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Impact of the COVID-19 Pandemic on the Macro-economy and Financial Market

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The coronavirus disease 2019 outbreak has dramatically impacted financial markets and macroeconomic indicators in the United States, which is facing a long-term economic downturn. We investigate connectedness transmitted from the infectious disease equity market volatility tracker to financial markets (financial stress, crude oil futures prices) and macroeconomic indicators (economic index, 1-month Treasury constant maturity rate) for the return and volatility series. This study analyzes weekly data from the United States between January 2008 and August 2020 (660 observations) in the time-domain and frequency dynamics.

Keywords connectedness, time dynamics, COVID-19, macroeconomic indicators, financial markets

1 INTRODUCTION

Reports indicate that as of September 12, 2020, coronavirus disease 2019 (COVID-19) has infected approximately 28.66 million people and caused an estimated 920,000 deaths worldwide. Many countries have declared COVID-19-induced national emergencies.

Because factories have halted operations and workers are out of work, an unprecedented level of risk now prevails in all markets, creating considerable short-term losses for investors. Some investigations have analyzed the impacts of the COVID-19 outbreak on financial uncertainty and economic outcomes. Baker et al. (2020b) evaluated a remarkable stock market reaction to the COVID-19 crisis. Fernandes (2020) demonstrated that service-oriented economies would be significantly negatively affected, more work types would become risky, and no coun-

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try would remain unchanged due to the COVID-19 crisis. Zhang, D. et al. (2020) depicted the general patterns of country-specific risks and systemic risk in global financial markets and indicated that unlimited quantitative easing and a 0% interest rate in the United States might introduce more uncertainties into global financial markets. Ashraf (2020) examined the responses of stock markets to the COVID-19 epidemics and revealed that stock market returns decreased when the number of confirmed COVID-19 cases increased. McKibbin and Fernando (2021) investigated seven scenarios of how the COVID-19 crisis impacted macroeconomic outcomes and financial markets. Maliszewska et al. (2020) employed a standard global computable general equilibrium approach to simulate the potential shocks of the COVID-19 epidemics on trade and GDP (gross domestic product).

Sharif et al. (2020) analyzed the connectedness among COVID-19, oil price volatility shocks, stock markets, geopolitical risks, and economic policy uncertainty using the time-frequency methodology. Albulescu's (2020) estimation indicated that the reported daily new COVID-19 infected cases had a marginally negative impact on long-term crude oil prices.

However, previous literature has focused only on COVID-19 confirmed cases or deaths. This study employs a newspaper-based infectious disease equity market volatility (IDEMV) tracker, including COVID-19, H1N1, flu, and other epidemics. Baker et al. (2020b) introduced the IDEMV. It provides real-time forward-looking uncertainty measures, constituted by stock market volatility, economic uncertainty based on newspapers, and subjective uncertainty in business expectation surveys.

Although several papers have explored the connectedness between COVID-19 and financial markets or macroeconomics (Baker et al., 2020b; Ashraf, 2020; McKibbin and Fernando, 2021; Albulescu, 2020; Sharif et al., 2020), this study contributes to the existing literature in two ways. First, we analyze the connectedness in the time–domain followed by Diebold and Yilmaz (2012, 2015) and in frequency dynamics developed by Barunik and Křehlík (2018). Second, previous studies have indicated the importance of the US market, which is one of the main spillover sources in other regions (Bekaert et al., 2014; Syriopoulos et al., 2015). Therefore, further research in the United States is necessary. We provide new insights vis-à-vis investigating the spillover and connectedness among IDEMVs, macroeconomic indicators (economic index, 1-month Treasury Constant Maturity Rate), and financial markets (crude oil futures prices, financial stress) to capture the impacts of the COVID-19 outbreak on this system. The spillover index shows the spillover effect of crises or their impacts on the system. Hence, it provides better insights into connectedness, thus encouraging policymakers and asset managers to develop appropriate policies.

The study uses weekly data from January 2008 to August 2020 (660 observations). The main findings are summarized as follows: First, the results show that the total return spillover mainly focuses on the short term. Second, in contrast to the first result, the long-term total return spillover index has the largest weight during the COVID-19 pandemic period based on the results of the moving window, revealing that extreme crises, shocks, or events can influence the return system on the long term. Third, both the return and volatility spillovers of moving-window peaks in the COVID-19 crisis and the plummet of crude oil prices indicate that the shocks of COVID-19 and oil price fluctuations are significant. When connectedness focuses on high frequencies, it indicates that the shocks or impacts in this system work in the short term; if it focuses on lower frequencies, it indicates persistent and long-lasting effects.

The rest of this manuscript is organized as follows: Section 2 presents the literature on returns and volatility. We briefly introduce our methodologies in Section 3, and Section 4 presents the data and summary statistics. In Section 5, we explain the empirical results, and Section 6 concludes the paper.

