International Review of Economics and Finance 104 (2025) 104701

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

# Navigating global financial turbulence: The evergrande collapse and its contagion effect

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A R T I C L E I N F O

*Keywords:*
Evergrande crisis
Real estate spillover
Systemic risk
Financial contagion
Quantile VAR

A B S T R A C T

This study investigates the contagion effects of the Evergrande collapse across international financial markets, with emphasis on tail-risk dynamics. Unlike prior work focusing on average spillovers or event windows, we employ a Quantile Vector Autoregression (QVAR) framework to capture state-dependent connectedness under bearish, median, and bullish market conditions, as well as calm versus turbulent volatility regimes. Using daily data for nine major stock indices (2015–2024), we find that the Evergrande crisis significantly amplified global spillovers, but with heterogeneous magnitudes across quantiles. At the 95 % volatility quantile, returns spillovers in the median quantile from Shanghai to the EU increased, during the Evergrande crisis, by approximately 3.5 % in the Net Pairwise Connectedness (NPC) case. In contrast, with very few exceptions, Canadian spillovers remained negligible, confirming its resilience and diversification potential. These results show that extreme market states reveal contagion patterns invisible in average-state analyses, underscoring the systemic role of Hong Kong as a transmission hub and the conditional global influence of Shanghai. The findings provide actionable insights for policymakers on monitoring tail-risk channels and for investors seeking hedging strategies in insulated markets.

## 1. Introduction

The real estate sector has been the cornerstone of economic development for centuries. Nowadays, it still plays a key role in international investment, employment, and wealth accumulation (Cai et al., 2020). The stability of the real estate sector is closely associated with overall economic sustainability, as shifts within the market significantly affect financial systems, influencing consumer and investor confidence and impacting the fiscal health of the country (Li et al., 2023). However, the real estate speculation bubble brought inappropriate debt levels and led to unsustainable growth models that would detrimentally undermine financial stability by boosting systemic risk (Fabozzi et al., 2020). This condition is particularly proper for economies like China, where the average

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https://doi.org/10.1016/j.iref.2025.104701
Received 29 July 2025; Received in revised form 7 October 2025; Accepted 17 October 2025
Available online 18 October 2025

household wealth and GDP are heavily skewed toward real estate. The Chinese real estate market accounts for nearly 30 % of China's GDP, along with its related sectors. The sector has been pivotal as the country's robust growth engine over the past decades (Kaaresvirta et al., 2021). However, it embraces several challenges, such as increasing debts, poor investments, speculative bubbles and unsustainable financing practices. These circumstances represent the primary threats exemplified by Evergrande, a leading firm in this sector.

Evergrande Group is one of the biggest Chinese conglomerates, with extensive functions in real estate, electric vehicles, and finance. Evergrande, once emblematic of the rapid ascent of China, is a stark example of a dominant global economic force that has now become a focal point of growing concerns affecting domestic and foreign financial performances (Altman et al., 2022). The transformation from the economic growth pillar to a source of systemic vulnerability highlights the fragility inherent in managing high debt levels. Evergrande epitomized the systemic risks; in 2023, the company reported more than $300 billion in debt, signaling potential contagion effects in global markets (Deng et al., 2024). The crisis dynamics are similar to Lehman Brothers' fall in 2008, which promoted an urgent call to analyze weaknesses in the Chinese financial system and their effects on international markets.

Given the worldwide connectedness of Evergrande affairs, its struggles provoked many effects within the international financial system. The company's influence extends across industries, transnational supply chains, and financial commodities (Ahmed et al., 2024). Chinese real estate companies have been quite frequently dependent on foreign capital, as the bonds issued by these companies constitute a meaningful part of emerging market debt indices. The specter of a default on these bonds has been sending shock waves across global markets. This uncertainty is reflected in asset prices and exchange rates and, thus, will increase risks that destabilize the financial performance (Acharya et al., 2017). For instance, in late 2021, at the peak of the Evergrande crisis, the MSCI Emerging Markets Index lost more than 4 % of its value. This event also adds to the sensitivity of the market to swings within China's real estate sector (Altman et al., 2022).

A broader context of financial instability in Evergrande reflects even more serious problems faced by China's domestic markets, such as slow GDP growth, tightening regulatory policies, and demographic shifts. The "three red lines" have also been introduced by the Chinese government as a preventive measure against overborrowing by developers, thus imposing further stress on liquidity for companies like Evergrande. Moreover, the strategic intents of Beijing to spread its economic model are also to be highlighted; however, they also incur a downside risk of unintended consequences, such as an aggravation of already precarious conditions (Wang et al., 2022).

With the international effects of the Evergrande crisis, there is an urgent need to understand the complexity between China's economic policy and the rest of the global financial markets. International markets create and enhance such interconnection within different markets and show how such localized events might spur considerable ripple effects in other areas of the world. This phenomenon is prominently pronounced in China, as it emerges as the world's second-largest economy and has become a growing facilitator in global trade and finance perspectives (Zhao, 2023).

To the best of our knowledge, we made several interesting contributions to the literature. First, we fill the corresponding literature gap on the occurrence of financial spillover effects from Evergrande to international financial markets. Second, we intend to capture tail behaviors of market conditions and volatilities by using a quantile vector autoregression methodology, which is generally ignored but crucial for understanding systemic risks. We adopt a comparative perspective to cover the broader context of system risks and interconnected financial events. In addition, we test the statistical significance of several relevant exogenous occurrences, such as the COVID-19 pandemic and the Russia-Ukraine.

Our results highlight how different financial conditions amplify the financial spillover and affect the market dynamics across diverse economic scenarios. We report the detrimental role of the Evergrande collapse in global financial stability, thus enhancing the financial spillovers around this period. We show a pronounced contagion mechanism from the Chinese markets to global hubs. Interestingly, Canada emerged as the most resilient market, which provides significant hedging opportunities due to the potential portfolio management strategies, confirmed by a portfolio backtest. In this analysis, we provide guidelines to policymakers to manage contagion pathways and for investors by highlighting opportunities for risk reduction and diversification by identifying markets less vulnerable to global financial fallout.

The rest of the paper proceeds as follows. Section 2 recaps the literature review of contagion and systemic risks, thus identifying our research gap. Section 3 explains the methodology and provides the details of the data used. Section 4 discusses the results and contextualizes the findings within the global financial system. Finally, Section 5 concludes and gives the main policy recommendations.

## 2. State of the art review

### 2.1. Theoretical underpinning

Systemic risk arises when local shocks propagate across markets and destabilize the broader financial system. The "financial instability hypothesis" of Archive (1975) emphasizes how leverage and speculative behavior can trigger instability, while Allen and Gale (2000) formalized contagion through network interdependencies. After the global financial crisis, systemic risk modeling became central to analyzing transmission channels (Acharya et al., 2017). These perspectives highlight that interconnectedness can amplify shocks, underscoring the need to study spillovers across both tranquil and stressed market states.

A key development in this literature is the recognition that risk transmission is heterogeneous across the distribution of returns. Ando et al. (2022) introduced the quantile connectedness framework, showing how tail dependencies reshape networks during crises. Relatedly, Chatziantoniou et al. (2021) and White et al. (2015) demonstrate that quantile-based VAR approaches capture directional dependence across normal and extreme conditions. These methodological advances justify our choice of quantile connectedness as the appropriate tool to evaluate spillovers surrounding the Evergrande crisis.

Fig. 1 exhibits the theoretical framework for this study, focusing on the key pathways of system risk transmission. It includes the financial spillover, its impact on financial stability, and the policy response required to mitigate these risks. The reciprocal association between financial spillover and global financial stability reflects the dynamic relationship where financial spillover disrupts global stability and vice versa, showing their mutual influence (Su et al., 2025). Likewise, the feedback loop between global financial stability and policy measures indicated how stability influences policy response, reinforcing stability in interconnected markets (Sun et al., 2024).

### 2.2. *Review of related studies*

Centering on Evergrande as a core subject in the debate over systemic risk transmission among the globally interconnected financial markets, the crisis has explained how corporate debt distress is carried across capital flows, asset prices, and exchange rates to influence worldwide stability. Financial contagion describes the rapid spread of financial shocks across markets and regions, usually due to interconnectivity and heightened investor sentiment (Allen & Gale, 2000).

A few studies explored the exposure of the Evergrande conglomerate to financial markets, providing interesting shards of evidence but leaving a gap in understanding the broader systemic implications of this crisis. For instance, using the event study approach, Almeida et al. (2022) investigated the Evergrande collapse spillover effects from 2020 to 2022 on Asian stock indices through daily data. They found that spillover from Evergrande impacted market volatility, with the investors' risk aversion sentiment accentuating this contagion mechanism. Consequently, the global spillovers led by the sharp decline in the real estate sector indicate that the corporate debt crisis can be a systemic risk conductor across worldwide interconnected economies. These findings are congruent with the current work, which concentrated on understanding the potential disruptions caused globally by localized financial distress.

Ahmed et al. (2024) extended this horizon to international markets using a dynamic spillover index considering a data span of 2021–2023. Their investigation revealed that the Chinese and Western economies are closely connected, with bond market repercussions occurring in Europe and the United States after the Evergrande collapse. The cross-market analyses incorporated into the study give an overall view of Evergrande's global presence, complementing Almeida et al. (2022)'s regional analysis. Likewise, Altman et al. (2022) used structural VAR models to analyze data over 2020–2022 to gauge disruptions in capital markets in China. The results supported the supposition that the crisis exemplified by Evergrande could propagate through capital markets and undermine larger financial systems.

Zhou et al. (2012) show that Chinese equity markets both absorb shocks from developed economies and transmit them regionally, with stronger spillovers under volatility extremes. The study discovered that the Chinese equity market plays a dual role; on one side, it receives shocks from developed economies, whereas on the other side, it transmits the spillover, particularly in the regional Asian market. Extreme market conditions intensified the contagion effects, demonstrating the asymmetric nature of volatility spillovers. Johansson and Ljungwall (2009) studied spillover effects within Chinese stock markets, thereby strengthening the interconnectedness of regional markets.

Risk transmission mechanisms describe the financial shock dissemination mechanism through various channels, such as monetary policy decisions, financial instruments, and market structures (Razi & Ramzan, 2025). In this context, different methodologies were used to analyze and quantify these transmissions. For instance, White et al. (2015) applied multivariate quantile regression to measure tail dependencies and highlighted the role of extreme market conditions in amplifying systemic risk, particularly after the 2008 financial crisis. It demonstrated that tail-risk behaviors play a central role in increasing the severity of systemic crises. Their methodological considerations on capturing tail risk behavior are relevant to justify the quantile VAR usage in the current paper. Chatziantoniou et al. (2021) applied a quantile connectedness approach to examining interest rate swaps as monetary policy shock transmission mechanisms. Using time series data from 2015 to 2020, they found that financial instruments often act as conduits of augmented volatility spillovers. The method used by the study provides a great point to start examining risk transmission across related financial markets, including those affected by the Evergrande crisis.

