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Investigating the dynamics of crisis transmission channels: A comparative analysis

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This paper analyzes the growing complexity of cross-market interdependence during financial crises. From macroeconomic, investor constraint, and quantitative easing policy perspectives, we investigate crisis transmission channels across major stock markets by comparing the 2008 global financial crisis, the 2020 COVID-19 crisis, and the 2022 Russo-Ukrainian crisis. We find that lower-tail contagion is mainly driven by the wealth effect and upper-tail contagion is mainly driven by the portfolio rebalancing, and shed light on the underlying dynamic mechanisms, such as credit spreads, risk aversion, economic policy uncertainty, and quantitative easing policy. Additionally, we show the impact of macroeconomic fundamentals, investor sentiment, and quantitative easing policy on lower-tail and upper-tail financial contagion.

1. Introduction

The rapid outbreak of COVID-19 and the subsequent rapid spread of financial crisis in 2020 strikingly highlight the similarity between the virus spread in the population and the financial crisis spread across countries. Not surprisingly, "contagion" – an epidemiological term – has been widely adopted to describe the nature of financial crises. As a financial systemic risk, financial contagion has attracted substantial attention from investors, regulators, and scholars (Apergis et al., 2019; Beltratti and Stulz, 2019; Gupta, 2019; Khabazian and Peng, 2019; Fan et al., 2020; Liu et al., 2020; Abduraimova, 2022; Martins and Amado, 2022; Wiersema et al., 2023). While the analogous use of "contagion" in the financial crisis is intuitive, the determinants and transmission mechanisms of financial contagion are convoluted.

The twenty-first century has already witnessed a spate of financial crises, including the 2008 global financial crisis that originated in the US subprime mortgage market and spread globally with devastating effects, and the dramatic 2020 cross-market crash triggered by the unexpected COVID-19 pandemic, followed by a V-shaped rebound due to the unprecedented reactions from central banks and governments. Although both crises were phenomenal, they occurred in different cross-market dynamics. In particular, 2020 was a year of the worst global pandemic since 1918 and the most rapid economic collapse since World War II. This necessitates a revisiting and reconsideration of all aspects of financial contagion research, particularly the possible changes in the transmission channels of financial contagion in the major crises.

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The development and subsequent reversal in the globalization trend (Balsa-Barreiro et al., 2020), together with greater global stock market integration (Kim et al., 2005), have led to more complex dynamics of cross-market interdependence and greater contagious risks from external shocks. For instance, in the years following the 2008 global financial crisis, the world saw an increasing disparity in the economic deglobalization process. After decades of intensifying globalization, the rise of deglobalization processes worldwide, such as Brexit, trade wars, and the ongoing COVID-19 pandemic, has caused a trend reversal in globalization. However, financial market integration continues to increase across markets, with emerging markets quickly catching up with developed markets (Sehgal et al., 2017; Akbari et al., 2020). The change in dynamics in the cross-market environment potentially leads to a change in crisis transmission channels. Despite its importance, transmission channels of financial contagion, in a changing cross-market environment, are still indeterminate.

As financial contagion is usually characterized by extreme risk events and tail dependence compared to traditional correlation (Wang et al., 2021), we use upper-upper and lower-lower tail dependence to measure upper-tail and lower-tail contagion, respectively. Motivated by the work of Boyer et al. (2006) on investor-induced contagion originating from wealth effect or portfolio rebalancing, we identify the main contagion channels in upper and lower tails as driven by the wealth effect or portfolio rebalancing in both the 2008 global financial crisis and the 2020 COVID-19 crisis. The liquidity channel for crisis spread, noted in Petmezas and Santamaria (2014), is crucial for the wealth effect and portfolio rebalancing and thus we further analyze the crisis transmission mechanism through credit market liquidity, risk aversion, economic policy uncertainty (EPU), and quantitative easing (QE) policy, which provide a measure of market liquidity. To explore the potential differences in financial contagion channels in different market conditions and stages of development, we divide the crisis period into melt-down and melt-up periods and markets into emerging and developed markets. We also examine the relationship between flight-to-quality, macroeconomic fundamentals, investor sentiment, and QE policy with lower-tail and upper-tail financial contagion.

Specifically, we first construct a dynamic mixture copula-EVT (extreme value theory) model to quantitatively investigate the asymmetric and non-linear corner (upper-upper and lower-lower) and diagonal (upper-lower and lower–upper) tail dependence in the context of financial contagion and flight-to-quality (safety), respectively. The constructed dynamic mixture copula-EVT model incorporates both the tail behavior of extreme market conditions and the complex dependency structure among different markets, which enable us to precisely measure financial contagion, especially for complex tail dependence, including non-linearity, asymmetry, and dynamic patterns. The constructed model also provides an effective analysis of financial contagion channels. Next, a non-linear financial contagion network is proposed based on the dynamic mixture copula-EVT model, which provides a powerful tool to analyze the topological features of financial contagion within the financial system. Finally, we explore the dynamics of transmission channels for the two major financial crises under different settings.

We employ the constructed dynamic mixture copula-EVT model and the proposed non-linear financial contagion network to investigate the inner mechanisms of financial contagion across 22 major emerging and developed stock markets. Our empirical results show evidence of both lower-tail contagion and upper-tail contagion. The lower-tail contagion is more prone to occur than the upper-tail contagion for both the 2008 global financial crisis and the 2020 COVID-19 financial crisis. Interestingly, our work shows that the wealth effect is the main lower-tail contagion channel and the portfolio rebalancing is the main upper-tail contagion channel for both crises. Moreover, we further reveal the dynamic transmission mechanism of credit spreads, risk aversion, EPU, and QE policy on the lower-tail contagion sourced by wealth effect and the upper-tail contagion sourced by portfolio rebalancing. Additionally, we also show evidence of dynamic influence of macroeconomic fundamentals, investor sentiments, and QE policy on financial contagion in both lower-tail and upper-tail during the two crises. To strengthen the reliability of our findings, we further examined the financial contagion and contagion channels for the 2022 financial crisis caused by the Russo-Ukrainian war. The change of dynamics in financial contagion transmission channels is clearly important to the financial systems and global economy and has important implications for portfolio, risk management, and public policy strategies.

The contributions of this work can be unfolded as follows: Unlike prior literature, which often focuses solely on the market crash itself when studying financial contagion, we conduct an in-depth investigation of the dynamic transmission channels for comparison between financial crises. Specifically, we further explore both the asymmetric upper- and lower-tail contagion channels under several different settings: during periods of both market melt-down and melt-up, across emerging and developed markets, and the relationship between flight-to-quality, macroeconomic fundamentals, investor sentiments, and QE policy with financial contagion. Moreover, we reveal the dynamic transmission mechanism of lower-tail contagion sourced by wealth effect and upper-tail contagion sourced by portfolio rebalancing, and provide evidence of the different performance of macroeconomic fundamentals, investor sentiments, and QE policy on financial contagion. This in-depth examination of the dynamic transmission mechanism of financial crises has great practical importance for both investors, to take preventive measures against the spread of crises, and for policymakers, to regulate the financial markets and manage market expectations.

The rest of this paper is structured as follows: Section 2 reviews the related literature. Section 3 introduces the proposed methodology. Section 4 describes the data and empirically investigates the contagion mechanisms for the crises. Section 5 conducts a further analysis of crisis transmission and provides robustness checks. Finally, Section 6 concludes.

2. Literature review

Financial contagion is defined as a statistically significant increase in cross-market linkages after the occurrence of extreme shocks (Forbes and Rigobon, 2002). Numerous empirical methods have been proposed to identify the existence of financial contagion, including conditional correlations (Forbes and Rigobon, 2002), the multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model (Niţoi and Pochea, 2019), the quantile regression approach (Iwanicz-Drozdowska et al., 2021; Ye et al., 2017), and the vector autoregression-based approach (Dungey et al., 2020). However, these methods cannot simultaneously capture the non-linear and entire dynamic tail dependence existing between any markets, which are both evident and critical for financial contagion. To overcome this, copula models have been proposed to capture the complex dynamics between financial markets and have been widely used to test the existence of financial contagion (c.f., Rodriguez, 2007; Horta et al., 2016; Alcock and Sinagl, 2022; Gong et al., 2022b). To accurately describe the tail behavior of the marginal distribution and the complex tail dependence, the dynamic copula-EVT model is constructed to detect financial contagion phenomenon and is proved to be a good tool for measuring financial contagion (Wang et al., 2021).

Previous literature has systematically investigated financial contagion and contagion mechanisms during several major stock market crises from the last century, including the 1987 US stock market crash, the 1994 Mexican peso crisis, the 1997 Asian financial crisis, and the 1998 Russian default crisis (Forbes and Rigobon, 2002; Boyer et al., 2006; Yang and Bessler, 2008). In examining these early crises, numerous theoretical and empirical studies have suggested possible channels for crisis transmission from both macroeconomic fundamentals and investor constraint perspectives. In particular, economic models imply that international trade linkages and foreign direct investment (FDI) could transmit a shock from one country to another. Macroeconomic fundamentals generally tend to explain a country's proneness to financial contagion before the shock (Calvo and Reinhart, 1996), while investor-induced contagion channels tend to explain transmission mechanisms during the shock (Boyer et al., 2006). Boyer et al., 2006 suggest that the investor-induced contagion stems from either the portfolio rebalancing behavior proposed by Kodres and Pritsker (2002) or the wealth effect proposed by Kyle and Xiong (2001), and they show a wealth effect for emerging markets and portfolio rebalancing for developed markets during the 1997 Asian financial crisis. Inspired by this work, Horta et al. (2016) and Jayech (2016) provide evidence of portfolio rebalancing as the major channel between stock markets. However, these works do not further explore the transmission mechanism behind contagion due to the wealth effect or portfolio rebalancing, and research on financial contagion is limited. To our knowledge, only Petmezas and Santamaria (2014) analyze the effect of credit market liquidity and the level of risk aversion on the investor-induced contagion channel between stock and bond markets. Additionally, QE policy has also been shown to drive the spread of financial crisis across markets (Yang and Zhou, 2017; Iwanicz-Drozdowska et al., 2021).

