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Time-frequency volatility spillovers between major international financial markets during the COVID-19 pandemic

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\textbf{ABSTRACT}

We examine volatility spillovers and their time-frequency dynamics among major global financial markets from the outbreak of COVID-19 to present. Results show that total spillovers, driven by low frequency components, peaks at the end of March 2020 and then decline, which is not consistent with the upward trend of COVID-19; Stock markets of US and UK are net spillover transmitters, while other markets are net spillover receivers. The findings suggest that markets rally in the short term, but investors need to beware of bubbles and liquidity tightening expectations, and policymakers can gradually start to resume conventional monetary policy.

1. Introduction

On January 30, 2020, WHO (World Health Organization) declared the COVID-19 outbreak a “public health emergency of international concern.” In late February 2020, the epidemic began to spread widely around the world and begins to cause global panic. Johns Hopkins University COVID-19 statistics show that as of January 26, 2021 EST, there have been a cumulative total of 100,032,461 confirmed cases and 2149,818 deaths worldwide. The real economy has suffered great losses, including shocks to the consumer and service industries, stagnation of production and operation, increased pressure to pay employees and worsening market expectations. Financial market has experienced severe shocks, that is, increased liquidity pressure, panic in the market, and so on.

A large literature has emerged examining the impact of COVID-19 on the global economy or financial markets during the COVID-19 (Baker et al., 2020; Caggiano et al., 2020; Goodell, 2020; McKibbin and Fernando, 2020; Ramelli and Wagner, 2020; Zhang et al., 2020; Albulescu, 2021). There is also some literature that studies risk contagion, correlation or called spillovers between COVID-19 and financial markets. One important approach is DY connectedness indexes (Diebold and Yilmaz, 2009, 2012, 2014). Bissoon-doyal-Bheenick et al. (2020) find that COVID-19 contributes to an increase in global stock market return contagion. Fasanya et al. (2020) examine the return and volatility spillovers between the epidemic and international exchange rate markets. Akhtaruzzaman et al. (2021) examine the risk contagion between financial and non-financial firms in China and G7 countries. Shahzad et al., 2021a uses the quantile DY index to examine return spillovers across sectors in the US. TVP-VAR (Time-Varying Parameter Vector Autoregressions, Antonakakis et al., 2020) has also been widely used in this study (e.g., Adekoya and Oliyide, 2021; Bouri et al., 2021a).

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There are also empirical analyses using wavelet methods (Sharif et al., 2020), CoVaR (Abuzayed et al., 2021), Markov regime-switching vector autoregressive (Shahzad et al., 2021c), tail event-driven network (Shahzad et al., 2021b) and network models (So et al., 2021).

In this paper, we investigate the dynamics volatility spillovers among international financial markets throughout the pre- and mid-period of the COVID-19, i.e., 2020. Different from the existing related literature, we also provide an economic explanation for the inconsistency of total spillovers and COVID-19 trend and decompose spillovers using the BK index (Baruník and Krehlík, 2018) to find the frequency sources.

This paper is organized as follows. In Section 2, DY and BK framework is introduced briefly. Section 3 shows preliminary description of data. Then, Section 4 presents the empirical results. Finally, conclusions and implications are listed in Section 5.

2. Methodologies

Empirical research on volatility spillovers and its frequency dynamics is implemented using DY connectedness indexes and BK time-frequency connectedness indexes, that is, using the generalized forecast error variance decompositions (GFEVD) and its spectral representation of the vector autoregressive model to calculate two types of connectedness. We briefly introduce these two models.

For a stable VAR(p) model, they use GFEVD from Koop et al. (1996) and Pesaran and Shin (1998), which is the ratio of the forecast error variance of the variable

\[ \sigma^2_{ij}(H) = \frac{\sum_{k=0}^{p-1} (e'_k A_k \Sigma e_j)^2}{\sum_{k=0}^{p-1} (e'_k A_k \Sigma e_j)} \]

where \( \sigma^2_{ij}(H) \) denotes the standard deviation of \( e_j \) of \( i^{th} \) equation, \( A_k \) denotes coefficient matrix of moving average representation for VAR(p) model, \( \Sigma \) is the covariance matrix of \( e \), and \( e_j \) is the selection vector with the \( i^{th} \) equaling to one and other elements equaling to zero. \( N \times N \sigma^2_{ij}(H) \) constitute the generalized variance decomposition matrix. To compare different pairwise connectedness of any two markets, we normalize each entry of the matrix and name it “pairwise directional connectedness from variable \( j \) to variable \( i \)” or “volatility spillover from variable \( j \) to variable \( i \)” using

\[ C_{ij}(H) = \frac{\sigma^2_{ij}(H)}{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)} \times 100 \]

It measures the sum proportion of volatility shocks from variable \( i \) generating to other variables in the total forecast error variance for each variable.