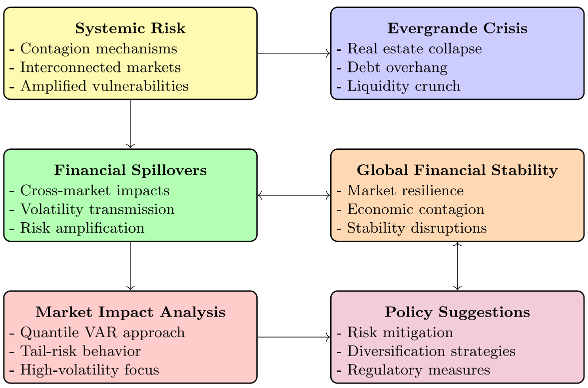


**Fig. 1.** Theoretical framework: Evergrande crisis and global financial spillover.

The financial markets' interconnectedness is influenced by diverse factors such as asset class behavior, policy-driven uncertainties, and volatility spillover. For instance, Akhtaruzzaman et al. (2021) studied financial contagion through the COVID-19 pandemic using high-frequency data and dynamic conditional correlation models. The study analyzes global equity and bond markets between 2020 and 2021 and shows that asset-class-specific responses, like gold and green investments, act as effective hedges during times of crisis. Such a finding gives comparative insights into the asset price behavior in systemic risks similar to those triggered by Evergrande's distress. Vuong et al. (2022) explored the volatility spillover between the Chinese and the US stock markets during the COVID-19 pandemic, focusing on interrelated patterns that can mirror the transmission dynamics of the Evergrande crisis. Thomson et al. (2022) examined health financing resilience to the COVID-19 pandemic and the 2008 financial crisis in European countries. In addition, Ullah et al. (2023) discussed the impact of the economic policy uncertainty on China's stock markets, thus offering insight into the risk transmission mechanism through policy changes.

Fluctuations in exchange rates during financial crises usually represent the interconnectedness of global markets and serve as a channel for transmitting economic shocks (Razi et al., 2025). Studies have focused on the role of currency markets in propagating systemic risks. Baillie and Bollerslev (1989) introduced a stochastic trend analysis of exchange rates during periods of market stress. Data from the 1980s used in this study provided foundational insights into exchange rate volatility that remain highly relevant for analyses of systemic crises. Arezki and Liu (2020) used a global spillover approach to compare macroeconomic asymmetries between developing economies and those of advanced economies for the years 1995–2020. Their findings indicated that emerging markets are sensitive to shocks from advanced economies. These results lead to a need to study Evergrande's effects on global spillover, especially for poorer economies that may not have the financial resources to absorb such a shock.

Financial crises serve as informative grounds for understanding the transmission mechanisms of systemic risk. Moreover, they are functional in understanding the effectiveness of policy interventions. Research has drawn comparisons between past crises and the crisis associated with Evergrande to identify some sectoral vulnerabilities. Levy et al. (2022) investigated the 2008 financial crisis, revealing that delays in identifying systemic risks often aggravate financial distress. This historical parallel emphasizes the need for timely interventions to avoid crises such as Evergrande, where delayed actions might exacerbate the effects of global contagion. Bischof et al. (2021) analyzed financial stability frameworks during the 2008 crisis, focusing on bank disclosures and loss recognition. Using quarterly data from 2006 to 2009, they proved that transparent financial reporting reduces systemic risks. Such findings exemplify how transparency regarding corporate debt would mitigate potential contagion effects from crises (such as Evergrande). Recently, several studies analyzed the role of geopolitical risk as a shock transmitter in financial markets. For instance, Palomba and Tedeschi (2024) documented robust transmission mechanisms across economies and clarified insights on systemic vulnerability triggered by significant financial downturns. This comparative perspective allows us to better assess the economic ramifications of the Evergrande saga in the broader frame of reference.

Wang et al. (2022) applied game theory to the Evergrande financial crisis, providing insights into decision-making processes and strategic interactions in the context of systemic events. The study identified key factors contributing to Evergrande's debt default, such as blind expansion, a high leverage ratio, poor cash flow management, and strict national policies. By applying the game theory model, they assess the decision-making process of stakeholders and propose the optimal solution in terms of coordinated efforts by all stakeholders. Kaaresvirta et al. (2021) analyzed the Chinese real estate sector and its potential effects on the Chinese economy and the Eurozone, stressing the global nature of such crises. The study highlights the debt-fueled growth and systemic vulnerabilities of this sector. Due to the government credit restrictions, the real estate market key players, such as Evergrande and Kaisa, defaulted in 2021 due to the intensified stress on the sector. Financial exposure to European markets remains evident, underlining that China's internal disruptions have an indirect impact on European markets through trade and supply chain channels. Qarni and Gulzar (2018) analyzed the spillover effects of returns and volatility among China's stock markets and its trading partners by focusing on relevant patterns of financial interdependence for this current scenario.

### *2.3. Research gap*

Despite these contributions, significant research gaps persist. Notably, the focus on quantile dynamics for crisis periods is inadequate, especially where transmission mechanisms connected with capital flows, asset prices, and exchange rates predominated. As a result, it would be hard to capture tail-end behavior, which is crucial for systemic risk assessments. Moreover, current studies focus predominantly on short-run effects and fail to emphasize the long-term implications for the stability of markets and policy decisions. Additionally, there is a lack of comprehensive frameworks that account for all the transmission mechanisms and their international effects. This study fills this knowledge gap by applying a quantile VAR methodology to assess systemic risks related to the Evergrande crisis. By examining the previously understudied tail-risk dynamics and interconnected responses of markets, this study aims to improve the understanding of the systemic vulnerabilities in global financial markets, which can then provide practical insights for policymakers and investors.

## 3. Methodology and data specification

### *3.1. Methodology*

Through a Vector Auto Regressive (VAR) model on quantiles, we aim to investigate the relationship across returns and volatilities of global financial market indices in the context of the current market distress. We develop a Quantile Connectedness Approach (Chatziantoniou et al., 2021) to understand the contagion mechanism across different market regimes. Following Tsai (2012) and

White et al. (2015), the Quantile VAR model is the optimal tool for assessing financial risk and has been recently employed to identify market contagion mechanisms.

In a nutshell, we can identify bearish and bullish sentiments, which correspond to lower and higher quantiles of the returns distribution. Quite the opposite, following Palomba and Tedeschi (2024b), when we discuss quantiles in volatilities, we can refer to low (high) quantiles of volatility distributions that are characteristic of periods of calm (turmoil) situations. While the discussion for returns is immediate, the implications of the volatility spillover need to be clarified. The first scenario (low volatility) typically identifies prolonged price stability in a given market, the median value (median volatility) represents the standard uncertainty perceived in the markets, whereas the latter quantile (higher volatility) typically describes periods of high instability when most investors are engaged in financial transactions (both buying and selling). As stated by Koenker (2005), the Quantile VAR (QVAR) model can be expressed as follows.

$$y_t = \mu(\tau_z) + \sum_{k=1}^{p} \Phi_k(\tau_z) y_{t-k} + \varepsilon_t(\tau_z) \tag{1}$$

Where $y_t$ represents the $n \times 1$ vector containing the endogenous variables, $\mu(\tau_z)$ is a $n$-dimensional vector of constants, $\Phi_i(\tau_z)$ denotes the $n \times n$ matrix of coefficients at the quantile $\tau_z$, and $p$ stands for the lag order, which is selected following the lowest Bayesian Information Criteria (BIC). Each quantile $\tau_z \in \{\tau_1, \tau_2, \ldots, \tau_m\}$ is defined between 0 and 1, while $\varepsilon_t(\tau_z)$ is the vector of marginal differences depending on $\tau_z$ with zero mean and covariance matrix $\boldsymbol{\Sigma}(\tau_z)$.

To employ the Quantile Connectedness Approach, it is necessary to calculate the Generalized Forecast Error Variance Decomposition (GFEVD) as outlined in Koop et al. (1996) and Pesaran and Shin (1998), which offers the advantage of independence from the variable order. Using the Wold's representation theorem, we obtain the Vector Moving Average (VMA $\infty$) form:

$$y_t = \mu(\tau_z) + \sum_{k=0}^{\infty} \Psi_k(\tau_z)\, \varepsilon_{t-k}(\tau_z) \tag{2}$$

This representation enables us to compute the $H$-step GFEVD for a specific quantile $\tau_z$ as follows:

$$\Theta_{ij}(H, \tau_z) = \Sigma_{ii}^{-1}(\tau_z) \sum_{h=1}^{H} \frac{\left(\nu_i' \Psi_{k,h}(\tau_z)\, \Sigma(\tau_z)\, \nu_j\right)^2}{\nu_i' \Psi_{k,h}(\tau_z) \Sigma(\tau_z) \Psi_{k,h}(\tau_z)' \nu_j}, \tag{3}$$

Where $\Theta_{ij}(H,\tau)$ represents the contribution of the $j$-th variable to the variance of the forecast error of the $i$-th variable, with $i = 1,2, \ldots,n$ and $j = 1,2, \ldots,n$. The scalar $\boldsymbol{\Sigma}(\tau)_{ii}$ corresponds to the $i$-th diagonal element of the error covariance matrix, and $\boldsymbol{\Psi}_h(\tau_z)$ denotes the coefficient matrix estimated by Equation (2) for the $\tau$-th quantile. It is important to note that both the numerator and the denominator represent two quadratic forms that yield two scalars obtained by applying the selection vectors $\nu_i$ and $\nu_j$.

To compare the $n(n-1)$ spillovers provided by equation (3), we need to normalize as follows:

$$\widetilde{\Theta}_{ij}(H, \tau_z) = \frac{\Theta_{ij}(H, \tau_z)}{\sum_{j=1}^{n} \Theta_{ij}(H, \tau_z)}, \tag{4}$$

this ensures that $\sum_{j=1}^{n} \Theta_{ij}(H, \tau_z) = 1$. We compute the Total Connectedness Index (TCI) as

$$\text{TCI}(\tau_z) = \frac{1}{n-1} \sum_{i=1}^{n} \sum_{j \neq i} \widetilde{\Theta}_{ij}(H, \tau_z)\ . \tag{5}$$

The $\text{TCI}(\tau_z)$ can be used as a proxy for market risk: higher TCI values indicate a strong level of network interconnection, while lower values suggest weaker interconnection. The overall impacts of variable $i$ on variable $j$ and vice versa are computed according to the following metrics:

$$\text{TO}(\tau_z)_{i \to j} = \sum_{j=1}^{n} \widetilde{\Theta}_{ij}(H, \tau_z) \tag{6}$$

$$\text{FROM}(\tau_z)_{j \to i} = \sum_{j=1}^{n} \widetilde{\Theta}_{ji}(H, \tau_z) \tag{7}$$

$$i \to j : NET(\tau_z) = FROM(\tau_z)_{i \to j} - TO\ (\tau_z)_{i \to j} \tag{8}$$

for each $j \neq i$. In conclusion, we compute the Pairwise Connectedness Index (PCI), which is essentially the sum of the FROM and TO spillovers and gives the total number of spillovers between the series.

In this specification, we do not construct bootstrap-based confidence intervals for the indices themselves, since our focus lies in analyzing their dynamics and event-driven shifts rather than making statistical inference on the underlying spillover network. Nevertheless, for readers whose primary interest is in inference on the connectedness structure, bootstrap-based approaches such as those proposed by Greenwood-Nimmo et al. (2024) could serve as a complementary extension.

Since we aim to understand the dynamics of the phenomena, we compute these spillovers following a rolling technique. We initially estimate the Quantile VAR model based on $t_0 = 250$ observations, and then we roll the estimation to compute $T - t_0$ values of the time series of spillovers. In particular, since our sample started in 2015, the training part for the estimation does not have any significant fluctuation in the markets that could bias our spillover estimates.

### 3.2. Data specification

We use data from a set of financial indices listed in Table 1 and downloaded from Yahoo Finance. The dataset includes observations from January 2, 2015, to December 30, 2024 (T = 2606). We decided not to include more recent observations in order to focus on the Evergrande collapse and its effects on global financial markets.

The selection of these specific financial indices is based on several crucial considerations. First, these indices represent some of the most significant and globally relevant economies, including indices from the stock markets of the United States, Europe, China (Shanghai and Shenzhen), Hong Kong, India, Japan, Canada, and the United Kingdom (see Table 1). These economies are well-known for their interconnectedness and play key roles in the global financial landscape (Karim & Naeem, 2022). Second, the decision to cover a broad range of geographies aims to capture the heterogeneity of financial markets across different regions of the world. This geographic diversification allows us to assess how events related to Evergrande (and more general of the Chinese market) may impact financial markets on a global scale. Furthermore, the selected indices represent various sectors of the economy, including technology, finance, and consumer goods. Lastly, the choice of indices is also guided by the availability of complete and reliable data (opening and closing values, max and min) for the study period.

