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The comovements of tail risks in time and frequency domains: evidence from US and emerging Asian stock markets

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Abstract

The study applies the wavelet local multiple correlations to investigate the level of comovements among the tail risks of US and emerging Asian stock markets in both time and frequency domains. Through this empirical investigation, we address the question of how the transmission of tail risk across the concerned stock markets is changing over specific timescales, varying from short term to long term. Empirical results from the multivariate time–frequency correlations show that the comovements of tail risks are distinctively higher during periods of economic and political turmoil in the short term. The multivariate long-term comovements are highly stable and extremely strong which can be taken as evidence of long-term integration. In contrast, the bivariate time–frequency correlations are remarkably weaker in the short term not only during periods of crises but over most of the sample period. The results of the bivariate analysis also highlight the instability of the long-term pairwise correlations of the tail risks, showing that it is susceptible to sudden changes, which indicates that the tail risks of the US and emerging Asian stock markets are actually not completely integrated in the long term. This finding also implies that the tail risks of US and emerging Asian stock markets are nonlinearly connected in the long term.

Keywords Stock markets, Value at risk, Tail risk, Multiple local correlations, Wavelet analysis, USA, Emerging Asia

JEL Classification G15, F39

Introduction

The level of comovements among international stock returns is an essential input for creating a well-diversified equity portfolio. In recent years, however, financial agents and international equity investors have become more attentive to the interconnection of financial losses of multiple financial institutions, markets, and assets. Kozlowski et al. [37] attribute this phenomenon to the persistent effect of crises which increased the perception of tail risk among agents of the economy. More specifically, the authors argue that economic agents have become, particularly after the 2008 global financial crisis (GFC), inclined to believe that the left-tail events are more likely to occur. This heightened perception of tail risk has led to an explosive increase in studies devoted to systemic risk modeling (see, e.g., [2, 3, 11]). Studying the cross-country transmission of tail risk is important also for policymakers because exposure to financial risk can lead to real macroeconomic decline. The importance of this issue compounds further in light of the evidence that global financial risk is more harmful to economic growth than local financial risk [14].

Our objective in this paper is to study the time–frequency comovements of tail risks, with a special focus on US and emerging Asian stock markets. US financial markets have a significant impact on global financial trends, especially in times of global distress, due to the large worldwide base of US equity and debt security investors.

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Therefore, it can be used as a proxy for global financial conditions. Emerging Asian markets, on the other hand, have become a favorable destination for return-chasing investors, principally from US and European developed markets, due to their high growth potential. In the meantime, the economic and financial correlations between developed and emerging Asian markets were progressively increasing as pointed out in many studies (see, e.g., [36, 49, 60]). Kim et al. [35] show that the correlation between developed and emerging Asian markets is significantly determined by foreign investments. This finding perfectly aligns with the fact that the movements of international capital were largely driven by emerging Asian markets. Between 1990 and 2009, these markets absorbed nearly two-thirds of total financial inflows to emerging market economies [46]. The attractiveness of emerging Asian equity markets as an international asset was mainly driven by relaxing the investment restrictions on foreign portfolio investors and the significant improvements in market infrastructures and governance. However, the rise of emerging Asian equity markets as a desirable international asset was accompanied by several concerns regarding the high-risk profile of these markets. In this respect, the high volatility of stock returns was one of the most concern-warranting characteristics of the emerging Asian markets. In addition, the volatility of emerging and Asian equity markets is believed to have the property of long memory (see, e.g., [13, 55]). Such a feature is particularly relevant because the perception of tail risk can be incorporated into the dynamics of the stock market index through volatility persistence.

The increasing role of emerging Asian markets in global finance motivated many researchers to study the connectedness between the stock markets of developed and emerging Asian countries (see, e.g., [12, 29, 42, 47], Kangogo et al. [33]). A common feature of these studies is that the connectedness is only evaluated at the first or second moment of the return distribution, while other parts of the distribution, particularly the left tail, are overlooked. In contrast, there have been very few recent studies that focused on the comovements and connectedness at the tails of return distribution in emerging and Asian stock markets (see, e.g., [44, 62]). Overall, the methods used in these studies do not typically look at the short-run and long-run comovements of the tail risks. In light of these limitations, the current study aims to analyze the comovements of tail risks over different frequencies and time horizons. To this end, the study employs the wavelet local multiple correlation (WLMC) technique recently developed by Fernández-Macho [25]. In this respect, it is important to mention that the literature is rich of methods that can be used to extend the connectedness and correlation to the frequency domain, the most notable of which is the method proposed by Baruník and Křehlík [6]. However, we adopt the WLMC approach because it has the ability to incorporate several frequencies at once; hence, it can provide more information on time-localized interdependence. The approach can also be applied to multivariate time series and to bivariate time series as well. Regarding the estimation of tail risks, the study employs the asymmetric slope conditional autoregressive value at risk (AS-CAViaR) of Engle and Manganelli [21]. Based on this empirical analysis, the study aims to answer the following questions: How does the correlation between the tail risks of US and emerging Asian stock markets evolve across time and space? In which frequencies does the transmission of tail risk between the concerned markets intensify?

The main contribution of this study is twofold. First, the current study fills an important gap in the related literature. To the best of the author's knowledge, this is the first study to examine the tail risk correlations in both time and frequency domains between US and emerging Asian stock markets. From a methodological perspective, the current study is more close to the study by Das et al. [15, 16] who used the WLMC approach to examine the interdependence and changes in correlation structure between developed and emerging markets after the GFC. However, our study goes deeper by focusing on the time–frequency dynamics of extreme risk comovements among the stock markets of the USA and emerging Asia. In addition, the distinction between the short-term, medium-term, and long-term parts of tail risk correlations is extremely important to increase our understanding of systemic risk transmission. As argued by Baruník and Křehlík [6], understanding the sources of connectedness in an economic system is crucially dependent on the understanding of the frequency dynamics of the connectedness, as shocks to economic activity impact variables at various frequencies with various strengths. For this reason, the dynamics of systemic risk in the frequency domain have recently become one of the main topics in international finance. Second, the study conducts both multivariate and bivariate analyses, providing a holistic view on the time–frequency correlations between the tail risks of US and emerging Asian markets. Another benefit of conducting such analyses is to show the structural differences between the developments of the pairwise and system-wide comovements over time and space.

The remainder of this study is organized as follows. "Review of the related literature" section provides a review of the related literature. "Data and empirical methodology" section describes the dataset and the research methodology. "Empirical results" section reports the empirical results. "Discussion" section includes a discussion of the empirical results. Finally, "Conclusion" section provides the conclusion of the study.

Review of the related literature

The current study is closely linked to a growing body of research that focuses on the interdependency of tail risks in international stock markets. The empirical methodology used in this strand of research can be broadly divided into multivariate and bivariate modeling of systemic risk. The multivariate modeling of risk spillovers appears to be mostly based on the quantile regression and the vector autoregressive (VAR) methodology of Diebold and Yilmaz [17]. Note that the latter was originally designed to model the systemic risk at the conditional mean. However, this method can also be directly applied to other moments of the distribution. For instance, Liu et al. [38] relied on the methods of Diebold and Yilmaz [18] and Baruník and Křehlík [6] to analyze the spillovers of intraday realized volatility among the major sixteen stock markets of the world during the recent pandemic. They found that the spillovers from the regions of Europe and America were rapidly increasing while those from the Asian region were decreasing. Similarly, Fang et al. [23] investigated the dynamics of short-, medium-, and long-term spillovers of risk across the major financial markets in the context of COVID-19. They found that the global index of stock markets was a prominent transmitter of risk to other financial markets after the breakout of the pandemic. Su [54], on the other hand, proposed the quantile variance decomposition approach as an extension of Diebold and Yilmaz [17], the method was applied to groups of G7 and BRICS countries and showed that the extreme risk predominantly spillover from developed to BRICS countries. The quantile regression approach, however, is inherently more flexible because it can be used to construct the network of the system at any desired quantile of the return distribution. Such a methodology has been used in many recent studies. Nguyen and Lambe [45] used the Least Absolute Shrinkage Operator (LASSO) quantile regression to construct a tail risk network for 32 OECD countries, the results show that the USA is resilient to tail risk while Japan is a significant transmitter of global shocks. Wu et al. [61] studied the network of 28 stock markets around the globe during the period of the COVID-19 pandemic. The results of this study showed a significant increase in tail risk correlations during the pandemic, Wu et al. [61] also found that tail risks of countries with lower economic correlation were more correlated during the period of the pandemic than the countries who are economically tightly correlated. Wang et al. [57] applied the ΔCoVaR and the cascading failure network model to measure systemic risk contributions of country-level stock markets. In this study, the southeast European markets were identified as the highest systemic risk contributors with time-varying and momentum features corresponding to significant financial crisis events. In the study of Shen [52], which applied a multivariate quantile regression approach known as VAR for VaR, the US stock market was found to be increasing the tail risks in the major Asian stock markets. In another study conducted by Baumöhl and Shahzad [7], the authors used the quantile coherency approach to map the tail dependence network of 49 international stock markets. They found that the strongest connection of tail risks is exhibited by European developed markets, whereas the connections exhibited by emerging and frontier markets are less strong. Overall, their results showed that the strength of the tail risk network has notably increased after the GFC. Finally, Gue et al. [28] combined the factor-adjusted regularized model selection (FARM-Selection) method with quantile regression to analyze the tail risk contagion between international financial markets during the COVID-19 pandemic. They found that the pandemic has affected the network of tail risk by increasing the channels of contagion and the number of risk drivers, and the latter is also found to be larger than risk takers. They also concluded that tail risk spillovers among Asian markets were mainly influenced by European and American markets and not China's market.

Besides the quantile regression and VAR methods, wavelet-based modeling of multivariate systemic risk has been used in a few studies. Among the latter is, for example, Ren et al. [50] who constructed a global multiscale partial correlation network of tail risk for global equity markets. The authors measured the tail risk of each equity market using GARCH-EVT-VaR, and then the time series of tail risks were decomposed into multiscale components using a wavelet technique. The results showed that US and Eurozone stock markets dominate the process of tail risk transmission, unlike stock markets of developing countries which remain inactive over all the frequency domains. In a similar fashion, Du et al. [19] constructed a LASSO-based network connectedness to study the multiscale tail risk spillover effects of global stock markets. According to the results of this study, the network of short-term risk spillovers appears to be centered around the stock markets of Europe and North America. In the long term, however, the center of the tail risk network is fairly dominated by emerging stock markets.