The 2008 global financial crisis and the 2020 COVID-19 pandemic have generated significant interest among scholars, as they have had significant impacts on the macroeconomies of various countries and the global financial markets. Research on the 2008 financial crisis is extensive, focusing on the influence of the crisis on the financial markets (e.g. Aloui et al., 2011; Wang et al., 2021; Hattori, 2023; Heil et al., 2022). One stream of research focuses on the analysis of crisis transmission channels in a single crisis event, rather than the evolution of crises over time (e.g. Apergis et al., 2019; Gupta, 2019; Liu et al., 2020; Abduraimova, 2022). On the other hand, much research on COVID-19 has focused on its impact on the financial market and real economy (e.g. Bizjak et al., 2022; Chen et al., 2022; Koijen and Yogo, 2022; Agoraki et al., 2023). The financial contagion aspect of the COVID-19 crisis has received relatively little attention (e.g. Wang et al., 2021; Gong et al., 2022a; Heil et al., 2022; Liu et al., 2022; Qiao and Han, 2023). We aim to fill this gap in the literature by examining the evolution of the financial contagion channel, using the 2008 global financial crisis, the COVID-19 crisis, and the recent Russo-Ukrainian crisis as comparative testing grounds.

3. Methodology

3.1. The dynamic mixture Copula-EVT model

Copulas are flexible and effective tools for modeling complex dependence among uncertainties (Wang and Dyer, 2012; Cherubini et al., 2011; Abbas, 2013; Christoffersen and Langlois, 2013; Abbas and Sun, 2017; Manzo and Picca, 2020; Gong et al., 2022b), such as non-linearity, asymmetry, dynamic pattern, and tail dependence, which are often neglected by the extant financial contagion literature. A copula is a multivariate cumulative distribution function whose marginal distributions are uniform on the interval [0, 1]. According to Sklar's (Sklar, 1959) theorem, every two-dimensional joint distribution function $F(z_1, z_2)$ of two continuous random variables (Z_1, Z_2) can be written as a copula function,

$$F(z_1, z_2) = C(F_1(z_1), F_2(z_2)) \tag{1}$$

where $F_1(z_1)$ and $F_2(z_2)$ are the marginal distribution functions, and C is the copula function that describes the dependence structure between Z_1 and Z_2. Assuming the C is differentiable, the joint density of the variables Z_1 and Z_2 is given by

$$f(z_1, z_2) = c(u, v) f_1(z_1) f_2(z_2), \tag{2}$$

where $u = F_1(z_1), v = F_2(z_2), c(u,v) = \partial^2 C(u,v)/\partial u \partial v$ is the copula density function, and $f_1(\cdot)$ and $f_2(\cdot)$ are the marginal densities of the variables Z_1 and Z_2. Hence, any bivariate density function can be represented by the product of two marginal distributions and a copula density. The log-likelihood function is:

$$\log f(z_1, z_2) = \log c(u, v) + \log f_1(z_1) + \log f_2(z_2). \tag{3}$$

According to Eq. (3), we can use a two-step procedure to estimate the parameters of $f(z_1, z_2)$. In the first stage, we estimate the parameter set θ_i of the marginal distributions separately by maximum likelihood, that is, $\hat{\theta}_i = \arg\max \sum_{t=1}^{T} \log f_i(z_{i,t}; \theta_i)$, where $i = 1, 2$ and T is the sample size. In the second stage, we estimate the parameter set δ of the copula by solving the following problem: $\hat{\delta} = \arg\max \sum_{t=1}^{T} \log c\left(F_1(z_{1,t}, \hat{\theta}_1), F_2(z_{2,t}, \hat{\theta}_2); \delta\right)$.

3.1.1. Marginal distribution modeling

To overcome the disadvantage of GARCH-type models in tail distribution modeling (Koliai, 2016; Wang et al., 2021), we model the marginal distribution with EVT in combination with the GARCH-type model. More specifically, the Generalized Pareto Distribution (GPD) is used to specify the extreme values of the standardized residuals from the AR(1)-GJR(1,1) model with skewed-*t* distribution (Wang et al., 2021). To do so, we use the peaks over threshold method according to which, the distribution of excess returns (i.e. return minus extreme threshold) follows the GPD. Following Koliai (2016), we use the 10th (lower-tail) and 90th (upper-tail) percentiles of the standardized residual series as the extreme thresholds, and model the tails of the marginal distributions beyond the extreme thresholds with GPD. The standardized residuals falling between the extreme thresholds are modeled using the empirical cumulative distribution function. The marginal distribution is thus given as follows:

$$F_i(\hat{Z}_i) = \begin{cases} \frac{N_{\mu_{i,L}}}{N}\left(1 - \xi_{i,L}\frac{\hat{Z}_i - \mu_{i,L}}{\beta_{i,L}}\right)^{-1/\xi_{i,L}}, & \text{if} \hat{Z}_i < \mu_{i,L}, \\ \varphi(\hat{Z}_i), & \text{if} \, \mu_{i,L} \leqslant \hat{Z}_i \leqslant \mu_{i,U}, \\ 1 - \frac{N_{\mu_{i,U}}}{N}\left(1 + \xi_{i,U}\frac{\hat{Z}_i - \mu_{i,U}}{\beta_{i,U}}\right)^{-1/\xi_{i,U}}, & \text{if} \hat{Z}_i > \mu_{i,U}, \end{cases}$$

where $\hat{Z}_i$ is the standardized residual series for stock index i, $\mu_{i,L}$ and $\mu_{i,U}$ are the lower and upper-tail thresholds, respectively; $N_{\mu_{i,L}}$ ($N_{\mu_{i,U}}$) is the number of observations below (above) the threshold $\mu_{i,L}$ ($\mu_{i,U}$); $\beta_{i,L}$ and $\xi_{i,L}(\beta_{i,U}, \xi_{i,U})$ are the scale parameter and the shape parameter of the GPD on the lower (upper) tail, respectively; N is the number of observations; and φ is the empirical cumulative distribution function about $\hat{Z}_i$.

3.1.2. Dynamic mixture copula function modeling

The nature of financial contagion requires the exploration of conditional extreme dependence rather than the widely used correlation between different markets in the literature (Rodriguez, 2007; Ye et al., 2017). Motivated by this fact, we use the corner tail dependence which captures the circumstances when both markets move in the same direction (either boom or crash) at the extreme dependence as the measure of financial contagion. During the financial turmoil, it is also possible to observe the flight-to-quality phenomenon occurring when investors sell what they perceive to be higher-risk investments and purchase perceived safe haven investments in a market crash. Therefore, we propose to use the diagonal tail dependence as the measure of potential flight-to-quality, i.e., the negative extreme dependence across markets during the financial contagion. More specifically, for two random variables Z_1 and Z_2 with marginal distribution functions F_1 and F_2, respectively, the four tail dependence is measured as

$$\lambda_{LL} = \lim_{u \to 0} P(Z_1 < F_1^{-1}(u) | Z_2 < F_2^{-1}(u)) = \lim_{u \to 0} \frac{C(u,u)}{u}, \tag{4}$$

$$\lambda_{UU} = \lim_{u \to 1} P(Z_1 \geqslant F_1^{-1}(u) | Z_2 \geqslant F_2^{-1}(u)) = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1 - u}, \tag{5}$$

$$\lambda_{LU} = \lim_{u \to 1} P(Z_1 > 1 - F_1^{-1}(u) | Z_2 \leqslant F_2^{-1}(u)) = \lim_{u \to 1} \frac{1 - u - C(1 - u, u)}{1 - u}, \tag{6}$$

$$\lambda_{UL} = \lim_{u \to 0} P(Z_1 \leqslant F_1^{-1}(u) | Z_2 > 1 - F_2^{-1}(u)) = \lim_{u \to 0} \frac{u - C(1 - u, u)}{u}, \tag{7}$$

where $\lambda_{LL}, \lambda_{UU}, \lambda_{LU}$, and λ_{UL} are the lower-lower, upper-upper, lower–upper and upper-lower tail dependence coefficients (TDCs), respectively. They belong to $[0, 1]$. Z_1 and Z_2 are asymptotically independent in tails if the four TDCs are all equal 0; otherwise, the larger the TDC values, the stronger the corresponding tail dependence.

The next step is to decide the functional form of the copula. As the dynamic mixture copula is more flexible and performs better than the single copula, it has been suggested in the literature to describe the dynamic and asymmetric tail dependence among financial markets (c.f., Kang et al., 2010; Jayech, 2016; Chabi-Yo et al., 2018). In this work, the dynamic mixture copula is adopted to estimate the dynamic tail dependence. The dynamic mixture copula is defined as a linear combination of several dynamic single copulas (c.f. Supper et al., 2020). For instance, a dynamic mixture copula $C_{M,t}$ combined by two dynamic single copulas is expressed as

$$C_{M,t}(u,v) = \omega C_{1,t}(u,v) + (1-\omega)C_{2,t}(u,v) \tag{8}$$

where $u = F_1(z_1)$ and $v = F_2(z_2)$; $C_{1,t}$ and $C_{2,t}$ are two single dynamic copulas; and $\omega \in [0,1]$ is the weight parameter.