Since we aim to understand the role of the market sentiment (bullish and bearish), we apply a Quantile VAR approach to allow for an investigation of the behavior of investors in the tails of the statistical distribution. We use the first log difference of the closing price to obtain returns:

$$r_{it} = \log\left(\frac{p_t}{p_{t-1}}\right) \tag{9}$$

Where $p_t$ is the closing price at time $t$ while $p_{t-1}$ is the closing price at $t-1$. Besides, due to the high uncertainty spread in financial markets, we also include a measure of weekly volatility called Parkinson's historical volatility, which is computed as follows:

$$\text{Park}_{HV} = \sqrt{\frac{1}{4N\ln 2}\sum_{i=1}^{V}\left(\ln\frac{h_i}{l_i}\right)^2}. \tag{10}$$

From Equation (10), V is the period of the volatility considered, $h_i$ is the daily high price, and $l_i$ is the daily low price. Fig. 2 shows the time series behavior of returns, and Fig. 3 reports Parkinson's historical volatility computed on a rolling (V = 5) weekly basis.

In Figure A.1, we report the Garman-Klass-Yang-Zhang (GKYZ) volatility estimator computed as follows

$$\text{GKYZ}_{HV} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\left(\ln\frac{o_i}{c_{i-1}}\right)^2 + \frac{1}{N}\sum_{i=1}^{N}\left(\ln\frac{h_i}{l_i}\right)^2 - \frac{1}{N}\sum_{i=1}^{N}(2\ln 2 - 1)\left(\ln\frac{c_i}{o_i}\right)^2}, \tag{11}$$

where $h_i$ denotes the daily high price, $l_i$ is the daily low price, $c_i$ is the daily closing price, and $o_i$ is the daily opening price of the stock on day $i$. We compare Parkinson's volatility behavior with that obtained from the GKYZ (Figure A.1 in the Appendix) to show that they are comparable and that these measures can be used interchangeably.

In Table 2, we report the unit root tests (ADF and PP) to guarantee that the time series we used are stationary and allow the application of the Wold representation theorem that leads to the vector moving average (VMA) representation (Equation (2)), which, therefore, permits the computation of spillover metrics based on Equation (3).

**Table 1**
Financial indices used.

| Geographic Area | Index | Yahoo Ticker |
|---|---|---|
| Canadian | Canadian S&P/TSX Composite Index | GSPTSE |
| European | EuroStoxx 50 | STOXX50E |
| Hong Kong | Hang Seng Index | HSI |
| India | Nifty 50 | NSEI |
| Japan | Nikkei 225 | N225 |
| Shanghai | Shangai Composite Index | 000001.SS |
| Shenzhen | Shenzhen Index | 399001.SZ |
| UK | FTSE 100 | FTSE |
| USA | S&P 500 | GSPC |

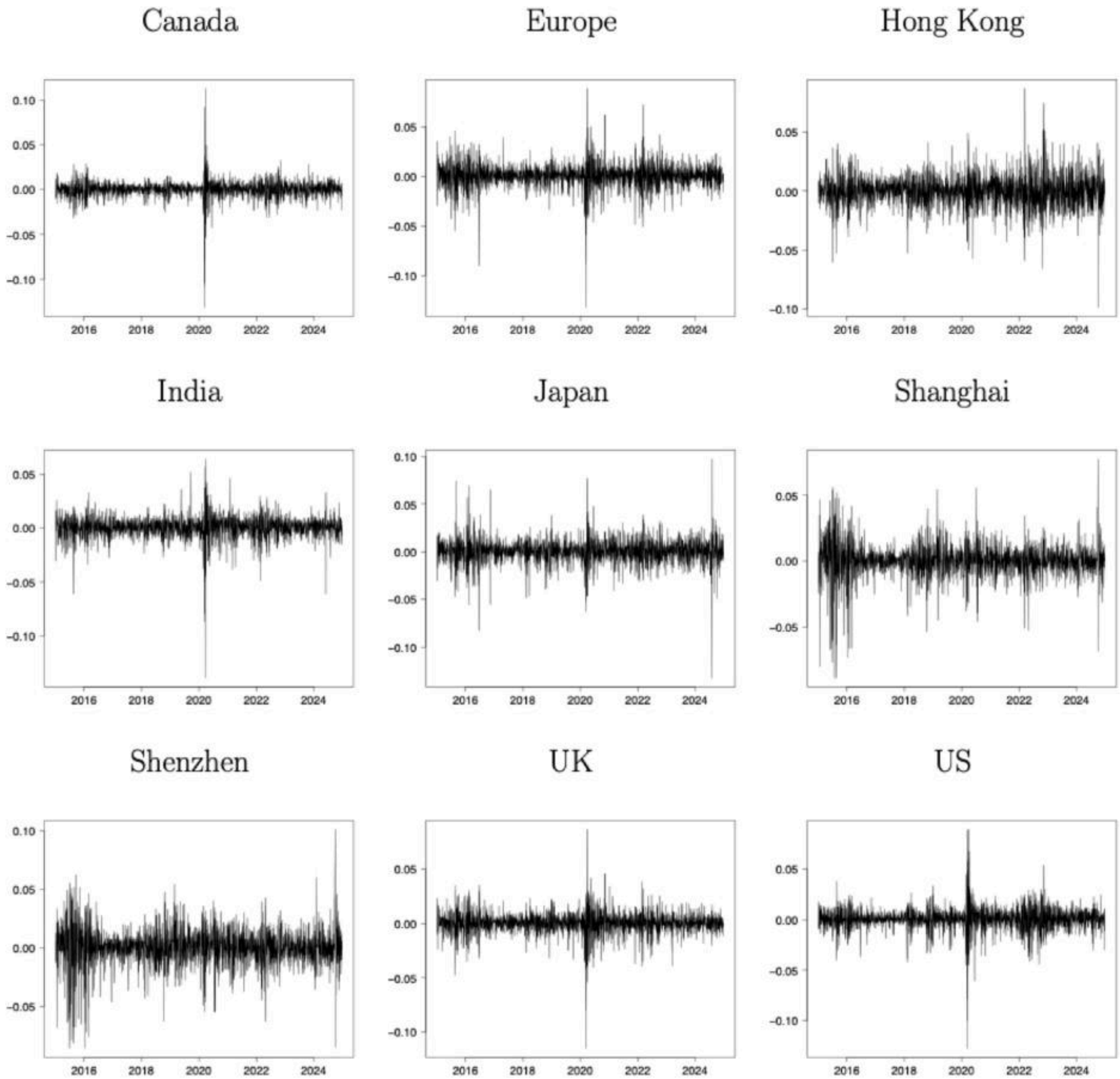


**Fig. 2.** Returns.

## 4. Empirical results and discussion

We divide our analysis into two sections. First, we conduct a graphical analysis of the rolling Total Connectedness Index (TCI) computed as in Equation (5), augmented with a brief graphical analysis of the static average networks. Second, we conduct a simple regression analysis using dummy variables to identify the impact of specific events on the relationship pairs across each financial pair. In the range of quantiles from 0 to 1, we specifically refer to three quantiles, 5 %, 50 %, and 95 %, for both returns and historical volatility. The use of quantiles in our modeling of returns (representing both bullish and bearish markets) and volatility (reflecting market calmness or turbulence) is the core of our analysis. To be more detailed, in both the returns and volatility cases, we use daily data for a total of $N = 2606$ observations. For comparability purposes we kept the same specification: the rolling-window is fixed at 250 trading day, which is a proxy for indicating the observations in a year and it is a standard in the Diebold and Yilmaz (2012) literature, the forecasts are based on $h = 30$ periods and the lag of the VAR model is fixed to the lowest Bayesian Information Criteria that in both cases is $p = 1$.

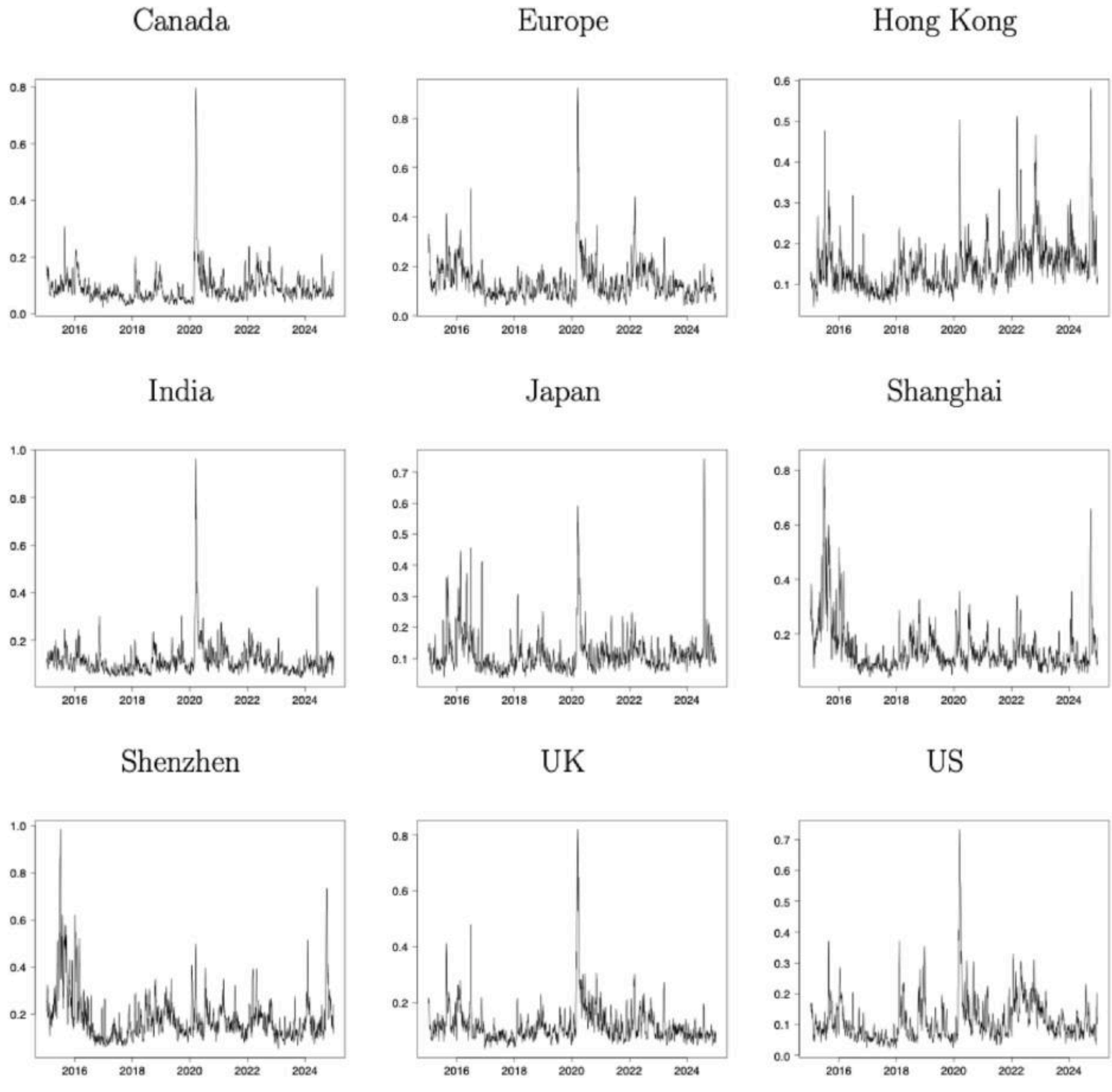


**Fig. 3.** Parkinson's volatility.

### 4.1. *The total connectedness index*

The Total Connectedness Index (TCI) analysis across the three quantiles provides insights into the persistent interconnectedness of global financial markets under different market volatility and sentiments. The first (second) column of Fig. 4 reports the returns (volatility) time series of the TCI across quantiles. Notably, the TCI achieves its highest values in the upper quantiles, corresponding to periods of bullish market sentiment in returns and heightened market volatility. This outcome indicates that during favorable market conditions, financial interconnectedness intensifies, amplifying the potential for spillover effects across regions and sectors. Interestingly, this pattern persists even for lower quantiles (downturn market occurrences and low volatility scenarios), where the TCI remains notably higher than the median level. This finding suggests that high levels of interconnectedness prevail, not just during turbulent market conditions but also when markets exhibit relative stability.