The bivariate modeling of risk spillovers is in general based on the CoVaR methodology pioneered by Adrian and Brunnermeier [2]. In this framework, the CoVaR is conditionally dependent on the VaR of another variable. However, the estimation of CoVaR cannot only be based on quantile regression as in Adrian and

Brunnermeier [2]. It can also be estimated using other statistical methods such as GARCH-type and copula models. The original CoVaR method and its variants have been used in many studies to model systemic risk in stock markets. Using copula-based CoVaR, Lu et al. [40] find that all market pairings exhibit significant increases in the upside and downside spillovers after the outbreak of COVID-19. Similarly, Aloui et al. [4] applied CoVaR-Copula to study the tail risk spillovers from China to the markets of G7 countries. They found that the stock markets of G7 had almost quantitatively similar exposure to the tail risk of the Chinese market before the breakout of the COVID-19 pandemic. The tail risk exposure, then, increased dramatically for all G7 countries when the pandemic started. Boako and Alagidede [8] also used the CoVaR-Copula approach to estimate the tail dependence structure between African stock markets and global indices of equity markets. In this study, except for Egypt, all other African markets exhibited low positive significant dependencies with the international equity indices. Warshaw [58] used a generalized autoregressive score (GAS) copula to analyze the risk spillovers across North American equity markets. The findings of this study showed that the spillovers at the downside tail are more severe than the upside tail for all the market pairings, particularly after the GFC. Copula-based CoVaR can also be combined with graphical methods to construct a tail risk network. An example of this methodology is found in the study of Wen et al. [59] who modeled the tail dependence network of stock markets by using the SJC copula function and planar maximally filtered graph method. The networks built by this study showed that the upper and lower tail dependence of the European stock markets is more influential than their counterparts from emerging economies.

For GARCH-based CoVaR, Fang et al. [22] combined the CoVaR approach proposed by Girardi and Ergün [27] with the ADCC-GARCH model to investigate the risk contributions of G7 and BRICS stock markets. The main finding of this study shows that the risk contribution of developed stock markets to global systemic risk is higher than the contributions of emerging markets. Using the same methodology, Abuzayed et al. [1] studied the total and bivariate connectedness between the global stock index and several national stock indices during the period of COVID-19. The bivariate analysis showed that tail risks of European and American developed stock markets are more interconnected with the global index than the Asian stock markets. The multivariate analysis, on the other hand, showed a high level of extreme tail risk connectedness in the network of global and national stock indices.

On a final note, from a methodological perspective, our work is related to the studies that follow the WLMC method to analyze the time–frequency interdependencies of economic and financial time series. A distinctive feature of these studies is that they tend to focus on macroeconomic variables and financial assets of different classes. Bouri et al. [9, 10] focused on the comovements of returns and implied volatilities of oil, gold, wheat, and copper. They found that the correlations across the selected commodities are heterogeneous, less stable in the short term, and more pronounced in the long term but vary in sign and magnitude. Umar et al. [56], in their study on the connectedness between cryptocurrencies and technology sectors, reported an almost exact linear relationship between global technology sectors for scales of quarterly length and longer. Polanco Martínez et al. [48] focused on crude oil and oil product prices and found strong wavelet correlations throughout the period of the study. Zhou et al. [63] studied the connection between environmental tax, economic growth, and renewable energy and found a significant positive connection in the short and long term. Bouri et al. [9, 10] analyzed the comovement between changes in expected inflation and US stock sector returns, and they found insignificant correlations in the short term but heterogeneous correlations in longer timescales.

Based on the above, we find a plethora of studies that focused on the interdependencies of stock market tail risks in the time dimension, while the frequency dimension has mostly been neglected. There are indeed few studies that have included the frequency dimension of tail risk correlations. These studies, however, investigate the tail risk connectedness in a global context using a network analysis. The current study adds to this line of studies by providing a special look on US and emerging Asian stock markets. In addition, it can also be observed that the applications of the WLMC approach have so far been limited to evaluating the conditional mean correlation. Thus, the use of WLMC to analyze the interdependencies of the left tails of stock returns distribution is unprecedented in the related literature.

Data and empirical methodology

Data

The study uses a daily dataset comprising seven stock market indices from the USA and emerging Asia, namely South Korea's stock market composite index (KOSPI), India's BSE SENSEX which is the benchmark index of the Bombay Stock Exchange, Malaysia's stock exchange index (KLSE), Thailand's stock exchange index (SET), Indonesia's stock exchange index (JKSE), and the index of Philippines stock exchange (PSEI). Finally, US stock markets are represented by the S&P 500 index. The data of the stock market indices are taken from the websites of Yahoo Finance and the Wall Street Journal. The logarithmic formula is applied to derive the stock returns from each index. The empirical sample extends over the period between January 6, 2004, and May 8, 2023, resulting in a sample of 5045 observations. The reason for selecting this period as a study sample is that it contains several events that have impacted the tail risks of stock markets to various degrees. Thus, the sample period captures significant changes in the tail risks of the selected stock markets, allowing for an informative analysis.

The descriptive statistics of the variables are provided in Table 1. All the variables of stock returns are leptokurtic as evidenced by the high coefficient of kurtosis. There is also evidence of negative skewness in the returns of all stock indices. It is also worth noting that the Jarque–Bera statistics are extremely large and statistically significant, rejecting the hypothesis of normality for all the variables. Furthermore, the Elliott–Rothenberg–Stock (ERS) unit root test by Elliott et al. [20] is used to check whether the time series of returns are stationary or not. The test was implemented with no intercept and no trend as well. As can be seen, the results of this test show that all the variables are stationary at level. Finally, the weighted portmanteau test by Fisher and Gallagher [26] is used to detect the autocorrelation in the residuals Q (10) and squared residuals Q^2 (10) up to 10 lags. The results of this test strongly indicate that autocorrelation exists in almost all returns and squared returns of the stock market indices. The only case where the autocorrelation is not found is the returns of the South Korean index (KOSPI). The existence of autocorrelation in returns and squared returns implies that the means and variances of the time series are time varying.

Empirical methodology

The empirical investigations begin by estimating the tail risk of the selected stock markets. For this purpose, the study uses the AS-CAViaR approach. The 10th percentile of stock return distribution is used as a threshold for the tail risk. After this step, the WLMC technique is applied to the resulting time series of tail risks to estimate the multivariate and bivariate time–frequency comovements.

Conditional autoregressive value at risk (CAViaR)

In their seminal paper, Engle and Manganelli [21] proposed the CAViaR model to calculate the value at risk. In essence, the CAViaR model is a semiparametric equation based on quantile regression. The model can be estimated using four different specifications, namely asymmetric slop, symmetric absolute value, indirect GARCH (1,1), and adaptive model. Asymmetric slope specification differs from others by allowing asymmetric response to past positive and negative returns. A generic form of CAViaR can be described as

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j l\left(x_{t-j}\right) \tag{1}$$

where $f_t(\beta) \equiv f_t(x_{t-1}, \beta_\theta)$ denote the time $t\theta$-quantile of the distribution of portfolio returns formed at $t-1$. The subscript θ is suppressed from β_θ for notational convenience. $p = q + r + 1$ represents the dimension of β and l is a function of a finite number of lagged values of observables. The autoregressive terms $\beta_i f_{t-i}(\beta)$, $i = 1, \ldots, q$, ensure that the quantile changes smoothly over time. The role of $l\left(x_{t-j}\right)$ is to link $f_t(\beta)$ to observable variables that belong to the information set. Since the asymmetric slop CAViaR allows the response to positive and negative returns to be different, Eq. (1) can be rewritten as follows

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 \left(y_{t-1}\right)^+ + \beta_4 \left(y_{t-1}\right)^- \tag{2}$$

Wavelet local multiple correlation (WLMC)

This method generalizes the standard wavelet correlation to a local multiple regression framework by using

Table 1 Descriptive statistics

	Mean	Variance	Skewness	Kurtosis	JB	ERS	*Q* (10)	*Q*^{2} (10)
KOSPI	0.022	1.47	−0.522*	8.727*	16,239.978*	−31.785*	8.925	2067.106*
BSE SENSEX	0.046	1.839	−0.353*	12.657*	33,778.000*	−10.272*	28.537*	918.949*
KLSE	0.012	0.518	−0.763*	13.057*	36,323.975*	−12.766*	42.882*	527.013*
JKSE	0.044	1.507	−0.623*	9.169*	17,999.062*	−29.071*	48.005*	1042.653*
SET	0.013	1.361	−1.148*	18.154*	70,387.607*	−5.435*	29.202*	739.515*
PSEI	0.03	1.56	−0.933*	11.060*	26,445.132*	−5.827*	28.967*	713.984*
S&P 500	0.026	1.437	−0.528*	13.573*	38,959.537*	−32.441*	91.870*	3148.830*

