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Systemic risk spillovers and the determinants in the stock markets of the Belt and Road countries

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ABSTRACT

We construct time-varying tail risk networks to investigate systemic risk spillovers in the Belt and Road (B&R) stock markets during 2008–2021. Network metrics clearly reflect aggregate risk level and individual risk accumulation for the B&R stock markets under extreme events (e.g., 2008 financial crisis and COVID-19 pandemic). Tail-event driven network quantile regression analysis shows that network impacts of the B&R stock markets under different risk levels are asymmetric and regional heterogeneity. Panel analysis on determinants of systemic risk spillovers shows that cross-border investment and international trade are significant contagion channels while economic freedom is potential driver.

1. Introduction

In 2013, China successively proposed the joint construction of the "Silk Road Economic Belt" and the "21st Century Maritime Silk Road", from which came the concept of the "Belt and Road Initiative" (the B&R Initiative). As a national top-level cooperation project, the B&R Initiative has been advancing rapidly in recent years, receiving extensive support and participation from the international community.[1] With the rise of nationalism and trade protectionism as obstacles to economic globalization, the B&R Initiative will help restructure a new pattern of economic opening-up. The B&R Initiative intends to enhance policy coordination and mutual trust, deepen benefit sharing, and provide a more stable international political environment for economic and trade cooperation. As a central feature

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[1] According to official statistics of the "Belt and Road", as of February 6, 2022, China has signed 206 cooperation documents for the joint construction of the "Belt and Road" with 206 countries and 32 international organizations (see, https://www.yidaiyilu.gov.cn/xwzx/roll/77298.htm).

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of the B&R Initiative, infrastructure connectivity has greatly stimulated factor flows and economic exchanges among member countries.[2] By giving full play to the factor endowment and optimizing resource allocation for member countries, the B&R Initiative will bring extensive trade and investment dividends and effectively promote structural adjustment and balance of regional economy (Liu and Wu, 2018; Wu and Pan, 2019). Recent studies (Du and Zhang, 2018; Yu et al., 2019; Foo et al., 2020; Bird et al., 2020; De Soyres et al., 2020) provide substantial empirical evidence that the B&R Initiative promotes trade flows, foreign investment, economic relations and social welfare of the countries along the Belt and Road. Although the B&R countries have a high degree of economic coupling and can form new production relations, there are still many uncertainties and potential risks in the concrete implementation (Sheng and Li, 2016; Huang, 2016).

Recent financial extreme events (e.g., the 2008 global financial crisis) and public health emergencies (e.g., the COVID-19 pandemic) severely damaged the global financial system and the real economy. Therefore, it is necessary to be cautious about the financial stability and macro-prudential supervision of the B&R system. With global financialization and frequent economic and trade activities,[3] the interconnectedness among capital markets in the B&R countries is increasingly strengthened. On the one hand, this can bring positive driving factors such as funds and information to the rapid development of the B&R capital market; on the other hand, this also can accelerate and exacerbate the contagion of tail risk events and financial crises, generating an unavoidable systemic risk impact. The B&R members are mostly emerging countries and cover many low-income economies with underdeveloped financial systems. The inherent financial fragility and backward regulatory mechanism make the B&R countries more vulnerable to systemic risk.

Acting as a "barometer" of economic and social activities, the stock market reflects investors' confidence in the future market value and economic development. This not only involves the individual interests of investors or institutions, but also profoundly affects the smooth operation of the economy and society. For the increasing dependence between the capital market and the real economy, the stock market (as the core of the capital market) is the key field of systemic risk research in the B&R countries. How to measure the systemic risk of the B&R stock markets? How to identify the systemic important stock markets of the B&R countries prospectively? How to analyze the systemic risk spillover effects of the B&R stock markets? The Belt and Road spans Asia, Europe and Africa, and is there heterogeneity in the systemic risk contagion effect among different regions? What are the potential drivers of systemic risk in the B&R stock markets? The above questions remain open, and we attempt to provide answers in this article.

Our research is motivated by the academic gaps in the risk spillovers and financial market integrations of B&R region. The proposal of the B&R Initiative has triggered heated discussions in academic circles and most studies focus on qualitative analysis in term of the significance, connotation, challenges, obstacles and countermeasures (Cheng, 2016; Zhang et al., 2017; Ascensão et al., 2018; Hurley et al., 2019). Also, the B&R quantitative studies enrich continuously, but mainly from the perspective of transport infrastructure (De Soyres et al., 2019, 2020; Wang et al., 2020), international trade (Herrero and Xu, 2017; Boffa, 2018), foreign direct investment (Du and Zhang, 2018; Yu et al., 2019; Li et al., 2022), and policy effects (Yin et al., 2019; Deng and Yu, 2021). In contrast, the research on financial risk prevention and regulation in the B&R countries is still insufficient, and furthermore, little attention has been paid to the potential linkages between increasing trade and investment activity and financial market contagion in B&R region.

With the deepening of regional economic integration, the financial market along the Belt and Road presents potential risk spillover effects (e.g., individual risk in the stock market rapidly accumulates in local areas and spreads to other member countries). This naturally inspires scholars to investigate the systemic risk and spillover effects in the B&R stock markets. For example, Guo and Wang (2018) analyze the dynamic correlation and dependence structure of the B&R stock markets. Luo et al. (2021) explore the financial risk spillover effects among the B&R stock markets under normal and extreme risk conditions; and other related studies include Wang and Yang (2019) and Wei and Sun (2021). Existing studies lay emphasis on the dynamic dependence characteristics and risk spillover effects (intensity, direction and scope) in the B&R stock markets. Nevertheless, those prior works mostly ignore the geographical spatial characteristics of the B&R economic data, and rarely further explore the potential drivers of risk contagion by considering economic fundamentals and important physical links (e.g., investment and trade activities) in the B&R region. Both of them are crucial for macro-prudential supervision of stock markets in the B&R countries with complex political and economic environments. The research work in this paper benefits from this motivation and attempts to fill in the specific knowledge gap.

Network analysis method has been widely used in recent systemic risk research for its good capacity in describing the complex structure of financial system and analyzing the potential linkages of financial entities (Allen et al., 2009; Minoiu and Reyes, 2013;

[2] Infrastructure is the antecedent capital for economic and social development, and a country or region must have a minimum stock of infrastructure before an economic takeoff may occur (Rostow, 1959). The B&R Initiative strengthens infrastructure planning and gradually forms an infrastructure network connecting sub-regions in Asia, Europe and Africa. This includes the China-Laos Railway, the Hungary-Serbia Railway, the Jakarta-Bandung High-Speed Railway, the Mombasa-Nairobi Railway, the China-Europe Freight Train, and the Silk Road Maritime Transport. By the end of August 2022, nearly 60,000 China-Europe freight trains with a total cargo value of nearly US $300 billion had been in operation, covering 82 transport routes reaching 200 cities in 24 European countries. Infrastructure connectivity is gradually breaking the "iceberg cost" of economic ties caused by backward infrastructure in B&R countries. The estimated results of De Soyres et al. (2019) show that the infrastructure construction of the B&R Initiative can shorten the average shipping time by 1.2%–2.5% and reduce trade costs by 1.1%–2.2% from a global perspective; the B&R countries, on the other hand, would experience the largest gains, with transportation times reduced by up to 11.9% and trade costs reduced by up to 10.2%.

[3] The scale of trade among the B&R countries continues to expand. Total merchandise trade between China and other B&R countries reached US $1.3 trillion in 2018, growing by 16.4% year on year, while the service trade grew by 18.4% from 2016 to reach US$97.76 billion in 2017 (https://eng.yidaiyilu.gov.cn/zchj/qwfb/86739.htm). Additionally, Baniya et al. (2020) investigate the impact of the B&R Initiative on trade in 71 potentially participating countries, and find that the Initiative increases trade flows among B&R member countries by up to 4.1%.

Acemoglu et al., 2015; Bongini et al., 2018). Methodologically, we adopt the network analysis techniques to explore the systemic risk and spillover effects of the stock markets in countries along the Belt and Road based on the risk profiles of the tail event. More specifically, the empirical work of this paper includes the following steps: (i) we first use conditional expected shortfalls (CoES) to measure the individual risk profile on the tail risk events for the B&R stock markets; (ii) we then construct a time-varying tail risk network of the B&R stock market based on the similarity of tail risk profiles, in which risk contagion and risk diversification attributes among stock markets can be characterized; (iii) for the purpose of monitoring systemic vulnerability, the systemic risk score index is constructed as the metric of "aggregate risk" in the tail risk network to quantify the overall systemic risk level of the B&R stock markets; and meanwhile, the individual risk contribution of the B&R stock market is described by the risk decomposition of "aggregate risk"; (iv) we adopt the Tail Event driven Network Quantile Regression (TENQR) model proposed by Chen et al. (2019) to analyze the impact of systemic risk on the B&R stock markets at different risk levels and test the asymmetry and regional heterogeneity of contagion effects; and (v) we finally perform the panel data analysis to further explore the potential drivers of systemic risk in the B&R stock markets from the perspectives of the economic fundamentals (i.e., transnational investment, international trade, economic freedom, and financial market maturity).

The estimated networks of B&R stock markets have several novel and interesting findings. Firstly, the tail risk profiles of the B&R stock market change continuously and present highly homogeneous network structures during global extreme financial events (particularly for the 2008 global financial crisis and the COVID-19 pandemic). Secondly, the dynamic evolution of the systemic risk score index clearly depicts the sensitivity of the B&R stock market to recent important financial events; the individual risk contribution index reflects the high level of systemic risk in the stock markets of China and India, and reveals the systemic importance of the dynamic East Asian economic circle from the regional perspective. Thirdly, both the dynamic evolution of network metrics and the static visualization of financial network indicate that the negative impact of COVID-19 pandemic on the B&R stock markets is more profound than that of the 2008 global financial crisis. Fourthly, the results of TENQR model reveal the asymmetry and regional heterogeneity of the risk spillover effects of the B&R stock markets, and also reflect that risk contagion could be a pervasive phenomenon of the international business cycle, which widely exists in the boom and crisis periods. Fifthly, the panel data analysis provides strong econometric evidence that cross-border investment and international trade are important channels of risk contagion; economic freedom is a potential driver of systemic risk in the B&R stock markets. While the first two findings are covered to varying degrees in the existing literature in different contexts or scenarios, the others are the original findings of this paper.

In this light, this paper has rich theoretical value, profound economic implication and broad application scenarios. Firstly, our work enriches the research on the systemic risk of the B&R stock markets from the perspective of network analysis. We construct the time-varying tail risk network based on the risk profiles similarity of the B&R stock markets, and reveal the tail risk dependence structure and spillovers characteristics (risk contagion and risk diversification). Secondly, the systemic risk score index of the tail risk network reflects aggregate risk level of the B&R stock markets and sensitively responses to extreme financial events, which can be used as an early warning indicator of systemic risk. The individual risk contribution index helps identify systemically important stock markets in the Belt and Road region. Both of them can provide effective tools and valuable information for regulatory authorities to prevent systemic risk and for investors to make portfolio decisions. Thirdly, the TENQR model describes the dynamic impulse response of the stock market encountered network shocks at different risk levels. This will facilitate policy makers to make reasonable policy adjustments according to the operating conditions (i.e., boom period, normal period and crisis period) of capital markets from different regions and prevent cross-border risk imports. Finally, the panel data analysis reveals potential drivers of systemic risk in the B&R stock markets, which helps the member countries to clarify the channels of risk contagion. At the same time, it is also conductive to fully dispatching various positive factors to guide the financial services to the real economy and further promote the great prosperity of the B&R initiative.

The rest of the paper is arranged as follows. We review the existing relevant literature in the next section. In Section 3, we describe empirical data and methodology respectively. In Section 4, we present the empirical results. Finally, we have a brief discussion and summary in Section 5.

2. Literature review

Risk spillovers among the international financial markets are a well-researched topic involving different crisis periods. Numerous studies provide key evidence of financial risk contagion among developed economies (MacDonald et al., 2018; Fan et al., 2020; Guo et al., 2021; Liu et al., 2022), and the topic in emerging countries are increasingly receiving attentions (Reboredo et al., 2016; Meng et al., 2020; Ji et al., 2020). The robust financial architecture requires a thorough understanding of the causes and consequences of risk spillovers. For the determinants of risk spillovers and contagion, the economic fundamentals have been broadly mentioned in the financial literature. Dornbusch et al. (2000) ascribe risk spillovers to macro fundamental interdependence (derived from trade links, competitive devaluations, and financial links) and non-fundamental contagion based on investors' behavior. As the recent evidence, the empirical results of Luo et al. (2015) on the Chinese stock market reflect that international trade is the fundamental channel of financial risk contagion compared with capital flow, liquidity, investor sentiment and behavior. Similarly, Luchtenberg and Vu (2015) and Leung et al. (2017) find that economic fundamentals such as trade structure and regional effects are important causes of international contagion by investigating risk spillovers in mature financial markets. The B&R Initiative has strengthened the interdependence of the economic fundamentals (e.g., trade, investment and financial links) among the member countries, and whether this will lead to stronger risk spillover effects deserves further discussion.

From the perspective of methodology, with the emergence of a large strand of vibrant literature on financial risk spillovers, a series of econometric approaches have been formed to measure the interdependence and contagion effects of financial entities. GARCH-Type model is one of the effective econometric methods in reflecting the return and volatility spillover effects of financial markets.[4] For example, Beirne et al. (2010) adopt the tri-variate vector autoregression (VAR)-GARCH(1,1) models to analyze global and regional spillovers in emerging stock markets from the channels of mean returns, volatility, and cross-market GARCH-in-mean effects. MacDonald et al. (2018) introduce financial stress indexes into the GARGH-BEKK model to investigate the volatility co-movements and spillovers between the Eurozone economies; they find significant spillovers in core eurozone countries and confirm the "decoupling" hypothesis that the spillover effects gradually weaken during Brexit. Undoubtedly, multivariate GARCH-based methods have gradually become a broad framework for analyzing spillover effects, which has been adopted and expanded by many studies (e.g., Hou et al., 2019; Sarwar et al., 2019; Yu et al., 2020). However, financial data exhibit the nature of non-normality, spikes, and fat tails, which makes the multivariate GARCH model based on the assumption of multivariate normal distribution prone to errors in capturing the non-linear dependence structure between financial variables (Wu and Zhang, 2010).

Due to the increasing concern of extreme financial risk, the Copula method, which is suitable for analyzing non-normal, nonlinear and tail asymmetric interdependent structures, can be served as a supplement to the GARCH-based models and widely used in tail risk spillover analysis. For instance, Philippas and Siriopoulos (2013) investigate the risk spillover effects among European Monetary Union (EMU) countries during the Greek currency crisis by combining spillover conversion model and time-varying Copula model. With a similar research paradigm, Reboredo et al. (2016) adopt the Copula method to explore the upward and downward two-way risk spillovers of stock prices and exchange rates in emerging economies, revealing the spillover asymmetry of the intensity and scope between upside and downside risks. GARCH models and some systemic risk measurements (e.g., conditional value-at-risk, CoVaR and conditional expected shortfall, CoES) are often introduced into Copula to quantify tail risk spillovers and contagion effects, ranging from GARCH-Copula (e.g., Meng et al., 2020). Copula-CoVaR (e.g., Ji et al., 2018), Copula-CoES (e.g., Zhu et al., 2020), and GARCH-Copula-CoVaR approach (e.g., Sun et al., 2020; Ji et al., 2020).

More recently, the disciplinary collision of econometrics and network topology theory has prompted a series of innovative model tools to comprehensively study the spillover effects of systemic risk. Billio et al. (2012) propose the Granger causality network and the corresponding connectedness measure by combining principal component analysis and Granger causality test, in which the Granger causality of asset returns can be regarded as the return-spillovers of market participants. Also based on the VAR model, Diebold and Yılmaz (2014) introduce the spillover index method (Diebold and Yılmaz, 2009, 2012) into the network framework, forming a variance decomposition network that can quantify the volatility connectedness and spillovers of financial entities. Adrian and Brunnermeier (2016) propose the CoVaR to capture the tail risk spillovers and cross-sectional comovement between financial institutions conditional on the stress event. The CoVaR is a popular systemic risk measure and widely accepted in the field of macro-prudential risk management. Hautsch et al. (2015) adopt the LASSO-CoVaR technique to quantify tail-interdependence and risk contributions among financial institutions in systemic risk networks, which extends the binary linear CoVaR model to a high-dimensional linear model. By adopting single-index quantile regression of semi-parametric framework, Härdle et al. (2016) extend the CoVaR model to a high-dimensional nonlinear model, i.e., tail event driven network (TENET) to quantify the tail risk spillover effects among financial institutions. Wang et al. (2017) propose an extreme risk spillover network to measure the connectedness among financial firms by combining the CAViaR model (Engle and Manganelli, 2004) and the Granger-causality risk test. In a nutshell, network analysis technology is quite capable of revealing the internal structure and topological characteristics of financial network, and infuses vigor into the study of risk spillover effects and contagion path.

Additionally, an interesting problem in the network analysis of risk spillover effects has aroused attention. The node responses or outputs in financial risk networks constitute high dimensional vectors, and how the stress impulse on nodes (or sets of these nodes) propagate through the network? To solve this problem, Zhu et al. (2017) propose network vector autoregression (NAR) to investigate dynamic response from network nodes in the time series dimension. Since the NAR model merely focuses on the mean level, Zhu et al. (2019) extend it to a network quantile autoregression (NQAR) model to examine tail risk dependency in the Chinese stock market on conditional quantiles, finding the significant asymmetric spillovers at different levels of quantiles. To further extend the NQAR model to panel scenarios, Chen et al. (2019) design the TENQR model to analyze the dynamic risk characteristics and spillover effects of systemically important financial institutions (SIFIs) from different regions. Their results confirm that the risk contagion effect is more significant under stress situation and varies in different geographic regions.

Compared with the earlier methods to study risk spillovers, the system-wide quantitative network framework proposed by Chen et al. (2019) has the following obvious advantages: (i) the time-varying tail risk network can not only describe the tail-dependent structure, but also reflect more connectedness information among financial entities including the risk spillover characteristics (i.e., risk contagion and diversification) and their dynamic and asymmetric performance; (ii) the aggregate risk score of the network can reflect the systemic risk level of the financial system, and systemically important financial entities can be identified by the individual risk contributions; and (iii) the TENQR model introduces spatial econometrics into the analysis of tail risk propagation and dynamics, reflecting the dynamic impulse process and potential regional heterogeneity of financial entities from different regions that encounter network effects or shocks at different stress levels. In terms of research methodology, the network technique of Chen et al. (2019) provides us with a useful analysis framework to understand the network dependency structure and risk propagation.

The complexity and diversity of political system, economic development, financial foundation, social governance and religious culture along the Belt and Road inspire us to explore the tail risk spillover effects among the B&R stock markets, and meanwhile, to investigate the time-varying impulse and regional heterogeneity when the participant countries are in financial trouble. To this end,

[4] GARCH model can capture variance changes under the phenomenon of volatility cluster and is suitable for the research of financial time series volatility analysis and risk management.

this paper adopts the tail risk network analysis framework and TENQR model to study the systemic risk and spillover effects of the stock markets in the B&R countries.

3. Data and methodology

3.1. Data

The Belt and Road Initiative is not a closed club, and it is open and inclusive to all countries willing to participate. In recent years, the number of countries participating in the B&R initiative has continued to increase. Currently, however, a group of 66 countries (including the organizer China) are widely used in academic research and official news reports on the subject of the B&R initiative (Liu et al., 2020), as shown in Table A1 of Appendix A. In this paper, the sample countries of the study on the systemic risk and spillover effects of the B&R stock markets follow this scope. Stock market price index for some B&R countries are not available because of lack of data. After data cleaning, we finally select the stock market indexes from 33 B&R countries, covering the period from 6 April 2007 to 28 May 2021. The stock index data are obtained from Datastream and the data frequency is weekly. Sample countries and stock indexes are shown in Table A2 of Appendix A. According to the geographical distribution, we heuristically divide the B&R sample countries into three regions: (i) East Asia and South Asia (EASA); (ii) West Asia and North Africa (WANA); and (iii) Central and Eastern Europe (CEE).

