




## RESEARCH ARTICLE

WILEY

# Global factors and the transmission between United States and emerging stock markets

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## Abstract

In this study, we examine the influence of global factors in driving connectedness among United States and emerging stock markets. For this purpose, we employ widely recognized approaches of and Barunik and Krehlik to estimate connectedness among the underlying markets in time-frequency domains. Also, we use the tests proposed by Péguin-Feissolle and Teräsvirta to examine the impact of global factors on the transmission relationship between United States and emerging stock markets utilizing the non-linear causality tests. The findings validate the influential role of global factors in channeling overall total spillovers between United States and emerging stock markets. However, the results for individual emerging markets show some degree of heterogeneous impact of global factors in driving connectedness across different emerging stock markets. Our robustness results also confirm the main findings. Important implications of findings are discussed for portfolio managers and policymakers.

## KEYWORDS

connectedness, crisis periods, emerging markets, global factors, non-linear causality, US stock market

## 1 | INTRODUCTION

Economic cooperation and global market integration has increased the dependence among financial markets resulting in soaring levels of connectedness. In this spirit, stock markets worldwide experience spillover effects due to close connectedness (Forbes & Rigobon, 2002). Consequently, the connectedness across financial markets has drawn the attention of policymakers, investors, and practitioners around the globe (Carrieri et al., 2007). Recent instances of extreme economic turmoil witnessed in international financial markets necessitate scrutinizing the connectedness and transmission among financial markets as volatility spillovers increase during crisis periods (Diebold and Yilmaz, 2012).

In this backdrop, a large body of academic literature investigates integration among stock markets to assess the interconnectedness and spillover effects (e.g., Longin & Solnik, 2001; Forbes & Rigobon, 2002; Soriano & Climent, 2006; Yu et al., 2010; Barunik, Kočenda, & Vácha, 2016; Labidi et al., 2018; Farid et al., 2021; Qureshi, 2021). Instability and volatility in financial markets and growing economic uncertainties have triggered soaring spillovers among financial markets in this era of globalization. This uproar has become a major concern for investors and policymakers. In particular, from investors' perspective, it significantly affects asset allocation, risk alleviation, and diversification strategies (Fong, 2003).

The role of global factors in driving spillovers among financial markets is well-recognized (Mensi et al., 2014).

In particular, the financial and economic repercussions of global factors for asset allocation, risk diversification, and policymaking are widely documented (Yang et al., 2016). In this vein, a thread of previous research has paid close attention to determining global factors' role in driving spillover effects between financial markets (e.g., Brooks & Del Negro, 2004; Gallegati, 2012; Dong & Yoon, 2019). For instance, Al Nasser and Hajilee (2016) uncover short-run linkages among stock markets of emerging and developed countries. Mollah et al. (2016) show contagion effects spillover from the US stock market to different stock markets worldwide.

Similarly, Prasad et al. (2018) show an elevated volatility connectedness among 16 major stock markets. The findings also show that the US market is the largest transmitter of volatility spillovers to other major stock markets globally. In addition, Boamah (2017) investigates the role of global factors in driving contagion effects among the stock markets of emerging countries. The presented evidence confirms the significant impact of global factors in igniting the volatility spillovers among emerging stock markets, especially during the Global Financial Crisis (GFC) 2007-08. The results also reflected the time-varying nature of global factors in driving volatility spillovers among emerging stock markets. More recently, Dong and Yoon (2019) documented the impact of different global factors on the connectedness of stock returns in emerging markets.

Another strand of similar literature explores the impact of global factors on stock returns in different regions. For example, Sugimoto et al. (2014) show that African stock markets are strongly affected by global stock markets, whereas the commodity and currency markets have a moderate impact on stocks markets in Africa. In the same way, many studies uncover the influence of global factors on stock markets in Asia (e.g., Li & Giles, 2015; Kim et al., 2015), Gulf region (Balcilar et al., 2014; Aloui et al., 2015; Mensi et al., 2017) and BRICS countries (Hammoudeh, Sari, Uzunkaya, & Liu, 2013; Mensi et al., 2014; Ji et al., 2018). However, scant attention has been paid to uncover the role of global factors in driving volatility spillovers among emerging stock markets and major stock markets. In this regard, the above context motivates us to explore the role of global factors in driving risk transmission and financial contagion among stock markets. To fill this theoretical void in the literature, we study the impact of global factors on driving connectedness between stock markets.

The strong influence of US stock market on other stock markets around the world is well recognized. Strong evidence illustrates that stock markets around the globe are integrated to US stock market, which clearly shows that

US economic policies and uncertainties affect borders. Given the leading role of US economy, countless research has been on the transmission dynamics between the United States and other economies (Rapach et al., 2013; Boubaker et al., 2016). In the same way, a growing strand of literature documents the volatility spillovers from United States to other stock markets. However, still, the question regarding potential drivers of spillover effects remained unexplored. Therefore, the study contributes to the literature that investigates the connectedness among United States and emerging stock markets. We also provide new insights on the drivers of the underlying relationships.

In order to establish connectedness among emerging stock markets and United States equity market, we estimate time- and frequency-based spillovers. For this purpose, we utilize widely recognized approaches of Diebold & Yilmaz (2012) and Baruník and Křehlík (2018) to estimate the time and frequency transmission between the United States and emerging stock markets. Previously, a long range of models have been employed to approximate the connectedness among financial markets. In the case of dynamic and multivariate models, VAR and VECM are taken as a natural selection. In such models, the relationship is quantified through impulse response functions. However, the effect of one variable depends on the constraints imposed on the covariance matrix, and there is no universal criterion for imposing such constraints. Hence, to avoid the problems associated with the conventional VAR framework, Koop et al. (1996) and Pesaran and Shin (1998) introduced the generalized forecasting error variance decomposition (FEVD) approach. The approach assists in a better understanding of VAR estimates. Using FEVD, Diebold & Yilmaz (2012) developed their measure of connectedness, which measures how variables in a system are closely related. Many studies have recently employed the model (e.g., Naeem et al., 2021; Umar et al., 2021) to measure connectedness among financial markets. In addition, the FEVD model is extended to frequency-domain by Baruník and Křehlík (2018) to investigate connectedness in short-, medium-, and long-run.

Our study supplements the current literature in several ways. First, this study expands the scope and empirical analysis by presenting international evidence on connectedness between the United States and 19 emerging stock markets. The research work in this domain has been confined to individual countries or selected regions.<sup>1</sup> Second, the present study explores various global factors such as US economic policy uncertainty index (EPU), US geopolitical risk index (GPR), stock market volatility (VIX), MSCI world index, TED spread, US

Dollar index, S&P GSCI index, Crude oil WTI, and Gold to determine the causality between United States and emerging stock markets. The existing literature provides various channels of connectedness between United States and emerging markets. Nevertheless, limited channels of transmission effect such as monetary policy, Oil price, currency markets, and EPU have been identified in prior research work (Colombo, 2013; Dakhlaoui & Aloui, 2016). Third, this study takes into account the impact of various economic and financial crises in driving the connectedness among United States and emerging stock markets. Finally, the study applies the Taylor-based nonlinear causality test proposed by Péguin-Feissolle and Terasvirta (1999) and Péguin-Feissolle et al. (2013). The customary Granger linear causality tests ignore important nonlinear assumptions and significant nonlinear causal linkages between the underlying variables (Benhmad 2012; Tiwari et al., 2013). On the contrary, Taylor-based nonlinear causality tests overcome these issues. Besides, Péguin-Feissolle et al. (2013) argue that their test is relatively simple to estimate than nonparametric tests, and the test can work under weak assumptions than the conventional parametric tests. In addition, the application of artificial neural network (ANN)-based nonlinear causality tests delivers robustness to our results.

Our findings provide meaningful insights into the connectedness between United States and emerging stock markets. The findings of the study unearth time- and frequency-based spillovers among United States and emerging stock markets. The findings unveil that connectedness cycles between the underlying stock markets tend to persist longer during financial crises, and contagion effects are also high due to global integration. More importantly, the findings clearly suggest the functional role of global factors in driving connectedness among United States and emerging stock markets. However, the findings for individual markets display the heterogeneous impact of global factors in driving connectedness across the underlying stock markets.

The rest of the paper is organized as follows. Section 2 provides the details regarding data and methodology. Section 3 describes the results and findings of the study. Section 4 offers concluding remarks on the study.

## 2 | DATA AND EMPIRICAL METHODOLOGY

### 2.1 | Data

The study uses daily data for analysis, and each of the individual time series (United States and emerging markets) contains

5957 observations. We collect the data for United States and emerging stock markets from the Morgan Stanley Capital Index (MSCI) database for the period covering 1st January 1996 to 31st December 2018. Also, the GFC period is specified from 1st August 2007 to 30th June 2009. In order to avoid problems relating to currency fluctuations, all the stock indices are denominated in USD. The sample emerging markets consists of Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, and Turkey.

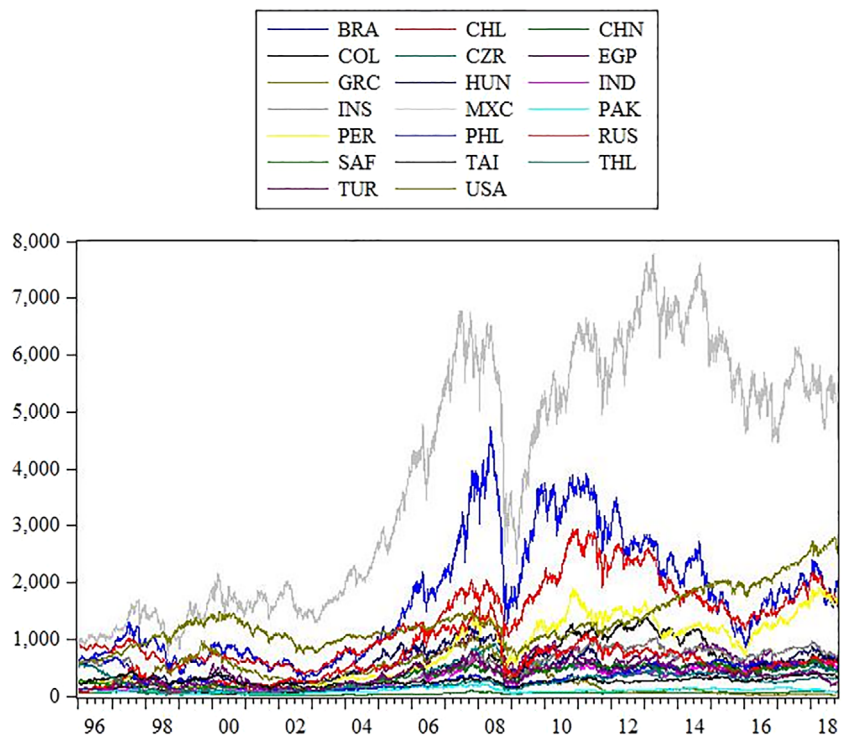
Figure 1 shows the evolution of stock prices for all the sample markets during the study period. In light of the previous research, the study selects various economic and financial global factors such as EPU, GPR, VIX, MSCI world index, TED spread, US Dollar index, S&P GSCI index, crude oil WTI, and gold. The data sources for global factors are listed in Table 1.

Table 2 illustrates the summary statistics of the daily returns for sample stock markets. The table reports name of the country (market), abbreviation, mean returns, standard deviation, skewness, kurtosis, Jarque Bera statistic, and augmented Dickey–Fuller (ADF) statistic. In our sample period, mean return of US market is 0.025%, with a standard deviation of 1.165%. Seven emerging markets, namely, Columbia, Egypt, Hungary, India, Mexico, Peru and Russia have higher mean returns than US market ranging from (0.026%–0.036%). In contrast, the mean return of US stock market is greater than rest of the sample emerging markets. Further, in our sample period, the statistics also unveil negative mean returns for four emerging markets, including Greece, Pakistan, Philippines, and Thailand.

Furthermore, the data also depicts that stock markets of Turkey, Russia, Indonesia, Greece and Brazil are the most volatile among the sample emerging markets. The results of skewness, kurtosis and Jarque-Bera tests highlight that all of the returns series are not normal. Finally, the ADF test results also suggest that all return series are stationary.