The dynamic mixture copulas significantly expand the most common asymmetric copulas such as the Clayton and Gumbel copulas to capture the complex asymmetric extreme dependence across markets (Liu et al., 2017). Three dynamic mixture copulas and their rotation-variation are respectively constructed to model corner and diagonal tail dependence based on the dynamic Clayton and Gumbel copulas, that are widely used and perform well in modelling tail dependence (Horta et al., 2016; Jayech, 2016; Wang et al., 2018). The three constructed dynamic mixture copulas and their rotation-variation are described in details in online Appendix A.

3.2. Network analysis of financial contagion

3.2.1. Financial contagion detection

According to Forbes and Rigobon (2002), if financial contagion exists between any two markets, then the correlation between them would increase significantly during crisis periods compared to tranquil periods. Unfortunately, Forbes and Rigobon (2002) only consider linear correlation and ignore the non-linearity and asymmetric tail dependence. In this work, the upper-upper and lower-lower tail dependence achieved by the dynamic mixture copula-EVT model are used as the measures of financial contagion to incorporate the complex tail dependence including non-linearity, asymmetry, and dynamic pattern as well as statistically account for the extreme risk of financial crises (Rodriguez, 2007). We formulate the hypothesis to examine the existence of lower-tail or upper-tail contagion as follows:

$$\begin{cases} H_0 : \bar{\lambda}_{crisis} \leqslant \bar{\lambda}_{pre-crisis} \\ H_1 : \bar{\lambda}_{crisis} > \bar{\lambda}_{pre-crisis} \end{cases} \tag{9}$$

where $\bar{\lambda}_{crisis}$ and $\bar{\lambda}_{pre-crisis}$ are the mean dependence coefficients for crisis and pre-crisis periods, respectively.

According to Apergis et al. (2019), the Fisher's z-transformation is used to test the existence of financial contagion. If there is no significant difference between the two dependence coefficients, the difference between the transformed dependence coefficients is approximately normally distributed, that is,

$$z = z_1 - z_2 \sim N\left(0, \frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}\right), \tag{10}$$

where $z_1 = \frac{1}{2}\ln\frac{1+\bar{\lambda}_{crisis}}{1-\bar{\lambda}_{crisis}}$, $z_2 = \frac{1}{2}\ln\frac{1+\bar{\lambda}_{pre-crisis}}{1-\bar{\lambda}_{pre-crisis}}$, n_1 and n_2 are the observations of the sample during the pre-crisis and crisis periods, respectively. Right-sided test is performed for the hypothesis. If the z-statistic is statistically significant, then there is financial contagion between the two markets.

3.2.2. Financial contagion network

The complex network is a collection of nodes linked by edges and the complex links between financial markets are shown as a complex network (Chen et al., 2016; Wang et al., 2017; Schuldenzucker et al., 2020; Dées and Galesi, 2021; He and Hamori, 2021; Raddant and Kenett, 2021). In this study, we propose a new financial contagion network based on the constructed dynamic mixture copula-EVT model, and investigate several structural metrics to quantify the topological features of the financial contagion network. Let $G(V,E)$ be an undirected financial contagion network, where $V = \{1, 2, \cdots, N\}$ is the set of nodes and E is the set of edges between the nodes. In our network, a node is a stock market index and an undirected edge represents the existence of financial contagion between markets. For any two markets $i, j \in V$, we draw an undirected edge between i and j if there is financial contagion at the 10% confidence level. E is the undirected binary connection matrix for all i and j such that

$$E_{i,j} = \begin{cases} 1, \text{if there is financial contagion between two different markets } i \text{ and } j, \\ 0, \text{otherwise.} \end{cases} \tag{11}$$

Furthermore, following Wang et al. (2017) and Liu et al. (2020), we investigate three metrics to analyze the structure characteristics of the financial contagion network, including network density, node degree, and clustering coefficient as described in details in online Appendix B.

4. Data description and empirical analysis

4.1. Data description

Considering the availability of data on macroeconomic fundamentals and investor sentiments, our data set consists of 22 major emerging and developed markets across North America, Europe, Latin America, South America, Asia, Africa, and Oceania as shown in Table 1.[1] The combination of these stock markets covers the significant majority of the world's stock market capitalization.

The complete sample period spans from April 8, 2005 to January 24, 2022.[2] As the interest of this study is to explore the differences of the financial contagion between the 2008 and 2020 financial crises, we focus on two sub-sample periods for the 2008 and 2020 financial crises. The sample period for the 2008 financial crisis is defined as April 8, 2005 through December 7, 2009.[3] Following Horta et al. (2016), August 1, 2007 is used to split the sample into pre-crisis and crisis periods. For comparison, the full sample of the 2020 financial crisis spans the period from January 1, 2018 to January 24, 2022. Since the Wuhan municipal commission released a briefing on its website about a pneumonia outbreak on December 31, 2019 and the number of infected cases has been reported on a daily basis thereafter, we define the pre-crisis period as January 1, 2018 through December 30, 2019 and define the crisis period as December 31, 2019 through January 24, 2022. We also examine different split of the pre-crisis and crisis periods in our robustness check. To avoid the measurement error from the nonsynchronous trading problem in different markets, the returns for all stock indexes are defined as the rolling-average of two-day logarithmic returns and the logarithmic return is calculated as $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the closing price at day t for stock index i. The data for stock indexes are obtained from the Wind database.

The descriptive statistics on the daily stock index returns in the full sample are summarized in Table C.1 (see online Appendix C). All returns are negatively skewed and they exhibit significant excess kurtosis, implying a non-normal distribution and the presence of extreme events. The non-normal distribution assumption is also supported by the Jarque–Bera test. Overall, all returns exhibit the asymmetric and extreme behavior. In addition, the augmented Dickey–Fuller (ADF) test results indicate that all return series are stationary at the 1% confidence level. Finally, the Ljung–Box Q and ARCH test show signs of autocorrelation and heteroscedasticity. To conclude, the dynamic mixture copula-EVT model is a good choice to estimate the complex tail dependence between markets.

4.2. Empirical analysis

The global economic structure has significantly changed since the 2008 financial crisis. On the one hand, after the 2008 financial crisis, global cross-border capital flows decreased sharply (McKinsey Global Institute, 2018)[4] and cross-border lending was reduced owing to regulatory tightening in the financial sector (Lane and Milesi-Ferretti, 2018). On the other hand, the change in economic structure is strikingly different between the developed markets and emerging markets. The type of 2008 crisis is also very different from that of the 2020 financial crisis, which potentially could influence the transmission of crises. The 2008 financial crisis was a financial shock that caused global financial asset prices to fall sharply, financial institution to fail and financial markets to collapse, and it took a severe toll on the real economy. In comparison, the 2020 financial crisis quickly evolved from a provincial health care crisis to a global meltdown. To contain the rapid spread of COVID-19, some stringent containment efforts imposed by policymakers have been taken, including economic lockdowns, transportation bans, and restrictions on public assembly. These efforts have shut down large sections of the global economy and brought the world economy to a standstill, affecting financial markets in unseen ways. As a result, the severity of the 2020 financial crisis already exceeds that of the 2008 financial crisis (World Economic Outlook, 2020).[5]

The change of dynamics in the cross-market environment and the different natures of these two financial crises necessitate the examination of potential changes of crisis transmission channels. The constructed dynamic mixture copula-EVT model and the proposed non-linear tail financial contagion network approach are employed to investigate the spread of both the 2008 and 2020 crises across these 22 major stock markets. Specifically, we first detect the existence of lower-tail and upper-tail contagion, and then identify their transmission channels.

4.2.1. Tail dependence estimation

As previously discussed, the AR-GJR-EVT model is used to estimate the marginal distribution, the best-fitting dynamic mixture copula for each paired stock markets is employed to estimate the asymmetric corner tail dependence. For the benchmark comparison purpose, the dynamic Gaussian copula (c.f., Chui and Yang, 2012) is used to estimate the linear dependence, and the dynamic Student-t copula (c.f., Christoffersen et al., 2012) is used to estimate the symmetric and linear tail dependence.

[1] We also carried out an investigation, as suggested by the reviewer, to exclude the US and Chinese stock markets from our analysis and found a significant impact on our results. The US and China are major global economies, accounting for 23.7% and 18.3% of the world's gross product respectively. Additionally, they play a substantial role in global trade, with the US accounting for 10.7% and China 12.1% in 2021. Therefore, including these markets in our analysis increases its reliability in capturing global economic changes (Çolak and Öztekin, 2021; Wang et al., 2021; Cortes et al., 2022). To conserve space, results are available upon request and not tabulated.

[2] April 8, 2005 is the official launch date of one of our sample markets – China Securities Index 300 stock index. January 24, 2022 is selected as the end date of the sample period because the Federal Open Market Committee held a two-day interest meeting on January 25th and 26th, 2022, signaling the recovery of the economy and the end of the 2020 COVID-19 crisis.

[3] On December 8, 2009, Fitch cut the rating of long-term Greek debt from A^- to BBB^+, putting the rating of the Greek debt below level A^- for the first time in 10 years, which marked the beginning of the sovereign debt crisis.

[4] https://www.mckinsey.com/industries/financial-services/our-insights/a-decade-after-the-global-financial-crisis-what-has-and-hasnt-changed.

[5] https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-April-2020.

Table 1
The 22 countries and the corresponding stock indexes.

Country	Stock Index	Country	Stock Index
Panel A: Emerging Markets			
Argentina	MERV	Brazil	IBOVESPA
China	CSI 300	India	SENSEX30
Indonesia	JKSE	South Korea	KOSPI
Mexico	MXX	Russia	RIS
South Africa	TOP40	Turkey	ISE100
Panel B: Developed Markets			
Australia	AORD	Austria	ATX
Canada	TSE 300	France	CAC 40
Germany	DAX 30	Italy	MIB
Japan	N225	Netherlands	AEX
New Zealand	NZSE	Switzerland	SPI
United Kingdom	FTSE 100	United States	S&P500

Notes: This table presents 22 emerging and developed countries and the corresponding stock indexes.

