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Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany

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ABSTRACT

We analyzed the return and volatility spillover between the COVID-19 pandemic in 2020, the crude oil market, and the stock market by employing two empirical methods for connectedness: the time-domain approach developed by Diebold and Yilmaz (2012) and the method based on frequency dynamics developed by Barunik and Krehlik (2018). We find that the return spillover mainly occurs in the short term; however, the volatility spillover mainly occurs in the long term. From the moving window analysis results, the impact of COVID-19 created an unprecedented level of risk, such as plummeting oil prices and triggering the US stock market circuit breaker four times, which caused investors to suffer heavy losses in a short period. Furthermore, the impact of COVID-19 on the volatility of the oil and stock markets exceeds that caused by the 2008 global financial crisis, and continues to have an effect. The impact of the COVID-19 pandemic on financial markets is uncertain in both the short and long terms. Our research provides some urgent and prominent insights to help investors and policymakers avoid the risks in the crude oil and stock markets because of the COVID-19 pandemic and reestablish economic development policy strategies.

1. Introduction

According to the World Health Organization, there have been 29,444,198 confirmed cases of COVID-19, including 931,321 deaths, as of 16 September, 2020[1]. In 1918—almost a century ago—the Spanish flu pandemic killed about 40 million people worldwide. As investigated by Barro et al. (2020), the number of deaths caused by the Spanish flu is expected to be higher than those caused by COVID-19, but the impact of the COVID-19 pandemic on the economy is expected to be far greater than that of the Spanish flu. As many countries adopted strict quarantine policies after the COVID-19 outbreak, economic activities have been greatly restricted. The long-term consequences of the COVID-19 pandemic may be high unemployment and business closures. Some industries, such as tourism and aviation, face various difficulties and challenges.

While the COVID-19 pandemic has triggered a sharp rise in uncertainty, the shock to the oil market and the stock market is unprecedented. In May 2020, coupled with the global spread of the COVID-19 pandemic, international oil prices saw a rare plunge, and the prices of WTI futures fell to the lowest price in four years. However, not only has the demand of crude oil been hit, but the supply of crude oil may also be affected. The Middle East is ushering in the "outbreak period" of the epidemic. If the Middle East's epidemic situation continues to worsen, the possibility of it affecting crude oil exports in the region cannot be ruled out. Thus, the supply in the oil market will rapidly expand. In March 2020, global investors experienced the most turbulent month in US stock market history: the circuit breakers were triggered four times within 10 days, and prices surged by 20% in 3 days. The last time the US stock market circuit breakers were triggered was once in 1997. After the US stock market crashed, European and Asian stock markets also plummeted. DAX, the main stock index in Germany, dropped by more than 10% on 18 March, 2020[2], and TOPIX, the main stock index in Japan, slumped by more than 20% from its high position on 3 December, 2019[3]. To restore economic development, the government issued many policies. For instance, on 15 March, 2020, the US government announced a $1 trillion economic stimulus plan, including a $500 billion check to the American people to alleviate the impact of the COVID-19 pandemic on the US economy. Although most stock markets have

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[1] The current global situation due to the COVID-19 pandemic is available at https://covid19.who.int/

[2] German stock index details are available at https://www.investing.com/indices/germany-30

[3] Japanese stock index details are available at https://www.investing.com/indices/topix

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recently begun to rebound, high levels of uncertainty remain as the COVID-19 epidemic continues.

As the COVID-19 pandemic is ongoing, usual social activities and economic trade activities are still restricted, which influences normal economic development. With nearly 3 billion people staying at home to prevent spread, the global oil demand dropped significantly. Furthermore, the large-scale outbreak of the COVID-19 pandemic in Europe and the US led to the collapse of the global stock market. Therefore, it is important to research the effect of the pandemic on the oil and stock markets in order to restore normal economic operations as soon as possible and reduce the economic losses incurred by the pandemic. Therefore, to explore the connectedness among the COVID-19 pandemic, the crude oil market, and the stock market, we choose the WTI crude oil prices, S&P 500 Stock index, TOPIX Stock index, and DAX Stock index across the United States, Japan, and Germany, as our research objects. The reasons for choosing these three countries were as follows. First, due to the impact of the COVID-19 pandemic, global stock markets have become extremely volatile. Therefore, we wanted to focus on investigating the impact of the pandemic on the stock markets of three different regions: the US, Europe, and Asia. Second, we chose the US, Germany, and Japan to represent the regions because these three countries are members of the G7 and thus representative of their regions. Third, we wanted to select only one country in each region to keep the data structure balanced. Understanding the return and volatility caused by event shocks is vital for investors to avoid risks when investing, especially during the COVID-19 pandemic, and for policymakers to formulate policies to ease the impact of the epidemic on the economy.

The main contributions of our paper are as follows. First, to our knowledge, our research is the first to evaluate return and volatility spillover effects among the crude oil market, the stock market, and the COVID-19 pandemic in 2020 across the US, Japan, and Germany by employing the time-domain approach developed by Diebold and Yilmaz (2012) and the method based on frequency dynamics developed by Barunik and Krehlik (2018) (hereafter, DK12 and BK18, respectively). Second, our results show that the return spillover mostly occurs in the short term, whereas the volatility spillover mostly occurs in the long term, consistent with the static analysis results. Third, from the moving window analysis, we find that the impact of COVID-19 on the volatility of the oil and stock markets exceeds that of the 2008 global financial crisis, and has a continuous effect.

The remainder of this paper is organized as follows. Section 2 presents the relevant literature. Section 3 describes the principles of the DY12 and BK18 methods. Section 4 illustrates the data variables and descriptive statistics of the preliminary analysis. In Section 5, we explain the results of the spillover effects and moving window analysis separately. In Section 6, we present the conclusions of our research.

2. Literature review

In 2020, the COVID-19 pandemic has been raging worldwide, and has had a traumatic impact on the global economy, trade, and other aspects. To minimize the impact of the COVID-19 pandemic on the global economy, economists began to analyze their relationship. However, as stock markets are the global economy's driving force, economists are focusing on research linking the stock markets and the COVID-19 pandemic. Baker et al. (2020a) investigated the reaction of the US stock to the COVID-19 pandemic. They found that the influence of the COVID-19 pandemic on the US stock market is unprecedented, and is comparable with the previous infectious disease outbreak, the Spanish Flu. They amassed evidence explaining that the government restrictions on commercial activity, international trade, and some other aspects resulted in the US stocks reacting to the COVID-19 as strongly as they did. Al-Awadhi et al. (2020) employed panel data analysis to evaluate the COVID-19 pandemic effect on the Chinese stock market. They used the companies' dataset included in the Hang Seng index and Shanghai Stock Exchange Composite index from 10 January, 2020 to 16 March, 2020, which is the period that includes when the COVID-19 pandemic was identified in China. They concluded that the daily increase in confirmed cases and the total number of deaths caused by COVID-19 have a significant negative impact on the stock returns of all companies. In addition, Onali (2020) applied a GARCH (1,1) model to calculate the volatility of the US stock market (Dow Jones and S&P500 indices), examining the impact of the COVID-19 pandemic and related deaths on the US stock market. They found that the reported number of deaths in Italy and France has a negative impact on US stock market returns, but has a positive effect on the VIX returns. Furthermore, Papadamous et al. (2020) applied the panel data analysis method to investigate the direct and indirect impact of the COVID-19 pandemic on implied stock market volatility across Europe, Asia, the US, and Australia. Their findings indicated that Google-based anxiety about the contagious effects of COVID-19 would lead to increased risk aversion in the stock market.

The COVID-19 pandemic in 2020 caused a sharp drop in oil prices, which led to a traumatic blow to the oil market. Sharif et al. (2020) investigated the connectedness between the COVID-19 pandemic, oil price volatility shock, the stock market, geopolitical risk, and economic policy uncertainty in the US in the time-domain approach and the method based on frequency dynamics by applying the coherence wavelet method and the wavelet-based Granger causality. They found that the unprecedented impact of the COVID-19 pandemic on these elements leads to the development of low-frequency bands, and the impact of the COVID-19 pandemic on the geopolitical risk is substantially greater than on the US economic uncertainty. Albulescu (2020) investigated the impact of the COVID-19 pandemic on crude oil prices while controlling for the influence of financial turmoil and the uncertainty of US economic policy. They found that the daily reported new infections of COVID-19 would have a marginally negative impact on crude oil prices. Furthermore, Narayan (2020) evaluated the relative significance of COVID-19 infections and oil price news in influencing oil prices. They concluded that when oil prices are used as the threshold, news about the COVID-19 pandemic and negative oil price will affect oil prices under high volatility. Gil-Alana and Monge (2020) investigated the effect of the COVID-19 on WTI crude oil prices by employing long memory techniques. They found that the oil price series is mean reverting, implying that the shock will be transitory, albeit with long-lasting effects.

