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Information spillover effects from media coverage to the crude oil, gold, and Bitcoin markets during the COVID-19 pandemic:
Evidence from the time and frequency domains

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ABSTRACT

Many scholars have explored the COVID-19 impact on the crude oil, gold, and Bitcoin markets, whereas most have ignored the media coverage influence. This paper focuses on examining information spillover from epidemic-related news to the crude oil, gold, and Bitcoin markets with the time-frequency analysis method. The empirical results reveal that both the return and volatility spillovers from epidemic-related news to the crude oil, gold, and Bitcoin markets are stronger in the short term (less than 1 week). In the long term, only the media sentiment index notably impacts crude oil, gold, and Bitcoin market returns. The volatility spillover from media coverage to crude oil mainly occurs in the short term. Regarding the gold and Bitcoin markets, the long-term volatility spillovers are significant. An obvious risk contagion path is found. Media hype is the main risk transmitter and transmits vast shocks to these three markets, especially the Bitcoin market, which subsequently transmits these shocks to the gold market. Risk accumulates systemically in the gold and Bitcoin markets. These findings have crucial empirical implications for policymakers and investors when formulating related short- or long-term decisions during the pandemic.

1. Introduction

The COVID-19 outbreak has caused over 36 million confirmed cases and over 1 million deaths worldwide as of September 18, 2020. This deadly virus has seriously deteriorated not only global healthcare systems but also the world economy. Additionally, due to the tremendous impacts on human livelihoods, COVID-19 has received much attention from the media worldwide. According to the existing literature, scholars have found that COVID-19-related news has significantly influenced financial markets during the epidemic period (Cepoi, 2020; Haroon & Rizvi, 2020; Salisu et al., 2020). Most studies have investigated the impact of media coverage on stock markets but have ignored the crude oil, gold, and Bitcoin markets (Ichev & Marinč, 2018). However, these assets are very important, and some scholars have reported that the crude oil, gold, and Bitcoin markets have been greatly affected by COVID-19 (Dutta et al., 2020; Goodell & Goutte, 2021; Mensi et al., 2020). Therefore, this paper provides a new perspective to explore the impact of COVID-19
on the crude oil, gold, and Bitcoin markets by applying media coverage as a COVID-19 proxy.

First, many studies have investigated the impact of COVID-19 on financial markets (Ashraf, 2020; Baek et al., 2020; Baig et al., 2020; Goodell & Goutte, 2021). Most scholars use the number of confirmed cases or deaths to measure the influence of COVID-19. Baig et al. (2020) find that increments in daily confirmed coronavirus cases and deaths are relevant to a significant increase in US equity market illiquidity and volatility. Moreover, from the perspective of behavioral finance, the impact of media coverage on financial markets has been confirmed by many scholars (Dang et al., 2020; Gao et al., 2021; Haroon and Rizvi, 2020; Liang et al., 2021; Umar et al., 2021; Zhang and Liu, 2021). For example, Dang et al. (2020) indicate that media coverage is negatively correlated with stock price synchronization. In addition, given the sufficient evidence of media coverage effects on the stock market, one could argue that media coverage yields a similar foreseeable impact on the crude oil, gold, and Bitcoin markets. Although most studies have investigated the impact of media coverage on stock markets, they have ignored the crude oil, gold, and Bitcoin markets (C. H. Wu & Lin, 2017). Therefore, this paper fills this gap.

Furthermore, most previous related studies have used only a single indicator to measure media coverage and have often ignored the heterogeneous impacts of different media report types, such as fake news and negative sentiment (Guegan & Renault, 2020; Smales, 2015; Z. Su et al., 2018). Some scholars indicate that there is heterogeneity between different media coverage types (Atri et al., 2021; Cepoi, 2020; Shi & Ho, 2021). For example, Haroon and Rizvi (2020) demonstrate that the panic emotion from news contributed to volatility to a greater extent in the transportation sector equity market than negative sentiment. Cepoi (2020) finds that fake news exerts a negative nonlinear impact on the inferior quantiles of stock returns and that news reports have no impact on inferior quantiles. Therefore, we consider five different COVID-19 news-related indices (the sentiment index, media hype heat index, fake news index, panic emotion index, and contagion index) to reveal the heterogeneous impacts of media coverage on the crude oil, gold, and Bitcoin markets rather than considering a single index.

At present, most relevant studies are based on the time domain (Huang et al., 2019; Rognone et al., 2020; Su et al., 2018), and the frequency domain relationship between media coverage and these three markets at diverse time scales has rarely been examined. However, the mutual effects of various investors change across time scales, and the relations between media coverage and financial markets are diverse at different frequency scales (Umar & Gubareva, 2021). Therefore, within this context, we explore the connect-edness of media coverage in the time-frequency domain in the system, including crude oil, gold, and Bitcoin, during the pandemic based on the frameworks presented by Diebold and Yilmaz (2012) and Barunik and Krehlík (2018). In addition, we analyze the risk spillover path from news to these three markets within this framework.

The following are our main contributions to the existing literature. First, due to the notable impact of COVID-19 on financial markets, this paper considers the effects of COVID-19-related media coverage on the crude oil, gold, and Bitcoin markets during the pandemic. This provides new insights to analyze the impact of COVID-19 on these markets. Second, because the impacts of the different types of news are diverse, this paper considers various types of COVID-19 news-related indices (the sentiment index, media hype heat index, fake news index, panic emotion index, and contagion index) to analyze their impact on the crude oil, gold, and Bitcoin markets rather than considering a single index. This can help us fully understand the impact of COVID-19-related media coverage on these markets. Third, we apply the DY (2012) and the method presented by Barunik and Krehlík (2018) (hereafter referred to as the BK (2018) method) to analyze the magnitude and direction of the spillover effects between these five news indices and the crude oil, gold, and Bitcoin markets in the time and frequency domains, which is highly important to both investors and policymakers during the pandemic. In general, the present paper provides a new perspective for the examination of the impact of the epidemic on the crude oil, gold, and Bitcoin markets and important references for participants in these markets.