Table 3 presents summary statistics for the global factors. The table displays global factor abbreviation, mean returns, standard deviation, skewness, kurtosis, Jarque-Bera statistic and ADF statistic. The series measured through index include EPU, GPR, VIX, MSCI world index, TED spread, USD dollar index and S&P GSCI, while spot price is taken for gold and oil. We calculate returns for variables such as MSCI world, USD dollar index, SP GSCI, oil, and gold. Also, we use the log-transformed EPU, GPR and VIX, while no transformation is performed on TED spread. The statistics display

**FIGURE 1** Evolution of stock markets price series [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**TABLE 1** Global factors

Series	Description	Source	Transformation
EPU	U.S. Economic Policy Uncertainty index	EPU ( <a href="http://www.policyuncertainty.com">www.policyuncertainty.com</a> )	Log
GPR	U.S. Geopolitical Risk index	GPR ( <a href="https://www.matteoiacoviello.com/gpr.htm">https://www.matteoiacoviello.com/gpr.htm</a> )	Log
VIX	Implied Volatility of the S&P 500 index	CBOE ( <a href="http://www.cboe.com">www.cboe.com</a> )	Log
MSCI	MSCI World index	Datastream	Returns
TED	TED Spread	FRED	-
USD	Trade weighted USD index	FRED	Returns
GSCI	S&P GSCI Commodity index	Datastream	Returns
OIL	Crude Oil WTI spot	Datastream	Returns
GLD	Gold Bullion spot	Datastream	Returns

that gold has the highest mean return among all the global factors, whereas the USD dollar index has the lowest volatility. Not surprisingly, the results of skewness, kurtosis and Jarque-Bera tests show that normality assumption for underlying variables does not hold. In the end, ADF statistic illustrates that all the series are stationary.

## 2.2 | Methodology

The empirical analysis of this paper is divided into two parts. First, we follow Diebold and Yilmaz's (2012) and Baruník and Křehlík (2018) connectedness framework to estimate time and frequency transmission between

United States and emerging stock markets. After estimating the spillovers, we then test the impact of global factors in driving connectedness among United States and emerging stock markets by applying nonlinear causality tests.

### 2.2.1 | Diebold and Yilmaz total transmission approach

We follow the connectedness framework of Diebold & Yilmaz (2012) to estimate spillovers among United States and emerging stock markets. The DY measure is derived from the forecast-error variance decomposition (FEVD) matrix centered on the generalized vector-autoregressive

TABLE 2 Descriptive statistics of United States and emerging stock markets

Country	ABB	Mean (%)	Std. dev. (%)	Skewness	Kurtosis	J-B	ADF
United States	USA	0.025	1.165	−0.280	11.523	18106.320 <sup>a</sup>	−58.573 <sup>a</sup>
Brazil	BRA	0.021	2.239	−0.193	10.264	13134.530 <sup>a</sup>	−71.925 <sup>a</sup>
Chile	CHL	0.010	1.281	−0.163	13.957	29826.410 <sup>a</sup>	−66.224 <sup>a</sup>
China	CHN	0.004	1.881	0.009	9.148	9382.592 <sup>a</sup>	−69.761 <sup>a</sup>
Columbia	COL	0.028	1.565	−0.133	12.271	21350.070 <sup>a</sup>	−64.307 <sup>a</sup>
Czech Republic	CZR	0.022	1.645	−0.182	13.793	28945.110 <sup>a</sup>	−38.155 <sup>a</sup>
Egypt	EGP	0.026	1.727	−2.207	48.805	525610.400 <sup>a</sup>	−69.560 <sup>a</sup>
Greece	GRC	−0.041	2.332	−0.442	11.850	19633.670 <sup>a</sup>	−70.874 <sup>a</sup>
Hungary	HUN	0.035	2.150	−0.211	11.875	19593.200 <sup>a</sup>	−71.921 <sup>a</sup>
India	IND	0.027	1.644	−0.086	10.342	13387.950 <sup>a</sup>	−71.083 <sup>a</sup>
Indonesia	INS	0.006	2.543	−1.087	33.523	232410.500 <sup>a</sup>	−33.989 <sup>a</sup>
Mexico	MXC	0.027	1.709	−0.272	14.252	31497.600 <sup>a</sup>	−70.220 <sup>a</sup>
Pakistan	PAK	−0.002	1.748	−0.463	10.168	12967.650 <sup>a</sup>	−70.004 <sup>a</sup>
Peru	PER	0.034	1.694	−0.307	10.995	15958.680 <sup>a</sup>	−54.747 <sup>a</sup>
Phillipines	PHL	−0.002	1.624	0.401	16.119	42877.050 <sup>a</sup>	−66.183 <sup>a</sup>
Russia	RUS	0.036	2.821	−0.441	16.134	43011.250 <sup>a</sup>	−71.167 <sup>a</sup>
South Africa	SAF	0.008	1.767	−0.368	7.663	5531.640 <sup>a</sup>	−72.349 <sup>a</sup>
Taiwan	TAI	0.007	1.554	−0.124	6.399	2883.435 <sup>a</sup>	−74.374 <sup>a</sup>
Thailand	THL	−0.002	1.947	0.467	14.587	33539.200 <sup>a</sup>	−67.450 <sup>a</sup>
Turkey	TUR	0.013	2.797	−0.190	10.487	13947.600 <sup>a</sup>	−73.832 <sup>a</sup>

Note: Std. Dev. represents standard deviation, J-B represents JarqueBera test of normality and ADF represents the Augmented Dickey-Fuller test of stationarity.

<sup>a</sup>Indicates significance at 1%.

TABLE 3 Descriptive statistics of global factors

Global factor	ABB	Mean	Std. dev.	Skewness	Kurtosis	J-B	ADF
Economic Policy Uncertainty	EPU	4.344	0.664	−0.211	3.398	79.849 <sup>a</sup>	−6.977 <sup>a</sup>
Geopolitical Risk	GPR	4.279	0.792	−0.137	3.300	39.240 <sup>a</sup>	−8.720 <sup>a</sup>
Stock market Volatility	VIX	2.939	0.364	0.472	3.105	213.979 <sup>a</sup>	−4.827 <sup>a</sup>
MSCI World index	MSCI	0.016	0.975	−0.395	10.722	14301.120 <sup>a</sup>	−52.980 <sup>a</sup>
TED Spread	TED	0.481	0.406	3.310	21.067	87869.340 <sup>a</sup>	−3.960 <sup>a</sup>
US Dollar index	USD	0.002	0.495	−0.123	4.589	613.841 <sup>a</sup>	−76.109 <sup>a</sup>
S&P GSCI index	GSCI	−0.005	1.385	−0.226	5.924	2077.521 <sup>a</sup>	−77.953 <sup>a</sup>
Crude oil WTI	OIL	0.016	2.391	0.020	8.029	6002.769 <sup>a</sup>	−77.506 <sup>a</sup>
Gold	GLD	0.021	1.050	−0.269	9.601	10411.110 <sup>a</sup>	−75.583 <sup>a</sup>

Note: Std. Dev. represents standard deviation, J-B represents JarqueBera test of normality and ADF represents the Augmented Dickey-Fuller test of stationarity.

<sup>a</sup>Indicates significance at 1%.

(VAR) model. Consider an n-variate covariance stationary VAR ( $p$ ) model,

$$x_t = \sum_{i=1}^p \gamma_i x_{t-i} + \epsilon_t \quad (1)$$

where,  $\epsilon_t \sim N(0, \Sigma)$  and the moving average component of the VAR process is represented by the following MA ( $\infty$ ) process

$$x_t = \sum_{i=0}^{\infty} \omega_i \epsilon_{t-i},$$



Here,  $\omega_i$  is a  $n \times n$  coefficient matrix and calculated recursively using  $\omega_i = \gamma_1 \omega_{i-1} + \gamma_2 \omega_{i-2} + \dots + \gamma_p \omega_{i-p}$ , and  $\omega_0$  represents the identity matrix. Taking help from the MA coefficient, we utilize the generalized FEVD, which permits splitting the H-step-ahead forecast error of each variable and attributed to various shocks in the system.

We utilize the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998) to achieve orthogonality since the Cholesky factor depends upon the ordering of the variables. The contribution of variable  $j$  to the H-step-ahead generalized variance of forecast error of variable  $i$  is denoted as  $\tau_{ij}(H)$  and computed as:

$$\tau_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i \omega_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e'_i \omega_h \sum \omega'_h e_i)^2} \quad (2)$$

where the  $j$ th diagonal component of the standard deviation is represented by  $\sigma_{jj}$ .  $\sum$  represents the covariance matrix of errors.  $e_i$  has a value 1 for  $i$ th component and 0 otherwise. Finally, the coefficient matrix that multiplies  $h$ -lagged error in the infinite moving-average representation of non-orthogonalized VAR is represented by  $\omega_h$ .

We measure the pairwise directional transmission,  $\tau_{ij}(H)$ , from  $j$  to  $i$  as:

$$T_{i \leftarrow j}^H = \tau_{ij}(H) \quad (3)$$

The ratio of the off-diagonal sum of rows to the sum of all the elements represents the total directional transmission from others to  $i$  as:

$$T_{i \leftarrow \cdot}^H = \frac{1}{N} \sum_{\substack{j=1 \\ j \neq i}}^N \tau_{ij}(H) \quad (4)$$

Furthermore, the ratio of the off-diagonal sums of columns to the sum of all the elements represents the total directional transmission to others from  $j$  as:

$$T_{\cdot \leftarrow j}^H = \frac{1}{N} \sum_{\substack{i=1 \\ i \neq j}}^N \tau_{ij}(H) \quad (5)$$

Finally, the total system-wide transmission is the ratio of the sum of the from-others (to-others) elements of the variance decomposition matrix to the sum of all its elements:

$$T^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ j \neq i}}^N \tau_{ij}(H) \quad (6)$$

## 2.2.2 | Barunik and Krehlik frequency transmission approach

Using the spectral representation of variance decomposition, the frequency dynamics of connectedness are described in the form of short-, medium- and long-term frequencies. Instead of impulse responses to shocks, these decompositions are based on frequency responses to shocks. Therefore, the building block of current theory considers the frequency response function,  $\eta(e^{-if}) = \sum_g e^{-i\omega_g} \eta_g$ , which can be obtained as the Fourier transform of the coefficients  $\eta_g$ , having  $i = \sqrt{-1}$ . The spectral density of  $AB$  at frequency  $f$  can therefore be defined as Fourier Transform for  $MA(\infty)$  filtered series as:

$$S_{AB}(f) = \sum_{g=-\infty}^{\infty} E(AB_t AB'_{t-g}) e^{-ifg} = \Re(e^{-if}) \sum \Re'(e^{+if}) \quad (7)$$

Understanding the frequency dynamics depends upon the key quantity power spectrum  $S_{AB}(f)$  because it describes how the variance of  $AB_t$  is distributed over the frequency components  $\omega$ . Nevertheless, frequency domains as counterparts of variance decompositions are explained by the spectral decomposition for covariance, that is,  $E(AB_t AB'_{t-g}) = \int_{-\varphi}^{\varphi} S_{\gamma}(f) e^{ifg} df$ .

Baruník and Křehlík (2018) describe the comprehensive derivation of quantities, while the current study describes the estimation of connectedness measures at varying frequencies. Hence, the standard Fourier transforms estimates the spectral quantities. The interval's cross-spectral density  $d = (a, b) : a, b \in (-\varphi, \varphi), a < b$  is estimated as:

$$\sum_f \hat{\eta}(f) \widehat{\sum} \hat{\eta}'(f) \quad (8)$$

for  $f \in \{[aG/2\pi], \dots, [bG/2\pi]\}$  where

$$\hat{\eta}(f) = \sum_{g=0}^{G-1} \hat{\eta}_g e^{-2iqf/G} \quad (9)$$

and  $\widehat{\sum} = \hat{\nu}'_{\hat{\nu}/(T-x)}$ , where  $x$  indicates the correction for loss of degrees of freedom and it exclusively depends on the specification of VAR.