Table 1 lists the descriptive statistics of weekly returns of the 33 B&R stock market indexes, which are defined as $X_{i,\ t} = \ln(P_{i,\ t}/P_{i,\ t-1})$, where $P_{i,\ t}$ is the closing price of stock market index i on week t. The absolute minimum of returns of most B&R stock markets is far greater than its maximum value, indicating that the B&R countries are generally negatively impacted by financial risk, and the negative shocks have caused the stock market to plummet. The mean values of the returns in the EASA region are greater than zero, while those in the WANA and CEE regions are less than zero. Since the 2008 global financial crisis, extreme financial events have caused persistent and serious negative impacts on capital markets in the WANA and CEE regions. The strong economic resilience in the EASA region helped them recover from the financial crisis, which also enabled the stock markets to enter a relatively stable stage. The skewness of all the B&R stock market returns deviates from zero, and their kurtosis is greater than 3 (except for China), which reflects that stock market returns do not obey the normal distribution, and shows that the “leptokurtosis and fat-tail” characteristic commonly

Table 1
Descriptive statistics of weekly returns of the 33 B&R stock market indexes during 4 January 2008 to 28 May 2021.

Region	Country	Abbr	Max	Min	Mean	Median	Std dev	Skew	Kurtosis
EASA	China	CHN	14.4998	−14.9958	0.0362	0.1340	3.3661	−0.3549	2.4907
	India	IND	16.9298	−16.7659	0.1744	0.3106	2.9452	−0.4103	4.9811
	Indonesia	IDN	11.7004	−23.5545	0.1373	0.2770	3.1115	−1.2641	7.9780
	Malaysia	MYS	6.2144	−10.3174	0.0333	0.0997	1.6311	−0.7990	4.5393
	Pakistan	PAK	9.4689	−19.5037	0.0561	0.2814	2.8207	−1.3769	7.3601
	Philippines	PHL	9.8356	−17.9397	0.0866	0.1979	2.6228	−1.1634	8.0841
	Singapore	SGP	13.6368	−17.1087	0.0015	0.1055	2.3252	−0.6356	8.6700
	Sri Lanka	LKA	12.8484	−10.5139	0.0969	−0.0006	2.2398	0.4509	4.2624
	Thailand	THA	11.9896	−27.8053	0.1069	0.2774	2.8803	−1.6830	15.3502
	Vietnam	VNM	14.0247	−17.1796	0.0382	0.2498	3.4592	−0.6497	3.6545
WANA	Bahrain	BHR	11.9681	−9.8612	−0.0489	−0.0098	1.5031	−0.4467	11.1405
	Egypt	EGY	14.2836	−21.5754	0.0105	0.3277	3.2649	−1.2273	7.1534
	Israel	ISR	9.0560	−14.0038	−0.0276	0.2073	2.4692	−0.8979	4.6032
	Jordan	JOR	9.1474	−14.5276	−0.0482	−0.0679	2.0532	−0.9503	11.0205
	Kuwait	KWT	14.4308	−13.9659	−0.0484	0.0504	2.4541	−0.8195	8.0200
	Oman	OMN	10.4379	−18.4251	−0.0326	0.0162	2.0837	−1.4306	14.1811
	Qatar	QAT	14.2122	−20.5354	0.0839	0.2664	3.0726	−1.0026	7.2384
	Saudi Arabia	SAU	12.2272	−21.8210	0.0213	0.2019	3.1161	−1.2497	7.3248
	Turkey	TUR	14.3058	−19.4574	0.1762	0.3571	3.6222	−0.5997	3.1059
	United Arab Emirates	ARE	13.6886	−19.5383	0.0690	0.1180	2.8075	−1.2360	8.7618
CEE	Bulgaria	BGR	12.2733	−15.2989	−0.1442	−0.0158	2.7286	−0.8185	6.6055
	Croatia	HRV	13.4987	−25.6000	−0.0665	0.0142	2.2836	−2.2071	28.9899
	Cyprus	CYP	15.9890	−104.6084	−0.5829	−0.3026	5.5505	−9.1935	166.3887
	Czech Republic	CZE	17.7732	−25.3410	−0.0239	0.0790	2.6279	−1.2018	17.2872
	Estonia	EST	15.2071	−17.7935	−0.0543	0.0695	2.8688	−0.7270	8.4726
	Greece	GRC	17.6481	−28.3302	−0.3439	−0.0398	4.7185	−0.8670	4.1883
	Hungary	HUN	14.9151	−28.9947	0.0377	0.0486	3.1933	−1.4386	12.6157
	Lithuania	LTU	23.7867	−15.0772	0.0047	0.1042	2.2825	0.2924	22.2605
	Poland	POL	12.8361	−23.5752	−0.0478	0.1535	2.8536	−1.2330	9.2964
	Romania	ROM	14.6820	−37.5882	−0.0068	0.2520	3.5468	−2.7869	23.4520
	Russia	RUS	32.3438	−27.4870	0.0839	0.2355	3.7272	−0.2682	14.4423
	Slovakia	SVK	10.2621	−17.4040	0.0059	0.0340	1.6688	−1.4665	20.1489
	Slovenia	SVN	9.7856	−18.0909	−0.0951	0.0310	2.2935	−1.3818	10.7622

Notes: The list of countries is divided by region and is sorted alphabetically. In the region column, EASA represents Eastern Asia and Southern Asia, WANA represents West Asia and North Africa, and CEE represents Central and Eastern Europe.

existed in the return series. From the results of descriptive statistics, we can conclude that the B&R stock markets experienced severe turbulence during the crisis period.

For the market-wide covariates of TENQR model, we follow Wang et al. (2022) and use 8 indexes to comprehensively reflect the macro financial environment of the B&R stock markets in terms of interest rate, investor panic, foreign exchange, short-term liquidity, bulk commodities, hedge products and economic policy uncertainty. The 8 market covariates are as follows:

(i) Chinese 10-year government bond yields;
(ii) European Monetary Union 10-years government bond yields;
(iii) CBOE VIX index;
(iv) The change in US Dollar Price Index;
(v) A short-term TED spread;
(vi) The S&P GSCI TR-3 month yield;
(vii) The weekly return of Spot London gold price;
(viii) Economic Policy Uncertainty (EPU) Index.

As the cornerstone of the interest rate system, government bond is the main way for the central bank to carry out open market operations, which is also an important medium for monetary policies. Government bond yield is often regarded as risk-free yield and the pricing benchmark for other bond yields and loan rates, playing an irreplaceable role in the real interest rate system. The Belt and Road region covers the developed European economic circle, the dynamic East Asian economic circle and the economically backward Middle East region. We choose the government bond yields of China and European Monetary Union to reflect the government credit risk profile, capital liquidity and bond market conditions of the two major economic engines in the Belt and Road region.

We use the Chicago Board Options Exchange's (CBOE) Volatility Index (VIX) as a proxy for global investor panic. This index is commonly known as the "fear index" or "fear scale", and it can timely reflect the rise of investor market "fear" during financial stress (Batten et al., 2022). The VIX has become the dominant measure of risk volatility in the financial world (Bardgett et al., 2019). Recent empirical evidence documents the profound impact of VIX on credit risk in the financial sector (Mensi et al., 2019; Shahzad et al., 2020).

The US dollar index (USDX) is chosen to comprehensively reflect the situation in the international foreign exchange market. Since most B&R countries are emerging economies, their weak currencies are vulnerable to violent fluctuations caused by external factors. The USDX measures the change of the exchange rate of the US dollar against a basket of currencies. Changes in the US dollar (appreciation or depreciation) have obvious spillover effects on other sovereign currencies, and also have long-term effects on the volatility of asset prices (Sun et al., 2017).

Following Adrian and Brunnermeier (2016) and Hautsch et al. (2015), we include the short-term TED spread, defined as the difference between three-month LIBOR and three-month US secondary market Treasury rates, to measures global short-term liquidity risk and the perception of credit risk.

The B&R countries have diverse resource endowments, including commodity producers and importers. International trade in bulk commodities has a profound impact on the steady development of national economy in B&R countries. We select the S&P Goldman Sachs Commodity Index (GSCI), the world's most tracked commodity index, to reflect the international bulk commodity trade.

For global safe-haven assets, we choose the spot price of gold on the London Bullion Market (the center of the world's gold trade). In period of financial stress and financial crisis, international capital is keener on safe haven products such as gold.

We select the global EPU index proposed by Baker et al. (2016) to reflect global macroeconomic and policy uncertainty. Economic policy uncertainty has moderately negative effects on financial stability (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015). Some studies point out that the uncertainty of economic policy is related to financial turmoil and abnormal volatility of financial markets (Pastor and Veronesi, 2012).

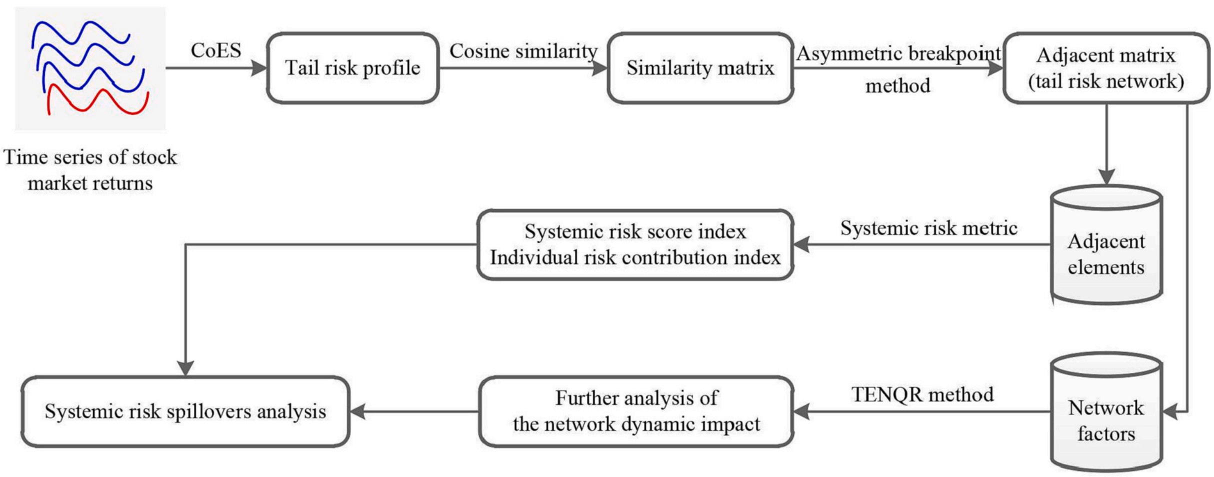

Fig. 1. Overall framework of the methodology.

3.2. Methodology

This paper constructs the quantitative network analysis framework based on the tail risk profiles similarity of the B&R stock markets. Under the tail risk network framework, we further introduce the TENQR model of Chen et al. (2019) to investigate the dynamic impact of the network factor. Fig. 1 show the overall framework of the methodology and we then discuss it in detail.

In the first step, we choose the conditional (marginal) expected shortfalls (CoES) to characterize the risk profile of the B&R stock markets conditional on tail events. Like the currently popular measurements such as CoVaR (Adrian and Brunnermeier, 2016), marginal expected shortfall (MES) (Acharya et al., 2017) and SRISK (Acharya et al., 2012; Brownlees and Engle, 2017), CoES is also an effective systemic risk measure. Given quantile level τ and the return (loss) $X_{i,\ t}$ of stock market i at time t, the CoES of stock market i conditional on the tail event that the return (loss) of stock market j exceeds its value-at-risk (VaR) can be defined as

$$\mathrm{CoES}_{ij,t}(\alpha) = \mathrm{E}\left[X_{i,t} | X_{j,t} < \mathrm{VaR}_{j,t}(\alpha)\right],\ \ i,j = 1,2,\dots,N, \tag{1}$$

where $N = 33$ is the sample size of the B&R stock markets. Therefore, the risk profile of each B&R stock market at time t is characterized by a N=33-dimensional vectors $\boldsymbol{Y}_{i,\ t} = \{\mathrm{CoES}_{ij,\ t}(\alpha)\}_{j=1,\ 2,\ \dots,\ N}$. Specifically, the risk profile vector $\boldsymbol{Y}_{i,\ t}$ includes $N - 1$ CoES ($i \neq j$) and one ES itself ($i = j$). Note that CoES is an extension of CoVaR, which is essentially a conditional risk measure. Compared with the CoVaR that only focuses on the information at a single tail risk point, the CoES pays more attention to the average loss of the tail when considering systemic financial risks, thus providing more abundant risk information for the regulatory authorities to improve the effectiveness of supervision (Acharya et al., 2017).

In the second step, we construct the similarity matrix of the B&R stock markets according to the cosine similarity of the tail risk profiles. The elements of the similarity matrix can be expressed as

$$\rho_{ij,t} = \frac{\boldsymbol{Y}_{i,t}^{T} \cdot \boldsymbol{Y}_{j,t}}{\parallel \boldsymbol{Y}_{i,t} \parallel \cdot \parallel \boldsymbol{Y}_{j,t} \parallel},\ \ j \neq i, \tag{2}$$

where $\rho_{ij,\ t} \in [-1, 1]$. Economically, the more similar risk state for any pairs (i,j), i.e., the angle between the risk profile vectors approaches 0 or the cosine similarity approaches 1, the more prone to risk contagion between the pairs. For example, if negative news causes asset prices to plummet, another financial entity with similar risk profiles is vulnerable to falling asset prices. In principle, some potential factors may lead to the similar risk profiles, including direct counterparty relationships, common asset holdings, similar fundamental structures, and homogeneity of regulatory regimes. On the contrary, if the risk profiles of any pairs (i,j) are not similar, and the portfolio investment of the pair is conducive to risk diversification from the perspective of asset portfolio. Therefore, the risk profiles similarity matrix of the B&R stock markets can be regarded as a risk similarity network. Network nodes represent the stock markets, and network edges represent the risk spillover characteristics among stock markets (that is, positive connectedness represents risk contagion, while negative connectedness represents risk diversification). Additionally, the tail risk network based on the risk profiles similarity analogous to the traditional correlation-based networks, but can reflect more information. The traditional correlation networks based on Pearson correlation coefficient, Spearman correlation coefficient, partial correlation coefficient only consider the binary correlation measure, while risk profiles similarity takes into account all the potentially related elements in the system, which can more accurately describe the network structure and potential linkage.

In the third step, we use asymmetric breakpoint method to transform the similarity matrix into adjacency matrix. Edges with slight connectedness are abundant in the risk similarity network calculated by Eq. (2). It is not advisable to take into account all the links and we only need to focus on the profound ones. Network analysis frameworks generally require dimension reduction techniques to highlight significant network connections (Hautsch et al., 2015; Härdle et al., 2016). Furthermore, the positive similarity of risk profiles contributes to risk contagion, while the negative one plays a role of risk dispersion, and the network effects of the two kinds of profile are asymmetric. Therefore, we use the asymmetric breakpoint method (Ng, 2006; Chen et al., 2019) to capture significant positive group, negative group and zero correlation group. Specifically, let the ascending order cosine similarity vector $\boldsymbol{\rho} = (\rho_1, \rho_2, \dots, \rho_n)^T$, where $\rho_1 < \rho_2 < \dots < \rho_n$ and $n = N(N-1)/2$. We further divide $\boldsymbol{\rho}$ into the positive correlation vector $\boldsymbol{\rho}^+ = (\rho_1^+, \rho_2^+, \dots, \rho_{n_1}{}^+)$ and negative correlation vector $\boldsymbol{\rho}^- = (\rho_1^-, \rho_2^-, \dots, \rho_{n_2}{}^-)$, where $n = n_1 + n_2$. Following Chen et al. (2019), we address the positive vector $\boldsymbol{\rho}^+$ and negative correlation vector $\boldsymbol{\rho}^-$ with the uniform spacings under standard normal distribution, and the normalized standard vectors are shown as follows:

$$\phi^+ = \left(\phi_1^+, \phi_2^+, \dots, \phi_{n_1}^+\right) = \left(\Phi\left(\sqrt{N} \cdot \rho_1^+\right), \dots, \Phi\left(\sqrt{N} \cdot \rho_{n_1}^+\right)\right)^T, \tag{3}$$

$$\phi^- = \left(\phi_1^-, \phi_2^-, \dots, \phi_{n_2}^-\right) = \left(\Phi\left(\sqrt{N} \cdot \rho_1^-\right), \dots, \Phi\left(\sqrt{N} \cdot \rho_{n_2}^-\right)\right)^T, \tag{4}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distributions. Since $\rho_k^+ \in [0,1]$ and $\rho_k^- \in [-1, 0]$, $\phi^+ \in [0.5,1]$ and $\phi^- \in [0,0.5]$.

To characterize the distance of the normalized ascending vector ϕ^+ and ϕ^-, we then respectively define positive spacings sequence Δ^+ and the negative one Δ^- as follow:

$$\Delta^+ = \left(\Delta_2^+, \Delta_3^+, \dots, \Delta_k^+\right) = \left(\phi_2^+ - \phi_1^+, \phi_3^+ - \phi_2^+, \dots, \phi_k^+ - \phi_{k-1}^+\right), \tag{5}$$

$$\Delta^- = \left(\Delta_2^-, \Delta_3^-, \ldots, \Delta_k^-\right) = \left(\phi_2^- - \phi_1^-, \phi_3^- - \phi_2^-, \ldots, \phi_k^- - \phi_{k-1}^-\right). \tag{6}$$

The basic idea of the asymmetric breakpoint method is to set two breakpoints to divide the spacing vector into three subsets (positive correlation, negative correlation and zero correlation), which belongs to the one-dimensional clustering method. Let θ^+ and θ^- be break fractions for highly positive and highly negative correlations, respectively. The positive break fraction θ^+ can divide the positive correlation group into large positive correlation part L^+ and small positive correlation part S^+, which is defined as the optimal solution that minimizes the total sum of squared residuals in large positive correlation part and small positive correlation part:

$$\widehat{\theta}^+ = \underset{\theta^+ \in \left[\underline{\theta}, \overline{\theta}\right]}{argmin} \left(\sum_{k=1}^{[\theta^+ \times n_1]} \left(\Delta_k^+ - u_S^+\right)^2 + \sum_{k=[\theta^+ \times n_1]+1}^{n_1} \left(\Delta_k^+ - u_L^+\right)^2 \right), \tag{7}$$

where $u_S^+ = \frac{1}{[\theta^+ \times n_1]} \sum_{k=1}^{[\theta^+ \times n_1]} \Delta_k^+$ and $u_L^+ = \frac{1}{n_1 - [\theta^+ \times n_1]} \sum_{[\theta^+ \times n_1]+1}^{n_1} \Delta_k^+$. Similarly, the negative break fraction θ^- can be divided into large negative correlation part L^- and small negative correlation part S^-, which is defined as follows:

$$\widehat{\theta}^- = \underset{\theta^- \in \left[\underline{\theta}, \overline{\theta}\right]}{argmin} \left(\sum_{k=1}^{[\theta^- \times n_2]} \left(\Delta_k^- - u_S^-\right)^2 + \sum_{k=[\theta^- \times n_2]+1}^{n_2} \left(\Delta_k^- - u_L^-\right)^2 \right), \tag{8}$$

where $u_S^- = \frac{1}{[\theta^- \times n_2]} \sum_{k=1}^{[\theta^- \times n_2]} \Delta_k^-$ and $u_L^- = \frac{1}{n_2 - [\theta^- \times n_2]} \sum_{[\theta^- \times n_2]+1}^{n_2} \Delta_k^-$. In the specific calculation, we set the break fraction interval $\left[\underline{\theta}, \overline{\theta}\right] = [0.1, 0.9]$ to obtain stable results.

