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## Tail-event driven NETwork dependence in emerging markets

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## ABSTRACT

This paper employs the Tail Event NETwork (TENET) to identify financial markets with greater potential risk, and simultaneously investigate the interdependence between them. We find strong time-varying connectedness across 23 emerging markets during the main crisis episodes, including the most recent COVID-19 pandemic, using data from January 1995 to May 2021. The network analysis revealed that emerging European markets are top risk transmitters, whereas emerging Asian markets are top risk receivers. China showed disconnection from the network, reflecting its diversification potential for investors. Our findings offer several policy and regulatory implications.

## 1. Introduction

Global financial integration of markets and a growing focus of companies and institutional investors to invest in the international markets have invoked the attention of financial market participants to understand the risks associated with these investments. Emerging markets, in particular, have attained tremendous growth in these foreign investments due to their remarkable growth potential, low cost of capital (Bathia et al., 2021; Karim et al., 2022a; Naeem et al., 2022a; Gozgor, 2014), low production costs, and improved credit ratings (Demir and Ersan, 2017). Therefore, investment in emerging markets can bring fewer damaging consequences due to less-developed economic and monetary systems, whereas severe crises can spill over in the indigenous markets. Das et al. (2018) pointed out that occurrences of considerable ephemeral correlations during extreme economic periods signal towards contagion theory where intensive relationships are developed under bearish circumstances. The global financial crisis and the recent COVID-19 pandemic have made systemic risk a focal point of interest for policymakers (Avramov et al., 2021; Curfman and Kandrak, 2021; Maurer and Tran, 2021; Mensi et al., 2022) with a significant impact on trade channels, financial streams, growth collapses and growth recoveries, monetary and fiscal policies where drastic reduction in interest rates, adopting procyclical policies than countercyclical steps, tax hikes to cope capital outflows, and currency pressures followed the macroeconomic and financial uncertainties (Dew-Becker et al., 2021) ultimately surmounted tail-risk in emerging economies (Demir and Javorcik, 2020; Zhang et al., 2020; Ashraf, 2020;

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Topcu and Gulal, 2020; Goodell, 2020; Bulutay et al., 2021; Pham et al., 2022; Naeem et al., 2022d).

Refers to the international portfolio diversification theory, investors should invest in those international markets which are not/weakly connected with each other to get maximum benefit of diversification (Levy and Sarnat, 1970; Solnik, 1974; Meric and Meric, 1989). In contrast, if the international markets are highly connected, especially in the crisis periods, then the volatility (risk) transfers from one market to another, which may ultimately lead towards the huge losses in the international investment portfolios, this phenomenon is called 'financial contagion'. Bouri (2015) suggests that investors should adjust their portfolios in these left tail events (crisis episodes) to avoid huge losses and get maximum benefit of diversification, as connectedness between markets change during these events. Hence, the analysis of tail event-based connectedness between emerging markets can provide useful information to portfolio managers regarding efficient portfolio management in presence of left tail events.

Specifically, the substantial differences in risk exposure between emerging and developed markets during crisis times are due to several structural, financial, geopolitical, institutional, political, and macroeconomic factors (Bunda et al., 2011; Jin and An, 2016; Gozgor, 2018; Salisu et al., 2020; Zhou et al., 2020; Umar et al., 2021; Harjoto et al., 2021). The rationale behind using two crisis periods (GFC and COVID-19) entails the varied nature of the shocks created by these distressing events. For instance, the global financial crisis is marked as a chain reaction of credit risk, which triggered liquidity shortfall in the US financial industry (Jin and An, 2016). Evidence suggests, though emerging economies performed better following the plain growth rates, but variations occur when plain growth rates are compared with pre-crisis growth rates (Didier et al., 2012).

In contrast, the COVID-19 pandemic appeared as a global health emergency with severe restrictions and standard operating procedures (SOPs) to avoid exponential death rates (World Health Organization, 2020).<sup>1</sup> The global financial crisis reported a drop in MSCI emerging market index to 495 on February 1, 2009, from 1331 on October 7, 2007, whereas the COVID-19 pandemic experienced MSCI fall from 1145 on January 20, 2020, to 758 on March 23, 2020.<sup>2</sup> Given the uncertainty of these extreme events, the change in return and risk profiles of emerging markets fetches the attention of investors and policymakers to escape the deteriorating effects of the crisis on the financial markets and explore the potential diversifiers. Asness et al. (2011) emphasized that diversification is the long-run phenomenon given the longer time horizons where economic stability is achieved and bubble components are calmed down.

A major challenge posed by the economic policymakers and financial market regulators is to overcome the instability of the markets and develop more resilient risk incumbent domestic markets. Systemic risk endangers the stability of the economic system where the collapse of one market may result in undesirable consequences for the other market (Härdle et al., 2016; Yousaf and Hassan, 2019). Since sources of risk are complex and integrated financial markets in an economic system stipulate serious repercussions for emerging markets particularly, extreme events-based integration analysis provides satisfactory responses to the investors, financial market constituents, and policymakers to escape the unfavorable outcomes of tail-events (Lai and Hu, 2021).

Against this backdrop, our study contributes to the existing literature by empirically examining the tail-event network dependence among 23 emerging economies. The focus of previous studies has remained few emerging markets from a specific region (i.e., BRIC, Asia, MENA, and Africa) while examining the integration between emerging markets (Gėbka and Serwa, 2007; Hammoudeh et al., 2009; Yilmaz, 2010; Beirne et al., 2010; Aloui, 2011; Joshi, 2011; Zhou et al., 2012; Korkmaz et al., 2012; Taşdemir and Yalama, 2014; Alotaibi and Mishra, 2015; Chow, 2017; Lu et al., 2019; Ahmed et al., 2021; Zhong and Liu, 2021; Elsayed et al., 2022). Our study provides in-depth information about the risk transmitter and recipient among emerging equity markets during the left tail events, which offers useful implications for portfolio managers and policymakers in deciding portfolio diversification, forecasting, and market stability.

Secondly, we choose the two most significant tail events for our analysis, namely, the global financial crisis and the COVID-19 pandemic, and compared the integration mechanism among emerging markets during these two crisis periods. This comparative analysis elaborates the major transmitter and emitter of risk and level of connectedness in both events assisting investors in designing portfolios less susceptible to extreme shocks. Previously, several studies have explored the connectedness between emerging markets in either of both crises (Baumöhl and Shahzad, 2019; Abuzayed et al., 2021; Lee and Lee, 2021), yet the comparative study of simultaneous investigation is inexistent. Thirdly, we apply the Tail-Event driven NETwork (TENET) approach proposed by Härdle et al. (2016), based on quantile regressions augmented with nonlinearity and variable selection in a high dimensional time-series setting. TENET approach is useful in ranking the risk recipients and transmitters in emerging equity markets through elliptic network dynamics. Prior studies employed quantile regression-based approach (Acharya et al., 2012; Brownlees and Engle, 2016), principal component analysis-based approach (Bisias et al., 2012; Rodríguez-Moreno and Peña, 2013), higher dimensions based linear model (Hautsch et al., 2015; Betz et al., 2016), partial-quantile based regression analysis (Giglio et al., 2016; Chao, 2015), default probabilities based approach (Lehar, 2005; Huang et al., 2009; Hutchison et al., 2010; Kato et al., 2021; Reinhart and Reinhart, 2009), network connectedness based approach (Boss et al., 2006; Chan-Lau et al., 2009; Diebold and Yilmaz, 2014). However, identifying the key risk emitters and recipients in a system-wide connectedness is the unique feature offered by the TENET methodology.