2 LITERATURE REVIEW

The COVID-19 epidemic has a universal effect on all countries (Fernandes, 2020) as well as on stock markets (Baker et al., 2020b; Ashraf, 2020), financial markets (Albulescu, 2020), and macroeconomic outcomes (McKibbin and Fernando 2021; Maliszewska et al., 2020). The global economy is expected to contract considerably by 3% in 2020, followed by the 2020 World Economic Outlook (6.1% for advanced economies and 1% for emerging markets and developing economies), much more than during the 2008–09 financial crisis. Capelle-Blancard and Desroziers (2020) also indicated that not all countries had been shocked in the same way, notwithstanding the global nature of the shock. Fernandes (2020) demonstrated that service-oriented economies are significantly negatively affected. Baker et al. (2020b) showed unprecedented impacts of COVID-19 on the stock market, although previous infectious disease outbreaks, including H5N1 in 1997–98, SARS (severe acute respiratory syndrome) in 2003, H1N1 in 2009, and MERS/Ebola in 2014–15, did not show such a trend. The overall impact of SARS was estimated to be approximately 0.5% of the Chinese GDP (Hanna and Huang 2004), while SARS only occurred in Asia. Corbet et al. (2021) also found that the COVID-19 pandemic persistently impacted Chinese financial markets compared to the effects of long-standing and traditional influenza indices. Some investigations have also confirmed the impact of the pandemic on job loss

(Montenovo et al., 2020; Coibion et al., 2020).

People often compared the impacts of the COVID-19 pandemic with those of the global financial crisis in 2008, which had extensive connectedness, systemic risk, and contagion (Kenourgios et al., 2011; Bekaert et al., 2014; Luchtenberg and Vu, 2015; Zhang, D. et al., 2020). However, as Sharif et al. (2020) mentioned, the major difference between the global financial crisis and the COVID-19 pandemic is the spread. Moreover, Harvey (2020) highlighted this difference and referred to the COVID-19 pandemic as the "Great Compression."

Rizwan et al. (2020) indicated that COVID-19 impacted systemic risk. Evidence shows that the US market is one of the main sources of spillovers (Bekaert et al., 2014; Syriopoulos et al., 2015). It is necessary to focus on the United States to study the impact of connectedness.

A considerable volume of literature exists on the transmission of returns and volatility. Black (1976) presented the leverage hypotheses, and Poterba and Summers (1984) introduced the volatility feedback hypotheses. Baur and Jung (2006) analyzed the return and volatility relationships between German and the US stock markets. Hibbert et al. (2008) found a negative asymmetric relationship between returns and volatility. Guesmi and Fattoum (2014) investigated the return and volatility transmission between oil prices and oil-importing/-exporting countries, and observed no difference.

Liu and Pan (1997) indicated that market contagion played a crucial role in the mean return and volatility spillover transmission mechanisms. Badhani (2009) analyzed spillovers from the United States to the Indian stock market and found a significant response asymmetry in spillover effects, both in return and volatility. Arouri et al. (2011) documented the return and volatility transmission between world oil prices and the stock markets of Gulf Cooperation Council countries from 2005 to 2010. The results revealed considerable returns and volatility spillovers in the system. Joshi (2011) researched the return and volatility spillovers among Asian stock markets.

3 EMPIRICAL TECHNIQUES

3. 1 Time–Domain Approach

We use variance decomposition to measure connectedness, as designed by Diebold and Yilmaz (2012).

First, we introduce an N-variable vector autoregression (VAR) with order p (AR (p)) as follows:

$$\boldsymbol{Z}_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{Z}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where the observed variable values $\boldsymbol{Z}_t$ at time t are $N\times1$ vectors, $\boldsymbol{\Phi}_i$ denotes the $N\times N$ dimension coefficient matrix, and $\boldsymbol{\varepsilon}_t$ represents white noise (possibly non-diagonal), where $\boldsymbol{\varepsilon}_t \sim (0, \Sigma)$.

The VAR process can become a moving average (i.e., MA (∞)) expression if the roots of $|\boldsymbol{\Phi}(\boldsymbol{z})|$ are outside the unit circle:

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

$\boldsymbol{\Psi}(L)$ is the $N\times N$ coefficient matrix of the infinite-lag polynomial. The variance decomposition in Cholesky factorization relies on the ordering of the variables. We explore variance decomposition, which is independent of the ordering. The VAR structure of Koop et al. (1996) and Pesaran and Shin (1998) can ensure that the generalized forecast error variance decomposition (GFEVD) does not depend on the ordering. According to Baruník and Křehlík (2018), we can conduct an H-step-ahead GFEVD:

$$\boldsymbol{\theta}_{ij}^{H}=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H}((\boldsymbol{\Psi}_h\boldsymbol{\Sigma})_{ij})^2}{\sum_{h=0}^{H}((\boldsymbol{\Psi}_h\boldsymbol{\Sigma}\boldsymbol{\Psi}_h')_{ii}}, \tag{3}$$

where $\boldsymbol{\Psi}_h$ is the $N\times N$ coefficient matrix for the moving average at lag h, $\sigma_{jj}^{-1}=(\Sigma)_{jj}$, and $\boldsymbol{\Sigma}$ is the variance matrix of the error vector $\boldsymbol{\varepsilon}_t$. $\boldsymbol{\theta}_{ij}^{H}$ shows the forecast error variance decomposition contribution from the j^{th} to the i^{th} variable at forecast horizon h.