**Directional connectedness from variable \( i \) to all other variables is**

\[ C_{i\cdot}(H) = \frac{\sum_{j=1}^{N} \sigma^2_{ij}(H)}{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)} \times 100 \]

which measures the proportion of volatility shocks received from other variables in the total forecast error variance for variable \( i \).

Analogously, **Directional connectedness from all other variables to variable \( i \)** is

\[ C_{\cdot i}(H) = \frac{\sum_{j=1}^{N} \sigma^2_{ij}(H)}{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)} \times 100 \]

Then, the **net directional connectedness from variable \( i \) to all other variables is**

\[ C_i(H) = C_{i\cdot}(H) - C_{\cdot i}(H) \]

If we add up all the non-diagonal \( \sigma^2_{ij}(H) \), total connectedness will be obtained as follows.

\[ C(H) = \frac{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)}{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)} = \frac{\sum_{i,j=1}^{N} \sigma^2_{ij}(H)}{N} \]

Now, we discuss the method for measuring frequency dynamics (long-term, medium-term, or short-term) of connectedness mentioned above following Baruník and Krehlík (2018). They use spectral representation of variance decompositions based on frequency responses to shocks.

The scaled generalized variance decomposition on the frequency band \( d = (a, b) \): \( a, b \in (-\pi, \pi) \), \( a < b \) is defined as

\[ \left( \bar{\sigma}_{jk} \right)_{ik} = (\theta_d)_{ik} \frac{1}{\sum_k (\theta_w)_{jk}} \]

where \( (\theta_d)_{ik} = \int \frac{1}{a} \Gamma_f(\omega) (f(\omega))_{jk} d\omega \) denotes generalized variance decompositions on frequency band \( d \), \( \Gamma_f(\omega) \) denotes frequency share of the variance of the \( j^{th} \) variable, \( (f(\omega))_{jk} \) is **generalized causation spectrum** over frequencies \( \omega \in (-\pi, \pi) \), and \( (\theta_w)_{jk} = \frac{1}{d} (\theta_d)_{ik} (d_\omega \)


denotes an interval on the real line from the set of intervals $D$.

The frequency connectedness on the frequency band $d$ is defined as

$$ C_d = 100 \cdot \left( \frac{\sum \theta_d}{\sum \theta} - \frac{\text{Tr} \{ \hat{\theta}_d \}}{\sum \theta} \right) $$

(8)

Which decomposes the total connectedness in Eq. (8). Short-, medium- and long-term connectedness will be accessible if we set frequency band $d$ to different intervals.

3. Data descriptions

In the empirical research, we select stock markets with top five market capitalization, including stock markets of the United States, United Kingdom, Japan, China, Hong Kong and take S&P 500, SZSE 300, Nikkei 225, Hang Seng, and FTSE 100 as proxies, respectively. GBP/USD exchange rate and WTI crude oil futures prices are considered because the COVID-19 also had a serious impact on international trade and oil market. Our study period covering pre-COVID-19 period (January 1, 2007 to December 31, 2019) and COVID-19 period (January 1, 2020 to December 31, 2020). Daily data of seven variables are obtained from Wind database. Then daily realized volatility can be estimated using the following formulation (Garman and Klass, 1980):

$$ \tilde{\sigma}^2 = 0.511 (H_t - L_t)^2 - 0.019 [(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383 (C_t - O_t) $$

(9)

where $H_t$, $L_t$, $O_t$, and $C_t$ denote natural logarithm of daily high price, opening price, low price and closing price, respectively.

From the descriptive statistics (Table 1) we can have a preliminary understanding of variable characteristics. In Table 1, it is apparent that the SD (standard deviation) of WTI is significantly greater than other markets. The daily volatility series of the seven financial markets have a right skew (Diebold and Yilmaz, 2015). The results of LB test, JB Test and ADF test show no variable is white noise, normally distributed or non-stationary.