The decomposition of impulse response function is estimated at given frequency band as  $\hat{\eta}(d) = \sum_f \hat{\eta}(f)$ . Hence, the generalized decompositions of variance are estimated at desired frequency band as:

$$(\hat{\partial}_d)_{j,l} = \sum_f \hat{\rho}_j(f) (\hat{\kappa}(f))_{j,l} \quad (10)$$

where  $(\hat{\kappa}(f))_{j,l} = \hat{\delta}_{ll}^{-1} \left( \left( \hat{\eta}(f) \hat{\Sigma} \right)_{j,l} \right)^2 / \left( \hat{\eta}(f) \hat{\Sigma} \eta'(f) \right)_{jj}$  is the estimated generalized causation spectrum, and  $\hat{\rho}_j(f) = \left( \hat{\eta}(f) \hat{\Sigma} \eta'(f) \right)_{jj} / (\emptyset)_{jj}$  is the estimate of weighted fraction and  $\emptyset = \sum_f \hat{\eta}(f) \hat{\Sigma} \eta'(f)$ . Hence, at a given desired frequency band, the measures of connectedness can be derived by substituting the estimate,  $(\hat{\partial}_k)_{j,l}$  into the traditional measures.

### 2.2.3 | Causality tests

In the second part of our analysis, we empirically examine the impact of global factors on the transmission relationship between United States and sample emerging stock markets utilizing the nonlinear causality tests.

#### Nonlinear causality tests

The pioneering work by Granger (1969) paved the way for other researchers to look deeply into the causal relationship between economic and financial time series. Péguin-Feissolle and Terasvirta (1999) proposed two nonlinear causality tests: (1) Taylor series approximation and (2) ANN based.

The Taylor series approximation causality test is based on the Taylor expansion of the nonlinear function:

$$x_t = f^*(x_{t-1}, \dots, x_{t-q}, y_{t-1}, \dots, y_{t-n}, \vartheta^*) + \varepsilon_t \quad (11)$$

where  $\vartheta^*$  is a vector,  $x_t$  and  $y_t$  are weakly stationary series, and  $f^*$  is an unknown function but assumed to represent the causal relationship between  $y_t$  and  $x_t$ . Moreover, for every point of the sample (parameter) space  $\vartheta^* \in \Theta$ ,  $f^*$  has a convergent Taylor expansion. In order to examine the non-causality hypothesis, that is,  $y_t$  does not cause  $x_t$ , we have:

$$x_t = f^*(x_{t-1}, \dots, x_{t-q}, \vartheta) + \varepsilon_t \quad (12)$$

To test Equation (9) against Equation (8), following Péguin-Feissolle and Terasvirta (1999) and later

Péguin-Feissolle et al. (2013) we linearize  $f^*$  and increase the function form into a  $k^{\text{th}}$  order Taylor series around an arbitrary sample space. After the approximation and re-parametrization of  $f^*$ , we obtain:

$$\begin{aligned} x_t = & \theta_0 + \sum_{j=1}^q \theta_j x_{t-j} + \sum_{j=1}^n \gamma_j y_{t-j} + \sum_{j_1=1}^q \sum_{j_2=1}^q \theta_{j_1 j_2} x_{t-j_1} x_{t-j_2} \\ & + \sum_{j_1=1}^q \sum_{j_2=1}^n \varphi_{j_1 j_2} x_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^n \sum_{j_2=1}^n \gamma_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \dots \\ & + \sum_{j_1=1}^q \sum_{j_2=1}^q \dots \sum_{j_k=j_k-1}^q \theta_{j_1 \dots j_k} x_{t-j_1} \dots x_{t-j_k} + \dots + \theta_{j_1 j_2} x_{t-j_1} x_{t-j_2} \\ & + \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_k=j_k-1}^n \gamma_{j_1 \dots j_k} y_{t-j_1} \dots y_{t-j_k} + \varepsilon_t^* \end{aligned} \quad (13)$$

where  $\varepsilon_t^* = \varepsilon_t + R_t^{(k)}(y, x)$ ,  $R_t^{(k)}$  represents the remainder with  $n \leq k$  and  $q \leq k$ .

Péguin-Feissolle and Terasvirta (1999) indicate two possible difficulties related to Equation (10). One being multicollinearity due to large  $k$ ,  $q$ , and  $n$ , and second is the small number of degrees of freedom, due to the rapid increase in the number of regressors with  $k$ . By replacing some observation matrices with their principal components, we can tackle both problems. Hence, we use the principal components and test the null hypothesis of zero coefficients of principal components, tested as:

$$\text{General} = \frac{(SSR_0 - SSR_1)/p^*}{SSR_1/(T - 1 - 2p^*)} \quad (14)$$

where we obtain  $SSR_0$  and  $SSR_1$  using the following methods. For  $SSR_0$ , we regress  $x_t$  on 1 and the first principal components  $p^*$  of the matrix of lags of  $x_t$  only, to estimate the residuals  $\hat{\varepsilon}_t$ ,  $t = 1, \dots, T$ . The squared residuals are summed to obtain  $SSR_0$ .  $SSR_1$  are obtained by regressing  $\hat{\varepsilon}_t$  on 1 and all the terms of the two principal component matrices. The problem of degree of freedom can be tackled by assuming that the general model is 'semi-additive':

$$x_t = f(x_{t-1}, \dots, x_{t-q}, \vartheta_f) + g(y_{t-1}, \dots, y_{t-n}, \vartheta_g) + \varepsilon_t \quad (15)$$

where  $\vartheta' = (\vartheta_f', \vartheta_g')'$  is the parameter vector. If  $g(y_{t-1}, \dots, y_{t-n}, \vartheta_g) = \text{constant}$ , then  $y_t$  does not cause  $x_t$ . In order to obtain the static called Additive, we linearize both functions into  $k^{\text{th}}$  - order Taylor series.

The ANN causality test uses a logistic function. The approximation of the equation  $g(y_{t-1}, \dots, y_{t-n}, \vartheta_g)$  is obtained using:

$$\vartheta_0 + \tilde{\mu}_t' \alpha + \sum_{j=1}^p B_j \frac{1}{1 + e^{-\gamma_j' \mu_t}} \quad (16)$$

where  $\vartheta_0 \in R$ ,  $\mu_t = (1, \tilde{\mu}_t')'$  is a  $(n+1) \times 1$  vector,  $\tilde{\mu}_t = (y_{t-1}, \dots, y_{t-n})'$ ,  $\alpha = (\alpha_1, \dots, \alpha_n)'$  are  $(n \times 1)$  vectors, and  $\gamma_j = (\gamma_{j0}, \dots, \gamma_{jn})'$  for  $j = 1, \dots, p$ , are  $(n+1) \times 1$  vectors. The null hypothesis of the test is  $\{y_t\}$  does not cause  $\{x_t\}$ . The estimation of the ANN-based causality test serves as (1) comparative analysis for the Taylor-based nonlinear causality test, and (2) serves as a robustness check (See estimation results of ANN-based Causality test available in online appendix). The use of nonlinear causality tests also helps minimize possible estimation errors, since we use the estimated transmission measures. Additionally, we utilize the VAR stability tests to ensure the stationarity of residuals.

### 3 | EMPIRICAL RESULTS

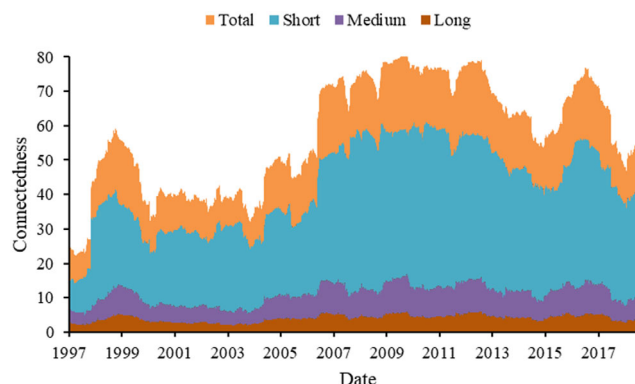
#### 3.1 | Time and frequency connectedness

In order to analyse the nature and magnitude of the connectedness between the underlying stock markets, we estimate the time and frequency connectedness between United States and emerging stock markets using Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approaches, respectively. Although static connectedness illustrates an effective design of connectedness over a total sample period, it is not very useful in understanding variation over time. We estimate the total time-varying total connectedness between United States and the sample emerging markets using the DY framework. In addition, we use BK approach to decompose total connectedness between United States and emerging markets

into three frequency bands, short (0–5 days), medium (6–20 days) and long term (21–262 days).

Figure 2 shows the time-varying total and frequency connectedness between United States and the sample emerging markets. First, we trace the connectedness cycles among the sample stock markets corresponding to major global events. The visual results unveil the significant influence of global events in driving the connectedness spillovers among the underlying stock markets due to increased globalization and financial integration. In fact, the results show that periods of economic and financial slowdown such as the Asian financial crisis 97–98, GFC 2007–09, European debt crisis 2011, and oil prices slump in 2015, the connectedness among the stock markets significantly increased. The findings suggest that during periods of crisis informational spillovers among stock markets rise causing major price movements. The findings agree with the notion that indicates strong contagion and spillover transmission among stock markets during crisis periods (Mensi et al., 2018; BenMim & BenSaïda, 2019). In addition, the findings also corroborate the evidence that stresses strong contagion effects between emerging and developed markets significantly increase during periods of the financial crisis (Al-Nasser & Hajilee, 2016; Sugimoto et al., 2014).

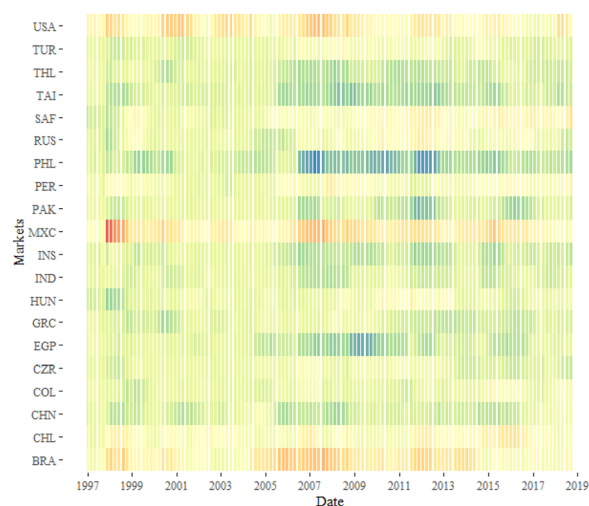
The findings also unearth that connectedness among United States and emerging stock markets is cyclic, and connectedness cycles persist for months or even years. The findings also highlight that during periods of financial distress, portfolio diversification across these markets might not be attained, and alternatively, investors should utilize other asset classes like commodities, fixed-income securities, cryptocurrencies. In addition, the results also demonstrate that under normal market conditions, connectedness among United States and emerging stock markets is primarily driven by transmission of tradable



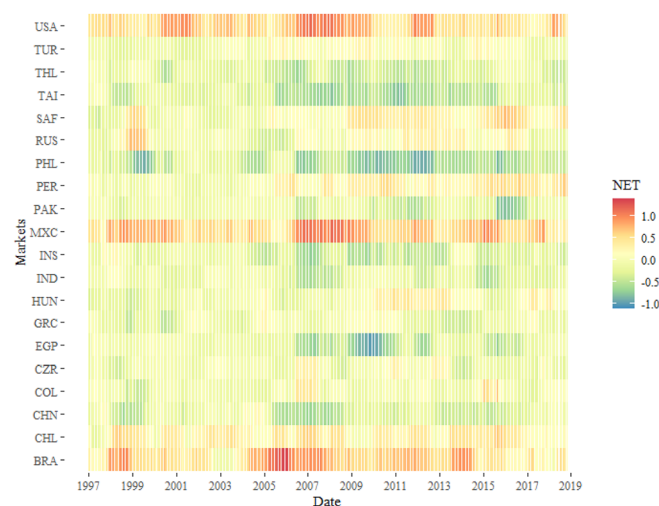
**FIGURE 2** Time-varying total, short-, medium-, and long-term connectedness of stock markets. Forecasting error variance decomposition is based on 1-variate VAR with a 262-day rolling window and a predictive horizon of 100 days. The sample period is from 01.01.1996 to 31.10.2018; short (1–5 days), medium (6–20 days), and long-term (21–262 days) connectedness of stock markets via return, respectively [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/jfe.2604)]