Every value is standardized by dividing it by the sum of raw values to keep the GFEVD sum of the variables of each row equal to 1.

$$\tilde{\boldsymbol{\theta}}_{ij}^{H}=\frac{\theta_{ij}^{H}}{\sum_{j=1}^{N}\theta_{ij}^{H}}, \tag{4}$$

where we can also refer to $\tilde{\boldsymbol{\theta}}_{ij}^{H}$ as the pairwise connectedness from the j^{th} to the i^{th} variable at horizon H. Furthermore, $\sum_{j=1}^{N}\tilde{\boldsymbol{\theta}}_{ij}^{H}=1$ and $\sum_{i,j=1}^{N}\tilde{\boldsymbol{\theta}}_{ij}^{H}=N$. We then obtain the total spillover index as follows:

$$S^{H}=100\times\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\boldsymbol{\theta}}_{ij}^{H}}{\sum_{i,j=1}^{N}\tilde{\boldsymbol{\theta}}_{ij}^{H}}=100\times\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\boldsymbol{\theta}}_{ij}^{H}}{N}=100\times\left(1-\frac{Tr\{\tilde{\boldsymbol{\theta}}_{ij}^{H}\}}{N}\right), \tag{5}$$

where S^{H} represents the spillover contributions of the return and volatility shocks in the system to the total forecast error variance, and $Tr\{\cdot\}$ is the trace operator.

Following Diebold and Yilmaz (2015), the study proposes two types of "total directional connectedness": "To" and "From."

To Spillover

$$S_{\cdot\leftarrow \mathrm{i}}^{H}=\frac{\sum_{\substack{\mathrm{j}=1\\ \mathrm{j}\neq \mathrm{i}}}^{N}\tilde{\theta}_{ij}^{H}}{\mathrm{N}}\times100, \tag{6}$$

$S_{\cdot\leftarrow \mathrm{i}}^{H}$ measures the directional connectedness from variable i to all other variables.

From Spillover

$$S^{H}_{i\rightarrow\cdot} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\boldsymbol{\theta}}^{H}_{ij}}{N} \times 100, \qquad (7)$$

The $S^{H}_{i\rightarrow\cdot}$ measures the directional spillovers variable I receives from all other variables.

3.2 Method based on Frequency Dynamics

Baruník and Křehlík (2018) developed a transform using a Fourier transform to obtain changes in connectedness with frequency dynamics by employing the general spectral representation of variance decomposition to conduct frequency-dependent connectedness measurements. First, we regulate three frequency bands (short, medium, and long terms) by exploiting the Fourier transform. We use a frequency response function, $\boldsymbol{\Psi}(\boldsymbol{e}^{-i\omega}) = \sum_h \boldsymbol{e}^{-iwh} \boldsymbol{\Psi}_h$, which can be obtained from the Fourier transform of the coefficients $\boldsymbol{\Psi}$, where $i=\sqrt{-1}$. The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ is defined as

$$(\boldsymbol{f}(\boldsymbol{\omega}))_{jk} \equiv \frac{\sigma_{kk}^{-1} |(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma})_{jk}|^2}{(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+i\omega}))_{jj}}, \qquad (8)$$

where $\boldsymbol{\Psi}(e^{-i\omega}) = \sum_h e^{-iwh} \boldsymbol{\Psi}_h$ is the Fourier transform of the impulse response $\boldsymbol{\Psi}$. $(\mathbf{f}(\boldsymbol{\omega}))_{jk}$ shows part of the spectrum of the j^{th} variable due to shocks in the k^{th} variable in the frequency band ω. The denominator represents the spectrum of the j^{th} variable at frequency ω as within-frequency causation. We can weigh $(\mathbf{f}(\boldsymbol{\omega}))_{jk}$, the frequency share of the variance in the j^{th} variable. Thereafter, we obtain the natural decomposition of the GFEVD to frequencies. The weighting function is defined as follows:

$$\boldsymbol{\Gamma j}(\omega) = \frac{(\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\boldsymbol{\Psi}(e^{-i\lambda})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{+i\lambda}))_{jj}d\lambda}, \qquad (9)$$

where $\boldsymbol{\Gamma j}(\omega)$ indicates the power of the j^{th} variable at a given frequency band, totaling the frequencies to a constant value of 2π. Even though the Fourier transform of the impulse response is, in general, a complex-valued quantity, we must consider that the generalized causation spectrum is the squared modulus of the weighted complex numbers and produces a real quantity.

Then, consider $b=(c, d)$ $c<d$, $c, d \in (-\pi, \pi)$. The GFEVD for frequency band b is stated as follows:

$$\boldsymbol{\theta}_{jk}(\boldsymbol{b}) = \frac{1}{2\pi}\int_{c}^{d} \Gamma j(\omega)(\mathbf{f}(\boldsymbol{\omega}))_{jk} d\omega, \qquad (10)$$