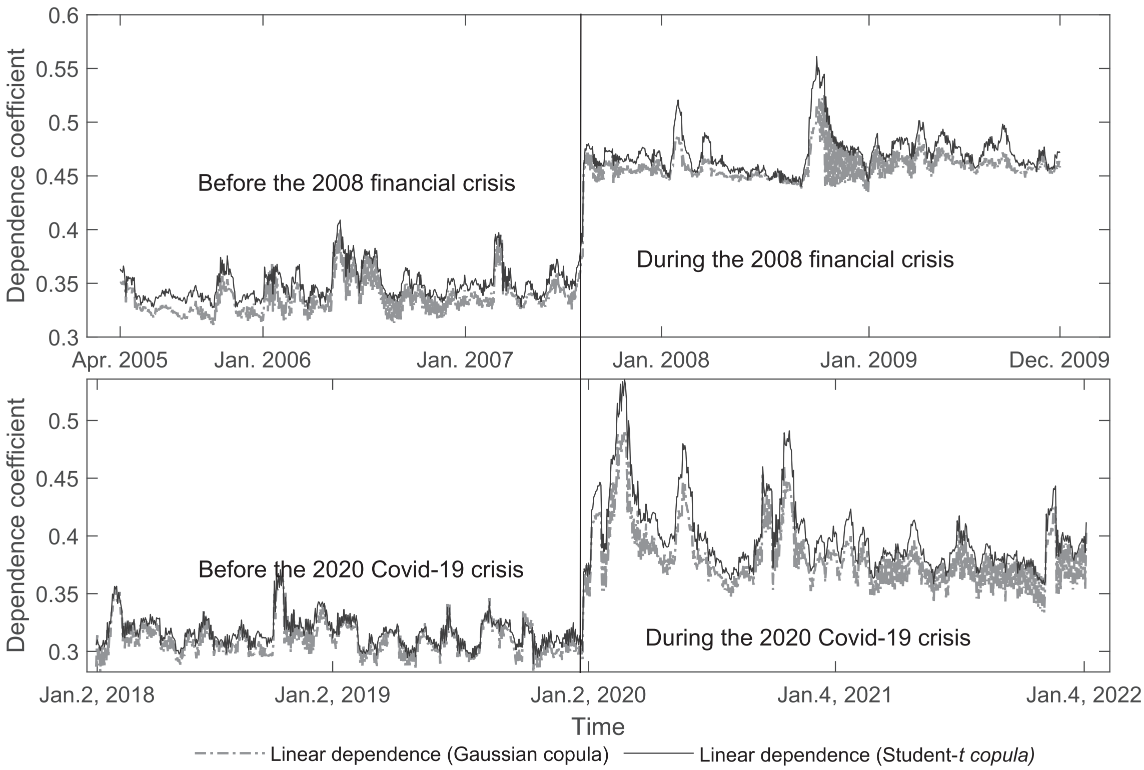

Fig. 1. Linear dependence for the 2008 and 2020 crises. This figure shows the linear dependence estimated by Student-t copula (solid line) and Gaussian copula (dashed line) for the 2008 crisis (top) and the 2020 crisis (bottom).

Fig. 1 and 2 illustrates the mean of all paired dynamic dependence for the sample periods of the 2008 and 2020 financial crises under the linear and non-linear dependence assumption, respectively.[6] First of all, the detection of both lower-lower and upper-upper tail dependence during the 2008 and 2020 crisis periods provides evidence that the linear dependence assumption is inaccurate. Second, the lower-lower tail dependence is much stronger than the upper-upper tail dependence, and both tail dependence is much stronger during the 2008 and 2020 crisis periods, which shows the clear sign of asymmetric non-linear tail contagion. Third, in comparison to the 2008 crisis, the lower-lower tail dependence was weaker prior to the 2020 crisis and is elevated to a much higher level after a sharp increase. The upper-upper tail dependence stays at a relatively lower level in the 2020 crisis instead of jumping up and staying at a higher level in the 2008 crisis. These findings also valid by the descriptive statistics on the linear and non-linear dependence summarized in Table C.2 (see online Appendix C).

[6] We also examine thees figures by using the median, 10^{th} and 90^{th} percentile. The plot looks similar.

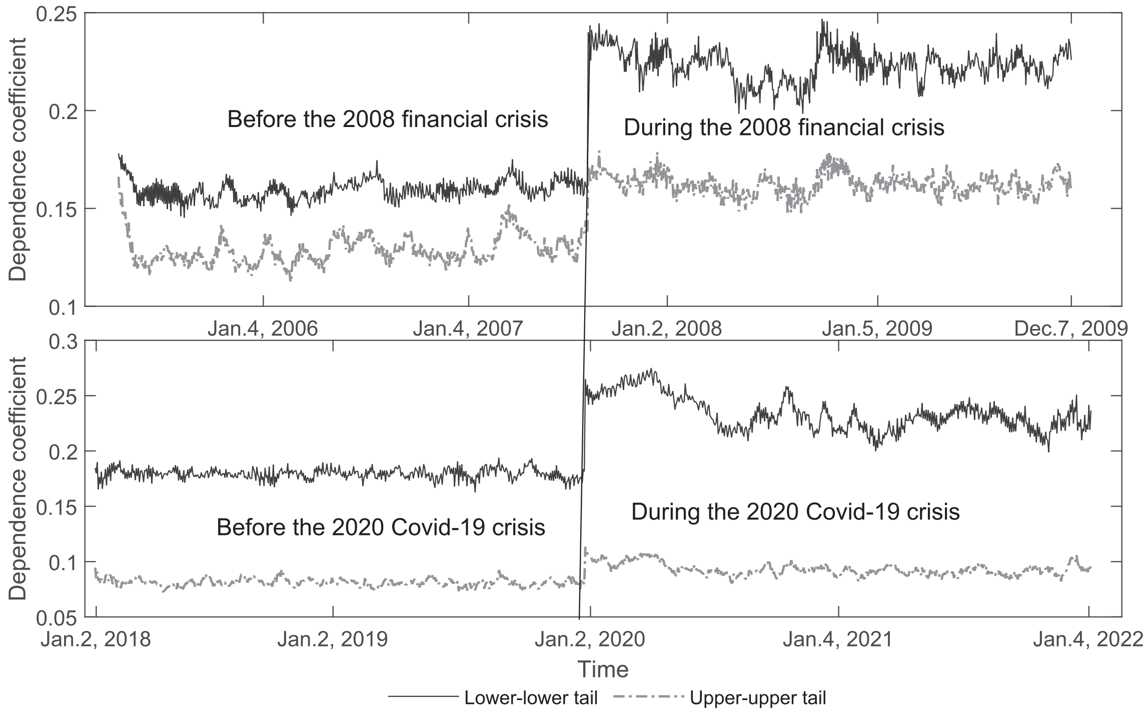

Fig. 2. Lower-lower and upper-upper tail dependence for the 2008 and 2020 crises. This figure shows the lower-lower tail dependence (solid line) and upper-upper tail dependence (dashed line) for the 2008 crisis (top) and the 2020 crisis (bottom).

4.2.2. Financial contagion detection

We verify the existence of linear and non-linear financial contagion for each paired stock markets at the 10% significance level and then construct the financial contagion network as shown in Figure C.1 and C.2 (see online Appendix C), which provide a visual representation of the linear and non-linear financial contagion between any two markets for the 2008 and 2020 financial crises, respectively. The topological placement within the network is helpful for analyzing the financial contagion and crucial for investors to adjust their risk hedging strategies.

The two figures and network metrics in Table 2 clearly show that there are much tighter links in the linear network than the non-linear network, which suggests that the inaccurate linear assumption provides a misleading picture of the financial contagion network and the financial contagion effect would be overestimated. Consistent with intuition, there is a tighter network structure in the lower-tail contagion network in Figure C.2, indicating that the financial contagion is more prevalent through the lower-tail in both crises. Moreover, compared with the 2020 financial crisis, both the lower-tail contagion and upper-tail contagion are more prevalent in the 2008 financial crisis. In addition, financial contagion capacity in each country is found to be different across different tails and economic cycles as shown in Table C.3 (see online Appendix C).

4.2.3. Financial contagion channel detection: wealth effect versus portfolio rebalancing

We next turn to determining the crisis transmission channels from the investor constraint for these contagious markets. Two competing theorems are often used to explain the investor-induced contagion channel. The first one is the wealth effect, proposed by Kyle and Xiong (2001), who develops an equilibrium model based on the changes in risk appetite that are determined by the wealth effect of convergence traders. The equilibrium model shows that convergence traders' wealth dynamically influences the prices of both risky assets, and can potentially cause dependence between the two asset prices. The equilibrium model is expressed as follows:

$$\begin{aligned} P^A &= P_F^A - k^A(\theta - X^A(\theta, W)), \\ P^B &= P_F^B - k^B(\bar{\theta}^B - X^B(\theta, W)), \end{aligned}$$

where P_F^A and P_F^B are the fundamental values of the two risky assets. X^A and X^B are the convergence traders' demand functions of the level of noise trading θ and the aggregate wealth of convergence traders W. $\bar{\theta}$ is the long-term mean of the noise trading level. The slopes k^A and k^B measure the liquidity provided by long-term investors, larger k^A and k^B mean less liquidity from long-term investors. In the equilibrium model, financial intermediaries are assumed as a group of perfectly competitive convergence traders who speculate that the transitory effect of noise trading on asset prices will induce temporary deviations of prices from their long-term mean. When convergence traders suffer trading losses in a negative shock, they will

Table 2
Statistical description of financial contagion network.