Fig. 1 presents the daily realized volatility. It is noticeable that during the COVID-19, the maximum volatility in all markets occurred in March 2020 (when the outbreak started) except for WTI. The maximum volatility of WTI occurred at the end of April when an unprecedented “negative oil price” event occurred.

4. Empirical results

By analyzing these dynamic volatility spillovers in this part, we can draw the differences of total spillovers or systemic risk between the COVID-19 period and the important events, spillovers of each market and the transmission of pairwise spillovers between two markets. In addition, we also study the frequency dynamics (long-, medium- and short-term) of these spillover indices. In each VAR model estimation, lag order is set to be two, and the rolling-sample window is set to be 200 days and the predictive horizon for the variance decomposition is set to be 100 days, which are consistent with settings in Barunik and Krehlik (2018).

4.1. Total spillover results

Fig. 2 displays total spillovers containing three main noteworthy phenomena. Firstly, total spillovers increased steeply at the end of February and peaked (62.4%) in late March 2020, far exceeding spillovers during subprime crisis from 2008 to 2009 and second half of 2016 (When Trump was elected president of America). On March 11, WHO declared the emerging coronavirus to be in global pandemic status, causing global panic and stock markets shakeout. Meanwhile, four of the only five meltdowns in U.S. stock market history occurred in March. These events led to the culmination of the turmoil in global financial markets at the end of March, a phenomenon that can also be found in the existing literature (e.g., Adekoya and Oliyide, 2021; Bouri et al., 2021; Corbet et al., 2021; Lin and Su, 2021).

Secondly, the COVID-19 also experienced three spikes after March 2020, notably from October to December 2020. But total

| Table 1 | Descriptive Statistics. |
|---------|-------------------------|
|         | United States | United Kingdom | Japan | China | Hong Kong | GBP/USD | WTI     |
| Mean    | 9.40E-05       | 1.03E-04        | 8.58E-05 | 1.93E-04 | 9.71E-05 | 4.50E-05 | 8.45E-04 |
| SD      | 2.66E-04       | 2.30E-04        | 2.25E-04 | 3.41E-04 | 2.68E-04 | 1.24E-04 | 1.28E-02 |
| Minimum | 8.36E-07       | 1.46E-06        | 1.25E-06 | 3.16E-06 | 2.63E-06 | 3.00E-09 | 6.00E-09 |
| Maximum | 5.95E-03       | 3.76E-03        | 6.14E-03 | 4.78E-03 | 1.03E-02 | 4.62E-03 | 6.89E-01 |
| Skew    | 10.20          | 8.68            | 12.41   | 5.81   | 21.86    | 22.27   | 51.88   |
| Kurtosis| 147.32         | 102.36          | 234.67  | 49.39  | 734.14   | 700.33  | 2772.70 |
| LB test | 8877.90***     | 7477.60***      | 3047.50*** | 6073.70*** | 2943.80*** | 1378.60*** | 150.54*** |
| ADF test| -8.21***       | -8.77***        | -8.34*** | -8.39*** | -8.77*** | -9.05*** | -12.58*** |

Notes: ***”, **” and *” denote the rejection of the null hypothesis at the 1%, 5% and 10% significance level, respectively.
spillovers have been declining after reaching the maximum. Why are the trends of these two variables out of sync? Lin and Su (2021) also find that the rise of total connectedness in energy commodity markets lasts only for half a month and then starts to decline. But they do not explain the economics of the decline. We suggest that this may be related to the fact that countries implemented accommodative monetary policies (quantitative easing, credit support instruments, etc.) in the first place and have continued until now. These measures quickly defused the financial market crash and liquidity crisis, and even produced a stock market boom. But because of the lack of effective control over the epidemic and unemployment, total spillovers of markets gradually diverged from the epidemic trend and economic fundamentals.

Thirdly, results of time-frequency decomposition of the spillovers in Fig. 3(b) show that total spillovers during the epidemic is driven mainly by the low-frequency component. A possible explanation might be that lower frequency spillovers indicate that shocks are transmitted over a longer period (low frequency response) and a fundamental change in investors’ expectations. Total spillovers driven by the low-frequency response to shocks then translates into longer-term uncertainty, leading to an increase in systemic risk (Barunik and Krehlik, 2018).