This paper is structured as follows. Section 2 exhibits a brief review of the related literature. Section 3 offers the methodology, the data sources, and descriptive statistics. Section 4 describes the empirical results and provides valuable findings. In Section 5, we test the results for robustness. Finally, Section 6 draws conclusions and proposes policy implications according to the empirical analysis.

2. Literature review

2.1. Media coverage and financial markets

In recent years, researchers have sufficiently investigated the impact of media coverage on the financial market, especially the stock market, which includes prices, returns, volatility, and liquidity (Aman & Moriyasu, 2017; Ichev & Marinč, 2018; Dang et al., 2020; Shyu et al., 2020; C. H. Wu & Lin, 2017). Aman and Moriyasu (2017) uses the number of reports in four newspapers to measure media coverage, and he finds that excessive media reports provoke extreme reactions in the stock market. Shyu et al. (2020) use media data from the China Core Newspapers Full-Tex Database to indicate that earnings dispersion spread by the news is helpful to reduce stock liquidity. Atri et al. (2021) use the percentage of all news sources associated with COVID-19 as the COVID-19 media coverage indicator (CMC), and by applying the AEDL approach, they determine that COVID-19 media coverage has positive effects on the dynamics of oil and gold prices. Meanwhile, behavioral finance studies uncover that investor sentiment influences investment decisions. Subsequently, some scholars have verified that media coverage greatly affects investor sentiment and further influences investment decisions in financial markets (Broadstock & Zhang, 2019; Gan et al., 2020; Dang et al., 2020; Haroon & Rizvi, 2020; Wu & Lin, 2017). Broadstock and Zhang (2019) extract sentiment information from Twitter and demonstrate that sentiment from media coverage has a significant impact on the stock market. C. H. Wu and Lin (2017) divide news into ten categories, including positive earnings news and negative revenue news. They show that positive or negative media coverage information is relevant to abnormal returns. Baig et al. (2020) find that negative sentiment that originates from COVID-19-related news deteriorates stock market liquidity and stability.

Moreover, some researchers indicate that there are heterogeneous media coverage types, such as media hype, negative sentiment,
panic emotion, and fake news (Atri et al., 2021; Cepoi, 2020; Shi & Ho, 2021). In the previous paragraph, we explained the relevant research on media sentiment, and most scholars support that different emotions tend to have different impacts on the financial market (Smales, 2015). Smales (2015) collects news sentiment data from Thomson Reuters News Analytics and finds that there is a significant asymmetric effect on the volatility of gold futures between news sentiment including positive sentiment and negative sentiment. Furthermore, some scholars suggest that media hype may have a greater influence on financial markets than news sentiment (Haroon & Rizvi, 2020; Biktimirov et al., 2021). Biktimirov et al. (2021) find that the media hype of COVID-19 is more related to stock market returns than sentiment by using text analytics in the Wall Street Journal. Aman and Moriyasu (2017) shares the same opinion about corporate news. In addition, in psychological studies, some scholars have shown that false information can significantly change an individual’s unconscious behavior (Bastick, 2021; Vosoughi et al., 2018). Vosoughi et al. (2018) find that fake information is spread significantly faster, farther, and more broadly than true information since fake news has broader audiences. Rognone et al. (2020) apply a vector autoregression with an exogenous model (VAR-X) to analyze the influence of Bitcoin-related news on the return and volatility of this cryptocurrency, and they indicate that fake news greatly decreases Bitcoin returns and volatility. In particular, false information-related health issues have been proven to cause public health threats (Hou et al., 2020; Waszak et al., 2018). Hou et al. (2020) found that rumors trigger public panic during the epidemic.

Accordingly, on the one hand, few scholars notice the impact of pandemic-relevant media coverage on the financial market, but the impact of media coverage on the financial market should never be ignored from the behavior finance perspective. On the other hand, different COVID-19-related news indices, such as fake news, panic emotion, and negative sentiment, may have different impacts on the financial market. This paper fills these gaps in the literature.

2.2. COVID-19 and the crude oil, gold, and Bitcoin markets

Before the COVID-19 outbreak, existing studies widely explored these assets regarding their ability to function as safe havens (Lei et al., 2019; Reboredo, 2013). Lei et al. (2019) find that traders take crude oil assets as risk hedging tools during the 2008 financial crisis. Reboredo (2013) indicates that gold can act as a safe haven to hedge against USD rate movements. After the COVID-19 outbreak, recent studies have determined that COVID-19 has a very serious impact on the crude oil, gold, and Bitcoin markets (Béjaoui et al., 2021; Depren et al., 2021; Goodell & Goutte, 2021; Shaikh, 2021). For instance, Goodell and Goutte (2021) use daily data on COVID-19 world deaths to measure COVID-19 and find that an increase in COVID-19 levels is accompanied by a rise in the price of Bitcoin. In addition, many scholars have contributed considerable work to revisiting the safe-haven property of these assets after the COVID-19 outbreak (Chkili et al., 2021; Dutta et al., 2020; Syuhada et al., 2021). Chkili et al. (2021) use a DCC-FIGARCH model to explore the safe-haven property of Bitcoin, and the results show that Bitcoin as a part of a hedge strategy leads to a higher cost during the epidemic. Syuhada et al. (2021) apply a vine copula approach to revisit the safe-haven property of gold and Bitcoin for energy commodities, and they indicate that gold still serves as a safe haven but that Bitcoin is too inconsistent to be a safe haven.

We study the crude oil, gold, and Bitcoin markets for two main reasons. First, these three assets have been used by investors as hedging assets to hedge against risks and lock in profits. This opinion is consistent with the aforesaid studies. Exploring the information spillovers from COVID-19-related media coverage to these three markets can further widely survey the performance of these assets during the COVID-19 pandemic. Second, the COVID-19 crisis has enhanced the interconnection of financial markets and increased financial infectivity (Baker et al., 2020). Taking these three assets into a system can provide more interesting and valuable findings. Moreover, to the best of our knowledge, this is the first article to explore the impact of COVID-19 on the crude oil, gold, and Bitcoin markets through epidemic news.