Metric	Lower-Lower Tail	Upper-Upper Tail	Linear (Gaussian)	Linear (Student-*t*)
	Panel A. Contagion for the 2008 Crisis			
Edge	98	59	193	181
Network Density	0.424	0.255	0.835	0.784
Average Degree	8.909	5.364	17.545	16.455
Average Clustering Coefficient	0.512	0.401	0.899	0.844
	Panel B. Contagion for the 2020 Crisis			
Edge	96	46	139	120
Network Density	0.416	0.199	0.602	0.519
Average Degree	8.727	4.182	12.636	12.636
Average Clustering Coefficient	0.540	0.156	0.724	0.724

Notes: This table presents the statistical description of financial contagion network for the lower-lower tail dependence, upper-upper tail dependence, and linear dependence described by Gaussian copula and Student-*t* copula for the 2008 crisis and the 2020 crisis.

reduce their risk-bearing capacity and increase their risk aversion attitude. This motivates them to liquidate positions in both markets, resulting in reduced market liquidity and magnified effects of the initial shock, which inevitably transmits from one asset to the other. Through this mechanism, there will be an increase in price volatility in both assets and co-movement between assets, and thereby, the wealth effect occurs. Therefore, under the wealth effect, the co-movement between assets would increase in times of negative shocks more than in bull markets, as highlighted by Jayech (2016).

The alternative investor-induced contagion channel theorem is the portfolio rebalancing behavior developed by Kodres and Pritsker (2002). They decompose the liquidation value of a country's asset v into the country-specific private information θ, the shared macroeconomic risks f, and country-specific macroeconomic risk η as: $v = \theta + Bf + \eta$. In their theoretical model, investors transmit idiosyncratic shocks from one market to others by adjusting their portfolios' exposures to shared macroeconomic risks in several countries. Once a shock occurs in a country, it affects other countries. Thus, investors adjust their portfolios to reduce the shared macroeconomic risks they are exposed to. This results in investors not only selling their assets in the country hit by the crisis, but also in other affected countries, which can cause the spread of the crisis. This postulates a scenario where investors faced with falling stock prices embark on a flight-to-quality from stocks. In such a scenario, investor-induced contagion sourced by the portfolio rebalancing hypothesis is characterized by a decline in the dependence during the negative shock. Like the wealth effect, the key aspect of portfolio rebalancing is that crisis spreads through the liquidity channel (Petmezas and Santamaria, 2014).

In this study, we consider that the portfolio rebalancing and wealth effect have different implications for the asymmetric co-movements during the periods of extreme market downturns and extreme market upturns. If the co-movements is stronger in extreme market downturns than in extreme market upturns, the financial contagion is driven by the wealth effect due to the presence of liquidity constraints during extreme market downturns. Conversely, if crises spread due to portfolio rebalancing behavior, co-movements are expected to be equal or weaker in extreme market downturns than in extreme market upturns. Similar to Horta et al. (2016) and Jayech (2016), we use the asymptotic tail dependence coefficients obtained from the estimated copula-EVT model to capture the dependence for extreme market downturns and upturns. Therefore, the hypothesis to check whether the financial contagion is caused by the wealth effect or by portfolio rebalancing can be formulated as

$$\begin{cases} H_0 : \bar{\lambda}^L_{crisis} \leqslant \bar{\lambda}^U_{crisis} \\ H_1 : \bar{\lambda}^L_{crisis} > \bar{\lambda}^U_{crisis} \end{cases}$$

where $\bar{\lambda}^L_{crisis}$ and $\bar{\lambda}^U_{crisis}$ are the mean lower-lower and upper-upper tail dependence coefficients during the crisis period, respectively.

Similar to the test of the existence of financial contagion in SubsubSection 3.2.1, the Fisher's z-transformation is used to test this hypothesis, the results for the contagious stock markets for the 2008 and 2020 crises are provided in Table 3. The z-statistic for the lower-tail contagion of the both crises is positive and significant at the 1% level, while that for upper-tail contagion of the both crises is not significant. Our findings show that the lower-tail contagion is primarily driven by the wealth effect, while the upper-tail contagion is primarily driven by portfolio rebalancing in both crises. This is consistent with Petmezas and Santamaria (2014), who highlights the similarities in financial contagion channels. In periods of extreme market downturns, traders are more likely to incur losses, reducing their risk tolerance and market liquidity, leading to the spread of the crisis. Conversely, during periods of extreme market upturns, traders are less concerned about wealth loss, leading them to adjust portfolios by investing in low-risk assets, causing the spread of shocks across countries.

4.2.4. Transmission mechanisms behind the investor-induced contagion channel

Considering the liquidity as crucial in crisis spread via wealth effect and portfolio rebalancing, we examine crisis transmission mechanisms using four market liquidity indicators: credit market liquidity, risk aversion, EPU, and QE policy, in both the 2008 and 2020 financial crises. Following the work of Petmezas and Santamaria (2014),Yang and Zhou (2017), Duan et al.

Table 3
Financial contagion channels for the whole crisis period in all sample markets.

	LL TDC	UU TDC	*z*-statistic	*p*-value	Channel
			Panel A. Channels for the 2008 Crisis		
Lower-Tail Contagion	0.302	0.146	2.804***	0.003	Wealth Effect
Upper-Tail Contagion	0.145	0.21	-1.139	0.873	Portfolio Rebalancing
			Panel B. Channels for the 2020 Crisis		
Lower-Tail Contagion	0.329	0.074	4.222***	0.000	Wealth Effect
Upper-Tail Contagion	0.170	0.154	0.258	0.398	Portfolio Rebalancing

Note: This table presents the test results of financial contagion channels for the whole crisis period in all sample markets. LL TDC and UU TDC refer to the lower-lower tail dependence coefficient and upper-upper tail dependence coefficient during the crisis period, respectively. * * * means significance at the 1% levels respectively.

(2021),Gnabo and Soudant (2022), we use the T-bill Euro dollar (TED) spread, the S&P 500 implied volatility (VIX) index, the US EPU index, and the size of US Treasury securities as proxies for credit market liquidity conditions, investor risk aversion, EPU, and QE policy, respectively. All data are obtained from Wind database and are standardized to eliminate the dimension influence. To analyze the impacts of these potential drivers on the wealth effect or portfolio rebalancing behavior, we use the asymmetric degree of tail dependence Asy_t calculated as the average of the difference between the lower-tail dependence and upper-tail dependence for all pairs of contagious markets at time t as the proxy variable for wealth effect or portfolio rebalancing behavior and formulate the following regression:

$$Asy_t = Constant + \alpha_1 Asy_{t-1} + \alpha_2 TED_t + \alpha_3 VIX_t + \alpha_4 EPU_t + \alpha_5 QE_t + \varepsilon_t.$$

Table 4 portfolio rebalancing behavior for the 2008 and 2020 financial crises. As shown in Table 4, the TED spread positively influences the wealth effect of both crises and negatively influences the portfolio rebalancing behavior of the 2020 financial crisis. This means that convergence traders tend to liquidate positions in risk markets when they experience trading losses following negative shocks in the 2008 and 2020 crises, which reduces market liquidity and causes lower-tail contagion. Thus, tight credit market liquidity magnifies the wealth effect. In contrast, narrow credit market liquidity magnifies the portfolio rebalancing behavior for the 2020 crisis as positive shocks in the 2020 crisis increase market liquidity and investors adjust their portfolios to reduce shared macroeconomic risks. Additionally, the positive significance of the VIX on the wealth effect of the 2008 financial crisis and the portfolio rebalancing behavior of the 2020 financial crisis provides evidence that increased investor risk aversion magnifies the wealth effect of the 2008 financial crisis and the portfolio rebalancing behavior of the 2020 financial crisis. This may be due to the negative shock of the 2008 financial crisis or the positive shock of the 2020 financial crisis reducing the risk-bearing capacity of convergence traders and increasing their risk aversion, leading to reluctance to invest during market downturns and a preference for safe assets during market upturns. Moreover, a high level of EPU causes investors to seek low-risk assets and positively influences the portfolio rebalancing behavior of the 2020 financial crisis. Finally, QE policy has a significant influence in different directions on the wealth effect of the 2008 and 2020 financial crises, as well as a significantly positive influence on the portfolio rebalancing of the 2020 financial crisis. The contrasting effects of QE policy on the wealth effect during the 2008 and 2020 financial crises may stem from differences in the utilization of excess reserves. In 2020, QE policy boosted the money supply in the banking system, and the excess reserves were promptly used by society to revitalize industry and financial market growth. Conversely, in 2008, the excess reserves accumulated in the banking system and did not fully circulate into society and financial markets.

5. Further analysis of financial contagion channel

5.1. Crisis transmission during market melt-down vs melt-up

The stock market exhibits a V-shape in the crisis periods for the 2008 crisis and 2020 crisis as displayed in Figure C.3 (see online Appendix C). The major US stock market index (S&P 500) bottomed out on March 9, 2009 during the 2008 financial crisis and on March 23, 2020 during the 2020 financial crisis. Most extent literature use the whole sample period to identify and measure financial contagion (c.f., Bekaert et al., 2014; Horta et al., 2016; Jayech, 2016; Liu et al., 2020). However, the transmission channels during the market melt-up are likely different from the market melt-down. This motivates us to investigate the tail contagion and its channels during the stock market melt-down and melt-up separately. March 9, 2009 and March 23, 2020 are used to split the sample periods of the 2008 and 2020 financial crises into two stages (market melt-down period and market melt-up period), respectively. Specifically, as for the 2008 crisis, the market melt-down period is taken from August 1, 2007 to March 9, 2009, and the market melt-up period is taken from March 10, 2009 to December 7, 2009. For the 2020 crisis, the market melt-down period is from January 1, 2020 to March 23, 2020, and the market melt-up period is from March 24, 2020 to January 24, 2022.