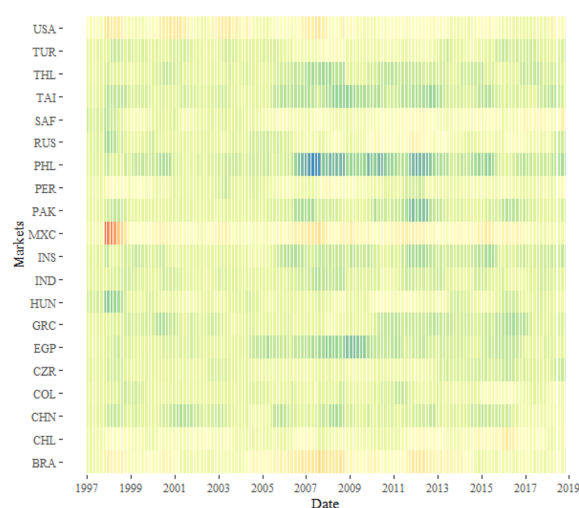
(a) Total NET connectedness



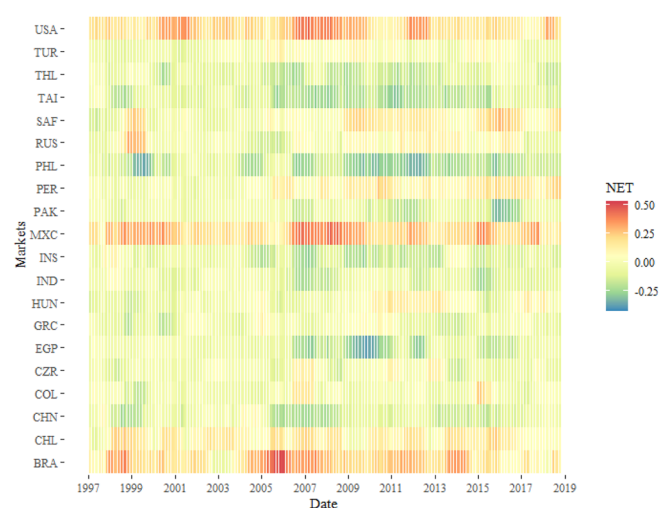
(c) Medium-term NET connectedness



(b) Short-term NET connectedness



(d) Long-term NET connectedness



**FIGURE 3** Dynamics of net directional connectedness at different frequency bands. Net directional connectedness of stock markets. (a) Total NET connectedness. (b) Short-term NET connectedness. (c) Medium-term NET connectedness. (d) Long-term NET connectedness [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

information, while contagion effects dominate during crisis periods.

Figure 2 also presents the frequency transmission analysis results. The results illustrate short, medium, and long-term connectedness among United States and emerging stock markets. As suggested by Ferrer et al. (2018) the connectedness among financial markets varies across frequencies due to heterogeneous responses. Since market participants in stock markets are interested in different investment horizons with varying objectives, preferences, risk appetite, thus economic and financial shock generate different frequency responses. The results depict strong connectedness among the underlying stock markets in the short-run as compared to medium-run and long run. In this backdrop, various connectedness cycles are traced. Similar to our previous findings, the results

also demonstrate high short-run connectedness among United States and emerging stock markets during GFC. The findings once again show an elevated level of connectedness due to global financial meltdown. In contrast, the medium and long-run results show relatively weak spillover transmission among the sample stock markets. The findings suggest that portfolio diversification opportunities exist for investors and portfolio managers interested in different investment horizons. Nevertheless, the results also reinforce our short-run findings and stress that connectedness among United States and emerging markets soars during crisis periods.

Figure 3 presents the dynamics of net directional connectedness among United States and emerging markets at different frequency bands. The results further shed light on the impact of global integration in driving

connectedness across stock markets. The results showcase net transmitters and receivers of spillovers among the sample markets. Also, the net connectedness for each of the sample stock market is displayed. As expected among the understudy equity markets, US stock market reports highest level of global integration. The findings advocate that US stock market holds significant predictive information content about other sample emerging stock markets. The results also show that net connectedness peaked during the GFC period, indicating strong contagion effects from the United States to sample emerging markets. The graphs also illustrate that markets, namely Mexico, Brazil, Chile, Columbia, Hungary, South Africa, Peru, and Russia are net transmitters of spillovers to other sample stock markets. In contrast, the stock markets of China, Czech Republic, Egypt, Greece, India, Indonesia, Pakistan, Philippines, Thailand, and Turkey are net receivers of spillovers of other sample stock markets.

### 3.2 | Causality results

The previous section presented strong evidence of connectedness among United States and emerging stock markets. In this section, we demonstrate the impact of global factors in driving connectedness among the underlying stock markets. We estimate causality results for both time and frequency-domain. Table 4 describes the causal relationship between total time-varying connectedness and global factors.

Many studies document the role of EPU in forecasting stock returns and driving spillovers among financial markets (e.g., Kang et al., 2017; Phan et al., 2018). In this regard, it is well established that EPU has a significant impact on both economic fundamentals (e.g., economic development, inflation, monetary policy, exchange rate) and market outcomes such as VIX, stock market comovement, and sources of global stock market risk. The results in Table 4 show that EPU causes overall connectedness from United States to emerging stock markets. The findings stress that EPU is an influential factor in driving the contagion from the United States to emerging stock markets. The findings are in line with literature that highlights the crucial role of EPU in driving spillovers among stock markets (e.g., Hasan et al., 2020; Youssef et al., 2021). In contrast, the results for individual markets show that EPU has a limited role in driving connectedness across sample stock markets. The findings showcase that domestic economic policies framework influences connectedness structure more than US economic policy decisions. The results of robustness analysis based on ANN tests illustrate the same findings.

Caldara and Iacoviello (2018) compare EPU and GPR indexes and conclude that the latter focuses on events that are exogenous to business and financial cycles. Such events are also likely to fuel stock market uncertainties. In this regard, Das et al. (2019) show that the influence of EPU on stock prices is more pronounced than of GPR in the case of emerging stock markets. In contrast, our results unveil a significant role of geopolitical risk in driving overall connectedness spillovers from the United States to emerging stock markets. Also, the results in Table 2 unearth that GPR has a more influential role than EPU in driving connectedness among United States and emerging stock markets, especially during marked with high contagion. The results are corroborated by the findings of Hedström et al. (2020), who also report the significant impact of GPR index in driving connectedness among stock markets. As far as the case of individual markets, GPR significantly causes connectedness for the United States to Brazil, Hungary, Mexico, Pakistan, Taiwan, and Turkey. In the case of remaining emerging markets, GPR has no role in spillover transmission.

It is well-recognized that post-GFC volatilities in emerging markets are increasingly dependent on United States and other developed stock markets. In this backdrop, a plethora of research has documented volatility spillovers and volatility contagion effects across stock markets (Jiang et al., 2019; Baur, 2012; Kenourgios & Dimitriou, 2015, among others). In general, the VIX index is a leading indicator of US VIX in academic and practice circles. In this respect, Badshah (2018) concluded that US VIX index holds significant information content to influence the volatilities in emerging stock markets. In the same way, our results also a functional role of US VIX index in driving connectedness between United States and emerging stock markets. The findings imply that the information content in VIX can effectively be used to forecast volatility spillovers between the United States and emerging stock markets. In addition, the results also show that the VIX index causes spillovers from United States to emerging markets of Chile, Columbia, Greece, Hungary, India, Mexico, and South Africa. The same findings are indicated by robustness analysis.

Table 4 also reports the results for the MSCI world index (a proxy for the global stock market portfolio) and TED spread (a proxy for global fluctuations in credit risk). The results unveil that the both under discussion global factors do not significantly cause overall spillovers from United States to emerging stock markets. However, the results of Taylor-based causality tests (robustness analysis) show a significant contribution of MSCI and TED in driving overall connectedness from United States to emerging stock markets. Also, individually MSCI world index strongly influences connectedness between

TABLE 4 Taylor-based causality tests for overall and from United States to emerging markets (whole sample)

	EPU	GPR	VIX	World	TED	USD	GSCI	Oil	Gold
Overall	28.334*** [0.000]	1004.37*** [0.000]	10.599*** [0.001]	0.690 [0.406]	6.018** [0.014]	1.087 [0.297]	1.757 [0.185]	0.635 [0.425]	1.615 [0.204]
From US to									
EMR	284.20*** [0.000]	172.56*** [0.000]	392.56*** [0.000]	4.365** [0.013]	342.10*** [0.000]	0.012 [0.914]	0.303 [0.738]	0.846 [0.429]	0.075 [0.927]
BRZ	0.471 [0.493]	3.239* [0.072]	0.439 [0.507]	2.328 [0.127]	2.056 [0.152]	1.072 [0.343]	0.817 [0.366]	0.846 [0.358]	0.202 [0.653]
CHL	0.456 [0.500]	0.000 [0.984]	10.137*** [0.002]	9.098*** [0.003]	8.060*** [0.005]	0.755 [0.470]	4.886** [0.027]	1.165 [0.280]	1.712 [0.191]
CHN	0.622 [0.430]	0.050 [0.823]	0.490 [0.484]	0.057 [0.812]	1.425 [0.233]	1.724 [0.179]	17.982*** [0.000]	8.645*** [0.003]	2.119 [0.146]
COL	0.063 [0.803]	0.902 [0.342]	0.537 [0.464]	48.154*** [0.000]	18.713*** [0.000]	1.419 [0.242]	5.639** [0.018]	3.119* [0.077]	0.622 [0.431]
CZR	0.055 [0.815]	0.017 [0.897]	10.486*** [0.001]	13.202*** [0.000]	9.824*** [0.002]	0.779 [0.459]	5.018** [0.025]	1.015 [0.314]	7.640*** [0.006]
EGP	0.164 [0.686]	0.693 [0.405]	0.588 [0.443]	20.761*** [0.000]	3.995** [0.046]	0.476 [0.621]	31.716*** [0.000]	7.577*** [0.006]	0.442 [0.506]
GRC	0.108 [0.743]	1.084 [0.298]	3.628* [0.057]	0.001 [0.970]	0.000 [0.991]	0.580 [0.560]	0.792 [0.374]	0.189 [0.664]	4.851** [0.028]
HUN	0.004 [0.947]	4.476** [0.034]	4.929** [0.027]	0.016 [0.901]	20.496*** [0.000]	0.677 [0.508]	0.314 [0.575]	0.228 [0.633]	0.159 [0.691]
IND	0.360 [0.549]	0.001 [0.974]	10.562*** [0.001]	1.192 [0.275]	1.092 [0.296]	3.822** [0.022]	10.239*** [0.001]	2.297 [0.130]	4.995** [0.026]
INS	0.301 [0.583]	1.568 [0.211]	0.326 [0.568]	3.052* [0.081]	0.886 [0.347]	0.717 [0.488]	0.340 [0.560]	0.222 [0.638]	14.241*** [0.000]
MXC	3.183* [0.075]	12.124*** [0.001]	2.794* [0.095]	1.033 [0.310]	1.985 [0.159]	0.182 [0.833]	1.108 [0.293]	0.202 [0.653]	0.307 [0.579]
PAK	0.463 [0.496]	3.224* [0.073]	0.219 [0.640]	4.669** [0.031]	3.071* [0.080]	3.864** [0.021]	0.250 [0.617]	0.007 [0.936]	0.037 [0.847]
PER	0.350 [0.554]	0.056 [0.813]	0.899 [0.343]	1.221 [0.269]	7.972*** [0.005]	2.229 [0.108]	1.910 [0.167]	1.314 [0.252]	1.014 [0.314]
PHL	0.865 [0.353]	0.332 [0.565]	1.146 [0.285]	1.568 [0.211]	2.044 [0.153]	4.171** [0.016]	3.702 [0.054]	0.741 [0.389]	0.843 [0.359]
RUS	0.081 [0.776]	1.675 [0.196]	0.441 [0.507]	4.004** [0.045]	0.043 [0.837]	0.078 [0.925]	9.283*** [0.002]	3.630* [0.057]	1.619 [0.203]
SAF	0.003 [0.955]	0.937 [0.333]	7.786*** [0.005]	5.868* [0.015]	1.058 [0.304]	2.107 [0.122]	3.253* [0.071]	3.322* [0.068]	0.444 [0.505]
TAI	0.716 [0.397]	3.904** [0.048]	0.575 [0.448]	3.591* [0.058]	3.086* [0.079]	5.106*** [0.006]	0.000 [0.996]	0.068 [0.794]	15.114*** [0.000]
THL	0.029 [0.865]	0.978 [0.323]	0.473 [0.492]	0.479 [0.489]	5.215** [0.022]	1.373 [0.254]	12.051*** [0.001]	5.083** [0.024]	1.220 [0.270]
TUR	1.257 [0.262]	7.216*** [0.007]	0.713 [0.398]	0.001 [0.981]	0.085 [0.771]	1.144 [0.319]	1.030 [0.310]	1.154 [0.283]	6.394** [0.016]

Note: This table reports the causality test results for the Taylor-based nonlinear causality test for the whole sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

United States and emerging economies, namely Chile, China, Columbia, Czech Republic, Indonesia, Pakistan, Russia, and South Africa. In the same way, TED spread significantly drives connectedness among United States and emerging stock markets such as Chile, China, Columbia, Czech Republic, Greece, Pakistan, Peru, Taiwan, and Thailand.