By using this novel methodology of tail-event network dependence, we reported time-varying total connectedness of emerging markets. Comparing the total connectedness with the average  $\lambda$  of CoVaR, the pattern shows relatively lower risk for the given period and for all emerging markets except Argentine's economic turmoil, global financial crisis, Chinese crisis, and the recent ongoing pandemic of COVID-19 where emerging markets showed extreme dependence. The elliptical network of adjacency matrix showed strong network connectedness with Turkey and Hungary (European Region) as the top transmitters of risk spillovers and Pakistan and

<sup>1</sup> Source: <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>

<sup>2</sup> Source: <https://markets.businessinsider.com>

Indonesia (Asian Region) as net receivers of spillovers. During the COVID-19 pandemic, Turkey maintained economic growth of 1.8%<sup>3</sup> with strong macroeconomic and fiscal policy frameworks<sup>4</sup> during the pandemic whereas Hungary reported fewer deaths and controlled circumstances when other regions of the world suffering severe deaths of citizens. China showed distinct disconnection from the system-wide connectedness reflecting its greater diversification potential among the emerging markets stock indices. Sub-sample analysis for the global financial crisis and COVID-19 showed varied risk spillovers, whereas China maintained its disconnection from the network. We offered sizeable policy and macro-prudential implications facilitating investors in the short- and long-run with these findings.

The remaining study is structured as follows: Section 2 reviews prior studies; Section 3 presents methodology; Section 4 elaborates empirical results along with discussion; in the end, Section 5 concludes the whole study.

## 2. Literature review

The literature on the spillover or connectedness of the emerging stock markets can be divided into two distinct groups. One group is based on GARCH, causality, and network connectedness models. [Gėbka and Serwa \(2007\)](#) use the GARCH model to examine the inter- and intra-regional connectedness between emerging stock markets of Asia, Central and Eastern Europe, and Latin America. They find that the intra-regional connectedness is stronger than the inter-regional connectedness. [Hammoudeh et al. \(2009\)](#) apply the VAR-GARCH model to investigate the volatility connectedness between the three sectors (service, insurance, and banking) of Kuwait, Saudi Arabia, Qatar, and UAE stock markets. They report moderate levels of connectedness between these sectors. [Yilmaz \(2010\)](#) employs [Diebold and Yilmaz \(2009\)](#) approach to estimate return and volatility connectedness between Thailand, Hong Kong, Korea, Japan, Indonesia, Malaysia, Philippines, Singapore, Taiwan, and Australia. The return and volatility connectedness among these stock markets is time-varying and became stronger during the global financial crisis.

[Beirne et al. \(2010\)](#) employed the VAR-GARCH in mean approach to examine the spillover from regional and global spillovers into the emerging equity markets and find that provide the evidence of spillovers from regional and global markets to emerging markets. Moreover, these spillovers vary across different regions as well. [Aloui \(2011\)](#) use the FIAPARCH-DCC approach and find the volatility connectedness between Latin American stock markets. [Joshi \(2011\)](#) utilized the BEKK-GARCH model to examine the integration between China, India, Japan, Hong Kong, Jakarta, and Korea's equity markets and find the bidirectional volatility connectedness among these equity markets. Using [Diebold and Yilmaz](#), [Zhou et al. \(2012\)](#) look at the connectedness between Chinese and world stock markets, including developed and emerging. They find that the Chinese equity market positively influences the other stock markets. Moreover, China, Taiwan, and Hong Kong markets are highly connected compared to China, Asia, and western equity markets.

[Korkmaz et al. \(2012\)](#) deployed the causality in mean and variance tests and find the weak connectedness between equity markets of Colombia, Vietnam, Indonesia, Turkey, Egypt, and South Africa. [Taşdemir and Yalama \(2014\)](#) estimate the volatility connectedness between Brazilian and Turkish stock markets using the causality-in-variance. They find the unidirectional transmission from Brazilian to Turkish stock markets, and this transmission became reverse in the crisis period. Using various GARCH models, [Alotaibi and Mishra \(2015\)](#) report the unidirectional spillover between Saudi Arabia and US to other GCC stock markets, including Bahrain, Oman, UAE, Qatar, and Kuwait. Using [Diebold and Yilmaz](#), [Chow \(2017\)](#) examine the volatility connectedness across US, China, Japan, and other Asian markets and find the stronger connectedness among these markets after the global financial crisis. The time-varying spillovers show that the US, China, and Japan highly influence the other Asian markets, respectively. [Lu et al. \(2019\)](#) employ the multivariate GARCH model to estimate spillovers between China and Belt and Road equity markets and find the weak volatility transmission from China to Belt and Road equity markets. Moreover, the spillovers are observed to be higher during financial crises.

Using the EGARCH model, [Ahmed et al. \(2021\)](#) find the unidirectional volatility spillovers from China to other emerging Asian stock markets. [Zhong and Liu \(2021\)](#) applied the Full BEKK-GARCH, Diagonal BEKK, VAR-GARCH, and DCC-GARCH models to examine the connectedness between China and other emerging markets of Singapore, Malaysia, Indonesia, Thailand, and the Philippines. They report positive connectedness between these markets and an increase in connectedness during different crisis episodes, like Asian financial crisis of 1997, the global financial crisis, and the Chinese equity market crash in 2015.

Another group of studies focuses on the tail/quantiles/extreme connectedness between the emerging stock markets. [Bala and Takimoto \(2017\)](#) use the asymmetric DCC-GARCH model to examine the risk connectedness for emerging and developed equity markets. They find that developed equity markets are strongly connected, whereas emerging equity markets are weakly connected. Moreover, volatility transmission is symmetric (asymmetric) between the emerging (developed) stock markets. [Shahzad et al. \(2018\)](#) use the cross-quantilogram analysis to investigate the interconnectedness between 58 developed and emerging stock markets in bullish and bearish market states and find that the US and Canada are the biggest transmitters of risk to the other countries. [Baumöhl and Shahzad \(2019\)](#) employ the quantile coherency analysis to investigate the quantile dependence network of 49 major equity markets and find that short- and long run dependence became higher during the bearish market state and after the global financial crisis. Moreover, the emerging stock markets are weakly integrated compared to the developed stock markets. Using the asymmetric Copula-EGARCH model, [Alqaralleh et al. \(2019\)](#) find the asymmetric volatility connectedness between the equity markets of Egypt, Jordan, Turkey, Palestine, and Tunisia. Using quantile-variance-decomposition analysis, [Su \(2020\)](#) examines the quantile connectedness between the stock markets of G7 and BRICS and provides evidence of extreme volatility spillover from G7 countries to emerging BRICS equity markets. [Abuzayed et al. \(2021\)](#) employ the CoVaR and  $\Delta$ CoVaR approaches to analyze the connectedness between

<sup>3</sup> Please see: <https://www.reuters.com/article/us-turkey-economy-gdp-idUSKCN2AT1UE>

<sup>4</sup> Please see: <https://www.worldbank.org/en/country/turkey/overview>

international equity markets during extreme events like the COVID-19 and conclude the higher connectedness among equity markets in the COVID-19 pandemic. Lee and Lee (2021) use Semi-variance measures and Diebold and Yilmaz for the asymmetric volatility transmission between Chinese, South Korean, and Japanese equity markets and find the weak volatility spillovers between these markets. China is the net transmitter of good and bad volatility effects to Japanese and South Korean equity markets. Moreover, good and bad volatility spillovers reached their peaks during the global financial and European debt crises.

Following these studies, we filled this literature gap by employing the Tail-Event driven NETwork approach to estimate the tail-risk in emerging markets, particularly during the global financial crisis and the current pandemic of COVID-19.