The asterisk * implies statistical significance at levels of 1%. JB: Jarque and Bera normality test, ERS: Elliott–Rothenberg–Stock unit root test. Q (10) and Q^2 (10): Fisher and Gallagher's [26] weighted portmanteau test was used to check the autocorrelation in the residuals and squared residuals up to 10 lags weighted or windowed wavelet coefficients. In so doing, the comovement dynamics across the different scales/frequencies can be analyzed over time as well. To illustrate this process, let $X \in \mathbb{R}^n \times \mathbb{R}$ be a multivariate time series where $X = (x_1, x_2, \ldots, x_n)$. Applying the maximal overlap discrete wavelet transform (MODWT) to each time series $x_n \in X$, we obtain $W_j = \left(w_{1j}, w_{2j}, \ldots, w_{nj}\right)$ where W_j is a $T \times n$ matrix of respective scale λ_j. A single global correlation for each scale is given by the wavelet multiple correlation (WMC) $\varphi_X\left(\lambda_j\right)$ as described in Fernández-Macho [24]. Therefore, $\varphi_X\left(\lambda_j\right)$ is obtained as

$$\varphi_{X,s}\left(\lambda_j\right) = \sqrt{1 - \frac{1}{\max \operatorname{diag} P_{j,s}^{-1}}}, s = 1 \ldots T, \tag{3}$$

where $P_{j,s}$ is the $(n \times n)$ weighted correlation matrix of W_j with weights $\theta(t-s)$ and maxdiag(•) operator selects the largest element in the diagonal of the argument. $\varphi_{X,s}\left(\lambda_j\right)$ can also be expressed as

$$\begin{aligned}\varphi_{X,s}\left(\lambda_j\right) &= \operatorname{Corr}\left(\theta(t-s)^{1/2} w_{ijt}, \theta(t-s)^{1/2} \hat{w}_{ijt}\right) \\ &= \frac{\operatorname{Cov}\left(\theta(t-s)^{1/2} w_{ijt}, \theta(t-s)^{1/2} \hat{w}_{ijt}\right)}{\sqrt{\operatorname{Var}\left(\theta(t-s)^{1/2} w_{ijt}\right) \operatorname{Var}\left(\theta(t-s)^{1/2} \hat{w}_{ijt}\right)}}, s \\ &= 1 \ldots T,\end{aligned} \tag{4}$$

where w_{ij} is chosen to maximize $\varphi_{X,s}\left(\lambda_j\right)$ and $\widehat{w}_{ij}$ are the fitted values in the local regression of w_{ij} on the rest of the coefficients at scale λ_j. From Eq. (3) the WLMC of scale λ_j is a nonlinear function of the $n(n-1)/2$ weighted correlation coefficients W_{jt}. Alternatively, it can be expressed as a function of all the weighted covariances and variances of W_{jt} as in Eq. (4). As a result, a consistent estimator of WLMC is given by

$$\widetilde{\varphi}_{X,s}\left(\lambda_j\right) = \sqrt{1 - \frac{1}{\operatorname{maxdiag} \widetilde{P}_{j,s}^{-1}}} = \operatorname{Corr}\left(\theta(t-s)^{1/2} \widetilde{w}_{ijt}, \theta(t-s)^{1/2} \widehat{\widetilde{w}}_{ijt}\right) = \frac{\operatorname{Cov}\left(\theta(t-s)^{1/2} \widetilde{w}_{ijt}, \theta(t-s)^{1/2} \widehat{\widetilde{w}}_{ijt}\right)}{\sqrt{\operatorname{Var}\left(\theta(t-s)^{1/2} \widetilde{w}_{ijt}\right) \operatorname{Var}\left(\theta(t-s)^{1/2} \widehat{\widetilde{w}}_{ijt}\right)}}, s = 1 \ldots T, \tag{5}$$

The weighted wavelet covariances and variance can be estimated as

$$\operatorname{Cov}\left(\tilde{w}_{ijt}, \widehat{\tilde{w}}_{ijt}\right) = \gamma_{j,s} = \sum_{t=L_j-1}^{T-1} \theta(t-1) \tilde{w}_{ijt} \widehat{\tilde{w}}_{ijt}, s = 1 \ldots \tilde{T}, \tag{5a}$$

$$\operatorname{Var}\left(\tilde{w}_{ijt}\right) = \delta_{j,s}^2 = \sum_{t=L_j-1}^{T-1} \theta(t-1) \tilde{w}_{ijt}^2, s = 1 \ldots \tilde{T}, \tag{5b}$$

$$\operatorname{Var}\left(\widehat{\tilde{w}}_{ijt}\right) = \xi_{j,s}^2 = \sum_{t=L_j-1}^{T-1} \theta(t-1) \widehat{\tilde{w}}_{ijt}^2, s = 1 \ldots \tilde{T}, \tag{5c}$$

where $\tilde{w}_{ij}$ is such that the local regression of $\tilde{w}_{ij}$ on the set of regressor $\left\{\tilde{w}_{kj}, k \neq i\right\}$ maximizes the corresponding coefficient of determination, $\widehat{\tilde{w}}_{ij}$ denotes the fitted values and $L_j = (2^j - 1)(L - 1) + 1$ is the number of wavelet coefficients affected by the boundary associated with the wavelet filter of length L at scale λ_j.

Empirical results

Multivariate time–frequency correlations

Recall that the estimation of WLMC requires that the tail risk of each stock market, shown in Fig. 1, to be decomposed into wavelet scales λ_j, this decomposition is performed by applying the MODWT with the Daubechies wavelet filter of length $L = 4$. The maximum decomposition level is set at $J = 9$. The frequency intervals of such a decomposition are ideally specified as $\left[2^{-j}\pi, 2^{1-j}\pi\right)$ for $j = 1 \ldots J$. Thus, the periods corresponding to these intervals are within $\left(2^j, 2^{j+1}\right]$. This means that scales λ_j are associated with the periods of, respectively, 2–4 days, 4–8 days (including the weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (quarterly scale), 64–128 days (quarterly to biannual scale), 128–256 days (biannual scale), 256–512 days (annual scale), and 512–1028 days (two to four-year scale). The results are presented through a heat map accompanied by a collection of multiscale line plots showing the 95% confidence intervals at different timescales.

Figure 2 shows the WLMC obtained as a measure of comovement dynamics among the tail risks of US and emerging Asian stock markets. As can be seen, the strong comovements of tail risks are highly prevalent in the area above the quarterly scale where the correlation coefficients range between 0.8 and 1. Economically, this can be interpreted as evidence of long-term integration between the left tails of the US and emerging Asian markets.

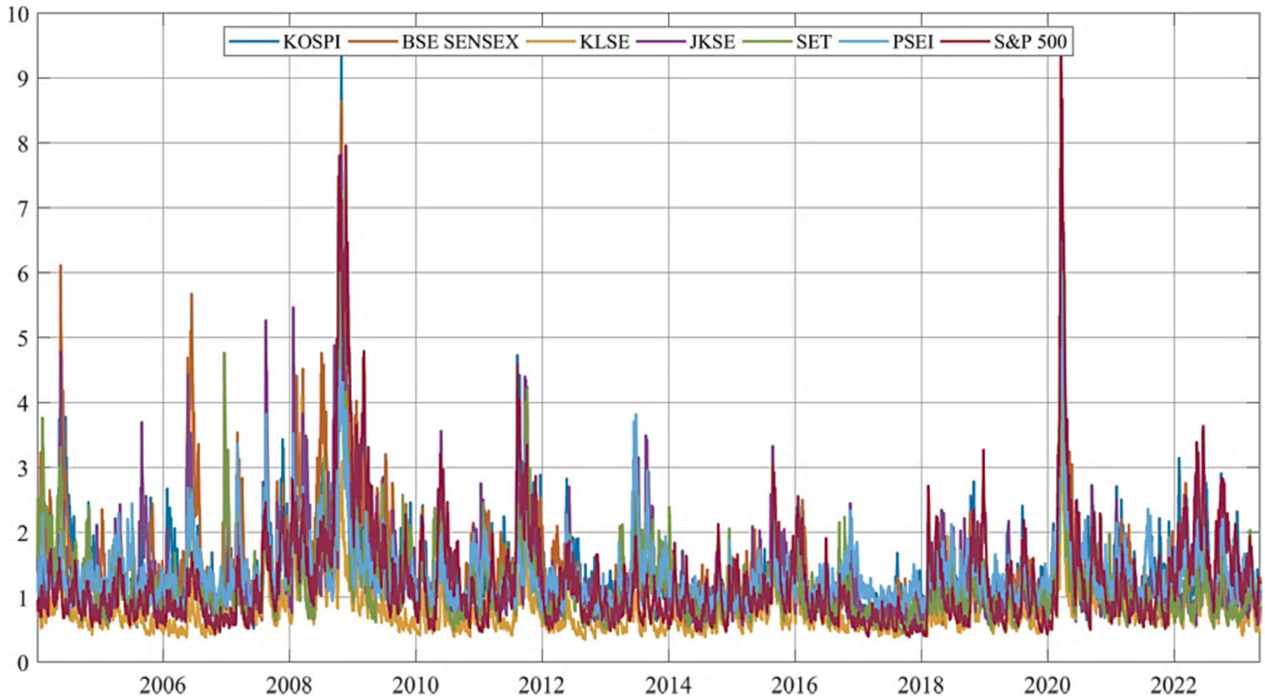

Fig. 1 Time series of the tail risks

Moreover, the integration of tail risks becomes more profoundly tight as we move beyond the yearly scale where the comovements of tail risks are near-perfectly synchronized ($\varphi \geq 0.95$). In contrast, the time–frequency correlations appear to be quite unstable for scales shorter than one month. In these scales, the correlations are shown to have dramatic changes going through several ups and downs over time. Most of these dramatic changes appear to be taking place around periods of economic and political turmoil such as the GFC, the Euro debt crisis in 2010, the massive devaluation of China's Renminbi that began in August 2015, the global health crisis of COVID-19, and lastly the Russia–Ukraine war which broke out in February 2022. Looking at the multiscale line plots, it becomes more evident that the correlations are more volatile at level 1 (2–4 scale) compared to other levels. The correlations at this level appear to highly fluctuate ranging between 0.4 and 0.85, with the highest correlation being recorded during the period of the COVID-19 pandemic. The comovements of tail risks have also significantly increased after the breakout of the ongoing Russia–Ukraine war, but this increase is slightly less severe compared to the increases during other crises. Lastly, it is also more apparent that the correlations progressively grow closer to the perfect integration level as we proceed from level 3, going through level 5, reaching level 7.