In addition, most of the aforesaid studies only research the time-domain relationship and ignore the frequency connections in the system (Diebold & Yilmaz, 2012). However, some scholars have determined that the connections are heterogeneous between media coverage and economic variables at different frequency scales (Umar & Gubareva, 2021). To address this issue, Barunik and Krehlik (2018) apply the wavelet transform method to realize variance decomposition in given frequency bands based on the work of Diebold and Yilmaz (hereafter called the DY (2012) method). Many scholars have used the DY (2012) method and BK (2018) method to research spillover effects in systems (Albulescu et al., 2019; Ashraf, 2020; Gozgor et al., 2019; Kang et al., 2019; Tiwari et al., 2020; Xu et al., 2019; Zhang and Wang, 2021; Zhang and Yan, 2020). Zhang and Wang (2021) use the DY (2012) and BK (2018) frameworks to analyze the time-frequency relation among gold, Bitcoin, and financial stress. Y. J. Zhang and Yan (2020) discuss the time-frequency connection between US economic policy uncertainty and West Texas Intermediate (WTI) crude oil returns by using the DY (2012) and BK (2018) methods. X. Su and Li (2020) apply the DY (2012) and BK (2018) methods to examine the sentiment spillovers among the oil, gold, and Bitcoin markets, and they determine that the total sentiment spillover among the crude oil, gold, and Bitcoin markets is greatly affected by major market events. Accordingly, the DY (2012) and BK (2018) frameworks are very suitable to explore the spillover information from COVID-19-related media coverage to the crude oil, gold, and Bitcoin markets in the time-frequency domains.

In short, this study extends existing research by examining the impact of the epidemic on the crude oil, gold, and Bitcoin markets by using epidemic-related news as a proxy variable. Meanwhile, we also investigate the heterogeneity of different types of media coverage indices. Moreover, we explore the impact of COVID-19-related media coverage on these markets in both the time and frequency domains. Accordingly, this work may be of interest to investors who want to recognize risk in time and adjust their investment strategy during the epidemic.
3. Methodology and data

In this section, we introduce the connectedness method applied in this article, the time domain spillover method proposed by Diebold and Yilmaz (2012) and the time-frequency connectedness framework proposed by Barunik and Krehlík (2018).

3.1. DY time domain spillover method

In this section, we introduce the connectedness method applied in this article, i.e., the time domain connectedness framework proposed by Diebold and Yilmaz (2012). The DY (2012) method mainly relies on forecast error variance decomposition with the VAR model. Thus, the main steps are as follows.

First, we build a $\text{VAR}(p)$ model, as expressed in Eq. (1):

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \varphi_3 X_{t-3} + \cdots \varphi_p X_{t-p} + \varepsilon_t$$

where $X_t$ is a variable vector, such as the five COVID-19 news-related indices and crude oil, gold, and Bitcoin market returns or volatility, $\varphi_i$ is the $i$th lag coefficient to be estimated, and $\varepsilon_t$ is the white noise term with a zero mean and covariance matrix $\sum$. In this manner, we suppose that the covariance is stabilized. Therefore, the moving average form of the VAR model can be expressed as Eq. (2):

$$X_t = \psi(L) \varepsilon_t = \sum_{h=0}^{\infty} \psi_h \varepsilon_{t-h} + \varepsilon_t$$

where $\psi(L)$ is a matrix that denotes the moving average coefficients at an infinite lag order.

Second, based on Diebold and Yilmaz (2012), we apply the generalized forecast error variance decomposition method to measure the connectedness, which is written as Eq. (3):

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H} (\psi_h \sum) \psi_h^2}{\sum_{h=0}^{n} (\psi_h \sum \psi_h)_{ij}}$$

where $\psi_h$ is the coefficient matrix of the moving average process of hysteresis order $h$, $H$ denotes the forecast horizon, and $\sigma_{jj}$ is the $j$th diagonal element of the covariance matrix $\sum$. In addition, we can normalize $\theta_{ij}(H)$ as Eq. (4):

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{n} \theta_{ij}(H)}$$

where $\sum_{j=1}^{n} \theta_{ij}(H) = 1$. After this normalization, $\tilde{\theta}_{ij}(H)$ denotes the directional spillover effect from $j$ to $i$ at forecast horizon $H$. According to the definition of directional spillover, other important measures of connectedness are proposed.

(1) Total spillover

The total spillover describes the capability of mutual interpretation between the COVID-19 news-related indices and the gold, crude oil, and Bitcoin markets, as expressed in Eq. (5):

$$C_H = 100 \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}(H)}{\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}(H)}$$

(2) TO spillover

The TO spillover is applied to assess the directional spillover from $i$ to all other variables in the system, as expressed in Eq. (6):

$$[C_H]_{i\cdot} = 100 \frac{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H)}$$

(3) FROM spillover
The FROM spillover is applied to assess the directional spillover from all other variables in the system to \( i \), as defined in Eq. (7):

\[
(C_H)_{i\rightarrow} = 100 \frac{\sum_{j=1, j\neq i}^{n} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H)}
\]  

(7)

(4) Net spillover

Accordingly, we define the net spillover of \( i \) as expressed in Eq. (8):

\[
(C_H)_i = (C_H)_{i\rightarrow} - (C_H)_{i\leftarrow}
\]

(8)

(5) Net pairwise spillover

Finally, we calculate the net pairwise spillover between any two variables with Eq. (9):

\[
(C_H)_{ij} = 100 \left( \frac{\tilde{\theta}_{ij}(H)}{\sum_{k=1}^{n} \tilde{\theta}_{ik}(H)} - \frac{\tilde{\theta}_{ji}(H)}{\sum_{k=1}^{n} \tilde{\theta}_{jk}(H)} \right)
\]

(9)

3.2. BK frequency domain spillover method

The DY (2012) method is useful to evaluate spillover effects in the time domain. However, we aim to determine whether the results are coincident across different frequency domains. Thus, according to the work of Baruník and Krehlík (2018), we apply a Fourier transform to the coefficients of the moving average process of hysteresis order \( h \) (\( \psi_h \)) and design a frequency response function, as expressed in Eq. (10):

\[
\psi(e^{i\omega}) = \sum_{h=0}^{\infty} e^{ih\omega} \psi_h
\]

(10)

