



Economic Policy Uncertainty and Volatility Spillovers Among International Stock Market Indices During the COVID-19 Outbreak

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Abstract

Using a sample of 16 international stock market indices spanning the period of January 2015 to June 2022, we examine how global equity markets interact with respect to volatility spillover, with a special focus on types of investment horizons, and how the connectedness structure evolves during the COVID-19 outbreak. Empirical results suggest that there is strong evidence of volatility spillovers among global stock markets, and the COVID-19 pandemic further strengthens such volatility spillovers. However, the structure of the frequency connectedness changes gradually when compared to the full sample period. We further investigate if economic policy uncertainty (EPU) affects volatility spillovers among global stock markets. The results suggest that EPU significantly affects the connectedness among global stock markets, particularly during the COVID-19 pandemic period. Overall, the findings suggest that volatility spillovers across international stock markets vary with time horizons and market conditions, which contributes to the academic literature on modelling global volatility spillovers. Practically, the findings of the study contribute to investors and policymakers in adjusting trading strategies and monitoring market risks.

Keywords Global stock market · Volatility spillovers · Economic policy uncertainty · COVID-19 pandemic

JEL Classification C50 · C53 · G14 · G15

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1 Introduction

The concept of connectedness of financial markets is considered to be the core of modern finance, particularly in financial risk measurement and management (Diebold & Yilmaz, 2012, 2014). The increasingly deepened integration of financial markets has enhanced the cross-market and cross-border information flows in complex financial systems. Higher financial market integration promotes further development and maturity of financial markets in different countries (regions), but at the same time magnifies the contagion effects of financial risks. Besides, the presence of heterogeneous market participants (e.g., long-term investors versus short-term speculators and traders) would lead to a dissimilarity in return and volatility connectedness between the short-term and long-term horizons. Recently, the financial market's reaction to the COVID-19 global pandemic outbreak since February 2020 has further led to a structural change in the connectedness among financial assets and across financial markets.

It's worth mentioning that the literature on the economic impacts of the COVID-19 has been burgeoning since 2020.¹ The outbreak of COVID-19, which has been perceived as a “black swan” event, has attracted much attention from researchers and posed numerous new questions regarding financial contagion in the era of COVID-19 (Yarovaya et al., 2021a, 2021b, 2022). The relevant research has widely examined the financial impacts of the COVID-19 pandemic and suggested that the COVID-19 outbreak induced finance contagion by affecting risk tolerance and uncertainty among investors in the crisis period (Akhtaruzzaman et al., 2022; Corbet et al., 2022; Guo et al., 2021; Iyer & Simkins, 2022; Nguyen et al., 2021; Su et al., 2023; Yarovaya et al., 2021a, 2021b). For example, Sharif et al. (2020) argue that COVID-19 outbreak has a greater effect on the US geopolitical risk and economic uncertainty than on the US stock market itself. The extant literature has also widely examined the impacts of economic policy uncertainty (EPU) on risk contagion in financial markets (Albulescu et al., 2019; Karanasos & Yfanti, 2020; Wang et al., 2019; Zhang & Yan, 2020; etc.). For example, Qian et al. (2020) find that most of the abnormal market correlations exist in periods with high levels of economic policy uncertainties (EPU). Similarly, Dai et al. (2021) show that the crash risk of the US stock market is more affected by EPU during the COVID-19 pandemic. However, there are few papers that investigate EPU's role in driving the dynamic volatility spillovers among global stock markets before and during the COVID-19 pandemic crisis.

Under this background, in this study we examine the volatility connectedness (a.k.a., volatility spillovers) of leading global stock market indices over a full sample period and a sub-period corresponding to the COVID-19 outbreak.²

¹ Several special issues on the economic and financial impacts of COVID-19 have been arranged and appeared in a large number of reputable economics and finance journals (i.e., Finance Research Letters, International Review of Financial Analysis, Journal of Economics and Business, etc.) over the past few years.

² In this study, we interchangeably use the term “spillover” and “connectedness”.

Methodologically, we apply the frequency-based connectedness approach of Baruník & Krehlík (2018), which allows us to uncover volatility spillovers while accounting for the investment horizons of heterogeneous market participants that often vary across frequencies. In addition, we explore the impact of economic policy uncertainty (EPU) on connectedness among global stock markets by utilizing time series regression. We particularly focus on how EPU affects the interactions between global stock markets (i.e., volatility connectedness) during the COVID-19 pandemic.

Our study offers several contributions. First, we extend the existing literature arguing that volatility spillovers across international stock markets vary with time horizons (e.g., Cheng et al., 2022; Ciaian et al., 2018; Ji et al., 2020), by using the novel methodology of Baruník and Krehlík (2018) which distinguishes between high-, medium-, and low-frequency bands that can reflect different investment horizons. This is important as value investors have long-term investment horizons, whereas speculators and high-frequency traders have short-term trading horizons that are reflected in high frequencies (Bouri et al., 2020). Second, we provide a discussion of the event of COVID-19 global pandemic and how it translates into the dynamics of volatility connectedness among global stock markets. Overall, the structural changes in return and volatility connectedness, as reactions to the COVID-19 pandemic, provides an ideal setting for examining the impact of COVID-19 pandemic on financial markets. Third and finally, we investigate EPU's role in driving the dynamic volatility spillover between global stock markets before and during the COVID-19 pandemic crisis, which have important implications for retail investors, portfolio managers, policymakers, and central banks.

The remainder of this paper proceeds as follows. Section 2 presents a brief review on extant studies of volatility connectedness and the impact of COVID-19 pandemic on volatility spillovers. Section 3 describes the data and introduces Baruník and Krehlík (2018)'s frequency connectedness methodology. Section 4 presents our main empirical results and robustness checks. Section 5 concludes with policy implications.

2 Literature Review

A vast amount of researchers have continuously proposed extended models of the Diebold and Yilmaz (2009, 2012, 2014) methodology to construct return and volatility spillover indices. Most of those studies use autoregressive (AR) model, vector autoregressive (VAR) model, multivariate GARCH-type models, or copula models (e.g., Aslanidis et al., 2019; Bouri et al., 2020; Ciaian et al., 2018; Ji et al., 2019a, 2019b, 2020; Katsiampa, et al., 2019; Moratis, 2021; Tiwari et al., 2020). However, those methods proposed are not suitable to study volatility spillovers and connectedness in a time-varying setting which differentiates between various investment horizons from short- to long-term. Baruník et al. (2016, 2017) propose the method of asymmetric volatility spillover by combining the Diebold and Yilmaz (2009)' connectedness measurement and realized semi-variance (RSV) which differentiates the variance caused by positive and negative returns, and can quantify asymmetric

connectedness more flexibly. Moreover, Baruník and Krehlík (2018) propose a new framework of variance decomposition spectrum representation, which can split the measurement of financial market connectedness into several cycles or different frequency bands. So far, discussions about the volatility spillovers among global stock markets under various investment horizons have been very limited.

With the spread of the COVID-19 pandemic and its increasing impacts on global equity markets, Corbet et al. (2022) investigate the existence of contagion between Chinese stock markets during the COVID-19 pandemic and find that COVID-19 has a significantly positive impact on the volatility of the Shanghai and Shenzhen Stock Exchanges. Rehan et al. (2022) examine the short-term stress of COVID-19 pandemic on 32 major stock markets covering American, European, Asian and Pacific countries. Das et al. (2023) investigate the downside potential of G7 stock markets in face of COVID-19 relative to other economic crises. Shen and Zhang (2021) explore the distinct market reactions to the COVID-19 outbreak in the Chinese stock market. Their results reveal that the go-outside (GO) stocks suffer significant losses on the event date, while for the stay-at-home (SAH) stocks, no significantly negative return is observed on the event date. In the same vein, Ashraf (2020) document that stock markets respond negatively to the increases in daily confirmed COVID-19 cases.