The perseverance of the TCI's highest values across both extreme market conditions is consistent with the study of Forbes and Rigobon (2002), who highlight the role of interdependent markets in spreading shocks under diverse market scenarios. However, this study demonstrates that interconnectedness is not only the response to crisis but also the consistent characteristic of the global markets. The findings are inconsistent with the study of Kaminsky and Reinhart (2000), who argue that financial turbulence causes the

**Table 2**
Unit Root tests.

| | Shanghai | Hong Kong | Shenzhen | US | European | India | UK | Canada | Japan |
|---|---|---|---|---|---|---|---|---|---|
| Returns | | | | | | | | | |
| DF | −13.86*** | −14.32*** | −13.46*** | −13.64*** | −13.93*** | −13.47*** | −14.29*** | −13.29*** | −14.17*** |
| PP(*100) | −2.505*** | −2.515*** | −2.509*** | −2.976*** | −2.679*** | −2.711*** | −2.575*** | −3.069*** | −2.573*** |
| Parkinson Volatility | | | | | | | | | |
| ADF | −7.87*** | −7.95*** | −8.70*** | −7.46*** | −8.30*** | −6.52*** | −6.69*** | −7.64*** | −7.28*** |
| PP(*10) | −1.24*** | −1.32*** | −2.00*** | −1.48*** | −1.78*** | −1.20*** | −1.33*** | −1.24*** | −1.14*** |

**Note:** ADF stands for Augmented Dicky-Fuller, and PP stands for Phillips and Perron tests; both are conducted, including a constant in the deterministic component.

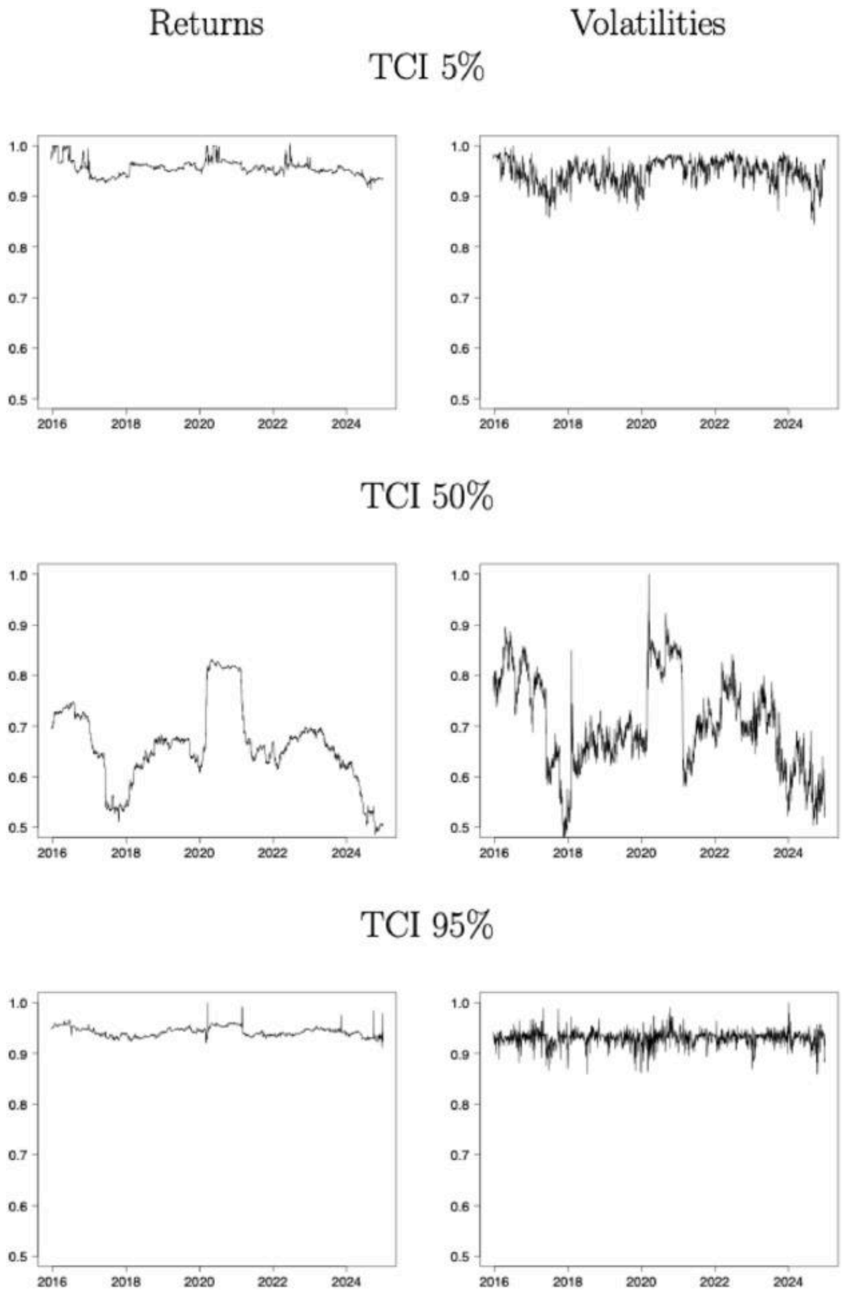


**Fig. 4.** Total connectedness index (TCI).

contagion effects predominantly. Alternatively, the TCI extended values in a stable period indicate a more entrenched and systemic nature of financial interconnectedness, aligning with the findings of Elsayed et al. (2023), who emphasized the structural persistence of interconnectedness of the global financial landscape.

Amid the unprecedented COVID-19 pandemic, a consistent pattern emerges as the TCI registers sudden increases across all three quantiles for both returns and volatility. This phenomenon signals the pronounced intensification of interconnectedness and interdependence within the financial realm during periods of global crises, thereby signifying an augmented presence of systemic risk that transcends both bullish and bearish market conditions. At the same time, in the context of the war between Russia and Ukraine, the TCI relating to returns in the 5 % and 50 % quantiles reaches its peak before gradually decreasing. This behavior indicates the initial disruption and market vicissitude that traditionally joins the onset of geopolitical hostilities, followed by market adaptation and eventual stabilization, followed by hedging operations and financial risk management.

The graphical evolution of the total connectedness index (TCI) at the 95 % volatility quantile reveals fluctuations that appear to coincide with the Evergrande episode. Importantly, these patterns should be understood as descriptive visual impressions rather than causal evidence. We did not conduct permutation or placebo tests that are outside the scope of this work, nor any formal variance-share calculations; hence, the link between the Evergrande timeline and the observed spikes in connectedness remains a conjecture drawn solely from the graphical display. The figure therefore, serves an illustrative purpose, highlighting that the episode temporally overlaps with elevated connectedness, but any stronger inference would require additional testing beyond the scope of this study.

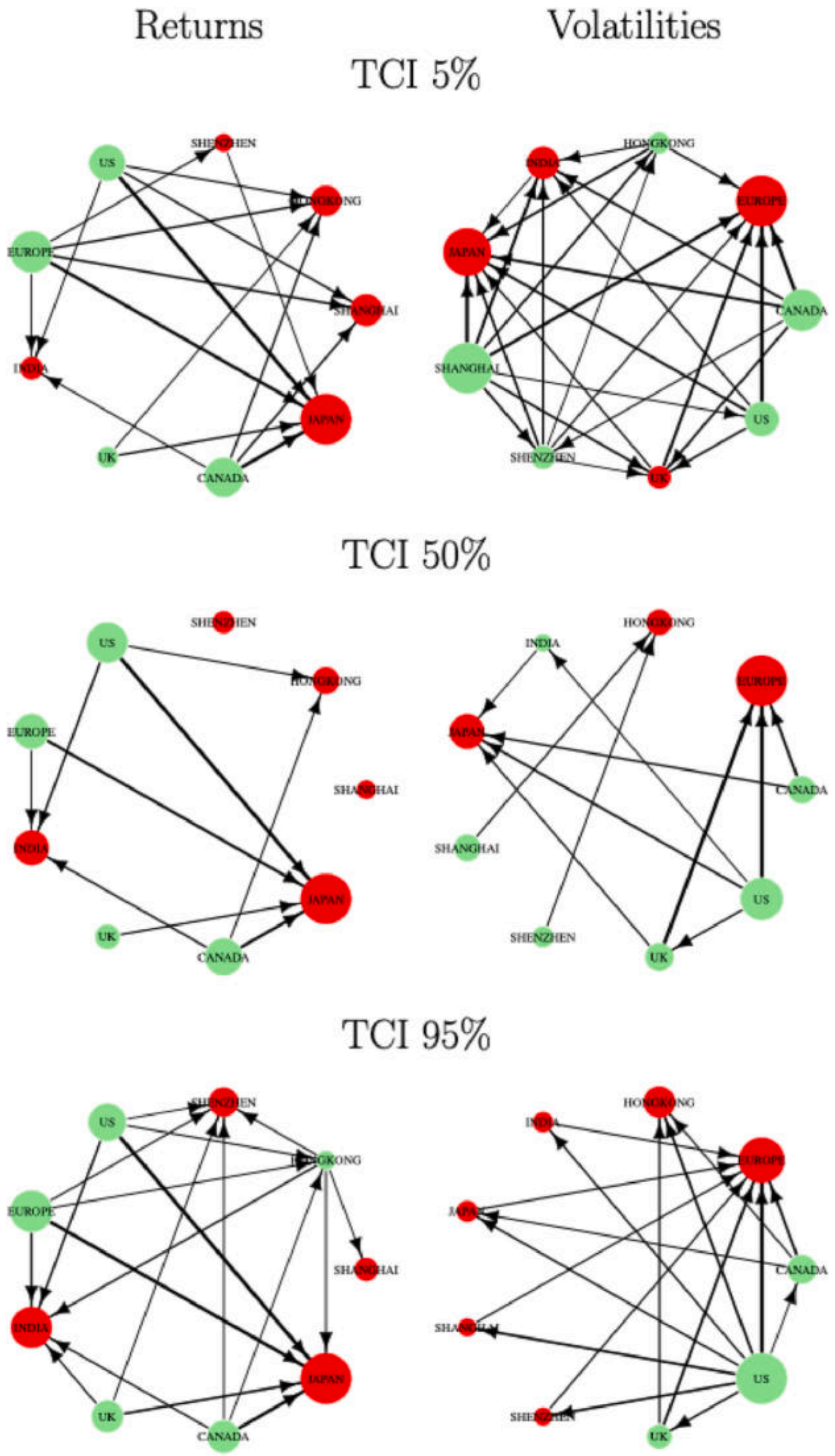


**Fig. 5.** Static Net Pairwise network.

The behavior shown in Fig. 4, denotes the potential contagion effect between markets. From the point of view of financial markets, these observations underline the sensibility nature of investors in the face of the most disparate crises and crucial events. Furthermore, they highlight the critical importance of carefully monitoring the degree of interconnectedness of economic systems to comprehensively assess market sentiment, resilience and susceptibility within an ever-changing financial environment. However, we draw these implications from a pure graphical conjecture. In the following subsection, we conduct a simple statistical significance analysis for the financial market contagion pairs to discuss the effect of these exogenous events.