The generalized forecast error variance decomposition at frequency \( \omega \) can be achieved with the following method (Eq. (11)):

\[
\tilde{\theta}_{ij}(\omega) = \frac{\sigma_{ij} \sum_{h=0}^{\infty} (\psi(e^{i\omega}) \sum_{h=0}^{\infty})^2}{\sum_{h=0}^{\infty} (\psi h \sum_{h=0}^{\infty})^2}
\]

(11)

where \( \tilde{\theta}_{ij}(\omega) \) denotes the portion of the scope of the \( i \)th variable at frequency \( \omega \) due to the shocks in the \( j \)th variable, and the normalized \( \tilde{\theta}_{ij}(\omega) \) is expressed as Eq. (12):

\[
\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{i=1}^{n} \theta_{ij}(\omega)}
\]

(12)

However, we are not interested in the connectedness of a single frequency but rather in the connectedness of descriptive frequencies such as the short, medium and long terms. Thus, it is vital to compute the cumulative connectedness within a given frequency band \( d = (d_1, d_2) \), as defined in Eq. (13):

\[
\tilde{\theta}_{ij}(d) = \int_{d_1}^{d_2} \tilde{\theta}_{ij}(\omega) d\omega
\]

(13)

In addition, to fully analyze the direction and magnitude of the spillover effects between epidemic-related news and the three assets, we calculate the following spillover indicators to assess the information spillover effects in the system.

(a) Overall connectedness within frequency band \( d \), as expressed in Eq. (14):

\[
C^d = \frac{\sum_{i=1, i\neq j}^{n} \tilde{\theta}_{ij}(d)}{\sum_{i=1}^{n} \theta_{ij}(d)} = 1 - \frac{\sum_{i=1}^{n} \tilde{\theta}_{ij}(d)}{\sum_{i=1}^{n} \theta_{ij}(d)}
\]

(14)

(b) Directional spillover indices within spectrum \( d \), including the FROM connectedness and TO connectedness:
Table 1

| Index                         | Description                                                                 |
|-------------------------------|-----------------------------------------------------------------------------|
| The panic Index (PI)          | It measures the level of news chatter that refers to panic or hysteria and coronavirus. Values range between 0 and 100. The higher the index value, the more references to panic found in the media. |
| The Media Hype Index (HY)     | It measures the percentage of news talking about the novel coronavirus. Values range between 0 and 100.                                                                 |
| The Fake News Index (FNI)     | It measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19. Values range between 0 and 100 where a value of 2.00 indicates that 2 percent of all news globally is talking about fake news and COVID-19. |
| The cosmopolitan Sentiment Index (CSI) | It measures the level of sentiment across all entities mentioned in the news alongside the coronavirus. The index ranges between –100 (most negative) and 100 (most positive) sentiment while 0 is neutral. |
| The Contagion Index (CTI)     | It calculates the percentage of all entities (places, companies, etc.) that are reported in the media alongside COVID-19. Values range between 0 and 100. |
4. Empirical analysis

The empirical analysis is conducted as follows. Based on the DY (2012) and BK (2018) methods, the first part studies the static spillover effects of both the return and volatility in the time and frequency domains. In the second part, we explore the dynamic spillover effects in the system. Finally, we further create and analyze the return and volatility of the connectedness networks.

4.1. Static spillover effect analysis

We apply the DY (2012) method to examine the static spillover effects in the time domain. Specifically, we estimate an eight-variable VAR model, with an optimal lag order of 1 based on Akaike’s information criterion (AIC), and the forecast period is 22 days. Table 3 presents the results of the return and volatility connectedness in the system. First, the empirical results demonstrate that
the total return (volatility) spillover index for the system is nearly 30% (35%), which indicates that a relatively high connectedness occurs in the system. Second, in general, the volatility spillover effects in the system are relatively greater than the return. Third, the impacts of news on the three markets are heterogeneous. Specifically, panic emotion (PI), media hype (HY), and news items related to COVID-19 (CTI) act as the main transmitters of information to the Bitcoin market during the epidemic. Regarding the gold market, CTI and HY function as the main transmitters. Interestingly, we find a high connectedness between the gold and Bitcoin markets, which implies that a relatively strong relation exists. This finding is in line with the findings of other scholars (Gkillas et al., 2020) who report a stronger relationship between the Bitcoin and gold markets over other markets. Then, in the crude oil market, panic sentiment contributes the most to the spillover effect on the WTI return, and media hype is the main spillover transmitter to WTI volatility. This finding agrees with existing studies that an overwhelming negative sentiment, as generated by news outlets, is associated with

Table 3
DY (2012) spillover results.

| PI    | CSI   | CTI   | FNI   | HY   | BTC   | GOLD  | WTI   | FROM |
|-------|-------|-------|-------|------|-------|-------|-------|-------|
| 46.711| 0.145 | 2.881 | 10.294| 31.773| 5.494 | 0.701 | 2.000 | 6.661 |
| 2.766 | 1.638 | 87.678| 0.736 | 1.872 | 1.014 | 2.113 | 2.183 | 1.540 |
| 12.441| 0.221 | 6.967 | 68.381| 9.412 | 1.548 | 0.786 | 0.243 | 3.952 |
| 32.924| 0.563 | 1.285 | 9.086 | 47.612| 5.381 | 0.696 | 2.453 | 6.548 |
| 7.333 | 1.13  | 4.652 | 1.892 | 8.197 | 61.668| 13.306| 1.821 | 4.791 |
| 0.013 | 1.631 | 3.110 | 0.252 | 1.837 | 3.338 | 88.222| 1.598 | 1.472 |
| 4.139 | 0.457 | 1.770 | 0.516 | 3.653 | 0.456 | 0.873 | 88.137| 1.483 |
| 7.534 | 0.723 | 2.878 | 3.014 | 7.246 | 2.469 | 2.623 | 1.385 | 27.872|

Table 4
BK (2018) Return spillover results.