According to the estimated break fractions θ^+ and θ^-, we define the adjacency matrix and its elements at each time point as:

$$A = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1N} \\ a_{21} & a_{22} & \ldots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \ldots & a_{NN} \end{bmatrix}_{N \times N} \text{ and } a_{ij} = \begin{cases} 1, \text{if } \rho^+_{v^+(i,j)} > \rho^+_{\hat{\theta}^+} \\ -1, \text{if } \rho^-_{v^-(i,j)} < \rho^-_{\hat{\theta}^-} \\ 0, \text{otherwise} \end{cases} \tag{9}$$

where $v^+(i,j)$ and $v^-(i,j)$ correspond to subscripts of the positive and negative ordered correlation vectors (i.e., $\boldsymbol{\rho}^+$ and $\boldsymbol{\rho}^-$); $\rho^+_{\hat{\theta}^+}$ and $\rho^-_{\hat{\theta}^-}$ are breakpoints in the positive and negative correlation vectors, respectively. So far, adjacency matrix based on risk profiles similarity and asymmetric breakpoint methods have been constructed. Adjacency matrix $\boldsymbol{A}$ can be regarded as financial network conditional on tail events. In order to unify the appellation, it is named tail risk network in the subsequent content of this paper.

In the fourth step, we construct the systemic risk score index and individual risk contribution index. Follow Das (2016) and Chen et al. (2019), we combine the node market capitalization vector $\boldsymbol{C} = (C_1, C_2, \ldots, C_N)^{\mathrm{T}}$ and adjacency matrix $\boldsymbol{A}$ to measure the aggregate risk level of the financial network. The systemic risk score index is defined as:

$$S(\boldsymbol{C}, \boldsymbol{A}) = \boldsymbol{C}^T \boldsymbol{A} \boldsymbol{C}. \tag{10}$$

The individual risk contribution index of each node can be obtained by risk decomposition at the systemic aggregate risk level:

$$S = \sum_{i=1}^{N} S_i = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + \cdots + \frac{\partial S}{\partial C_N} C_N, \tag{11}$$

$$S_i = \frac{\partial S}{\partial C_i} C_i = 2 \cdot \sum_{j=1}^{N} a_{ij} C_j, \tag{12}$$

where a_{ij} is the adjacency connection of node pair (i,j), and C_j is the market capitalization of node j.[5] From a regulatory perspective, both the systemic risk score index and individual risk contribution index take into account size and connectedness. We should be wary of moments when the financial system has a higher aggregate risk level, and network nodes with greater risk contributions.

In the fifth step, we adopt the TRNQR model of Chen et al. (2019) under the tail risk network framework to analyze the network factors dynamic. We convert the adjacency matrix of Eq. (9) into positive adjacency matrix $\boldsymbol{A}^+$ and the negative one $\boldsymbol{A}^-$ with the elements expressed as:

$$a^+_{ij} = \begin{cases} 1, \rho^+_{v^+(i,j)} > \rho^+_{\hat{\theta}^+} \\ 0, \text{else} \end{cases} \text{ and } a^-_{ij} = \begin{cases} 1, \rho^-_{v^-(i,j)} < \rho^-_{\hat{\theta}^-} \\ 0, \text{else.} \end{cases}, \tag{13}$$

where $\rho^+_{\hat{\theta}^+}$ and $\rho^-_{\hat{\theta}^-}$ are the break points defined in Eqs. (7) and (8). Eq. (13) distinguishes the positive and negative adjacency matrices.

[5] Raw data of market capitalization for the B&R stock markets are displayed in millions of units of local currency. We convert all capitalization data into trillion U.S. dollars based on the exchange rate of local currencies against the U.S. dollar.

$\boldsymbol{A}^{+}$ captures the strong positive network linkages, while $\boldsymbol{A}^{-}$ reflects the strong negative connectedness information. We define the positive and negative network factors of node i at time $t-1$ as:

$$f_{i,t-1}^{+}=\sum_{j=1}^{N}m_{i}^{+}(X_{j,t-1})=\frac{\sum_{j=1}^{N}a_{ij,t-1}^{+}X_{j,t-1}}{\sum_{j=1}^{N}a_{ij,t-1}^{+}}, \tag{14}$$

$$f_{i,t-1}^{-}=\sum_{j=1}^{N}m_{i}^{-}(X_{j,t-1})=\frac{\sum_{j=1}^{N}a_{ij,t-1}^{-}X_{j,t-1}}{\sum_{j=1}^{N}a_{ij,t-1}^{-}}, \tag{15}$$

where the network factor ($f_{i,t-1}^{+}$ and $f_{i,t-1}^{-}$) can be seen as the $m(\cdot)$ function of the adjacency linkages and node output (e.g., the stock market return in this paper), reflecting the average impact of node i on other network nodes at time $t-1$.

The TENQR model can be further defined as follows:

$$\begin{aligned}Q_{r,X_{i,t}}(\tau_k)&=\gamma_{r_i}+\beta_{r0}(\tau)+\beta_{r1}(\tau)X_{i,t-1}+\beta_{r2}(\tau)X_{i,t-2}\\&+\sum_{\ell=1}^{L}\beta_{r\ell}^{(w)}(\tau)W_{\ell,t-1}+\beta_{r}^{+}(\tau)f_{i,t-1}^{+}+\beta_{r}^{-}(\tau)f_{i,t-1}^{-}, i\in\mathscr{R}_r.\end{aligned} \tag{16}$$

In Eq. (16), $\mathcal{R}_r$ is the stock market index set belonging to region r, where r=1, 2, 3, and 4 correspond to East Asia and South Asia, West Asia and North Africa, Central and Eastern Europe, and the whole Belt and Road region, respectively. Coefficients $f_{i,t-1}^{+}$ and $\beta_r^{-}(\tau)$, which only depend on the quantile level τ, describe the impacts of positive and negative network factors. W_ℓ represents the market-wide covariates (see Section 3.1 for details). Combining quantile regression and spatial econometric techniques, the TENQR model can effectively capture the ripple effects and asymmetric effects of tail risk, and is conducive to assessing the regional impacts and dynamic impulse of network shocks.

4. Empirical results

In this section, we use the rolling time window method to construct a time-varying tail risk network analysis framework. We mainly consider the tail risk at the quantile level $\tau=0.05$. For time window parameters, we set the window size $S=52$ (corresponds to one year) and the window step $H=1$, which divided the whole sample period into 688 windows ($T=688$). Under such parameter settings, the time point of the starting window is 28 March 2008, and the last window is on 28 May 2021. We then discuss empirical work on the following four aspects.

4.1. Risk profiles similarity and tail risk networks

We estimate CoES of the B&R stock markets conditional on extreme financial events (tail quantile level $\tau=0.05$) to characterize the tail risk profiles. Fig. 2 shows the similarity matrix based on cosine similarity of risk profiles for the B&R stock markets from 2008 to 2021. Some interesting findings can be obtained from the dynamic evolution of risk profiles similarity matrix. The B&R stock system experienced its severest time during the 2008–2010 global financial crisis and the 2020–2021 global public health emergency (the COVID-19 pandemic). Risk profiles showed strong homogeneity in global extreme financial events. In addition to slight negative correlation in some countries, there was significant systemic risk contagion effect (positive correlation) among the B&R stock markets. The 2011–2012 European sovereign debt crisis is also noteworthy, and there is a high level of positive correlation among the B&R stock markets, especially those from Central and Eastern Europe. As the negative impact of the global financial crisis gradually eased, the systemic risk level in the B&R stock markets began to decrease in 2013. The increasing negative correlation in financial networks is conducive to risk diversification. In 2020, COVID-19 broke out and spread around the world, causing unprecedented life crisis, economic recession and social upheaval in many countries. As a sensitive reaction, the similarity matrix has changed from negative correlation to strong positive correlation. In general, we can have rough insights into the risk profiles of the B&R stock markets from the visualization of similar matrix.

To accurately quantify the risk characteristics of the B&R stock markets, we use the asymmetric breakpoint method to eliminate the non-significant positive and negative correlation in the financial network, and then divide the network linkages into strong positive correlation group, strong negative correlation group and zero correlation group. Fig. 3 displays the gray scale image of the adjacency matrix of the B&R stock markets where white represents strong positive correlation ($a_{ij}=1$), black represents strong negative correlation ($a_{ij}=-1$), and gray represents zero correlation or weak correlation ($a_{ij}=0$). The adjacency matrix reflects clearer risk characteristics and spillover effects under the outline of the similar matrix. In addition to reflecting financial shocks on a global scale (e.g., the 2008 global financial crisis and the COVID-19 pandemic), the adjacency matrix also reveals the negative impact of local extreme financial events on the B&R stock market. For example, during the 2010–2012 European sovereign debt crisis, the stock markets in Central and Eastern Europe initially have strong intra-regional risk contagion effects (the 2011 subgraph of Fig. 3). Subsequently, the European sovereign debt crisis released global spillover effects, which affects other emerging countries along the Belt and Road through potential channels such as capital flows, overseas remittances, commodity prices and trade, and ultimately led to the overall risk contagion effect of the B&R stock system (the 2012 subgraph of Fig. 3). In 2015, the economic growth of emerging countries slowed down and commodity prices plummeted, which had a negative impact on the real economy and financial stability of

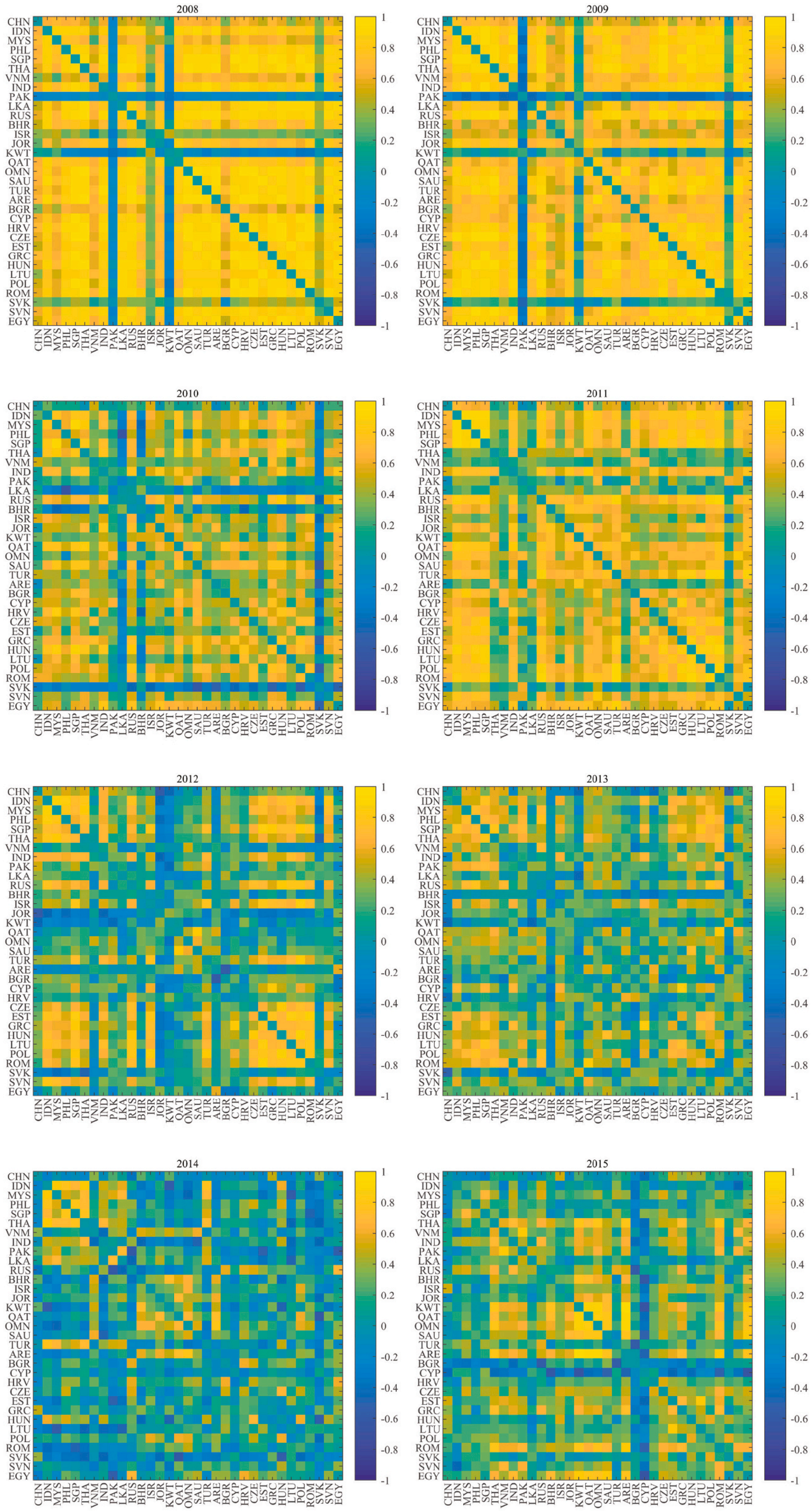

Fig. 2. Similarity matrix of the 33 B&R stock markets during the period from 2008 to 2021. Note: Colour reflects the intensity of correlation. The closer the colour level to yellow, the stronger the positive correlation, while the closer to blue, the more significant the negative correlation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

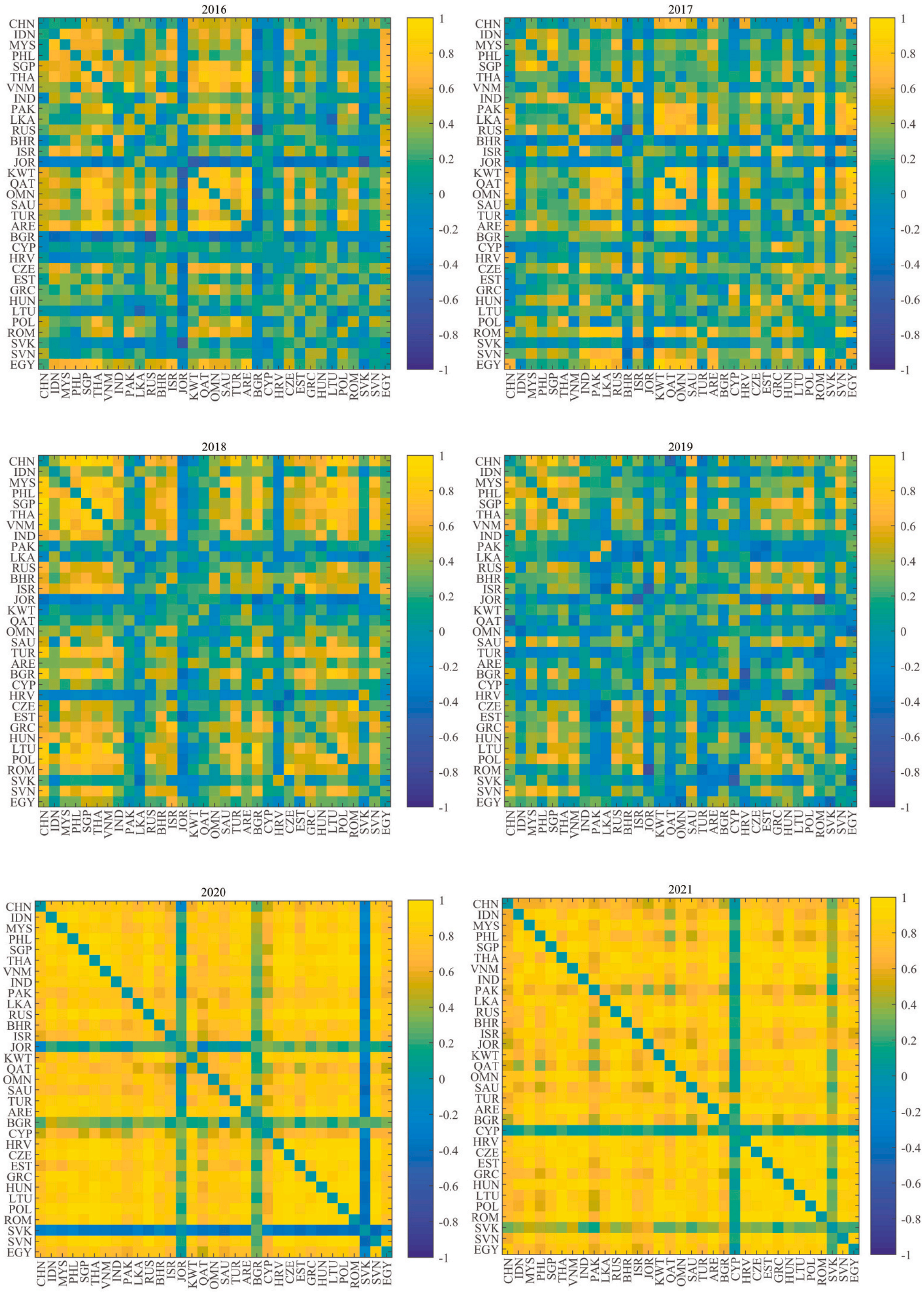

Fig. 2. (*continued*).

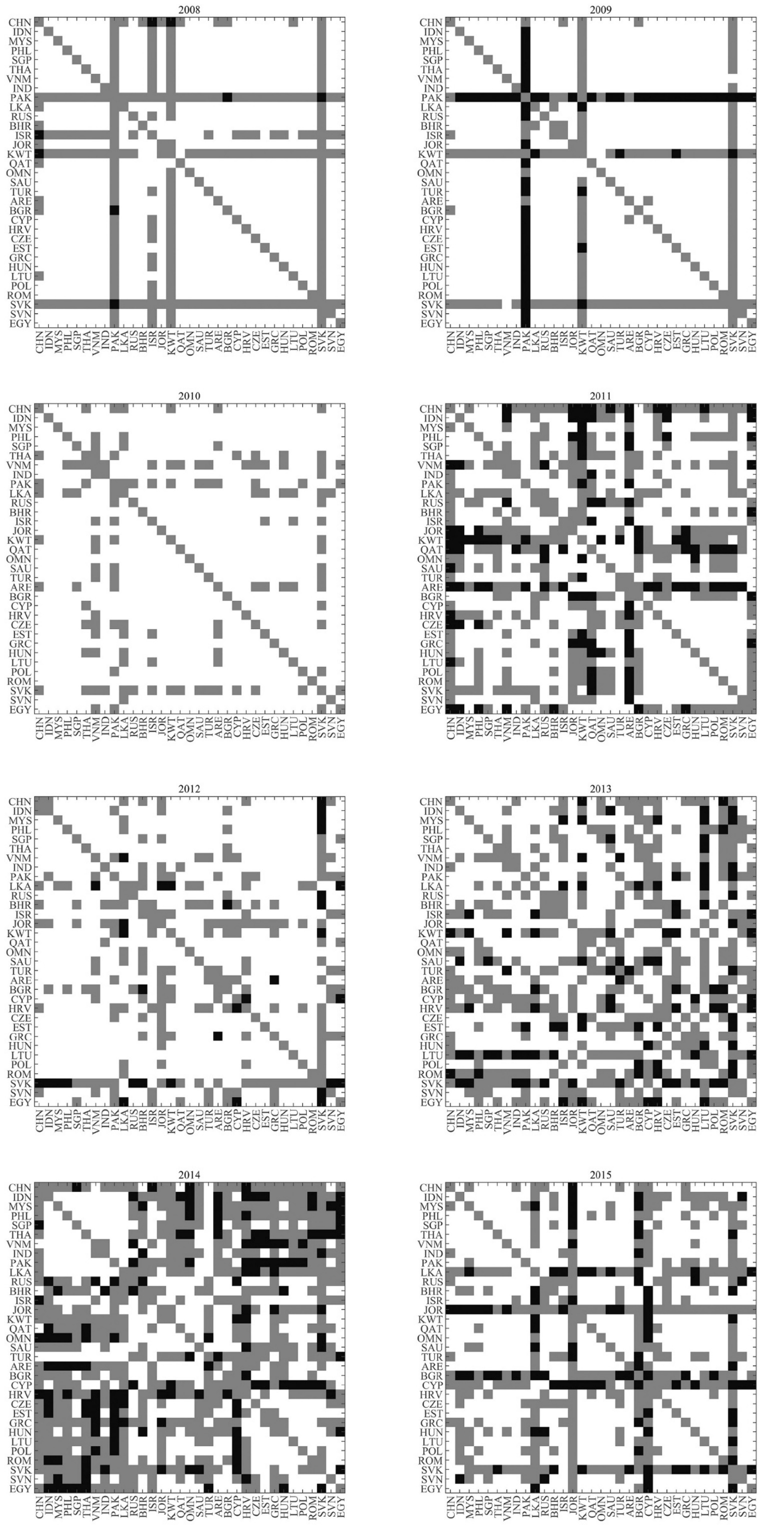

Fig. 3. Adjacency matrix of the 33 B&R stock markets during the period from 2008 to 2021. Note: The adjacency matrix contains only three values: 1 (white, strong positive correlation), −1 (black, strong negative correlation), and 0 (gray, weak correlation or zero correlation).