Fig. 5 illustrates the system's behavior from a static perspective using a network plot. For the lower quantile of returns (5 %), the Shanghai, Hong Kong, and Shenzhen indices appear to absorb a larger share of spillovers, although Shenzhen plays only a marginal role. Japan emerges as the primary recipient, while Europe acts as the dominant source of spillovers. The connectedness pattern at the median quantile remains qualitatively similar to that observed at the 5 % quantile. The picture changes when moving to the upper quantile, reflecting bullish market conditions. In this case, Hong Kong shifts from being a receiver to becoming an emitter of spillovers, particularly toward Shanghai and Shenzhen.

The volatility network (right-hand side of Fig. 5) conveys a markedly different structure. In low-volatility conditions, the roles of the three Chinese indices are reversed: they act as volatility transmitters, with Shanghai exerting the strongest influence, especially on the European index. Japan, which was a key emitter in the return network, becomes a notable receiver, primarily of foreign-origin spillovers (Onwe et al., 2024). At the median volatility level, the intensity of interconnections weakens overall. Under high-volatility conditions, however, Europe emerges as the principal receiver of spillovers, while the US assumes the role of the largest emitter, underscoring its global centrality during episodes of financial turmoil.

These patterns highlight important asymmetries in the global transmission of shocks. The fact that Europe emerges as a net emitter in the return network but a net receiver in the volatility network suggests that European markets play a leading role in price discovery, but remain highly vulnerable to uncertainty originating elsewhere. The reversal of Japan's role - from a spillover source in returns to a recipient in volatility - indicates that while Japanese markets influence international returns, they are more sensitive to risk shocks from abroad.

The dominant role of the US as a volatility transmitter under stress conditions is consistent with its systemic relevance: in periods of global turmoil, US markets act as the primary channel through which shocks are propagated worldwide. Finally, the shifting roles of the Chinese indices reflect the dual nature of these markets: while they absorb return shocks in bearish conditions, they increasingly act as volatility transmitters in stable or bullish phases, signaling their growing integration and influence in global financial dynamics.

To sum up, the network visualization highlights that Hong Kong nodes appear more central relative to other Chinese markets when transmitting shocks to Europe and the UK. This impression arises directly from the density of outgoing links and their relative prominence in the plot. While Shanghai and Shenzhen continue to play relevant roles, the visual structure underscores Hong Kong's stronger outward connectivity in this window. Given the purpose of this study, the interpretation should be read as a descriptive account of relative prominence in the plotted networks rather than as a quantified ranking.

### *4.2. The pairwise statistical analysis*

Based on Equation (8) - Net Pairwise Directional Index (NPDC) - and summing Equations (6) and (7) - Pairwise Connectedness Spillover (PCI) -, we build a simple Ordinary Least Square (OLS) regression including different dummy variables for each of the rolling pairs to understand the impact of Covid-19 pandemic, the Russian invasion of Ukraine and the deployment of the Evergrande collapse. Since systemic crises such as the Evergrande collapse, the COVID-19 pandemic, and the Russia–Ukraine war unfolded gradually rather than on a single day, we incorporate several key events for each case to strengthen our identification strategy. For Evergrande, these include the initial missed offshore bond payments (September 2021), the official default on dollar-denominated debt (December 2021), the sharp collapse in financial markets (August 2023), and the liquidation order issued by a Hong Kong court (January 2024). For COVID-19, we mark the reporting of the first pneumonia cases in Wuhan (December 2019), the WHO's global pandemic declaration (March 11, 2020), and the US emergency declaration (March 13, 2020). For the Russia–Ukraine war, we highlight the full-scale invasion (February 24, 2022), given that the conflict is still ongoing. Therefore, the three dummies are active in correspondence with these dates, and the main idea of the work is to understand their impact on each pairwise relationship.

While the propagation of Evergrande-related shocks may also operate through channels such as sectoral equity indices, offshore property bonds, CDS markets, and foreign exchange, consistent daily data for these instruments across our full sample (2015–2024) are not fully accessible. Our focus, therefore, is on cross-market transmission among major national equity indices**,** which allows us to capture the systemic dimension of international spillovers rather than sector-specific dynamics.[1]

Tables 3A, 3B, 4A, and 4B report the results for the NPDC and PCI metrics. In Appendix (see Figure A.2 and A.3), we report the graphical time series of the dependent variable for each regression. To keep the analysis as simple as possible, we do not model the behavior of the univariate time series. However, to avoid over-rejection in the presence of strong autocorrelation, we include the HAC standard errors in parentheses, and this could guarantee the inference of our results.

NPDC measures highlight how specific markets influence one another, while PCI aggregates the broader transmission of risks. When there is statistical evidence of impact for the NPDC case, it means that the higher the impact, the higher the event effect on the pairs. On the contrary, when the statistical evidence is on the PCI, it means that the higher the impact, the higher the aggregate risk

[1] We acknowledge this limitation and highlight that future research could extend the present framework to sectoral indices and alternative asset classes to provide a more granular view of contagion mechanisms.

transmission (Ramzan et al., 2024). This distinction highlights the NPDC's focus on bilateral dynamics and the PCI's utility in understanding systemic transmission. It is crucial to understand the difference since, in the first case, we can understand how investors react to exogenous events, while in the second, we can conclude the total risk transmission between pairs. In other words, identifying net spillover transmitters (via NPDC) can guide regulatory and risk management decisions, targeting the stabilization of dominant markets during crises. Recognizing strong bilateral relationships (via PCI) informs investors and policymakers about potential contagion risks or diversification strategies.

The NPDC estimates for returns reveal that Evergrande-driven shocks produced heterogeneous cross-market effectsdepending on quantile regimes. At the 5 % quantile (bearish states), spillovers from Shanghai to the EU increased by about 3.7 %, while effects on other indices were modest. By contrast, spillovers from Shenzhen to the US in bullish quantiles were negative (−5.9 %), indicating that Shenzhen's influence remained mostly regional and sometimes dampened cross-border transmission. Hong Kong displayed the most consistent role as a transmitter; its spillovers to European and UK indices were positive and significant across quantiles, with median increases of 7–10 %, underscoring its role as a global hub rather than a purely regional conduit.

Volatility-based NPDCs indicate even stronger asymmetries. During Evergrande shocks at the 95 % quantile (turbulent volatility regimes), Hong Kong → EU spillovers declined by about 7.5 %, while Shanghai → UK spillovers fell by 9.3 %. In contrast, some relationships turned positive; for instance, spillovers from Shanghai to the US rose by roughly 14.9 %, showing that volatility shocks can amplify risks in certain advanced markets.

The PCI results further confirm Hong Kong's systemic role in returns connectedness. Evergrande shocks raised Hong Kong's spillovers to the US by 7.2 % and to the UK by 6.3 %, while Shanghai–US connectedness increased by about 8.3 %. In contrast, Canadian market pairs displayed only negligible changes, with PCI variations of 2–4 %, reinforcing Canada's insulation from Chinese systemic risk and its potential as a diversification hedge.

For other events such as COVID-19 and the Russia–Ukraine war, the effects were much more pronounced compared to Evergrande alone. This suggests that while the Evergrande collapse did amplify spillovers in specific pairs, it did not generate a fully systemic global crisis.

### 4.3. Portfolio robustness

The section aims to assess whether the findings from the general analysis can be corroborated through a simple portfolio-based approach. To this end, we conduct two types of portfolio analyses: a minimum-variance (minvar) and a risk-parity (rp) portfolio. This allows us to examine, from a rolling perspective, whether the dynamic weights of each series can provide additional insight into

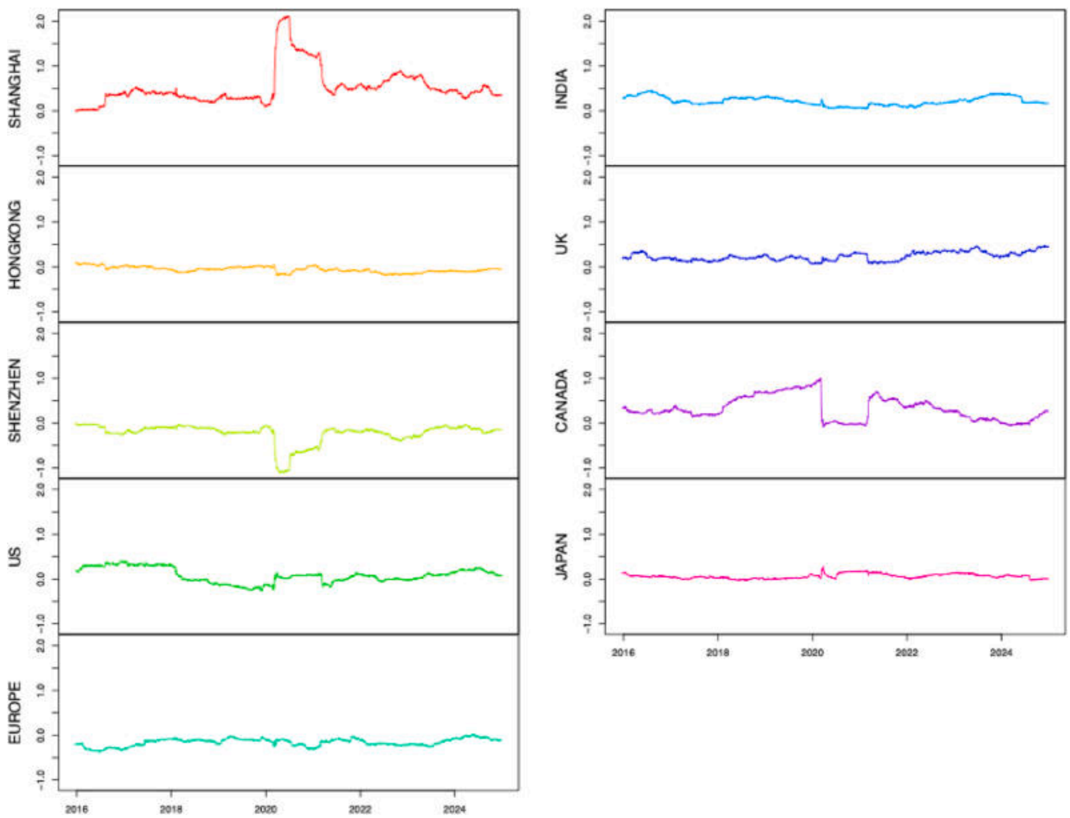


**Fig. 6.** Minimum variance portfolio weights.

hedging performance. For simplicity, we focus on a portfolio comprising the nine indices previously analyzed. Figs. 6 and 7 present the dynamic weights derived from the rolling (same specification of the connectedness analysis) portfolio analysis.

Additionally, Figure A.4 displays the cumulative returns corresponding to the two portfolio measures, along with the associated index weights. A preliminary visual inspection reveals a marked improvement in performance following the Covid-19 pandemic, indicating a clear shift in return behavior. This observation suggests that the computed weights can provide meaningful insights into the assessment of the hedging properties of the sectoral indices.

On average, the primary differences between Figs. 6 and 7 lie in the magnitude of the weights, while the overall dynamic patterns remain largely consistent. Chinese indices exhibit distinctive behaviors: both Shanghai and Hong Kong indices generally maintain positive weights, peaking at the onset of the Covid-19 pandemic, whereas the Shenzhen index consistently carries negative weights, which intensify during the pandemic. This pattern mirrors that of the Canadian index, which also declines during periods of market stress, highlighting its hedging characteristics. In contrast, the remaining indices display more stable behavior over time, without pronounced peaks or troughs.