| PI    | CSI   | CTI   | FNI   | HY   | BTC   | GOLD  | WTI   | FROM |
|-------|-------|-------|-------|------|-------|-------|-------|-------|
| 42.146| 0.101 | 2.876 | 9.758 | 28.684| 4.899 | 0.639 | 1.728 | 6.086 |
| 0.357 | 63.277| 1.482 | 1.300 | 0.663 | 1.372 | 0.997 | 0.356 | 0.816 |
| 13.138| 0.276 | 6.759 | 68.924| 9.613 | 8.887 | 0.844 | 0.829 | 6.671 |
| 13.138| 0.276 | 4.164 | 1.817 | 5.961 | 46.724| 8.662 | 1.491 | 3.534 |
| 0.011 | 0.827 | 3.036 | 0.240 | 1.798 | 1.960 | 0.606 | 0.897 | 1.096 |
| 0.511 | 0.294 | 1.49  | 0.499 | 3.258 | 0.412 | 0.708 | 78.807| 1.302 |
| 0.673 | 0.441 | 2.615 | 2.861 | 6.240 | 1.870 | 1.758 | 1.119 | 23.476|
| 0.375 | 0.294 | 1.49  | 0.499 | 3.258 | 0.412 | 0.708 | 78.807| 1.302 |
| 0.771 | 0.221 | 0.210 | 0.124 | 0.807 | 0.472 | 0.677 | 0.210 | 3.493 |

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increased volatility in financial markets (Haroon & Rizvi, 2020).

However, the above analysis is conducted only in the time domain and does not reveal the system spillover effects at different frequencies. Therefore, this study employs the BK (2018) method to analyze the static spillover effect in the short term (less than 1 week), medium term (1 month), and long term (more than 1 month). Table 4 summarizes the return spillover results, and Table 5 lists the volatility spillover results at the three different frequencies.

In the system, compared to the medium and long terms, the total return (volatility) connectedness in the short term dominates at 23.48% (18.9%). This suggests that the interactions among COVID-19-related news and the WTI, gold and Bitcoin markets are significant within one week. By focusing on the spillover effects from media coverage to these markets, we observe that the majority of the significant directional spillovers, as listed in Table 3, persist at different frequencies. For example, PI and HY remain the main transmitters for the Bitcoin market at the different frequency scales. Accordingly, we determine that the spillover effects from news to these markets largely occur in the short term (less than 1 week). This can be explained by investors being worried about the development of COVID-19, and most can adjust their investment strategies in the short term (less than 1 week).

Table 5
BK (2018) Volatility spillover results.

| FROM | PI | CSI | CTI | FNI | HY | BTC | GOLD | WTI | TO |
|------|----|-----|-----|-----|----|-----|------|-----|----|
| PANEL A: frequency 1 of short-term: 1–5 days |
| PI   | 44.540 | 0.133 | 3.367 | 10.439 | 30.094 | 3.219 | 0.207 | 0.230 | 5.961 |
| CSI  | 0.421 | 65.783 | 2.008 | 1.613 | 0.917 | 1.255 | 0.098 | 0.546 | 0.857 |
| CTI  | 2.877 | 1.584 | 77.722 | 0.569 | 1.509 | 5.455 | 0.062 | 0.229 | 1.535 |
| FNI  | 11.856 | 0.266 | 6.543 | 61.767 | 8.232 | 6.225 | 0.047 | 0.061 | 3.454 |
| HY   | 28.659 | 0.459 | 1.244 | 8.307 | 41.596 | 5.176 | 0.307 | 0.548 | 5.980 |
| BTC  | 0.832 | 0.207 | 0.766 | 0.144 | 1.584 | 6.724 | 0.008 | 0.162 | 0.515 |
| GOLD | 0.077 | 0.032 | 0.130 | 0.036 | 0.177 | 0.843 | 0.004 | 0.061 | 0.162 |
| WTI  | 0.807 | 0.081 | 0.951 | 0.026 | 1.588 | 0.145 | 0.167 | 58.708 | 0.471 |
| TO   | 5.691 | 0.345 | 1.876 | 2.642 | 5.513 | 2.482 | 0.183 | 0.203 | 18.936 |
| PANEL B: frequency 2 of medium-term: 6–22 days |
| PI   | 3.373 | 0.021 | 0.014 | 0.448 | 2.245 | 0.156 | 0.192 | 0.135 | 0.401 |
| CSI  | 0.104 | 20.085 | 0.853 | 0.040 | 0.333 | 0.260 | 0.115 | 0.559 | 0.283 |
| CTI  | 0.016 | 0.349 | 5.835 | 0.049 | 0.185 | 0.416 | 0.110 | 0.128 | 0.157 |
| FNI  | 1.116 | 0.009 | 0.140 | 5.770 | 0.995 | 0.128 | 0.012 | 0.015 | 0.302 |
| HY   | 2.620 | 0.134 | 0.088 | 0.368 | 3.882 | 0.386 | 0.263 | 0.208 | 0.508 |
| BTC  | 1.303 | 0.595 | 1.451 | 0.098 | 2.848 | 9.167 | 1.771 | 0.054 | 1.015 |
| GOLD | 0.413 | 0.278 | 0.575 | 0.022 | 0.990 | 2.692 | 0.700 | 0.039 | 0.626 |
| WTI  | 0.037 | 0.035 | 0.119 | 0.033 | 0.307 | 0.354 | 0.122 | 28.491 | 0.126 |
| TO   | 0.701 | 0.178 | 0.405 | 0.132 | 0.988 | 0.549 | 0.323 | 0.142 | 3.418 |
| PANEL C: frequency 3 of long-term: longer than 22 days |
| PI   | 0.646 | 0.000 | 0.018 | 0.094 | 0.356 | 0.021 | 0.020 | 0.031 | 0.067 |
| CSI  | 0.001 | 4.729 | 0.116 | 0.007 | 0.011 | 0.094 | 0.003 | 0.140 | 0.035 |
| CTI  | 0.007 | 0.175 | 1.814 | 0.012 | 0.181 | 0.413 | 0.285 | 0.020 | 0.136 |
| FNI  | 0.366 | 0.001 | 0.076 | 1.386 | 0.387 | 0.144 | 0.049 | 0.008 | 0.129 |
| HY   | 0.734 | 0.063 | 0.055 | 0.079 | 1.150 | 0.187 | 0.274 | 0.073 | 0.183 |
| BTC  | 4.964 | 2.960 | 6.320 | 0.055 | 11.368 | 31.557 | 14.261 | 0.384 | 5.039 |
| GOLD | 3.913 | 2.763 | 5.464 | 0.000 | 9.182 | 22.439 | 37.615 | 0.433 | 5.524 |
| WTI  | 0.001 | 0.001 | 0.005 | 0.010 | 0.033 | 0.016 | 0.169 | 7.793 | 0.029 |
| TO   | 1.248 | 0.745 | 1.507 | 0.032 | 2.690 | 2.903 | 1.883 | 0.136 | 11.144 |