In our study, we calculate the return and volatility spillover in the time-domain approach and the method based on frequency dynamics. Diebold and Yilmaz (2012) developed the time-domain approach based on the variance decomposition of the forecast error to evaluate the share of forecast error variation in terms of size and direction. Barunik and Krehlik (2018) employed the Fourier transformation on Diebold and Yilmaz's (2012) results, extending it to the method based on frequency dynamics. Zhang et al. (2020a) investigated the connectedness of natural gas, crude oil, and electricity utility stocks of North America and Europe, two contrasting regions, by applying the new methods DY12 and BK18. Zhang et al. (2020b) also employed these two methods to evaluate the connectedness between oil, natural gas, and US macroeconomic indicators. In addition, Toyoshima and Hamori (2018) used the approaches of Diebold and Yilmaz (2012, 2014, 2015) and Barunik and Krehlik (2018) to evaluate the link between the return and volatility of global crude oil markets, and found that WTI crude oil contributes least to the total return and volatility spillover.

To obtain the dynamic results of return and volatility, we also employed the moving window method in terms of the time domain approach and the method based on frequency dynamics. Liu and Hamori (2020) used the rolling analysis method to check the dynamic results of return and volatility spillover among renewable energy stocks between the US and Europe. Zhang and Wang (2014) also applied rolling samples to better understand and capture the return and volatility spillover effects in the dynamic relationship between the Chinese and global oil markets.

3. Empirical techniques

3.1. DY12 model

Our study applies the methodology developed by Diebold and Yilmaz (2012) to measure spillovers in the generalized vector autoregression (VAR) framework. This approach designs the connectedness concept by combining the Generalized Forecast Error Variance Decomposition (GFEVD) with the VAR model. The *K*-variable VAR (*p*) model can be conceived as (1) below:

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{\phi}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{y}_t$ defines the $K\times1$ vector of the employed variables at time *t*, and ϕ denotes the $K\times K$ coefficient matrices. The error vector ε_t is independent and identically distributed, and white noise (0, $\sum$) with covariance matrix $\sum$ is non-diagonal.

The VAR process in our study can also be transformed by the vector moving average (MA(∞)), which is shown in (2). Assuming that the roots of $|\phi(z)|$ are outside the circle of a unit:

$$\boldsymbol{y}_t = \boldsymbol{\Psi}(L)\boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{\Psi}(L)$ is a $(K\times K)$ matrix of infinite lag polynomials, which can be obtained from $\boldsymbol{\phi}(L) = [\boldsymbol{\Psi}(L)]^{-1}$. However, since the order of variables in the VAR model may affect the impulse response or variance decomposition results, to ensure the independence of variance decomposition on ordering, Diebold and Yilmaz (2012) employed the generalized VAR framework conceived by Koop et al. (1996) and Pesaran and Shin (1998). Based on this framework, the *H*-step-ahead GFEVD can be expressed in the form of (3):

$$(\boldsymbol{\theta}_H) = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\boldsymbol{\Psi}_h\boldsymbol{\Sigma})_{jk}\right)^2}{\sum_{h=0}^{H}(\boldsymbol{\Psi}_h\boldsymbol{\Sigma}\boldsymbol{\Psi}'_h)_{jj}} \tag{3}$$

where $\boldsymbol{\Psi}_h$ is a $K\times K$ coefficient matrix of *the polynomial at lag h*, and $\sigma_{kk} = (\boldsymbol{\Sigma})_{kk}$. $(\boldsymbol{\theta}_H)_{jk}$ defines the contribution of the model's *k*th variable to the variance of forecast error of the factor *j* at horizon *h*. To sum the elements in each GFEVD row to a total of one, each entry is standardized by the sum of the rows in the form (4):

$$\widetilde{\boldsymbol{\theta}}_{jk}^{H} = \frac{\boldsymbol{\theta}_{jk}^{H}}{\sum_{k=1}^{N}\boldsymbol{\theta}_{jk}^{H}} \tag{4}$$

$\widetilde{\boldsymbol{\theta}}_{jk}^{H}$ is denoted as pairwise spillover from *k* to *j* at horizon H, which is used to measure the spillover effect from market *k* to *j*. Furthermore, the total spillover is denoted as the share of variance in the forecasts, which is contributed by errors other than own errors. We can aggregate the pairwise spillover into the total spillover in the form of (5):

$$S^H = 100\times\frac{\sum_{j\neq k}^{N}\widetilde{\boldsymbol{\theta}}_{jk}^{H}}{\Sigma\widetilde{\boldsymbol{\theta}}^{H}} = 100\times\left(1-\frac{Tr\{\widetilde{\boldsymbol{\theta}}^{H}\}}{\Sigma\widetilde{\boldsymbol{\theta}}^{H}}\right) = 100\times\left(1-\frac{Tr\{\widetilde{\boldsymbol{\theta}}^{H}\}}{N}\right) \tag{5}$$

where *Tr{.}* is the trace operator. The total spillover in all markets demonstrates the overall spillover. In addition, the DY12 model has two metrics that define the relative importance of each variable in the system:

Directional Spillover (From): $S_{k\leftarrow\cdot}^{H} = 100\times\frac{\sum_{j=1}^{N}\widetilde{\boldsymbol{\theta}}_{kj}^{H}}{N}$ $j\neq i$. The directional spillovers (from) measure the spillover that market k receives from all other markets; and

Directional Spillover (To): $S_{\cdot\leftarrow k}^{H} = 100\times\frac{\sum_{j=1}^{N}\widetilde{\boldsymbol{\theta}}_{jk}^{H}}{N}$ $j\neq i$. The directional spillovers (to) measure the spillover that market k transmits to all other markets.

3.2. BK18 model

The technique developed by Barunik and Krehlik (2018) explains the method based on frequency dynamics (the short-term, medium-term, and long-term). BK18 employs the Fourier transform to transform the DY12 model results into the method based on frequency dynamics. The function of the frequency response is obtained as a Fourier transformation of the coefficients $\boldsymbol{\Psi}_h : \boldsymbol{\Psi}(e^{-i\omega}) = \sum_h e^{-i\omega h}\boldsymbol{\Psi}_h$, where $i = \sqrt{-1}$. The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ is denoted in the form of (6):

$$(\boldsymbol{f}(\omega))_{jk} = \frac{\sigma_{kk}^{-1}\left|(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma})_{jk}\right|^2}{(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+iw}))_{jj}} \tag{6}$$

where $\boldsymbol{\Psi}(e^{-i\omega}) = \sum_h e^{-i\omega h}\boldsymbol{\Psi}_h$ is the Fourier transform of the impulse response $\boldsymbol{\Psi}_h$. It should be emphasized that $(\boldsymbol{f}(\omega))_{jk}$ is the component of the *j*th variable's spectrum at the ω frequency due to shocks in the *k*th variable. As the denominator holds the spectrum of the *j*th variable at a given frequency ω, within the frequency causation, we can explain the form of (6) for the number. We can weight $(\boldsymbol{f}(\omega))_{jk}$ by the frequency share of the jth variable variance to obtain the generalized decomposition of variance decomposition in the frequency dynamics. This weighting function can be denoted in the form of (7):

$$\boldsymbol{\Gamma}_j(\omega) = \frac{(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+i\omega}))_{jj}d\lambda} \tag{7}$$

It exhibits the power of the *j*th variable at a given frequency, which amounts to a constant value of 2π through frequencies. When the impulse Fourier transform is a complex number, the weighted complex numbers' square coefficients are the generalized factor spectrum, and hence the real number. Formally, we build the frequency band d=(a, b): a, b∈(-π, π), a<b.

The GFEVD under the frequency band d is:

$$\boldsymbol{\theta}_{jk}(d) = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)(\boldsymbol{f}(\omega))_{jk}d\omega \tag{8}$$

However, (8) still needs to be normalized. The scaled GFEVD on the frequency band d=(a, b): a, b∈(-π, π), a<b can be conceived as (9):

$$\widetilde{\boldsymbol{\theta}}_{jk}(d) = \frac{\boldsymbol{\theta}_{jk}(d)}{\Sigma_k\boldsymbol{\theta}_{jk}(\infty)} \tag{9}$$

where $\widetilde{\boldsymbol{\theta}}_{jk}(d)$ is denoted as the pairwise spillover at a given frequency band d. Furthermore, the total spillover (frequency connectedness) can be defined on the frequency band d, and is defined as (10):

$$S^F(d) = 100\times\left(\frac{\Sigma\widetilde{\boldsymbol{\theta}}(d)}{\Sigma\widetilde{\boldsymbol{\theta}}(\infty)} - \frac{Tr\{\widetilde{\boldsymbol{\theta}}(d)\}}{\Sigma\widetilde{\boldsymbol{\theta}}(\infty)}\right) \tag{10}$$

where *Tr{.}* is the trace operator, and $\Sigma\widetilde{\boldsymbol{\theta}}(d)$ is the summation of all factors of the $\widetilde{\boldsymbol{\theta}}(d)$ matrix. The total spillover frequency decomposes the total spillover into different sections of the frequency, and can be applied to the total spillover S established by the DY12 model.