## 5. Conclusion

This study analyzed the role of the Evergrande crisis and its broader implications for volatility and returns in highly interconnected global financial markets. The outcomes revealed that Hong Kong and Shanghai play the leading roles in risk transmission, while Shenzhen's influence is more limited and regionally focused. Specifically, Evergrande-driven shocks increased Hong Kong's spillovers to European and UK markets by 7–10 %, confirming its position as a global financial hub embedded in international market dynamics. Shanghai demonstrated a context-dependent role, with spillovers to the US market rising by about 15 % during high-volatility periods, reflecting global sensitivity to systemic risks originating in China's real estate sector. Conversely, Shenzhen's spillover effects remained modest and occasionally negative, reinforcing its primarily regional rather than global impact.

The results also highlight heterogeneous spillover responses across global markets. Developed markets such as the US and Europe were most sensitive to Evergrande-driven contagion, especially during turbulent periods, while the Canadian market remained largely insulated (spillovers of only 2–4 %). This underscores Canada's potential as a hedge or diversification tool for investors seeking to mitigate exposure to Chinese systemic risk. The Evergrande crisis thus amplified spillover effects through specific channels (notably Shanghai-US and Hong Kong–Europe), but unlike COVID-19 or the Russia–Ukraine war, it did not trigger fully systemic global contagion. The persistence of elevated connectedness across both bullish and bearish conditions nevertheless signals that systemic risk

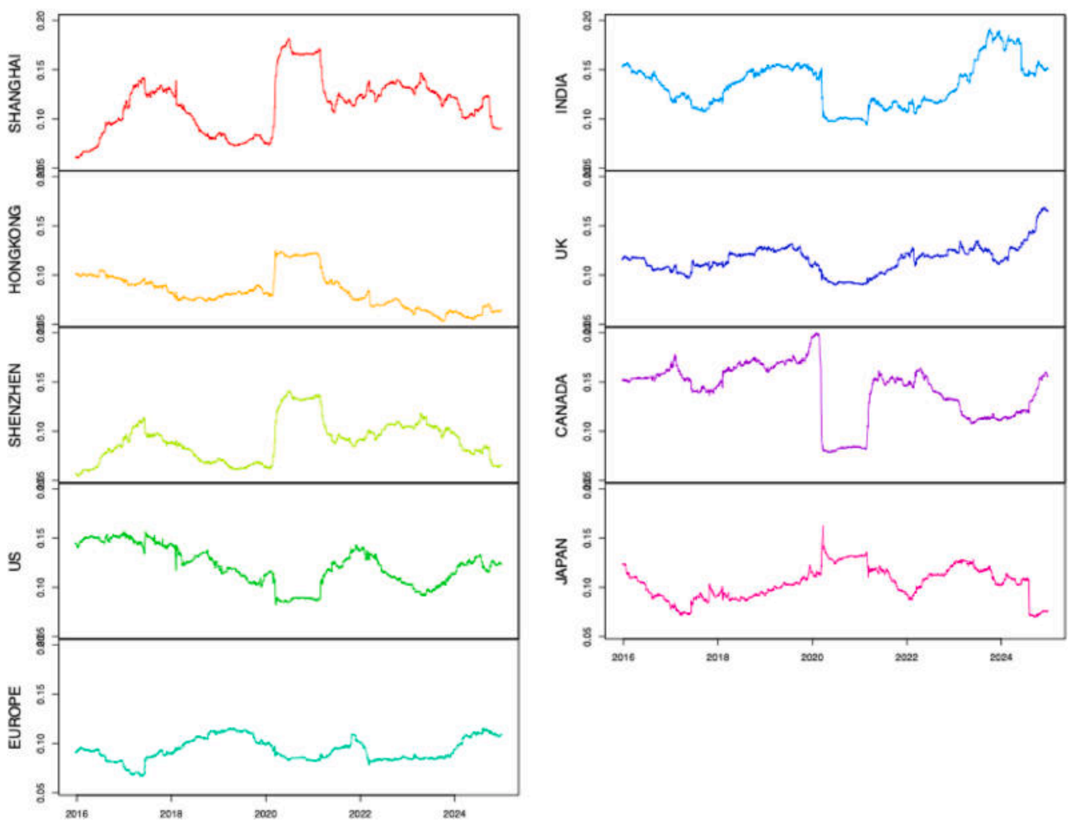


**Fig. 7.** Risk Parity Porfolio weights.

remains a structural feature of global markets, with contagion mechanisms that are asymmetric and event-driven.

From these findings, several policy implications emerge. Financial markets require strengthened cross-border surveillance and regulatory coordination to mitigate contagion effects. A global risk monitoring framework under institutions such as the Financial Stability Board or the IMF could facilitate the early detection of vulnerabilities in highly leveraged sectors like real estate. Bilateral cooperation between China and its major partners (US, UK, and EU) should be reinforced to improve transparency and information sharing during exogenous shocks such as the Evergrande collapse. Within domestic financial sectors, stress testing for institutions heavily exposed to Chinese assets is essential to assess potential losses under real estate defaults and to prepare for adverse scenarios.

Regulators should also mandate counter-cyclical capital buffers to protect banks and investment funds from external shocks. Institutional investors are advised to adopt hedging instruments and diversify portfolios geographically, with special consideration of resilient markets such as Canada. On the Chinese side, greater transparency and disclosure standards for systemically important firms like Evergrande are essential, particularly on bond issuance, liabilities, and asset valuations. International cooperation on benchmark leverage ratios and the adoption of macroprudential tools (e.g., debt-to-equity caps, loan-to-value restrictions) would help stabilize high-risk sectors such as real estate. In addition, establishing global stabilization mechanisms—including crisis contingency funds and central bank swap lines - can provide critical support during episodes of market stress. These measures would enhance the resilience of the global financial system, limit contagion risks, and foster sustainable growth in an increasingly interconnected world.

Finally, it should be noted that the primary objective of this study is to provide a broader understanding of the risks and interconnections among financial indices. In particular, we focus on evaluating whether external events affect the relationships across index pairs, thereby contributing to the existing literature. The portfolio-level analysis is performed to further validate the robustness of our findings. Future research could extend this approach by incorporating weighted constraints on specific market instruments, such as ETFs, to assess whether the results can be generalized to alternative portfolio baselines.

## Credit author statement

**Umar Shahzad:** Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Supervision, Project Administration. **Marco Tedeschi:** Visualization, Investigation, Writing – Review & Editing. **Ummara Razi:** Literature Review, Data Curation, Writing – Review & Editing, Resources. **Dariusz Cichoń:** Software, Technical Support, Writing – Review & Editing, Funding Acquisition.

## Declaration of competing interests

Authors have no financial or non-financial competing interests. No conflict of interest.