Bivariate time–frequency correlations

This section provides additional insights into the dynamic comovements of tail risks between US and emerging Asian markets from a bivariate perspective. This time the procedures of estimating the multivariate correlations are applied to bivariate time series in which the left tail of the US market is paired with the left tail of a single market from the emerging Asia region. The pairwise time–frequency correlations of the USA with the markets of South Korea, India, Malaysia, Indonesia, Thailand, and the Philippines are shown in Figs. 3, 4, 5, 6, 7, and 8, respectively. Looking at the heat map of each figure, it can be clearly noticed that the structure of time–frequency correlations is considerably different across all pairings. More precisely, the pairings of US–India, USA–Thailand, USA–Indonesia, and USA–Philippines appear to have the least stable structure of time–frequency correlations, whereas the correlations of the USA with South Korea and Malaysia follow a relatively less changeable structure across time and space compared to the left-tail correlations between other emerging Asian markets and US market. This finding is evidenced by the sudden changes in the long-term correlations which appear to be more prevailing in the correlations of the USA with India, Thailand, Indonesia, and the Philippines. These pairings more often exhibit strong negative long-term correlations of tail risks as indicated by dark blue areas.

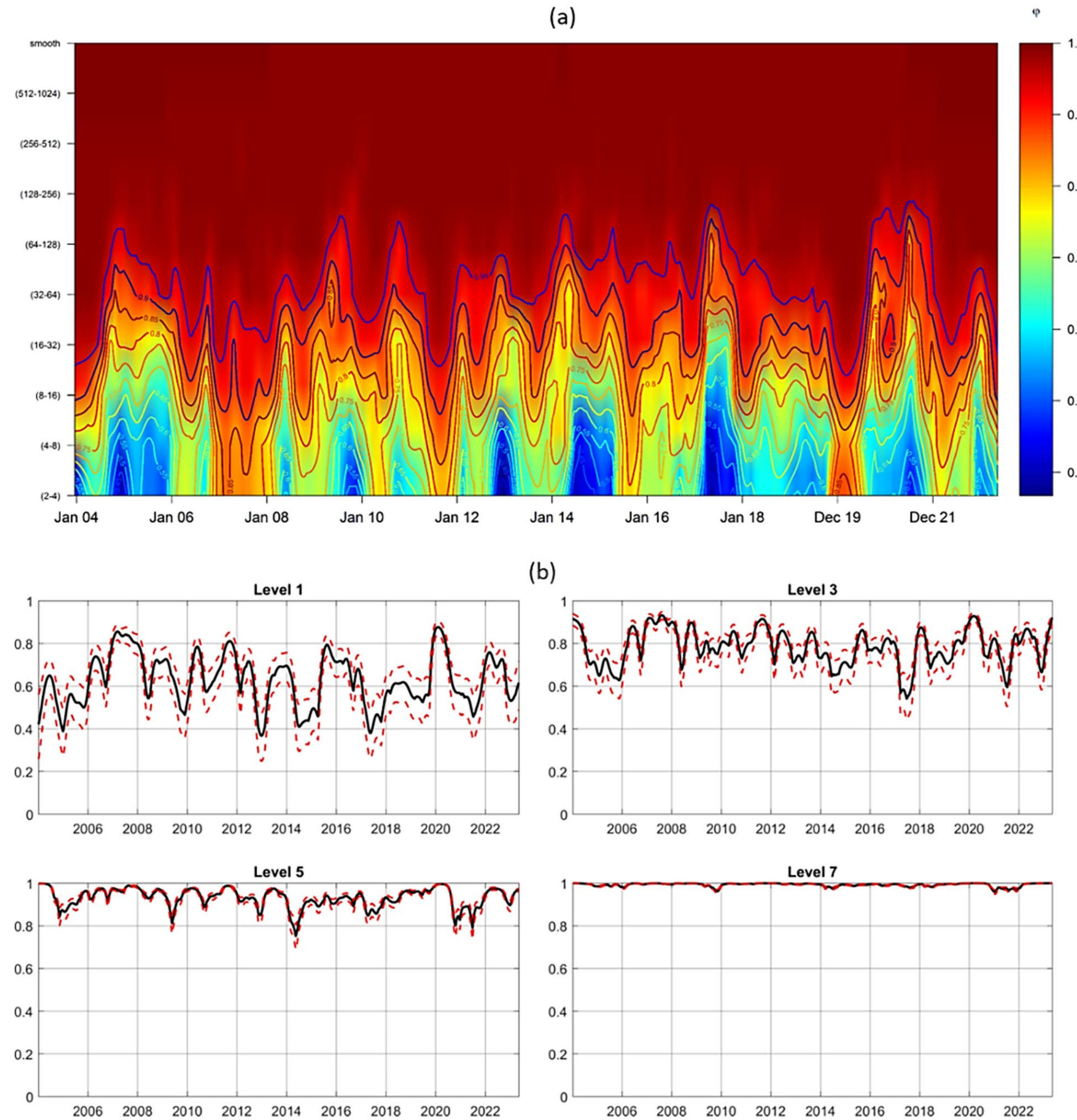

Fig. 2 Total comovements of the tail risks. *Notes* **a** WLMC heat map for a multivariate time series with varying multiple correlation across scales and along time. The parameters of the WLMC estimations are based on 5045 daily observations, with a Gaussian window length of 90 days. The wavelet filter used is Daubechies of length $L = 4$ at level $J = 9$. The x axis shows the wavelet scales λ_j. The wavelet scales λ_j are associated with the periods of, respectively, 2–4 days, 4–8 days (including the weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (quarterly scale), 64–128 days (quarterly to biannual scale), 128–256 days (biannual scale), 256–512 days (annual scale), and 512–1028 days (two to four-year scale). The color code bar on the right of the heat map indicates the range of the correlation strength from weak correlation (blue color) to strong correlation (red color). **b** WLMC line plots for the multivariate time series at different timescale levels. The dashed lines correspond to the upper and lower bounds of the 95% confidence interval

On the other hand, the presence of these strong negative long-term correlations is clearly very limited in the cases of US correlations with South Korea and Malaysia. Interestingly, a common feature of these negative long-term correlations is that they tend to emerge arbitrarily, spreading irregularly over the area above the quarterly

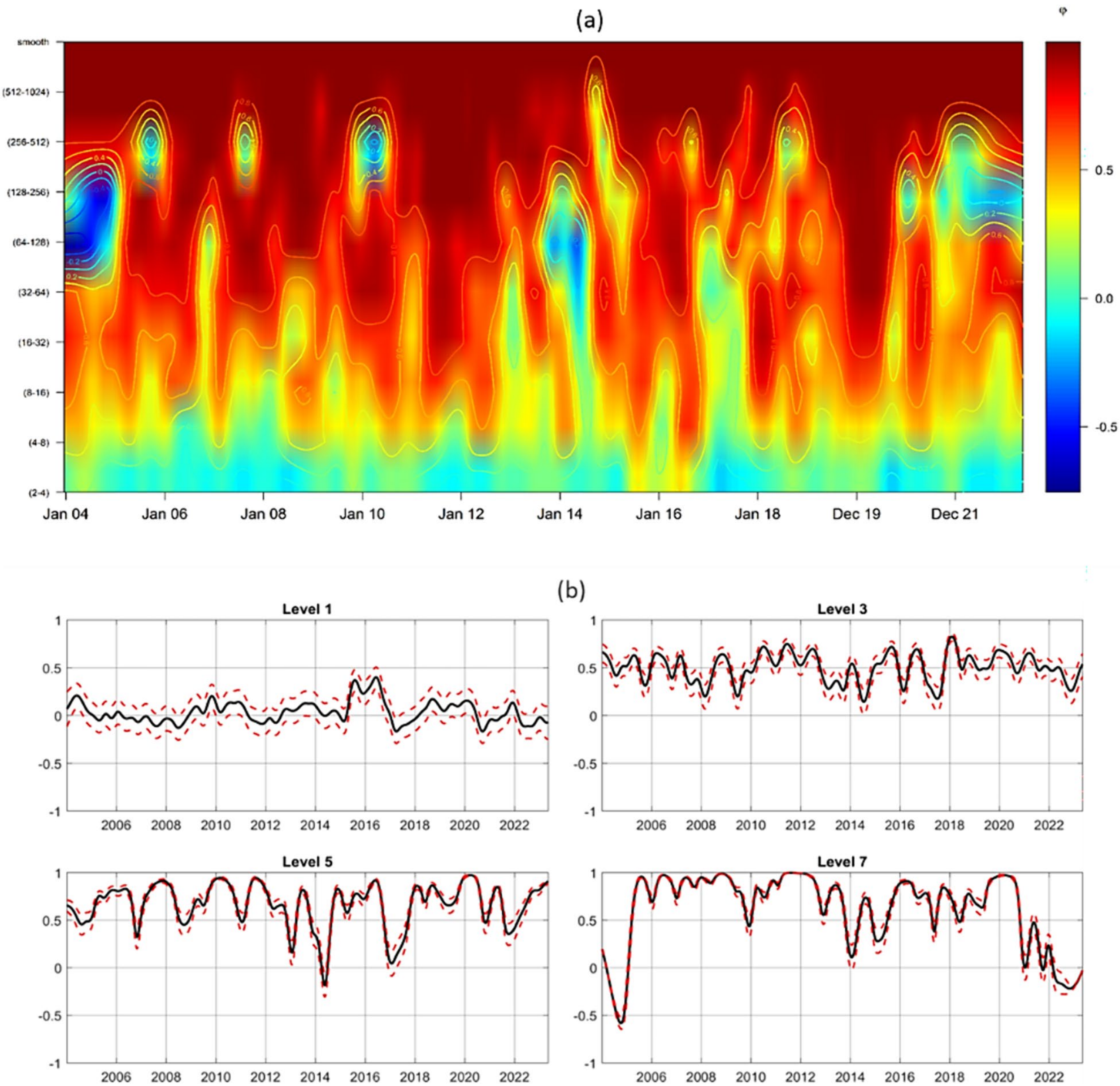

Fig. 3 Time–frequency correlations between the USA and South Korea. *Notes* **a** WLMC heat map for a bivariate time series with varying multiple correlation across scales and along time. The parameters of the WLMC estimations are based on 5045 daily observations, with a Gaussian window length of 90 days. The wavelet filter used is Daubechies of length $L = 4$ at level $J = 9$. The x axis shows the wavelet scales λ_j. The wavelet scales λ_j are associated with the periods of, respectively, 2–4 days, 4–8 days (including the weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (quarterly scale), 64–128 days (quarterly to biannual scale), 128–256 days (biannual scale), 256–512 days (annual scale), and 512–1028 days (two to four-year scale). The color code bar on the right of the heat map indicates the range of the correlation strength from strong negative correlation (blue color) to strong positive correlation (red color). **b** WLMC line plots at different timescale levels. The dashed lines correspond to the upper and lower bounds of the 95% confidence interval

scale. This observation is plainly manifested by multiscale line plots where it can be seen that correlations at some time points begin to move to the negative territory starting from level 5 (quarterly scale). The negative correlations at this level are somewhat benign, but they become notably stronger as we move to level 7 (biannual scale). This result indicates that the financial losses of emerging Asian markets are not fully integrated with the financial losses of US markets in the long term. In other words, the common financial losses are not systemic across all horizon investments during some periods. Theoretically, one could anticipate that the systemic risk of the major global