The extant literature has also examined volatility spillovers among stock markets during the COVID-19 outbreak, including global stock markets (BenSaida et al., 2018; Gamba-Santamaria et al., 2019), Asia–Pacific stock markets (Li et al., 2023), U.S. and BRICS stock markets (McIver & Kang, 2020). Yadav et al. (2023) apply Granger causality and dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) to investigate the spillover between Chinese and emerging economies. The result reveals that there is no spillover effect from China to emerging economies in full period (i.e., from January 3, 2000 to February 7, 2020), except for Indonesian stock market. Liu et al. (2021) and Lin and Chen (2021) utilize econometric models to evaluate the impact of the COVID-19 outbreak on major global stock market indices. Their empirical results show that all major global stock market indices fell sharply immediately after the virus outbreak. Zhang et al., (2020a, 2020b) investigate the general pattern of country-specific risk and systematic risk in the global financial markets during the COVID-19 pandemic and find evidence of increasing financial market volatility due to the pandemic. So et al. (2021) examine the impact of the COVID-19 pandemic on Hong Kong stock market connectedness and imply increased network connectedness in financial networks during the COVID-19 outbreak.

During financial crisis and market stress periods, the degree of spillovers in financial markets could also be influenced by economic policy uncertainty (EPU). In this context, previous studies have documented that the EPU index as developed by Baker et al. (2016) affects stock market returns (Antonakakis et al., 2013; Arouri et al., 2016; Christou et al., 2017; Guo et al., 2021; He et al., 2020; Hu et al., 2018; Phan et al., 2018; Xiong et al., 2018) and volatility (Balcilar et al., 2019; Mei et al., 2018; Yu & Song, 2018; Yu et al., 2022; Wang et al., 2020). A recent strand of literature has focused on the impact of EPU on the co-movement among various financial assets, including connectedness among regional stock markets (Li et al.,

2015; Li & Peng, 2017), bond and stock markets (Fang et al., 2017), commodity and stock markets (Badshah et al., 2019), and Bitcoin and conventional financial markets (Fang et al., 2018; Matkovskyy et al., 2020). Most of these studies find evidence of a significantly negative relationship between EPU and the co-movement between these variables, which highlights a significant portfolio implication related to EPU (Badshah et al., 2019). Li et al. (2021) unveil the impact of EPU on the financial markets in the Asia–Pacific region and find that the correlations between EPU and financial network connections have risen after the COVID-19 outbreak.

Another strand of literature investigates the impact of EPU on volatility spillovers. For example, the relevant studies have been focusing on the impact of EPU among global stock markets (Shi & Wang, 2023), the spillover effect of U.S. EPU in the post-epidemic era (Li et al., 2023), the asymmetric volatility spillovers between international EPU and the U.S. stock market (He et al., 2020), and the driving force of EPU on volatility spillovers in electricity markets (Ma et al., 2022). However, there are few papers that investigate EPU's role in driving the dynamic volatility spillovers among global stock markets before and during the COVID-19 pandemic crisis.

The above literature review points to three research gaps which we attempt to address in this study. First, we extend the existing literature by analyzing time-varying volatility spillovers across international stock markets, based on the novel methodology of Baruník and Krehlík (2018) which distinguishes between high, medium, and low frequency bands that reflect different types of investment horizons, which is crucial to investment decisions regarding portfolio diversification and hedging strategies. Second, there is a lack of evidence on volatility spillovers among major stock markets during the catastrophic event of the COVID-19 outbreak. Third, whether EPU affects stock market volatility spillovers, particularly in the context of the COVID-19 pandemic, has not been fully explored. Considering the fact that EPU could drive the connectedness among financial variables, it is highly possible that volatility connectedness arises due to heterogeneous frequency responses to shocks in financial variables. Compared to previous studies, our research contributes to the strand of literature about volatility spillovers among major stock markets, by systematically analyzing a comprehensive data set of 16 major stock markets before and during the COVID-19 outbreak, both in the time domain and the frequency domain.

3 Data and Methodology

3.1 Data

Our study covers 16 most popular stock market indices worldwide, including China, India, and 14 developed markets, spanning the period from 2015 to 2022. For a full list of the stock market indices used in this study, please see Table 6 in the Appendix.

The daily price data is downloaded from the Oxford-Man Institute's realized library (<https://realized.oxford-man.ox.ac.uk/data>). We compute daily logarithmic returns and realized variances of major global stock market indices based on intraday data.³ A list of stock market indices utilized in this study is provided in Table 6 in the Appendix. To examine the impact of economic and policy uncertainty on global stock market connectedness, the global economic policy uncertainty index (GEPUI) is retrieved from Federal Reserve Bank of St. Louis (FRED). We also obtain data on the number of confirmed COVID-19 cases (deaths) per million inhabitants from Johns Hopkins University (<https://coronavirus.jhu.edu/data>). Finally, we control for the uncertainty index represented by the CBOE market volatility index (VIX). The time series of VIX index is obtained from the website of the Chicago Board Options Exchange (<https://www.cboe.com/indices/>).

3.2 Methodology

3.2.1 Measure of Realized Volatility

Following the pioneering work of Andersen and Bollerslev (1998), Andersen (2000), Andersen et al., (2003, 2007) introduce the concept of realized volatility which utilizes the intraday data to construct the model-free estimate of asset price volatility. The realized variance (RV) is calculated as the sum of squared log-price differences sampled over intraday intervals. Following Liu et al. (2015) and Bollerslev et al. (2018), the tick-level data can be aggregated into 5-min intervals which strikes a good trade-off between speed and accuracy.

Note that the realized volatility is approximately free of measurement error only under particular conditions. Therefore, the existing studies have proposed alternative approaches to reduce the impact of the noise term induced by microstructure noise on the estimation of the integrated variance (see, e.g., Ait-Sahalia, et al., 2005; Barndorff-Nielsen & Shephard, 2004, 2006; Barndorff-Nielsen, et al., 2008, 2010). Among the alternative measures, the realized bi-power variation (BV) and realized semivariance (RSV) are the most popular ones, both of which prove to be robust to market microstructure noise. Please refer to McAleer and Medeiros (2008) and Bollerslev et al. (2018) for some useful reviews on measures of realized volatility.

3.2.2 Measure of Volatility Spillover

The traditional understanding of connectedness in financial systems through simple correlations and related measures turns out to be insufficient to explain the

³ In this paper, we adopt three measures appropriate to describe stock return variances, including realized variance, realized semi-variance, and bi-power variation to account for microstructure noise and jumps in stock price process, with the availability of tick-level data. Liu et al. (2015) show that the choice of 5-min sampling frequency can largely circumvent the impact of market microstructure noise. Therefore, all the realized volatility measures are calculated by rolling sampling of transaction price series at 5-min frequency (i.e., 5-min sub-sampled).

systematic dynamics of the complicated networks that modern financial markets own. Following Diebold and Yilmaz (2012, 2014) and Baruník and Krehlík (2018), we examine the volatility connectedness of major international stock market indices through the generalized vector autoregression (VAR) framework and imply forecast error variance decomposition to form a numerical spillover score among a system of variables (Belke et al., 2016; Kumar et al., 2022). Namely, Diebold and Yilmaz (2012) derive the procedure from the standard VAR model as following:

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \dots + \Phi_p x_{t-p} + \varepsilon_t$$

where Φ_1, \dots, Φ_p are coefficient matrices and ε_t is the residual term. Assuming that the roots of $|\Phi_1|$ are outside the unit-circle, the VAR process is represented through the MA(∞) process as $x_t = \Psi(L)\varepsilon_t$, where $\Psi(L)$ is a matrix of infinite lag polynomials.

Building on the infinite moving average representation of the VAR model, the generalized forecast error variance decomposition (GFEVD) can be written in the following form:

$$(\Phi_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^H \left((\Psi_h \Sigma)_{j,k} \right)^2}{\sum_{h=0}^H \left((\Psi_h \Sigma \Psi_h')_{i,j} \right)}$$

where Ψ_h is a $(N \times N)$ matrix of moving average coefficients at lag h , $\sigma_{k,k} = (\Phi_H)_{j,k}$ is the contribution of the k^{th} variable for the forecast error variance of the element j for H horizon, and Σ is the variance matrix of residuals.⁴

According to Diebold and Yilmaz (2012), we can thus define connectedness measure of the spillover index as the ratio of the sum of the off-diagonal elements to the sum of the whole matrix, which is given by:

$$C_H = 100 \times \frac{\sum_{j \neq k} (\Phi_H)_{j,k}}{\sum \Phi_H} = 100 \times \left(1 - \frac{\text{Tr}\{\Phi_H\}}{\sum \Phi_H} \right)$$

where $\text{Tr}\{\cdot\}$ denotes the trace operator, and the total of all elements of Φ_H matrix is presented in the denominator.