4.2. Total directional spillover results

This subsection discusses directional volatility spillovers of seven markets during the COVID-19 (Fig. 3). From the graph, firstly,
From spillovers do not differ significantly across markets, but there are significant differences in To spillovers (Diebold and Yilmaz, 2014). Spillovers from the US, UK and Japan to other markets increased significantly after the outbreak, showing huge impact of COVID-19 on the economies of these countries and triggers a huge panic in the markets. However, spillovers from Japan are smaller than the first two, so only the US and the UK become net spillover senders. Others are net spillovers recipients. Secondly, China’s economy was most affected in the early stage, but because the correlation between China’s stock market and other markets is not strong, it did not cause huge shock to other markets, so total spillovers did not increase significantly. These two findings are consistent with those obtained by Abuzayed et al. (2021) using CoVAR method.

Then, GBP/USD and WTI are subject to greater spillovers from stock markets than they are to stock markets. However, the crude oil market experienced some major events from March to April, with no agreement reached at the OPEC+ production reduction meeting on March 6, and WTI crude oil futures physical delivery date approaching on April 20, but a severe shortage of oil storage space in the US led to negative oil prices for two consecutive days. This, coupled with a significant drop in oil demand due to the COVID-19, led to significant spillover from WTI from March to April (Bouri et al., 2021; Corbet et al., 2021; Lin and Su, 2021).

Finally, time-frequency decomposition of the net spillovers in Fig. 3(b) suggests that components are still primarily long-term components, i.e., the transmission of spillovers between markets is likely to be more persistent. This is consistent with the results in previous subsection.

4.3 Pairwise directional spillover results

This subsection explores the pairwise volatility spillovers between two markets (Fig. 4(a)) and decomposition of net pairwise volatility spillovers in terms of time frequency (Fig. 4(b)). There are 21 pairs of pairwise spillovers between the seven markets, and only 9 pairs of significant spillovers are selected here.

First, spillovers between the US, UK, and Japan are more significant, but the “TO” spillovers are decreasing in order. Second, there are only one-way spillovers from the US and the UK to Hong Kong, which is consistent with the pre-epidemic period. Hong Kong is mainly influenced by the unidirectional shocks from the US and European markets. China, on the other hand, has insignificant spillovers with all the other six markets. Third, time-frequency decomposition of net pairwise spillover remains largely driven by the low frequency component, which is consistent with results of total and directional spillovers.
Conclusions

This paper empirically analyzes volatility spillovers among major financial markets during the COVID-19 and explores the frequency dynamics of spillovers. Results indicate that total spillovers of global financial markets increased significantly during the epidemic, reaching a historical peak in the end of March and has been declining since then, which is inconsistent with the trend of the COVID-19. This may be due to monetary and fiscal policies stabilized financial markets in the short term but could not compensate for the lack of preventive measures. Directional spillover results show that US and UK are net volatility spillover senders, while other markets are net spillover receivers. Pairwise spillovers results reveal significant correlation between US, UK and Japan. Decomposition results at the time-frequency level for spillover indices suggest that spillovers are mainly driven by the low-frequency component.

The findings of this paper provide some suggestions for investors and policy makers. Firstly, both stock investors and crypto traders should be wary of market bubbles and liquidity tightening expectations. Secondly, we suggest that policy makers pay attention to the damage to monetary credit caused by liquidity flooding, and that the epidemic can be followed by a gradual tightening of liquidity and a gradual return to prudent monetary and fiscal policies.

Fig. 3. Directional spillovers and frequency decomposition for net directional spillovers

Notes: Plot (a) presents directional spillovers of each market from January 2020 to December 2020. Purple/dotted line “To” denotes spillovers of a market generating to others. Green/dashed line “From” denotes spillovers of a market receiving from others. gray/solid line “Net” equals to “To” minus “From”, denoting net spillovers. The legend settings in Plot (b) are the identical to those in Fig. 2. 
Author statement

**Dong Wang:** Conceptualization, Data Curation, Methodology, Writing - Original Draft. **Ping Li:** Conceptualization, Supervision, Project administration. **Lixin Huang:** Writing - Review & Editing.

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