### 3. Methodology

The traditional method of measuring tail-risk involves value-at-risk (VaR), which includes firm-level characteristics and integrated macro-state constructs accounting for the general state of the economy. In this way, the VaR of an emerging market  $i$  at  $\tau \in (0, 1)$  is defined as:

$$P(X_{it} \leq VaR_{it,\tau}) \stackrel{\text{def}}{=} \tau \tag{1}$$

where  $\tau$  is the quantile level and  $X_{it}$  is the log return of an emerging market  $i$  at time  $t$ . the CoVaR approach proposed by Adrian and Brunnermeier (2011) considers spillover effects and its association with the macro-state of the economy. The CoVaR of an emerging economy  $j$  given  $X_{it}$  at level  $\tau \in (0, 1)$  at time  $t$  is computed as:

$$P\{X_{jt} \leq CoVaR_{j|it,\tau} | R_{it}\} \stackrel{\text{def}}{=} \tau \tag{2}$$

where  $R_{it}$  is the information set including the event of  $X_{it} = VaR_{it,\tau}$  and  $M_{t-1}$  as  $M_{t-1}$  denotes a vector of macro-state variables in the general state of the economy.

Starting with the concept of CoVaR, the estimations begin with two steps of linear quantile regression:

$$X_{it} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{it} \tag{3}$$

$$X_{jt} = \alpha_{ji} + \gamma_{ji} M_{t-1} + \beta_{ji} X_{it} + \varepsilon_{j|it} \tag{4}$$

Assuming  $F_{\varepsilon_{it}}^{-1}(\tau | M_{t-1}) = 0$  and  $F_{\varepsilon_{j|it}}^{-1}(\tau | M_{t-1}, X_{it}) = 0$ , the first step determines VaR of an emerging market  $i$  by applying quantile (tail event) regression of log return market  $i$  on macro state variables.  $\beta_{ji}$  defines standard linear regression, which measures the sensitivity of log return of an emerging market  $i$  to changes in tail event log return on another emerging market  $j$ . The second step involves the calculation of CoVaR in the initial VaR measure of an emerging market  $i$  at level  $\tau$ .

$$\widehat{VaR}_{it,\tau} = \widehat{\alpha}_i + \widehat{\gamma}_i M_{t-1} \tag{5}$$

$$Co\widehat{VaR}_{j|it,\tau}^{AB} = \widehat{\alpha}_{ji} + \widehat{\gamma}_{ji} M_{t-1} + \widehat{\beta}_{ji} \widehat{VaR}_{it,\tau} \tag{6}$$

Here  $\beta_{ji}$  measures the degree of interconnectedness where  $j$  is set to be the return of a system and  $i$  to be the return of an emerging market which results in contribution CoVaR characterizing how a market  $i$  influences the rest of the emerging markets. In other words, it describes the extent to which a single market is exposed to the overall risk of a system.

Following this method, TENET is measured in three steps. The first step estimates VaR for each emerging market by using linear quantile regression as follows:

$$X_{it} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{it} \tag{7}$$

$$\widehat{VaR}_{it,\tau} = \widehat{\alpha}_i + \widehat{\gamma}_i M_{t-1} \tag{8}$$

VaR estimates the linear quantile regression by taking log return of a market  $i$  on macro state variables justified by Chao (2015).

Step two consists of connectedness analysis and spectral clustering. The connectedness analysis involves risk interdependence network capturing non-linear dependency through a network analysis. Precisely,

$$X_{jt} = g\left(\beta_{j|R_j}^T R_{jt}\right) + \varepsilon_{jt} \tag{9}$$

$$Co\widehat{VaR}_{j|R_j} \Big|_{\tau, \tau^{TENET}} \stackrel{\text{def}}{=} \widehat{g}\left(\widehat{\beta}_{j|R_j}^T \widetilde{R}_{jt}\right) \tag{10}$$

$$\widehat{D}_{j|R_j} \stackrel{\text{def}}{=} \left. \frac{\partial \widehat{g}\left(\widehat{\beta}_{j|R_j}^T R_{jt}\right)}{\partial R_{jt}} \right|_{R_{jt} = \widetilde{R}_{jt}} = \widehat{g}'\left(\widehat{\beta}_{j|R_j}^T \widetilde{R}_{jt}\right) \widehat{\beta}_{j|R_j} \tag{11}$$

Here  $R_{jt} \stackrel{\text{def}}{=} \{X_{-jt}, M_{t-1}, B_{jt-1}\}$  is the set of information that includes  $p$  variables whereas  $X_{-jt} \stackrel{\text{def}}{=} \{X_{1t}, X_{2t}, \dots, X_{kt}\}$  are the explanatory variables which include log-returns of all emerging markets.  $B_{jt-1}$  represents firm-specific characteristics. CoVaR not only influences the

emerging markets system but also incorporates nonlinearity function.

Network denotes a directed graph with a set of vertices and links and edges in the form of an adjacency matrix. The weighted adjacency matrix contains absolute values in the form of an upper and lower triangular matrix, which reveal impacts of a market  $i$  to market  $j$  whereas impact lower triangular matrix exhibits the impact of market  $j$  to market  $i$ .

$$A_s = \begin{pmatrix} 0 & \widehat{D}_{12,t} \cdots \widehat{D}_{1K,t} \\ \widehat{D}_{21,t} & 0 \cdots \widehat{D}_{2K,t} \\ \vdots & \vdots \\ \widehat{D}_{K1,t} & \widehat{D}_{K2,t} \cdots 0 \end{pmatrix} \quad (12)$$

The matrix represents total connectedness across variables which shows rows of this matrix correspond to the incoming edges, and columns exhibit outgoing edges for a variable. The spectral clustering technique is applied to identify time-varying risk clusters with a weighted adjacency matrix, and it allows for detecting window risk clusters of emerging markets.

The final step involves the risk estimation of emerging markets to systematically identify the important emerging markets through their total in and out connections evaluated by market capitalization.

$$SRR_{js} = \sum_{j \in Z_w^{IN}} \left( \left| \widehat{D}_{ij}^s \right| \right) \quad (13)$$

Where  $SRR$  denotes the systematic risk receiver index for emerging market  $i$ . Similarly, we also estimate the systematic risk emitter (SRE) index for a market  $i$  by using the following equation.

$$SRE_{js} = \sum_{j \in Z_w^{OUT}} \left( \left| \widehat{D}_{ij}^s \right| \right) \quad (14)$$

Where,  $Z_w^{IN}$  and  $Z_w^{OUT}$  denotes the group of emerging market returns linked with returns of market  $j$  by incoming and outgoing links at window “w”, respectively. Thus, both  $SRR_{js}$  and  $SRE_{js}$  take into account the market’s  $j$  and connected market capitalization and its connectedness within the network.

## 4. Data and empirical results

### 4.1. Data and descriptive statistics

We used monthly data of MSCI emerging markets stocks indices for 23 countries from Datastream to examine tail-event network dependence from January 1995 to May 2021. The MSCI emerging market indices are computed in US dollars to mitigate the currency risk, and for estimation purposes, the indices are converted into a logged first difference returns. In addition to these stock returns, we utilize the four-factor model of asset pricing based on Fama and French (2015), which are widely adopted as a predictor of stock returns. Moreover, the comprehensive Fama-French five-factor model by Foye (2018) also confirmed that the five-factor model outperforms the three-factor model except for few Asian regions. The macro-state variables include: (i) Emerging Market Return (MKT); (ii) Small Minus Big (SMB); (iii) High Minus Low (HML); (iv) Winner Minus Loser (WML). We employed the monthly data of these factors as the data source<sup>5</sup> only contains monthly data. Meanwhile, earlier empirical studies of asset pricing also support the use of monthly data for the use of these factors as given in Bali et al. (2017) and Atilgan et al. (2020).