Similarly, we can define the two directional spillovers in the frequency dynamics as follows:

Frequency Directional Spillovers (From): $S_{k\leftarrow\cdot}^{F}(d) = 100\times\frac{\sum_{j=1}^{N}\widetilde{\boldsymbol{\theta}}_{kj}(d)}{N}$ $j\neq i$. The frequency directional spillovers (from) measure the spillover obtained by market k from all other markets at frequency band d; and

Frequency Directional Spillovers (To): $S^{F}_{\cdot \leftarrow k}(d) = 100 \times \frac{\sum_{j=1}^{N} \widetilde{\theta}_{jk}(d)}{N}$, $j \neq i$. The frequency directional spillovers (to) measure the spillover transmitted by market k to all other markets at frequency band d.

4. Data and variables

We use daily data of the Infectious Disease Equity Market Volatility Tracker (IDEMVT), Crude Oil WTI Futures (WTI), S&P 500 Index (SP500), TOPIX Index (TOPIX) and DAX index (DAX) from 4 January, 2006 to 31 August, 2020 for America, Japan, and Germany, excluding uncommon business days. We employ the data set from 4 January, 2006 to compare the impact of the 2008 global financial crisis with that of the 2020 COVID-19 on the US stock index, the Japanese stock market, and the German stock market. To eliminate the influence of the exchange rate on the research results, we unified all variables' currency units into US dollars. More precisely, we use the data of five variables, as shown in Table 1.

We use the IDEMVT data from the Economic Policy Uncertainty Index, following Baker et al. (2020b). IDEMVT was constructed by the following procedure. First, the following terms are specified in four sets:

- E: {economic, economy, financial}
- M: {"stock market", equity, equities, "Standard and Poors"}
- V: {volatility, volatile, uncertain, uncertainty, risk, risky}
- ID: {epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1}.

Second, the daily counts are collected from newspaper articles that include at least one word from each E, M, V, and ID set in each of the approximately 3,000 US newspapers. Third, the raw EMV-ID counts are scaled by the count of all products on the same day. Finally, the resulting series representing our strategy is rescaled to a categorical EMV series scale. Assessing the COVID-19 pandemic's economic effect is critical for policymakers in the current situation, but daunting because the crisis has unfolded at such an extreme pace. For the crude oil market, we employ the daily futures price of WTI, which is a benchmark price in the international oil market and used as a reference price reflecting the current world oil market. For the stock market, we employ the S&P 500 Index in the US, the TOPIX Index in Japan, and the DAX index in Germany. The S&P 500 index tracks the stock performance of 500 major companies listed on US stock exchanges, and is considered the best representation of the US stock market. Meanwhile, the TOPIX index is a significant stock market index for the Japanese Tokyo Stock Exchange, and tracks all domestic companies in the first part of the exchange period. The DAX Index consists of 30 large German companies listed on the Frankfurt Stock Exchange and the blue-chip stock market index that represent the vitality of Germany's economy.

Fig. 1 shows the raw data series plot of our data. Note that the IDEMVT index indicates the volatility indicator, while the other four variables indicate price indices. As shown in Fig. 1, we can see some similar patterns among the WTI and four stock indexes, such as all of them decreasing during the global financial crisis, 2007–2009, and the COVID-19 pandemic, 2020. Furthermore, we can see that IDEMVT also fluctuates around 2008–2009 and 2020, showing a dramatic rise due to its volatility.

Table 1
Variables in the model.

Variable	Data	Source
IDEMVT	Infectious Disease Equity Market Volatility Tracker	Economic Policy Uncertainty
WTI	Crude Oil WTI Futures (USD/Barrel)	Investing.com
SP500	S&P 500 Index	Investing.com
TOPIX	TOPIX Index	Investing.com
DAX	DAX Index	Bloomberg

Our study calculates the daily return WTI, SP500, TOPIX, and DAX by employing logarithmic differences, except for IDEMVT, a volatility tracker, as exhibited in Fig. 2. After we obtain the return data series, we employ the autoregressive moving average (ARMA)-GARCH model to compute the volatilities of WTI, SP500, TOPIX, and DAX, as shown in Fig. 3.[4] From Fig. 3, we can observe that compared with three stock indices, IDEMVT and WTI exhibit a relatively stable trend. There are two clear fluctuations around 2009 and 2020, which have been influenced by the 2008 global financial crisis and the 2020 COVID-19 epidemic. Furthermore, we can see that the volatility plots of the three stock indices show a similar trend, and the fluctuation ranges from 0.01 to 0.06. The three stock indices also wildly fluctuate around 2009 and 2020.

Table 2 presents the descriptive statistics for the daily return series of WTI and the set of three stock indexes. Regarding the mean of the return, only WTI has a negative value. Furthermore, WTI has the largest maximum daily return value and smallest minimum daily return value. Next, we can see that WTI is the most volatile according to the standard deviation value. Moreover, according to the skewness value, four variables' skewness values indicate that all of them are left-skewed. Since the four variables' kurtosis value is positive, it demonstrates that leptokurtic is the return of four properties, meaning that the four variables will see more peaked and fat tails.

Table 3 shows the descriptive statistics for the daily volatility series of IDEMVT, WTI, and the three stock indexes. We can see that IDEMVT has the largest maximum daily volatility value and the smallest daily volatility value, and it is the most volatile among the five variables. It is the same as the results of the return situation that they are also left-skewed and leptokurtic. We employed the Jarque–Bera test by Jarque and Bera (1987) for skewness and kurtosis to check whether the returns and volatility of all variables are normally distributed. The Jarque–Bera test statistics reject normality at the 1% level for each variable. Furthermore, to ensure that these variables' returns and volatility are stationary, we adopt Augmented Dickey-Fuller (ADF) developed by Said and Dickey (1984). The results of the ADF tests show that the null hypothesis of each variable with a unit is rejected, meaning that each variable does not have unit root.

5. Empirical results

5.1. Spillover results

We apply the VAR model to calculate the return and volatility spillover in the time domain. Following the DY12 model, we apply the generalized variance decomposition to set up the spillover table of return and volatility. We use the generalized variance decomposition, which can calculate the direction and strength in the time domain across selected markets.

In addition, in the method based on frequency dynamics (BK18), which applies the Fourier transform to decompose the spillover table split into three different frequency bands. More precisely, the three frequency bands are defined by Toyoshima and Hamori (2018) as the following: "Freq S," the short term, roughly corresponds to a period of 1 to 5 days (1 week without a weekend), "Freq M," the medium term, corresponds to a period of 6 to 21 days (one month without weekends), "Freq L," the long term, corresponds to a period of 22 days to infinity.

In our study, we choose the VAR model's lag length based on the Schwarz criterion (SC) developed by Schwarz (1978). In addition, according to Barunik and Krehlik (2018), we set the 100-day forecasting horizon (H) for variance decomposition that the model cannot work if (H)<100.

Tables 4 and 5 show the results of the return and volatility spillover

[4] Appendix A reports the empirical results of ARMA-GARCH model.