For these contagious market pairs, channels for lower-tail contagion and upper-tail contagion in the market melt-down and market melt-up periods are further identified and the results are listed in Table 5. The *z*-statistic for the lower-tail contagion in both the market melt-down and market melt-up periods of the 2008 and 2020 crises, is positive and significant;

Table 4
Transmission mechanism behind the wealth effect and portfolio rebalancing.

Dep. Variable	Asy_t			
Variable	Panel A. Contagion for the 2008 Crisis		Panel B. Contagion for the 2020 Crisis	
	Wealth Effect	Portfolio Rebalancing	Wealth Effect	Portfolio Rebalancing
Constant	0.601***	-0.233***	0.461***	0.066***
	(11.20)	(−14.94)	(7.59)	(15.00)
Asy_{t-1}	0.562***	0.328***	0.793***	0.010
	(14.40)	(7.38)	(29.10)	(0.22)
TED_t	0.012***	-0.003	0.010*	-0.009*
	(2.59)	(−0.85)	(1.70)	(−1.89)
VIX_t	0.011**	-0.002	-0.002	0.015***
	(2.23)	(−0.45)	(−0.33)	(2.91)
EPU_t	-0.003	-0.005	0.004	0.011**
	(−0.63)	(−1.64)	(0.76)	(2.57)
QE_t	0.025***	0.000	-0.020***	0.027***
	(5.18)	(−0.10)	(−4.17)	(7.09)
Observations	458	458	472	472
Adj R^2	0.466	0.143	0.811	0.141

Note: This table reports the transmission mechanism behind the investor-induced contagion for the 2008 and 2020 crises. *t*-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

while that is not significant for the upper-tail contagion. This indicates that the main contagion channel keeps the same for both the market melt-down and market melt-up periods of the 2008 and 2020 crises. The lower-tail contagion is more likely to be driven by the wealth effect and the portfolio rebalancing behavior is more likely to spread the upper-tail contagion.

5.2. Crisis transmission across emerging and developed markets

The development level of financial markets has obvious differences between the emerging and developed markets. The change of global economic structure is also strikingly different between developed markets and emerging markets after the 2008 financial crisis. For instance, the shares of global output and trade, FDI holdings, reserves, and financial globalization decline among developed markets, but increase among emerging markets (Lane and Milesi-Ferretti, 2018; Doidge et al., 2020). These differences motivate us to investigate the financial contagion channels across the emerging and developed markets. We group the markets into developed and emerging markets, and investigate the financial contagion channels within and between emerging markets and developed markets. The results are listed in Table 6.

The *z*-statistic for the lower-tail contagion of the 2008 and 2020 crises is significant across the emerging and developed markets, except for the lower-tail contagion within emerging markets in the 2008 crisis. Moreover, there is the biggest value of *z*-statistic within developed markets for both crises. These indicate that the lower-tail contagion between developed markets is more likely to spread through wealth effect for the 2008 and 2020 crises, and the lower-tail contagion channels of the 2008 crisis are different across emerging and developed markets. As for the upper-tail contagion, the main channel is portfolio rebalancing and the same across emerging and developed markets for both crises. We also further identify the financial contagion channels across emerging and developed markets in the market melt-down and melt-up periods of the two crises. The empirical results show the wealth effect as the main lower-tail contagion channel and the portfolio rebalancing behavior as the main upper-tail contagion channel for all cases (see Table C.4 in online Appendix C).

5.3. Flight-to-quality

The corner tail dependence investigates the extreme financial dependence that moves in the same direction (Kang et al., 2010; Supper et al., 2020). However, in some circumstances, financial assets may move in the opposite direction at the extreme market environment, leaving the corner tail dependence inadequate to describe such kinds of extreme dependence. Motivated by these observations, we capture the diagonal tail dependence and analyze the flight-to-quality phenomenon among stock markets by employing the rotation-variation of dynamic mixture copula functions.

Fig. 3 plots the dynamic means of all paired dependence in upper-lower and lower–upper tail for both the 2008 and 2020 crises. Interestingly, the upper-lower tail dependence and lower–upper tail dependence are significantly weaker in during the crisis periods than the pre-crisis period. This suggests that flight-to-quality across stock markets is actually more challenging during the financial crisis at the global level, consistent with our intuition that flight-to-quality usually occurs across asset classes instead of across different countries' equity markets during the crisis.

5.4. Impact of macroeconomic fundamentals, investor sentiments, and QE on contagion

Macroeconomic fundamentals such as bilateral trade and financial links, investor sentiments, and QE policy have been identified as drivers of cross-market co-movements and the spread of financial contagion from one country to another

Table 5
Financial contagion channels in market melt-down vs melt-up periods.

	LL TDC	UU TDC	z-statistic	p-value	Channel
Panel A. Channels in the Market Melt-down Period of the 2008 Crisis					
Lower-Tail Contagion	0.293	0.119	2.555***	0.005	Wealth Effect
Upper-Tail Contagion	0.131	0.233	-1.479	0.930	Portfolio Rebalancing
Panel B. Channels in the Market Melt-up Period of the 2008 Crisis					
Lower-Tail Contagion	0.433	0.109	1.773**	0.038	Wealth Effect
Upper-Tail Contagion	0.139	0.351	-1.136	0.872	Portfolio Rebalancing
Panel C. Channels in the Market Melt-down Period of the 2020 Crisis					
Lower-Tail Contagion	0.359	0.155	3.520***	0.000	Wealth Effect
Upper-Tail Contagion	0.229	0.279	-0.868	0.807	Portfolio Rebalancing
Panel D. Channels in the Market Melt-up Period of the 2020 Crisis					
Lower-Tail Contagion	0.354	0.075	4.402***	0.000	Wealth Effect
Upper-Tail Contagion	0.126	0.184	0.878	0.810	Portfolio Rebalancing

Note: This table presents the test results of financial contagion channels in Market melt-down and melt-up periods for the 2008 and 2020 crisis periods. LL TDC and UU TDC refer to the lower-lower and upper-upper tail dependence coefficients during the crisis period, respectively. *** and ** mean significance at the 1% and 5% levels respectively.

Table 6
Financial contagion channels across emerging and developed markets.

	Lower-Tail Contagion		Upper-Tail Contagion	
	z-statistic	Channel	z-statistic	Channel
Panel A. Channels for the 2008 Crisis				
Within Emerging Markets	0.729	Portfolio Rebalancing	-0.937	Portfolio Rebalancing
Within Developed Markets	4.160***	Wealth Effect	-1.156	Portfolio Rebalancing
Between Emerging and Developed Markets	2.723***	Wealth Effect	-1.218	Portfolio Rebalancing
Panel B. Channels for the 2020 Crisis				
Within Emerging Markets	2.172**	Wealth Effect	0.031	Portfolio Rebalancing
Within Developed Markets	6.153***	Wealth Effect	0.276	Portfolio Rebalancing
Between Emerging and Developed Markets	3.391***	Wealth Effect	0.324	Portfolio Rebalancing

Note: This table presents the test results of financial contagion channels across emerging and developed markets for the 2008 and 2020 crises. *** and ** mean significance at the 1% and 5% levels respectively.

(Rijckeghem and Weder, 2001; Boyer et al., 2006; Bekaert et al., 2014; Jayech, 2016; Yang and Zhou, 2017; Niţoi and Pochea, 2019). We investigate the relationship between these macroeconomic fundamentals, investor sentiments, and QE policy to non-linear and asymmetric tail contagion for the 2008 and 2020 crises. The global economic structure has significantly changed since the 2008 financial crisis, as evidenced by changes in the trade and financial structure, as shown in Figure C.4 (see online Appendix C). Trade linkages and foreign direct investment (FDI) flows have decreased since 2008, which suggests that trade linkages were stronger during the 2008 crisis, making it easier for the crisis to spread through trade linkages.

Similar to the gravity model that has been widely used to explain the influence of paired variables on co-movements (c.f., Beine and Candelon, 2011; Niţoi and Pochea, 2019; Lee and Kim, 2020), we develop a cross-sectional probit model to examine the paired driving factors for the spread of financial crises expressed as

$$P(Y_{ij,t} = 1) = \int_{-\infty}^{\alpha + X_{ij,t}\beta + \varepsilon_{ij,t}} f(\gamma) d\gamma$$

where $Y_{ij,t}$ represents the existence of financial contagion for the paired markets i and j ($Y_{ij,t} = 1$ when there exists financial contagion between markets i and j, otherwise $Y_{ij,t} = 0$), $f(\gamma) = \frac{1}{\sqrt{2\pi}} e^{-\gamma^2/2}$, and $X_{ij,t}$ represents a vector of variables that corresponds to the paired markets i and j at time t.[7] In line with Beine and Candelon (2011) and Niţoi and Pochea (2019), we create a trade intensity measure to reflect the significance of trade between two countries. We choose FDI flows (as a percentage of GDP) and current account balance (as a percentage of GDP) as proxies for financial links (Bekaert et al., 2014; Niţoi and Pochea, 2019). Additionally, based on Lemmon and Portniaguina (2006) and Lehrer et al. (2021), we use the consumer confidence index (CCI)[8] and stock market volatility as proxies for investor sentiments. All variables are described in detail in Table C.5 (see online Appendix C).

7 The influence of quantitative easing policy on financial contagion is not investigated in the probit model, since the size of U.S. Treasury securities is selected as the proxy variable of QE policy, it does not correspond to the paired markets.

8 We also replace the CCI with business confidence index and composite leading indicator for robustness analysis, the results are consistent.