## Appendix

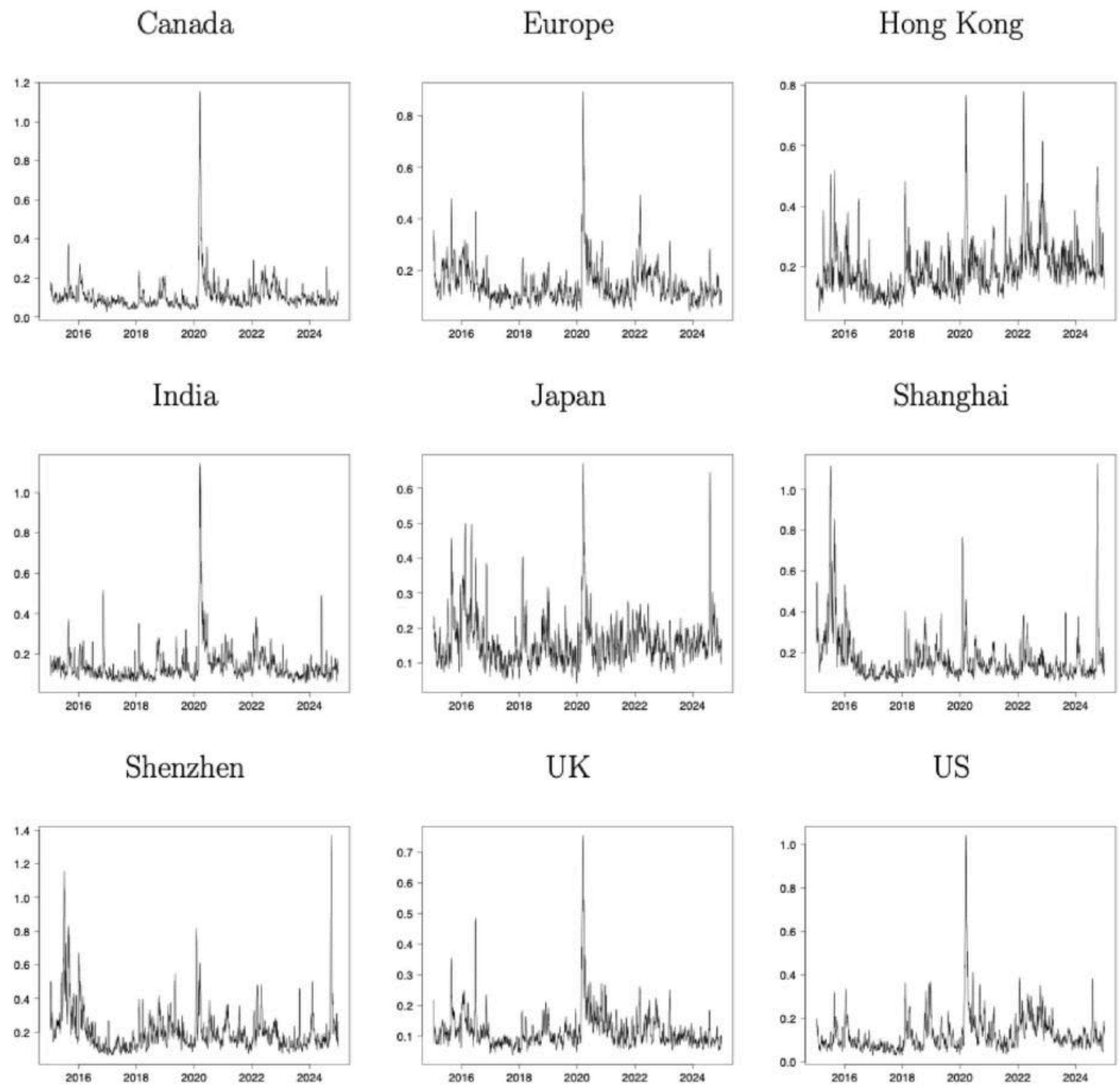


**Fig. A.1.** Garman-Klass-Yang-Zhang (GKYZ) Volatility.

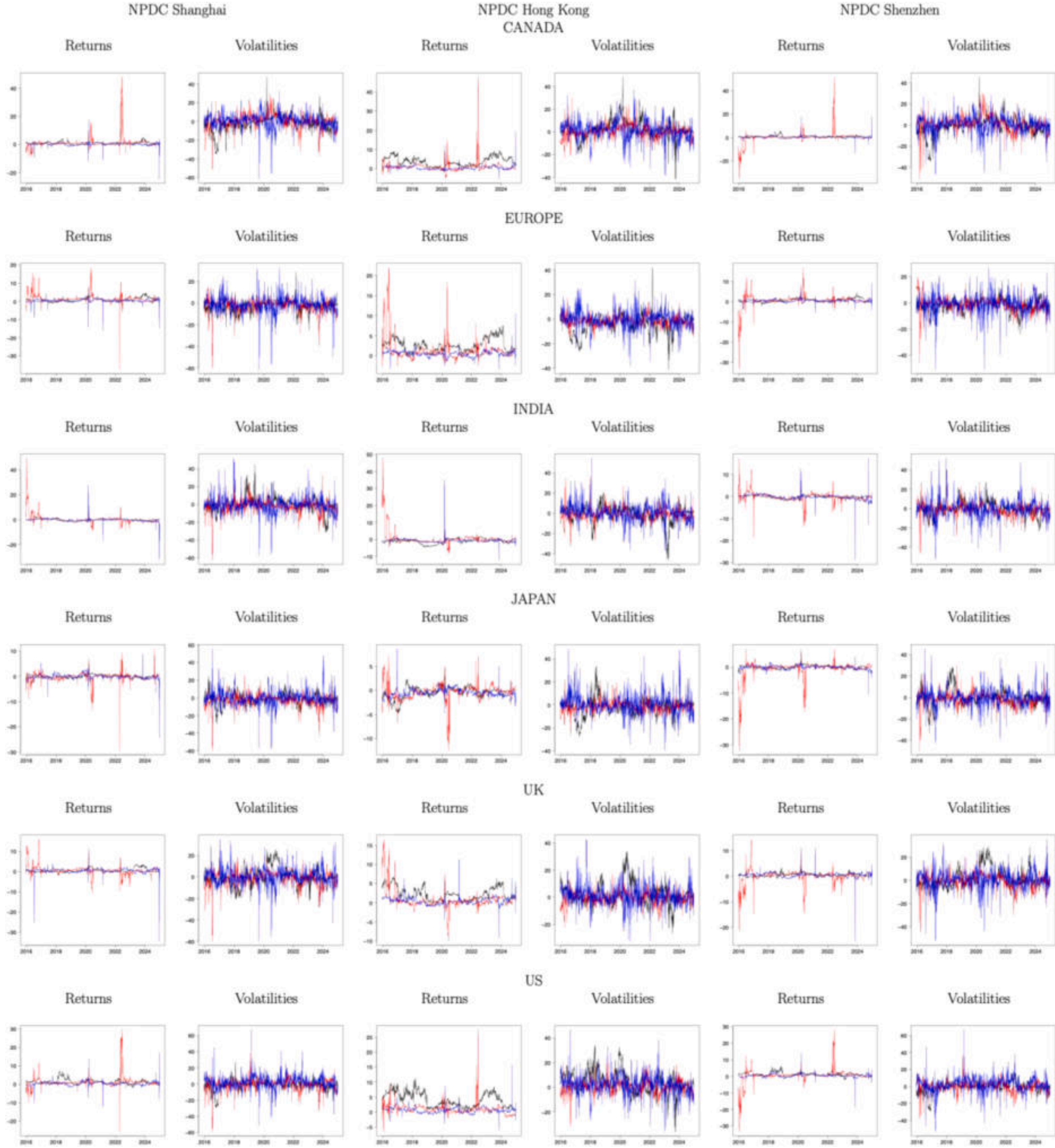


**Fig. A.2.** Net pairwise directional spillovers.
**Note:** The red line refers to the 5 % quantile estimation. The black line for the median quantile (50 %). The blue line is ascribable to the highest quantile (95 %).

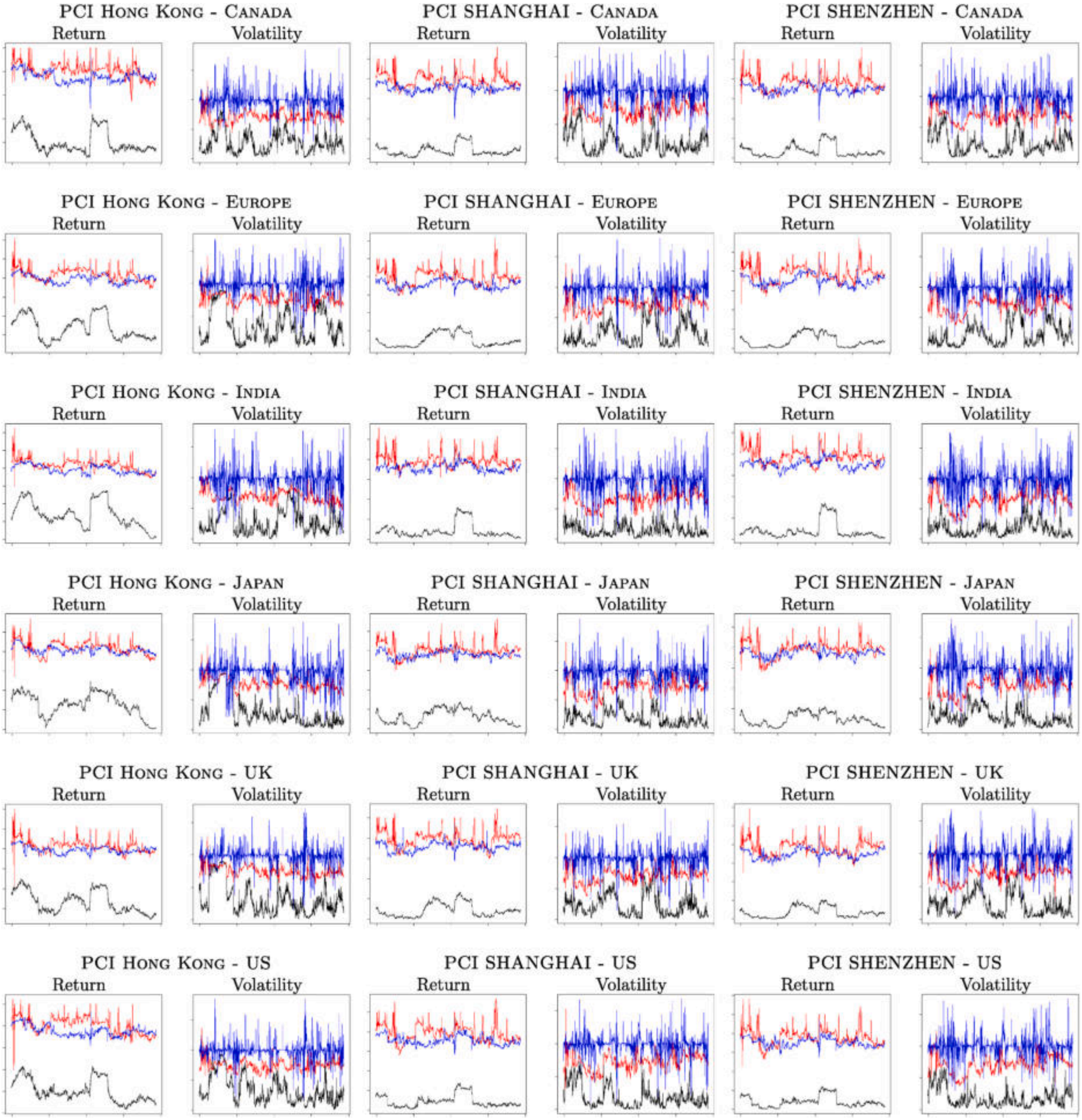


**Fig. A.3.** Pairwise Connectedness Index.
**Note:** The red line refers to the 5 % quantile estimation. The black line for the median quantile (50 %). The blue line is ascribable to the highest quantile (95 %).

**Table 3A**
Net Pariwise Directional Spillovers on Returns

| Quantile | Variable | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Hong Kong | | | | | | Shenzhen | | | | | | Shanghai | | | | | |
| 5 | (Intercept) | 0.034*** | 0.056*** | 0.008*** | 0.041*** | 0.022*** | -0.056*** | 0.018*** | 0.047*** | -0.015*** | 0.002 | 0.007*** | -0.093*** | 0.037*** | 0.071*** | 0.005*** | 0.027*** | 0.024*** | -0.026*** |
| | | -0.001 | -0.003 | -0.002 | -0.003 | -0.001 | -0.005 | -0.003 | -0.004 | -0.003 | -0.004 | -0.002 | -0.01 | -0.002 | -0.002 | -0.001 | -0.003 | -0.002 | -0.003 |
| 5 | Date_COVID | 0.094* | 0.113* | 0.022 | 0.184* | 0.045 | 0.34** | 0.143** | 0.243** | 0.176 | 0.343** | 0.082* | 0.543** | 0.121* | 0.197* | 0.054 | 0.3** | 0.079 | 0.34*** |
| | | -0.052 | -0.063 | -0.032 | -0.096 | -0.045 | -0.172 | -0.069 | -0.11 | -0.113 | -0.141 | -0.048 | -0.212 | -0.064 | -0.101 | -0.038 | -0.122 | -0.048 | -0.131 |
| 5 | Date_Ukraine | -0.021*** | -0.027*** | -0.005*** | -0.022*** | 0.013*** | 0.03*** | -0.008*** | 0.013*** | 0.054*** | 0.042*** | 0.015*** | 0.087*** | -0.025*** | 0.007*** | 0.016*** | 0.022*** | 0.004** | 0.027*** |
| | | -0.001 | -0.003 | -0.002 | -0.003 | -0.001 | -0.005 | -0.003 | -0.004 | -0.003 | -0.004 | -0.002 | -0.01 | -0.002 | -0.002 | -0.001 | -0.003 | -0.002 | -0.003 |
| 5 | Date_Evergrande | -0.001 | -0.009 | 0.007 | -0.001 | 0.004 | 0.078*** | 0.016* | 0.006 | 0.022 | 0.024 | 0.007 | 0.08* | -0.017* | -0.035*** | -0.001 | -0.015 | -0.009 | -0.013 |
| | | -0.005 | -0.01 | -0.007 | -0.01 | -0.003 | -0.011 | -0.009 | -0.007 | -0.017 | -0.016 | -0.005 | -0.043 | -0.009 | -0.009 | -0.009 | -0.011 | -0.007 | -0.039 |
| 50 | (Intercept) | 0.362*** | 0.351*** | -0.576*** | 0.333*** | 0.388*** | -0.081*** | 0.171*** | 0.153*** | -0.165*** | 0.106*** | 0.112*** | 0.026*** | 0.169*** | 0.174*** | -0.121*** | 0.134*** | 0.167*** | -0.01*** |
| | | -0.004 | -0.004 | -0.015 | -0.005 | -0.005 | -0.005 | -0.004 | -0.004 | -0.01 | -0.003 | -0.003 | -0.004 | -0.004 | -0.005 | -0.007 | -0.005 | -0.004 | -0.003 |
| 50 | Date_COVID | -0.058* | -0.009 | -0.496** | -0.055 | -0.283*** | 0.649*** | 0.06 | 0.2*** | -0.243* | 0.17** | 0.012 | 0.466** | 0.11* | 0.294** | -0.226*** | 0.318* | -0.058 | 0.423* |
| | | -0.032 | -0.054 | -0.247 | -0.096 | -0.055 | -0.182 | -0.039 | -0.046 | -0.137 | -0.07 | -0.037 | -0.21 | -0.057 | -0.12 | -0.057 | -0.164 | -0.057 | -0.242 |
| 50 | Date_Ukraine | -0.145*** | -0.046*** | 0.769*** | -0.182*** | -0.113*** | 0.084*** | -0.015*** | -0.139*** | 0.033*** | 0.001 | -0.057*** | 0.095*** | 0.102*** | -0.132*** | 0.061*** | -0.119*** | 0.033*** | -0.012*** |
| | | -0.004 | -0.004 | -0.015 | -0.005 | -0.005 | -0.005 | -0.004 | -0.004 | -0.01 | -0.003 | -0.003 | -0.004 | -0.004 | -0.005 | -0.007 | -0.005 | -0.004 | -0.003 |
| 50 | Date_Evergrande | -0.081 | 0.139 | 0.16 | 0.022 | 0.106 | 0.132** | -0.045 | 0.072 | -0.099 | 0.041 | -0.021 | 0.034 | -0.034 | 0.079 | 0.026 | 0.099 | 0.057 | -0.013 |
| | | -0.098 | -0.15 | -0.111 | -0.145 | -0.143 | -0.065 | -0.048 | -0.109 | -0.106 | -0.059 | -0.037 | -0.045 | -0.032 | -0.12 | -0.108 | -0.141 | -0.076 | -0.054 |
| 95 | (Intercept) | 0.038*** | 0.052*** | -0.022*** | 0.036*** | 0.024*** | -0.056*** | 0.034*** | 0.062*** | -0.018*** | 0.045*** | 0.029*** | -0.017*** | 0.021*** | 0.057*** | -0.012*** | 0.029*** | 0.016*** | -0.014*** |
| | | -0.001 | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.003 | -0.001 | -0.003 | -0.001 | -0.003 | -0.001 | -0.002 |
| 95 | Date_COVID | 0.059*** | 0.042* | -0.025*** | 0.044 | -0.023*** | 0.111*** | 0.142*** | 0.091* | -0.021 | 0.115** | 0.021 | 0.276*** | 0.108** | 0.189*** | 0.016 | 0.089*** | 0.056 | 0.146** |
| | | -0.02 | -0.023 | -0.009 | -0.047 | -0.006 | -0.025 | -0.039 | -0.052 | -0.028 | -0.052 | -0.034 | -0.053 | -0.042 | -0.069 | -0.015 | -0.031 | -0.042 | -0.073 |
| 95 | Date_Ukraine | -0.106*** | -0.125*** | -0.005*** | -0.086*** | -0.031*** | -0.051*** | 0.014*** | -0.036*** | 0.024*** | -0.018*** | 0.007*** | 0.083*** | -0.022*** | -0.029*** | 0 | -0.021*** | -0.004*** | 0.011*** |
| | | -0.001 | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.003 | -0.001 | -0.003 | -0.001 | -0.003 | -0.001 | -0.002 |
| 95 | Date_Evergrande | -0.032 | -0.007 | 0.012** | 0.006 | 0.007 | 0.007 | -0.059** | -0.012 | -0.01 | -0.023 | -0.004 | -0.034 | -0.046 | -0.002 | 0.002 | -0.043* | 0.011 | -0.038* |
| | | -0.026 | -0.038 | -0.005 | -0.045 | -0.01 | -0.019 | -0.026 | -0.027 | -0.013 | -0.035 | -0.019 | -0.063 | -0.03 | -0.027 | -0.012 | -0.022 | -0.021 | -0.023 |