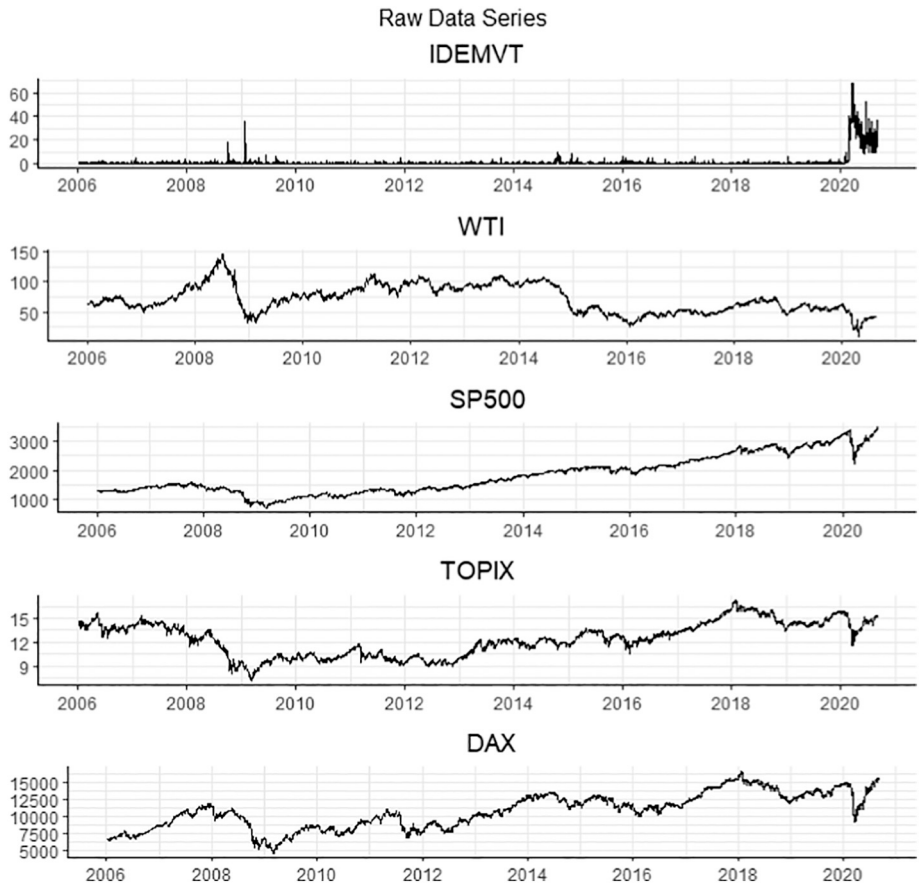

Fig. 1. Time-variations of raw data series.
Notes: IDEMVT refers to Infectious Disease Equity Market Volatility Tracker; WTI refers to Crude Oil WTI Futures; SP500 refers to the S&P 500 Index; TOPIX refers to TOPIX Index; DAX refers to DAX Index. IDEMVT is volatility data; SP500, TOPIX, and DAX are price data.

tables separately. The DY12 model results, followed by the short-term, medium-term, and long-term results from the BK18 model, are at the top of each table. In addition, the value in the *i*-th row and the *j*-th column indicates the spillover effect from the *j*-th market to the *i*-th market, and vice versa. In the last row, "TO" means "To spillover" which indicates the spillover effect to all other variables, while "FROM" means "From spillover" which suggests the spillover effect from all other variables. Finally, the value displays the summation value of both "To spillover" or "From spillover", labeled "Total spillover" in the right-hand corner of the table.

From the return spillover table and volatility spillover table, as shown in Tables 4 and 5, we can see that the total connectedness of return is 27.509%, which is smaller than the total connectedness volatility of 39.75%. This indicates that the returns of IDEMVT, WTI, and the three other stock indexes are not more closely connected than the volatilities of these variables.

From Table 4, which shows the results based on the method based on frequency dynamics, we can see that the total return spillover in the short-term frequency (Freq S, 1 to 5 days; 19.683%) is the highest, followed by the medium-term (Freq M, 6 to 21 days; 4.279%) and the long-term (Freq L, 22 days to infinity; 3.547%). This implies that return shocks from one market transmitted to other markets have short-lasting effects. Then, we can see the return spillover results under the time-domain approach of the DY12 model. First, IDEMVT delivers the most return spillover to WTI (0.608%), followed by TOPIX (0.304%), DAX (0.247%), and SP500 (0.146%). This implies that, among the crude oil markets and the other three stock markets, IDEMVT has a great impact on the return of WTI. Second, we can see that WTI receives the most return spillover from SP500 (6.089%); SP500 receives the most return spillover from DAX (30.795%); TOPIX receives the most return spillover from SP500 (21.428%); and DAX receives the most return spillover from SP500 (31.036%).

From Table 5, in contrast to the total return spillover results, we can see that the total volatility spillover in the long-term frequency (Freq L, 1 to 5 days; 38.404%) is the highest, followed by the medium-term (Freq M, 6 to 21 days; 1.049%) and the short-term frequency (Freq S, 1 to 5 days; 0.297%), which indicates that the volatility spillover effect from any market transmitted to other markets has long-lasting effects. More precisely, under the pure time-domain approach (DY12), we can see that IDEMVT contributes most of the volatility spillover to WTI (32.233%), followed by SP500 (6.525%), DAX (3.136%), and TOPIX (1.726%). Furthermore, we can observe that WTI receives the most volatility spillover from IDEMVT (32.233%), consistent with the volatility spillover transmitted from the most, IDEMVT. This result indicates that the volatility spillover effect is more closely linked than the return spillover effect between WTI and IDEMVT. Meanwhile, SP500 receives the most volatility spillover from DAX (24.556%); TOPIX receives the most volatility effect from SP500 (38.195%); and DAX also receives the most volatility effect from SP500 (46.901%).

Barunik and Krehlik (2018) explained that periods in which high-frequency connectivity is generated are periods in which financial markets seem to process information quickly and calmly, and a shock in the system to one asset would have a mostly short-term effect. This implies that shocks are persistent for longer periods when the relation is produced at lower frequencies. Because volatility is generated after a return, volatility needs more time to transmit from one market to another market. Liu and Hamori (2020) investigated the return and volatility spillover effect transmitted from fossil energies, in terms of

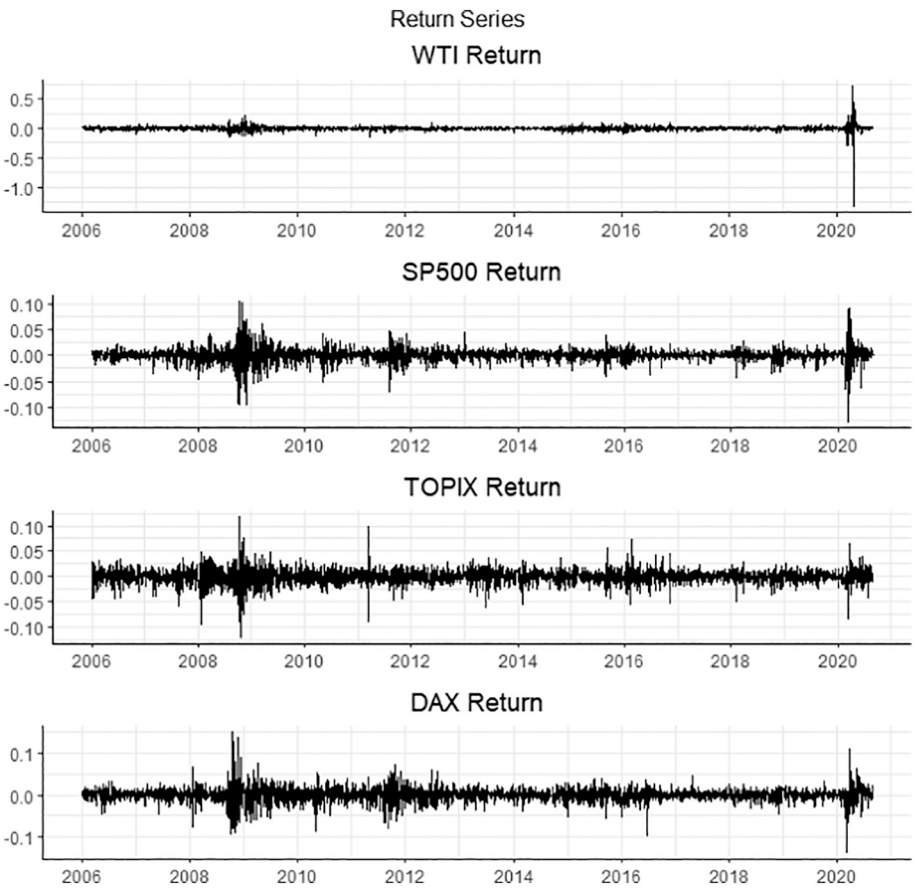

Fig. 2. Time-variations of return series.
Notes: WTI Return refers to the return of crude oil WTI futures; SP500 Return refers to the return of the S&P 500 Index; TOPIX Return refers to the return of TOPIX Index; and DAX Return refers to the return of the DAX Index. IDEMVT is a volatility data, so we do not need to calculate the return of the IDEMVT.

several important financial variables, to renewable stock markets, and they also found that most of the return spillover effect concentrates at a high frequency (in the short term), but most volatility spillovers are developed at a low frequency (in the long term).