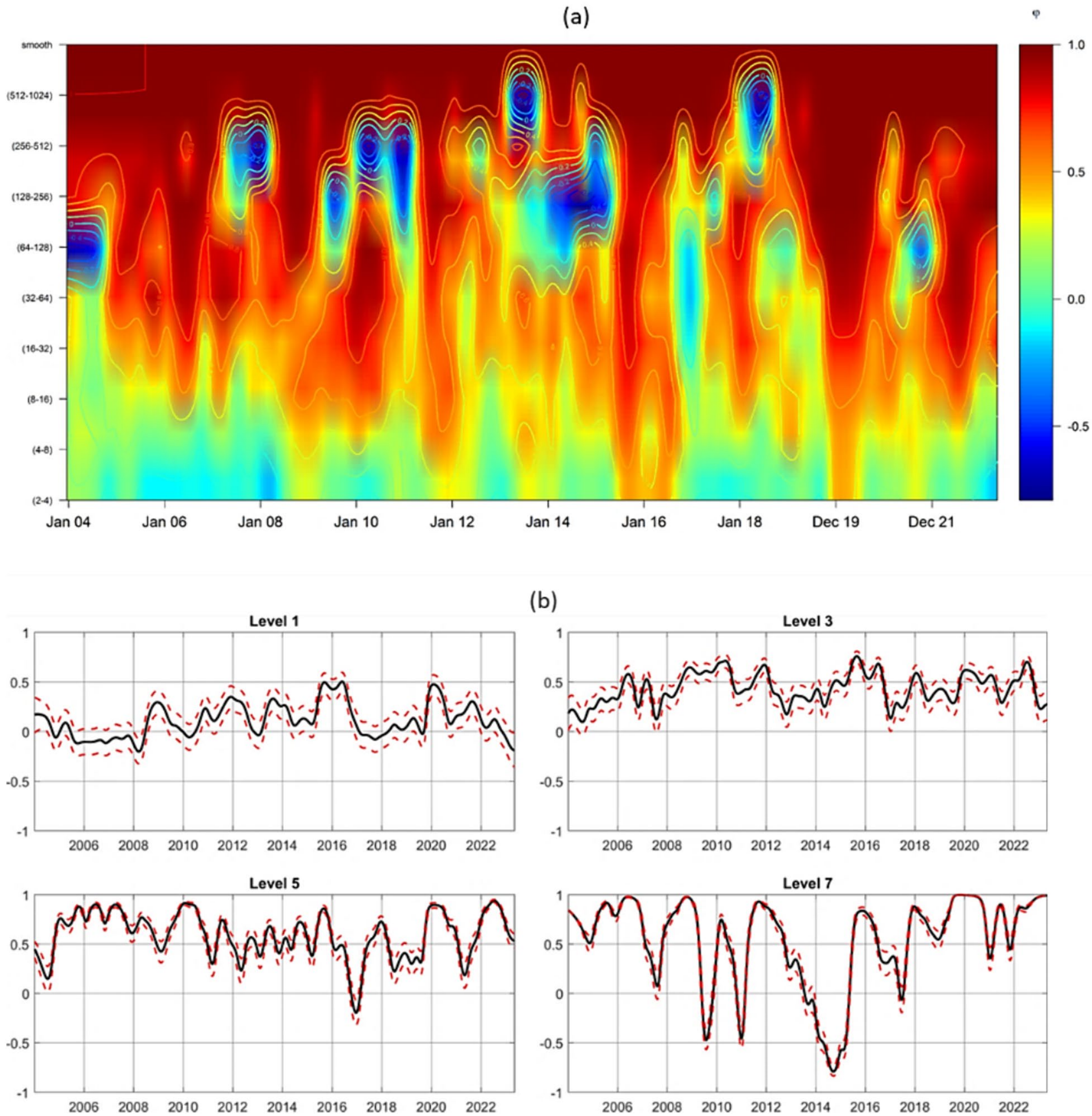

Fig. 4 Time–frequency correlations between the USA and India. *Notes* See notes in Fig. 3

crises such as the GFC, Euro debt crisis, and COVID-19 pandemic could cross over all frequencies because of the long-lasting impact of these crises. However, this anticipation seems to be contradicted by the long-term correlations of the US market with some emerging Asian markets such as India, Thailand, and Philippines during the Euro debt crisis where we see that biannual scales are exhibiting deep negative correlations.

Furthermore, the correlations of the tail risks of US and emerging Asian markets during the GFC tend to be positively strong as we move beyond the biannual scale. During the period of COVID-19, however, the extremely positive correlations of the left tails expand over most of the frequencies in all pairings. This finding speaks of the deep impact that the COVID-19 pandemic had on the systemic risk in global stock markets. Meanwhile, it appears that the period of the Russia–Ukraine

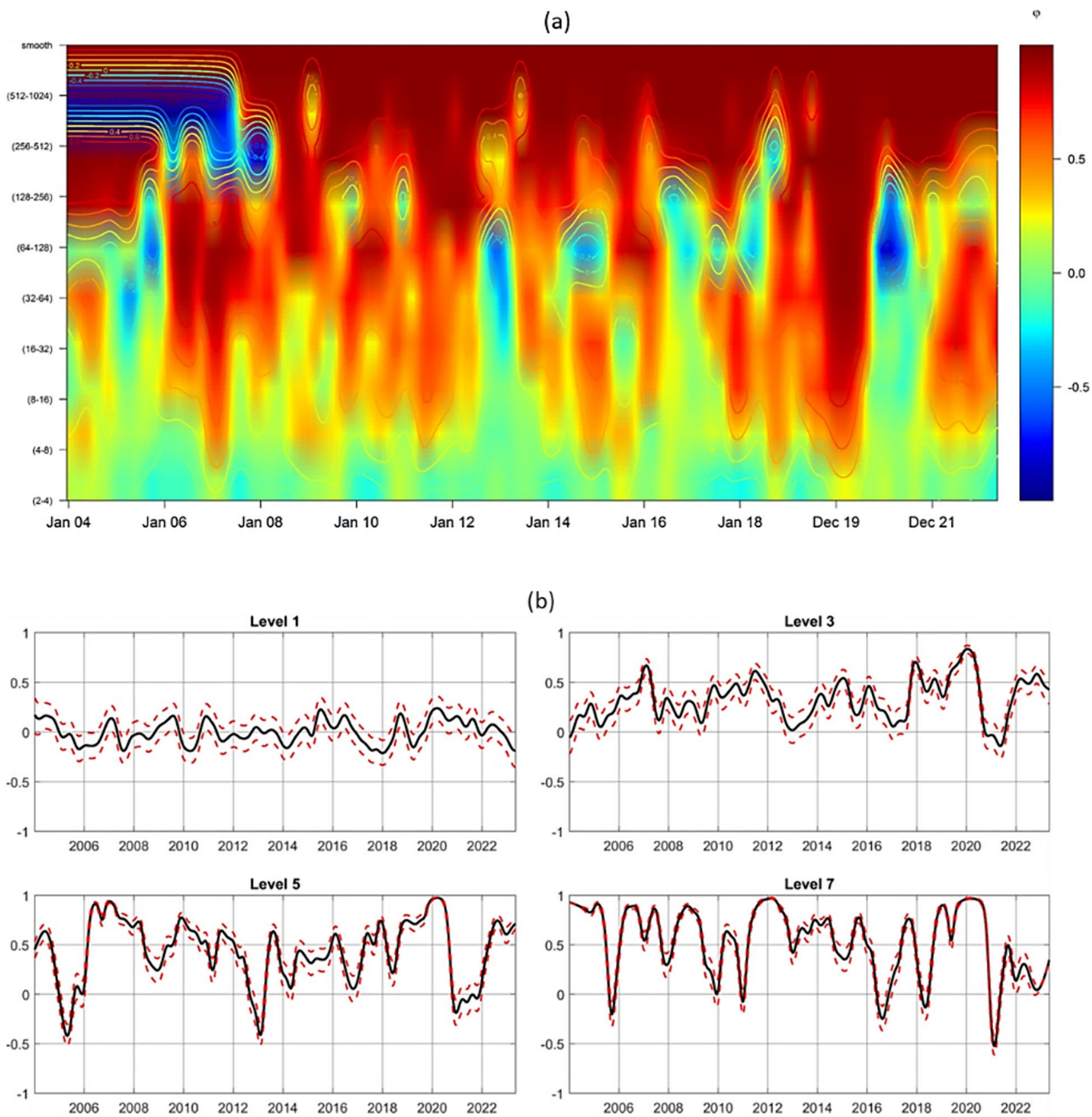

Fig. 5 Time–frequency correlations between the USA and Malaysia. *Notes* See notes in Fig. 3

war is less dominated by the strong comovement of tail risks along the frequency dimension compared to other major global crises, except in the case of US and Indian market correlations. This is somewhat surprising considering that the time–frequency tail risk correlations between the US and the Indian markets have withstood the long-term impact of more severe crises such as the Euro debt crisis.