In the last few decades, international capital flows in global currency markets soared. In consequences, the dynamics of exchange rate volatility are maintained to influence stock markets (Kanas, 2000). In this spirit, Dong and Yoon (2018) found a strong association among United States exchange rate and emerging stock markets due to the rapid transmission capability of United States exchange rate. In fact, they asserted that the exchange rate's influence is more significant compared to the interest rate because the transmission mechanism of the interest rate is weaker and slower. In contrast, our results suggest that US Dollar does not cause overall connectedness among United States and emerging stock markets. In the same way, it also has a negligible role in driving connectedness spillovers from United States to emerging markets. Nevertheless, once again, our robustness analysis suggests otherwise. In the case of individual markets USD rate drives connectedness from the US to India, Pakistan, Philippines, and South Africa. Here, the findings imply that the liberalization of emerging markets and changes in the US Dollar can increase capital flows between the United States and emerging stock markets. Thus, volatilities in USD can intensify the volatility dynamics in emerging equity markets.

After GFC crisis, due to the financialization of commodity market and large institutional portfolio investments in commodities, the linkages among commodities and stock markets intensified. In this backdrop, Ordu-Akkaya and Soytaş (2020) argue that spillovers among developed and emerging markets have increased after the financialization of the commodity market. In contrast, our results show that S&P GSCI has no role in driving overall connectedness among United States and emerging stock markets. However, in the case of emerging markets such as Chile, China, Columbia, Czech Republic, Hungary, Russia, South Africa, and Taiwan the commodity index has a significant influence on spillover connectedness. The findings imply that shocks in commodity market lead to contagion effects in emerging stock markets. Also, the findings indicate that in the presence of strong connections among stocks and commodities, the opportunities for portfolio diversification are limited.

A large thread of literature discusses the strong impact of oil prices on stock markets. In this regard, numerous studies highlight spillovers among crude oil and stock markets, whereas negative spillovers dominate

over positive spillovers (e.g., Wen et al., 2019; Xu et al., 2019). In fact, emerging markets are generally more exposed to bad news spillovers resulting in uncertain market conditions. In accordance with these findings, our results also show that crude oil prices drive overall connectedness among United States and emerging stock markets. Also, the results unveil that oil prices significantly drive connectedness between United States and emerging markets of China, Columbia, Czech Republic, Russia, South Africa, and Taiwan. Naeem et al. (2021) also find the strong role of oil prices in driving connectedness among international financial markets. The findings suggest that portfolio managers should consider the conditions of the crude oil market before formulating portfolio diversification hedging strategies in stock markets.

Many authors have documented the crucial role of gold prices in stock market outcomes. In general, gold is considered a diversifier and safe-haven asset during periods of economic slowdown (Baur and Lucey, 2010) due to its low correlation with other asset classes (Ciner et al., 2013). In this view, our results demonstrate that gold prices do not drive connectedness spillovers from the United States to emerging markets. Once again, the weak linkages among gold-stocks highlight the potential hedging and diversification potential of gold for market participants in United States and emerging stock markets. In addition, the findings also show that gold prices strongly influence connectedness from United States to emerging markets of Czech Republic, Greece, India, and South Africa (Tables 5–7).

In order to provide insights for investors interested in different investment horizons, we estimate our causality results for three other frequency bands, short-term (0–5 days), medium-term (6–20 days), and long-term (21–262 days). The findings show no major divergence from our total sample findings and validate the significant influence of global factors in determining connectedness spillovers from United States to emerging stock markets. The findings unveil the functional role of global factors in influencing the spillovers among United States and emerging stock markets in different frequency bands.

Overall, the findings illustrate that the information contained in global factors can be effectively utilized to predict spillovers between United States and emerging stock markets. The findings also indicate that global factors drive synchronized behaviour of investors across different emerging stock markets. Hence, market participants should carefully evaluate the movements in global factors before making investment decisions because soaring spillovers among stock markets destroy the benefits of portfolio diversification, in particular during periods of high contagion. In addition, the findings also suggest that investors should recognize the influence of US stock market on

TABLE 5 Taylor-based causality tests for overall and from United States to emerging markets 'short-term' (whole sample)

	EPU	GPR	VIX	World	TED	USD	GSCI	Oil	Gold
Overall	42.267*** [0.000]	1259.249*** [0.000]	11.767*** [0.000]	0.533 [0.465]	57.486*** [0.000]	0.584 [0.445]	2.608 [0.106]	1.086 [0.298]	0.459 [0.498]
From US to									
EMR	121.073*** [0.000]	160.752*** [0.000]	31.749*** [0.000]	22.116*** [0.000]	746.535*** [0.000]	1.929 [0.165]	4.057* [0.017]	0.071 [0.789]	1.401 [0.247]
BRZ	0.540 [0.463]	3.897** [0.048]	0.397 [0.529]	0.092 [0.762]	5.069** [0.024]	0.829 [0.437]	1.047 [0.306]	0.521 [0.471]	0.005 [0.946]
CHL	0.256 [0.613]	0.339 [0.561]	13.980*** [0.000]	6.210** [0.013]	16.571*** [0.000]	0.131 [0.878]	4.796** [0.029]	0.001 [0.977]	3.416* [0.065]
CHN	0.639 [0.424]	0.000 [0.991]	0.002 [0.968]	2.304 [0.129]	0.416 [0.519]	1.338 [0.263]	8.950*** [0.003]	8.626*** [0.003]	0.866 [0.352]
COL	0.099 [0.753]	1.795 [0.180]	1.139 [0.286]	24.295*** [0.000]	32.058*** [0.000]	1.468 [0.231]	1.026 [0.311]	3.992** [0.046]	2.965* [0.085]
CZR	0.283 [0.595]	0.037 [0.847]	11.669*** [0.001]	5.344** [0.021]	15.404*** [0.000]	3.505** [0.030]	0.217 [0.641]	0.311 [0.577]	15.245*** [0.000]
EGP	0.001 [0.979]	0.468 [0.494]	0.095 [0.758]	13.804*** [0.000]	4.018** [0.045]	0.910 [0.403]	34.373*** [0.000]	8.110*** [0.004]	2.835* [0.092]
GRC	0.069 [0.793]	1.297 [0.255]	5.856** [0.016]	0.916 [0.339]	0.137 [0.711]	0.046 [0.955]	0.412 [0.521]	0.571 [0.450]	8.297*** [0.004]
HUN	0.279 [0.598]	3.294* [0.070]	5.383** [0.020]	1.222 [0.269]	25.685*** [0.000]	2.142 [0.118]	3.308* [0.069]	0.679 [0.410]	0.275 [0.600]
IND	0.293 [0.588]	0.267 [0.605]	7.058*** [0.008]	0.284 [0.594]	0.443 [0.506]	2.175 [0.114]	4.840** [0.028]	3.100* [0.078]	4.593** [0.032]
INS	0.748 [0.387]	0.887 [0.346]	0.456 [0.499]	7.719*** [0.006]	1.471 [0.225]	0.707 [0.493]	1.018 [0.313]	0.019 [0.891]	12.988*** [0.000]
MXC	1.999 [0.158]	3.139* [0.077]	2.422 [0.120]	2.756* [0.097]	2.598 [0.107]	0.021 [0.979]	0.861 [0.353]	0.001 [0.970]	0.003 [0.958]
PAK	2.139 [0.144]	3.968** [0.046]	0.294 [0.588]	8.041*** [0.005]	2.274 [0.132]	1.758 [0.172]	0.124 [0.724]	0.004 [0.949]	0.022 [0.882]
PER	0.500 [0.479]	0.612 [0.434]	7.573*** [0.006]	16.472*** [0.000]	15.477*** [0.000]	0.589 [0.555]	2.266 [0.132]	0.076 [0.783]	0.371 [0.542]
PHL	0.570 [0.450]	0.652 [0.419]	0.512 [0.474]	0.034 [0.854]	0.372 [0.542]	2.347* [0.096]	0.209 [0.648]	0.161 [0.688]	0.667 [0.414]
RUS	0.182 [0.670]	1.605 [0.205]	1.281 [0.258]	2.839* [0.092]	0.012 [0.913]	0.444 [0.641]	1.386 [0.239]	0.709 [0.400]	0.076 [0.783]
SAF	0.910 [0.340]	0.434 [0.510]	10.458*** [0.001]	3.663** [0.056]	1.291 [0.256]	0.424 [0.655]	0.021 [0.885]	1.027 [0.311]	0.661 [0.416]
TAI	0.376 [0.540]	4.533** [0.033]	0.115 [0.735]	0.094 [0.759]	1.725 [0.189]	1.402 [0.246]	0.130 [0.718]	0.827 [0.363]	8.836*** [0.003]
THL	0.326 [0.568]	2.319 [0.128]	0.475 [0.491]	0.608 [0.436]	3.853** [0.050]	0.316 [0.729]	0.938 [0.333]	0.080 [0.778]	1.939 [0.164]
TUR	1.232 [0.267]	6.689** [0.010]	0.086 [0.769]	0.419 [0.517]	0.279 [0.598]	0.859 [0.424]	0.676 [0.411]	0.043 [0.836]	12.123*** [0.001]

Note: This table reports the causality test results for the Taylor-based nonlinear causality test for the whole sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.



**TABLE 6** Taylor-based causality tests for overall and from United States to emerging markets ‘medium-term’ (whole sample)