Fig. 2. Dynamic total spillover indices.
4.2. Dynamic spillover effect analysis

In fact, the above static analysis does not reveal the time-varying characteristics of the spillover effects during the sample period. Therefore, we analyze the dynamic spillover effects of the system to better understand the relationship between news and these three markets. To identify the dynamic spillover effects in the system, we apply the rolling window method, and the window size is set to 33 days, which is close to 20% of the sample size (Plakandaras et al., 2020). Then, we evaluate the dynamic total information spillover effects in the time and frequency domains. In addition, we further explore the dynamic net pairwise spillover effect between COVID-19-related news and the crude oil, gold, and Bitcoin markets.

4.2.1. Total information spillover effect
As shown in Fig. 2, we implement the DY (2012) method to calculate the dynamic total spillover index of the return and volatility in...

![Graphs showing spillover effects between various markets](image)

Fig. 3. Total spillover indices of three frequencies.

![Graphs showing net pairwise return spillover](image)

Fig. 4. Net pairwise return spillover.
Note: If the spillover index is negative (positive), then the corresponding epidemic news index is the net information transmitter (receiver) of the return spillover.
the time domain. The results reveal that the total return and volatility spillover index values of the system are higher than 40% and 30%, respectively, which suggests that all variables in the system influence one another to a great extent during the sample period.

On average, the total spillover effect may significantly increase when impactive events occur. More specifically, from March to April and July, both the return and volatility of the system attain relatively high total spillover index values (higher than 40% and even higher than 85%, respectively). The following is a brief introduction to these important events. The WHO assessed and determined that COVID-19 can be classified as a pandemic on March 11. On March 10, Brent crude oil and West Texas light crude oil prices both plummeted by 25%, the largest one-day drop since the 1991 Gulf War. The US stock market was fused four times (on March 9, 12, 16 and 19, 2020). On April 20, the price of West Texas light crude oil fell to $36.98 per barrel. At the beginning of July, the total spillover effects of the system exhibited a gradually increasing trend. This most likely occurred because of media hype when it was reported on June 28 that the total number of COVID-19 cases exceeded 10 million worldwide. Subsequently, the total spillover effect of the return and volatility attained a peak on August 10. The total number of confirmed COVID-19 cases worldwide has exceeded 20 million thus far, which has attracted much attention from the worldwide media.

Based on the BK (2018) method, we extend the research from the time domain to the high-frequency (1–5 days), medium-frequency (5–22 days), and low-frequency (over 22 days) domains. Fig. 3 shows the dynamic total spillover curves of the return and volatility at the different frequencies. First, it is evident that the total return and volatility spillover effects in the short term (1–5 days) are greater than those in the medium and long terms. Specifically, the short-term information spillover effects are mostly maintained above 30%. This suggests that the shocks that originate from the epidemic to these markets are more likely to spread to one another within a week. Second, we find that the spillover effects significantly increase at the different frequencies when impactive events occur. For instance, the medium- and long-term spillover effects from March to April are significantly greater than those during normal periods. This denotes that impactive international events may cause long-lasting influences (more than 1 week). Both investors and policymakers should carefully evaluate the impact of major events.

| PI-BTC net spillover index | PI-GOLD net spillover index | PI-WTI net spillover index |
|---------------------------|-----------------------------|---------------------------|
| CTI-BTC net spillover index | CTI-GOLD net spillover index | CTI-WTI net spillover index |
| CSI-BTC net spillover index | CSI-GOLD net spillover index | CSI-WTI net spillover index |
| HY-BTC net spillover index | HY-GOLD net spillover index | HY-WTI net spillover index |
| FNI-BTC net spillover index | FNI-GOLD net spillover index | FNI-WTI net spillover index |

Fig. 5. Net pairwise volatility spillover.

Note: If the spillover index is negative (positive), then the corresponding epidemic news index is the net information transmitter (receiver) of the volatility spillover.
4.2.2. Net pairwise information spillover effect

In this part, we analyze the time-varying net pairwise information spillover effects between news and these three markets in the time and frequency domains. Figs. 4 and 5 reveal the time-varying relation between news and the crude oil, gold, and Bitcoin markets. First, as shown in Fig. 4, the results indicate that panic emotion and media hype are the main information transmitters to the crude oil, gold, and Bitcoin markets during most of the sample period. Specifically, regarding the crude oil and Bitcoin markets, PI, CTI, and HY generally act as information transmitters during the sample period, while CSI largely functions as the receiver of information spillover from these markets. Similarly, in the gold market, PI, CTI, CSI, and HY mostly function as information transmitters. Thus, investors should give more attention to the assessment of the influences of panic emotion and media hype on these markets during the COVID-19 pandemic and flexibly adjust investment decisions to avoid risk and maximize profits. In general, the relationships between FNI and the returns of these three assets are more complex. None of the assets or FNI acts as a transmitter or receiver during the sample period. This indicates that no dominant relationship exists between FNI and these three assets during the COVID-19 pandemic. COVID-19-related fake news significantly affected investment decisions and thereafter impacted financial markets (Carvalho et al., 2011). Simultaneously, tremendous fluctuations in these markets could intensify panic emotion across society and increase fake news.