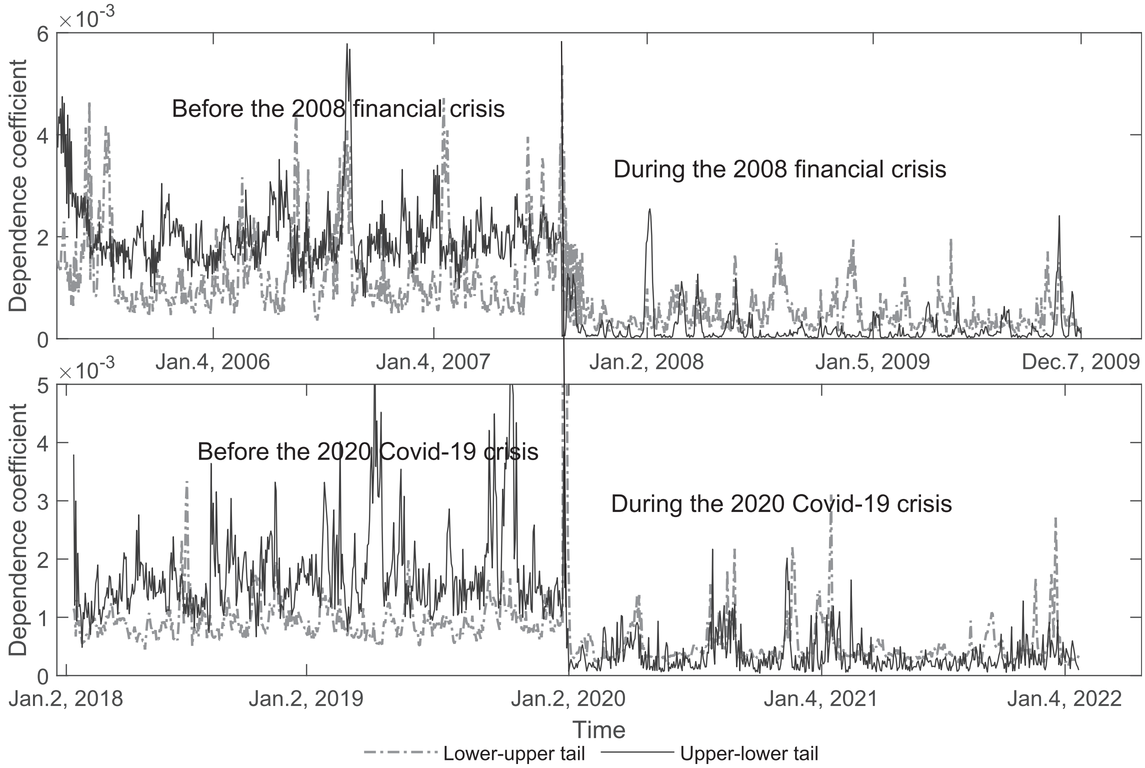

Fig. 3. Lower–upper tail and upper-lower tail dependence for the 2008 and 2020 crises. This figure displays lower–upper tail dependence (dashed line) and upper-lower tail dependence (solid line) for the 2008 crisis (top) and the 2020 crisis (bottom).

The results of the probit model are reported in Table 7. The impact factors for the 2008 and 2020 crises are varying and different in the lower-tail contagion and upper-tail contagion. As for the 2008 financial crisis, bilateral trade is found to be positively correlated with the lower-tail contagion, and CCI and stock market volatility are significant for the upper-tail contagion at the 5% and 1% levels, respectively. This shows that the lower-tail contagion is more likely to happen between two countries with higher trade linkages, while investor sentiments are more influential for the upper-tail contagion. On the other hand, CCI and volatility are found to be negatively correlated with the lower-tail contagion of the 2020 financial crisis, while current account balance is found to be significant for the upper-tail contagion of the 2020 financial crisis at the 5% level. This implies that the lower-tail contagion of the 2020 financial crisis is more driven by investor sentiments, while the upper-tail contagion is more driven by financial links.

To investigate the impact of QE on the lower-tail contagion and upper-tail contagion for both the 2008 and 2020 financial crises, we constructed a regression model with the average of tail dependence between the contagious markets as the dependent variable and QE policy as the independent variable for the entire sample period, including the pre-crisis and crisis periods. The results, which are summarized in Table 8, indicate a negative influence of QE policy on the upper-tail contagion for the 2008 financial crisis, while the influence is not significant for the lower-tail contagion. However, for the 2020 financial crisis, QE policy has a positive influence on both the lower-tail contagion and upper-tail contagion. Our results indicate that QE policy has distinct impacts on financial contagion in the two crises, echoing the findings of Cortes et al. (2022), who found that unconventional monetary policies in the 2008 and 2020 financial crises had negative and positive spillovers to international equity markets, respectively.

5.5. Financial contagion channel for the Russo-Ukrainian War

On February 24, 2022, Russia began an invasion of Ukraine, sparking the outbreak of the Russo-Ukrainian war. The war poses a significant concern for the global economy, surprising most of the global population and being the most prominent war since World War II. The war has caused a severe reaction in the international community, and economic sanctions against Russia have become more severe, such as restrictions on Russian imports and exports, removal of selected Russian banks from the SWIFT interbank system, and prohibition of the Russian Central Bank from obtaining foreign exchange reserves, to name a few. Motivated by this, we investigate the contagious influence of the Russo-Ukrainian crisis on the stock market.

Table 7
Impact of macroeconomic and investor sentiments on financial contagion.

Variable	Panel A. Contagion for the 2008 Crisis		Panel B. Contagion for the 2020 Crisis	
	Lower-Lower Tail	Upper-Upper Tail	Lower-Lower Tail	Upper-Upper Tail
Constant	-0.496**	-0.647***	0.373	-0.341
	(−2.23)	(−2.76)	(1.52)	(−1.33)
Trade	2.962**	-2.061	0.458	-0.432
	(2.50)	(−1.52)	(0.47)	(−0.43)
FDI	0.024	0.004	0.029	0.025
	(0.64)	(0.10)	(0.58)	(0.43)
Account	-0.038	0.012	-0.017	-0.072**
	(−1.55)	(0.44)	(−0.61)	(−2.12)
CCI	0.104	0.250**	-0.174*	-0.152
	(1.06)	(2.34)	(−1.87)	(−1.60)
Volatility	0.012	-0.635***	-1.225***	0.171
	(0.07)	(−2.87)	(−3.02)	(0.42)
Observations	190	190	190	190
Pseudo R^2	0.047	0.058	0.083	0.039

Note: This table reports the impact of macroeconomic fundamentals and investor sentiments on the lower-tail contagion and upper-tail contagion for the 2008 and 2020 crises. *t*-statistics are in parentheses. * * *, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 8
Impact of QE on Non-linear Tail Contagion.

Variable	Panel A. Contagion for the 2008 Crisis		Panel B. Contagion for the 2020 Crisis	
	Lower-Lower Tail	Upper-Upper Tail	Lower-Lower Tail	Upper-Upper Tail
Constant	0.032***	0.077***	0.052***	0.013***
	(2.78)	(6.79)	(3.07)	(3.65)
Dependence textsubscript*t−1*	0.985***	0.920***	0.978***	0.968***
	(185.73)	(78.84)	(132.14)	(115.45)
QE	-0.004	-0.007***	0.010**	0.006***
	(−1.21)	(−3.51)	(2.10)	(3.01)
Observations	1150	1150	986	986
Adj R^2	0.977	0.889	0.980	0.975

Note: This table reports the impact of quantitative easing policy on the lower-tail contagion and upper-tail contagion for the 2008 and 2020 crises. *z*-statistics in parentheses. * * * and ** denote significance at 1% and 5% levels, respectively.

In this subsection, we expand our sample to November 21, 2022 to analyze the contagious influence of the Russo-Ukrainian crisis on the stock market. We use the dynamic mixture copula-EVT model to measure the non-linear tail dependence before and during the Russo-Ukrainian crisis period. The normal times for analyzing financial contagion are defined as the period from January 1, 2018 to December 30, 2019. The Russo-Ukrainian crisis period is defined as the period from February 24, 2022 to November 21, 2022. Fig. 4 illustrates the mean of all paired dynamic dependence in the lower-tail and upper-tail for the Russo-Ukrainian crisis. As shown in Fig. 4, the lower-lower tail dependence is much weaker during the Russo-Ukrainian crisis period, while the upper-upper tail dependence is weaker prior to the Russo-Ukrainian crisis and is elevated to a much higher level after a sharp increase during the Russo-Ukrainian crisis period. This indicates that in comparison to the lower-tail, financial contagion may be more likely to spread in the upper-tail around the world. This conjecture is supported by the statistical analysis of the financial contagion network for the Russo-Ukrainian crisis as summarized in Table 9, which clearly shows that lower-tail contagion is spread across only 18 paired markets, while upper-tail contagion is spread across 81 paired markets. These findings differ from the results of the 2008 and 2020 financial crises where lower-tail contagion was found to be easier to spread, with 98 and 96 pairs of stock markets for lower-tail contagion in the 2008 and 2020 financial crises, respectively. In other words, the negative impact of the Russo-Ukrainian crisis is weaker than the 2008 and 2020 financial crises.

Regarding these pairs of contagious markets, we further distinguish whether the lower-tail contagion (or upper-tail contagion) is mainly driven by the wealth effect or by the portfolio rebalancing. The test results, summarized in Table 10, are consistent with those from the 2008 and 2020 financial crises and indicate that lower-tail contagion is spread through the wealth effect, while upper-tail contagion is spread through the portfolio rebalancing.