	<b>EPU</b>	<b>GPR</b>	<b>VIX</b>	<b>World</b>	<b>TED</b>	<b>USD</b>	<b>GSCI</b>	<b>Oil</b>	<b>Gold</b>
Overall	8.914*** [0.003]	75.001*** [0.000]	12.684*** [0.000]	1.356 [0.244]	44.063*** [0.000]	2.949* [0.086]	0.964 [0.326]	9.105* [0.000]	3.228* [0.072]
From US to									
EMR	34.191*** [0.000]	6.520** [0.011]	209.031*** [0.000]	7.196*** [0.007]	2.277 [0.131]	2.138 [0.118]	1.673 [0.196]	0.679 [0.404]	0.990 [0.320]
BRZ	3.245* [0.072]	1.237 [0.266]	0.326 [0.568]	28.270*** [0.000]	0.200 [0.655]	0.422 [0.656]	11.699*** [0.001]	4.226** [0.040]	2.294 [0.130]
CHL	8.009*** [0.005]	1.650 [0.199]	7.568*** [0.000]	34.966*** [0.000]	0.003 [0.954]	2.144 [0.117]	34.926*** [0.000]	10.104*** [0.002]	3.132* [0.077]
CHN	0.022 [0.882]	1.085 [0.298]	0.927 [0.336]	31.528*** [0.000]	1.956 [0.162]	4.785*** [0.008]	29.724*** [0.000]	8.123*** [0.004]	8.826*** [0.003]
COL	0.217 [0.641]	0.099 [0.753]	0.331 [0.565]	3.856** [0.050]	1.382 [0.240]	0.080 [0.923]	8.767*** [0.003]	1.349 [0.814]	0.078 [0.780]
CZR	3.195* [0.074]	0.075 [0.784]	6.318** [0.012]	16.373*** [0.000]	2.105 [0.147]	1.258 [0.284]	21.864*** [0.000]	4.780** [0.029]	0.056 [0.814]
EGP	0.367 [0.545]	0.362 [0.547]	0.364 [0.546]	3.482* [0.062]	3.375* [0.066]	0.764 [0.466]	3.718* [0.054]	1.846 [0.174]	1.670 [0.196]
GRC	0.960 [0.327]	0.162 [0.688]	0.414 [0.520]	27.775*** [0.000]	0.063 [0.803]	2.988* [0.051]	17.295*** [0.000]	8.604*** [0.003]	0.584 [0.445]
HUN	0.076 [0.783]	3.128 [0.077]	3.397* [0.065]	24.144*** [0.000]	3.747* [0.053]	2.798* [0.061]	9.970*** [0.002]	0.403 [0.525]	0.006 [0.936]
IND	1.687 [0.194]	0.779 [0.378]	11.819*** [0.001]	34.722*** [0.000]	1.262 [0.261]	7.846*** [0.000]	16.344*** [0.000]	2.259 [0.133]	6.012** [0.014]
INS	0.021 [0.886]	1.515 [0.219]	0.059 [0.809]	20.799*** [0.000]	0.193 [0.660]	3.383** [0.034]	18.308*** [0.000]	4.379** [0.036]	4.281** [0.039]
MXC	2.497 [0.114]	0.657 [0.418]	0.598 [0.440]	48.152*** [0.000]	0.241 [0.624]	1.944 [0.143]	14.820*** [0.000]	5.323** [0.021]	5.293** [0.022]
PAK	0.668 [0.414]	0.421 [0.516]	0.199 [0.659]	0.836 [0.361]	2.969* [0.085]	3.211** [0.040]	0.738 [0.391]	1.615 [0.204]	0.017 [0.898]
PER	0.158 [0.691]	1.196 [0.274]	0.016 [0.901]	7.963*** [0.000]	0.020 [0.889]	1.628 [0.197]	31.979*** [0.000]	13.235*** [0.000]	1.010 [0.315]
PHL	1.439 [0.230]	0.229 [0.632]	0.258 [0.611]	6.800*** [0.009]	0.079 [0.778]	3.724*** [0.005]	15.918*** [0.000]	3.998** [0.018]	2.056 [0.128]
RUS	0.811 [0.368]	0.356 [0.700]	0.213 [0.644]	22.785*** [0.000]	0.314 [0.575]	2.136* [0.074]	8.818*** [0.000]	2.496* [0.083]	2.093 [0.124]
SAF	0.128 [0.720]	0.513 [0.474]	2.763 [0.097]	16.683*** [0.000]	0.039 [0.844]	2.786** [0.025]	2.888* [0.056]	0.957 [0.384]	4.294** [0.014]
TAI	0.339 [0.560]	0.953 [0.329]	0.689 [0.407]	16.962*** [0.000]	3.123* [0.077]	1.616 [0.199]	10.422*** [0.000]	4.112** [0.016]	2.051 [0.129]
THL	1.141 [0.286]	0.352 [0.703]	1.626 [0.202]	3.854** [0.021]	1.520 [0.218]	3.231** [0.012]	20.765*** [0.000]	4.269** [0.014]	3.127 [0.044]
TUR	0.025 [0.874]	3.972** [0.046]	0.037 [0.848]	21.583*** [0.000]	0.002 [0.966]	2.068* [0.082]	10.876*** [0.000]	0.886 [0.412]	1.227 [0.293]

*Note:* This table reports the causality test results for the Taylor-based nonlinear causality test for the whole sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

TABLE 7 Taylor-based causality tests for overall and from United States to emerging markets 'long-term' (whole sample)

	EPU	GPR	VIX	World	TED	USD	GSCI	Oil	Gold
Overall	2.260 [0.133]	5.848** [0.016]	11.186*** [0.001]	5.952*** [0.000]	92.767*** [0.000]	3.677** [0.025]	1.436 [0.752]	0.823 [0.481]	1.616 [0.167]
From US to									
EMR	4.126** [0.042]	8.999*** [0.003]	93.359*** [0.000]	36.855*** [0.000]	0.241 [0.623]	3.013 [0.017]	5.162*** [0.006]	0.433 [0.649]	4.668*** [0.009]
BRZ	2.267 [0.132]	0.868 [0.351]	0.649 [0.420]	7.064*** [0.000]	3.767* [0.052]	0.960 [0.466]	17.887*** [0.000]	0.527 [0.468]	1.112 [0.292]
CHL	7.025*** [0.008]	2.130 [0.145]	0.096 [0.757]	82.646*** [0.000]	1.039 [0.308]	4.404** [0.012]	50.363*** [0.000]	2.734* [0.098]	0.217 [0.641]
CHN	0.048 [0.826]	1.377 [0.241]	2.031 [0.154]	8.873*** [0.003]	4.191** [0.041]	5.156*** [0.006]	21.935*** [0.000]	1.616 [0.204]	3.705* [0.054]
COL	0.167 [0.683]	0.142 [0.706]	1.230 [0.268]	41.097*** [0.000]	1.268 [0.260]	1.516 [0.195]	0.933 [0.393]	0.062 [0.940]	1.182 [0.277]
CZR	0.071 [0.790]	0.209 [0.648]	4.255** [0.039]	21.857*** [0.000]	0.023 [0.879]	2.041 [0.130]	47.523*** [0.000]	2.437 [0.119]	0.079 [0.779]
EGP	0.594 [0.441]	0.827 [0.363]	0.514 [0.474]	15.823*** [0.000]	1.610 [0.205]	1.035 [0.355]	8.525*** [0.004]	1.882 [0.170]	1.455 [0.228]
GRC	1.122 [0.290]	0.193 [0.661]	0.056 [0.814]	4.008** [0.045]	1.066 [0.302]	2.676* [0.069]	13.386*** [0.000]	0.112 [0.738]	0.166 [0.684]
HUN	0.063 [0.802]	2.973* [0.085]	1.529 [0.216]	7.477*** [0.006]	0.038 [0.845]	3.298** [0.037]	9.989*** [0.002]	0.168 [0.682]	0.204 [0.652]
IND	1.757 [0.185]	0.857 [0.355]	12.828*** [0.000]	14.607*** [0.000]	2.025 [0.155]	6.393*** [0.002]	15.167*** [0.000]	0.300 [0.584]	3.068* [0.080]
INS	0.130 [0.718]	1.530 [0.216]	0.104 [0.747]	2.340 [0.126]	0.105 [0.746]	2.746* [0.064]	15.684*** [0.000]	0.756 [0.385]	4.232** [0.040]
MXC	1.708 [0.191]	0.622 [0.430]	0.000 [0.989]	0.665 [0.514]	0.912 [0.340]	1.305 [0.266]	11.928*** [0.001]	0.256 [0.613]	1.581 [0.209]
PAK	1.048 [0.306]	0.270 [0.604]	0.378 [0.539]	0.031 [0.861]	2.264 [0.133]	5.943*** [0.003]	0.551 [0.458]	0.010 [0.920]	0.017 [0.895]
PER	0.071 [0.790]	1.328 [0.249]	0.053 [0.818]	4.310** [0.014]	0.460 [0.498]	0.446 [0.775]	8.427*** [0.000]	3.519** [0.030]	4.212** [0.015]
PHL	3.695* [0.055]	0.177 [0.674]	0.202 [0.653]	2.608* [0.074]	0.502 [0.479]	1.572 [0.179]	4.304** [0.014]	1.949 [0.143]	2.279 [0.103]
RUS	0.220 [0.639]	0.629 [0.428]	0.115 [0.735]	6.458*** [0.002]	1.227 [0.268]	2.071* [0.082]	1.482 [0.227]	0.526 [0.591]	2.381* [0.093]
SAF	0.869 [0.351]	0.624 [0.430]	1.202 [0.273]	4.677*** [0.009]	0.032 [0.858]	2.053* [0.084]	0.067 [0.935]	0.784 [0.457]	5.121*** [0.006]
TAI	2.554 [0.110]	0.540 [0.463]	0.718 [0.397]	6.797*** [0.001]	5.067** [0.024]	3.345** [0.010]	1.835 [0.160]	0.485 [0.616]	2.886* [0.056]
THL	0.764 [0.382]	0.534 [0.465]	2.567 [0.109]	3.245** [0.039]	1.749 [0.186]	2.324* [0.054]	6.564*** [0.001]	2.387* [0.092]	5.560*** [0.004]
TUR	0.194 [0.660]	4.210** [0.040]	0.027 [0.869]	6.313*** [0.002]	0.163 [0.687]	1.854 [0.116]	1.135 [0.321]	0.520 [0.594]	0.808 [0.446]

Note: This table reports the causality test results for the Taylor-based nonlinear causality test for the GFC sub-sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States TO the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

**TABLE 8** Taylor-based causality tests for overall and from United States to emerging markets (GFC sub-sample)

	<b>EPU</b>	<b>GPR</b>	<b>VIX</b>	<b>World</b>	<b>TED</b>	<b>USD</b>	<b>GSCI</b>	<b>Oil</b>	<b>Gold</b>
Overall	9.435*** [0.002]	1.303 [0.254]	0.903 [0.343]	1.195 [0.275]	43.488*** [0.000]	0.019 [0.889]	0.000 [0.984]	0.018 [0.892]	0.881 [0.349]
From US to									
EMR	0.239 [0.625]	0.348 [0.556]	1.646 [0.200]	5.520*** [0.004]	0.924 [0.337]	4.168** [0.042]	5.793*** [0.003]	1.673 [0.197]	0.846 [0.430]
BRZ	1.289 [0.257]	1.312 [0.253]	4.226** [0.041]	10.690*** [0.001]	5.381** [0.021]	2.123 [0.146]	0.706 [0.401]	0.693 [0.406]	0.775 [0.379]
CHL	1.190 [0.276]	0.027 [0.869]	1.904 [0.169]	14.458*** [0.000]	3.947** [0.047]	1.987 [0.159]	4.061** [0.045]	0.286 [0.593]	6.336** [0.012]
CHN	8.564*** [0.004]	0.779 [0.378]	17.646*** [0.000]	1.182 [0.278]	2.066 [0.151]	0.013 [0.908]	9.708*** [0.002]	2.088 [0.149]	2.723 [0.100]
COL	0.678 [0.411]	0.266 [0.606]	12.305*** [0.001]	33.289*** [0.000]	19.313*** [0.000]	3.658* [0.057]	4.379** [0.037]	0.767 [0.382]	5.523** [0.019]
CZR	1.520 [0.218]	0.841 [0.360]	5.101** [0.025]	11.957*** [0.001]	4.929** [0.027]	0.741 [0.390]	2.450 [0.118]	0.738 [0.391]	4.473** [0.035]
EGP	0.573 [0.450]	0.581 [0.447]	4.107** [0.043]	17.563*** [0.000]	2.407 [0.122]	7.876*** [0.005]	22.858*** [0.000]	2.563 [0.110]	1.122 [0.290]
GRC	0.709 [0.400]	0.641 [0.424]	4.748** [0.030]	0.009 [0.926]	0.026 [0.871]	3.474* [0.063]	0.460 [0.498]	0.426 [0.514]	11.976*** [0.001]
HUN	3.725* [0.054]	0.431 [0.519]	16.497*** [0.000]	6.432** [0.012]	22.850*** [0.000]	0.905 [0.342]	0.181 [0.671]	0.001 [0.974]	0.157 [0.692]
IND	4.636** [0.032]	0.030 [0.863]	3.019* [0.083]	0.901 [0.343]	0.358 [0.550]	0.882 [0.348]	10.786*** [0.001]	2.280 [0.132]	1.585 [0.209]
INS	0.255 [0.614]	0.001 [0.982]	0.052 [0.819]	2.525 [0.113]	0.290 [0.591]	0.157 [0.692]	1.723 [0.190]	0.386 [0.535]	3.819* [0.051]
MXC	3.846* [0.051]	3.961** [0.047]	9.807*** [0.002]	4.152** [0.042]	9.262*** [0.003]	0.231 [0.631]	0.312 [0.577]	0.024 [0.878]	1.467 [0.227]
PAK	7.007*** [0.008]	0.017 [0.897]	8.948*** [0.003]	1.058 [0.304]	3.952** [0.048]	1.555 [0.213]	0.924 [0.337]	0.015 [0.902]	2.899* [0.089]
PER	3.218* [0.074]	0.058 [0.809]	4.734** [0.030]	3.460* [0.064]	10.704*** [0.001]	1.124 [0.290]	1.990 [0.159]	0.673 [0.413]	0.939 [0.333]
PHL	5.165* [0.024]	0.909 [0.341]	4.109** [0.043]	5.409** [0.021]	0.041 [0.841]	1.658 [0.199]	6.526** [0.011]	1.132 [0.288]	0.831 [0.363]
RUS	0.002 [0.967]	0.298 [0.586]	0.004 [0.949]	10.329*** [0.001]	0.353 [0.553]	1.004 [0.317]	4.254** [0.040]	1.083 [0.299]	0.278 [0.598]
SAF	0.089 [0.765]	0.197 [0.658]	2.620 [0.106]	15.102*** [0.000]	0.019 [0.889]	12.260*** [0.001]	12.326*** [0.001]	4.049** [0.045]	0.014 [0.907]
TAI	2.200 [0.139]	2.103 [0.148]	9.876*** [0.002]	1.407 [0.236]	4.201** [0.041]	0.669 [0.414]	0.348 [0.556]	1.067 [0.302]	12.700*** [0.000]
THL	2.170 [0.142]	1.158 [0.283]	1.363 [0.244]	1.970 [0.161]	11.002*** [0.001]	1.112 [0.292]	8.444*** [0.004]	1.848 [0.175]	0.174 [0.677]
TUR	3.969** [0.047]	0.012 [0.914]	1.951 [0.163]	0.166 [0.684]	0.160 [0.690]	0.601 [0.439]	1.158 [0.283]	0.007 [0.936]	0.822 [0.365]