$\boldsymbol{\theta}_{jk}(b)$ is standardized as $\boldsymbol{\theta}^{H}_{ij}$ follows; thus, the scaled GFEVD on frequency band b can be written as:

$$\tilde{\boldsymbol{\theta}}_{jk}(\mathbf{b})=\frac{\boldsymbol{\theta}_{jk}(\boldsymbol{b})}{\sum_{k=1}^{N}\boldsymbol{\theta}_{jk}(\infty)}, \tag{11}$$

where $\tilde{\boldsymbol{\theta}}_{jk}(b)$ is the pairwise connectedness on frequency band b. Following Equation (5), we can set the total frequency connectedness band b as well:

$$S^{\mathcal{F}}(b)=100\times\left(\frac{\sum\tilde{\boldsymbol{\theta}}(\boldsymbol{b})}{\sum\tilde{\boldsymbol{\theta}}(\infty)}-\frac{Tr\{\sum\tilde{\boldsymbol{\theta}}(\boldsymbol{b})\}}{\sum\tilde{\boldsymbol{\theta}}(\infty)}\right), \tag{12}$$

$Tr\{\cdot\}$ is the trace operator.

Similarly, the “To” and “From” directional connectedness can also be defined as follows:

To Spillovers based on frequency band d

$$S^{\mathcal{F}}_{\cdot\leftarrow k}(b)=\frac{\sum_{\substack{j=1\\ j\neq k}}^{N}\tilde{\boldsymbol{\theta}}_{jk}(\boldsymbol{b})}{N}\times 100. \tag{13}$$

We consider the directional spillover (To) $S^{\mathcal{F}}_{\cdot\leftarrow k}(b)$ that variable k transmits to all other variables in frequency band b.

From Spillovers based on frequency band d

$$S^{\mathcal{F}}_{k\leftarrow\cdot}(b)=\frac{\sum_{\substack{j=1\\ j\neq k}}^{N}\tilde{\boldsymbol{\theta}}_{kj}(\boldsymbol{b})}{\mathrm{N}}\times 100. \tag{14}$$

As mentioned earlier, the directional spillovers (From) $S^{\mathcal{F}}_{k\leftarrow\cdot}(b)$ measures the connectedness all other variables give to variable k in frequency band b.

4 DATA

The present study employs weekly data, including the IDEMV tracker, financial stress index, economic index, 1-month Treasury constant maturity rate (WGS1MO), and crude oil futures ending on Friday, taken from January 2008 to August 2020 (660 observations). All data sources are listed in Table 1. We obtained the IDEMV data from the homepage of Economic Policy Uncertainty. Regarding the financial stress index, we consider the STLFSI presented by the Federal Reserve Bank of St. Louis as a proxy for the economic index. We employ the weekly economic index (WEI) provided by the Federal Reserve Bank of New York. The WGS1MO was obtained from the Economic Research of the Federal Reserve Bank of St. Louis. We consider the crude oil futures prices of the West Texas Intermediate (WTI). The price of crude oil is measured in USD per barrel. Table 2 lists the construction components of the IDEMV in detail. Baker et al. (2019) constructed the newspaper-based equity market volatility (EMV) tracker that varies with VIX and the realized volatility of the S&P 500 returns. The IDEMV index (Baker et al., 2020a) is derived from the EMV tracker multiplied by the proportion of EMV articles that include one or more of the following words: epidemic, pandemic, disease, virus, flu, MERS, Ebola, H5N1, H1NI, SARS, and coronavirus. It considers the influence of infectious diseases.

Because the STLFSI and WEI change around zero, we cannot take the log return logarithm. Thus, we add 100 to each STLFSI and WEI to use 100 as the benchmark and take the first difference of the logarithm to obtain the return data. Moreover, because the WGS1MO data represent the yields in percentage per annum, we consider the first difference as the WGS1MO return data. The WEI is an index of 10 daily and weekly economic activity indicators, and its scale is consistent with the GDP growth rate in 4 quarters.

Table 1: Variables in the model.

Variable	**Data**	**Data Source**
IDEMV	Infectious Disease Equity Market Volatility Tracker	Economic Policy Uncertainty
STLFSI	St. Louis Fed Financial Stress Index	Economic Research of Federal Reserve Bank of St. Louis
WEI	Weekly Economic Index	Federal Reserve Bank of New York
WGS1MO	1-Month Treasury Constant Maturity Rate	Economic Research of Federal Reserve Bank of St. Louis
WTI	West Texas Intermediate Crude Oil Future Prices	Investing.com

Note: IDEMV: Infectious Disease Equity Market Volatility Tracker. STLFSI: St. Louis Fed Financial Stress Index. WEI: Weekly Economic Index. WGS1MO: 1-Month Treasury Constant Maturity Rate. WTI: West Texas Intermediate crude oil futures prices.

Table 2: The definition of IDEMV.

IDEMV	Definition
ID	epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, H5N1, Ebola, H1N1
E	economic, economy, financial
M	"stock market," equities, equity, "Standard and Poors"
V	volatility, volatile, uncertainty, uncertain, risk, risky

Note: IDEMV is the abbreviation for Infectious Disease Equity Market Volatility Tracker.

We present the summary statistics of returns and volatilities for each variable in Table 3. For the return series, WEI had the lowest minimum and highest maximum in the weekly return series. Furthermore, WEI is the most volatile, followed by WGS1MO, WTI, and STLFS in the return variation. Regarding return skewness, the STLFSI was right-skewed, and the other variables were all left-skewed. All return variables are leptokurtic according to the kurtosis value, meaning that the returns have higher peaks and heavier tails. According to Dickey and Fuller (1979), we use the augmented Dickey-Fuller test to confirm whether each variable has a unit root. The results indicate that the WTI return has no unit root at the 10% significance level, and the other return data have no unit root at the 1% significance level in Table 3.