5.2. *Dynamic (moving-window) analysis*

Although we have obtained the full-sample return and volatility spillover tables, we cannot observe the dynamic change of this spillover and the VAR model in the whole sample, perhaps resulting in smooth results when there is time variation in the relationship between the variables (Lovcha and Perez-Laborda, 2020). To observe and understand spillover dynamics, we employ the moving-window method to analyze the time-varying spillover under the DY12 and BK18 models. Regarding the window size, Jorion (1995) set 20 days as the length of the windows. Toyoshima and Hamori (2018) employed 100-day rolling samples. We choose 500 days as the window size in our study to keep the rolling sample size large enough to ensure the stationarity of the series in each VAR estimation.[5]

The dynamics of the total spillover and frequency decomposition for the return sequence are shown in Fig. 4. In general, we can see that the total return spillover occurs in the short-term, followed by the medium-term and long-term frequency dynamics, consistent with Table 4. More precisely, we can observe that from late-2008, the total connectedness of returns increased due to the 2008 global financial crisis. After 2008, the total return spillover exhibits a relatively flat situation, fluctuating between 10% and 40%. However, due to the impact of the COVID-19 pandemic in 2020, the total return spillover suddenly increases to 80%. Hence, compared with the impact of the 2008 global financial crisis, the impact of the COVID-19 pandemic in 2020 on the returns of the oil and stock markets is unprecedented.

Fig. 5 shows the total spillover and frequency decomposition for the volatility series. Compared with Fig. 4, it is evident that the total volatility spillover fluctuates sharply, and has several surge points. This implies that volatility is more sensitive to extreme events. Overall, we can find that the total volatility spillover occurs in the long-term, followed by the medium-term and the short term, contrary to the return spillover results in the frequency dynamics. Furthermore, we can identify several sudden fluctuations, such as the sharp increase in late-2008, late-2014, and 2020, which are influenced by the 2008 global financial crisis, 2014 international crude oil crisis, and the COVID-19 pandemic, respectively. More precisely, we can observe that the impact of the COVID-19 in 2020 on the volatility of the oil and stock markets is almost 80%, which is almost consistent with the impact of the 2008 global financial crisis.

In addition, we also calculate the spillover effects between the IDEMVT and the three other stock indices through pairwise directional spillovers. Figs. 6 and 7 show the pairwise directional return and volatility spillover plots, respectively. In Fig. 6, we can observe that the connectedness between IDEMVT and the return of three stock indices is most substantial in 2020 and is influenced by the COVID-19 pandemic. Furthermore, we can see that, except for the WTI-Volatility from IDEMVT, the spillover from IDEMVT to the volatility of three stock

[5] We also set window size equal to 370-day (almost 1 and a half years) to check the robustness of our empirical results in APPENDIX B. We find that we have almost the same trend.

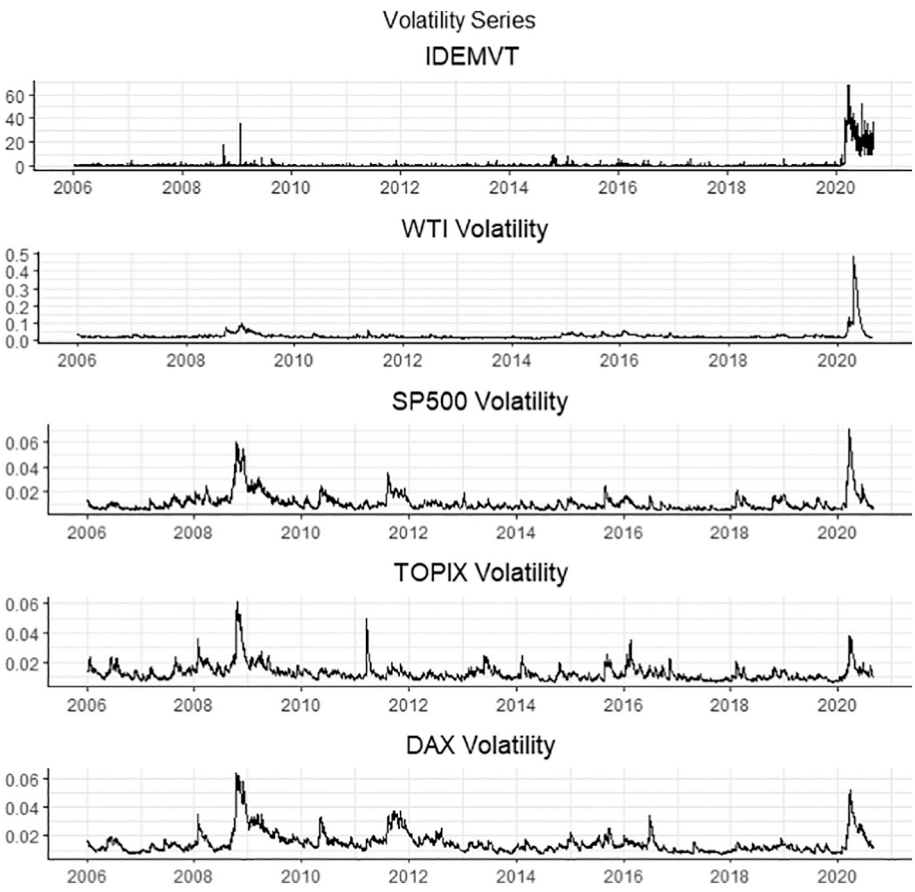

Fig. 3. Time-variations of volatility series.
Notes: IDEMVT refers to Infectious Disease Equity Market Volatility Tracker; WTI Volatility refers to the volatility of crude oil WTI futures; SP500 Volatility refers to the volatility of the S&P 500 Index; TOPIX Volatility refers to the volatility of the TOPIX Index; and DAX Volatility refers to the volatility of the DAX Index. IDEMVT is the raw data; WTI, SP500, TOPIX, and DAX are volatility by the ARMA-GARCH model.

Table 2
Descriptive statistics of the return series

Descriptive Statistics for Return				
	WTI	SP500	TOPIX	DAX
Mean	−0.00011	0.00030	0.00002	0.00025
Median	0.00068	0.00076	0.00042	0.00068
Maximum	0.72254	0.10424	0.11770	0.15016
Minimum	−1.32422	−0.12765	−0.11930	−0.13803
Std. Deviation	0.03875	0.01323	0.01436	0.01661
Skewness	−9.37973	−0.66006	−0.33089	−0.12949
Kurtosis	441.52510	13.01252	6.88412	9.61835
Jarque-Bera	27837868	24384	6817.6	13196
Probability	0.000	0.000	0.000	0.000
ADF	−51.31900***	−43.82510***	−46.96290***	−41.75950***

Note. ADF: Augmented Dickey and Fuller Unit Root Test (1979); *** denote rejection of the null hypothesis at 1% significance levels, respectively. IDEMVT is a volatility data, so we do not need to calculate the return of the IDEMVT. Jarque-Bera indicates the p-value of Jarque- Bera test statistic.

indices has three obvious surge points around late-2008, late-2014, and 2020, which may be influenced by the 2008 global financial crisis, the 2015 Asia Middle East respiratory syndrome, and the COVID-19 pandemic, respectively. Thus, we can see that around late-2014, the spillover from IDEMVT to TOPIX is strongest (almost 70%), and the crude oil market was virtually unaffected by IDEMVT.

6. Concluding remarks

Our study analyzes the connectedness among the crude oil market, the stock market, and the COVID-19 pandemic. Specifically, according to our investigation, this study is the first to examine the return and volatility spillover among the crude oil market, the stock market, and the COVID-19 pandemic in 2020 across the United States, Japan, and Germany by employing the time-domain approach (DY12) and the method based on frequency dynamics (BK18). The novel coronavirus has claimed thousands of lives and poses significant challenges for nations around the world. The financial market has undergone unprecedented drastic changes. Therefore, it is crucial to investigate the impact of the COVID-19 pandemic on the financial market.

In the time domain approach, the total volatility spillover (39.75%) is stronger than the total return spillover (27.509%), indicating that the returns of IDEMVT, WTI, and the three other stock indexes are not more closely connected with each other than the volatilities of these variables. In the situation of return spillover, IDEMVT delivers the most return spillover to WTI (0.608%), followed by TOPIX (0.304%), DAX (0.247%), and SP500 (0.146%). This indicates that, compared with the return of stock indexes, IDEMVT has a greater impact on crude oil return. In the situation of volatility spillover, IDEMVT contributes most volatility spillover to WTI (32.233%), followed by SP500 (6.525%), DAX (3.136%), and TOPIX (1.726%).

In the method based on frequency dynamics, our results show that the return spillover mostly occurs in the short term, whereas the volatility spillover mostly occurs in the long term, and is consistent with the static analysis results. This indicates that volatility spillover has a long-lasting effect.