Second, according to Fig. 5, we obtain different findings in terms of the volatility of the system. Particularly, in the Bitcoin and gold markets, PI, CTI, CSI, and HY are the transmitters of information during most of the sample period, and FNI is the main receiver. Researchers have shared similar findings (López-Caharcos et al., 2020; Smales, 2015). Similarly, in the crude oil market, PI, CTI, and HY are the transmitters of information during most of the sampling period, and CSI receives much information from the market. There is no doubt that crude oil is a necessary resource that receives considerable attention from the media, but the crude oil market collapsed...
after the COVID-19 outbreak, which could significantly affect the media coverage sentiment. Smales (2015) reported that the shocks that originate from oil prices yield notable impacts on sentiment, which supports our opinion.

Third, we observe more obvious directional spillover effects between the five epidemic-related news indices and financial markets during the impactive event period, such as the US stock market triggering the circuit breaker mechanism. Fourth, the impact of media coverage may be greater on the WTI market than on the gold and Bitcoin markets. Specifically, it should be noted that in the gold and Bitcoin markets, the pairwise spillover effect ranges from 2 to 2, while the net pairwise spillover effect on crude oil returns varies between 3 and 5. This suggests that the information spillover effect between COVID-19-related media coverage and WTI returns is greater. There is a reasonable explanation for this finding. On the one hand, crude oil is involved in every aspect of human life and is more important than gold and Bitcoin. On the other hand, the impacts of COVID-19 are greater on the crude oil market than on the other markets, which could receive too much attention from the media. Therefore, the spillover effects between media coverage and the crude oil market are probably more significant than the spillover effects between media coverage and the other markets. Dutta et al. (2020) obtained a similar conclusion.

Next, we further study the net pairwise spillover in the frequency domain. Fig. 6 shows the frequency domain decomposition results of the net pairwise return spillover in the system. We observe that the net return spillover effects between most COVID-19 news-related indices except for CSI and the three assets mainly occur in the short term (less than 1 week), and the short-term return spillover exhibits a similar variation mode to that of the total return spillover. This demonstrates that the information spillover that originates from PI, CTI, FNI, and HY to these three markets mainly occurs in the short term. However, the spillover effects between CSI and the three markets are also evident in the long term, especially during the impactive event period. A reasonable explanation could be that CSI

Fig. 7. Frequency decomposition of net pairwise volatility spillover.

Note: If the spillover index is negative (positive), the corresponding COVID-19 news-related index is the net transmitter (receiver) of the volatility spillover information. The blue area represents high frequency (1–5 days), the red area represents medium frequency (5–22 days), and the green area represents low frequency (more than 22 days). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
exerts a longer lasting impact on financial markets than the other COVID-19 news-related indices. Gan et al. (2020) determined that the relationship between sentiment and return is relatively persistent, which is in line with our findings.

Fig. 7 shows the frequency domain decomposition results of the net pairwise volatility spillover. We obtain interesting findings. First, the volatility spillover effects between epidemic-related news and the crude oil market are more notable in the short term. This probably occurred because the crude oil market collapsed after the pandemic outbreak, and market participants gave more attention to COVID-19-related media coverage to avoid risk. Thus, the spillover effect between media coverage and the crude oil market is more notable in the short term. Second, the long-term volatility spillover effects from news to the gold and Bitcoin markets are highly significant except for FNI. However, a rational explanation for this exists. Fake news does not persist; therefore, its influence largely prevails in the short term (less than 1 week). Finally, it is important to note that PI, CSI, HY, and CTI functioned as both short-term information receivers and long-term information transmitters of the volatility of the gold and Bitcoin markets when impactive events occurred, such as the triggering of the circuit breaker mechanism in the US stock market.

4.3. Return and volatility of the connectedness network

In this section, we aim to research the spillover mechanism of each variable in the system. Through the above analyses, we determine that the shocks that originate from COVID-19 significantly impact the crude oil, gold, and Bitcoin markets during the epidemic, but these three markets exhibit different responses to the occurrence of COVID-19. Fig. 8 shows the return and volatility of the connectedness network.

On the one hand, regarding the volatility of the connectedness network, we observe an obvious risk contagion path. The risk spillover mechanism can be summarized as follows. In the first step, we find that the shocks that originate from the epidemic are mainly transmitted to the Bitcoin and gold markets through the media hype. In the second step, the Bitcoin market transmits most of the shocks to the gold market. Therefore, systemic risk accumulation may occur in the gold and Bitcoin markets during the sample period. To reduce systemic risk accumulation, policymakers should fully realize the influence of media hype during the epidemic and implement strict supervisory measures to reduce any unnecessary media hype, which may reduce the system risk and facilitate financial market stability. On the other hand, regarding the return of the connectedness network, we find that more complexity exists than volatility, without an obvious risk contagion path. Moreover, the strongest return spillover effect originates from the gold market to the Bitcoin market, which indicates that a strong connection remained between the gold and Bitcoin markets during the epidemic (Gkillas et al., 2020).

Fig. 9 shows the return and volatility of the connectedness network in the frequency domain. First, the short-term return connectedness network is roughly similar to the return connectedness network in the time domain, which implies that the return spillover is more significant in the short term than in the long term. Second, we find that there is a large difference between the short- and long-term effects based on an analysis of the volatility of the connectedness network in the different frequency domains. More specifically, the roles of the major variables in the system are transformed when the frequency domain changes. In comparison, we determine that the long-term volatility spillover network is very similar to the volatility network in the time domain, which shows that

![Fig. 8. Return and volatility connectedness network.](image-url)
the volatility spillover yields a significant long-term influence. Actually, volatility spillover measures market risk, and significant long-term volatility spillover effects suggest that more than 1 month is required in these markets to absorb the shocks that originate from media coverage. Similarly, in the short term, the Bitcoin and gold markets are transmitters, and the WTI market acts as a receiver. However, in the long term, the Bitcoin and gold markets become receivers, and the WTI market and most of the COVID-19 news-related indicators act as information transmitters. These results demonstrate that it is necessary to analyze the spillover mechanism at varying frequencies.