We employ a univariate autoregressive moving average with conditional heteroskedasticity (ARMA-GARCH) model to extract the conditional variance series as each variable's volatility, except for IDEMV (Note that IDEMV itself is a volatility series). We use the Akaike information criterion (AIC) to select the order or ARMA-GARCH model. As shown in Table 3, IDEMV has the highest maximum and the lowest minimum in the weekly volatility series. Furthermore, IDEMV is the most volatile in the volatility series, followed by WEI, WGS1MO, WTI, and STLFSI. Additionally, all the volatility series are right-skewed. According to the kurtosis value, all volatility variables are leptokurtic, meaning that these volatilities have higher peaks and heavier tails. We also find that WTI has no unit root at the 5% significance level, whereas IDEMV, STLFSI, WGS1MO, and WEI have no unit root at the 1% significance level.

Table 3: Descriptive statistics for return and volatility variations.

A. Descriptive statistics for the return series				
	STLFSI	WEI	WGS1MO	WTI
Minimum	−0.0238	−11.4500	−1.2000	−0.3469
Maximum	0.0239	4.6300	0.5900	0.2758
Mean	0.0000	1.3200	−0.0045	−0.0012
Std. Dev.	0.0035	2.4358	0.1019	0.0572
Skewness	1.1740	−2.8054	−4.8165	−0.7698
Kurtosis	19.0361	8.9001	54.0779	6.5704
ADF	−17.0303 ***	−1.8799 *	−19.3854 ***	−17.2956 ***

B. Descriptive statistics for the volatility series					
	IDEMV	STLFSI	WEI	WGS1MO	WTI
Minimum	0.0000	0.0011	0.2165	0.0168	0.0325
Maximum	55.7100	0.0212	2.8837	0.8050	0.1784
Mean	1.3730	0.0028	0.3656	0.0554	0.0502
Std. Dev.	5.2900	0.0025	0.2976	0.0867	0.0227
Skewness	6.2070	4.1417	5.9326	4.4791	3.4628
Kurtosis	44.3500	20.5816	38.3245	23.4559	13.4219
ADF	−3.8501 ***	−3.4175 ***	−3.1831 ***	−4.9541 ***	−3.7859 **

Notes: IDEMV is the abbreviation for Infectious Disease Equity Market Volatility Tracker. STLFSI is the abbreviation for St. Louis Fed Financial Stress Index. WEI is the abbreviation for Weekly Economic Index. WGS1MO: 1-Month Treasury Constant Maturity Rate. WTI is the abbreviation for West Texas Intermediate crude oil futures prices. ADF refers to the Augmented Dickey-Fuller Unit Root Test (1979). We define ***, **, and * to represent a rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

5 EMPIRICAL RESULTS

5. 1 Static Analysis for Full-sample

Table 4 reports the return and volatility connectedness followed by the time–domain approach (Diebold and Yilmaz, 2012). In every sub-table, the ij^{th} value estimates the forecast error variance contribution from variable j to i. We define the value of the last column as “From spillover,” meaning the total directional spillover that other variables give the specified variable. The last row value, called “To spillover,” displays the total directional spillover that the specified variable gives to other variables. And the total spillover index is defined in the lower right corner of each sub-table, totaling all the “From spillover” or “To spillover.”

Panels A and B in Table 4 indicate the return and volatility spillovers, respectively. The lag length of all VAR models is set to two for each return and volatility system, according to the Schwarz Criterion. The study set 100 as the forecast horizon (h) for the analysis. From Table 4, we find that the total return spillover index is 36.570%, while the total volatility connectedness index is 52.587%. The total return spillover index is much lower than that of volatility, consistent with Zhang, Y. et al. (2020).

By analyzing the impact of IDEMV on the other variables in Table 4, we find that IDEMV is the largest contributor to STLFSI, WEI, and WTI for return spillover (11.069%, 72.651%, and 5.781%, respectively). Notably, IDEMV is the largest contributor to all the volatility series for volatility spillovers. These results indicate that IDEMV significantly influences the system.

Additionally, WEI was found to be the largest receiver (18.836%), followed by STLFSI (6.820%) for return spillover, and WEI was the largest receiver (17.642%), followed by STLFSI (13.596%) and WTI (12.566%) for volatility spillover.

Table 5 displays the return and volatility spillovers based on frequency dynamics (Baruník and Křehík, 2018). We employ Fourier transform to divide the Diebold–Yilmaz spillover tables into three frequency bands in the frequency domain following Baruník and Křehík (2018). Here, the short-term, “Freq S,” is roughly consistent with a month (1 to 4 weeks); the medium-term, “Freq M,” implies a quarter (5 to 12 weeks); and the long-term, “Freq L,” corresponds to more than a quarter (13 weeks to infinity)[1).]