Table 1 provides the summary statistics of 23 emerging markets. The results show that Hungary (0.69%) has the highest average return for the sample period, whereas Peru and Russia have comparable returns (0.64%). Contrarily, the lowest average returns are revealed by Greece (−0.74%). The highest variability of returns is denoted by Russia, followed by Turkey and Argentina, whereas Chile revealed the lowest variability in the return series. The slightly negative values of skewness of emerging markets indicate consequential losses of economic shocks experienced by these markets. The Jarque-Bera test of normality denotes abnormal values for all emerging markets indicating that markets are not normally distributed.

Fig. 1 presents a correlation heat-map of emerging markets where blue colour shows significantly positive correlations whereas red colour shows significantly negative correlations. Overall, the heat-map illustrates a positive correlation among emerging markets. However, the strength of each correlation varies depending on the emerging markets.

### 4.2. Empirical results

#### 4.2.1. VaR and CoVaR estimates

The three-step TENET involves calculating Tail-Event VaR for all emerging markets, NETWORK analysis in the second step, and systematically risky emerging markets are identified using  $SRR$  and  $SRE$  indices. For estimating VaR, the monthly log returns are regressed against macro-state variables at the quantile level  $\tau = 0.05$  for the whole sample period given  $T = 255$  using the rolling window size  $n = 60$  months corresponding to monthly data used in the study.

Fig. 2 displays log-returns and CoVaR estimates for BRIC countries where dotted lines (black) show log returns, VaR is exhibited by

<sup>5</sup> Please see: [https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data\\_Library/f\\_f\\_5emerging.html](https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f_f_5emerging.html)

**Table 1**  
Descriptive statistics.

Country	Symbol	Mean (%)	Max	Min	SD	SK	KT	JB
Argentina	ARG	0.14	42.47	-70.38	12.39	-1.10	7.66	350.82***
Brazil	BRA	0.31	31.12	-49.44	11.03	-0.89	5.74	140.63***
Chile	CHI	0.07	18.28	-34.40	6.95	-0.72	5.41	103.85***
China	CHN	0.14	38.18	-32.40	9.02	-0.10	5.38	75.08***
Columbia	COL	0.31	26.47	-53.69	9.38	-0.80	6.61	205.90***
Czech Republic	CZR	0.38	26.30	-34.88	8.07	-0.63	5.33	93.04***
Egypt	EGY	0.48	35.08	-40.82	9.17	-0.35	5.83	112.36***
Greece	GRE	-0.74	26.77	-45.78	10.91	-0.80	4.96	84.27***
Hungary	HUN	0.69	37.96	-56.83	10.42	-1.02	7.75	353.26***
India	IND	0.52	31.21	-33.63	8.22	-0.36	4.29	29.12***
Indonesia	INDO	0.13	44.20	-52.47	11.85	-0.70	7.05	242.46***
South Korea	KOR	0.43	53.41	-37.48	9.89	0.19	6.93	205.49***
Malaysia	MAL	-0.02	40.51	-36.11	7.50	-0.20	9.44	550.29***
Mexico	MEX	0.48	17.76	-41.95	8.08	-1.30	7.35	339.18***
Pakistan	PAK	-0.32	31.68	-70.33	10.57	-1.31	10.84	902.26***
Peru	PER	0.64	30.44	-44.70	8.45	-0.83	7.17	266.46***
Philippines	PHI	-0.07	36.01	-34.65	8.00	-0.33	6.03	126.74***
Poland	POL	0.16	33.93	-42.98	9.89	-0.39	5.03	62.45***
Russia	RUS	0.64	47.71	-93.07	14.12	-1.05	10.03	711.15***
South Africa	SAF	0.28	17.73	-36.88	7.83	-0.92	5.26	111.84***
Taiwan	TAI	0.24	25.64	-24.68	7.49	-0.12	3.88	11.06***
Thailand	THL	-0.10	35.90	-41.63	10.21	-0.53	6.31	160.04***
Turkey	TUR	0.16	54.41	-53.18	13.70	-0.24	4.95	53.10***

Note: Max = Maximum, Min = Minimum, SD = Standard Deviation, SK = Skewness, KT = Kurtosis, and JB = Jarque-Bera test of normality. \*\*\* indicates significance at 1%.

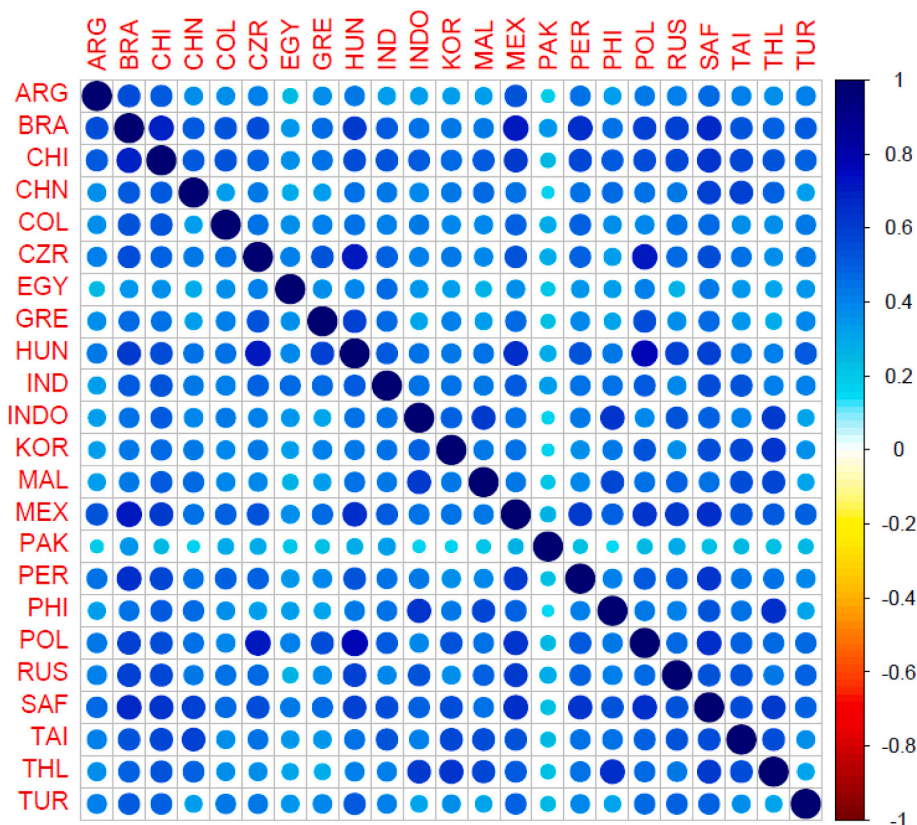


Fig. 1. Correlation heat-map of Emerging markets.