From the moving window analysis, we observe that the impact of COVID-19 on the volatility of the oil and stock markets exceeds that of the 2008 global financial crisis, and is ongoing. During the COVID-19 pandemic, government-authorized nonprofit organizations took many actions: restricting international travel, closing schools, introducing lockdowns, banning public gatherings, closing unnecessary businesses, and making wearing masks compulsory. These measures have had a

Table 3
Descriptive statistics of the volatility series

Descriptive Statistics for Volatility					
	IDEMVT	WTI	SP500	TOPIX	DAX
Mean	1.34700	0.02586	0.01089	0.01312	0.01491
Median	0.00000	0.02070	0.01089	0.01171	0.01284
Maximum	68.37000	0.48273	0.07082	0.06135	0.06402
Minimum	0.00000	0.01160	0.00472	0.00653	0.00677
Std.Deviation	5.50821	0.02637	0.00719	0.00563	0.00749
Skewness	6.74627	9.97700	3.48395	3.18132	2.61019
Kurtosis	52.18016	128.14050	16.21578	15.59847	9.08017
Jarque-Bera	414058	2397288	44402	40453	15637
Probability	0.000	0.000	0.000	0.000	0.000
ADF	−8.36880***	−9.20790***	−5.41820***	−7.33490***	−4.99640***

Note. ADF: Augmented Dickey and Fuller Unit Root Test (1979); *** denote rejection of the null hypothesis at 1% significance levels, respectively. Jarque-Bera indicates the p-value of Jarque- Bera test statistic.

Table 4
Return spillover

Return Spillover Results (DY12)						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	89.126	0.709	6.183	0.716	3.265	2.175
WTI	**0.608**	87.239	**6.089**	0.209	5.856	2.552
SP500	0.146	4.604	63.44	1.015	**30.795**	7.312
TOPIX	0.304	1.485	**21.428**	61.602	15.181	7.68
DAX	0.247	4.453	**31.036**	3.215	61.049	7.79
TO	0.261	2.25	12.947	1.031	11.019	**27.509**
Return Spillover Results (BK18)						
Frequency S 1–5 Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	6.09	0.116	0.062	0.012	0.045	0.047
WTI	0.477	79.244	5.013	0.168	4.792	2.09
SP500	0.12	3.915	54.565	0.915	25.409	6.072
TOPIX	0.3	0.924	16.16	55.299	9.75	5.427
DAX	0.235	3.373	23.841	2.787	49.478	6.047
TO	0.226	1.666	9.015	0.776	7.999	**19.683**
Frequency M 6–21 Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	3.391	0.017	0.213	0.027	0.125	0.077
WTI	0.043	5.873	0.753	0.029	0.746	0.314
SP500	0.019	0.507	6.665	0.084	3.977	0.917
TOPIX	0.001	0.412	3.939	4.814	3.972	1.665
DAX	0.01	0.791	5.387	0.341	8.576	1.306
TO	0.015	0.345	2.059	0.096	1.764	**4.279**
Frequency L 22–Infinite Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	79.646	0.576	5.908	0.677	3.094	2.051
WTI	0.087	2.121	0.323	0.011	0.318	0.148
SP500	0.006	0.183	2.21	0.017	1.409	0.323
TOPIX	0.003	0.15	1.328	1.489	1.459	0.588
DAX	0.003	0.289	1.808	0.088	2.994	0.437
TO	0.02	0.239	1.873	0.159	1.256	**3.547**

Notes: WTI refers to the return of crude oil WTI futures; SP500 refers to the return of the S&P 500 Index; TOPIX refers to the return of TOPIX Index; and DAX refers to the return of the DAX Index.

Table 5
Volatility spillover

Volatility Spillover Results (DY12)						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	93.041	0.839	4.827	0.25	1.044	1.392
WTI	**32.233**	49.943	12.818	0.039	4.967	10.011
SP500	6.525	0.542	67.129	1.249	**24.556**	6.574
TOPIX	1.726	0.221	**38.195**	44.02	15.838	11.196
DAX	3.136	0.388	**46.901**	2.459	47.116	10.577
TO	8.724	0.398	20.548	0.799	9.281	**39.75**
Volatility Spillover Results (BK18)						
Frequency S 1–5 Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	6.248	0.283	0.058	0.024	0.035	0.08
WTI	0.061	2.559	0.006	0.004	0.01	0.016
SP500	0.014	0.023	1.177	0.021	0.354	0.082
TOPIX	0.012	0.01	0.178	2.12	0.183	0.077
DAX	0.002	0.015	0.149	0.044	0.887	0.042
TO	0.018	0.066	0.078	0.019	0.117	**0.297**
Frequency M 6–21 Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	3.648	0.153	0.311	0.016	0.054	0.107
WTI	0.225	9.216	0.043	0.011	0.022	0.06
SP500	0.035	0.089	3.377	0.143	1.483	0.35
TOPIX	0.012	0.008	0.616	8.316	1.116	0.35
DAX	0.004	0.057	0.55	0.297	2.511	0.182
TO	0.055	0.061	0.304	0.093	0.535	**1.049**
Frequency L 22–Infinite Days						
	IDEMVT	WTI	SP500	TOPIX	DAX	FROM
IDEMVT	83.145	0.403	4.458	0.21	0.954	1.205
WTI	31.948	38.169	12.769	0.023	4.934	9.935
SP500	6.476	0.43	62.575	1.086	22.719	6.142
TOPIX	1.702	0.204	37.401	33.584	14.539	10.769
DAX	3.13	0.316	46.201	2.118	43.718	10.353
TO	8.651	0.271	20.166	0.687	8.629	**38.404**

Notes: IDEMVT refers to Infectious Disease Equity Market Volatility Tracker; WTI refers to the volatility of Crude Oil WTI Futures; SP500 refers to the volatility of S&P 500 Index; TOPIX refers to the volatility of TOPIX Index; and DAX refers to the volatility of DAX Index.

significant impact on economic development, such as plummeting oil prices and triggering the US stock market circuit breaker four times, which caused investors to suffer significant losses in a very short time.

The novelty of this article compared with the existing literature can be summarized as follows. First, according to our knowledge, our study is the first to employ the time-domain approach and a method based on frequency dynamics to investigate the connectedness of return and volatility between the COVID-19 pandemic in 2020, the crude oil market, and the stock market. Onali (2020) employed the GARCH (1, 1) model to investigate the impact of the COVID-19 pandemic and related deaths on the US stock market (Dow Jones and S&P 500 indices). Papadamous et al. (2020) used the PVAR framework to assess the direct and indirect effects of the COVID-19 pandemic on the implied stock market volatility. Furthermore, Al-Awadhi et al. (2020) examined whether the pandemic is affecting stock market returns. Since the impact of the COVID-19 pandemic on the crude oil market is unprecedented, Gil-Alana and Monge (2020), Albulescu (2020), and Sharif et al. (2020) investigated the pandemic's effects on the prices of crude oil by employing various models. However, our study clearly characterized the directions and dynamics of return and volatility spillover through the time-domain approach. Second, we observed the volatility from different frequency bands in the model based on the frequency dynamics, which Onali (2020) and Papadamous et al. (2020) were unable to achieve. Third, we also employed the Infectious Disease Equity Market Volatility Tracker data to reflect the impact of the COVID-19 pandemic. For policymakers, evaluating the economic effects of the pandemic is critical but daunting because the crisis has unfolded at an