In addition, Baruník and Krehlík (2018) use a frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h$ that is obtained from the Fourier transform of the coefficients Ψ , with i being an imaginary constant. Therefore, the frequency-based connectedness for frequency band d can be calculated as⁵:

⁴ For highly correlated financial variables such as stock market returns and volatilities we examine in this study, the variance-covariance matrix Σ is not necessarily a diagonal matrix, so that the shocks in ε_t are allowed to be contemporaneously correlated. As the values of the entries in each row of the Φ_H matrix may not add up to one, each entry is then normalized by scaling the sum of the entries in each row.

⁵ For more details about the frequency-domain modelling approach, please refer to Baruník and Krehlík (2018).

$$C_d^F = 100 \times \left(\frac{\sum \bar{\theta}_d}{\sum \theta_\infty} - \frac{\text{Tr}\{\bar{\theta}_d\}}{\sum \theta_\infty} \right) = C_d^w \times \frac{\sum \theta_d}{\sum \theta_\infty}$$

where $\text{Tr}\{\cdot\}$ is the trace operator, and the sum of all the elements of Φ_d matrix is presented in the denominator. C_d^w stands for the within connectedness measure, which reflects the connectedness within the specific frequency band. Thus, the frequency-based connectedness splits the overall connectedness into various components (or cycles) that add up to the original connectedness measure.

By adopting the methodology of Baruník and Krehlík (2018) which distinguishes between high, medium, and low frequency bands that can reflect various investment horizons and risk preferences of heterogeneous investors, we can conduct a thorough inspection of the time evolution of dynamic overall and horizon-specific connectedness among major stock markets.

3.2.3 EPU and Dynamic Connectedness Between Stock Markets

Several recent studies have argued that the dependence and connectedness among financial assets and across countries (regions) are affected by EPU (Badshah et al., 2019; Fang et al., 2017, 2018; Li & Peng, 2017; Li et al., 2018; Matkovskyy et al., 2020). These studies document that EPU negatively impacts the correlations between these variables. Therefore, we argue that EPU is a potential common factor that drives the connectedness among financial variables attributed to heterogeneous frequency responses to shocks.

After computing the time-varying spillover indices based on the TVP-VAR model, we examine whether EPU and confirmed COVID-19 cases simultaneously drive the volatility connectedness among global stock markets during the COVID-19 crisis. To this end, we estimate the following model using OLS, which is similar to those of Erdem (2020) and Engelhardt et al. (2021):

$$\text{Connectedness}_t = \alpha_t + \beta_1 \text{GEP}U_t + \beta_2 \text{Cases}_t + \beta_3 \text{GEP}U_t * \text{Cases}_t + \beta_4 \text{VIX}_t + \varepsilon_t$$

where connectedness is the weekly measure for volatility connectedness among the 16 global stock market indices, calculated as the 5-day moving average of total volatility spillover index with realized variance (RV).⁶ Changes in governments' economic policies in different countries are controlled by including the GEPU constructed by Baker et al. (2016), and Cases_t is the logarithm of one plus the number of confirmed COVID-19 cases (deaths) per million inhabitants in week t .⁷ VIX is the CBOE stock market volatility index. We also add the interaction terms between EPU

⁶ In the robustness check, we also use weekly measure for volatility connectedness index with realized variance (RV), realized semi-variance (RSV) and bi-power variation (BV) in time–frequency domain.

⁷ GEPU is a GDP-weighted average of national EPU indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States (Baker et al., 2016, 2022). The EPU index is provided at monthly frequency, while our spillover indices are calculated weekly. Therefore, we interpolate the monthly EPU index to weekly frequency by cubic spline.

and confirmed COVID-19 cases (deaths) per million inhabitants to examine the confounding effects of EPU on volatility connectedness among global stock markets.

4 Empirical Results

4.1 Descriptive Statistics

Descriptive statistics of the daily returns and all volatility measures are given in Table 1. All the time series of daily returns are leptokurtic, i.e., with extreme outliers. None of the time series are close to Gaussian distributions, which is confirmed by the statistics of the Jarque–Bera test. Shanghai stock exchange (SSEC) of China has the highest daily average return of 0.13% during our sample period, while NIFTY 50 (NSEI) of India has the lowest daily average return of -0.10%.

Regarding the volatility, we observe that the SSEC of China exhibits the highest average realized volatility, while Madrid general index (SMSI) has the lowest average volatility during our sample period. The magnitude of volatility of Shanghai composite index is almost twice that of Madrid general index. In fact, the investor structure in China's stock market differs substantially from that of developed markets. For example, the ratio of turnover by retail investors in Chinese stock market is much higher than that in developed countries' stock markets. In addition, unlike the US stock market, Chinese investors are prone to buy stocks with recent extreme gains (i.e., chasing winners) (Wang et al., 2022a, 2022b). Therefore, China's stock market is largely dominated by retail investors who prefer to speculate and buy winners, which partially explains the puzzle of excess stock price volatility in China's stock market (Li et al., 2018; Su & Wang, 2021).

However, Russel 2000 (RUT) exhibits the largest maximum value of volatility, indicating frequent volatility jumps. The volatility series are unsurprisingly positively skewed. All the realized volatility series deviate from normal distributions as indicated by the skewness and kurtosis values, as well as by the Jarque–Bera test. The results also show evidence of serial correlations of volatilities as demonstrated by the Ljung-Box test. There is also very strong evidence of stationarity for all the daily time series as indicated by the ADF test.

4.2 Volatility Spillovers for the Full Sample Period

Our full sample covers the period spanning from January 2015 to June 2022. Panel A of Table 2 presents the results of volatility spillover index with realized variance (RV) over the whole sample period by utilizing Diebold and Yilmaz (2012)'s spillover index, which indicates the degree of volatility spillover across all frequency bands. The spillover index lies between 0 and 100. FROM represents shocks from others, TO represents shocks to others, and NET indicates the net directional connectedness of spillover, calculated by subtracting the total directional connectedness "TO" others from "FROM". If NET is greater than zero, it indicates that the country is a net transmitter of shocks during the period, otherwise, it will

Table 1 Descriptive statistics

Index	N	Mean	Std Dev	Min	Max	Skew	Kurt	ADF	J-B test
<i>Descriptive statistics for daily return</i>									
AEX	1957	0.14	7.93	-60.38	49.18	-0.78	9.42	-13.14***	0.74***
BFX	1957	-0.02	8.39	-103.43	46.91	-1.51	19.67	-12.26***	3.23***
FCHI	1957	0.18	8.61	-71.62	57.94	-0.93	11.70	-13.37***	1.15***
FTMIB	1957	-0.33	10.06	-129.76	37.89	-1.71	19.47	-12.67***	3.19***
FTSE	1957	0.21	10.42	-103.00	71.84	-0.90	13.06	-13.34***	1.42***
GSPTSE	1957	-0.21	6.92	-84.53	54.05	-1.81	43.97	-12.83***	15.88***
IXIC	1957	0.23	9.56	-68.31	46.29	-0.83	10.09	-12.86***	0.85***
KS11	1957	-0.60	7.81	-102.08	54.95	-0.30	9.4	-13.23***	0.72***
SPX	1957	-0.62	10.34	-69.93	51.51	-0.16	5.45	-13.09***	0.24***
N225	1957	-0.11	8.65	-56.02	29.58	-1.47	21.05	-11.84***	3.68***
NSEI	1957	-0.85	9.09	-63.47	95.14	-0.79	8.48	-12.61***	0.61***
OSEAX	1957	0.41	11.10	-98.30	58.31	-1.17	14.18	-12.23***	1.69***
RUT	1957	-0.09	11.59	-123.79	69.37	-1.49	17.88	-12.94***	2.68***
SMSI	1957	-0.59	10.07	-90.05	66.92	-0.97	18.11	-12.78***	2.71***
SSEC	1957	1.27	12.18	-70.23	77.51	-1.21	8.04	-11.80***	0.58***
STI	1957	-0.23	6.66	-40.83	48.10	-0.53	9.11	-12.40***	0.69***
<i>Descriptive statistics for daily realized variance (5-min sub-sampled)</i>									
AEX	1957	0.77	1.74	0.03	31.83	10.87	153.33	-7.79***	195.96***
BFX	1957	0.75	1.55	0.04	27.09	9.42	118.12	-7.67***	116.90***
FCHI	1957	0.88	1.83	0.05	36.61	10.42	149.44	-7.86***	186.03***
FTMIB	1957	0.89	1.94	0.02	28.13	8.17	88.26	-7.77***	65.83***
FTSE	1957	0.54	0.70	0.04	10.89	5.85	55.48	-6.53***	26.27***
GSPTSE	1957	0.54	0.73	0.05	22.59	16.59	446.51	-7.71***	1638.03***
IXIC	1957	0.61	1.67	0.00	38.14	14.76	264.84	-7.93***	580.24***
KS11	1957	0.80	1.86	0.02	29.53	10.07	126.94	-7.51***	134.97***
SPX	1957	0.72	2.07	0.01	36.91	10.51	137.11	-7.80***	157.22***
N225	1957	0.68	1.99	0.01	47.42	13.61	236.08	-8.04***	461.47***
NSEI	1957	0.51	1.05	0.00	22.78	11.54	181.87	-8.09***	274.63***
OSEAX	1957	0.49	2.65	0.05	45.31	8.18	91.89	-6.58***	71.18***
RUT	1957	0.65	1.70	0.06	54.90	20.04	562.79	-8.06***	2601.14***
SMSI	1957	0.42	1.12	0.01	19.89	10.54	136.93	-7.36***	156.83***
SSEC	1957	0.93	1.61	0.06	27.81	8.96	108.22	-8.21***	98.31***
STI	1957	0.82	1.40	0.01	29.79	9.32	136.53	-7.54***	155.15***
<i>Descriptive statistics for daily realized semi-variance (5-min sub-sampled)</i>									
AEX	1957	0.45	1.11	0.01	23.22	11.59	174.50	-8.32***	253.19***
BFX	1957	0.43	0.95	0.03	19.19	10.59	153.42	-7.54***	196.00***
FCHI	1957	0.50	1.12	0.02	24.31	11.27	175.02	-8.17***	254.47***
FTMIB	1957	0.48	1.35	0.01	46.35	21.98	698.37	-8.30***	4000.93***
FTSE	1957	0.32	0.98	0.01	36.85	27.61	987.28	-8.67***	7989.30***
GSPTSE	1957	0.35	1.16	0.03	45.72	31.79	1204.74	-10.66***	11,892.31***
IXIC	1957	0.36	0.98	0.00	27.18	15.69	338.71	-8.98***	945.43***