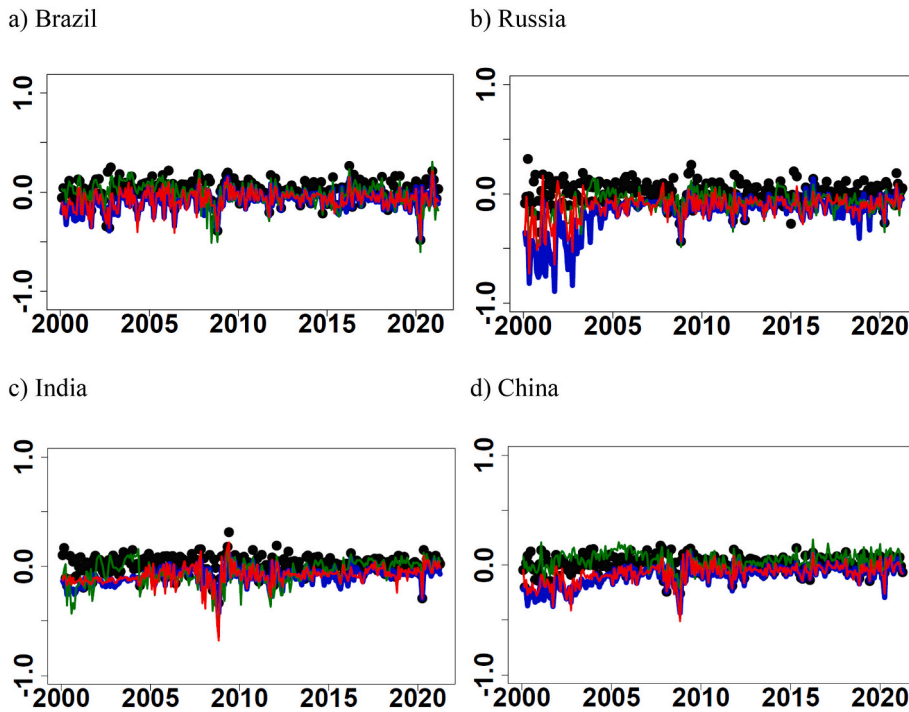


Fig. 2. Log returns and CoVaR estimates for BRIC.

Note: Log difference returns (black points), VaR (red),  $\text{CoVaR}^{\text{TENET}}$  (blue), and  $\text{CoVaR}^{\text{L}}$  (green).  $\tau = 0.05$ ,  $n = 60$ ,  $T = 255$ . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

red (thinner line),  $\text{CoVaR}^{\text{TENET}}$  represents blue (thicker line), and  $\text{CoVaR}^{\text{L}}$  denotes green (thinner line) in the upward and downward trends. In order to confirm the nonlinearity of the model, the estimated  $\text{CoVaR}$  based risk network is compared with  $\text{CoVaR}$  based linear quantile LASSO ( $\text{CoVaR}^{\text{L}}$ ). BRIC countries are selected based on their significant growth in global trade and direct contribution to the economy since the last two decades (Caporale et al., 2017; Demir and Ersan, 2017; Naeem et al., 2022b, 2022c).

The analysis of BRIC country log-returns indicates that VaR-based spillovers dominated the  $\text{CoVaR}^{\text{TENET}}$  in the downward trend for Brazil, India, and China and dominance is prominent during the global financial crisis. Russia showed varying spillovers where  $\text{CoVaR}^{\text{TENET}}$  dominantly spilled over VaR in the downward trend during Argentina's economic default and financial collapse for 2001–2003 (Feldstein, 2002; Anwer et al., 2022; Alawi et al., 2022; Yarovaya et al., 2022a, 2022b), where spillovers intensified due to the collapse of the Latin American emerging market (Karim and Naeem, 2022; Karim and Naeem, 2021; Karim et al., 2022b, 2022c). Overall, Fig. 2 highlights that spillovers are asymmetric and are dominant in the downward trends given Argentina's economic default and global financial crisis supported by Didier et al. (2012) who documented structural breaks in the emerging economies policies following the episodes of crisis. Our findings corroborate Bathia et al. (2021), who reported that emerging markets stocks are largely concentrated at lower quantiles indicating shock transmission from one market to another. Moreover, Das et al. (2018) stressed a weaker contagion effect for Latin American emerging markets during the global financial crisis, whereas the contagion effect surmounts for the emerging markets. In this way, a diversification potential in other emerging markets exists, which will reap profits in the long-run.

#### 4.2.2. Total connectedness and CoVaR estimates

Fig. 3 plots the total connectedness of 23 emerging markets where risk is classified as the total connectedness of emerging markets and the average value of lambda ( $\lambda$ ) estimated by  $\text{CoVaR}$ . The trends shown in the graph denote total connectedness by a solid blue line, whereas the black dotted line represents the average lambda ( $\lambda$ ) value of  $\text{CoVaR}$  estimates indicating the pattern of systemic risk during the sample period. Noticeably, the total connectedness and average  $\lambda$  showed a spike in the graph during 2001–2003, pointing to Argentina's economic downfall where emerging markets showed higher connectedness due to stressed circumstances. The subsequent decline in the graph denotes a return to stable economic conditions and low risk for both total connectedness and  $\text{CoVaR}$  estimates, respectively. The total connectedness showed a sheer spike in the graph during 2008–2010, reflecting the global financial crisis, whereas the systemic risk showed a moderate jump. However, the consequent trend in average  $\lambda$  revealed a significant rise indicating the aftermaths of GFC on the systemic risk of emerging markets. Our findings are somewhat different from Härdle et al. (2016), who reported a sharp increase in the trend during GFC in the US financial institutions indicating higher systemic risk for the financial industry. However, the differences in the results are due to variation in the selection of the industry where the financial industry mainly experienced sharp integration of financial institutions. In contrast, emerging markets showed exposure to high risk after the period of GFC, as shocks from the US spill over to other markets globally (Yarovaya and Zięba, 2022; Naeem and Karim,

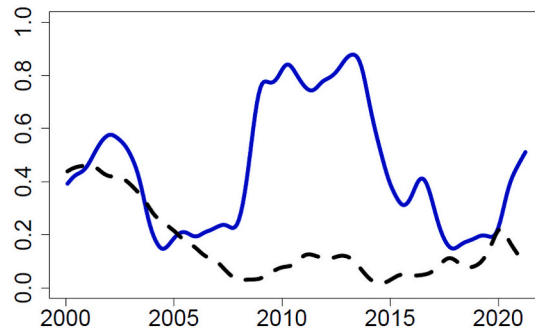


Fig. 3. Total connectedness and average lambda.

Note: Total connectedness (blue line) and average lambda (dashed black line) of 23 Emerging markets from Jan 2000 to May 2021.  $\tau = 0.05$ ,  $n = 60$ ,  $T = 255$ . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2021). In line with Lee and Lee (2021), we also reported peaks in the graph, which indicated major economic shocks such as the Argentinian economic downfall and global financial crisis.

The succeeding spikes in the total connectedness of emerging markets denote China's stock market crash in 2015, but the lower variation in  $\lambda$  confirms that the crisis did not vary the level of systemic risk for emerging markets. Womack (2017) highlighted the collapse of Chinese financial market and compared it to the GFC. Interestingly, the sharp increase in the total connectedness and  $\lambda$  estimates during the onset of COVID-19 substantiates a higher level of risk posed by emerging markets given the alarming global health crisis with severe lockdowns, travel and trade restrictions, and closure of almost all business operations. The higher risk and connectedness of emerging markets during the global pandemic is in line with Naifar and Shahzad (2021), who also reported high connectedness and higher  $\lambda$  estimates for sovereign credit risk spreads in 15 most affected countries with COVID-19.

In the coming step, the group connectedness depending on incoming links is explained as follows:  $CC_{p,w}^{IN} = \sum_{i=1}^k \sum_{j \in p} |\hat{D}_{j/i}^w|$  where  $p = 1, 2, \dots, 5$  representing the five most affected countries whereas  $CC_{p,w}^{OUT} = \sum_{j=1}^k \sum_{i \in p} |\hat{D}_{j/i}^w|$  represents the group connectedness based on the outgoing links. The top incoming links are presented in Fig. 4.