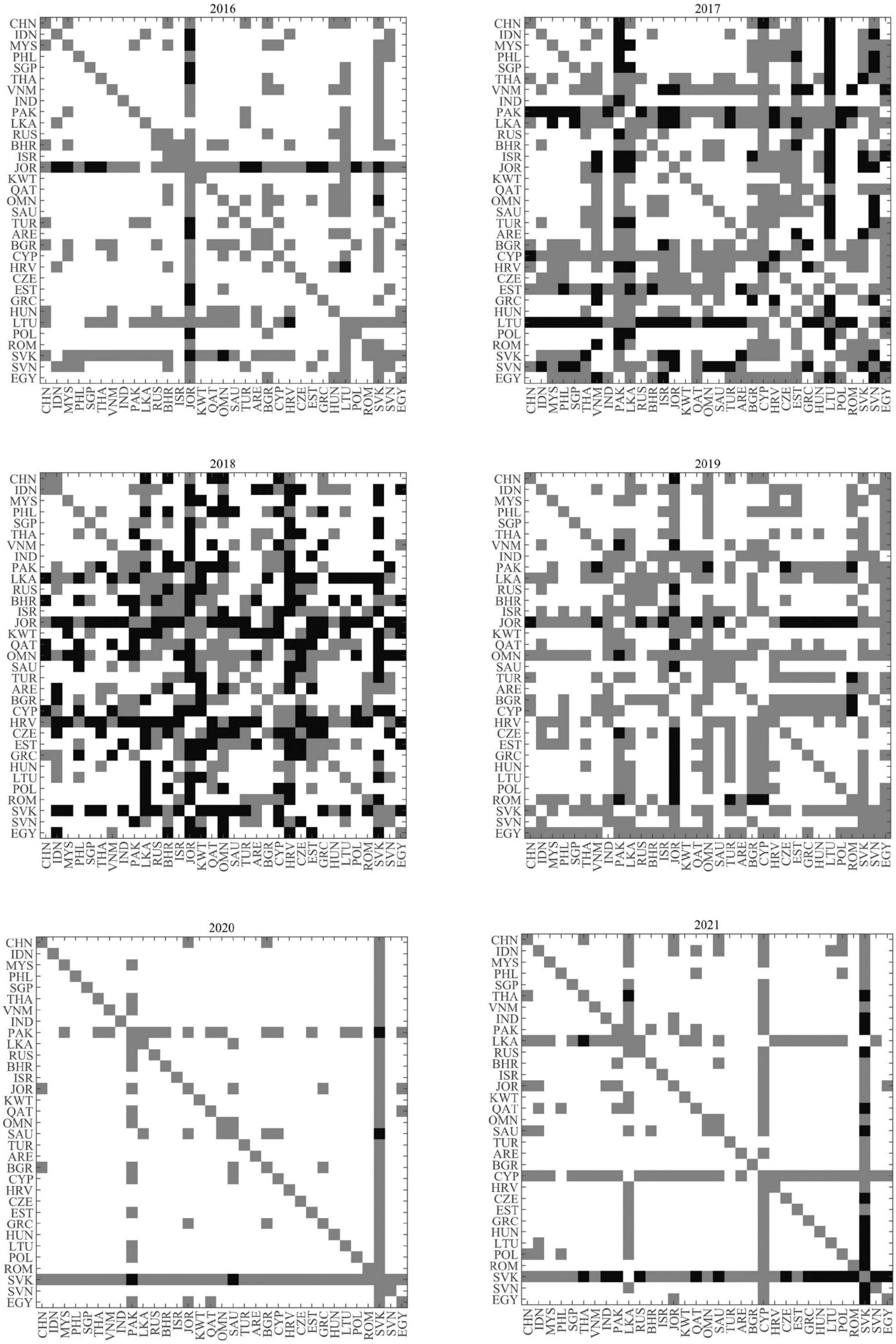

Fig. 3. (*continued*).

Average A+

	CHN	IDN	MYS	PHL	SGP	THA	VNM	IND	PAK	LKA	RUS	BHR	ISR	JOR	KWT	QAT	OMN	SAU	TUR	ARE	BGR	CYP	HRV	CZE	EST	GRC	HUN	LTU	POL	ROM	SVK	SVN	EGY
CHN	0.00	0.61	0.71	0.74	0.78	0.62	0.70	0.63	0.52	0.49	0.65	0.48	0.55	0.19	0.44	0.46	0.55	0.63	0.59	0.49	0.33	0.43	0.51	0.61	0.59	0.67	0.60	0.57	0.73	0.65	0.14	0.68	0.50
IDN	0.61	0.00	0.88	0.95	0.88	0.88	0.48	0.87	0.56	0.49	0.69	0.53	0.64	0.37	0.40	0.62	0.50	0.55	0.85	0.54	0.50	0.54	0.47	0.58	0.63	0.63	0.70	0.53	0.75	0.62	0.23	0.60	0.52
MYS	0.71	0.88	0.00	0.97	0.99	0.90	0.72	0.86	0.51	0.42	0.83	0.45	0.74	0.39	0.41	0.68	0.57	0.69	0.85	0.62	0.55	0.47	0.57	0.84	0.69	0.79	0.86	0.66	0.84	0.72	0.19	0.72	0.65
PHL	0.74	0.95	0.97	0.00	0.98	0.90	0.71	0.95	0.56	0.49	0.76	0.49	0.67	0.33	0.37	0.54	0.50	0.55	0.78	0.52	0.51	0.53	0.53	0.73	0.67	0.68	0.76	0.62	0.78	0.70	0.19	0.70	0.52
SGP	0.78	0.88	0.99	0.98	0.00	0.90	0.69	0.93	0.65	0.45	0.88	0.46	0.81	0.36	0.42	0.68	0.60	0.70	0.85	0.60	0.60	0.65	0.64	0.85	0.81	0.91	0.89	0.72	0.90	0.82	0.27	0.83	0.63
THA	0.62	0.88	0.90	0.90	0.90	0.00	0.69	0.92	0.57	0.49	0.76	0.52	0.75	0.39	0.48	0.69	0.57	0.64	0.76	0.64	0.49	0.51	0.47	0.69	0.61	0.75	0.69	0.55	0.81	0.68	0.14	0.64	0.50
VNM	0.70	0.48	0.72	0.71	0.69	0.69	0.00	0.57	0.55	0.41	0.66	0.59	0.51	0.43	0.48	0.53	0.69	0.69	0.53	0.56	0.50	0.39	0.55	0.60	0.49	0.72	0.46	0.54	0.63	0.68	0.16	0.61	0.49
IND	0.63	0.87	0.86	0.95	0.93	0.92	0.57	0.00	0.53	0.46	0.84	0.38	0.76	0.35	0.42	0.65	0.57	0.62	0.84	0.64	0.46	0.52	0.59	0.71	0.70	0.81	0.86	0.60	0.84	0.76	0.17	0.69	0.68
PAK	0.52	0.56	0.51	0.56	0.65	0.57	0.55	0.53	0.00	0.49	0.39	0.30	0.41	0.33	0.44	0.50	0.51	0.53	0.48	0.50	0.38	0.37	0.31	0.29	0.39	0.47	0.42	0.41	0.40	0.51	0.29	0.48	0.40
LKA	0.49	0.49	0.42	0.49	0.45	0.49	0.41	0.46	0.49	0.00	0.41	0.41	0.37	0.36	0.36	0.40	0.51	0.50	0.49	0.50	0.36	0.38	0.36	0.34	0.33	0.43	0.36	0.35	0.41	0.40	0.17	0.49	0.53
RUS	0.65	0.69	0.83	0.76	0.88	0.76	0.66	0.84	0.39	0.41	0.00	0.38	0.74	0.45	0.56	0.69	0.71	0.78	0.74	0.64	0.52	0.46	0.68	0.83	0.74	0.78	0.82	0.72	0.89	0.86	0.13	0.67	0.67
BHR	0.48	0.53	0.45	0.49	0.46	0.52	0.59	0.38	0.30	0.41	0.38	0.00	0.41	0.47	0.70	0.60	0.66	0.58	0.41	0.62	0.45	0.41	0.48	0.29	0.51	0.52	0.39	0.49	0.45	0.50	0.22	0.57	0.57
ISR	0.55	0.64	0.74	0.67	0.81	0.75	0.51	0.76	0.41	0.37	0.74	0.41	0.00	0.43	0.54	0.71	0.64	0.72	0.64	0.68	0.39	0.44	0.61	0.66	0.66	0.77	0.72	0.67	0.79	0.75	0.26	0.55	0.51
JOR	0.19	0.37	0.39	0.33	0.36	0.39	0.43	0.35	0.33	0.36	0.45	0.47	0.43	0.00	0.50	0.60	0.60	0.51	0.40	0.56	0.44	0.36	0.45	0.32	0.35	0.33	0.34	0.37	0.42	0.47	0.21	0.46	0.55
KWT	0.44	0.40	0.41	0.37	0.42	0.48	0.48	0.42	0.44	0.36	0.56	0.70	0.54	0.50	0.00	0.73	0.58	0.64	0.29	0.75	0.31	0.29	0.51	0.41	0.35	0.47	0.38	0.38	0.43	0.61	0.16	0.43	0.54
QAT	0.46	0.62	0.68	0.54	0.68	0.69	0.53	0.65	0.50	0.40	0.69	0.60	0.71	0.60	0.73	0.00	0.77	0.80	0.61	0.92	0.45	0.33	0.60	0.57	0.58	0.63	0.53	0.49	0.73	0.75	0.09	0.67	0.61
OMN	0.55	0.50	0.57	0.50	0.60	0.57	0.69	0.57	0.51	0.51	0.71	0.66	0.64	0.60	0.58	0.77	0.00	0.73	0.53	0.74	0.47	0.46	0.53	0.51	0.55	0.70	0.43	0.55	0.61	0.78	0.21	0.59	0.62
SAU	0.63	0.55	0.69	0.55	0.70	0.64	0.69	0.62	0.53	0.50	0.78	0.58	0.72	0.51	0.64	0.80	0.73	0.00	0.66	0.81	0.45	0.51	0.57	0.68	0.61	0.71	0.62	0.59	0.79	0.76	0.16	0.72	0.86
TUR	0.59	0.85	0.85	0.78	0.85	0.76	0.53	0.84	0.48	0.49	0.74	0.41	0.64	0.40	0.29	0.61	0.53	0.66	0.00	0.51	0.45	0.63	0.40	0.70	0.63	0.76	0.75	0.61	0.84	0.63	0.28	0.55	0.50
ARE	0.49	0.54	0.62	0.52	0.60	0.64	0.56	0.64	0.50	0.50	0.64	0.62	0.68	0.56	0.75	0.92	0.74	0.81	0.51	0.00	0.41	0.28	0.56	0.47	0.42	0.55	0.54	0.39	0.66	0.62	0.13	0.54	0.77
BGR	0.33	0.50	0.55	0.51	0.60	0.49	0.50	0.46	0.38	0.36	0.52	0.45	0.39	0.44	0.31	0.45	0.47	0.45	0.45	0.41	0.00	0.62	0.49	0.50	0.48	0.49	0.58	0.57	0.49	0.51	0.29	0.57	0.38
CYP	0.43	0.54	0.47	0.53	0.65	0.51	0.39	0.52	0.37	0.38	0.46	0.41	0.44	0.36	0.29	0.33	0.46	0.51	0.63	0.28	0.62	0.00	0.42	0.45	0.47	0.67	0.57	0.58	0.54	0.53	0.21	0.45	0.37
HRV	0.51	0.47	0.57	0.53	0.64	0.47	0.55	0.59	0.31	0.36	0.68	0.48	0.61	0.45	0.51	0.60	0.53	0.57	0.40	0.56	0.49	0.42	0.00	0.63	0.67	0.65	0.51	0.59	0.63	0.73	0.19	0.72	0.50
CZE	0.61	0.58	0.84	0.73	0.85	0.69	0.60	0.71	0.29	0.34	0.83	0.29	0.66	0.32	0.41	0.57	0.51	0.68	0.70	0.47	0.50	0.45	0.63	0.00	0.79	0.79	0.94	0.74	0.95	0.90	0.25	0.69	0.63
EST	0.59	0.63	0.69	0.67	0.81	0.61	0.49	0.70	0.39	0.33	0.74	0.51	0.66	0.35	0.35	0.58	0.55	0.61	0.63	0.42	0.48	0.47	0.67	0.79	0.00	0.64	0.74	0.92	0.82	0.85	0.36	0.77	0.57
GRC	0.67	0.63	0.79	0.68	0.91	0.75	0.72	0.81	0.47	0.43	0.78	0.52	0.77	0.33	0.47	0.63	0.70	0.71	0.76	0.55	0.49	0.67	0.65	0.79	0.64	0.00	0.77	0.72	0.85	0.85	0.18	0.74	0.61
HUN	0.60	0.70	0.86	0.76	0.89	0.69	0.46	0.86	0.42	0.36	0.82	0.39	0.72	0.34	0.38	0.53	0.43	0.62	0.75	0.54	0.58	0.57	0.51	0.94	0.74	0.77	0.00	0.72	0.97	0.88	0.31	0.77	0.56
LTU	0.57	0.53	0.66	0.62	0.72	0.55	0.54	0.60	0.41	0.35	0.72	0.49	0.67	0.37	0.38	0.49	0.55	0.59	0.61	0.39	0.57	0.58	0.59	0.74	0.92	0.72	0.72	0.00	0.67	0.74	0.26	0.65	0.48
POL	0.73	0.75	0.84	0.78	0.90	0.81	0.63	0.84	0.40	0.41	0.89	0.45	0.79	0.42	0.43	0.73	0.61	0.79	0.84	0.66	0.49	0.54	0.63	0.95	0.82	0.85	0.97	0.67	0.00	0.91	0.27	0.87	0.55
ROM	0.65	0.62	0.72	0.70	0.82	0.68	0.68	0.76	0.51	0.40	0.86	0.50	0.75	0.47	0.61	0.75	0.78	0.76	0.63	0.62	0.51	0.53	0.73	0.90	0.85	0.85	0.88	0.74	0.91	0.00	0.18	0.78	0.64
SVK	0.14	0.23	0.19	0.19	0.27	0.14	0.16	0.17	0.29	0.17	0.13	0.22	0.26	0.21	0.16	0.09	0.21	0.16	0.28	0.13	0.29	0.21	0.19	0.25	0.36	0.18	0.31	0.26	0.27	0.18	0.00	0.24	0.13
SVN	0.68	0.60	0.72	0.70	0.83	0.64	0.61	0.69	0.48	0.49	0.67	0.57	0.55	0.46	0.43	0.67	0.59	0.72	0.55	0.54	0.57	0.45	0.72	0.69	0.77	0.74	0.77	0.65	0.87	0.78	0.24	0.00	0.57
EGY	0.50	0.52	0.65	0.52	0.63	0.50	0.49	0.68	0.40	0.53	0.67	0.57	0.51	0.55	0.54	0.61	0.62	0.86	0.50	0.77	0.38	0.37	0.50	0.63	0.57	0.61	0.56	0.48	0.55	0.64	0.13	0.57	0.00

Fig. 4. The averaged positive adjacency matrices $\boldsymbol{A}^{+}$ of the B&R stock markets over the full sample period (2008–2021).

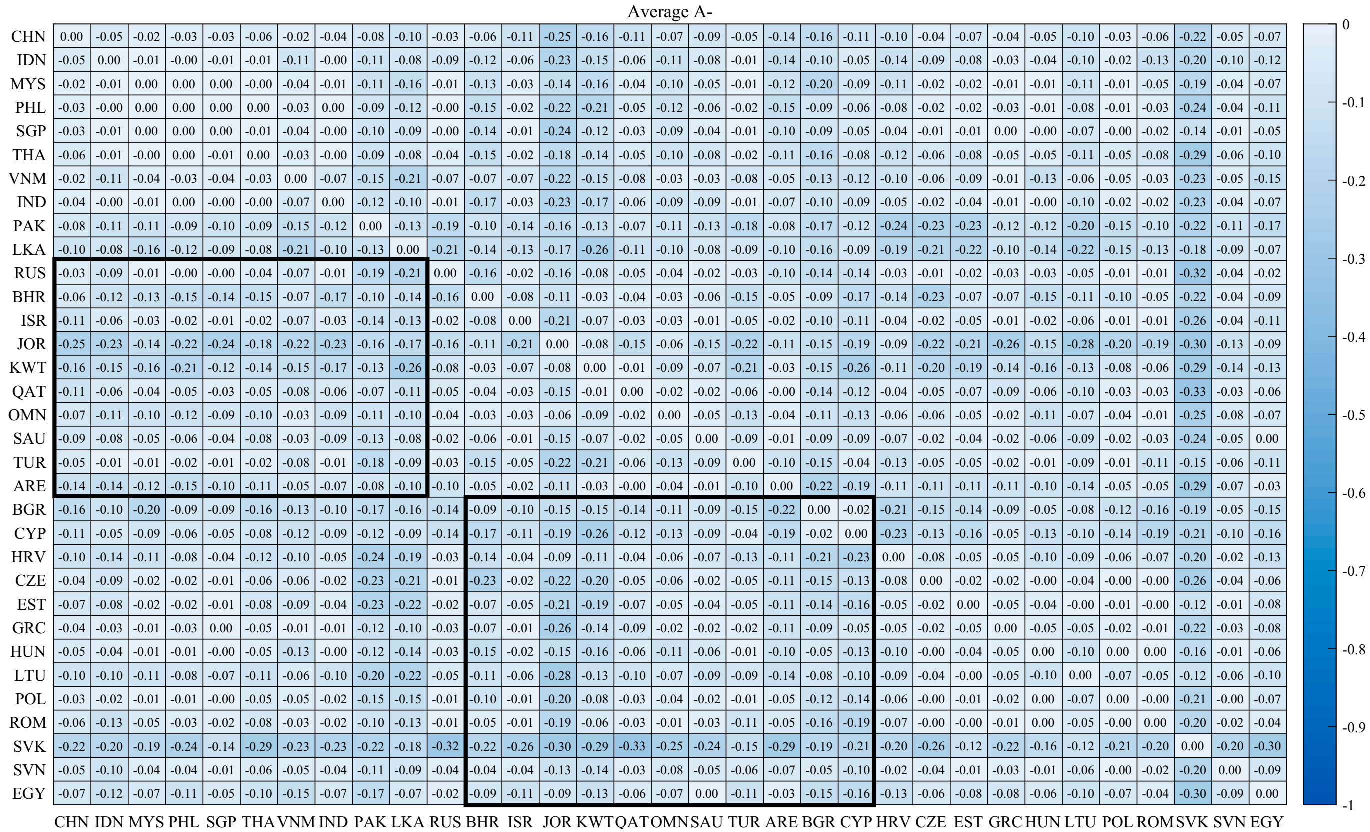

Fig. 5. The averaged negative adjacency matrices $\boldsymbol{A}^{-}$ of the B&R stock markets over the full sample period (2008–2021).

Middle Eastern countries that are highly dependent on commodity production and trade. The corresponding adjacency matrix records the transition from negative correlation and zero correlation to strong positive correlation of the B&R stock market in the Middle East. The adjacency matrix provides an intuitive and quantitative visualization method for the analysis of spillover effects among financial entities.

In Figs. 4 and 5, we merge the adjacency sequences throughout the sample period from 2008 to 2021 to present the average level of the adjacency matrix. Specifically, the average positive adjacency matrix $\boldsymbol{A}^{+}$ and average negative one $\boldsymbol{A}^{-}$ are extracted and analyzed separately. The risk characteristics of the B&R stock markets are asymmetric, which shows that the effect of risk contagion is much greater than risk diversification. In the positive average adjacency matrix of Fig. 4, the B&R stock markets from EASA and CEE regions both show intra-regional risk contagion effects, while the positive adjacency in the WANA region is not so obvious as the aforementioned two regions. EASA also has a strong positive adjacency relationship with the CEE region. In contrast, the average adjacency level of the negative aspect in Fig. 5 is much weaker, and there is no obvious intra-regional risk diversification in the three regions. However, the slight cross-regional negative interdependence still exists in the B&R stock markets. Although there is no significant risk diversification in stock markets between the EASA and CEE regions, WANA stock market has a certain negative adjacency relationship with those from EASA and CEE region. These findings bring enlightenment for multinational asset portfolio.