Moving to the dynamic correlations in the medium term, which are described in the areas between the weekly and monthly scales, it can be seen that these areas are fairly dominated by the yellow color, indicating weak correlations between the tail risks. More importantly, the appearance of such weak correlations in the medium term is also remarkable during periods of severe crises such as the GFC and the Euro debt crisis. However, this seems to be not the case during the period of the

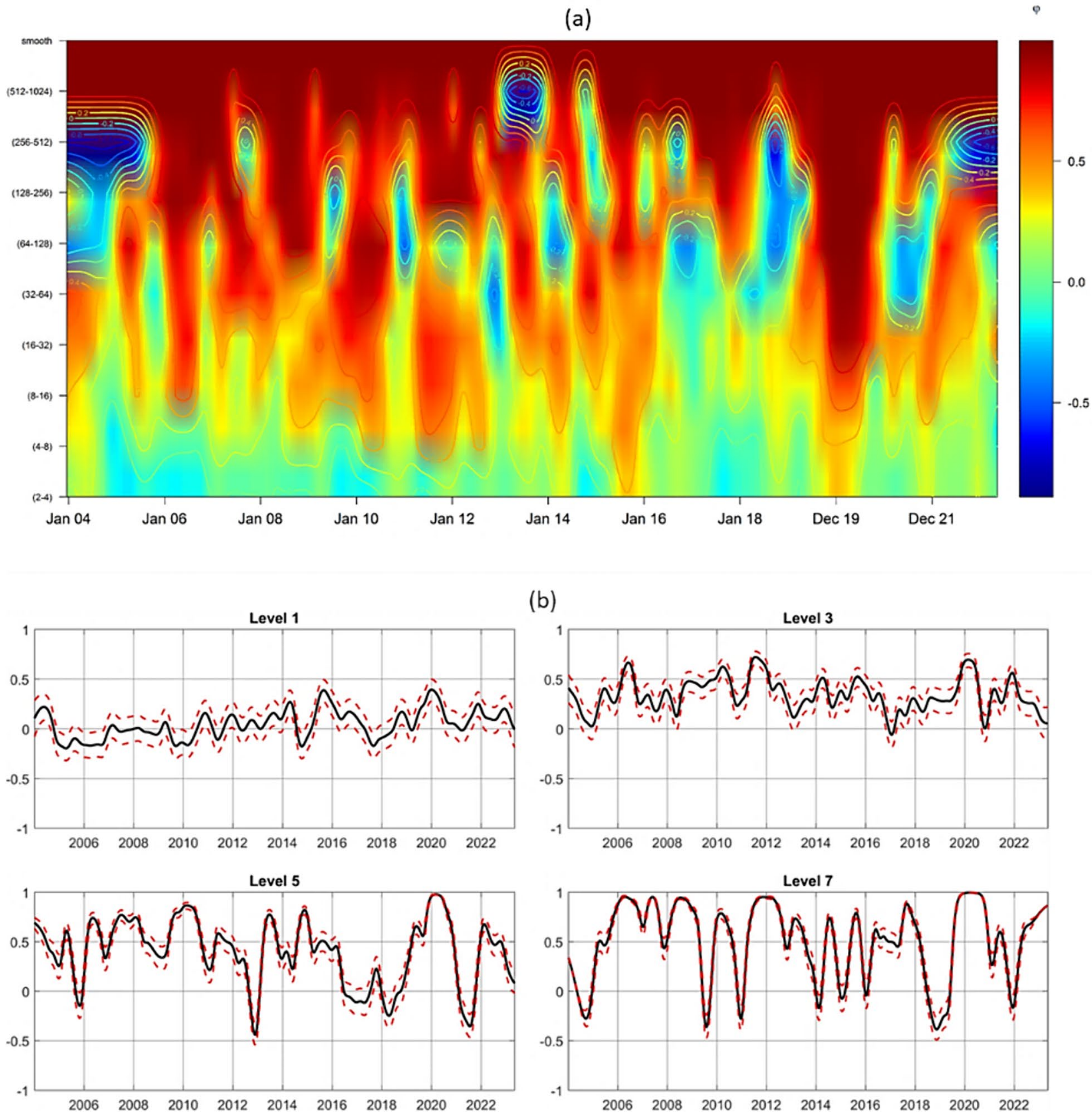

Fig. 6 Time–frequency correlations between the USA and Indonesia. *Notes* See notes in Fig. 3

COVID-19 pandemic where the medium-term weak correlations are scarcely notable along the frequency dimension in all the pairwise tail risk correlations. In addition, if we look at the tail risk correlations between the US market and the markets of South Korea and India, we can see that the yellow color, which underlines the weak correlations, is even less noticeable during the period of China's Renminbi devaluation compared to the period of COVID-19 pandemic. Based on this finding, it can be argued that the deterioration of financial conditions caused by China's Renminbi devaluation was strongly felt across all medium-term and long-term investment horizons in the stock markets of the USA, India, and South Korea. This could be due to the reason that these countries have more trading connections with China. However, this does not necessarily mean that the impact of China's Renminbi devaluation on these three markets

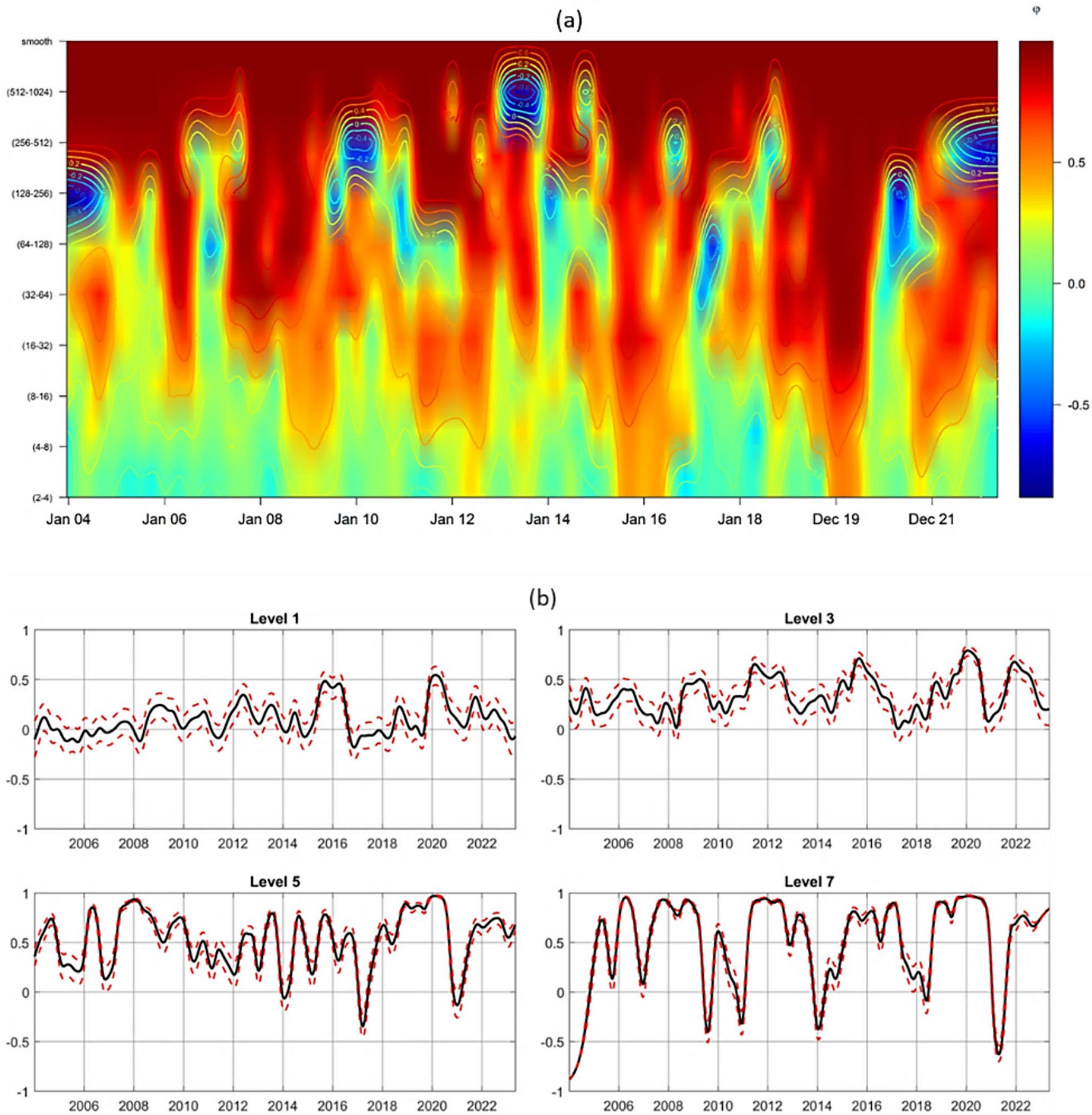

Fig. 7 Time–frequency correlations between the USA and Thailand. *Notes* See notes in Fig. 3

was economically more severe than the impact of the COVID-19 pandemic.