Previous studies, such as those by Wang et al. (2019), Zhang, W. et al. (2020), Liu et al. (2020), and Zhang, Y. et al. (2020) report that the total return spillover index decreases with the frequency band. This shows the importance of short-term return spillovers in the Baruník and Křehlík (2018) approach.

As shown in Table 5, the total return spillover index of Freq L (24.828%) is the largest among the three frequency bands (Freq S: 7.249%, Freq M: 4.493%), indicating that shocks from the return system have a considerable impact on the long-term rather than the short-term. However, our results are slightly different.

Additionally, the total spillover index for volatility increases with a decrease in frequency. It is consistent with previous findings, such as Toyoshima and Hamori (2018) and Baruník and Křehlík (2018). Here, the total volatility connectedness index is 1.360% for Freq S, 4.956% for Freq M, and 46.271% for Freq L.

The IDEMV index is the largest contributor to the WEI return (72.243%) and WEI volatility (70.427%) in the long term. It implies that the crisis or shocks coming from IDEMV will influence the WEI return and WEI volatility in the long term.

Table 4: Return and volatility spillovers for full sample.

Panel a: Return spillover						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	80.271	5.015	2.079	2.172	10.463	3.946
STLFSI	11.069	65.901	2.885	10.999	9.146	6.820
WEI	72.651	4.881	5.820	3.860	12.788	18.836
WGS1MO	8.556	11.756	0.444	76.739	2.505	4.652
WTI	5.781	2.093	2.431	1.278	88.416	2.317
To	19.611	4.749	1.568	3.662	6.98	36.570
Panel b: Volatility spillover						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	78.028	3.477	8.932	2.866	6.698	4.394
STLFSI	28.802	32.022	9.964	21.243	7.969	13.596
WEI	75.562	2.515	11.792	2.096	8.036	17.642
WGS1MO	8.707	7.993	3.554	78.052	1.694	4.390
WTI	36.953	9.979	7.567	8.330	37.172	12.566
To	30.005	4.793	6.003	6.907	4.879	52.587

Notes: IDEMV is the abbreviation for Infectious Disease Equity Market Volatility Tracker. STLFSI is the abbreviation for St. Louis Fed Financial Stress Index. WEI is the abbreviation for Weekly Economic Index. WGS1MO: 1-Month Treasury Constant Maturity Rate. WTI is the abbreviation for West Texas Intermediate crude oil futures prices. The values are expressed as percentages.

5. 2 Rolling-window Analysis

The full-sample spillover index or spillover table cannot display the potentially important cyclical and secular variations in dynamics, although it provides a convenient average spillover behavior summary. We get the dynamic total connectedness index developing a time dynamic

Table 5: Rerun and volatility spillovers for BK 18.

	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
Panel a: Return spillover						
Freq S: 1–4 weeks						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	5.400	0.431	0.093	0.332	0.527	0.277
STLFSI	4.422	47.911	1.452	6.802	5.582	3.652
WEI	0.030	0.018	0.478	0.007	0.013	0.014
WGS1MO	3.417	6.822	0.379	55.89	0.777	2.279
WTI	1.929	0.622	2.093	0.497	64.112	1.028
To	1.960	1.579	0.804	1.528	1.380	7.249
Freq M: 5–12 weeks						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	6.625	0.594	0.159	0.337	1.130	0.444
STLFSI	4.177	11.852	0.875	2.831	2.561	2.089
WEI	0.377	0.072	0.950	0.101	0.135	0.137
WGS1MO	2.671	3.066	0.055	13.645	1.020	1.362
WTI	1.007	0.748	0.155	0.393	14.664	0.461
To	1.646	0.896	0.249	0.733	0.969	4.493
Freq L: 13 weeks-infinity						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	68.246	3.990	1.827	1.503	8.806	3.225
STLFSI	2.471	6.138	0.558	1.365	1.003	1.079
WEI	72.243	4.791	4.393	3.752	12.639	18.685
WGS1MO	2.469	1.867	0.011	7.204	0.708	1.011
WTI	2.845	0.723	0.183	0.388	9.641	0.828
To	16.005	2.274	0.516	1.402	4.631	24.828
Panel b: Volatility spillover						
Freq S: 1–4 weeks						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	4.789	0.361	0.491	0.891	0.615	0.472
STLFSI	0.605	3.865	0.265	0.538	0.276	0.337
WEI	0.304	0.017	1.029	0.068	0.075	0.093
WGS1MO	0.324	1.296	0.225	8.086	0.069	0.383
WTI	0.248	0.042	0.040	0.048	1.980	0.076
To	0.296	0.343	0.204	0.309	0.207	1.360
Freq M: 5–12 weeks						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	7.029	0.139	1.144	0.517	0.635	0.487
STLFSI	4.378	6.503	1.434	2.550	0.928	1.858
WEI	4.830	0.056	3.875	0.294	0.526	1.141
WGS1MO	1.974	1.586	0.981	9.179	0.314	0.971
WTI	1.631	0.420	0.175	0.268	3.813	0.499
To	2.563	0.440	0.747	0.726	0.481	4.956
Freq L: 13 weeks-infinity						
	IDEMV	STLFSI	WEI	WGS1MO	WTI	From
IDEMV	66.209	2.976	7.297	1.457	5.448	3.436
STLFSI	23.819	21.654	8.265	18.155	6.765	11.401
WEI	70.427	2.442	6.887	1.734	7.434	16.407
WGS1MO	6.408	5.112	2.347	60.787	1.311	3.036
WTI	35.073	9.517	7.352	8.014	31.378	11.991
To	27.145	4.009	5.052	5.872	4.192	46.271