Table 1 (continued)

Index	N	Mean	Std Dev	Min	Max	Skew	Kurt	ADF	J-B test
KS11	1957	0.46	1.05	0.01	21.93	10.37	152.37	-7.71***	193.22***
SPX	1957	0.42	1.37	0.00	28.09	12.92	210.91	-8.28***	368.91***
N225	1957	0.52	2.15	0.01	61.47	19.74	488.44	-8.29***	1962.12***
NSEI	1957	0.28	0.61	0.01	17.61	15.50	366.16	-7.63***	1103.34***
OSEAX	1957	0.44	1.50	0.02	20.89	7.35	71.30	-6.82***	43.30***
RUT	1957	0.62	4.50	0.01	187.13	36.88	1506.25	-9.67***	18,582.32***
SMSI	1957	0.25	1.05	0.01	29.91	21.15	536.76	-8.29***	2368.74***
SSEC	1957	0.55	1.97	0.02	59.47	23.75	655.21	-9.60***	3526.24***
STI	1957	0.45	0.81	0.00	17.36	9.93	153.00	-7.47***	194.51***
<i>Descriptive statistics for daily bi-power variation (5-min sub-sampled)</i>									
AEX	1957	0.87	2.10	0.03	42.00	11.97	186.08	-7.99***	287.61***
BFX	1957	0.85	1.80	0.04	36.89	10.31	146.65	-7.57***	179.20***
FCHI	1957	0.99	2.12	0.04	43.62	10.80	160.48	-7.89***	214.25***
FTMIB	1957	0.94	2.27	0.03	59.63	13.03	263.24	-8.02***	571.78***
FTSE	1957	0.62	1.26	0.03	36.96	15.52	380.81	-7.45***	1192.77***
GSPTSE	1957	0.68	1.41	0.06	52.25	26.36	922.00	-9.50***	6968.58***
IXIC	1957	0.70	2.56	0.00	93.36	26.55	896.27	-9.50***	6586.69***
KS11	1957	0.88	1.89	0.03	30.83	9.20	110.24	-7.58***	102.07***
SPX	1957	0.81	2.36	0.01	41.53	11.05	152.64	-8.06***	194.38***
N225	1957	0.99	2.77	0.01	66.68	14.42	277.47	-7.68***	635.86***
NSEI	1957	0.54	1.08	0.01	26.08	12.54	223.93	-7.48***	414.88***
OSEAX	1957	0.79	2.86	0.05	41.46	7.68	78.68	-6.64***	52.52***
RUT	1957	1.16	5.02	0.07	196.96	31.26	1184.43	-8.20***	11,494.66***
SMSI	1957	0.47	1.49	0.02	36.86	15.44	311.66	-7.77***	801.45***
SSEC	1957	1.03	2.47	0.09	61.05	16.59	362.43	-8.55***	1082.28***
STI	1957	0.88	1.46	0.01	27.28	8.48	105.69	-7.65***	93.64***

This table presents the descriptive statistics of daily returns and realized volatility measures of the 16 major stock market indices. The sample period is January 2015 to Jun 2022. For Mean, Std Dev, Min, and Max, the values are expressed in scientific notation as $\times 10^{-4}$. For J-B test, the values are expressed in scientific notation as $\times 10^4$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively. For a full list of the stock market indices adopted in this study, please see Table 6 in the Appendix

be a net receiver of shocks. The results in Panel A of Table 2 show that there is substantial evidence of volatility spillovers in the global stock markets, as the total spillover index is as high as 80.55. In fact, the forecast error variance of each stock market index can be logically divided into two parts—its own contribution and contributions from other stock markets. The untabulated results suggest that the dynamic volatility spillovers in global stock markets are apparently dominated by the own-market structure, as the values in the diagonal are much larger than those in the non-diagonal cells which represents cross-market effects. Among the 16 major stock markets, China's Shanghai composite index (SSEC) exhibits the highest

Table 2 Volatility spillover measures for RV—DY method

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KS11	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM
<i>Panel A: full sample</i>																	
TO	8.11	5.53	7.74	7.69	0.27	2.85	1.17	6.18	10.57	5.04	0.96	0.18	3.20	9.84	2.70	8.53	80.55
FROM	5.52	5.52	5.49	5.27	5.05	4.52	5.73	5.38	5.27	5.30	5.64	2.02	4.61	5.18	4.93	5.13	N.A
NET	2.59	0.01	2.25	2.42	-4.78	-1.67	-4.56	0.80	5.30	-0.26	-4.68	-1.84	-1.41	4.66	-2.23	3.40	N.A
<i>Panel B: COVID-19 period</i>																	
TO	7.08	3.92	6.58	6.32	0.30	5.43	0.35	4.96	11.15	6.17	0.27	0.45	3.85	11.33	7.22	10.66	86.03
FROM	5.67	5.70	5.64	5.56	5.62	4.80	6.09	5.66	5.35	5.42	5.88	3.76	4.80	5.28	5.49	5.32	N.A
NET	1.41	-1.78	0.94	0.76	-5.32	0.63	-5.74	-0.70	5.80	0.75	-5.61	-3.31	-0.95	6.05	1.73	5.34	N.A

This table presents the results of volatility spillovers among global stock markets over the whole sample period and during the COVID-19 period, by utilizing Diebold and Yilmaz (2012)'s spillover index in the time domain. The COVID-19 period in this study is defined as spanning from February 4, 2020 to June 30, 2022. To measure volatility, we utilize realized variance (RV), realized semi-variance (RSV), and bi-power variation (BV), all calculated based on rolling sampling price series at 5-min intervals. To conserve space, the results for RSV and BV are provided in Table 7 in the Appendix. FROM represents shocks from others, TO represents shocks to others, and NET indicates the net directional connectedness of spillover, calculated by subtracting the total directional connectedness "TO" others from "FROM". If NET is greater than zero, it indicates that the country is a net transmitter of shocks during the period, otherwise, it will be a net receiver of shocks. The total spillover index is highlighted, as shown in the bottom right cell of the matrix of each panel

own-market volatility spillovers, followed by Nikkei 225 (N225) and Oslo exchange all-share index (OSEAX). Overall, the cross-market volatility spillover effects are mostly evident for stock markets in the same region. Interestingly, Shanghai Composite Index (SSEC) has the lowest volatility spillover from (to) other major stock markets (i.e., volatility spillover index of 0.18 and 2.02), probably due to strict capital controls in mainland China. For example, Kitano and Zhou (2022) document that China's capital controls are very effective in controlling the volume of equity flows in China, which mitigates the volatility spillover effect.