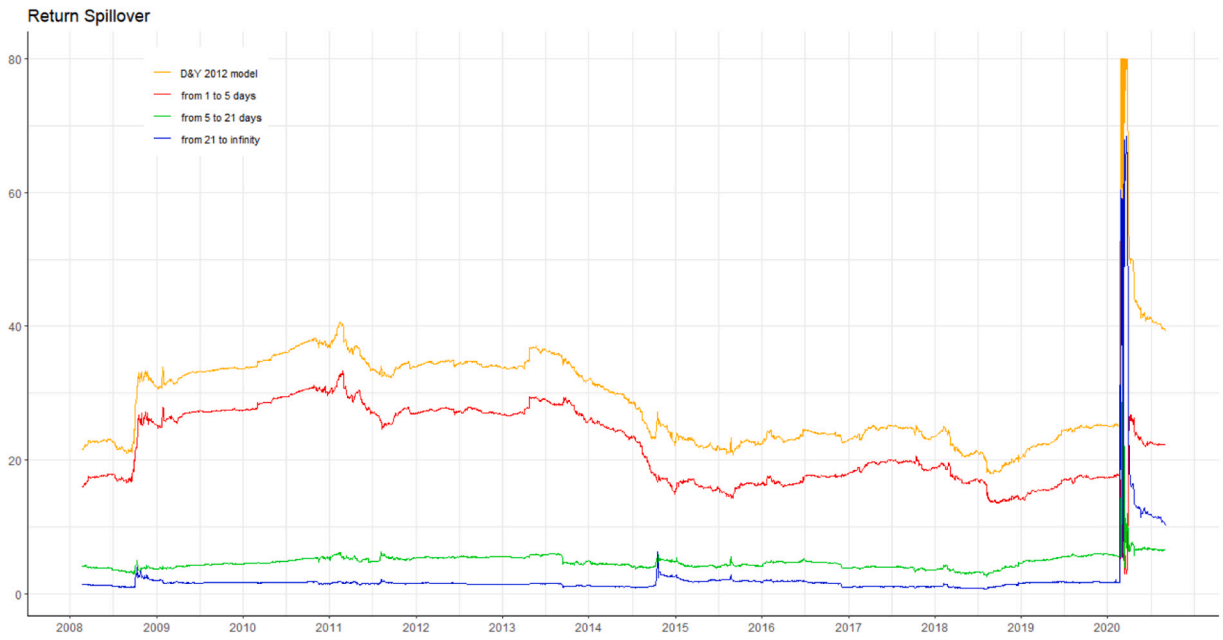

Fig. 4. Total return spillover plot (window size = 500).
Note: The yellow line indicates the total spillover index of DY12 model; the red line indicates the total spillover index of the BK18 model "Fre S"; the green line indicates the total spillover index of the BK18 model "Fre M"; and the blue line indicates the total spillover index of the BK18 model "Fre L." The variable unit of the vertical axis is expressed as a percentage.

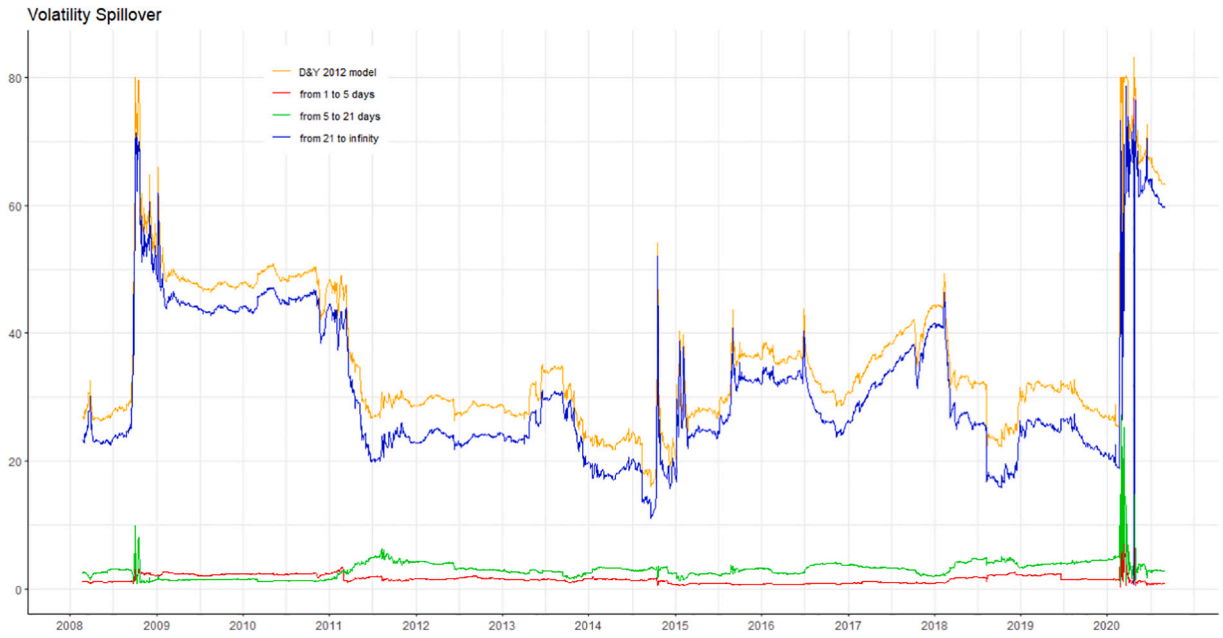

Fig. 5. Total volatility spillover plot (window size = 500).
Note: The yellow line indicates the total spillover index of DY12 model; the red line indicates the total spillover index of the BK18 model "Fre S"; the green line indicates the total spillover index of the BK18 model "Fre M"; and the blue line indicates the total spillover index of the BK18 model "Fre L". The variable unit of the vertical axis is expressed as a percentage.

extreme pace. Therefore, employing Infectious Disease Equity Market Volatility Tracker data can help to document and measure the enormous increase in economic uncertainty; these data were not employed by Gil-Alana and Monge (2020), Albulescu (2020) and Sharif et al. (2020) in their studies assessing the impact of the pandemic on the crude oil market. Finally, we also used the moving window method, which allowed us to observe dynamic changes in the spillover effects. Therefore, we were able to observe pairwise directional spillovers and find that the connectedness between IDEMVT and the returns of three stock indices was the greatest in 2020 and influenced by the COVID-19 pandemic; this was not demonstrated by Al-Awadhi et al. (2020).

We believe that our conclusion provides a basis for reflecting on the extensive and severe commercial activity restrictions imposed to contain the COVID-19 pandemic. Traveling restrictions and business closures, for instance, have shown to have brought substantial economic losses. Therefore, the government urgently needs to shift to a broader

Fig. 6. Pairwise directional return spillover plot (window size = 500).
Note: The yellow line indicates the total spillover index of DY12 model; the red line indicates the total spillover index of the BK18 model "Fre S"; the green line indicates the total spillover index of the BK18 model "Fre M"; and the blue line indicates the total spillover index of the BK18 model "Fre L." The variable unit of the vertical axis is expressed as a percentage.

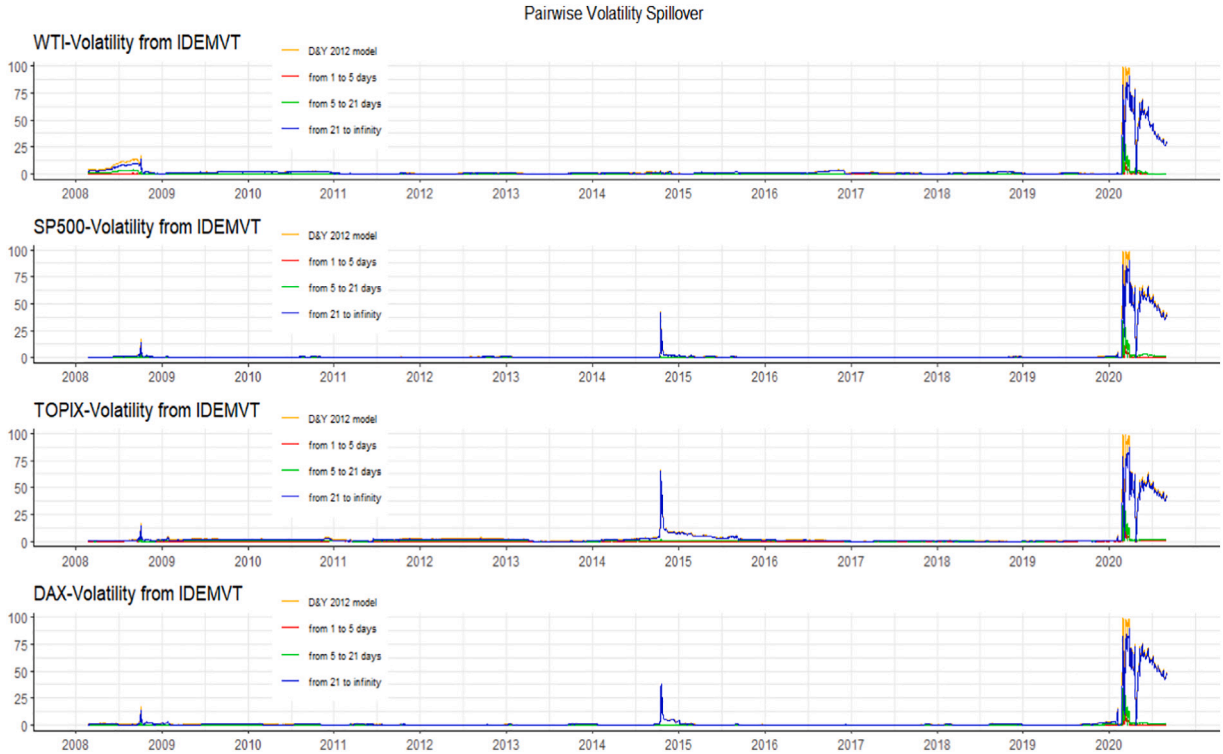

Fig. 7. Pairwise directional volatility spillover plot (window size = 500).
Note: The yellow line indicates the total spillover index of DY12 model; the red line indicates the total spillover index of the BK18 model "Fre S"; the green line indicates the total spillover index of the BK18 model "Fre M"; and the blue line indicates the total spillover index of the BK18 model "Fre L." The variable unit of the vertical axis is expressed as a percentage.

containment policy that does not affect the economy, as suggested by Baker et al. (2020b), Wagner (2020), and Ichino et al. (2020), to resolve the health crisis caused by COVID-19. In the current situation in which the COVID-19 epidemic is still raging, we believe that our research will inspire researchers in the future, especially in the study of the crude oil market and the stock market.