The tail risk correlations become even more weak in the short term, consistently falling below 0.5 in all market pairings and barely exceeding this level even during crisis periods. This is indicated by the light blue color, which seems to be spreading throughout most of the sample period at the 2–4 days and 4–8 days scales. This observation is more apparently reflected by the plot lines of level 1 where all tail risk correlations are shown to be most of the time closely revolving around the zero line. It also seems that the light blue area is spreading vertically through medium frequencies reaching the quarterly scale at some time points. Although not very abundant, this type of dynamics is noticed across all pairings of tail risk correlations. It is, however, more notable in the pairwise tail risk correlations between the US market and the markets of Indonesia and Philippines. This finding

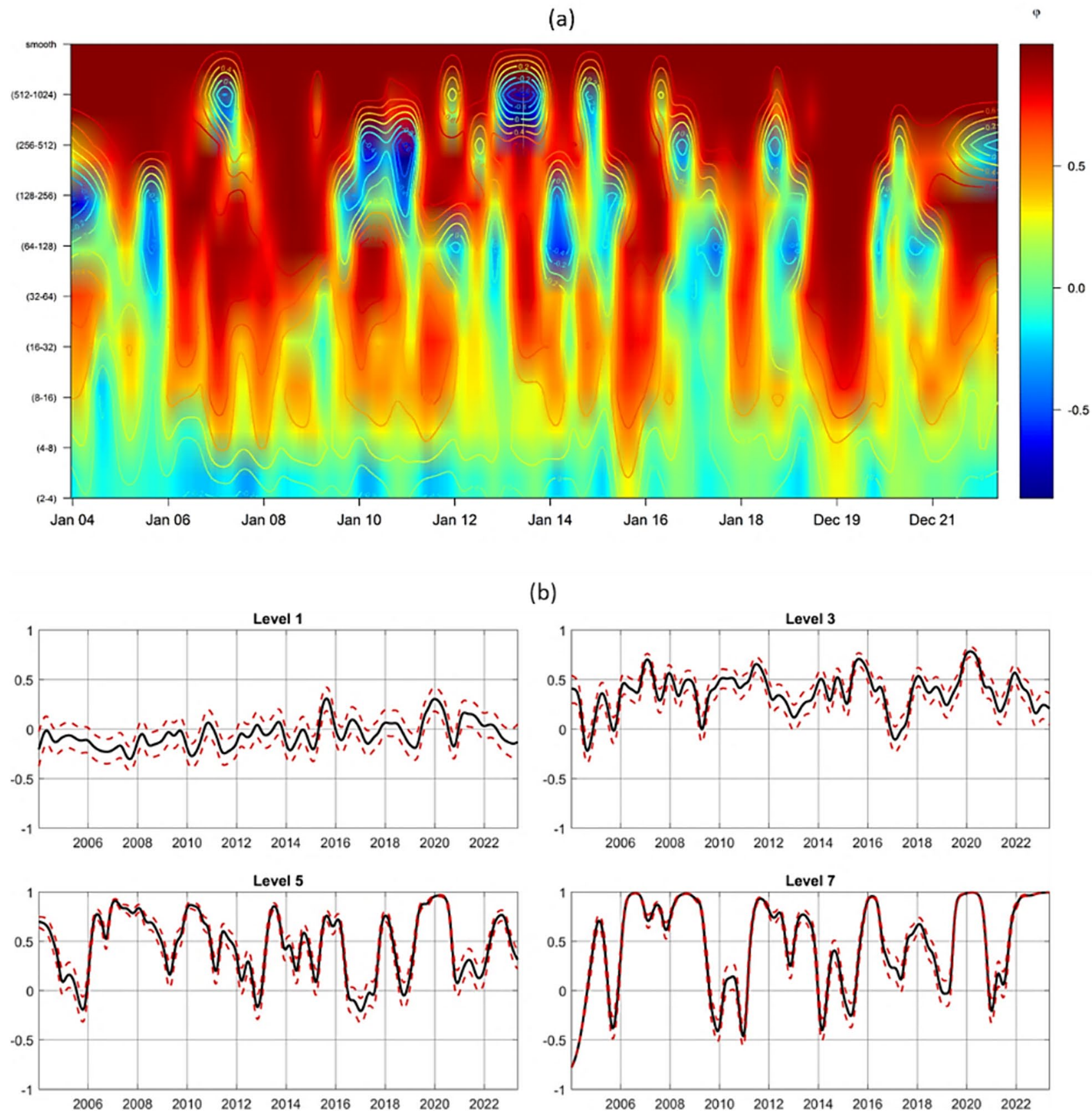

Fig. 8 Time–frequency correlations between the USA and Philippines. *Notes* See notes in Fig. 3

indicates that short-term investors are very unlikely to be affected by the cross-market transmission of extreme tail risk to the same extent as medium-term and long-term investors.

Overall, the structure of the bivariate time–frequency correlations is strikingly different from the structure of multivariate correlations. In the latter, the strong synchronization of tail risks is attainable at the quarterly scale, the appearance of such a process takes far longer timescales in the case of the bivariate comovements. In fact, the bivariate correlations show that the tail risks can be negatively correlated in the long term during some periods. In addition, the multivariate correlations are stronger at the medium terms ranging between 0.6 and 0.85, while the medium-term bivariate correlations for all pairs are shown to be mostly fluctuating below 0.5, except during crisis periods. Another difference is that multivariate correlations show strong comovements of tail risk at the short-term scales during times of financial and political turmoil. In the same scale, however, the pairwise tail risk correlations are shown to be comparatively weaker not only during periods of crises but over most of the sample period. The reason that the results of multivariate and bivariate correlations came out differently is that multivariate correlations describe a common trend in a group of variables. Therefore, it may neglect some details that could be captured by bivariate correlations.

Finally, we complement the results with a comparison between the peak impact of each crisis at each frequency (level). To this end, we select the maximum correlation for the concerned pairs of stock markets at each level during the periods of financial downturns and political turmoil, these maximum correlations represent the strongest impact of each crisis at each level. Then, we make a levelwise comparison by selecting the highest and lowest peak impacts among crises at the same level. Table 2 displays this information with the values of the highest and lowest peaks being formatted in bold and italic fonts, respectively. As can be seen, most of the highest cross-level peak impacts appear to be associated with the period of the COVID-19 pandemic. Note that the tail risk correlation between the USA and India at level 3 is the only peak impact of COVID-19 that is found to be lower than the peak impacts of other crises at the same level. However, the peak impact of China's Renminbi devaluations is shown to be higher than the peak impacts of COVID-19 and other crises at levels 1 and 2 in the pairs of USA–South Korea and USA–India. The peak impact of China's Renminbi devaluations in the pair of USA–India at level 3 is also the highest among the peak impacts. In addition, the Euro debt crisis (ESDC) appears to have the highest peak impacts in the pair of USA–South Korea at levels 3, 4, 7, and 8. This is the only case where we see that the Euro debt crisis is having multiple higher peak impacts compared to other crises. The other peak impacts of ESDC that are higher than peak impacts of other crises are found in the pairs of USA–India at level 6, USA–Malaysia at level 9, and USA–Indonesia at levels 2 and 3. On the other hand, most of the lowest peak impacts are associated with the ongoing Russia–Ukraine war. Nevertheless, there are a few cases where we see that the ongoing Russia–Ukraine war is having the highest peak impact among crises. Surprisingly, many of GFC's peak impacts are shown to be the lowest peak impacts among crises. It also has a single peak impact which is considered the highest among peak impacts at the same level. This peak impact is found in the pair of USA–Thailand at level 9.

Discussion

The results of the study generally indicate that the total comovements of the tail risks are more concentrated in the scales of medium and long terms. Similar results have been reported in global-wide studies such as Ren et al. [50] and Du et al. [19]. In another study, Jian et al. [32] find that it is only during the non-crisis periods that the short-term connectedness at the lower tail exceeds the long-term connectedness at the same tail. This may indicate that the strong correlation in the medium and long terms is a general characteristic of the total tail risk connectedness and correlation. Note that the aforementioned studies did not look into the bivariate correlations. From this perspective, the current study provides nuanced findings that are critical to investors and policy makers. First, we find that the pairwise connections between the tail risks of US and emerging Asian stock markets are remarkably weaker in the short-term scales. The weakness of short-term pairwise correlations of tail risks is also observed during some severe global crises, which is more clearly highlighted in Table 2. This means that tail risks of emerging Asian markets are not highly sensitive to extremely negative shocks from the US market in the short term (2–4 and 4–8 days scales). This finding can be linked to the increasing resilience of emerging Asian markets, which has been demonstrated in many studies such as Gupta and Miniane [30] and Kenç et al. [34]. It may also be one of the implications of the capital control policies imposed by these countries on foreign capital. Such policies are designed to mitigate systemic risk and the volatility of foreign capital flows by imposing barriers and capital limitations. Studies such as Stulz [53] and Henry [31] have shown that these barriers can segment international markets, thus reducing the exposure to international financial risk. Second, the bivariate analysis documents the instability of tail risk correlations over the long-term scales, suggesting that the tail risks of US and emerging Asian stock markets are not always completely integrated. This finding also indicates that the tail risks are nonlinearly connected in the long term. In contrast, many studies that focused on the conditional mean correlation have concluded that stock markets are strongly integrated in the long term, which limits the portfolio diversification opportunities (see, e.g., [51], Madaleno and Pinho, [41]; [15, 16, 39, 43]). However, it has been demonstrated that the conditional mean correlation differs significantly from the tail risk correlation (see, e.g., [5, 32]). Therefore, it is natural that the two approaches entail different implications.

Speaking of implications, the findings of the study are practically relevant to cross-market portfolio diversification and financial risk management. Equity investors