The adjacency matrix is obtained by using asymmetric breakpoint method for similar matrix. Note that the asymmetric breakpoint method (Ng, 2006; Chen et al., 2019) is a clustering technique that relies on the minimization of intra-group spacing to find breakpoints in the ordered positive and negative correlation sequences. This method does not depend on the statistical characteristics of the spacing, so it is necessary to add corresponding tests to reflect the statistical significance of the partition results. Following Chen et al. (2019), we conduct joint spacings variance ratio test (Joint SVR Test)[6] for the small groups (S^{+} and S^{-}) and large groups (L^{+} and L^{-}) at the 0.05 significance level. Fig. 6 shows the *p*-values of small and large groups under Joint SVR Test respectively. Most *p*-values in small group are greater than 0.05, which reflects that we cannot reject the hypothesis that elements in the small group are jointly zero. The statistical inference that small groups (S^{+} and S^{-}) are different from zero is not supported by statistical significance, and thus small groups converge to zero correlation. Next, similar Joint SVR Test is carried out in large groups (L^{+} and L^{-}). Another necessary investigation shows that almost all the *p*-values in the large group are less than 0.05. This shows that the null hypothesis that the large groups (L^{+} and L^{-}) are jointly zero can be rejected at the significance level of 5%, which reflects that the large groups are significantly different from the zero correlation. According to the above Joint SVR Test results, the large groups are significantly different from zero correlation, while the small groups are jointly zero, which reveals the effectiveness of the asymmetric breakpoint method as well as the statistical significance of the adjacency structure.

4.2. Aggregate risk level and individual risk decomposition

Due to the excellent capacity in reflecting the attribute of risk contagion and risk diversification among financial entities, the adjacency matrix, based on the similarity of tail risk profiles and the spacing statistical significance, can be regarded as a tail risk network. This section focuses on two core points: systemic risk and the nodes' characteristics in the financial network of the B&R stock markets. To this end, we construct the systemic risk score index and individual risk contribution index under the tail risk network to measure the aggregate risk level and individual risk accumulation, respectively. Fig. 7 displays the dynamic evolution of the total connectedness, negative correlation ratio and systemic risk score in the tail risk network of the B&R stock markets throughout the sample period. The dynamic network connectedness clearly captures the recent extreme financial events, covering the 2008 global financial crisis, the 2010–2012 European sovereign debt crisis, the 2015 commodities plunged, the 2016 Brexit vote, the 2018 currency crisis in emerging countries and the 2020–2021 global public health emergency.

In September 2008, since some large US financial institutions failed or were taken over by the government,[7] the US subprime mortgage crisis was completely out of control and then evolved into a global financial crisis, which triggered a sharp drop in global stock markets, including those along the Belt and Road. The apparent leap in total connectedness in September 2008 was a timely response to this, and it has been maintained at a relatively high level during the 2008 global financial crisis. A series of rescue measures by governments around the world eased the crisis to some extent, and total connectedness began to decline in the second half of 2009. The European sovereign debt crisis in 2010 further escalated the turmoil in the global financial market, exacerbating social conflicts in the Euro area countries and trade frictions among countries around the world. Its global spillovers enhanced the tail connectedness of stock markets along the Belt and Road region. Under the negative impact of the European sovereign debt crisis, Central and Eastern European countries were subjected to fundamentals contagion and regional spillover of sovereign risks, while the financial markets of other B&R emerging countries were temporarily overreacted, leading to the so-called “herding contagion” (Beirne and Fratzscher, 2013). In June 2016, the systemic risk of the B&R stock market accumulated during the Brexit referendum, and the total connectedness showed a gentle upward trend. The Brexit referendum has injected great uncertainty into the international political and economic environment and disrupted the world economic order centered on globalization. This rare political event undoubtedly triggered

[6] For the derivation process of Joint SVR Test and the logical process of judging whether the adjacency structure based on the asymmetric breakpoint method is statistically significant, see Section 3.3.2 of Chen et al. (2019).

[7] On September 14, 2008, Lehman brothers filed for bankruptcy after the Federal Reserve refused to provide financial support. On the same day Merrill Lynch announced its acquisition by Bank of America. On September 16, American International Group (AIG) was downgraded for holding many mature contracts with defaulted credit. On September 21, Goldman Sachs Securities and Morgan Stanley applied to the Federal Reserve to be converted into bank holding companies. That leaves the two companies with more regulatory constraints but easier access to capital.

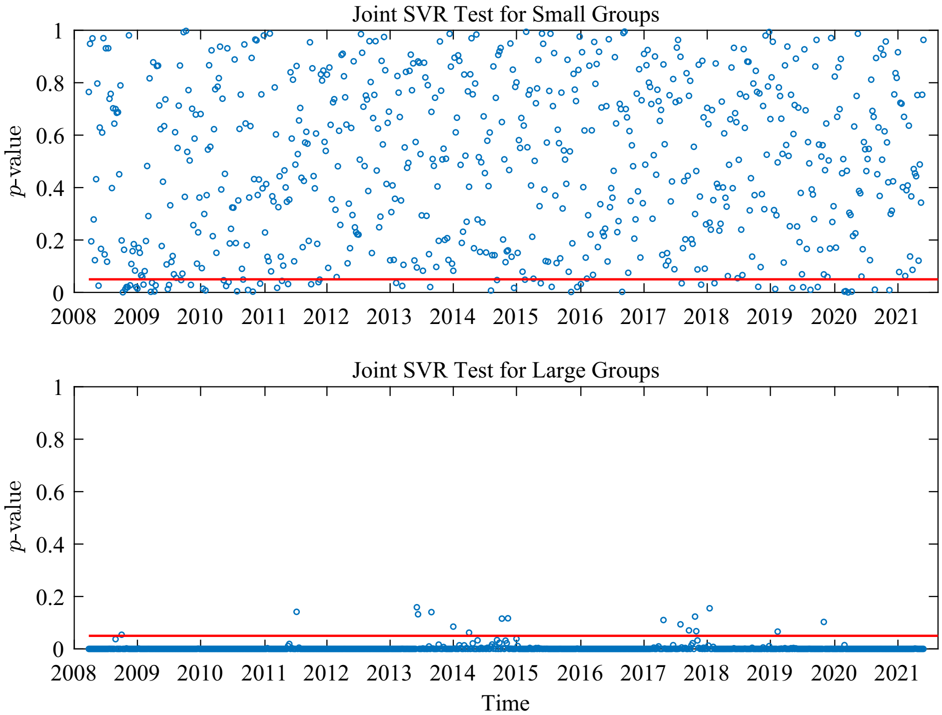

Fig. 6. Results of the joint SVR test for the small groups and the large groups. Notes: For small groups (large groups), each blue hollow dot represents the *p*-value of the Joint SVR Test for S^+ and S^- (L^+ and L^-) in the corresponding time window. The figure visually shows the Joint SVR Test results of small groups and large groups in 688 time windows (T=688) during the full sample period. The red horizontal line represents the benchmark bound at the 0.05 significance level. Obviously, the blue hollow dots above the red baseline (i.e., p-value$\geq$0.05) reflect that the null hypothesis cannot be rejected at the 0.05 significance level. In contrast, blue hollow dots below the red baseline (i.e., p-value$<$0.05) indicate that the null hypothesis can be rejected at the 0.05 significance level. The judgment logic of whether the adjacency structure obtained by the asymmetric breakpoint method is statistically significant is detailed in Chen et al. (2019). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

foreseeable short-term effects of severe turmoil in global financial markets and currency devaluation in the eurozone.

In 2018, the Federal Reserve raised interest rates four times, tightening global financial conditions and triggering capital flight from emerging countries around the world. The B&R countries such as Russia, Indonesia, India and Turkey have suffered severe currency devaluations. Although central banks of various countries have continuously raised interest rates, it is still difficult to reverse the devaluation of their currencies, which eventually evolved into a local currency crisis. At the same time, the escalating trade frictions between the US and China also have a negative impact on globalization and the world economy. These two factors together pushed up the total connectedness of the B&R stock markets. In 2020, a sudden global public health event broke out and quickly swept the world. The COVID-19 pandemic has triggered major global financial turmoil, and the stock market has fallen into crisis under the impact of multiple factors.[8] The international financial market slump has eased in April 2020, but the risk is still not substantially eliminated. As the most noteworthy part, the total connectedness reacted sensitively and jumped sharply from a low of 122 to a historical high of 906 at the beginning of 2020, and it fluctuated at a relatively high position during the COVID-19 pandemic. Whenever global extreme financial events occur, the negative correlation ratio reaches its trough, reflecting that the homogenization of risk profiles and the lack of internal mitigation mechanism of risk diversification are the reasons for systemic risk accumulation in the B&R stock markets.

Similar findings of total connectedness can be obtained from the dynamic evolution of the systemic risk score which is obviously sensitive to the financial events mentioned above. We also note some subtle differences in systemic risk score and total connectedness. For example, during the 2008 global financial crisis and the European sovereign debt crisis, the total connectedness of the B&R stock markets was the second and third highest in the entire sample period respectively, while the systemic risk score did not have a significantly high level. After the outbreak of the global financial crisis in 2008, risks were transmitted from the financial sector to the

[8] On February 3, 2020, the first trading day of the year, more than 3000 Chinese A-shares fell by the daily limit. The Shanghai Composite index closed down 7.72% and the Shenzhen Component Index fell 8.45%. From March 9 to March 18, 2020, the U.S. stock market triggered the circuit breaker four times, which was the first time in history. On March 16, 2020, global stock markets plummeted. The Brazilian stock market has triggered "circuit breakers" 5 times in 6 consecutive trading days; Canadian and Colombian stock markets have also experienced "circuit breakers" one after another. At that time, Germany DAX index and France CAC 40 index hit a new low since 2013; the British FTSE 100 index is at its lowest since 2011.

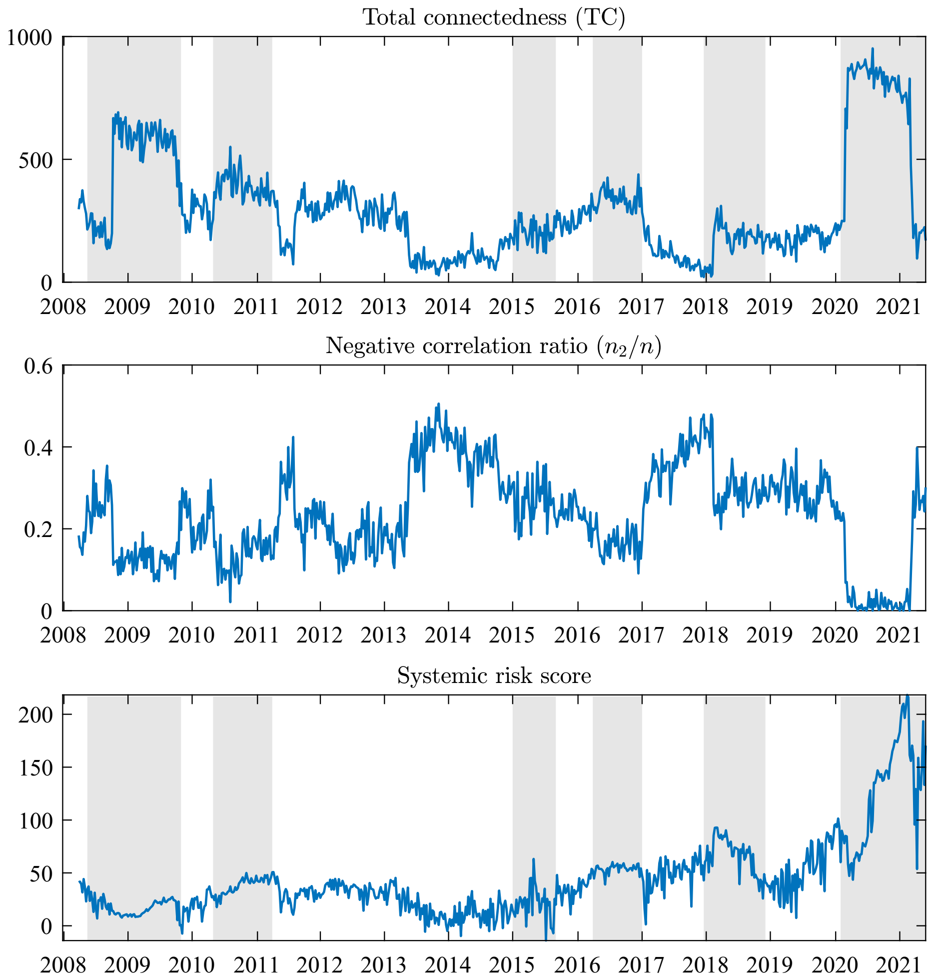

Fig. 7. Total connectedness, negative correlation ratio and systemic risk score in the tail risk network of the B&R stock markets. Notes: The period of dynamic evolution is from 28 March 2008 to 28 May 2021. Network total connectedness is the sum of the adjacency matrix elements under each window. The negative correlation ratio is defined as the ratio of the number of elements in the negative correlation vector ρ^{-} to that in the correlation vector ρ under each window. The calculation of systemic risk score is shown in Eq. (11).

real economy. Developed countries generally fell into a long-term economic recession, and economic growth slowed down continually. On the contrary, emerging economies represented by China and India gradually got rid of the haze of the crisis and took the lead in achieving economic recovery, becoming the engine of world economic growth in the post-crisis period. World capital poured into the dynamic financial markets of emerging economies. Compared with ten years ago, the financial markets of emerging countries have been greatly improved in terms of asset liquidity, diversity of financial institutions, market capitalization scale and regulatory mechanism. By introducing market capitalization and connectedness, the systemic risk score is a measure that considers moral-hazard problems both "too big to fail" and "too connected to fail". The total connectedness can be viewed as a special case of the systemic risk score with the same and constant capitalization size in the B&R stock markets. Market capitalization of the B&R stock markets has generally increased significantly compared with 10 years ago.[9] This is the reason why the systemic risk score did not increase obviously during the 2008 financial crisis. From a development perspective, this seems reasonable. Although it is difficult to compare the depth of the impact, the amount of direct economic losses caused by the same systemic financial crisis ten years later is far greater than that occurred ten years ago. Therefore, the total connectedness, which is sensitive to extreme financial events, can be served as the systemic risk early warning indicator, while the systemic risk score gives substantial economic implication when quantifying the aggregate risk

[9] Fig.B1 in Appendix B displays the market capitalization of 8 representative B&R stock markets. Generally, the market capitalization scale is showing an upward trend.

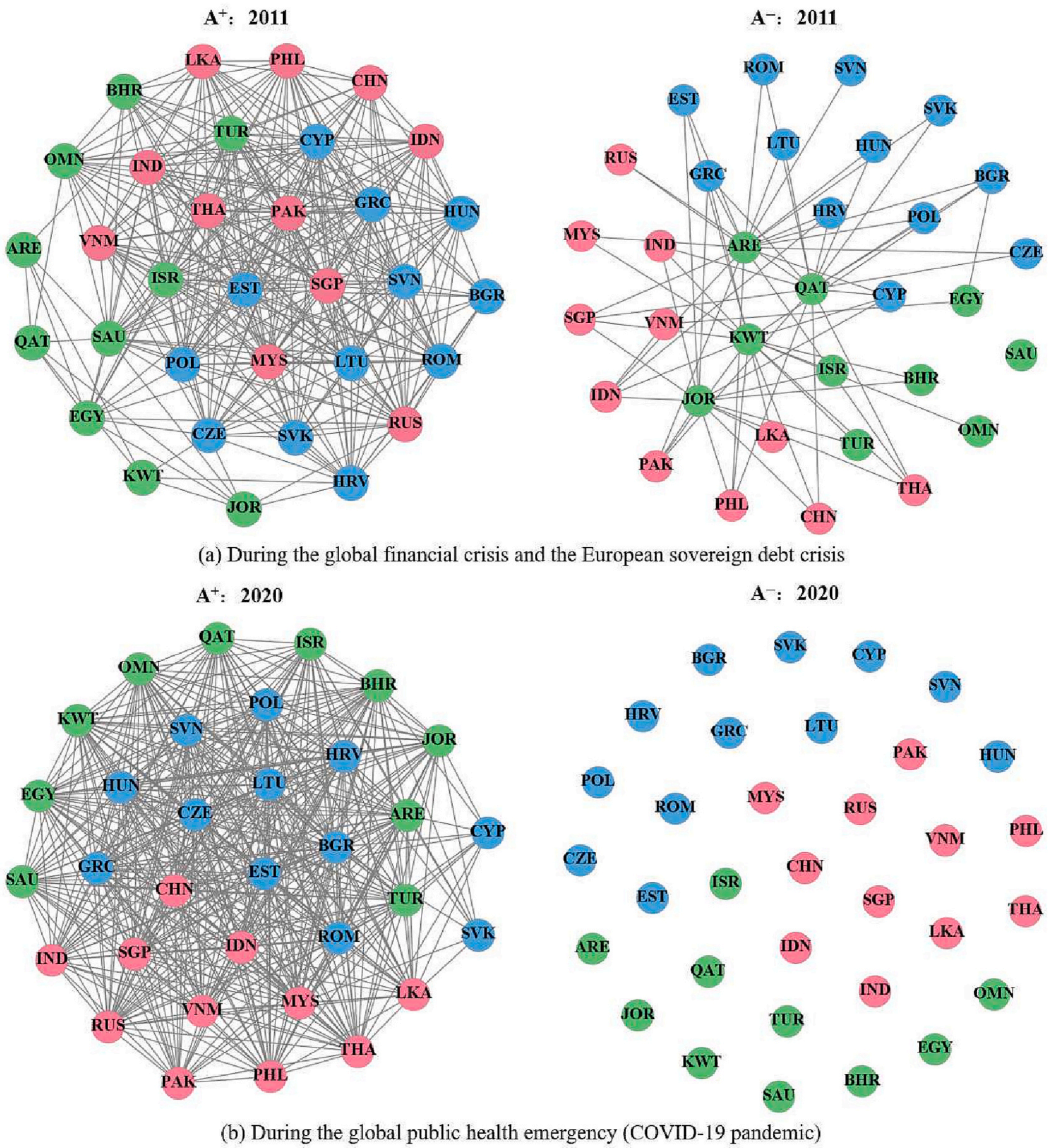

Fig. 8. Network visualization of the tail risk network (left: $\boldsymbol{A}^{+}$; right: $\boldsymbol{A}^{-}$) at the 5% risk level for the 33 B&R stock markets. Note: The sample period of subgraph (a) is 2011 (corresponding to global financial crisis and European sovereign debt crisis). The sample period of subgraph (b) is 2020 (corresponding to the COVID-19 pandemic). The B&R stock markets can be represented by different colors based on 3 regions: (i) East Asia and South Asia (EASA, red), (ii) West Asia and North Africa (WANA, green), and (iii) Central and Eastern Europe (CEE, blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

level of financial system.

To further compare the impact of the 2008 global financial crisis and the COVID-19 epidemic on the B&R stock markets, we depict the tail risk networks at these two moments in Fig. 8. We divide the tail risk network into $\boldsymbol{A}^{+}$ network and $\boldsymbol{A}^{-}$ network for separate consideration, in which the positive network connections characterize the risk contagion effect and the negative ones reflect the risk diversification. Compared with the risk characteristics, when the B&R stock market encountered these two global financial extreme events, the $\boldsymbol{A}^{+}$ network was highly correlated, while the $\boldsymbol{A}^{-}$ network was very sparse. This reflects that the risk spillover effects among the B&R stock markets played a leading role during the crisis. Comparing these two global financial extreme events, the $\boldsymbol{A}^{+}$ network in 2020 is denser than that in 2011, reflecting the stronger risk contagion effect during the COVID-19 pandemic. In the $\boldsymbol{A}^{-}$ network in 2011, interestingly, stock markets from the WANA region situated at the network center established some negative connections with stock markets from the EASA region and the CEE region, showing the weak risk diversification effect. However, there are no negative network linkages in the 2020 $\boldsymbol{A}^{-}$ network. Such results indicate that the negative impact of COVID-19 on the B&R stock markets seems to be more profound than that during the 2008 global financial crisis.