In addition, Table 7 in the Appendix shows the magnitudes of volatility spillovers among the 16 sample stock markets with realized semi-variance (RSV) and bi-power variation (BV) respectively, during the whole sample period and the COVID-19 period. The total spillover index is 76.88 and 82.28 for realized semi-variance and bi-power variation respectively, for the full sample period. Unsurprisingly, the connectedness index with bi-power variation is substantially higher, which corrects for jumps in stock price process and therefore increases the co-movements between stock returns and volatility. Overall, the results consistently suggest the existence of strong volatility spillovers among global stock markets.

4.3 Volatility Spillovers During the COVID-19 Pandemic

In this subsection, we test whether the COVID-19 global pandemic outbreak initially reported since February 2020 has led to a structural change in the volatility connectedness among global financial markets. Specifically, we examine volatility spillovers and their time–frequency dynamics among the 16 major global financial markets from the outbreak of COVID-19 to present. In Panel B of Table 2, the total spillover index measures the average proportion of volatility forecast error variance explained by shocks emanating from other stock markets for the period between February 2020 and June 2022 (i.e., the COVID-19 outbreak period), by utilizing the Diebold and Yilmaz (2012)'s spillover methodology.

Similar to the results as shown in Panel A of Table 2, we observe that own-country stock market spillovers contribute to the largest portion of forecast error variances, as the diagonal cells possess higher values compared to the non-diagonal elements. During the COVID-19 period, the total spillover index with realized variance (RV) increases to approximately 86.03 as shown in Panel B of Table 2. The result indicates that global stock markets are not independent of each other, particularly during turbulent times, and the volatility spillovers accounts for as high as 86% of volatility forecast error variances on average. This large value indicates that the transmission of international stock market shocks is an important source of domestic stock price fluctuations. The result also signifies an intensification of the volatility connectedness during turbulent periods, which is in line with previous studies of fiat currencies (e.g., Greenwood-Nimmo et al., 2016), cryptocurrencies (e.g., Yi et al., 2018; Kumar et al., 2022), and equity markets (Wang et al., 2022a, 2022b; Youssef et al., 2021). During the COVID-19 period, China's Shanghai composite index (SSEC) still has the lowest volatility spillover from other major stock markets (i.e., volatility spillover index of 3.76), but Korea Composite stock price index

(KOSPI) exhibits the lowest volatility spillover to other stock markets (i.e., volatility spillover index of 0.27).

In addition, Table 7 in the Appendix reports the magnitudes of volatility spillovers for realized semi-variance (RSV) and bi-power variation (BV) during the COVID-19 period respectively. The total spillover index increases to 83.64 and 87.70 for realized semi-variance and bi-power variation respectively, which is obviously larger than that of the full sample, indicating that the volatility spillover effect intensifies over the COVID-19 pandemic period, probably due to the rising risk uncertainty and risk contagion in the turbulent period (Su et al., 2023).

4.4 Time–Frequency Volatility Spillovers for the Full Sample Period

Along with the overall connectedness among major stock market indices around the world, we also inspect the investment-horizon-specific connectedness among these markets. We follow the conventional standard and split the spectrum into three bands—short-term (i.e., one day to one week), medium-term (i.e., one week to one month), and long-term (i.e., over one month) (Kumar et al., 2022). Table 3 presents the results of volatility spillover index with realized variance (RV) in the short-term, medium-term, and long-term frequency bands, following Baruník and Krehlík (2018)'s frequency connectedness methodology.⁸ The total spillover index in the short-, medium-, and long-term, as shown in the bottom right cell of Panel A to Panel C of the matrix, is 69.97, 82.22, and 87.52 respectively, indicating a fairly sizable level of volatility spillovers in the frequency domain and an increasing inter-connectedness with the larger frequency ranges.

Panel A to Panel C of Table 3 show the volatility connectedness and spillovers split between the frequency bands. In addition, *ABS* and *WTN* in Table 3 refer to absolute- and within- connectedness measures, respectively. Note that the pairwise spillover indices with realized variance for different frequency bands sum to the overall spillover index as shown in Table 2. The results suggest the dominance of the low frequency component (i.e., long-term horizon) in the spillover dynamics, which accounts for 33.97 (i.e., the sum of *To_ABS* or *From_ABS* in Panel C of Table 3) of the total spillover index of 80.55, i.e., almost 42.18% of the total spillover index. In contrast, the high frequency component (i.e., short-term horizon) in the spillover dynamics only accounts for 26.46% of the total spillover index (i.e., $21.31/80.55 = 26.46\%$). The untabulated results for BV and RSV provide similar evidence that the total spillovers among global stock markets are mostly driven by low frequency components for the full sample. Our results are consistent with the findings of Wang et al., (2022a, 2022b). Wang et al., (2022a, 2022b) show that the total spillovers among stock markets have been driven by low frequency components. However, the dominance of the long-term volatility connectedness

⁸ To measure volatility, we utilize realized variance (RV), realized semi-variance (RSV), and bi-power variation (BV), all calculated based on rolling sampling price series at 5-min intervals. However, due to space limitation, we omit the results for RSV and BV, which are available upon request by contacting the authors.

Table 3 Volatility spillover measures for RV—BK method

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KS11	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM_ABS	FROM_WTH	
Panel A: short time horizon—1–7 days																			
TO_ABS	2.18	1.29	1.98	1.79	0.15	0.98	0.41	1.37	2.71	1.95	0.40	0.09	0.95	2.49	0.90	1.68	21.31	N/A	
TO_WTH	7.15	4.23	6.50	5.89	0.48	3.21	1.35	4.49	8.91	6.42	1.33	0.28	3.10	8.18	2.95	5.51	N/A	69.97	
FROM_ABS	1.18	1.03	1.07	1.07	0.77	2.93	1.69	0.53	1.41	1.91	0.48	0.43	2.31	1.86	1.65	1.00	N/A	N/A	
FROM_WTH	3.87	3.37	3.50	3.51	2.54	9.63	5.55	1.75	4.62	6.26	1.57	1.40	7.57	6.12	5.43	3.28	N/A	N/A	
Panel B: medium time horizon—7–30 days																			
TO_ABS	2.53	1.84	2.46	2.50	0.06	0.84	0.37	2.09	3.27	1.36	0.29	0.04	0.94	3.07	0.81	2.79	25.27	N/A	
TO_WTH	8.24	6.00	8.02	8.13	0.19	2.73	1.19	6.80	10.63	4.43	0.96	0.15	3.05	9.98	2.65	9.09	N/A	82.22	
FROM_ABS	1.90	1.93	1.87	1.92	1.25	0.88	1.46	1.89	1.76	1.53	1.77	1.00	1.14	1.42	1.64	1.90	N/A	N/A	
FROM_WTH	6.17	6.29	6.09	6.26	4.06	2.87	4.76	6.16	5.72	4.98	5.75	3.27	3.71	4.61	5.33	6.18	N/A	N/A	
Panel C: long time horizon—beyond 30 days																			
TO_ABS	3.40	2.40	3.29	3.39	0.07	1.04	0.40	2.72	4.59	1.72	0.27	0.05	1.31	4.29	0.99	4.05	33.97	N/A	
TO_WTH	8.76	6.17	8.49	8.74	0.17	2.67	1.02	7.02	11.82	4.44	0.68	0.12	3.39	11.05	2.55	10.44	N/A	87.52	
FROM_ABS	2.45	2.56	2.56	2.27	3.03	0.70	2.58	2.95	2.11	1.86	3.39	0.59	1.16	1.90	1.64	2.24	N/A	N/A	
FROM_WTH	6.31	6.59	6.58	5.86	7.80	1.81	6.64	7.60	5.43	4.79	8.74	1.51	3.00	4.89	4.22	5.76	N/A	N/A	

This table presents the results of volatility spillovers in the frequency domain over the whole sample period. Panel A to Panel C show the volatility spillovers in the short-term, medium-term, and long-term frequency bands, following Barunik and Krehlík (2018), respectively. Due to space limitation, the results for realized semi-variance (RSV) and bi-power variation (BV) are available upon request. FROM represents shocks from others, and TO represents shocks to others. The abbreviations ABS and WTH refer to absolute and within, respectively. The total spillover index is highlighted, as shown in the bottom right cell of the matrix of each panel

in the stock market is in striking contrast to that of cryptocurrency market and commodity market, where most of the return and volatility connectedness occurs in the short-term (Ferrer et al., 2018; Kumar et al., 2022).

