus on the COVID-19 outbreak, which is widely regarded as a shock for global financial markets. However, financial shocks are also very important for gold and stocks. What is the main difference between this shock with the financial shocks? In this section, we examine the extreme causality between gold and stocks during the 2008 global financial crisis and further compare these results with that during the post-COVID-19 (thereafter, Phase I). For containing enough information related to the financial crisis, we choose the sample covering from January 2007 to December 2009 (thereafter, Phase II).

Fig. 5 plots the returns of gold and S&P 500 during Phase II. Comparing Table 3 and Panel A of Table 11, we can find that the average gold-stocks causality is significant during Phase II, which is the same as during Phase I. However, this financial crisis affects this causality in the middle run while this epidemic has a long-run effect on it. Further, causality from G to $S$ is significant during Phases I and II.

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Notes: $S$ stands for the HSI, and $G$ is gold. This table denotes the statistic of the null hypothesis at significance levels of 5% (bold font).

Table 8
Time-domain and frequency-domain results for HSI.

| Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
|-----------------|--------------|---------------|
| Time            | $\omega - 0.5$ | $\omega - 1.5$ | $\omega - 2.5$ | $\omega - 0.5$ | $\omega - 1.5$ | $\omega - 2.5$ |
| Panel A         |              |               |               |               |               |               |
| $G\rightarrow S$| 6.2871       | 9.4605        | 1.7274        | 7.8351        | 14.5090       | 5.4569        | 0.4765        | 4.6709        |
| $G \leftrightarrow S$ | 2.2485 | 7.0637 | 2.0317 | 1.2276 | 4.2477 | 1.5892 | 0.0934 | 2.3903       |
| $G \rightarrow S$ | 0.5621 | 0.1904 | 0.3310 | 1.2889 | 1.1182 | 1.4602 | 0.2435 | 0.4241       |
| $G \rightarrow S$ | 0.6132 | 5.1168 | 8.6626 | 4.5948 | 1.8996 | 8.5520 | 5.0873 | 2.3099       |
| $G \rightarrow S$ | 0.2247 | 4.0454 | 2.0409 | 0.3624 | 2.0288 | 0.7763 | 1.8003 | 1.0643       |
| $G \rightarrow S$ | 0.0130 | 2.0489 | 2.6038 | 1.7855 | 0.5877 | 0.0168 | 0.0620 | 0.0766       |
| $G \rightarrow S$ | 0.2602 | 1.7003 | 1.6118 | 1.9617 | 0.2562 | 3.2982 | 4.1526 | 2.2408       |
| $G \rightarrow S$ | 0.7349 | 4.0045 | 9.1608 | 4.0298 | 0.3216 | 5.0489 | 0.0034 | 0.9428       |
| $G \rightarrow S$ | 0.0139 | 2.7473 | 1.0915 | 0.3488 | 1.3152 | 0.9658 | 0.8745 | 1.9180       |
| $G \rightarrow S$ | 16.0588 | 25.6083 | 8.5657 | 9.3713 | 24.3708 | 13.5135 | 7.3756 | 4.0904       |

Table 9
Time-domain and frequency-domain results for Stoxx 50.

| Null hypothesis | Pre-COVID-19 | Post-COVID-19 |
|-----------------|--------------|---------------|
| Time            | $\omega - 0.5$ | $\omega - 1.5$ | $\omega - 2.5$ | $\omega - 0.5$ | $\omega - 1.5$ | $\omega - 2.5$ |
| Panel A         |              |               |               |               |               |               |
| $S \rightarrow G$ | 0.0218 | 5.0684 | 3.8834 | 1.3260 | 5.1430 | 5.6379 | 8.0563 | 8.4842       |
| $S \rightarrow G$ | 0.8718 | 4.3744 | 3.2574 | 0.0316 | 1.0037 | 0.7416 | 1.5202 | 1.1478       |
| $G \rightarrow S$ | 0.5491 | 0.3381 | 0.2528 | 0.8730 | 0.0587 | 0.4791 | 0.8306 | 0.8286       |
| $G \rightarrow S$ | 1.5666 | 0.6377 | 1.5840 | 2.0012 | 1.1849 | 2.7821 | 1.8114 | 1.7306       |
| $G \rightarrow S$ | 0.1317 | 4.1487 | 1.6207 | 0.2558 | 1.6617 | 1.9018 | 2.2767 | 2.1284       |
| $G \rightarrow S$ | 0.0514 | 10.0909 | 11.9772 | 10.2482 | 4.6474 | 2.1638 | 2.4012 | 0.2550       |
| $G \rightarrow S$ | 2.6676 | 0.8958 | 1.0770 | 5.2874 | 1.2594 | 1.0037 | 1.6453 | 8.0352       |
| $G \rightarrow S$ | 8.3379 | 4.5049 | 1.5106 | 0.5306 | 1.3422 | 10.8253 | 2.6267 | 15.6660      |
| $G \rightarrow S$ | 1.3168 | 2.3696 | 3.6321 | 3.9745 | 2.6690 | 0.9359 | 1.1570 | 1.1619       |
| $G \rightarrow S$ | 19.2471 | 2.2352 | 0.0124 | 2.2963 | 1.9952 | 14.5792 | 19.2348 | 9.6757       |

Notes: $S$ stands for the HSI, and $G$ is gold. This table denotes the statistic of the null hypothesis at significance levels of 5% (bold font).