5. Robustness test

5.1. Connectedness under different rolling window sizes

To verify the robustness of the conclusions in this article, we analyze the sensitivity of the spillover effect to the selected rolling window size. Based on the DY (2012) method, we set three different rolling window sizes, i.e., 28, 33, and 38 days. The 33-day rolling window size is considered the benchmark in this article. With the use of these different window sizes, we can determine whether the window length affects the spillover effect in the system. The results are shown in Fig. 10. We observe that the trend of the total spillover curve remains highly similar across the different rolling window sizes, which indicates that the window size does not affect the findings in this article.
5.2. Different crude oil prices

Academics and practitioners have always chosen WTI and Brent crude oil as global oil benchmarks. Therefore, it is necessary to examine the sensitivity of the conclusions via the method of variable substitution. Accordingly, to study the return spillover, we apply the Brent crude oil spot price to replace the WTI spot price. Fig. 11 shows the results. We observe that after variable replacement, the two curves remain very similar. This result verifies that the crude oil spot price does not impact the findings in this study.

Fig. 10. Dynamic total spillover indices using different rolling window sizes.

Fig. 11. Dynamic total spillover indices using different variable.

Fig. 12. Dynamic total spillover indices using different measures of volatility.
5.3. Different measures of volatility

Many researchers have considered the GARCH(1,1) model and the square of the return to measure volatility in financial markets. Therefore, we further assess the robustness of the results by choosing different methods to measure market volatility. Fig. 12 shows the dynamic total volatility spillover effects with the different methods. The red curve is mostly in line with the blue curve during the sample period. This indicates that the findings remain consistent across the different measurement methods of market volatility.

6. Conclusions and policy implications

This paper examines the different impacts of media coverage on three important financial markets, namely, the crude oil, gold, and Bitcoin markets, during the COVID-19 pandemic. The present paper innovatively analyzes the time-frequency domain spillover effects based on the DY (2012) and BK (2018) methods. In addition, we evaluate the major risk contagion paths in the system from media coverage to these markets. Our main empirical findings are as follows.

First, the static spillover effect analysis results reveal that the overall return and volatility connectedness of the system are approximately 30% during the entire sample period. This suggests that relatively stronger interactions occur among the variables in the system. We also find that media coverage exerts a notable influence on fluctuations in the crude oil, gold, and Bitcoin returns during the sample period. Specifically, panic sentiment and media hype easily affect the Bitcoin market. In the gold market, media hype acts as the main transmitter, whereas panic sentiment contributes the most to the crude oil market. Additionally, in the frequency domain, it is evident that the interactions among the variables are significantly greater in the short term (1–5 days) than in the long term.

Second, based on an analysis of the dynamic overall spillover effect, we determine that a notable connection exists between the epidemic-related news indices and these three markets, especially during the period of major events, and the system total spillover effect significantly increases. For example, the circuit breaker mechanism was triggered in the US stock market and COVID-19 was designated by the WHO as a pandemic in March and April 2020. In addition, from the perspective of the frequency domain, we find that the levels of the total connectedness are higher in the short term than in the other terms. This is in line with our static conclusions.

Furthermore, by focusing on the study of the net pairwise spillover in the system, we determine that the spillover effects between the five COVID-19 news-related indices and the three assets exhibit slight differences, and the spillover effect is significantly greater in the crude oil market than in the gold and Bitcoin markets. In addition, it is consistently observed that panic emotion and media hype function as information transmitters to the crude oil, gold, and Bitcoin markets during most of the sample period. We find that the short-term spillover effects are much stronger than the long-term spillover effects. In addition, we obtain noteworthy observations in the frequency domain. On the one hand, we find that sentiment due to media coverage imposes long-term influences on the returns of these three markets. On the other hand, we determine that heterogeneity occurs in these three markets regarding volatility spillover. Specifically, there is no obvious long-term spillover effect between epidemic-related news and the crude oil market, while significant long-term spillover effects are observed that originate from most COVID-19 news-related indices to the gold and Bitcoin markets.

During the period of major events, the COVID-19 news-related indices mainly function as information transmitters, which is quite different from the short term.

Finally, in the network analysis, we focus on the risk contagion path in the system. An obvious risk contagion path is observed. Accordingly, we find that the shocks that originate from COVID-19 are mainly transmitted to the gold and Bitcoin markets through media hype, and the Bitcoin market transmits most of the information to the gold market. Therefore, the gold and Bitcoin markets may experience systemic risk accumulation during the COVID-19 pandemic. Investors should exercise caution in the gold market during the COVID-19 pandemic.

Based on the above findings, we propose the following policy implications. First, in this information age, policymakers should give more attention to COVID-19-related media hype monitoring and regulation, especially during this pandemic period. Epidemic-related media hype acts as a key risk transmitter to the gold and Bitcoin markets. Second, for most investors, our analysis can help them optimize their investment decisions. The impacts of COVID-19 on these markets are different. If investors know the intensities of the directional spillover effects from media coverage to these markets, then they can choose the best investment portfolio to reduce their risk and maximize their profits. More specifically, investors should carefully assess the degree of COVID-19-related panic emotion and media hype when deciding to invest in the gold and Bitcoin markets during the COVID-19 period. Similarly, the sentiment should be considered when investing in the crude oil market. Finally, policymakers should focus on the time-varying spillover effects among the variables. The spillover effects in the system are greatly associated with the stability of the economic environment and international conditions. Therefore, it is necessary for policymakers to monitor the international situation in realtime and establish a risk prevention and control mechanism.

Our research can potentially motivate further research. The ongoing COVID-19 pandemic can profoundly and persistently influence every country. A future path of research can consider whether COVID-19 has different impacts in diverse countries, such as the United States and China. Another future path of research can consider collecting high-frequency financial data to disassemble the realized volatility into diffusive and discontinuous volatilities to uncover the contribution of the jump and continuous elements of volatility in the network of spillovers in these three markets during COVID-19.

Author statement

H.Z.: Supervision; Visualization; Writing - original draft; Revising.
H.H.: Methodology; Writing - original draft; Writing - review & editing.
Y.G.: Conceptualization; Formal analysis; Roles/Writing – original draft.
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Acknowledgements

The authors gratefully acknowledge the financial support provided by the National Natural Science Foundation of China (Nos. 72074228, 71874210 and 71633006), Chinese National Funding of Social Sciences (Nos. 19BJY076, 18ZDA061) and the Innovation Driven Project of Central South University (No. 2020CX049).

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