Fig. 4 reflects that during the Argentinian financial collapse, Russia, Indonesia, and Pakistan are the highest receiver of the risk from the system, whereas Poland received moderate risk given the global financial crisis. The subsequent incoming links show moderate risk reception except for Poland and Pakistan, given the aftermaths of the Global Financial Crisis together with the onset of Eurozone Debt Crisis (EDC) (2010–2012). Interestingly, Argentina reflected high-risk acceptance during the COVID-19 outbreak as the graph substantially peaked, indicating a higher level of risk exposure in the face of global pandemic and uncertain economic conditions. Besides, the picture is different for outgoing links (Fig. 5), which shows top 5 markets with high-risk spillovers. Russia, Turkey, and Indonesia reflected high-risk transmission to other emerging markets given Argentina's economic default during 2001–2003, whereas India and Hungary transmitted moderate risk to other emerging economies. Afterward, the risk transmission becomes lower as markets tend to stabilize after the prevailing economic crisis. The prominent risk transmission of Hungary and Russia during EDC (2010–2012) indicates the stronger influence of the crisis on the spillovers of these markets as they belong to Eastern Europe (Foye, 2018). Meanwhile, Russia, Indonesia, and India transmitted moderate spillovers. The COVID-19 outbreak in the graph signifies the high information transmission of Turkey to other emerging economies. Similar findings are also reported by Topcu and Gulal (2020), where they find a negative impact of the pandemic on emerging markets stocks, and the impact is pronounced in Asian markets compared to other European and American emerging markets.

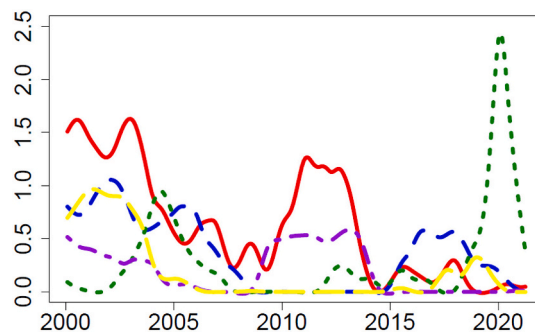


Fig. 4. Top incoming links.

Note: Pakistan (red), Indonesia (blue), Argentina (green), Poland (purple), Russia (yellow).  $\tau = 0.05$ ,  $n = 60$ ,  $T = 255$ . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



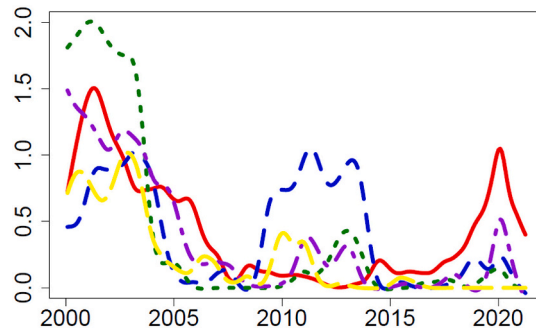


Fig. 5. Top Outgoing links.

Note: Turkey (red), Hungary (blue), Russia (green), Indonesia (purple), India (yellow). Tau = 0.05, n = 60, T = 255.

#### 4.2.3. Adjacency matrices

This step examines the country-level interconnectedness where the directional connectedness of market  $i$  to market  $j$  is focused. Fig. 6 represents the directional connectedness of 23 emerging markets where strong volatility spillovers are exhibited by the pairs POL-HUN, CZR-HUN, MAL-INDO, and PAK-IND. We also reported weak spillovers among the pairs of COL-TUR, INDO-THL, CHI-RUS, and PHI-THL, manifesting moderate to weak spillovers among the emerging markets during the full sample period. Overall, the figure reveals a varying intensity of risk spillovers for emerging markets with strong, moderate, and weak dependence. In line with Lee and Lee (2021), Topcu and Gulal (2020), and Zhang et al. (2020), global financial markets, particularly emerging markets, showed intense spillovers when faced with uncertainty in the global economic conditions. In addition, noticeable disconnections from the network are reported for CHN. The substantial disconnection of the Chinese market highlights their diversification potential for stocks of other emerging economies, as investing in the Chinese market would greatly enhance the risk absorbance when faced with uncertainty. Demir and Ersan (2017) support this finding by contending that growth in Chinese market would mature after 2020 than those of US and European markets. In this way, the dynamic nature of Chinese market would provide diversification potential to the investors while mitigating the risk of economic turbulence.

To further investigate the detailed links among the emerging markets, we aggregate the absolute values of  $|\hat{D}_{j/i}^w|$  and  $|\hat{D}_{i/j}^w|$  to rank the emerging markets based on risk reception and risk emission for the whole sample. Table 2 shows that the strongest spillovers are

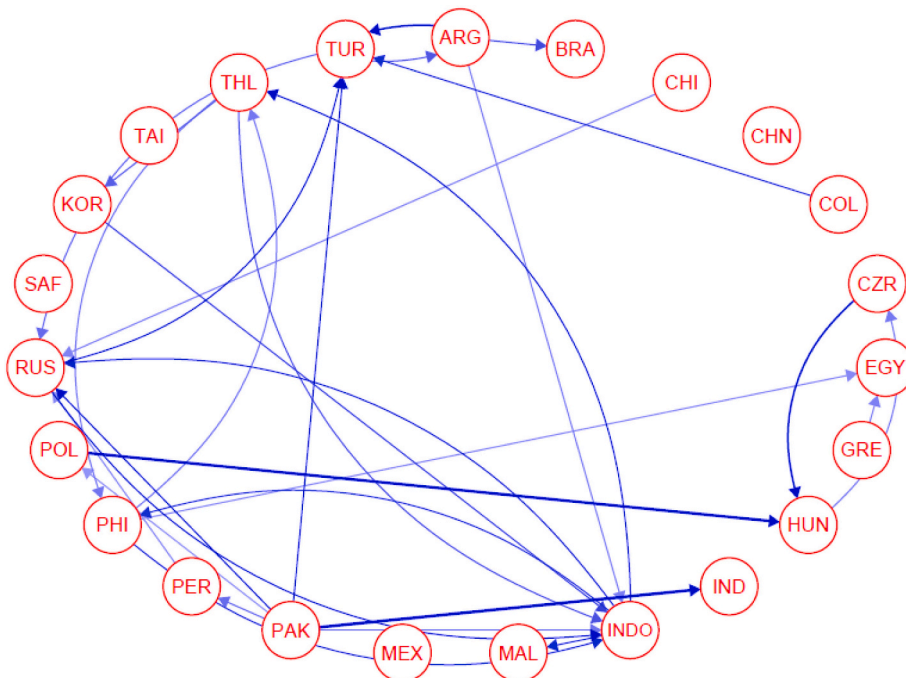


Fig. 6. Network representation of a weighted adjacency matrix – Full sample.

Note. This elliptical network representation is weighted adjacency matrices for the full sample. The values smaller than average of first 100 largest partial derivatives are set to be 0.