Finally, although the oil and stock markets are gradually returning to normal at the moment, the oil prices and stock prices remain unstable as the COVID-19 pandemic continues. Thus, there is still much room for investigating the impact of the COVID-19 pandemic on the oil and stock markets. For example, by using high-frequency data, we could compare the empirical results between the GARCH model and realized volatility. In addition, we could extend our analysis by using other techniques such as those described by Diebold and Yilmaz (2014, 2016), as well as entropy, wavelets, etc. These issues remain for our future research agenda.

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Declaration of Competing Interest

none.

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Appendix A

This appendix reports a summary of the empirical results of the ARMA-GARCH model of WTI, SP500, TOPIX, and DAX. We chose the lag of the GARCH model using the Akaike Information Criterion. We also report the results of the Ljung–Box test to check the serial correlation of the residuals. Q (20) is a test statistic for the null hypothesis that there is no autocorrelation up to order 20 for the standard residuals, and $Q^2(20)$ is for the standard residuals squared.

Table A
Empirical results of ARMA-GARCH model

	WTI		SP500		TOPIX		DAX	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
μ	0.0000***	0.0000	0.0008***	0.0001	0.0004**	0.0002	0.0007***	0.0002
AR (1)	0.9221***	0.0001	−0.0657***	0.0193				
AR (2)	−0.8969***	0.0001						
AR (3)	−0.0941***	0.0000						
MA (1)	−1.0180***	0.0001			−0.1483***	0.0185		
MA (2)	1.0044***	0.0000			−0.0163	0.0190		
ω	0.0000***	0.0000	0.0000***	0.0000	0.0000*	0.0000	0.0000***	0.0000
α_1	0.1123***	0.0164	0.1430***	0.0122	0.1208***	0.0118	0.0937***	0.0096
β_1	0.8725***	0.0080	0.8360***	0.0127	0.8567***	0.0172	0.8946***	0.0103
$Q(20)$	14.432		24.615		19.225		27.238	
p-value	0.808		0.217		0.507		0.129	
$Q^2(20)$	24.627		11.109		16.455		23.092	
p-value	0.216		0.943		0.688		0.284	

Note: "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels, respectively. Q (20) and Q^2 (20) are the Ljung–Box statistics with 20^{th} lags for the standard residuals and standard residuals squared, respectively.

Appendix B

This appendix reports the rolling-window analysis setting the window size equal to 370-day (almost 1 and a half years) to check the robustness of our empirical results. Fig. A and B indicate the dynamic analysis of return spillover and volatility spillover, respectively.

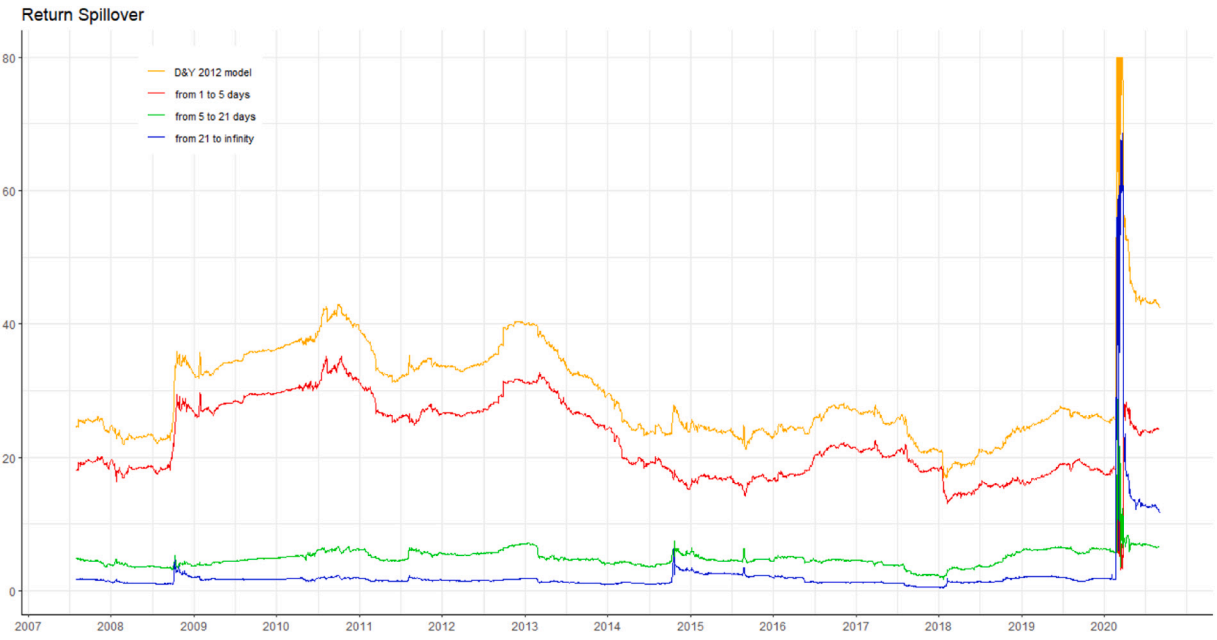

Fig. A. Total return spillover (window size = 370)

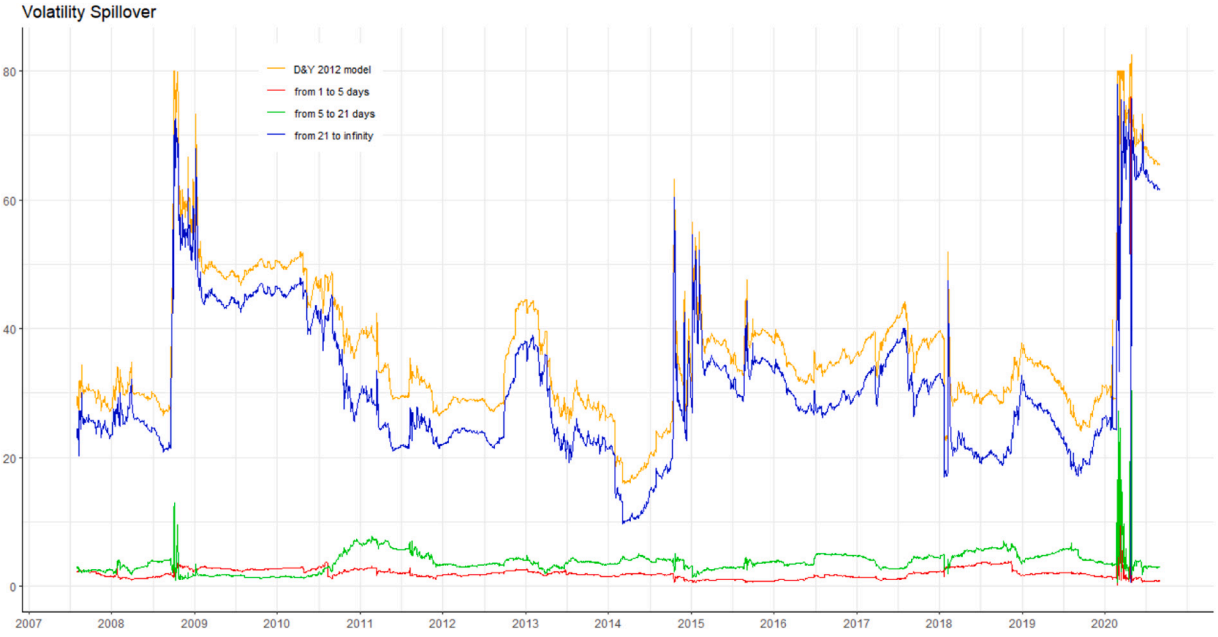

Fig. B. Total volatility spillover (window size = 370)

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