*Note:* This table reports the causality test results for the Taylor-based nonlinear causality test for the GFC sub-sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

**TABLE 9** Taylor-based causality tests for overall and from United States to emerging markets 'short-term' (GFC sub-sample '1/08/2007 – 30/06/2009')

	EPU	GPR	VIX	World	TED	USD	GSCI	Oil	Gold
Overall	1.853 [0.174]	0.437 [0.509]	5.601** [0.018]	2.359 [0.125]	3.894** [0.049]	0.501 [0.480]	1.148 [0.285]	0.005 [0.945]	8.537* [0.004]
From US to									
EMR	0.118 [0.731]	1.808 [0.180]	1.871 [0.172]	0.738 [0.479]	4.366** [0.037]	1.536 [0.216]	0.008 [0.992]	1.172 [0.280]	4.095** [0.017]
BRZ	0.388 [0.534]	3.313* [0.070]	4.634** [0.032]	4.372** [0.037]	10.080*** [0.002]	3.018** [0.050]	6.340** [0.012]	3.547* [0.060]	5.335** [0.021]
CHL	1.947 [0.164]	0.067 [0.797]	9.276*** [0.003]	5.920** [0.015]	12.663*** [0.000]	0.501 [0.607]	2.757* [0.098]	0.652 [0.420]	0.427 [0.514]
CHN	10.376*** [0.001]	2.723 [0.100]	15.667*** [0.000]	41.105*** [0.000]	0.598 [0.440]	0.947 [0.389]	9.045*** [0.003]	0.590 [0.443]	3.052* [0.081]
COL	0.090 [0.765]	1.306 [0.254]	13.477*** [0.000]	1.624 [0.203]	16.785*** [0.000]	1.507 [0.223]	0.372 [0.542]	0.886 [0.347]	3.671* [0.056]
CZR	0.505 [0.478]	0.171 [0.680]	4.655** [0.032]	8.812*** [0.003]	4.783** [0.029]	0.741 [0.477]	0.776 [0.379]	1.084 [0.298]	0.994 [0.319]
EGP	0.450 [0.503]	0.362 [0.548]	2.270 [0.133]	2.374 [0.124]	4.461** [0.035]	4.971*** [0.007]	2.007 [0.157]	0.455 [0.501]	5.445** [0.020]
GRC	0.104 [0.748]	0.048 [0.827]	3.335* [0.069]	0.000 [0.989]	0.865 [0.353]	1.324 [0.267]	1.255 [0.263]	1.520 [0.218]	5.043** [0.025]
HUN	1.322 [0.251]	0.139 [0.710]	17.322*** [0.000]	3.041* [0.082]	24.554*** [0.000]	0.686 [0.504]	2.653 [0.104]	1.607 [0.206]	0.588 [0.444]
IND	6.531** [0.011]	0.025 [0.875]	3.546* [0.060]	21.041*** [0.000]	0.079 [0.779]	0.438 [0.646]	6.249** [0.013]	0.239 [0.625]	13.331*** [0.000]
INS	0.514 [0.474]	1.097 [0.296]	0.113 [0.737]	6.037** [0.014]	0.926 [0.337]	0.542 [0.582]	1.468 [0.226]	0.053 [0.819]	9.893*** [0.002]
MXC	6.132 [0.137]	4.784** [0.029]	11.518*** [0.001]	1.173 [0.279]	9.875*** [0.002]	1.111 [0.330]	1.503 [0.221]	0.290 [0.591]	1.387 [0.240]
PAK	4.374** [0.037]	0.008 [0.927]	7.071*** [0.008]	12.349*** [0.001]	3.303* [0.070]	0.346 [0.708]	1.326 [0.250]	0.350 [0.555]	5.187** [0.023]
PER	3.212* [0.074]	0.053 [0.819]	10.967*** [0.001]	0.968 [0.326]	18.504*** [0.000]	0.765 [0.466]	0.847 [0.358]	1.818 [0.178]	0.372 [0.542]
PHL	5.287** [0.022]	2.306 [0.130]	3.086* [0.080]	7.236*** [0.007]	0.073 [0.787]	0.654 [0.521]	1.444 [0.230]	0.192 [0.662]	1.092 [0.297]
RUS	0.028 [0.867]	1.071 [0.301]	0.678 [0.411]	1.120 [0.291]	3.561* [0.060]	0.274 [0.760]	0.584 [0.445]	0.162 [0.688]	1.288 [0.257]
SAF	0.168 [0.682]	0.008 [0.929]	3.646* [0.057]	0.305 [0.571]	0.255 [0.614]	5.714*** [0.004]	2.274 [0.132]	0.218 [0.641]	2.229 [0.136]
TAI	2.763* [0.097]	4.650** [0.032]	8.540*** [0.004]	6.811*** [0.009]	1.545 [0.215]	1.197 [0.303]	0.490 [0.485]	0.624 [0.430]	5.143** [0.024]
THL	5.820** [0.016]	3.601* [0.059]	1.061 [0.304]	0.206 [0.651]	12.054*** [0.001]	0.056 [0.945]	0.322 [0.571]	0.003 [0.959]	4.025** [0.046]
TUR	3.257* [0.072]	0.263 [0.608]	0.394 [0.531]	1.437 [0.231]	0.004 [0.951]	0.872 [0.419]	1.937 [0.165]	0.355 [0.552]	4.418** [0.036]

*Note:* This table reports the causality test results for the Taylor-based nonlinear causality test for the GFC sub-sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

**TABLE 10** Taylor-based causality tests for overall and from United States to emerging markets 'medium-term' (GFC sub-sample '1/08/2007 – 30/06/2009')

	EPU	GPR	VIX	World	TED	USD	GSCI	Oil	Gold
Overall	5.565** [0.019]	2.352 [0.126]	4.663** [0.031]	1.821 [0.178]	0.017 [0.897]	2.465 [0.117]	1.989 [0.159]	2.403* [0.092]	2.783* [0.096]
From US to									
EMR	1.232 [0.268]	0.824 [0.365]	4.892** [0.028]	25.572*** [0.000]	25.397*** [0.000]	10.917*** [0.000]	43.586*** [0.000]	6.933*** [0.009]	2.530 [0.113]
BRZ	0.864 [0.353]	0.219 [0.640]	9.353*** [0.002]	15.275*** [0.000]	9.904*** [0.002]	4.622** [0.010]	28.034*** [0.000]	6.984*** [0.009]	0.095 [0.758]
CHL	0.605 [0.437]	0.030 [0.863]	11.001*** [0.001]	5.170** [0.024]	3.129* [0.078]	9.393*** [0.000]	33.819*** [0.000]	8.689*** [0.003]	0.419 [0.518]
CHN	0.177 [0.674]	1.452 [0.229]	2.913* [0.089]	31.559*** [0.000]	8.184*** [0.005]	9.756*** [0.000]	35.336*** [0.000]	5.482** [0.020]	4.511** [0.034]
COL	1.159 [0.282]	0.880 [0.349]	0.137 [0.712]	0.638 [0.425]	0.774 [0.379]	3.216** [0.041]	10.162*** [0.002]	1.313 [0.253]	0.915 [0.340]
CZR	5.272** [0.022]	3.555* [0.060]	5.411** [0.021]	4.344** [0.038]	0.030 [0.863]	5.313*** [0.005]	25.071*** [0.000]	2.622 [0.106]	0.576 [0.449]
EGP	1.630 [0.203]	0.087 [0.768]	4.865** [0.028]	0.543 [0.462]	0.636 [0.426]	0.841 [0.432]	3.393* [0.066]	0.146 [0.703]	0.023 [0.879]
GRC	1.377 [0.241]	3.340* [0.068]	0.484 [0.487]	15.002*** [0.000]	2.325 [0.128]	8.565*** [0.000]	22.764*** [0.000]	2.114 [0.147]	4.387** [0.037]
HUN	5.158** [0.024]	3.898** [0.049]	2.796* [0.095]	0.801 [0.371]	0.002 [0.969]	3.182** [0.043]	16.846*** [0.000]	2.379 [0.124]	0.133 [0.716]
IND	0.064 [0.801]	0.493 [0.483]	0.138 [0.710]	18.852*** [0.000]	2.951* [0.087]	5.989*** [0.003]	29.107*** [0.000]	3.074* [0.080]	2.425 [0.120]
INS	0.143 [0.705]	2.427 [0.120]	5.359** [0.021]	5.886*** [0.003]	0.393 [0.531]	2.383* [0.051]	4.717*** [0.009]	0.530 [0.589]	6.516*** [0.002]
MXC	0.007 [0.935]	0.913 [0.340]	2.188 [0.140]	3.604* [0.058]	3.563* [0.060]	4.244** [0.015]	20.330*** [0.000]	4.942** [0.027]	0.502 [0.479]
PAK	9.867*** [0.002]	0.001 [0.982]	10.644*** [0.001]	0.127 [0.722]	3.822* [0.051]	0.602 [0.438]	0.462 [0.497]	0.024 [0.877]	0.040 [0.842]
PER	0.357 [0.550]	0.511 [0.475]	0.505 [0.478]	9.093*** [0.003]	3.211* [0.074]	7.767*** [0.006]	32.779*** [0.000]	2.189 [0.140]	1.875 [0.172]
PHL	2.297 [0.130]	0.260 [0.610]	7.860*** [0.005]	3.657* [0.057]	4.589** [0.033]	4.022** [0.046]	22.113*** [0.000]	1.337 [0.248]	6.630** [0.010]
RUS	0.948 [0.331]	0.325 [0.569]	6.030** [0.015]	7.833*** [0.005]	5.202** [0.023]	1.125 [0.290]	8.909*** [0.003]	0.579 [0.447]	0.739 [0.391]
SAF	0.001 [0.975]	1.040 [0.308]	0.411 [0.522]	13.176*** [0.000]	3.485* [0.063]	5.730** [0.017]	14.973*** [0.000]	0.970 [0.325]	0.741 [0.390]
TAI	0.346 [0.557]	0.531 [0.467]	7.305*** [0.007]	3.757* [0.053]	16.119*** [0.000]	3.226*** [0.007]	25.883*** [0.000]	2.060 [0.152]	0.992 [0.320]
THL	0.224 [0.636]	0.152 [0.697]	0.880 [0.349]	6.937*** [0.009]	0.004 [0.953]	6.024** [0.015]	27.768*** [0.000]	1.959 [0.162]	0.433 [0.511]
TUR	1.970 [0.161]	0.403 [0.526]	11.770*** [0.001]	6.292** [0.013]	3.340* [0.068]	1.724 [0.190]	12.849*** [0.000]	0.357 [0.551]	2.650 [0.104]

*Note:* This table reports the causality test results for the Taylor-based nonlinear causality test for the GFC sub-sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.