We attribute these results to two parts. First, the COVID-19 pandemic has more severe impact on the real economy of countries around the world. With high infectivity and fatality rate, the COVID-19 exerts negative influence on social order, economic activities, people's life and social distance.[10] The COVID-19 has caused great damage to the global supply chain from three aspects: the supply of means of production, the supply of capital, and the final consumption market. The risks of industrial chain globalization exposed by the epidemic may evolve into long-term risks of anti-globalization. Meanwhile, the negative impact of COVID-19 has spread from the real economy to financial markets. The economy improved somewhat in 2021, but the trajectory of the recovery is "fragile and highly uncertain". As the panic and negative expectations in the financial market continue to ferment, the liquidity tools and rescue measures adopted by the central banks of various countries seem to be not enough, and turmoil in the financial market is inevitable (see footnote 11). Second, the international coordination in the COVID-19 crisis is obviously inadequate. Developed countries and emerging economies focused on domestic macroeconomic measures, and both launched large-scale relief measures, but the global response was far less powerful than during the 2008 global financial crisis.

Table 2 summarizes the annual risk diversification results for the B&R stock markets from 2008 to 2021. The Chinese stock market with large market capitalization formed the largest risk contributions in almost every year of the sample period. During 2013–2014, under the circumstances of the stock market downturn in other B&R countries, investors have positive expectations of China's economic development and market-oriented reforms. With huge inflows of international capital, the Chinese stock market was once an ideal place to diversify risk. In 2015, the domestic economy went down, the clean-up of OTC funds and passive deleveraging triggered a sharp drop in the Chinese stock market, which made its risk contributions rebound. In 2020, as the COVID-19 pandemic swept the world, individual systemic risk contributions of all B&R stock markets increased to varying degrees, pushing the aggregate risk level to the highest level in history. Benefiting from the effective containment of the epidemic, China's national economy continued to show a recovery trend in 2020, becoming the only major economy with positive global economic growth. Individual risk contribution of the Chinese stock market in 2021 decreased by 36.2558 compared with previous years. On the contrary, in 2021, the COVID-19 pandemic has completely out of control in India (the number of infections and deaths soared rapidly), causing the paralysis of various social functions and the shortage of medical supplies. The negative impact of the severe epidemic spilled over from the real economy to the financial level, which makes India replace China and rise to the top of individual risk contributions. This reminds us that epidemic prevention and social stability are the foundation of financial stability in the face of global public health emergencies. In terms of regional average risk contribution, EASA>WANA>CEE, which shows that the dynamic East Asian economic circle is a key area of systemic risk regulation.

4.3. Dynamic network effects on stock market returns

In this part, we use the TENQR model to investigate the dynamic impact of network factors (f^{+} and f^{-}) on the B&R stock market returns at different risk level (different quantiles) from the perspective of geographic regions. In the TENQR model, we use 8 market covariables to describe the macro financial environment of the B&R stock markets (see Section 3.2 for details). The regression results of network factors are detailed in Tables C1–C4 in Appendix C. Fig. 9 shows the slopes from the quantile regressions of the B&R stock market index returns in different geographic regions on network factors. We divide the Belt and Road region into East Asia and South Asia (EASA, red), West Asia and North Africa (WANA, green), Central and Eastern Europe (CEE, blue), and the Belt and Road stock markets system covering the three regions mentioned above (System, black). Different quartiles of the return distribution can reflect the risk state in the B&R stock markets (i.e., lower quantile represents periods of economic downturn or crisis, middle quantile represents normal period, and higher quantile represents prosperity period).

We first discuss the dynamic impact of positive network factors f^{+}. The risk contagion effect of positive network factors at different risk states is statistically significant in four regions (see Tables C1–C4 in Appendix C). This provides empirical evidence for the substantial effect of risk shock and profile similarity depicted by tail risk network on stock returns in the B&R region. In Fig. 9(a), the EASA region and the B&R system present U-shaped network coefficient curves, indicating that the risk contagion effects of stock markets in these two regions is considerable both in crisis and prosperity periods, while the risk contagion effect in calm periods is weaker. The WANA region exhibits a monotonically decreasing network coefficient curve, representing that stock markets in this region have stronger risk contagion effects at the lower quantile (crisis period). The network coefficient curve in CEE region is moderate at different risk levels.

The above results imply that risk contagion is not just a crisis-related matter. Instead, risk contagion among financial markets could be a pervasive phenomenon of the international business cycle theory. During the period of economic prosperity, the excess liquidity generated by credit expansion amplifies the boom cycle and encourages financial risk accumulation, while credit crunch can further exacerbate economic depression and financial instability in the periods of economic downturn. A large number of previous studies (Aloui et al., 2013; Balcilar et al., 2015; Sim and Zhou, 2015; Mensi et al., 2017) exploring risk contagion and the dependence structure of financial markets in different market states support our arguments.[11] The bursting of asset bubbles is often accompanied by a sharp

[10] According to authoritative statistics released by the International Labor Organization, the COVID-19 that lasted for more than a year has caused a total of 255 million job losses, and its harm is four times that of the 2008 financial crisis.

[11] For example, Balcilar et al. (2015) adopt the Markov-Switching vector error-correction model to explore the co-movement between the U.S. energy market and the stock market, and find that the high-volatility regime occurs more frequently before the Great Depression in 1929 and after the oil price shock caused by the Organization of Petroleum Exporting Countries (OPEC) in 1973. Similarly, Sim and Zhou (2015) also provide evidence that negative oil price shocks have substantial impacts on the U.S. stock market during the boom period.

Table 2
The systemic risk decomposition of the B&R stock markets during the period of 2008 to 2021. Notes: Stock market with the largest positive contribution to systemic risk are marked in red, and stock markets with negative contributions are marked in blue. In the region column, EASA represents Eastern Asia and Southern Asia, WANA represents West Asia and North Africa, and CEE represents Central and Eastern Europe.

Region	Country	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
EASA	CHN	12.1167	8.1886	15.1508	7.6765	12.2042	2.1649	1.9559	16.1462	18.8863	20.7112	30.8869	29.7994	71.3219	35.0661
	IND	6.9373	4.4441	8.3690	6.3110	6.3026	2.8027	2.2862	8.3420	10.1181	13.7189	16.0259	16.5439	33.4402	35.8986
	IDN	1.1689	0.9576	2.1245	2.0954	2.2535	1.2121	0.3821	1.9574	1.2985	2.8091	3.6308	2.9273	6.3245	2.6007
	MYS	1.7310	1.2087	2.2785	2.2056	2.5317	1.5051	1.5276	0.5288	2.6457	3.3575	4.3475	3.3874	5.9244	0.0678
	PAK	−0.2402	−0.0660	0.2168	0.1877	0.2309	0.1362	0.3387	0.4318	0.5730	0.1930	0.0643	0.2974	0.6021	−0.1125
	PHL	0.5241	0.3945	0.9703	0.8085	1.1729	0.7136	1.1007	0.7648	1.7747	1.9503	2.3739	2.5159	3.8770	2.7177
	SGP	1.6205	2.0470	3.7626	3.1036	3.4710	3.3682	2.2927	3.4751	3.9762	4.7288	6.0606	5.1944	8.5013	0.0955
	LKA	0.0080	0.0359	−0.0063	0.0511	0.0565	0.0547	0.0407	0.0216	0.1178	0.0313	0.0202	0.1036	0.2211	0.1048
	THA	0.6774	0.8140	1.2475	1.4463	1.8616	1.1761	0.0254	2.1231	2.4542	3.1022	4.4479	4.0100	6.6226	3.1454
	VNM	0.0684	0.1329	−0.0023	0.0554	0.1954	0.1152	0.1387	0.3807	0.4568	0.9716	1.5324	1.5724	3.5151	3.6823
WANA	BHR	0.1037	0.0593	0.0976	0.0526	0.0573	0.0443	−0.0415	0.0634	0.1050	0.0810	0.2072	0.0312	0.4085	0.2679
	EGY	0.8287	0.3863	0.4834	−0.0891	0.3692	0.1844	0.1701	0.3297	0.1931	0.0817	0.3614	0.3877	0.6175	0.2373
	ISR	1.1429	0.1402	1.1665	0.8873	0.8882	0.3325	0.2310	1.2469	1.1353	0.9927	1.4163	1.5779	2.5872	1.3872
	JOR	0.2521	0.0983	0.1974	−0.0688	−0.0981	0.0764	0.0195	−0.1609	0.1533	0.0279	−0.1491	−0.0822	0.1494	0.2212
	KWT	0.3004	−0.2624	0.7736	−0.4120	0.3841	−0.0094	0.3101	0.6141	0.6296	0.1031	−0.0095	−0.0305	1.5774	0.3706
	OMN	0.1859	0.0984	0.1401	0.0501	0.1279	0.0942	−0.0264	0.0874	0.1818	0.0309	0.1778	0.0218	0.2591	0.1350
	QAT	0.8138	0.3191	0.8883	−0.3153	0.7442	0.8648	0.5864	1.3290	1.3374	0.3286	1.5449	1.6126	2.7543	1.4510
	SAU	2.8420	1.5173	2.3176	1.1302	2.3818	0.4248	0.3962	3.0316	3.3486	0.3404	4.0874	4.6243	34.3899	35.3309
	TUR	1.3567	1.0279	2.3190	1.2311	1.4484	0.5636	0.6854	1.2371	1.1408	−1.0639	1.8310	1.5040	2.9804	1.0281
	ARE	1.6062	0.6563	−0.6138	−0.2871	0.4267	0.5022	0.4336	1.6058	1.7315	2.0015	2.1295	2.4259	4.8143	2.2049
CEE	BGR	0.0319	0.0067	0.0077	0.0031	0.0022	0.0127	0.0302	−0.0264	0.0167	−0.0060	0.0559	0.0190	0.2830	−0.1388
	HRV	0.2881	0.1208	0.1437	0.0502	0.1496	0.1310	−0.0949	0.0680	0.1620	0.1755	0.1340	0.1552	0.3732	−0.0514
	CYP	0.2342	0.1046	0.0935	0.0464	0.0200	0.0049	−0.0044	0.0021	0.0393	0.0175	0.0595	−0.0040	0.0012	−0.0954
	CZE	0.3294	0.2984	0.3485	0.1473	0.1881	0.1352	0.1986	0.2120	0.2114	0.0874	0.3160	0.2746	0.4597	0.1968
	EST	0.0220	0.0097	0.0175	0.0135	0.0138	0.0090	0.0063	0.0168	0.0213	0.0017	0.0294	0.0184	0.0594	0.0318
	GRC	0.8838	0.4701	0.3375	0.2038	0.1125	0.1885	−0.0547	0.1799	0.2946	0.0489	0.4811	0.4544	0.6623	0.0287
	HUN	0.1832	0.1651	0.2411	0.1611	0.1495	0.0807	0.0751	0.0863	0.1883	0.1233	0.3501	0.3170	0.4803	−0.0668
	LTU	0.0217	0.0067	0.0204	0.0143	0.0253	−0.0002	0.0120	0.0293	0.0108	−0.0109	0.0524	0.0308	0.0976	0.0536
	POL	1.1000	0.5961	1.2762	0.9505	0.9116	0.2781	0.9614	0.7685	0.9532	1.4835	1.7766	1.3684	2.4998	1.3005
	ROM	0.2280	0.0757	0.1144	0.1116	0.1224	0.0232	0.0454	0.1292	0.1188	0.0172	0.2194	0.2242	0.4433	0.0134
	RUS	6.6728	3.1851	5.3882	2.6175	5.3540	2.3707	2.4793	3.0280	4.6417	1.0338	5.7676	6.8914	10.8893	6.0586
	SVK	0.0064	−0.0270	0.0102	0.0192	0.0058	−0.0024	0.0064	0.0002	−0.0059	0.0049	0.0015	0.0066	0.0089	0.0055
	SVN	0.1451	0.0706	0.0699	0.0520	0.0294	0.0403	0.0438	0.0020	0.0470	0.0456	0.0731	0.0623	0.1534	−0.0235
Systemic risk score		44.1911	27.2803	49.9499	30.5106	44.0944	19.5983	16.5573	48.0516	58.9569	57.5203	90.3041	88.2424	207.2998	133.2133
Average score (EASA)		2.4612	1.8157	3.4111	2.3941	3.0280	1.3249	1.0089	3.4172	4.2301	5.1574	6.9391	6.6352	14.0350	8.3266
Average score (WANA)		0.9432	0.4041	0.7770	0.2179	0.6730	0.3078	0.2764	0.9384	0.9956	0.2924	1.1597	1.2073	5.0538	4.2634
Average score (CEE)		0.7805	0.3910	0.6207	0.3377	0.5449	0.2517	0.2850	0.3458	0.5153	0.2325	0.7167	0.7552	1.2624	0.5625

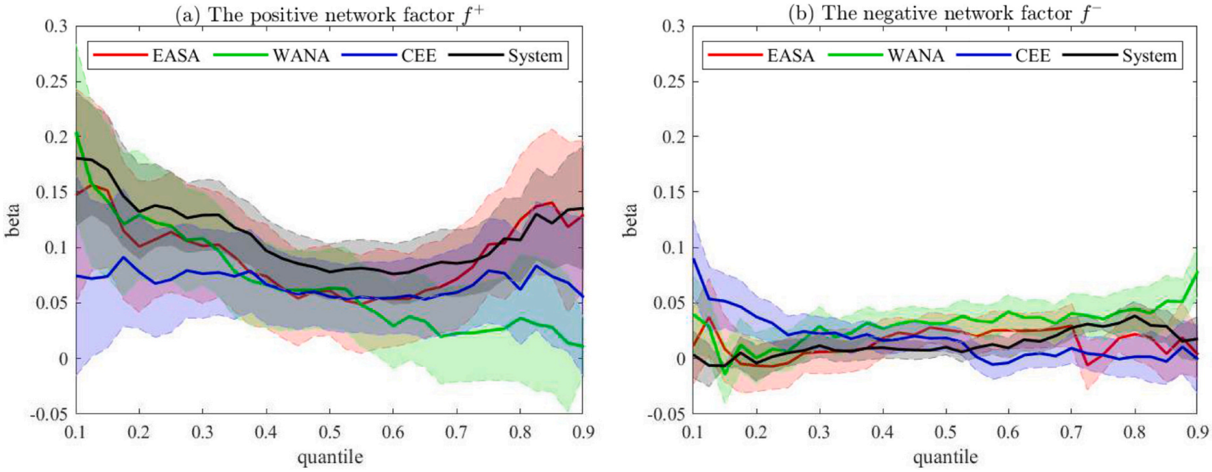

Fig. 9. Slopes from the quantile regressions of the B&R stock market index returns from different geographic regions on the network factor (left: positive f^+; right: negative f^-). Note: The colored area between two dotted lines represents the 95% pointwise confidence intervals (full sample estimation). The geographic regions of B&R stock markets can be represented by different colors based on 4 regions: (i) East Asia and South Asia (EASA, red), (ii) West Asia and North Africa (WANA, green), (iii) Central and Eastern Europe (CEE, blue), and (iv) the Belt and Road stock markets system covering the three regions mentioned above (System, black). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

rise in risks, shaping the nonlinear characteristics of “slow accumulation and rapid release” of financial risks in macroeconomic operation; the risk spillovers in a particular market state increases obviously, and the intensity shows obvious asymmetry in different investment fields with the change of time (Benoit et al., 2017). Moreover, systemic risk accumulates during boom phases and materializes in crisis times (Adrian and Brunnermeier, 2016). In fact, people tend to ignore the build-up of systemic risk and engage in more ambitious and expansionary activities in good times. If too loose during booms (when imbalances accumulate) and too tight during crises (when imbalances erupt), such pro-cyclical framework will exacerbate the negative impact of financial shocks and amplify balance sheet growth and risk-taking behavior. In this way, the positive network factor is a good measure of risk contagion effect and also highlights the importance of countercyclical macroprudential regulation.

We then focus on the negative network factor f^-. Compared with the positive network factor, the risk diversification of the negative network factor is quite weak and insignificant in many different market states. From Fig. 9(b), the negative network factor coefficient curves of all the four regions (i.e., EASA, WANA, CEE and the B&R system) are highly homogenous, showing relatively flat and slow growth characteristics from low quantile to high quantile. This further indicates that the risk diversification component in the tail risk network of the B&R stock markets is very faint and hardly affect the stock returns either on the whole or on the regional panel.

The dynamic impact of network factors on the B&R stock market returns contains abundant profound connotations: (i) there is asymmetric impact in positive and negative network factors. Comparing Fig. 9 (a) with (b), we find that the risk contagion effect of the B&R stock market network is generally stronger than that of risk diversification. This finding is consistent with Diebold and Yılmaz (2014), Härdle et al. (2016), and Chen et al. (2019). Also, the contrary example exists in the results. For instance, risk diversification in CEE region is stronger than risk contagion in the low quantile risk level; (ii) network effects of the B&R stock markets from different regions show the coexistence of regional homogeneity and heterogeneity. For example, when impacted by positive network factor f^+, the curves of EASA region and the B&R system show similar U-shaped characteristics (homogeneity), while that of the WANA region shows monotonically decreasing trend and that of the CEE region is relatively flat (heterogeneity); and (iii) network impacts of the B&R stock market at different risk levels shows the coexistence of symmetry and asymmetry. For instance, the U-shaped curve of the EASA region and the B&R system shows that the risk contagion effect is symmetric and considerable both in the crisis period and prosperity period (symmetry). The WANA region affected by positive network factor f^+ and the CEE region affected by negative network factor f^- both show monotonically decreasing characteristics, which reveals that the stock markets in the WANA region and the CEE region respectively have stronger risk contagion and risk diversification during the crisis time (asymmetric). The above valuable information deepens our academic understanding of the risk spillovers and contributes to the coordinated cross-regional regulation of systemic risk in the B&R stock markets. Therefore, the tail risk network based on risk profile similarity provides an alternative framework to measure the risk spillover effects, which go beyond the existing related literature by further dividing the risk characteristics into risk contagion and risk diversification and investigating their dynamics, heterogeneity and asymmetry among different regions and in different market states.

4.4. Potential drivers of systemic risk

So far, we have analyzed the systemic risk level, the risk contribution of network nodes and the dynamic impact of network factors under the tail risk network of the B&R stock markets. A natural question has aroused our attention, that is, what contributes to systemic

Table 3
Potential drivers of systemic risk in the B&R stock markets – Panel regression (fixed effects) using the least squares dummy variable model.

Dependent Variable: Systemic risk contribution of the B&R stock market *i*						
	(1)	(2)	(3)	(4)	(5)	(6)
FDI inflow	0.0538* (1.67)					
FDI outflow		0.0594** (2.50)				
Trade import			0.0050*** (26.19)			
Trade export				0.0059*** (21.65)		
Economic freedom					0.0803* (1.98)	
Financial market development						0.1428 (0.80)
Economic development	−0.0224 (−0.10)	0.1040 (0.80)	0.0411 (0.26)	0.0468 (0.32)	0.0337 (0.17)	0.0519 (0.27)
Natural resources endowment	−0.0156 (−1.51)	0.0081 (0.38)	0.0045 (0.18)	−0.0134 (−0.51)	−0.0084 (−0.46)	−0.0036 (−0.16)
Corruption level	0.0159 (0.36)	0.0034 (0.10)	0.0082 (0.38)	0.0119 (0.51)	0.0037 (0.18)	0.0104 (0.48)
Government governance level	−0.0123 (−0.71)	−0.0090** (−2.22)	−0.0162 (−1.27)	−0.0143 (−1.47)	−0.0147 (−1.52)	−0.0134 (−1.14)
Globalization degree	−0.0119 (−0.18)	−0.0120 (−0.16)	−0.0577 (−0.50)	−0.0701 (−0.62)	−0.0543 (−0.55)	−0.0363 (−0.35)
Infrastructure quality	0.1212 (0.30)	−0.0457 (−0.23)	0.0935 (0.28)	0.0541 (0.17)	−0.1837 (−0.71)	−0.0092 (−0.03)
Year fixed effect	YES	YES	YES	YES	YES	YES
Country fixed effect	YES	YES	YES	YES	YES	YES
Adj R-squared	0.723	0.744	0.715	0.725	0.708	0.705
Number of observations	363	363	363	363	363	363

Notes: The sample data had an annual frequency from 2008 to 2018. Regression results for the country and year dummy variables are not listed in the table. The reported *t*-statistics are in parentheses. All the *t*-statistics are presented after clustering robust standard error at the region-level by using the Wild Cluster Bootstrap Procedure for the limited number of clusters. The symbols of *, **, and *** respectively refer rejection of the null hypothesis of significance test at levels of 10%, 5% and 1%.

risk of the B&R stock markets? For illustrative purposes, we conduct panel data analysis to further explore the main determinants of systemic risk in the B&R stock markets.