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domains, but the stock has an impact on gold under some extreme shocks. In summary, both the results before and during the COVID-19 outbreak are almost unaffected by the threshold selection. This further verifies the robustness of our approach.

We are grateful to an anonymous reviewer for providing this suggestion.
But the former is significant in all runs while the latter is in the long and middle run. \( G^+ (G^-) \) will influence \( S^- (S^+) \) during Phase I while this effect does not exist during Phase II. In Panel B of Table 11, the average stocks-gold causality is not apparent during Phase II, as shown during Phase I. Causality from \( S^- \) to \( G^- \) during Phase II is totally similar to that during Phase I, in the time and frequency domains. \( S^- \) can affect \( G^- \) in the long and middle run, during Phase II. But the short-run effect of \( S^- \) on \( G^- \) exists during Phases I. \( S^- \) influences \( G^- \) during Phase I while this effect does not exist during Phase II. But it is the opposite in the case of the causality from \( S^- \) to \( G^- \).

### Table 10

Results of extreme Granger causality test (different thresholds).

| Null hypothesis | Pre-COVID-19 \( \delta_1 = 5\% \) \( \delta_1 = 20\% \) | Post-COVID-19 \( \delta_1 = 5\% \) \( \delta_1 = 20\% \) |
|-----------------|-----------------------------------------------|-----------------------------------------------|
|                 | Time \( \omega = 0.5 \) \( \omega = 1.5 \) \( \omega = 2.5 \) | Time \( \omega = 0.5 \) \( \omega = 1.5 \) \( \omega = 2.5 \) |
| \( G^+ \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( G^+ \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( G^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( G^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( G^+ \) \( \rightarrow \) \( G^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( G^+ \) \( \rightarrow \) \( G^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( G^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( G^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( G^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |
| \( S^- \) \( \rightarrow \) \( S^- \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) | \( x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \quad x \) |

**Notes:** \( S \) stands for the S&P 500, and \( G \) is gold. “\( \times \)” and “\( \checkmark \)” denote “Granger-cause” and “Not Granger-cause,” respectively.

### Fig. 5

Daily returns of gold and S&P 500 during the 2008 financial crisis.

8. Conclusions

The COVID-19 outbreak causes injuries and deaths worldwide and has paralyzed the economy around the world. Gold and stock markets suffered huge losses due to this crisis. Inevitably, the relation between the two markets may have changed, and hence, investors have also been affected by this sudden virus infection. As a popular hedging tool for stock risks, gold plays a crucial part in our lives. Will the risk transmission between gold and stock change during the COVID-19 outbreak? Is gold still a good hedging choice? In the present paper, we focus on these questions by examining the causality between gold and stock markets, especially considering the extreme shocks within them, and further explore how it is affected by the COVID-19 outbreak.
By applying a time- and frequency-domain extreme Granger causality analysis test to the daily dataset of gold and stock returns, this study produces some new discoveries and provides important implications. First, the causality between gold and stocks usually comes from extreme shocks, which implies that more attention should be given to internal extreme fluctuations in asset prices. Second, the causality under different shocks shows dynamic changes over time, displaying as the long-term gold-to-stocks causality while the spike impact of stock shocks on gold shocks. These findings not only reflect the instability of the macroeconomic but also the flexibility of the investment activity. Third, the COVID-19 outbreak drives the change in the risk transmission progress across gold and stocks. It is probable that the current impact that we have been affected by this epidemic will continue and keep enlarging if we only care about the time-domain relationships. Meanwhile, such dynamic changes in causality emphasize the necessity of the real-time monitoring of regulators for financial markets. This paper can provide a new thought for understanding the relationship between gold and stocks and further making beneficial strategies when facing other extreme shocks in the future.

CRediT authorship contribution statement

Yanran Hong: Writing—original draft, Data collection, Validation. Ma Feng: Revision, Supervision, Funding acquisition. Lu Wang: Methodology, Writing—review & editing, Funding acquisition. Chao Liang: Completed the introduction, Literature and conclusions, Writing—review & editing.

Declaration of competing interest

We declare that there is no conflict of interest.

Acknowledgements

The authors are grateful to the National Natural Science Foundation of PR China [71701170, 71902128, 72071162], the Humanities and Social Science Fund of the Ministry of Education [17YJC790105, 17XJCXZ002], Sichuan Provinicial Philosophy and Social Science Planning Project [SC17ZJ004], Sichuan Provinicial Science and Technology Planning Project [21RKKX0637], Soft Science Research Project in Chengdu [2020-RK00-00070-2F] and the Fundamental Research Funds for the Central Universities [2682020ZT98].

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