4.5 Time–Frequency Volatility Spillovers During the COVID-19 Pandemic

Similarly, Table 4 presents the connectedness and spillover measures split between the frequency bands for the period between February 2020 and June 2022, i.e., the COVID-19 pandemic period. Foremost, the structure of the connectedness changes significantly when compared to the full sample period. Interestingly, we document the dominance of the volatility spillover over the medium- to long-term horizon as the low- to medium-frequency components (i.e., approximately 7 to 30 days and over 30 days) in the spillover dynamics now accounts for as high as 78.04% of the total spillover index (i.e., $30.67/86.03=35.65\%$ for the medium-term horizon and $36.46/86.03=42.37\%$ for the long-term horizon respectively), which show that the volatility connectedness during this pandemic period is even more driven by medium-frequency components compared to that of the full sample period. That is, the magnification effects mostly apply to the medium-term frequency connectedness, i.e., the COVID-19 has a substantial impact on the connectedness among global stock markets in the medium- to long-term horizon. Similarly, cross-market spillovers of realized semi-variance (RSV) and bi-power variation (BV) magnify during the COVID-19 pandemic period and the frequency-based analysis suggests that the volatility spillover over the medium- to long-term horizon dominates that over the short-term horizon.⁹

Recent research has widely examined the impacts of the COVID-19 pandemic on volatility spillovers and unveiled that the COVID-19 outbreak induces finance contagion, probably due to the deteriorating economic situation and risk sentiment among global investors in the crisis period (Akhtaruzzaman et al., 2022; Corbet et al., 2022; Guo et al., 2021; Nguyen et al., 2021; Yarovaya et al., 2021a, 2021b). Unlike the conclusions drawn by Kumar et al. (2022) that the short-term horizon dominates in both returns and volatility spillovers in the cryptocurrency market during the COVID-19 period, we find that the COVID-19 pandemic has mostly strengthened the volatility connectedness among global stock markets over the medium- to long-term horizon, consistent with previous studies which have documented that crisis such as global financial crisis and Eurozone sovereign debt crisis (Mensi et al., 2018), and the outbreak of COVID-19 (Cheng et al., 2022) can lead to intensified volatility spillovers in global stock markets. Our results are in line with those of earlier studies. Wang et al., (2022a, 2022b) show that the total spillovers among stock markets driven by low frequency components peak at the end of March 2020 and then decline. However, our findings suggest that the COVID-19 has led to some fundamental changes in the global economy and its impact on contagion in financial markets can be long-lasting. Even with its importance regarding policy implications, there are few influential papers on this issue yet, which certainly needs to be addressed more intensively.

⁹ Due to space limitation, we omit the results for RSV and BV, which are available upon request by contacting the authors.

Table 4 Volatility spillover measures for RV during the COVID-19 outbreak—BK method

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KS11	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM_ABS	FROM_WTH	
<i>Panel A: short time horizon—1–7 days</i>																			
TO_ABS	1.45	0.65	1.28	1.55	0.14	1.11	0.26	1.35	2.39	1.77	0.19	0.17	0.96	2.45	1.40	1.78	18.90	NA	
TO_WTH	5.85	2.62	5.16	6.25	0.56	4.47	1.05	5.42	9.60	7.11	0.76	0.68	3.86	9.85	5.64	7.16	N.A	76.03	
FROM_ABS	0.88	0.87	0.82	0.94	1.06	1.64	2.20	0.56	1.02	1.55	0.57	1.10	2.63	1.32	0.91	0.84	N.A	N.A	
FROM_WTH	3.54	3.49	3.28	3.77	4.27	6.61	8.86	2.26	4.12	6.22	2.29	4.43	10.57	5.32	3.65	3.36	N.A	N.A	
<i>Panel B: medium time horizon—7–30 days</i>																			
TO_ABS	2.57	1.49	2.40	2.26	0.08	1.93	0.07	1.83	3.98	1.93	0.07	0.11	1.25	4.16	2.62	3.95	30.67	NA	
TO_WTH	7.34	4.27	6.85	6.46	0.22	5.52	0.21	5.25	11.37	5.53	0.19	0.30	3.57	11.89	7.48	11.29	N.A	87.75	
FROM_ABS	2.24	2.23	2.22	2.33	1.50	1.35	1.57	2.23	2.05	1.78	2.14	1.78	1.15	1.70	2.30	2.12	N.A	N.A	
FROM_WTH	6.40	6.37	6.35	6.66	4.28	3.85	4.48	6.38	5.88	5.09	6.12	5.08	3.30	4.88	6.58	6.06	N.A	N.A	
<i>Panel C: long time horizon—beyond 30 days</i>																			
TO_ABS	3.06	1.78	2.90	2.50	0.08	2.39	0.02	1.78	4.79	2.47	0.02	0.17	1.64	4.72	3.20	4.94	36.46	NA	
TO_WTH	7.61	4.43	7.21	6.23	0.20	5.95	0.04	4.42	11.91	6.15	0.04	0.43	4.08	11.75	7.97	12.28	N.A	90.72	
FROM_ABS	2.55	2.61	2.61	2.29	3.07	1.81	2.32	2.87	2.27	2.09	3.17	0.88	1.02	2.25	2.28	2.37	N.A	N.A	
FROM_WTH	6.35	6.49	6.50	5.71	7.63	4.51	5.77	7.13	5.65	5.20	7.90	2.20	2.53	5.59	5.67	5.90	N.A	N.A	

This table presents the results of volatility spillovers in the frequency domain during the COVID-19 pandemic period. Panel A to Panel C show the volatility spillovers in the short-term, medium-term, and long-term frequency bands, following Baruník and Krehlík (2018), respectively. Due to space limitation, the results for realized semi-variance (RSV) and bi-power variation (BV) are available upon request. FROM represents shocks from others, and TO represents shocks to others. The abbreviations ABS and WTH refer to absolute and within, respectively. The total spillover index is highlighted, as shown in the bottom right cell of the matrix of each panel

4.6 Robust Checks

In this subsection, we have conducted a series of robustness checks to check the sensitivity of our results. First, to ensure the same time lengths of estimation periods, we compare the results regarding the COVID-19 pandemic period with other periods of the same window length. Namely, we calculate Diebold and Yilmaz (2012)'s spillover index among the 16 global stock market indices for two sub-periods of the same time length, i.e., pre-COVID (February 2019 to January 2020) and COVID-19 period (February 2020 to January 2021). The results as shown in Table 8 in the Appendix suggest that the total volatility spillover index of the COVID-19 period is significantly larger than that of the pre-COVID-19 period (i.e., 88.61 versus 63.98), indicating a structural change in volatility spillovers among global stock markets since the outbreak of COVID-19. The untabulated results for realized semi-variance (RSV) and bi-power variation (BV) provide similar evidence that the volatility spillovers among global stock markets increase sharply during the turbulent period disrupted by the pandemic.

Second, we re-estimate the results by utilizing the rolling window method. However, the results are omitted for the sake of brevity. Again, the untabulated results confirm our conjecture that the volatility connectedness among global stock markets intensifies during turbulent periods, i.e., the COVID-19 period, as the estimated Diebold and Yilmaz (2012)'s spillover index is significantly larger over the COVID-19 pandemic period, compared to that of the full sample period.

Last but not the least, the number of parameters in the VAR model will increase dramatically as the number of markets under consideration increases, which may lead to the estimation infeasible when the sample size is small. For example, if the VAR model includes $N = 17$ markets and $p = 2$ lag periods, there will be 595 parameters to be estimated. Thus, traditional VAR models may experience insufficient degrees of freedom and encounter the so-called "curse of dimensionality" problem.