Specifically, we mainly consider the potential drivers of cross-border investment, international trade, economic freedom, financial market development in the Belt and Road region. Since the B&R Initiative was put forward, trade and investment cooperation among member countries has deepened, and such frequent activities tend to serve as channels for systemic risk contagion (Luo et al., 2015; Du and Zhang, 2018). In addition to trade and investment activities, we introduce two economic fundamentals variables, i.e., economic freedom and financial market development. Economic freedom is an important index for the international community to evaluate the degree of marketization, which means that the government does not interfere in or protect free competition, free market, free choice, free trade and private property within the scope of the constitution. The more economically free a country is, the better chance it has of achieving the expected gains. Economic freedom is accompanied by vigorous financial activities, which is conducive to the accumulation of systemic risk. Meanwhile, we take into account the financial market development of the B&R countries. The improvement of financial market maturity can provide more abundant financial products, financing channels and capital allocation (Islam and Mozumdar, 2007). Financial markets with increasing openness, scale and internationalization could face more market speculation factors, and are more likely to encounter the negative impact of financial market and spillover effects of national policy in the international community. Empirical evidence from developed countries shows that financial market development has a strong positive relationship with the idiosyncratic risk of listed institutions (Brown and Kapadia, 2007). However, some studies show that financial market development is a by-product of economic expansion, which facilitates the transfer of resources from savers to investors; financial market development promotes economic growth by appropriately allocating risk and by helping to strengthen the resilience of economies to shocks (Levine, 2005; Chami et al., 2010). The B&R region covers many emerging economies and low-income countries with generally low financial market maturity. Actual effects of financial market development on systemic risk in the B&R countries remains ambiguous and deserves further discussion.

Following the recent literature (Li et al., 2019; Wu et al., 2019; Li et al., 2022), we introduce economic development, natural resources endowment, corruption level, government governance, globalization degree and infrastructure quality as control variables to describe the macro fundamentals of the Belt and Road countries. Variable selection and data source are detailed in Table A3 in Appendix A. In this setting, the panel regression specification is shown as follows:

$$S_{it} = \beta_0 + \beta \boldsymbol{Z}_{it} + \gamma \boldsymbol{D}_{it} + \alpha_i + u_t + \varepsilon_{it} \tag{17}$$

where S_{it} is the systemic risk contribution of B&R stock market i at rolling window t, $\boldsymbol{Z}_{it}$ is the explanatory variable set, $\boldsymbol{D}_{it}$ is the control variable set, and α_i, u_{it} and ε_{it} represent the country fixed effect, year fixed effect and the stochastic disturbance term, respectively.

Table 3 presents results of the panel regressions with country and year fixed effects. In columns (1) and (2), the coefficients of foreign direct investment (FDI) inflow and outflow are both significantly positive, which implies that the FDI plays significant roles in promoting systemic risk contributions in the B&R countries. As an important form of international capital flow, FDI is often endowed with the financial attributes of high leverage, strong liquidity and low circulation cost, which is a dynamic force in allocating global financial assets. When participants engaged in FDI (e.g., sovereign countries, international organizations, financial institutions, non-financial corporations, ordinary residents) experience financial distress, their liquidity problems are easily transmitted to counterparties through the channel of cross-border capital flows, thus triggering large-scale capital flight, liquidity depletion, and interruption of investment and financing projects in the host country (Kellard et al., 2022). In addition, the current investment situation in the B&R region is complex and the country risks are severe.[12] Foreign business environment with high uncertainty makes both inward and outward FDI of the B&R countries face potential risk and financial challenges. FDI changes the internationalization of production geographies. The mutual economic relationship arising from the FDI under internationalization strategies creates possible paths of economic contagion and constitutes a source of systemic risk (De Masi and Ricchiuti, 2020).

In columns (3) and (4), we find significant positive effects of trade import and trade export on systemic risk contributions of the B&R countries, indicating that international trade is indeed an important factor affecting systemic risk. Compared with the FDI, international trade has stronger statistical significance in promoting systemic risk and is more likely to be active channel for risk spillovers in the B&R stock markets. With diversified resource endowments and refined international division of labor, the world has established close trade links in goods and services. International trade is the engine of world economic growth and plays an important role in improving global supply and demand relations. At the same time, it has become an important channel for the spread of the financial risk. Trade spillover effects can be manifested that the negative impact of a country encountered macro shocks or financial distress leads to speculative attacks and deterioration of macro fundamentals in countries with which it has trade cooperation relationships.

Although empirical evidence on the performance and economic impact of the B&R Initiative is scarce due to the difficulties in quantitative evaluation, potential welfare effects of the B&R Initiative are significant. By adopting the global computable general equilibrium model, Zhai (2018) estimate welfare gains for the B&R member countries in the range of 1.1%–7.5% of GDP. These gains are potential dividends of infrastructure investments and also benefit from the formation of trade and investment networks. On this basis, our empirical results further reveal that international trade and cross-border investment are important channels of systemic risk contagion in B&R countries. This evidence is not surprising and is in line with the standard theory of financial risk contagion (Masson, 1998, 1999). The main form of financial risk contagion among different countries is the “touch-type” spillover effect formed by trade and financial channels. That is, the close linkages among the B&R countries in the real economy and finance facilitates the international spread of regional or global financial shocks. Also, our results are consistent with the recent empirical evidence (Bostanci and Yılmaz, 2020; Wang et al., 2022).

Subsequently, we turn to focus on two other macro fundamental variables, economic freedom and financial market development, and present the regression results in columns (5) and (6). We find that economic freedom is positively associated with systemic risk contribution. The result provides empirical evidence for the ongoing academic discussion on the association between economic freedom and financial crises that economic freedom could promote the accumulation of systemic risk. Substantial economic freedom is conducive to economic growth and the efficient operation of social resources, but it seems to be associated with more frequent and deeper crises. Market-oriented liberalization contributes to financial deepening, and it is also is expected to cripple economic growth by leading to instability, stimulating domestic capital flight and increasing the risk of financial fragility (Ahmed, 2013). Excessive economic freedom encourages risk-taking or outright fraudulent behavior by financial participants, which can trigger frequent economic disruptions and be detrimental to human well-being (Stiglitz, 2009).

In contrast, the positive effect of financial market development on the systemic risk contribution is not supported by statistical significance. This indicates that financial market development (market and investor confidence-seeking) that plays horizontal spillover effects for financial activities do not exerts substantial impacts on systemic risk in the B&R stock markets. In other words, financial market development does not significantly promote or inhibit systemic risk. Financial markets are important objects for diversified asset allocation. However, the underdeveloped financial infrastructure of the B&R countries (limited market size, and inactive market volume and turnover) restricts the supporting utility of finance to the real economy, and weakens the desire and motivation of financial participants' risk-taking behavior as well. Many member countries along the Belt and Road achieve national wealth growth mainly relying on commodity trade (energy and agricultural products), labor-intensive and service-oriented goods exports and tourism. These physical objects are more likely to be the main target of external risk. Additionally, underdeveloped financial markets are generally

[12] According to “Research Report on The Status of Chinese Private Enterprises along the Belt and Road” released by All-China Federation of Industry and Commerce on 21 November 2019, optimizing the business environment along the Belt and Road is still a continuous, comprehensive and multi-dimensional project. The B&R business environment remains extremely challenging. Political instability or policy uncertainty in some B&R countries leads to high political risk. Due to government corruption, some member countries lack economic vitality and have higher operational risks. What's more, some transnational investments face great potential risks for the great differences in laws and regulations, labor policies, religion and culture between the host country and the home country (see, https://www.yidaiyilu.gov.cn/xwzx/gnxw/110501.htm).

accompanied by imperfect institutional and regulatory environment, which also weakens the inhibitory effect of financial regulatory on systemic risks in the B&R region to some extent.

Therefore, we further draw conclusions that cross-border investment and international trade are the transmission channels of systemic risk in the B&R stock markets. Additionally, economic freedom is the noteworthy potential driver, while financial market development has not shown significant roles in promoting or inhibiting systemic risk. This provides the implications that the regulatory authorities in B&R countries need to be cautious about international risk contagion in trade and investment channels and financial instability caused by excessive economic freedom. Although the effect of financial market development is statistically insignificant, the government authorities along the Belt and Road still need to work on improving financial markets. Financial market development is a creative transition to a more robust market institution, which establishes and nurtures a sound financial environment. For strengthening the financial service capacity and financial risk resilience, it is necessary to establish supervision mechanisms, examine incentives faced by the players and monitor financial stability (i.e., the adequate supervision, appropriate incentives and necessary constraints).

5. Conclusion

The economic development of the latecomer countries along the Belt and Road has long been constrained by backward infrastructure, limited production capacity, lack of technology and financing difficulties. In all fairness, the B&R initiative gives full play to the complementary economic structure and specialized division of labor in the region, providing member countries with huge potential for economic cooperation. Financial fragility is an unavoidable common challenge for B&R countries to achieve regional economic prosperity. In addition to the common external shocks during the crisis, we mainly explore the contagion and spillover effects of systemic risk in the B&R stock markets. Turbulence in financial markets has the potential to spread from one market to another, creating a domino effect of financial instability. Theoretically, financial contagion is related to economic fundamentals theory, efficient market hypothesis, behavioral finance, and international trade theory to some extent. This is different from a common external shock, which is a single event that affects all markets in the same way. Financial contagion and spillovers can cause a more widespread and prolonged disruption to the financial system, as the effects of the initial disturbance can spread to other markets. Understanding the risk contagion mechanism and spillover effects in the financial sector and identifying the risk drivers and transmission paths are conducive to maintaining regional financial stability. To this end, this paper constructs a network analysis framework tailored for the B&R stock market, aiming to provide in-depth insights into the regional systemic financial risk prevention and macro-prudential supervision.

Specifically, we construct a time-varying tail risk network based on the risk profiles similarity of the B&R stock markets, which can dynamically describe the risk characteristics. Positive linkages reflect risk contagion and negative ones can be interpreted as risk diversification. The adjacency structure of the network is proved to be statistically significant by the joint spacings variance ratio (SVR) test. Under tail risk network framework, we construct systemic risk score index and individual risk contribution index to reflect the aggregate risk level and individual risk accumulation of the B&R stock market system. As early warning indicators, these two risk measurement indicators clearly capture the negative effects of extreme financial events (e.g., the 2008 global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic) at the system and individual levels, and can provide regulators with valuable information for precise regulation of financial risks. In addition, the results of the TENQR model show that positive and negative network factors have complex dynamic effects on the returns of B&R stock markets at different risk levels. For example, positive and negative network factors have asymmetric influence, which is manifested as the risk contagion effects is stronger than the risk dispersion. The network impacts of the B&R stock markets present the coexistence of regional homogeneity and heterogeneity. The impacts of network factors on the B&R stock markets at different risk levels is characterized by the coexistence of symmetry and asymmetry. Also, the results reflect that risk contagion among financial markets could be a pervasive phenomenon of the international business cycle theory, which exists widely in boom times and crisis times. Finally, we conduct panel data analysis to explore the main determinants of systemic risk in the B&R stock markets. We find that cross-border investment and international trade are significant channels of risk contagion, and economic freedom is an important driver of systemic risk. Financial market development does not significantly promote or inhibit systemic risk. In conclusion, the practical model framework and valuable research findings of this paper contribute to the international coordination of supervision and governance of systemic risk in the Belt and Road region.

Some extension work could be carried out for future research. It seems to be insufficient to explore systemic risk of the B&R countries only based on the stock market. Future work can take other financial markets into common consideration. Methodologically, the similarity network framework based on risk profiles in this paper belongs to a single-layer network for tail risk analysis. With the development of network science theory, the single-layer network is gradually expanded to multilayer complex network. The research in financial field based on the multilayer network framework is emerging (Musmeci et al., 2017; Wang et al., 2021a, 2021b). Multilayer network technique can provide innovative perspectives for the exploration of systemic risk in the Belt and Road region.

CRediT authorship contribution statement

Yusen Feng: Data curation, Software, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Gang-Jin Wang:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition. **You Zhu:** Writing – review & editing. **Chi Xie:** Writing – review & editing, Resources, Supervision.

Data availability

The data and code for this study can be accessed on Mendeley Data by https://doi.org/10.17632/c9t5swh4vz.1.

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Appendix A

In Table A1, we show the country scope of the Belt and Road initiative widely recognized by academic research at present, and the countries marked with an asterisk (*) are sample countries of this paper. In Table A2, we show stock market index of the B&R sample countries. Table A3 lists the variable selection and data source for the panel data analysis.

Table A1
The country scope of the Belt and Road initiative currently widely used in academic research and official news reports.

Region	The member countries in the B&R Initiative			
East Asia and Central Asia (1)	China*	Mongolia	Kazakhstan	Kyrgyzstan
	Tajikistan	Turkmenistan	Uzbekistan	
Southeast Asia (6)	Brunei	Cambodia	Indonesia*	Laos
	Malaysia*	Myanmar	Philippines*	Singapore*
	Thailand*	Vietnam*		
South Asia (3)	Bangladesh	Bhutan	India*	Maldives
	Nepal	Pakistan*	Sri Lanka*	
West Asia and north Africa (10)	Afghanistan	Armenia	Azerbaijan	Bahrain*
	Egypt*	Georgia	Iran	Iraq
	Israel*	Jordan*	Kuwait*	Lebanon
	Qatar*	Oman*	Palestine	Saudi Arabia*
	Syria	Turkey*	United Arab Emirates*	Yemen
Central and Eastern Europe (13)	Albania	Belarus	Bosnia and Herzegovina	Bulgaria*
	Cyprus*	Croatia*	Czech Republic*	Estonia*
	Greece*	Hungary*	Latvia	Lithuania*
	Moldova	Montenegro	Serbia	Macedonia
	Poland*	Romania*	Russia*	Slovakia*
	Slovenia*	Ukraine		

Notes: In data collection, data are not available in some B&R countries. We perform data cleaning on the collected data. Due to holidays, stock suspension or other factors, some time series have data missing. If the missing data of a sequence do not exceed 4 consecutive weeks, the interpolation method is used to complete the missing data; otherwise, the corresponding stock market index is removed and not included in our sample. The country marked with an asterisk (*) indicates that the stock market index in this country is included in our sample.

Table A2
Sample country and stock market index.

Region	Country	Abbr.	Stock market index
East Asia and South Asia (EASA)	China	CHN	Chinese Shanghai Composite Index
	India	IND	India SENSEX Stock Market Index
	Indonesia	IDN	Indonesian Jakarta Composite Index
	Malaysia	MYS	FTSE Bursa Malaysia KLCI index
	Pakistan	PAK	Pakistan Fka Karachi Stock Exchange 100 Index
	Philippines	PHL	Philippine Stock Exchange Composite Index
	Singapore	SGP	Singapore Stock Market Straits Times Index
	Sri Lanka	LKA	Sri Lanka Colombo All-Share Index
	Thailand	THA	Thailand SET Composite Index
	Vietnam	VNM	Vietnam Ho Chi Minh Stock Index

(*continued on next page*)

Table A2 (*continued*)

Region	Country	Abbr.	Stock market index
West Asia and North Africa (WANA)	Bahrain	BHR	Bahrain Bourse All-Share Index
	Egypt	EGY	Egypt Stock Market EGX 30 Index
	Israel	ISR	Turkey Istanbul 100 Index
	Jordan	JOR	Jordan Amman Composite Index
	Kuwait	KWT	Kuwait Stock Exchange Index
	Oman	OMN	Oman Stock Market 30 Index
	Qatar	QAT	Qatar Stock Exchange General Index
	Saudi Arabia	SAU	Saudi Arabia Stock Market Tadawul All Share Index
	Turkey	TUR	Istanbul Stock Exchange National 100 Index
	United Arab Emirates	ARE	United Arab Emirates Stock Market ADX General Index
Central and Eastern Europe (CEE)	Bulgaria	BGR	Bulgaria Stock Market SOFIX Index
	Croatia	HRV	Croatia Zagreb Stock Exchange Index
	Cyprus	CYP	Cyprus Stock Exchange General Index
	Czech Republic	CZE	Czech Republic Stock Market PX Index
	Estonia	EST	Estonia Stock Market OMX Tallin Index
	Greece	GRC	Athens Stock Exchange General Index
	Hungary	HUN	Budapest Stock Exchange Index
	Lithuania	LTU	Lithuania Stock Market OMX Index
	Poland	POL	Warsaw Stock Exchange WIG Index
	Romania	ROM	Bucharest Exchange Trading Index
	Russia	RUS	Moscow Exchange Russia Index
	Slovakia	SVK	Slovakia Stock Market SAX Index
	Slovenia	SVN	Slovenian Blue Chip Index SBI Top Index

Notes: According to the geographical distribution, we heuristically divide the B&R sample countries into three regions including (i) East Asia and South Asia (EASA), (ii) West Asia and North Africa (WANA), and (iii) Central and Eastern Europe (CEE).

Table A3
Variable selection and data source.

Attributes	Variable name	Variable meaning	Data source
Explained variable	Systemic risk contribution	Systemic risk contribution S_i quantifies the risk accumulation and individual level of B&R stock market *i*.	Calculated by risk decomposition at the systemic aggregate risk level [Eqs. (11) and (12)].
Explanatory variable	FDI inflow	Total foreign direct investment inflow of the country	UNCTAD
	FDI outflow	Total foreign direct investment outflow of the country	UNCTAD
	Trade import	Total merch trade import of the country	UNCTAD
	Trade export	Total merch trade export of the country	UNCTAD
	Economic freedom	Economic Freedom Index	Heritage Foundation
	Financial market development	The financial market development pillar of the Global Competitiveness Index dataset	The World Economic Forum
Control variable	Economic development	Gross domestic product (GDP) of the country	UNCTAD
	Natural resources endowment	Natural resources endowment is measured by host countries' ratio of natural resource export to total exports	UNCTAD
	Corruption level	Corruption Perceptions Index	Transparency International
	Government governance level	The score results of the first two factors after factor analysis for the world governance indicator dataset's comprehensive index in six dimensions.	World Bank
	Globalization degree	KOF Globalization Index	ETH
	Infrastructure quality	The overall infrastructure quality group of the Global Competitiveness Index dataset	The World Economic Forum

Notes: Due to space constraints, we did not present the factor analysis process of the government governance.

Appendix B

Fig. B1 shows the dynamic evolution of the market capitalization of eight representative B&R stock markets from 2008 to 2021. The units of market capitalization series are unified into trillions of US dollars. The Chinese stock market has the largest market capitalization, and the market capitalization of 2021 has nearly tripled that in the 2008 financial crisis. Other emerging economies such as India, the United Arab Emirates have also shown a continuous upward trend in their market capitalization. After the outbreak of the 2008 financial crisis, the stock markets of Singapore, Russia and Turkey were affected, and the market value of the stock market plunged and then recovered. In general, with the economic recovery, the size of financial markets in countries along the Belt and Road has significantly increased.