Notes: IDEMV is the abbreviation for Infectious Disease Equity Market Volatility Tracker. STLFSI is the abbreviation for St. Louis Fed Financial Stress Index. WEI is the abbreviation for Weekly Economic Index. WGS1MO: 1-Month Treasury Constant Maturity Rate. WTI is the abbreviation for West Texas Intermediate crude oil futures prices. Freq S is the abbreviation of "Frequency S," which roughly corresponds to 1–4 weeks; Freq M is the abbreviation of "Frequency M," which roughly corresponds to 5–12 weeks; Freq L is the abbreviation of "Frequency L," which roughly corresponds to 13 weeks-infinity. The values are expressed as percentages.

analysis of the moving-window method. Here, we show the 144 weeks' rolling-window samples and consider a 100-period-ahead forecast horizon (H), as in the full sample.[2)]

We display the rolling sample total spillover index for returns and volatility in Figures 1 and 2, respectively. The black line represents the total return and volatility spillovers in the time–domain followed by DY 12 approach (Diebold and Yilmaz, 2012). The other lines in Figures 1 and 2 are the total spillover indices in the frequency domain; the red line, named from 1 to 4 weeks, means "Freq S"; the green line, named from 5 to 12 weeks, means "Freq M"; and the blue line, named from 13 weeks to infinity, indicates the "Freq L." The total spillovers in the frequency domain are decomposed from the time domain into three frequency dynamics.

From Figures 1 and 2, we can obtain results that are consistent with those of previous studies. The return spillover movement shows a gently increasing trend without any bursts, whereas the volatility spillover change displays clear bursts without any trend consistent with readily identified "crisis" events. The return index in Figure 1 changes between 9.264% and 80.086%. The volatility index in Figure 2 changes between 12.700% and 80.056% in the time-domain approach.

Moreover, Figure 1 shows a sudden rise from 22.870% to 45.193% of the total return spillovers on February 21. It then surged to 80.000% in the second week after the CDC presented that COVID-19 was heading toward pandemic status on February 25, and the IDEMV index soared directly from single digits to more than 40 on February 28. The total return spillovers move relatively smoothly from October 2010 to August 2020, while the total volatility spillovers change drastically, particularly when extreme events occur (see Figure 2). The volatility maintained a high level of approximately 60% until early June 2011 due to the global crisis; this phenomenon can also be seen in Zhang, Y. et al. (2020). There is a skyrocketing trend to approximately 80% by the end of February 2020 (the same time as the quick increase in the return spillover), with crude oil price volatilities occurring and COVID-19 spreading globally. Therefore, the 2020 increase in return and volatility can also be explained by the COVID-19 crisis and the plunge of crude oil in early March 2020.

The period of the total return and volatility spillover responses are consistent with the stock markets facing the COVID-19 pandemic in Capelle-Blancard and Desroziers (2020). This indicated that the stock markets initially ignored the epidemic until February 21 before reacting greatly to the increasing number of infected cases (February 23 to March 20, 2020).

The spillover curves vary between low and high connectedness, indicating that shocks and crises transmit different strengths across this system. There were calm and turbulent times

Figure 1: Total return spillover.

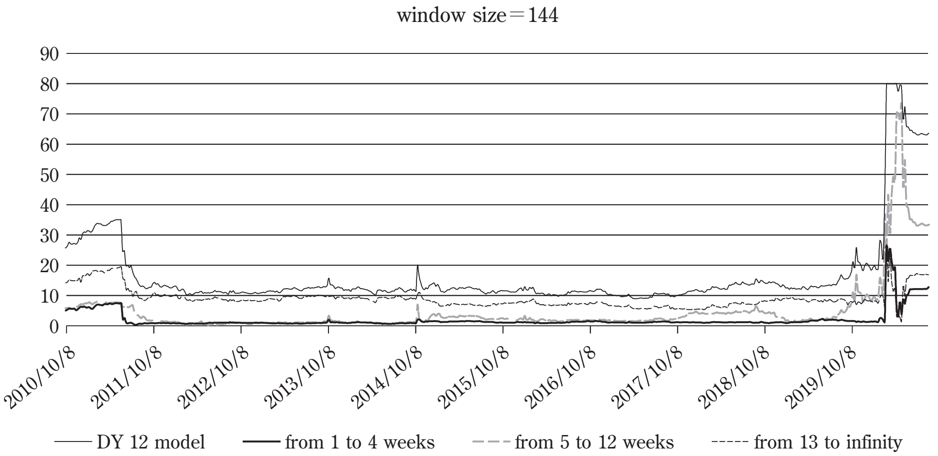
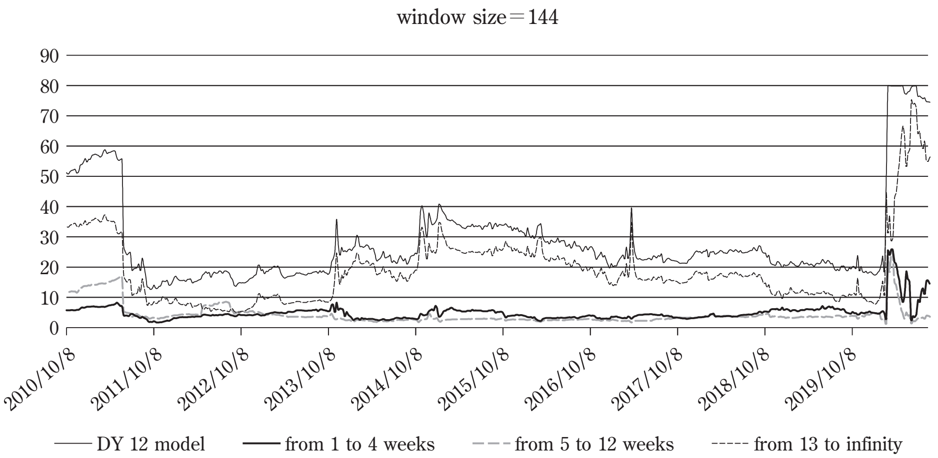