In order to address the above issue, following Demiret et al. (2018), we propose the least absolute shrinkage and selection operator (LASSO) to reduce the number of parameters to be estimated in the VAR model. The basic idea of LASSO method is to use regularization methodology to constrain the sum of absolute values, compress the values of some coefficients to 0 through penalty terms, and thereby obtain a model with much smaller degrees of freedom (Tibshirani, 1996). The code for implementing LASSO method using the R software is provided in Appendix 2. The results of the volatility spillover indices using LASSO method, as provided in Table 9 in the Appendix, show similar findings that the volatility spillovers among global stock markets increase sharply during the turbulent period of the COVID-19 pandemic.

4.7 EPU and Volatility Spillovers

The rapid spread of COVID-19 has caused unprecedented effects on global financial markets and substantially increased geopolitical risks and EPU worldwide. We further

investigate the effect of EPU on the connectedness between the 16 stock market indices examined in this study. For comparison, we examine the effect of the EPU during the entire period and during the COVID-19 pandemic. Namely, we conduct the OLS estimations over the full sample period and across different sub-periods.

To determine whether mean connectedness between stock markets varies through time and how it is affected by the COVID-19 pandemic, we estimate the time-varying connectedness measures using rolling-sample estimation, and perform OLS estimations separately. For the full sample period, the coefficient on EPU is positive and statistically significant. Similarly, for the COVID-19 pandemic period, we find a positive and statistically significant coefficient on EPU and Cases (Deaths) growth rate, as reported in Table 5, implying that volatility spillovers among major stock markets increase with an increase in global economic uncertainty as well as growth rate of confirmed COVID-19 cases (deaths). The empirical findings are generally in line with Erdem (2020), Engelhardt et al. (2021), and Cheng et al. (2022).

To examine the potentially confounding effect of EPU on stock market connectedness during the COVID-19 pandemic, we add the interaction terms between EPU and the growth rate of confirmed COVID-19 cases (deaths) per million inhabitants. We again find a positive and statistically significant coefficient on the interaction term between EPU and growth rates of confirmed COVID-19 cases (deaths), supporting our conjecture that volatility connectedness in global stock markets significantly increases when the growth rate of confirmed COVID-19 cases increases, which may be generated partly by increased selling pressure from panic-stricken investors.¹⁰ Similar results are documented for the impact of the CBOE market volatility index (VIX) on connectedness before and during the COVID-19 outbreak.

5 Conclusion

We uncover the dynamic volatility spillovers in both time and frequency domains among 16 major stock market indices, spanning the period January 2015 to June 2022. Moreover, we examine the mediating effect of EPU on that relationship. We investigate those for the full sample period and the COVID-19 outbreak period (i.e., February 2020 to June 2022). The results show that there is substantial evidence of volatility spillovers in the global stock markets and that volatility connectedness is magnified during the turbulent period of COVID-19, which is in line with previous studies on various financial markets (Cheng et al., 2022; Kumar et al., 2022). However, the magnification effects mostly apply to the medium-term frequency connectedness, i.e., the COVID-19 has a strengthening impact on the connectedness among global stock markets mainly in the medium to long term, which have important implications for individual

¹⁰ Although not reported for reasons of brevity, we perform several robustness tests to ensure the validity of our results. First, we perform pooled OLS regressions for all stock markets examined in this study, where we include the two main effects as well as the interaction term, and find qualitatively similar results. Second, we use the connectedness index with realized semi-variance (RSV) and bi-power variation (BV) as our dependent variables and obtain similar results for both the full sample and the subsample of the COVID-19 period. Third, we utilize the overall index as well as the frequency-specific connectedness indices as the dependent variables and draw similar conclusions.

Table 5 The relationship between EPU and connectedness among global stock markets

Dep. Var. =					
Total spillover index	(1)	(2)	(3)	(4)	(5)
<i>Panel A: before the COVID-19 period</i>					
Intercept	50.23*** (26.28)				
GEPU	0.039*** (5.12)				
Cases	N.A				
Deaths	N.A				
Cases * GEPU	N.A				
Deaths * GEPU	N.A				
VIX	0.035*** (19.08)				
Observations	389				
R-squared	0.450				
<i>Panel B: during the COVID-19 period</i>					
Intercept	65.93*** (38.99)	62.03*** (29.11)	61.93*** (26.97)	52.19*** (25.35)	58.88*** (24.97)
GEPU	0.042*** (7.22)			0.033*** (4.99)	0.035*** (5.76)
Cases		0.057*** (8.99)		0.028*** (5.32)	
Deaths			0.014** (2.02)		0.000 (1.34)
Cases * GEPU				0.035*** (5.88)	
Deaths * GEPU					0.022*** (3.41)
VIX	0.022*** (4.18)	0.033*** (3.38)	0.034*** (3.56)	0.017*** (3.82)	0.012*** (3.17)
Observations	73	73	73	73	73
R-squared	0.442	0.467	0.570	0.654	0.616

This table presents the results regarding the relationship between EPU and volatility connectedness from OLS regressions over the pre-COVID-19 period in Panel A and the COVID-19 period (i.e., February 4, 2020 to June 30, 2022) in Panel B. The dependent variable is weekly rolling estimates of the total spillover index as calculated in Table 2. GEPU stands for the Global Economic Policy Uncertainty Index retrieved from FRED, Federal Reserve Bank of St. Louis. Cases (Deaths) is the log growth rate of confirmed COVID-19 cases (deaths) per million inhabitants. VIX is the stock market volatility index of CBOE. In columns (4) and (5) of Panel B, we additionally include the interaction between EPU and growth rates of confirmed COVID-19 cases (deaths). Standard errors corrected for heteroskedasticity and autocorrelation are reported in parentheses. *, ** and *** indicates statistical significance at the 10%, 5% and 1% level respectively

investors, portfolio managers, policymakers, and central banks. Moreover, we find that EPU significantly affects the volatility spillovers among global stock market indices, particularly under the context of COVID-19.

Undoubtedly, a good understanding of volatility spillover among global financial markets can enhance the design of policies to contain it and improve the accountability of central banks, which allows policymakers to take appropriate actions to reduce the systemic risk and properly target the main factors responsible for driving those catastrophic events (Cappiello et al., 2015). However, this requires a clearer view of financial market interdependencies and volatility spillovers, as well as a deeper understanding of the incentives and motivations behind such relationships (Jackson & Pernoud, 2021). In the future, new analytical tools such as data mining, machine learning, as well as artificial intelligence could be applied to financial market interconnectedness and contagion analysis to form a holistic and systematic view of risk spillover and financial contagion.

There are several possible avenues for further research. First, it will be interesting to investigate the evolution of industry-level connectedness network for the full sample period and the COVID-19 outbreak period. For example, healthcare and tourism sectors might have vastly different responses to the shocks emanating from the COVID-19. Second, an intraday analysis of connectedness and volatility spillovers using tick-level data appears to be an interesting and promising solution, which allows for a more in-depth discussion on the mechanisms behind financial contagion. Last but not the least, the impact of economic policy uncertainty on risk contagion in financial markets should be considered more widely and comprehensively in academia and government practices.

Appendix 1

See Appendix Tables 6, 7, 8, and 9.

Table 6 List of stock market indices

Symbol	Description	Country (Region)
AEX	Amsterdam stock exchange index	Netherlands
BFX	Bell 20 index	Belgium
FCHI	CAC 40	France
FTMIB	FTSE MIB	Italy
FTSE	FTSE 100	UK
GSPTSE	S&P/TSX composite index	Canada
IXIC	Nasdaq 100	US
KS11	Korea composite stock price index (KOSPI)	Korea
N225	Nikkei 225	Japan
NSEI	NIFTY 50	India
OSEAX	Oslo exchange all-share index	Norway
RUT	Russel 2000	US
SMSI	Madrid general index	Spain
SPX	S&P 500 index	US
SSEC	Shanghai composite index	China
STI	Straits times index	Singapore