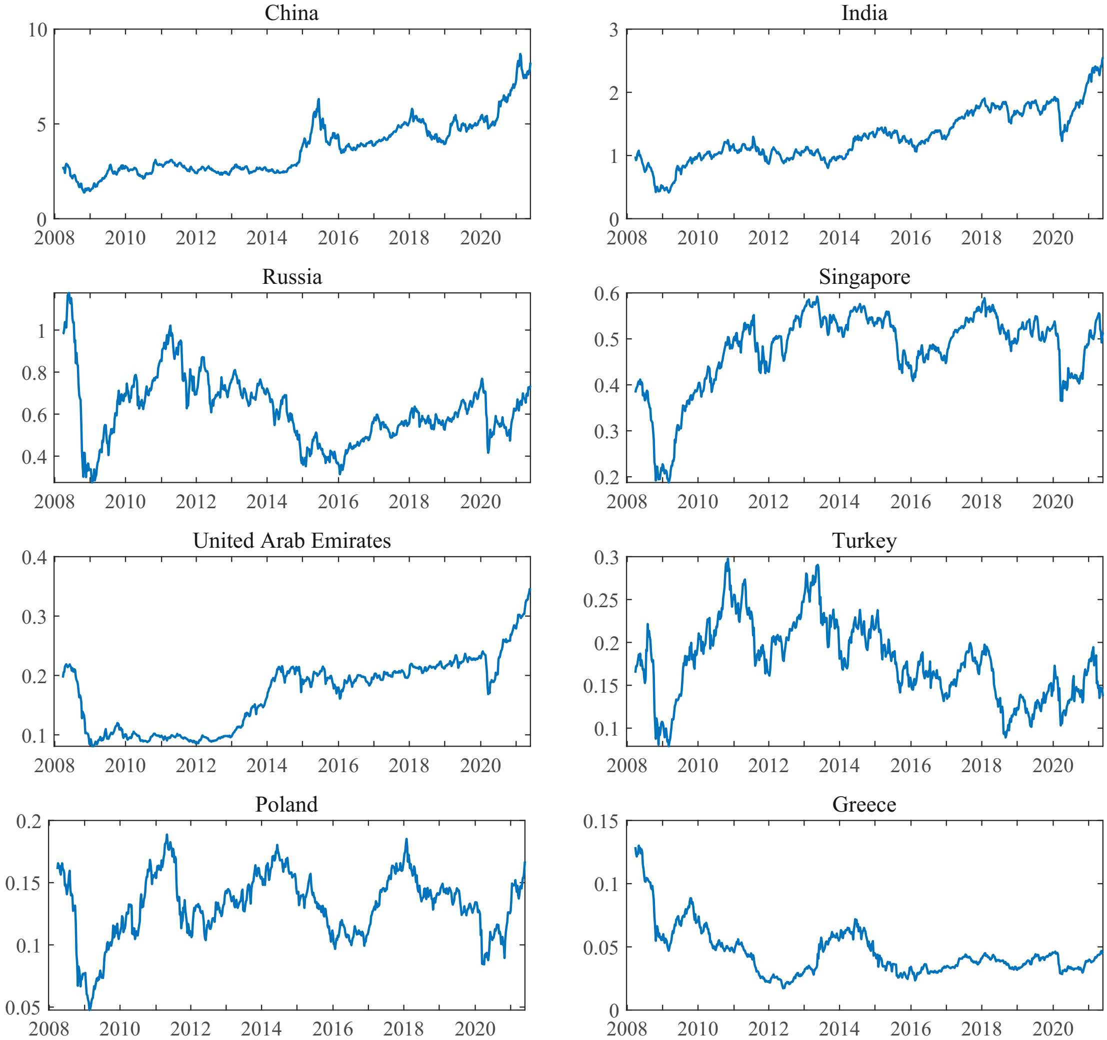

Fig. B1. The market capitalization of the representative stock markets of B&R countries. Note: Due to space constraints, the figure only shows market capitalization of stock markets of the 8 representative B&R countries including China, India, Russia, Singapore, United Arab Emirates, Turkey, Poland and Greece. The units of stock market capitalization are unified into trillions of US dollars.

Appendix C

Tables C1–C4 show the parameter estimation results of positive and negative network factors on stock market returns under different market conditions, covering EASA, WANA, CEE and B&R systems respectively. Due to the limited space, we do not present detailed regression results for market covariates in the TENQR model.

Table C1
The TENQR result of the B&R stock market index returns on the network factor from the East Asia and South Asia region.

Quantile	The positive network factors f^{+}				The negative network factors f^{-}			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.1000	0.1471***	0.0491	2.9942	0.0028	0.0114	0.0430	0.2642	0.7917
0.1250	0.1562***	0.0394	3.9607	0.0001	0.0373	0.0434	0.8589	0.3904
0.1500	0.1512***	0.0351	4.3022	0.0000	0.0085	0.0370	0.2283	0.8194
0.1750	0.1151***	0.0316	3.6476	0.0003	−0.0048	0.0330	−0.1460	0.8840
0.2000	0.1008***	0.0301	3.3496	0.0008	−0.0065	0.0291	−0.2242	0.8226
0.2250	0.1072***	0.0270	3.9730	0.0001	−0.0071	0.0259	−0.2757	0.7828

(continued on next page)

Table C1 (*continued*)

Quantile	The positive network factors f^+				The negative network factors f^-			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.2500	0.1139***	0.0276	4.1293	0.0000	−0.0042	0.0279	−0.1511	0.8799
0.2750	0.1061***	0.0257	4.1206	0.0000	0.0047	0.0223	0.2122	0.8320
0.3000	0.1014***	0.0265	3.8262	0.0001	0.0059	0.0247	0.2399	0.8104
0.3250	0.1024***	0.0242	4.2417	0.0000	0.0062	0.0248	0.2485	0.8038
0.3500	0.0914***	0.0249	3.6655	0.0002	0.0073	0.0242	0.3009	0.7635
0.3750	0.0773***	0.0244	3.1668	0.0015	0.0091	0.0230	0.3975	0.6910
0.4000	0.0741***	0.0238	3.1117	0.0019	0.0181	0.0217	0.8340	0.4043
0.4250	0.0633***	0.0228	2.7766	0.0055	0.0231	0.0172	1.3420	0.1796
0.4500	0.0541**	0.0218	2.4783	0.0132	0.0212	0.0171	1.2382	0.2157
0.4750	0.0601***	0.0205	2.9355	0.0033	0.0279	0.0173	1.6089	0.1077
0.5000	0.0611***	0.0206	2.9609	0.0031	0.0258	0.0175	1.4682	0.1421
0.5250	0.0521**	0.0223	2.3404	0.0193	0.0237	0.0198	1.1967	0.2315
0.5500	0.0489**	0.0226	2.1607	0.0308	0.0197	0.0207	0.9516	0.3413
0.5750	0.0539**	0.0230	2.3481	0.0189	0.0251	0.0218	1.1512	0.2497
0.6000	0.0538**	0.0221	2.4318	0.0151	0.0254	0.0208	1.2234	0.2212
0.6250	0.0537***	0.0205	2.6241	0.0087	0.0248	0.0194	1.2740	0.2027
0.6500	0.0611***	0.0217	2.8193	0.0048	0.0254	0.0201	1.2650	0.2059
0.6750	0.0645***	0.0211	3.0506	0.0023	0.0266	0.0198	1.3421	0.1796
0.7000	0.0716***	0.0232	3.0829	0.0021	0.0294	0.0252	1.1682	0.2428
0.7250	0.0824***	0.0230	3.5883	0.0003	−0.0062	0.0278	−0.2221	0.8242
0.7500	0.1026***	0.0227	4.5305	0.0000	0.0036	0.0195	0.1822	0.8554
0.7750	0.1039***	0.0260	3.9912	0.0001	0.0183	0.0161	1.1333	0.2571
0.8000	0.1248***	0.0296	4.2158	0.0000	0.0219	0.0292	0.7474	0.4549
0.8250	0.1369***	0.0313	4.3808	0.0000	0.0189	0.0325	0.5821	0.5605
0.8500	0.1404***	0.0337	4.1680	0.0000	0.0042	0.0322	0.1304	0.8963
0.8750	0.1184***	0.0393	3.0135	0.0026	0.0187	0.0405	0.4626	0.6437
0.9000	0.1295***	0.0339	3.8171	0.0001	0.0033	0.0260	0.1272	0.8988

Note: Due to the limited space, the results do not show the regression coefficients of market covariables, and only list the effects of positive and negative network factors at different quantiles.

Table C2
The TENQR result of the B&R stock market index returns on the network factor from the West Asia and North Africa region.

Quantile	The positive network factors f^+				The negative network factors f^-			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.1000	0.2039***	0.0410	4.9762	0.0000	0.0396	0.0426	0.9303	0.3523
0.1250	0.1572***	0.0376	4.1774	0.0000	0.0287	0.0353	0.8128	0.4164
0.1500	0.1417***	0.0350	4.0482	0.0001	−0.0142	0.0327	−0.4328	0.6652
0.1750	0.1207***	0.0326	3.7002	0.0002	0.0122	0.0299	0.4076	0.6836
0.2000	0.1293***	0.0296	4.3638	0.0000	0.0004	0.0283	0.0124	0.9901
0.2250	0.1223***	0.0260	4.7115	0.0000	0.0082	0.0244	0.3361	0.7368
0.2500	0.1195***	0.0247	4.8430	0.0000	0.0064	0.0224	0.2849	0.7757
0.2750	0.1065***	0.0240	4.4447	0.0000	0.0172	0.0228	0.7522	0.4520
0.3000	0.1081***	0.0215	5.0396	0.0000	0.0290	0.0218	1.3327	0.1827
0.3250	0.0971***	0.0209	4.6447	0.0000	0.0193	0.0196	0.9823	0.3260
0.3500	0.0784***	0.0210	3.7366	0.0002	0.0228	0.0205	1.1118	0.2662
0.3750	0.0700***	0.0201	3.4769	0.0005	0.0319*	0.0184	1.7363	0.0826
0.4000	0.0663***	0.0196	3.3816	0.0007	0.0269	0.0177	1.5257	0.1271
0.4250	0.0613***	0.0185	3.3093	0.0009	0.0312*	0.0175	1.7850	0.0743
0.4500	0.0614***	0.0181	3.3830	0.0007	0.0337**	0.0167	2.0184	0.0436
0.4750	0.0614***	0.0177	3.4625	0.0005	0.0315*	0.0162	1.9439	0.0519
0.5000	0.0632***	0.0184	3.4440	0.0006	0.0315*	0.0173	1.8249	0.0681
0.5250	0.0625***	0.0192	3.2614	0.0011	0.0380**	0.0186	2.0453	0.0409
0.5500	0.0481**	0.0191	2.5218	0.0117	0.0338*	0.0185	1.8263	0.0678
0.5750	0.0405**	0.0193	2.0931	0.0364	0.0327*	0.0195	1.6811	0.0928
0.6000	0.0294	0.0196	1.4990	0.1339	0.0420**	0.0191	2.1987	0.0279
0.6250	0.0378*	0.0200	1.8879	0.0591	0.0368*	0.0190	1.9397	0.0525
0.6500	0.0333	0.0213	1.5635	0.1180	0.0370*	0.0206	1.7945	0.0728
0.6750	0.0198	0.0218	0.9077	0.3641	0.0313	0.0215	1.4606	0.1442
0.7000	0.0224	0.0221	1.0169	0.3093	0.0406*	0.0223	1.8186	0.0690
0.7250	0.0230	0.0223	1.0314	0.3024	0.0386*	0.0234	1.6513	0.0987
0.7500	0.0251	0.0228	1.1002	0.2713	0.0355	0.0239	1.4842	0.1378
0.7750	0.0268	0.0239	1.1214	0.2622	0.0421*	0.0231	1.8230	0.0683
0.8000	0.0364	0.0293	1.2450	0.2132	0.0447*	0.0238	1.8743	0.0609
0.8250	0.0308	0.0308	1.0009	0.3169	0.0408	0.0311	1.3129	0.1892
0.8500	0.0281	0.0296	0.9500	0.3422	0.0515*	0.0290	1.7730	0.0763

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Table C2 (*continued*)

Quantile	The positive network factors f^+				The negative network factors f^-			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.8750	0.0140	0.0317	0.4409	0.6593	0.0511**	0.0250	2.0459	0.0408
0.9000	0.0107	0.0123	0.8769	0.3806	0.0788***	0.0279	2.8236	0.0048

Note: Due to the limited space, the results do not show the regression coefficients of market covariables, and only list the effects of positive and negative network factors at different quantiles.

Table C3
The TENQR result of the B&R stock market index returns on the network factor from the Central and Eastern Europe region.

Quantile	The positive network factors f^+				The negative network factors f^-			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.1000	0.0745	0.0459	1.6225	0.1047	0.0902**	0.0435	2.0738	0.0381
0.1250	0.0719**	0.0360	1.9975	0.0458	0.0536	0.0366	1.4654	0.1429
0.1500	0.0739***	0.0329	2.2476	0.0246	0.0516*	0.0306	1.6841	0.0922
0.1750	0.0912***	0.0318	2.8705	0.0041	0.0465	0.0301	1.5453	0.1223
0.2000	0.0779***	0.0261	2.9850	0.0028	0.0374	0.0231	1.6187	0.1056
0.2250	0.0675***	0.0247	2.7316	0.0063	0.0318	0.0229	1.3868	0.1655
0.2500	0.0711***	0.0242	2.9302	0.0034	0.0211	0.0213	0.9898	0.3223
0.2750	0.0792***	0.0218	3.6386	0.0003	0.0244	0.0198	1.2318	0.2180
0.3000	0.0763***	0.0205	3.7250	0.0002	0.0221	0.0191	1.1592	0.2464
0.3250	0.0775***	0.0195	3.9820	0.0001	0.0230	0.0167	1.3747	0.1693
0.3500	0.0740***	0.0197	3.7509	0.0002	0.0177	0.0169	1.0486	0.2944
0.3750	0.0788***	0.0189	4.1634	0.0000	0.0217	0.0161	1.3510	0.1767
0.4000	0.0667***	0.0184	3.6292	0.0003	0.0161	0.0151	1.0671	0.2860
0.4250	0.0622***	0.0169	3.6710	0.0002	0.0172	0.0154	1.1152	0.2648
0.4500	0.0580***	0.0165	3.5255	0.0004	0.0201	0.0150	1.3450	0.1787
0.4750	0.0601***	0.0154	3.9078	0.0001	0.0181	0.0143	1.2670	0.2052
0.5000	0.0557***	0.0159	3.5119	0.0004	0.0184	0.0150	1.2294	0.2189
0.5250	0.0537***	0.0154	3.4756	0.0005	0.0148	0.0147	1.0108	0.3121
0.5500	0.0553***	0.0162	3.4024	0.0007	0.0012	0.0152	0.0809	0.9355
0.5750	0.0539***	0.0167	3.2223	0.0013	−0.0054	0.0167	−0.3256	0.7448
0.6000	0.0546***	0.0165	3.3045	0.0010	−0.0040	0.0145	−0.2761	0.7825
0.6250	0.0567***	0.0174	3.2574	0.0011	0.0029	0.0150	0.1967	0.8441
0.6500	0.0531***	0.0182	2.9274	0.0034	0.0046	0.0160	0.2905	0.7715
0.6750	0.0574***	0.0186	3.0891	0.0020	0.0021	0.0126	0.1647	0.8692
0.7000	0.0593***	0.0200	2.9681	0.0030	0.0092	0.0171	0.5384	0.5903
0.7250	0.0659***	0.0197	3.3454	0.0008	0.0044	0.0183	0.2430	0.8080
0.7500	0.0790***	0.0239	3.2999	0.0010	0.0030	0.0208	0.1446	0.8850
0.7750	0.0768***	0.0244	3.1471	0.0017	−0.0005	0.0207	−0.0263	0.9790
0.8000	0.0620**	0.0254	2.4374	0.0148	0.0015	0.0225	0.0684	0.9455
0.8250	0.0835***	0.0293	2.8460	0.0044	0.0015	0.0290	0.0527	0.9580
0.8500	0.0739**	0.0320	2.3087	0.0210	−0.0027	0.0258	−0.1055	0.9160
0.8750	0.0682**	0.0314	2.1708	0.0300	0.0103	0.0297	0.3468	0.7287
0.9000	0.0550	0.0365	1.5061	0.1321	−0.0008	0.0387	−0.0209	0.9833

Note: Due to the limited space, the results do not show the regression coefficients of market covariables, and only list the effects of positive and negative network factors at different quantiles.

Table C4
The TENQR result of the B&R stock market index returns on the network factor from the B&R region.

Quantile	The positive network factors f^+				The negative network factors f^-			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.1000	0.1803***	0.0311	5.7953	0.0000	0.0034	0.0261	0.1300	0.8965
0.1250	0.1789***	0.0252	7.0961	0.0000	−0.0063	0.0238	−0.2670	0.7895
0.1500	0.1698***	0.0254	6.6962	0.0000	−0.0066***	0.0012	−5.6330	0.0000
0.1750	0.1462***	0.0231	6.3392	0.0000	0.0051	0.0183	0.2801	0.7794
0.2000	0.1321***	0.0219	6.0429	0.0000	−0.0042	0.0200	−0.2113	0.8326
0.2250	0.1378***	0.0191	7.1994	0.0000	0.0016	0.0175	0.0890	0.9291
0.2500	0.1348***	0.0168	8.0035	0.0000	0.0050	0.0149	0.3378	0.7355
0.2750	0.1266***	0.0161	7.8768	0.0000	0.0071	0.0137	0.5185	0.6041
0.3000	0.1291***	0.0164	7.8657	0.0000	0.0115	0.0126	0.9091	0.3633
0.3250	0.1293***	0.0159	8.1388	0.0000	0.0072	0.0127	0.5689	0.5694
0.3500	0.1179***	0.0149	7.9348	0.0000	0.0064	0.0110	0.5770	0.5639
0.3750	0.1122***	0.0143	7.8655	0.0000	0.0092	0.0130	0.7085	0.4787
0.4000	0.0970***	0.0145	6.7023	0.0000	0.0096	0.0119	0.8080	0.4191
0.4250	0.0901***	0.0140	6.4447	0.0000	0.0082	0.0103	0.7901	0.4295
0.4500	0.0854***	0.0134	6.3850	0.0000	0.0076	0.0107	0.7041	0.4813

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Table C4 (*continued*)

Quantile	The positive network factors f^{+}				The negative network factors f^{-}			
	coefficient	std. Error	*t* statistic	*p*-value	coefficient	std. Error	*t* statistic	*p*-value
0.4750	0.0824***	0.0128	6.4442	0.0000	0.0074	0.0091	0.8166	0.4142
0.5000	0.0778***	0.0128	6.0768	0.0000	0.0101	0.0084	1.2047	0.2283
0.5250	0.0803***	0.0131	6.1515	0.0000	0.0059	0.0111	0.5261	0.5988
0.5500	0.0814***	0.0131	6.2061	0.0000	0.0098	0.0113	0.8685	0.3851
0.5750	0.0797***	0.0132	6.0237	0.0000	0.0126	0.0112	1.1281	0.2593
0.6000	0.0760***	0.0139	5.4591	0.0000	0.0094	0.0117	0.8088	0.4186
0.6250	0.0777***	0.0144	5.4046	0.0000	0.0169	0.0124	1.3598	0.1739
0.6500	0.0830***	0.0145	5.7346	0.0000	0.0153	0.0130	1.1793	0.2383
0.6750	0.0868***	0.0151	5.7386	0.0000	0.0205	0.0125	1.6447	0.1000
0.7000	0.0856***	0.0155	5.5242	0.0000	0.0277***	0.0124	2.2390	0.0252
0.7250	0.0876***	0.0153	5.7259	0.0000	0.0309***	0.0092	3.3693	0.0008
0.7500	0.0935***	0.0168	5.5845	0.0000	0.0287***	0.0039	7.3877	0.0000
0.7750	0.1079***	0.0185	5.8210	0.0000	0.0318	0.0156	2.0343	0.0419
0.8000	0.1066***	0.0193	5.5293	0.0000	0.0383**	0.0162	2.3704	0.0178
0.8250	0.1300***	0.0212	6.1410	0.0000	0.0299*	0.0179	1.6638	0.0962
0.8500	0.1218***	0.0210	5.7907	0.0000	0.0288	0.0186	1.5499	0.1212
0.8750	0.1339***	0.0246	5.4488	0.0000	0.0154	0.0196	0.7868	0.4314
0.9000	0.1351***	0.0285	4.7443	0.0000	0.0178	0.0251	0.7068	0.4797

Note: Due to the limited space, the results do not show the regression coefficients of market covariables, and only list the effects of positive and negative network factors at different quantiles.

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