5.6. Robustness checks

To verify the effectiveness of our results above, we perform an extensive series of sensitivity checks. We repeat the test procedure described in Section 4.2 and test for the impact of modifying the return definition, the cutoff of the 2008 and 2020

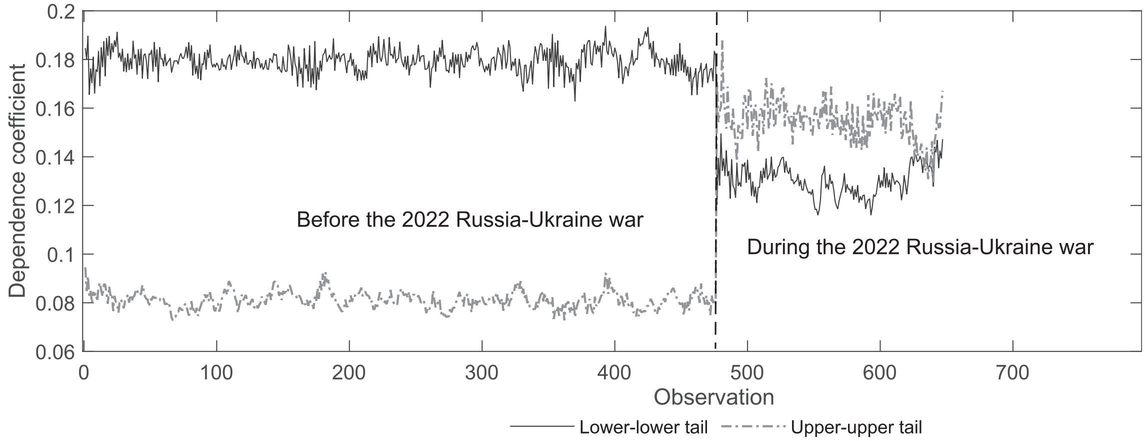

Fig. 4. Lower-lower tail and upper-upper tail dependence for the 2022 Russo-Ukrainian crisis. This figure displays lower-lower tail dependence (solid line) and upper-lower tail dependence (dashed line) before and after the 2022 Russo-Ukrainian crisis.

Table 9
Statistical description of financial contagion network for the Russo-Ukrainian Crisis.

Metric	Lower-Lower Tail	Upper-Upper Tail
Edge	18	81
Network Density	0.078	0.351
Average Degree	1.636	7.364
Average Clustering Coefficient	0.056	0.466

Notes: This table presents the statistical description of financial contagion network for the lower-lower tail and upper-upper tail for the 2022 Russo-Ukrainian crisis.

Table 10
Financial contagion channels for the Russo-Ukrainian Crisis.

	LL TDC	UU TDC	*z*-statistic	*p*-value	Channel
Lower-Tail Contagion	0.292	0.109	1.801**	0.036	Wealth Effect
Upper-Tail Contagion	0.146	0.274	1.260	0.896	Portfolio Rebalancing

Note: This table presents the test results of financial contagion channels for the Russo-Ukrainian crisis period. LL TDC and UU TDC refer to the lower-lower tail dependence coefficient and upper-upper tail dependence coefficient during the crisis period, respectively. ** means significance at the 5% levels respectively.

crises, and the dynamic mixture copula function. More specifically, we adjust the definition of return to $r_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, where $P_{i,t}$ is the closing price on day t for index i. We also examine different definitions for the pre-crisis and crisis periods. We use the date of August 9, 2007 (when BNP Paribas ceased all banking operations) to split the full sample into pre-crisis and crisis periods, and redefine the cutoff of the 2020 crisis as the peak of the market on February 12, 2020. We also adjust the copula function by using the dynamic Gumbel-survival Gumbel and the rotation-variation of dynamic Clayton-Gumbel copula to describe the corner and diagonal tail dependence, respectively.

The results of the robustness checks on financial contagion channels are tabulated in Table 11, which provides robust evidence of wealth effect as the lower-tail contagion channel and portfolio rebalancing as the upper-tail contagion channel for both crises.

5.7. Additional insights

The existence of financial contagion would make financial institutions more exposed to risk. Our analysis offers fresh and prominent policy implications for regulators, as it allows better understanding of the different transmission mechanisms for lower-tail and upper-tail contagion in the financial crisis period and the periods of market melt-down and melt-up, as well as within or between markets at different development levels. Our findings also have strong implications for asset allocation and financial risk management. Our results suggest both lower-tail contagion and upper-tail contagion should be taken into account by international investors to design investment portfolios with corresponding risk hedging strategies, and that linear contagion is an inaccurate measurement and will overestimate financial contagion. The advantage of portfolio diversi-

Table 11
Robustness check results of financial contagion channels.

	Lower-Tail Contagion		Upper-Tail Contagion	
	z-statistic	Channel	*z*-statistic	Channel
	Panel A. Channels during the 2008 crisis			
Adjust Return Definition	3.958***	Wealth Effect	-1.364	Portfolio Rebalancing
Refine the Cutoff	2.227**	Wealth Effect	-2.783	Portfolio Rebalancing
Adjust the Copula	2.956***	Wealth Effect	0.017	Portfolio Rebalancing
	Panel B. Channels during the 2020 crisis			
Adjust Return Definition	4.595***	Wealth Effect	-0.018	Portfolio Rebalancing
Refine the Cutoff	4.999***	Wealth Effect	-0.210	Portfolio Rebalancing
Adjust the Copula	4.732***	Wealth Effect	-1.233	Portfolio Rebalancing

Note: This table presents the impact of modifying the return definition, the cutoff of the 2008 and 2020 crises, and the dynamic mixture copula function on financial contagion channel for both the 2008 and 2020 crises. * * * and ** mean significance at the 1% and 5% levels respectively.

fication including these markets will be reduced if there is lower-tail contagion after a country experiences a negative shock, and the advantage of portfolio diversification will be increased if there is upper-tail contagion. The insights on financial contagion would facilitate timely adjustment of the asset allocation and enable a strategy for hedging portfolio risk.

6. Conclusions

A notable feature of contagious financial crises is the rapid transmission of an initial market shock from one country to financial markets of various sizes and structures in other countries, similar to a virus. The 2008 and 2020 financial crises both caused exceptional volatility in financial markets, but have distinct characteristics. The 2008 crisis originated from a changing economy and market and had the banking system as its primary cause of the financial system's malfunction. Meanwhile, the 2020 crisis was directly caused by the spread of COVID-19 and initially impacted the production and real sector due to supply chain disruptions. This prompted a resurgence of academic interest in financial contagion and in crisis transmission channels. In this research, we formally examine whether these changes are reflected in the dynamics of crisis transmission channels.

Since financial contagion features dynamic extreme dependence in a complex network, we construct a dynamic mixture copula-EVT model to quantitatively investigate the complex non-linear and (both corner and diagonal) tail dependence in the context of financial contagion and flight-to-quality phenomenon. Moreover, we propose a non-linear financial contagion network based on the dynamic mixture copula-EVT model. Specifically, we first examine the existence of upper- and lower-tail contagion phenomena. We then analyze the topological features of the financial contagion in the financial system. Furthermore, we distinguish the main contagion channel from the wealth effect and portfolio rebalancing and analyze the transmission mechanism of the credit spreads, risk aversion, EPU, and QE on it. Finally, we explore the tail contagion channels in the periods of market melt-down and melt-up for emerging and developed markets, and explore the relation of flight-to-quality, macroeconomic fundamentals, investor sentiments, and QE policy on financial contagion in lower-tail and upper-tail. Our findings provide compelling evidence on the evolution of crisis transmission mechanisms, which can aid in effectively regulating the financial market and preventing the spread of crises across international markets.

We confirm the wealth effect as the main lower-tail contagion channel and the portfolio rebalancing behavior as the main upper-tail contagion channel for varies crises. This suggests similarities in the financial contagion channels for different crises, consistent with the finding of Petmezas and Santamaria (2014) that highlights the similarities in financial contagion channels. Our results also demonstrate the dynamic impact of credit spreads, risk aversion, EPU, and QE policy on both lower-tail and upper-tail contagion sourced by wealth effect and portfolio rebalancing during the 2008 and 2020 crises. Our results reveal heterogeneous lower-tail contagion channels during the 2008 crisis, with lower-tail contagion being sourced by portfolio rebalancing in emerging markets and wealth effect in developed markets, complementing the findings of Boyer et al. (2006) who reported financial contagion due to wealth effect in emerging markets and portfolio rebalancing in developed markets during the 1997 Asian financial crisis. These differences in results may be due to changes in cross-market conditions that affect crisis transmission channels. Additionally, our focus on contagion in upper-tail and lower-tail is distinct from the focus of Petmezas and Santamaria (2014) and Boyer et al. (2006) on overall contagion. Lastly, our results also provide evidence of the varying effect of QE policy on financial contagion during different crises, which is supported by the work of Yang and Zhou (2017) and Cortes et al. (2022).

Understanding financial contagion and its dynamic transmission mechanisms is of great importance for policymakers, regulators, and international investors. Our findings provide new insights into the transmission mechanisms of financial contagion, which can be used to effectively regulate and invest in the markets. For example, the volatile movements of international stock markets during the 2020 COVID-19 crisis highlight the potential risks that financial institutions and investors face due to contagion, which can weaken the benefits of portfolio diversification in the event of lower-tail contagion. A deeper understanding of the transmission channels of financial contagion can help investors and risk managers make more informed decisions, adjust asset allocation in a timely manner, and develop strategies for hedging portfolio risk.

This research focuses on the financial contagion among international stock markets. For future research, we can further investigate the factors of debt and regional variations in financial contagion (e.g., Lucas et al., 2014), and the transmission channels of financial contagion across other important types of financial markets, such as foreign exchange, credit derivatives, and energy markets.

Declaration of Competing Interest

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

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2023.102857.

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