This table lists the market indices adopted in this study

Table 7 Volatility spillover measures for RSV and BV—DY method

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KSII	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM
<i>Panel A: RSV</i>																	
Full sample																	
TO	7.78	5.06	7.15	4.30	0.37	2.39	0.64	6.13	9.72	5.77	1.38	0.29	3.72	9.63	2.04	10.50	76.88
FROM	5.47	5.21	5.39	5.45	5.03	4.11	5.78	5.15	5.23	4.91	5.24	1.82	4.26	4.98	4.04	4.79	N.A
NET	2.31	-0.15	1.76	-1.15	-4.66	-1.72	-5.14	0.98	4.49	0.86	-3.86	-1.53	-0.54	4.65	-2.00	5.71	N.A
COVID-19 period																	
TO	6.69	3.37	5.80	4.16	0.31	2.90	0.25	4.92	10.35	5.69	0.79	0.18	3.86	10.89	11.00	12.49	83.64
FROM	5.66	5.45	5.60	5.73	5.65	4.31	6.07	5.57	5.36	5.14	5.71	3.29	4.60	5.20	5.21	5.12	N.A
NET	1.03	-2.08	0.20	-1.57	-5.34	-1.41	-5.82	-0.65	4.99	0.55	-4.92	-3.11	-0.74	5.69	5.79	7.37	N.A
<i>Panel B: BV</i>																	
Full sample																	
TO	7.90	6.31	7.82	8.24	0.27	3.73	0.69	6.55	9.69	4.99	1.15	0.04	4.38	7.41	6.48	6.65	82.28
FROM	5.58	5.58	5.55	5.29	4.84	4.97	5.76	5.48	5.32	5.46	5.72	1.21	5.12	5.52	5.48	5.40	N.A
NET	2.32	0.73	2.27	2.95	-4.57	-1.24	-5.07	1.07	4.37	-0.47	-4.57	-1.17	-0.74	1.89	1.00	1.25	N.A
COVID-19 period																	
TO	8.21	5.54	7.85	8.35	0.20	5.95	0.21	5.61	9.97	8.27	0.24	0.32	4.13	8.41	6.75	7.70	87.70
FROM	5.62	5.69	5.62	5.42	5.62	5.13	6.04	5.71	5.43	5.52	5.95	3.94	5.25	5.57	5.58	5.60	N.A
NET	2.59	-0.15	2.23	2.93	-5.42	0.82	-5.83	-0.10	4.54	2.75	-5.71	-3.62	-1.12	2.84	1.17	2.10	N.A

This table presents the results of volatility spillovers among global stock markets over the whole sample period and during the COVID-19 period, by utilizing Diebold and Yilmaz (2012)'s spillover index in the time domain. The COVID-19 period in this study is defined as spanning from February 4, 2020 to June 30, 2022. Here, we utilize realized semi-variance (RSV) and bi-power variation (BV), all calculated based on rolling sampling price series at 5-min intervals, as proxies for volatility measures. FROM represents shocks from others, TO represents shocks to others, and NET indicates the net directional connectedness of spillover, calculated by subtracting the total, directional connectedness "TO" others from "FROM". If NET is greater than zero, it indicates that the country is a net transmitter of shocks during the period, otherwise, it will be a net receiver of shocks. The total spillover index is highlighted, as shown in the bottom right cell of the matrix of each panel

Table 8 Spillover measures for volatility before and during the COVID-19 outbreak—RV

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KS11	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM
<i>Panel A: pre – COVID-19 period</i>																	
TO	6.92	2.97	5.86	8.54	0.57	2.46	0.84	6.34	8.35	2.02	1.59	1.43	0.96	5.60	4.87	4.67	63.98
FROM	5.12	4.62	5.14	4.91	1.36	3.52	2.22	4.73	4.98	4.21	3.11	1.51	4.08	4.63	4.94	4.88	N.A
NET	1.80	-1.65	0.72	3.63	-0.79	-1.06	-1.38	1.61	3.37	-2.19	-1.52	-0.08	-3.12	0.97	-0.07	-0.21	N.A
<i>Panel B: COVID-19 period</i>																	
TO	7.44	5.79	6.62	6.01	0.60	5.36	0.39	5.34	10.38	7.15	0.30	1.09	5.18	10.76	6.38	9.81	88.61
FROM	5.69	5.71	5.72	5.72	5.90	5.08	6.13	5.78	5.48	5.42	6.06	4.58	4.86	5.41	5.62	5.47	N.A
NET	1.75	0.08	0.90	0.29	-5.30	0.28	-5.74	-0.44	4.90	1.73	-5.76	-3.49	0.32	5.35	0.76	4.34	N.A

This table presents the results of volatility spillovers among global stock markets in the pre-COVID-19 and COVID-19 period respectively, by utilizing Diebold and Yilmaz (2012)'s spillover index in the time domain. To ensure that the two sub-sample periods are of the same time length, the pre-COVID-19 period is defined as spanning from February 2019 to January 2020, and the COVID-19 period is defined as spanning from February, 2020 to January 2022, i.e., each period includes 12 months in total. To measure volatility, we utilize realized variance (RV), realized semi-variance (RSV), and bi-power variation (BV), all calculated based on rolling sampling price series at 5-min intervals. To conserve space, we omit the results for RSV and BV, which are available upon request. FROM represents shocks from others, TO represents shocks to others, and NET indicates the net directional connectedness of spillover, calculated by subtracting the total directional connectedness "TO" others from "FROM". If NET is greater than zero, it indicates that the country is a net transmitter of shocks during the period, otherwise, it will be a net receiver of shocks. The total spillover index is highlighted, as shown in the bottom right cell of the matrix of each panel

Table 9 Volatility spillover measures for RV—LASSO method

	AEX	BFX	FCHI	IXIC	SPX	N225	NSEI	RUT	STI	FTSE	KS11	SSEC	OSEAX	GSPTSE	SMSI	FTMIB	FROM
<i>Panel A: full sample</i>																	
TO	78.87	71.54	78.43	70.20	7.43	40.36	25.07	69.99	106.50	88.98	13.24	7.60	61.53	71.72	75.07	82.99	949.52
FROM	82.47	80.03	82.33	78.01	21.83	57.87	55.92	80.14	81.98	78.86	36.66	24.03	71.80	80.93	80.14	78.51	N.A
NET	-3.60	-8.49	-3.90	-7.81	-14.40	-17.51	-30.85	-10.15	24.52	10.12	-23.42	-16.43	-10.27	-9.21	-5.07	4.48	N.A
<i>Panel B: COVID-19 period</i>																	
TO	106.12	93.10	104.77	89.03	11.11	53.90	26.52	79.60	105.06	90.11	40.54	10.61	75.20	88.28	81.23	71.41	1126.59
FROM	83.99	83.25	84.12	80.48	27.33	66.33	52.53	79.24	82.75	79.24	61.99	37.15	75.05	78.03	78.12	76.99	N.A
NET	22.13	9.85	20.66	8.56	-16.21	-12.44	-26.01	0.36	22.31	10.87	-21.45	-26.54	0.15	10.25	3.11	-5.59	N.A

This table presents the results of volatility spillovers among global stock markets during the full sample period and the COVID-19 period respectively, by utilizing the LASSO method. The COVID-19 period in this study is defined as spanning from February 4, 2020 to June 30, 2022. To measure volatility, we utilize realized variance (RV), realized semi-variance (RSV), and bi-power variation (BV), all calculated based on rolling sampling price series at 5-min intervals. To conserve space, we omit the results for RSV and BV, which are available upon request. FROM represents shocks from others, TO represents shocks to others, and NET indicates the net directional connectedness of spillover, calculated by subtracting the total directional connectedness “TO” others from “FROM”. If NET is greater than zero, it indicates that the country is a net transmitter of shocks during the period, otherwise, it will be a net receiver of shocks. The total spillover index is highlighted, as shown in the bottom right cell of the matrix

Appendix 2: code for LASSO regression

```

path = file.path(file.choose())

DATA = read.csv(path)

setwd (dir = "D:/R-4.3.0/workspace")

library(Spillover)
library(vars)
library(tidyverse)
library(xts)
library(devtools)
library(frequencyConnectedness)
library(ConnectednessApproach)
library(glmnet)
library(foreign)

DATA$DATE <- as.Date(DATA$DATE)
class(DATA$DATE)

xtsdata0 = xts(DATA[,2:17], order.by = DATA[, "DATE"])

##Rolling estimation spilloverRollingDY12 LASSO

dca99 = ConnectednessApproach(xtsdata0,
                              nlag=4,
                              nfore=10,
                              window.size=250,
                              model="LASSO",
                              connectedness="Time",

Connectedness_config=list(TimeConnectedness=list(generalized=TRUE)))

table99 <- as.data.frame(dca99$TABLE)
write.table(table99,"sample99.csv",sep=",")

PlotTCI(dca1)
PlotTO(dca1)
dca = ConnectednessTable(dca1)

write.table(table1,"sample1.csv",sep=",")

```

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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