**Table 2**  
Country ranking and top three links.

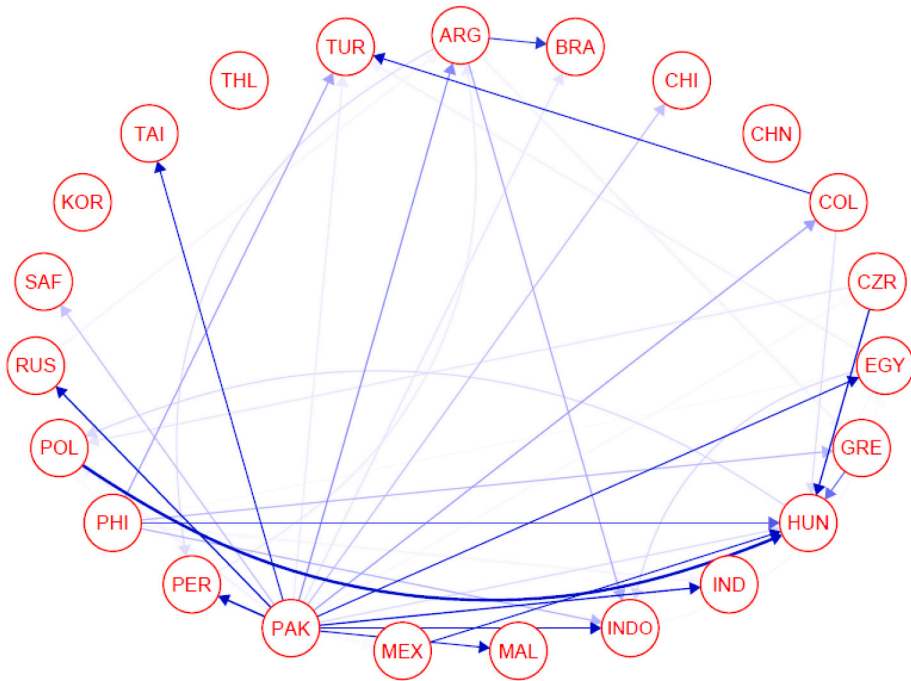
Risk receivers				Risk transmitters							
Rank	Country	Percentage	Incoming links			Rank	Country	Percentage	Outgoing links		
1	PAK	62.04%	TUR	BRA	INDO	1	TUR	42.87%	INDO	EGY	
2	INDO	35.78%	RUS	ARG	BRA	2	HUN	40.41%	ARG	COL	PAK
3	ARG	29.93%	RUS	ARG	BRA	3	RUS	38.47%	ARG	PAK	INDO
4	POL	19.57%	RUS	BRA	MAL	4	INDO	35.64%	TAI	PAK	COL
5	RUS	19.39%	TUR	BRA	PAK	5	IND	22.18%	PAK	INDO	EGY
6	CZR	18.41%	HUN	POL	GRE	6	THL	15.95%	HUN	EGY	GRE
7	PHI	16.00%	CZR	TUR	RUS	7	BRA	13.16%	GRE	PHI	INDO
8	THL	13.52%	EGY	CZR	HUN	8	PHI	12.50%	PAK	ARG	CZR
9	COL	12.01%	CZR	RUS	GRE	9	EGY	11.89%	POL	CZR	MEX
10	EGY	11.28%	PAK	GRE	TUR	10	ARG	8.39%	PAK	INDO	ARG
11	TUR	10.77%	THL	RUS	MAL	11	MAL	8.38%	RUS	PHI	KOR
12	HUN	8.49%	INDO	RUS	MAL	12	CZR	8.19%	INDO	PAK	ARG
13	KOR	8.27%	RUS	HUN	BRA	13	GRE	8.06%	EGY	PAK	ARG
14	GRE	7.19%	INDO	TUR	RUS	14	POL	7.07%	INDO	COL	ARG
15	PER	6.14%	RUS	BRA	THL	15	PAK	5.98%	PAK	EGY	ARG
16	MEX	4.47%	INDO	THL	EGY	16	KOR	4.79%	INDO	THL	PAK
17	MAL	4.12%	HUN	PAK	GRE	17	PER	4.68%	PAK	CZR	ARG
18	CHI	3.55%	TUR	INDO	GRE	18	COL	4.15%	PAK	INDO	TUR
19	CHN	2.87%	THL	RUS	ARG	19	TAI	2.93%	EGY	PAK	CZR
20	IND	2.72%	INDO	THL	ARG	20	CHI	1.56%	THL	PAK	CHN
21	BRA	2.45%	CHN	RUS	ARG	21	MEX	0.96%	PAK	ARG	MAL
22	TAI	0.37%	INDO	KOR	PHI	22	CHN	0.67%	INDO	PHI	KOR
23	SAF	0.14%	ARG	RUS	BRA	23	SAF	0.57%	ARG	RUS	PAK

from the countries of European region such as TUR, HUN, and RUS. Simultaneously, mainly Asian economies, for instance, PAK, INDO, and North American economy, ARG received strongest spillovers. TUR is the highest risk emitter to INDO and EGY, and the total risk transmission is at 42.87%, whereas HUN transmitted spillovers to ARG, COL, and PAK with risk transmission at 40.41%. Finally, the third top risk transmitter is RUS which emitted risk to ARG, PAK, and INDO at 38.47%. PAK, INDO, and ARG are the top three risk receivers in the system-wide dependence where PAK received risk spillovers from TUR, BRA, and INDO at 62.04%, followed by INDO, which received volatility spillovers from RUS, ARG, and BRA at 35.78%. Overall, we reported that TUR, HUN, and RUS mainly transmitted risk spillovers to PAK, INDO, and ARG. Our findings echo [Manopimoke et al. \(2018\)](#), who reported that spillovers of advance emerging economies are higher than Asian emerging markets, which act as net recipients of spillovers, and intraregional connectedness in the Asian region remains strong when compared with other emerging economies.

For further evidence of risk spillovers across emerging markets during the global financial crisis and COVID-19 pandemic, we focused on the net directional connectedness of emerging markets given these two sub-samples. [Fig. 7](#) illustrates adjacency matrices for the global financial crisis comparable to the full sample adjacency matrices given in [Fig. 6](#). The prominent spillovers are transmitted by POL, COL, CZR, and PAK during global financial crisis. Recalling the estimates of total connectedness and average  $\lambda$  in [Fig. 3](#), emerging markets showed higher system-wide integration during the global financial crisis, whereas average  $\lambda$  showed higher connectedness afterward intriguing aftermaths of GFC. Consistent with [Das et al. \(2018\)](#), emerging economies' stock markets showed a decline in comovement following the global financial crisis period.

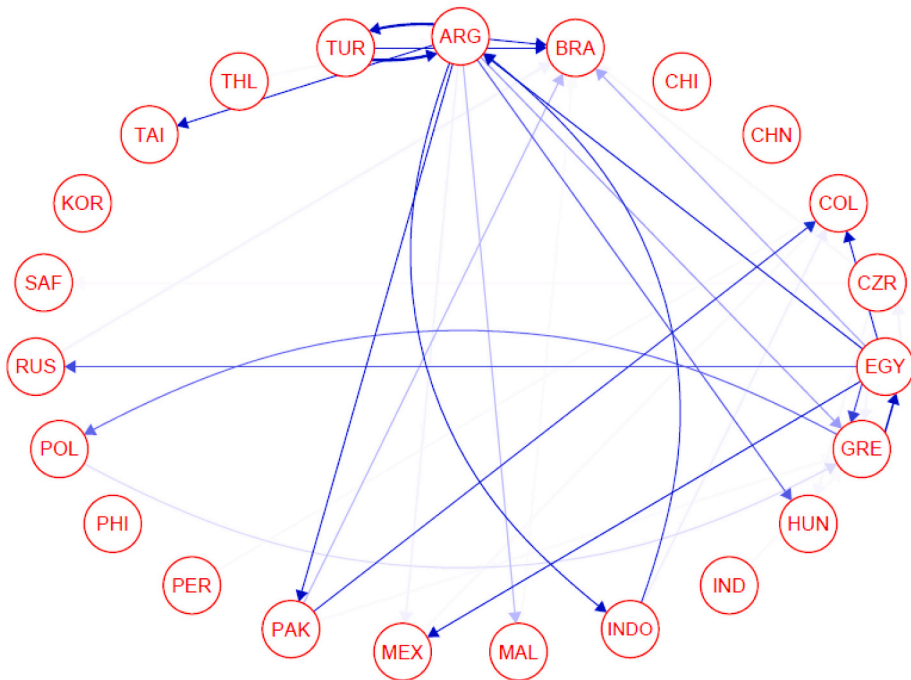
Alternatively, [Fig. 8](#) plots network connectedness of weighted adjacency matrix during COVID-19 crisis where pronounced risk transmission is evident by TUR and ARG. Referring to [Table 2](#), TUR and ARG are two main risk transmitters, which confirms our findings in [Fig. 8](#) in terms of high information transmission, particularly during COVID-19. In this way, ARG transmitted risk to BRA, PAK, INDO, and TUR and showed strong network connectedness given coronavirus outbreak. This finding aligns with the studies of [Naifar and Shahzad \(2021\)](#), [Topcu and Gulal \(2020\)](#), and [Zhang et al. \(2020\)](#), ([Huynh et al., 2021](#); [Karim et al., 2022d](#); [Naeem et al., 2021](#)) where European and Latin American emerging markets transmitted significant risk spillovers to other emerging economies.