**TABLE 11** Taylor-based causality tests for overall and from United States to emerging markets ‘long-term’ (GFC sub-sample ‘1/08/2007 – 30/06/2009’)

	<b>EPU</b>	<b>GPR</b>	<b>VIX</b>	<b>World</b>	<b>TED</b>	<b>USD</b>	<b>GSCI</b>	<b>Oil</b>	<b>Gold</b>
Overall	1.691 [0.194]	0.344 [0.558]	1.883 [0.171]	3.402** [0.034]	1.825 [0.178]	3.040* [0.082]	12.467*** [0.000]	3.107** [0.046]	1.398 [0.248]
From US to									
EMR	1.047 [0.307]	0.657 [0.418]	7.685*** [0.006]	23.022*** [0.000]	16.555*** [0.000]	10.344*** [0.000]	46.549*** [0.000]	9.196*** [0.003]	2.803* [0.095]
BRZ	0.989 [0.321]	0.261 [0.610]	12.415*** [0.001]	17.704*** [0.000]	10.375*** [0.001]	4.599** [0.011]	29.456*** [0.000]	7.742*** [0.006]	0.540 [0.463]
CHL	0.821 [0.365]	0.016 [0.899]	13.345*** [0.000]	6.531** [0.011]	3.637* [0.057]	8.885*** [0.000]	34.349*** [0.000]	9.366*** [0.002]	0.068 [0.795]
CHN	0.262 [0.609]	1.086 [0.298]	4.133** [0.043]	27.731*** [0.000]	9.237** [0.003]	9.783*** [0.000]	38.001*** [0.000]	6.478** [0.011]	4.318** [0.038]
COL	0.766 [0.382]	0.977 [0.323]	0.018 [0.894]	1.328 [0.250]	0.219 [0.640]	3.320** [0.037]	12.482*** [0.001]	2.148 [0.144]	0.336 [0.562]
CZR	3.825* [0.051]	3.186* [0.075]	3.195* [0.075]	7.662*** [0.006]	1.819 [0.178]	6.137*** [0.002]	29.587*** [0.000]	3.240* [0.073]	1.273 [0.260]
EGP	1.538 [0.216]	0.176 [0.675]	4.593** [0.033]	0.106 [0.745]	0.182 [0.670]	0.883 [0.414]	4.452** [0.036]	0.379 [0.539]	0.010 [0.922]
GRC	0.556 [0.456]	2.732* [0.099]	0.027 [0.869]	19.265*** [0.000]	4.181** [0.042]	9.473*** [0.000]	29.474*** [0.000]	3.615* [0.058]	5.058** [0.025]
HUN	3.021* [0.083]	3.321* [0.069]	0.381 [0.537]	2.952* [0.087]	0.772 [0.380]	4.211** [0.016]	22.372*** [0.000]	3.900** [0.049]	0.545 [0.461]
IND	0.013 [0.908]	0.366 [0.546]	0.217 [0.642]	16.048*** [0.000]	3.353* [0.068]	6.447*** [0.002]	30.626*** [0.000]	3.627* [0.058]	2.272 [0.133]
INS	0.037 [0.848]	1.973 [0.161]	0.848 [0.358]	21.867*** [0.000]	6.759** [0.010]	10.015*** [0.000]	38.258*** [0.000]	5.888** [0.016]	7.739*** [0.006]
MXC	0.049 [0.825]	0.000 [0.993]	2.370 [0.125]	4.563** [0.033]	3.737* [0.054]	3.849** [0.022]	19.416*** [0.000]	4.764** [0.030]	0.880 [0.349]
PAK	11.202*** [0.001]	0.061 [0.806]	12.062*** [0.001]	3.706* [0.055]	3.899** [0.049]	0.177 [0.838]	2.650 [0.104]	1.699 [0.193]	2.511 [0.114]
PER	0.086 [0.769]	0.342 [0.559]	1.787 [0.182]	9.080*** [0.003]	3.476* [0.063]	4.291** [0.014]	38.573*** [0.000]	8.690*** [0.003]	0.000 [0.987]
PHL	2.728* [0.099]	2.343 [0.629]	10.948*** [0.001]	8.213*** [0.004]	3.872** [0.050]	9.003*** [0.000]	33.563*** [0.000]	9.891*** [0.002]	1.735 [0.189]
RUS	2.413 [0.121]	0.350 [0.555]	12.841*** [0.000]	26.728*** [0.000]	8.305*** [0.004]	2.455* [0.087]	17.958*** [0.000]	5.636** [0.018]	2.009 [0.157]
SAF	0.149 [0.699]	0.622 [0.431]	1.464 [0.227]	9.571*** [0.002]	3.153* [0.077]	4.789*** [0.009]	15.869*** [0.000]	3.574* [0.059]	1.631 [0.202]
TAI	0.804 [0.370]	0.479 [0.490]	9.563*** [0.002]	28.984*** [0.000]	11.383*** [0.001]	5.382*** [0.005]	29.363*** [0.000]	7.174*** [0.008]	1.297 [0.255]
THL	0.085 [0.771]	0.091 [0.763]	1.963 [0.162]	3.172* [0.076]	0.004 [0.953]	8.271*** [0.000]	25.157*** [0.000]	6.700*** [0.010]	1.449 [0.229]
TUR	1.343 [0.247]	0.416 [0.519]	11.136*** [0.001]	17.027*** [0.000]	2.953* [0.087]	4.995*** [0.007]	31.427*** [0.000]	7.064*** [0.008]	3.197* [0.075]

*Note:* This table reports the causality test results for the Taylor-based nonlinear causality test for the whole sample period. In each panel, we report the causality test results for the null hypothesis that Global factor does not Granger cause overall spillover, spillover from United States to all emerging markets, and spillovers from United States to the Brazil, Chile, China, Columbia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Mexico, Pakistan, Peru, Philippines, Russia, South Africa, Taiwan, Thailand, Turkey, respectively. In different columns, we report the causality test results different global factors used in the study.

stock market outcomes in emerging economies. This reinforces the idea that US stock market is a barometer of world stock market conditions (Ko & Lee, 2015).

Second, the findings of the study show heterogeneous impact of global factors in driving connectedness among United States and emerging stock markets. The findings indicate that the response of emerging stock markets to information content in global factors differs according to their microstructure. Moreover, the influence of global factors in driving connectedness between United States and emerging stock markets depends on the economic and financial dependencies between the underlying markets. Considering the market reaction hypothesis posits that investors do not always consider all the public information available for making investment decisions; thus, investor behaviour may drive heterogeneous responses across different stock markets. Our results suggest that heterogeneous response to global factors across different markets aids investors in formulating more informed international portfolio diversification and hedging strategies.

Finally, the findings also report the existence of non-linearities in the association among global factors and spillovers between United States and emerging stock markets. The findings imply that market participants should consider the existence of structural breaks and non-linearities before evaluating the underlying relationship to make more prudent portfolio and risk management decisions.

### 3.3 | Crisis period and causality

In this section, we compare our total sample period results with GFC period using the same methods. Once again, we estimate the connectedness among United States and emerging stock markets in the time and frequency domains. Afterward, we approximate the impact of global factors on spillover transmission among United States and emerging markets. First, Table 8 illustrates the causality results for total time-varying total connectedness between the underlying stock markets. The findings reveal some interesting insights. In the crisis period, only two global factors, EPU and TED, significantly drive the overall connectedness. Also, MSCI world index, commodity index and TED are responsible for driving connectedness among United States and emerging stock markets. The findings highlight a relatively weak contribution of global factors in driving contagion effects between United States and emerging stock markets during the crisis.

Nevertheless, the results do not posit that information content in global factors cannot be effectively utilized to predict spillovers between underlying stock markets in

crisis periods. Instead, they exhibit that their causal effects in driving connectedness are relatively weak during GFC. For instance, we note VIX index does not significantly drive overall spillovers between U.S and emerging stock markets. Still, it is found to be the second strongest factor after MSCI world index in driving connectedness between the United States and many sample countries in this crisis period. Also, we found a limited role of news-based indexes (EPU and GRP) in driving bi-lateral connectivity between United States and emerging stock markets in the crisis period, which corresponds to evidence that suggests the causal effects of news-based indexes strengthen the post-crisis period (Albulescu, Demirer, Raheem, & Tiwari, 2019). Following earlier presented evidence, the findings indicate the heterogeneous impact of global factors in transmission relationship of stock markets during the GFC period. In addition, the findings once again show the existence of a non-linear relationship between global factors and connectedness spillovers for United States to emerging stock markets (Tables 9–11).

Afterward, we estimate causality results of GFC for three other frequency bands, short-term (0–5 days), medium-term (6–20 days), and long term (21–262 days). The causality results in different frequency bands validate the influential role of global factors in spillover transmission among United States and emerging stock markets. The findings also demonstrate the heterogeneous impact of global factors across different frequency bands. The findings highlight various meaningful insights for portfolio diversification strategies. In fact, the findings validate the effectiveness of estimating results using different frequency bands because it can lead to a better understanding of the relationship between global factors and spillovers between United States and emerging markets.

## 4 | CONCLUSIONS

The study investigates the impact of various global factors in driving connectedness among United States and 19 emerging stock markets. In order to approximate the connectedness among the underlying stock markets, the study employs Diebold and Yilmaz (2012) time-domain and Baruník and Křehlík (2018) frequency-domain approaches. Also, nonlinear causality tests proposed by Péguin-Feissolle and Terasvirta (1999) are utilized to determine the influence of global factors in transmitting spillovers among United States and emerging stock markets. In addition, we also conduct a sub-sample analysis for the underlying relationship during GFC period. The findings of the study unveil some interesting insights.

First, the results display strong spillovers among United States and emerging stock markets, especially during economic and financial turmoil. The results suggest that increased liberalization and globalization of financial markets worldwide, leads to an escalated level of connectedness among United States and emerging stock markets. Higher market integration and contagion effects between United States and emerging stock markets adversely affect portfolio diversification opportunities for international investors. Second, the findings also uncover the strong influence of global factors in driving connectedness from United States to emerging stock markets. However, the findings also demonstrate the heterogeneous impact of global factors in driving connectedness across different emerging stock markets. The findings imply that various market-specific factors may drive this heterogeneity in the results, but still, the results provide useful information to portfolio managers in formulating more prudent international investments and hedging strategies. Third, the findings of the study also validate the existence of nonlinearities between global factors and connectedness among United States and emerging markets. Four, the study's findings also reinforce the causal impact of global factors in transmitting spillovers among United States and emerging markets during the GFC period. Finally, the findings also stress using different frequency domains to understand better spillovers among the underlying stock markets and related portfolio decisions.

The evidence presented by the study holds various meaningful implications for portfolio managers and investors. The findings recommend that stock market participants recognize the crucial role of global factors in driving connectedness across United States and emerging stock markets. Hence, the information content of global factors can be effectively employed to forecast the contagion among the underlying stock markets to formulate more effective risk management and portfolio decisions. As the crisis events enhance the contagion among financial markets, investors in emerging markets need effective mechanisms to hedge against the risk transmitted by developed stock markets. In addition, policy makers should also formulate regulations to shield emerging markets from contagion effects transmitted from developed stock markets like United States. Although the study contributes to spillover literature, there are a few limitations that researchers should consider for future research.

First, the sample stock markets utilized for analysis contains some major developing countries. Still, this sample could be extended to give more global

importance to such findings. Second, the study employed methods such as Diebold & Yilmaz (2012) and Baruník and Křehlík (2018) to measure connectedness. Although they are established methods, both underlying methods estimate mean-based spillovers, whereas the newly developed measure of connectedness known as quantile connectedness extends these two conventional approaches. So, future research could employ the suggested method to estimate extreme connectedness among United States and emerging markets. Finally, the recent pandemic crisis also necessitates fresh evidence on this topic because the growing literature thread suggests strong spillovers among stock markets during this period. Hence, the role of global factors in driving connectedness among United States and developing markets could be re-examined for the pandemic period.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## ENDNOTE

<sup>1</sup> See studies such as, Colombo (2013), Dakhlaoui and Aloui (2016).

## DATA AVAILABILITY STATEMENT

Codes and data used for this paper are available upon request.

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**How to cite this article:** Naeem, M. A., Farid, S., Qureshi, F., & Taghizadeh-Hesary, F. (2023). Global factors and the transmission between United States and emerging stock markets. *International Journal of Finance & Economics*, 28(4), 3488–3510. <https://doi.org/10.1002/ijfe.2604>