Table 2 Cross-frequency comparison of peak impact during crises

Pairs	Levels	GFC	ESDC	CRD	COVID-19	RUS-UKR
USA–South Korea	level 1	*0.094503*	0.140481	**0.400468**	0.15376	0.107643
	level 2	0.471397	0.503677	**0.716362**	0.398598	*0.305665*
	level 3	0.640139	**0.748174**	0.718035	0.684285	*0.504397*
	level 4	0.660526	**0.905832**	0.695597	0.857301	*0.624938*
	level 5	0.912534	0.944445	0.919652	**0.971467**	*0.690927*
	level 6	0.949378	0.916756	0.946389	**0.978397**	*0.623402*
	level 7	0.987535	**0.997087**	0.908641	0.972491	*0.221754*
	level 8	0.994321	**0.996021**	0.933326	0.994091	*0.348285*
	level 9	*0.992981*	0.996828	0.998977	0.996833	**0.999938**
USA–India	level 1	0.294811	0.235029	**0.503135**	0.475487	*0.119519*
	level 2	0.423633	0.521694	**0.663746**	0.511897	*0.347318*
	level 3	0.645922	0.711711	**0.757969**	*0.619251*	0.698426
	level 4	*0.710552*	0.849824	0.831448	0.774352	**0.855638**
	level 5	*0.770258*	0.915164	0.858719	0.895195	**0.936994**
	level 6	0.930146	**0.972027**	*0.906975*	0.967991	0.953621
	level 7	0.976148	0.853757	*0.837372*	**0.996603**	0.872421
	level 8	0.969833	0.874101	0.953291	**0.998954**	*0.793281*
	level 9	*0.993213*	0.998031	0.997314	0.99877	**0.99972**
USA–Malaysia	level 1	0.151798	0.158	0.225836	**0.238661**	*0.074408*
	level 2	0.396969	0.391567	0.394536	**0.595805**	*0.318548*
	level 3	*0.340625*	0.614218	0.460229	**0.834504**	0.535838
	level 4	*0.561121*	0.666448	0.578452	**0.910097**	0.800668
	level 5	0.734516	0.754143	*0.610743*	**0.973721**	0.708969
	level 6	0.916105	0.893689	0.891052	**0.982276**	*0.567257*
	level 7	0.890022	0.855489	0.777344	**0.970438**	*0.306074*
	level 8	0.964304	0.954424	*0.907855*	**0.996963**	0.964443
	level 9	*0.95939*	**0.997077**	0.992829	0.995219	0.9954
USA–Indonesia	level 1	*0.067183*	0.158892	0.387622	**0.393015**	0.196864
	level 2	0.355316	**0.559918**	0.536111	0.393517	*0.212685*
	level 3	*0.478081*	**0.714999**	0.524596	0.69386	0.526636
	level 4	0.624621	0.740408	*0.557022*	**0.928533**	0.595179
	level 5	0.746463	0.866529	*0.508965*	**0.97889**	0.677602
	level 6	0.93327	0.928701	0.850486	**0.995452**	*0.766127*
	level 7	0.944984	0.866805	0.791605	**0.996073**	*0.655642*
	level 8	0.972063	0.845073	0.818678	**0.99681**	*0.577376*
	level 9	*0.988881*	0.989186	0.995944	0.997808	**0.998116**
USA–Thailand	level 1	0.242763	*0.178991*	0.484265	**0.545065**	0.197479
	level 2	0.407298	*0.388661*	0.524058	**0.615634**	0.421655
	level 3	*0.50333*	0.655166	0.712091	**0.79051**	0.668945
	level 4	*0.654425*	0.68883	0.831981	**0.954475**	0.787834
	level 5	0.935687	*0.710809*	0.784164	**0.970044**	0.740085
	level 6	0.954343	*0.539385*	0.74516	**0.966211**	0.708409
	level 7	0.929956	0.91838	0.818234	**0.970225**	*0.771041*
	level 8	0.947659	0.977936	0.971668	**0.982551**	*0.495103*
	level 9	**0.998269**	0.99653	*0.996095*	0.997146	0.998195

Table 2 (continued)

Pairs	Levels	GFC	ESDC	CRD	COVID-19	RUS-UKR
USA–Philippines	level 1	*-0.03136*	0.064797	**0.307723**	0.303105	0.045276
	level 2	0.408556	0.363018	**0.532272**	0.359866	*0.263906*
	level 3	0.564044	0.655875	0.707092	**0.783507**	*0.555043*
	level 4	0.648739	0.750066	0.800553	**0.890976**	*0.595315*
	level 5	0.835915	0.867951	0.759298	**0.964208**	*0.725081*
	level 6	0.977514	0.933091	0.928908	**0.991586**	*0.803666*
	level 7	0.983935	*0.892207*	0.957625	**0.994031**	0.965562
	level 8	0.986393	0.806891	0.978067	**0.997194**	*0.667378*
	level 9	*0.987517*	0.995213	0.995831	0.997416	**0.99878**

The highest correlations are formatted in bold font, while the lowest correlations are formatted in italic font. GFC: the global financial crisis in 2008, ESDC: European sovereign debt crisis in 2010, CRD: China's Renminbi devaluation in August 2015, COVID-19: COVID-19 pandemic, RUS-UKR: Russia–Ukraine war. The nine levels correspond to the wavelet scales λ_j where $j = 9$

are known to have substantial heterogeneity in terms of investment horizons. This phenomenon is one of the principles of the fractal market hypothesis (FMH), one of the frontier theories in finance. FMH was formulated upon the notion that markets consist of agents trading at different scales. For instance, some investors like hedge funds and day traders typically tend to follow short-term trading strategies, unlike government agents and pension funds who are known to engage in long-term trading. For such traders, the study provides insightful information on the impact of extreme left-tail events on their respective investment horizons. One of the practical benefits of such information is that market participants will have a better understanding of the size of tail risk exposure at different investment horizons. As a result of this, they will be able to determine the potential financial risk associated with their respective investment horizon. The results of the study are also insightful in terms of portfolio allocation decisions across multiple scales. In this regard, our results can be used to change the weighting scheme of equity portfolios according to the risk level at each frequency. For instance, short-term investment horizons could be more appealing to equity investors due to lower tail risk exposure. Although there is also evidence that tail risks are negatively correlated in the long term, this finding suggests that portfolio diversification is still possibly achievable even in the long term.

Another underlying principle of FMH is the heterogeneity in the investors' reaction and interpretation of information (shocks). The basic idea of this principle is that some information is perceived to have a long-term impact inducing instant reactions by investors across all scales. This type of behavior is typically seen during periods of global crises. On the other hand, some information of other types does not warrant the attention of long-term investors because it is believed to have a short-term impact. However, our results show that this behavioral mechanism is often not reflected in the time–frequency correlations of tail risks during some severe global crises, particularly in the 2–4 days scale where it can be seen that the tail risk correlations can be extremely weak or even negative like in the case of tail risk correlation between US and Philippines markets during GFC at level 1. In contrast, events like the massive devaluation of China's Renminbi, which is not seen as severe and global as the GFC, had a higher impact on the short-term correlations between the tail risks of some pairs like USA–South Korea and USA–India. Considering that the three countries are among the top trading partners of China, it may be reasonable to assume that trading connections are the potential cause of such high short-term correlations among the tail risks of these markets during the period of China's Renminbi devaluation. Nguyen and Lambe [45] have established that trade partnership is a facilitator of cross-market transmission of tail risk. However, it remains unclear whether extreme left-tail shocks from top trading partners could end up affecting all investment horizons in the shock-receiving market. This could be an interesting topic for future research. In the meantime, the study recommends that equity investors, especially medium-term and long-term investors, should pay more attention to drastic tail risk events in large trading partners because they could generate disruptive shocks with long-lasting impacts.

Policy makers are also as concerned as equity investors about the transmission of tail risks across stock markets. Since the GFC in 2008, many emerging Asian markets have increasingly been implementing policies to control systemic risk and monitor financial stability. For such a purpose, quantifying the systemic risk is crucial. In this regard, the results of the current study can help policy makers to understand the size of the exposure to external financial risk from global markets. Policy makers should closely monitor the interconnection of tail risks to timely counteract possible risk spillovers from another stock market. In addition, identifying the frequency-specific source of the tail risk transmission is important for policy makers to calibrate the appropriate regulatory tool. The results indicate that the transmission and comovements of tail risks intensify in the long term. These strong long-term comovements of tail risks are merely a reflection of the positive feedback between the domestic and US stock markets, which is highly likely to be driven by the dependence on external finance and the flows of short-term foreign capital. Regulating these items may help tame the level of correlations between the tail risks of US and emerging Asian stock markets.

Conclusion

This study applies the WLMC approach to estimate the multivariate and bivariate time–frequency comovements among the tail risks in the stock markets of the US and emerging Asian countries. Empirical results from the multivariate time–frequency correlations show that the total comovements of tail risk are distinctively higher during the periods of economic and political turmoil in the short term. The strongest short-term comovements of tail risks are associated with the period of the COVID-19 pandemic. It is also shown that the breakout of the ongoing Russia–Ukraine war has caused a significant increase in the comovement of tail risks at the short-term scales, but this increase is not as high as the increases of tail risk comovements during previous crises. Throughout the sample period, we notice that the multivariate time–frequency comovements gradually grow stronger along the frequency dimension. More specifically, the short-term comovements of tail risks are found to be less strong but highly volatile. However, the long-term comovements above the quarterly scale are shown to be highly stable and extremely strong which can be taken as evidence of long-run integration between the tail risks of US and emerging Asian markets. This process of gradual increase in tail risk comovements is also observed in the bivariate time–frequency correlations. In spite of this, the multivariate and bivariate correlations are also shown to have striking differences. Unlike multivariate correlations, long-term bivariate correlations are shown to be susceptible to sudden changes which arbitrarily appear in the area above the quarterly scale. Based on this finding, we conclude that the tail risks of US and emerging Asian markets are not always integrated. In fact, there are some periods where the tail risks are negatively correlated in the long term. The sudden changes in tail risk correlations also indicate that the tail risks are nonlinearly connected in the long term. In addition, the medium-term bivariate correlations are found to be more volatile but notably less strong than the multivariate medium-term correlations. Another important difference is that all pairwise tail risk correlations become remarkably weaker in the area below the weakly scale not only during periods of financial and political turmoil but throughout most of the sample period. This finding indicates that short-term investors are highly unlikely to be affected by the extreme left-tail events to the same extent as medium-term and long-term investors who are at risk of incurring significant financial losses. Therefore, it can be concluded that the extreme financial losses are not systemic across all investment horizons.

The current study is by design limited to the stock markets of US and emerging Asian markets. Therefore, the results may not necessarily hold for other markets. The study also specifically looks at the correlation of the tail risk of the US stock market with the tail risks of emerging Asian stock markets. This is due to the leading role of the US market as a global influencer. However, emerging Asian markets have also tight connections with other influencing markets such as Japan, the Eurozone, and China. Considering these markets is a possible avenue for future studies.

Abbreviations

ADCC	Asymmetric dynamic conditional correlations
AS-CAViaR	Asymmetric slope conditional autoregressive value at risk
BRICS	Brazil, Russia, India, China, and South Africa
CoVaR	Conditional value at risk
COVID-19	The global crisis of coronavirus pandemic
CRD	China's renminbi devaluation
ESDC	European sovereign debt crisis
ERS	Elliott–Rothenberg–Stock unit root test
EVT	Extreme value theory
FMH	Fractal market hypothesis
GARCH	Generalized autoregressive conditional heteroskedasticity
GFC	Global financial crisis
JB	Jarque–Bera normality test
MODWT	Maximal overlap discrete wavelet transform
RUS-UKR	The Russo-Ukrainian war
VAR	Vector autoregressive
VaR	Value at risk
WLMC	Wavelet local multiple correlations

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Consent for publication
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