Overall, our results highlight that emerging markets are exposed to tail-risk when there are unfavorable economic conditions. Further, network connectedness revealed time-varying patterns spotting significant crises, such as the Argentinian economic downturn, global financial crisis, European debt crisis, Chinese crisis, and the recent global pandemic of COVID-19. The top risk transmitters are TUR and HUN, whereas the top recipients are PAK and INDO. In consonance with previous studies, we reported sound evidence supporting our findings where global crisis circumstances increased integration in the global and emerging markets. Chinese market showed disconnection from other emerging markets for full sample and two sub-samples of GFC and COVID-19, highlighting diversification potential for risk-averse investors as adding Chinese stocks into the equity portfolio will substantially offer a greater off-setting position to avoid financial risk.



**Fig. 7.** Network representation of a weighted adjacency matrix – Global Financial Crisis.

Note. This elliptical network representation is weighted adjacency matrices for the financial crisis sample. The values smaller than average of first 100 largest partial derivatives are set to be 0.



**Fig. 8.** Network representation of a weighted adjacency matrix – COVID-19 crisis.

Note. This elliptical network representation is weighted adjacency matrices for the COVID-19 sample. The values smaller than average of first 100 largest partial derivatives are set to be 0.

### 4.3. Policy discussions

Given the tremendous liberalization and integration of emerging market economies, the present study draws significant policy implications. The current ongoing pandemic reported about 4.5 million deaths<sup>6</sup> so far with the policies of worldwide lockdown, travel restrictions, and other health measures to stop the devastating effects of the virus has created serious repercussions for the economic world (Zhang et al., 2020), which also did not spare financial markets to face critical outcomes of the pandemic. Emerging markets having strong reliance on trade and bilateral relationships, travel, tourism, and return on investment,<sup>7</sup> the policy reforms in the wake of COVID-19 stipulated severe economic uncertainty for the emerging economies.

As an early sign of the pandemic, consumers in the developed and emerging economies experienced a large negative wealth effect as a result of stock market plummetation. With decline in the global demand, the prices of stocks, commodities, and goods collapsed. In other words, a sharp reduction in export volumes accompanied by a drop in the prices of commodities and stocks badly affected the international trade causing serious repercussions for emerging economies. The increase in the uncertainty, risk re-pricing, and flight-to-safety are manifested in stock prices and capital flows around the world which synchronously collapsed the financial markets with stagnated credits, asset prices, and generalized deterioration of domestic financial as well as economic systems. Tail-risk, in these circumstances, is the state of heightened uncertainty where markets are exposed to turbulent economic and financial crises. Thus, in the face of COVID-19, tail-risk played an important role in determining risk spillovers across various emerging markets.

Correspondingly, the regulatory authorities and monetary bodies have implemented rigorous policy measures to rescue the dwindling economies and financial markets. Apart from these preventive steps of tail-risk exposure, given policies can only work in the short-run, substantiating the investors' fears and concerns in the long-run (Gormsen and Koijen, 2020). Conspicuously, the risk policies introduced by the US may enhance insecurity among the market participants and create unrest for the emerging markets (Yang and Zhou, 2017). In this bewildering state of affairs, examining the tail-risk among emerging economies to assess uncertainty in the markets will also support policymakers to treat the economic fragility appropriately, particularly when economies are exposed to travel bans, trade limitations, and lower returns on investments.

## 5. Conclusion

We investigated the tail-event network dependence of 23 emerging markets sourced from the MSCI emerging markets indices from January 1995 to May 2021. By employing the Tail-Event NETWORK technique in our analysis, we find that total connectedness of emerging markets is time-varying. Compared with average  $\lambda$  of CoVaR, the pattern shows relatively lower risk for the given period and emerging markets except for Argentina's economic turmoil, Chinese crisis, and recent ongoing pandemic of COVID-19. The elliptical network of adjacency matrix showed strong network connectedness where Turkey and Hungary are the top transmitters of risk spillovers, whereas Pakistan and Indonesia are net receivers of spillovers. China showed distinct disconnection from the system-wide connectedness reflecting its greater diversification potential among the emerging markets stock indices. Sub-sample analysis for global financial crisis and COVID-19 showed varied risk spillovers, whereas China maintained decoupled from the rest of markets analysed.

Our results draw several implications for policymakers, international investors, regulatory authorities, and financial market constituents. For policymakers, findings help reformulate the existing policies and build decoupling approaches to safeguard the emerging markets from adverse shocks. Moreover, findings provide useful diversification opportunities for international investors to curb the tail-event risk in their investments. Resuming international trade and bilateral relationships across the globe will assist investors and financial market participants in regaining substantial returns on their investments. For portfolio management and risk mitigation in the emerging markets stocks, findings play a central role in redesigning the portfolios and including diversifiers to escape the uncertainty in the markets.

Our findings are of particular interest for policymakers, regulatory bodies, investors, financial market participants and fund managers. Policymakers and regulatory bodies can relish the findings of the study by devising useful strategies to mitigate tail risk in the face of uneven circumstances. For investors and financial partners, the risk of various investments can be diversified by investing in the stocks which possess greater risk absorption capacity and offset the risk of volatile markets. Apart from these implications, the study suffers from some limitations, for instance, the study employed the data of only emerging markets to estimate tail-risk. However, as a future research direction, the current study can be conducted in various regional backgrounds with varying economic statistics. Moreover, the study utilized TENET approach to unveil the mechanism of tail-risk among emerging markets while future studies can employ other statistical methods to emphasize on the aspect of tail risk.

### Authors statement

Muhammad Abubakr Naeem: Conceptualization; Methodology; Software; Formal Analysis; Visualization; Writing - Original Draft; Writing - Review & Editing; Project Administration.

Imran Yousaf: Conceptualisation; data analysis; writing the first draft.

Sitara Karim: Conceptualization; Theory Development; Writing and Formatting; Visualization; Writing - Original Draft; Writing - Review & Editing; Preparing Final Draft;

<sup>6</sup> Please see: [https://www.worldometers.info/coronavirus/?utm\\_campaign=homeAdvegas1?](https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1?)

<sup>7</sup> Please see: <https://corporatefinanceinstitute.com/resources/knowledge/economics/emerging-markets/>

Larisa Yarovaya: Conceptualisation; writing and formatting; editing.  
Shoaib Ali: Conceptualisation; data analysis; writing the first draft.

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