Figure 2: Total volatility spillover.



Note: It displays the total return connectedness index among the Infectious Disease Equity Market Volatility Tracker (IDEMV), Weekly Economic Index (WEI), St. Louis Fed Financial Stress Index (STLFSI), WTI crude oil futures prices (WTI), and 1-Month Treasury Constant Maturity Rate (WGS1MO). The total return connectedness in the time and frequency domains is calculated, followed by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), respectively. The ordinate represents the percentage value.

during these periods. Along with COVID-19, which created future uncertainties, the total return and volatility spillovers peaked in February 2020 and caused the highest connectedness level.

However, according to Baruník and Křehlík's (2018) approach in the frequency domain, in the previous studies (Toyoshima and Hamori, 2018; Zhang, Y. et al., 2020; Liu et al., 2020), the total return spillovers concentrate in the short term (1 to 4 weeks), indicating that the shocks or crisis from the return system mainly influence in the short term. Conversely, the total volatility is concentrated in the long term (13 weeks to infinity), indicating that the shocks are persistent and influence the long term. Moreover, some discoveries have been made in the frequency domain. Because of COVID-19, the total return and volatility spillovers increased steeply in February 2020 in the moving-window analysis (Diebold and Yilmaz, 2012). The long return spillover also rises relatively and accounts for the highest proportion, indicating that extreme events will influence the long-term return system. This finding corresponds with the global financial crisis period of Zhang, Y. et al. (2020).

6 CONCLUSION

We investigate the spillovers transmitted from the IDEMV index to the financial environment (STLFSI), macroeconomic indices (WEI and WGS1MO), and crude oil (WTI) in the United States. We explore the return and volatility connectedness among these five variables from January 2008 to August 2020 (660 observations) by employing a mixed empirical technique, which is proposed by Diebold and Yilmaz (2012) in the time–domain and Baruník and Křehlík (2018) in the frequency-domain. Moreover, we use a moving-window methodology to explore the considerable cyclical and secular movements in the return and volatility connectedness. Finally, we explore the pairwise spillovers of "IDEMV to the other variables." We can summarize the findings as follows:

a) Our time-domain results indicate that the total connectedness index for volatility is larger than that for returns among IDEMV, STLFSI, WEI, WGS1MO, and WTI. We find huge impacts of IDEMV on WEI (72.651%) in the return system. Regarding the volatility system, the spillover index from IDEMV to WEI is 75.562%, while that of WTI is 36.953% and that of STLFSI is 28.802%, which shows the unprecedented influence of IDEMV in the volatility system.

b) Our frequency–domain results imply that the total return spillover does not decrease with frequency. Volatility spillovers increase with decreasing frequency. The novelty is that total return spillover in the long-term accounts for the largest proportion, meaning that the return system will mainly impact in the long term than in the short term.

c) According to the moving-window approach, the results show that total return connectedness focuses on the short term. It indicates that the shocks will mostly influence the short-term system; the total volatility connectedness is concentrated in the long-term, indicating that the impacts are long-lasting in this system. Both the connectedness of the rolling window for return and volatility peaks in the COVID-19 crisis and the plummet of the crude oil price indicate that these shocks are significant. The most striking observation is that the long-term total connectedness for return has the largest proportion during the COVID-19 period in February 2020, which implies that extreme crises or events, such as the COVID-19 outbreak, can influence this return system in the long term.

Assuming that policymakers and asset managers understand the connectedness among IDEMVs, financial markets, and macroeconomic indicators, they can formulate appreciable financial policies and provide accurate endorsements. These findings could become signals when they want to reach their goals in different periods.

Notes

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1) We also consider the other frequency band, consisting of a month (1–4 weeks) for “Freq S,” half a year (5–24 weeks) for “Freq M,” and more than half a year (25 weeks–infinity) for “Freq L.” to check the robustness. Similar results are shown in Appendix A.

2) We also use several different moving windows (144 and 192 weeks) to test the robustness. And We show the results in the Appendix.

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