**Table 3B**
Net Pariwise Directional Spillovers on Volatilities

| Quantile | Variable | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Hong Kong | | | | | | Shenzhen | | | | | | Shanghai | | | | | |
| 5 | (Intercept) | 0.015*** | 0.002 | 0.039*** | 0.024*** | 0.086*** | 0.093*** | -0.031*** | -0.08*** | 0.027*** | 0.017*** | -0.024*** | 0.012*** | -0.042*** | -0.081*** | 0.004 | -0.019*** | -0.07*** | -0.037*** |
| | | -0.002 | -0.004 | -0.002 | -0.002 | -0.004 | -0.003 | -0.003 | -0.004 | -0.002 | -0.003 | -0.005 | -0.004 | -0.003 | -0.004 | -0.003 | -0.003 | -0.004 | -0.007 |
| 5 | Date_COVID | -0.046 | 0.151 | -0.097*** | -0.047*** | 0.072 | -0.12** | 0.056** | 0.399*** | -0.03 | 0.029 | 0.422*** | -0.003 | -0.093 | 0.002 | -0.119** | -0.063 | 0.051 | -0.503** |
| | | -0.04 | -0.095 | -0.028 | -0.017 | -0.126 | -0.055 | -0.025 | -0.046 | -0.019 | -0.023 | -0.064 | -0.019 | -0.102 | -0.097 | -0.048 | -0.049 | -0.101 | -0.246 |
| 5 | Date_Ukraine | -0.033*** | 0.047*** | -0.007*** | 0.096*** | -0.135*** | 0.055*** | -0.098*** | 0.17*** | -0.045*** | 0.059*** | 0.128*** | 0.094*** | 0.03*** | 0.081*** | 0.104*** | 0.121*** | -0.092*** | 0.234*** |
| | | -0.002 | -0.004 | -0.002 | -0.002 | -0.004 | -0.003 | -0.003 | -0.004 | -0.002 | -0.003 | -0.005 | -0.004 | -0.003 | -0.004 | -0.003 | -0.003 | -0.004 | -0.007 |
| 5 | Date_Evergrande | -0.058*** | -0.147*** | -0.02 | -0.089** | -0.026 | 0.035 | 0.065** | 0.272 | 0.068 | 0.017 | 0.036 | 0.327*** | -0.072** | -0.017 | -0.021 | -0.076** | -0.013 | 0.255*** |
| | | -0.021 | -0.034 | -0.026 | -0.042 | -0.078 | -0.049 | -0.029 | -0.188 | -0.071 | -0.046 | -0.06 | -0.107 | -0.031 | -0.075 | -0.056 | -0.03 | -0.053 | -0.095 |
| 50 | (Intercept) | 0.068*** | 0.027*** | 0.11*** | 0.078*** | 0.306*** | 0.362*** | -0.033*** | -0.052*** | 0.185*** | 0.197*** | 0.065*** | 0.123*** | -0.002 | -0.206*** | 0.063*** | 0.04*** | -0.124*** | 0.096*** |
| | | -0.002 | -0.003 | -0.004 | -0.004 | -0.006 | -0.004 | -0.008 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.004 | -0.005 | -0.005 | -0.005 | -0.007 | -0.004 |
| 50 | Date_COVID | 0.003 | -0.049* | -0.091*** | -0.103*** | 0.104 | 0.133 | 0.225*** | 0.041* | -0.16*** | -0.176*** | 0.486*** | 0.404*** | -0.587*** | -0.617*** | -0.699** | -0.801*** | -0.174* | -0.429 |
| | | -0.01 | -0.028 | -0.023 | -0.03 | -0.113 | -0.129 | -0.087 | -0.021 | -0.022 | -0.016 | -0.186 | -0.133 | -0.157 | -0.22 | -0.323 | -0.278 | -0.103 | -0.267 |
| 50 | Date_Ukraine | 0.09*** | -0.374*** | -0.345*** | -0.113*** | -0.081*** | -0.263*** | -0.033*** | 0.154*** | -0.334*** | -0.316*** | -0.087*** | -0.097*** | 0.259*** | -0.101*** | -0.074*** | -0.052*** | 0.215*** | 0.313*** |
| | | -0.002 | -0.003 | -0.004 | -0.004 | -0.006 | -0.004 | -0.008 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.004 | -0.005 | -0.005 | -0.005 | -0.007 | -0.004 |
| 50 | Date_Evergrande | -0.134*** | -0.02 | -0.123 | -0.102 | -0.025 | 0.007 | 0.087 | -0.046 | -0.174 | 0.017 | -0.089** | -0.087 | 0.047 | -0.101 | -0.071 | -0.098 | -0.316*** | -0.124* |
| | | -0.049 | -0.055 | -0.076 | -0.098 | -0.063 | -0.03 | -0.07 | -0.063 | -0.164 | -0.075 | -0.035 | -0.085 | -0.101 | -0.114 | -0.069 | -0.105 | -0.099 | -0.073 |
| 95 | (Intercept) | 0.021*** | 0.022*** | 0.018*** | 0.023*** | 0.045*** | 0.052*** | 0.008** | 0.012*** | 0.011*** | 0.008*** | 0.032*** | 0.042*** | -0.004 | -0.017*** | -0.009*** | -0.01*** | -0.011*** | 0.016*** |
| | | -0.003 | -0.003 | -0.002 | -0.003 | -0.003 | -0.002 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.002 | -0.002 | -0.003 | -0.004 | -0.003 |
| 95 | Date_COVID | 0.104 | 0.068*** | 0.001 | 0.007 | 0.21* | 0.022 | -0.078 | 0.072 | -0.388 | -0.331* | 0.216** | 0.087 | -0.042 | -0.055** | -0.038 | -0.027 | -0.009 | -0.089** |
| | | -0.098 | -0.022 | -0.043 | -0.085 | -0.108 | -0.04 | -0.098 | -0.057 | -0.244 | -0.182 | -0.087 | -0.084 | -0.034 | -0.025 | -0.044 | -0.093 | -0.035 | -0.041 |
| 95 | Date_Ukraine | -0.239*** | -0.015*** | -0.042*** | -0.253*** | 0.07*** | 0.062*** | -0.008*** | -0.011*** | 0.016*** | 0.022*** | -0.035*** | 0.061*** | -0.089*** | 0.084*** | -0.106*** | -0.181*** | 0.317*** | 0.213*** |
| | | -0.003 | -0.003 | -0.002 | -0.003 | -0.003 | -0.002 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.002 | -0.002 | -0.003 | -0.004 | -0.003 |
| 95 | Date_Evergrande | 0.032 | -0.116** | -0.075** | -0.1** | 0.029 | 0.012 | 0.018 | -0.097 | -0.022 | -0.095* | -0.037 | -0.063 | -0.053 | -0.046 | -0.03 | -0.092* | 0.149* | -0.005 |
| | | -0.031 | -0.055 | -0.031 | -0.042 | -0.03 | -0.065 | -0.014 | -0.072 | -0.065 | -0.053 | -0.027 | -0.063 | -0.064 | -0.048 | -0.03 | -0.047 | -0.077 | -0.055 |

**Table 3C**
Pariwise Connectedness Spillovers on Returns

| Quantile | Variable | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Hong Kong | | | | | | Shenzhen | | | | | | Shanghai | | | | | |
| 5 | (Intercept) | 0.603*** | 0.777*** | 0.754*** | 0.783*** | 0.796*** | 0.777*** | 0.557*** | 0.708*** | 0.738*** | 0.755*** | 0.695*** | 0.772*** | 0.592*** | 0.703*** | 0.683*** | 0.696*** | 0.743*** | 0.678*** |
| | | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.002 | -0.001 | -0.001 | -0.002 | -0.001 |
| 5 | Date_COVID | 0.112*** | 0.105** | 0.094* | 0.098** | 0.101 | 0.118*** | 0.108** | 0.137** | 0.101 | 0.13* | 0.111 | 0.153*** | 0.112*** | 0.124*** | 0.101 | 0.111** | 0.103 | 0.13*** |
| | | -0.027 | -0.042 | -0.05 | -0.048 | -0.068 | -0.031 | -0.049 | -0.055 | -0.085 | -0.069 | -0.073 | -0.054 | -0.04 | -0.047 | -0.066 | -0.054 | -0.069 | -0.035 |
| 5 | Date_Ukraine | -0.043*** | -0.002 | -0.066*** | -0.038*** | -0.01*** | -0.067*** | -0.032*** | -0.03*** | -0.006*** | -0.11*** | -0.064*** | -0.014*** | -0.052*** | -0.041*** | -0.001 | -0.09*** | -0.069*** | -0.021*** |
| | | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.002 | -0.001 | -0.001 | -0.002 | -0.001 |
| 5 | Date_Evergrande | -0.049*** | -0.03*** | -0.046*** | -0.044*** | -0.02 | -0.035** | -0.024** | -0.017*** | -0.009 | -0.028** | -0.021 | -0.011 | -0.036*** | -0.026*** | -0.021** | -0.03* | -0.027 | -0.011 |
| | | -0.012 | -0.009 | -0.014 | -0.008 | -0.025 | -0.014 | -0.01 | -0.006 | -0.013 | -0.012 | -0.021 | -0.011 | -0.013 | -0.004 | -0.01 | -0.015 | -0.02 | -0.008 |
| 50 | (Intercept) | 0.459*** | 0.51*** | 0.456*** | 0.515*** | 0.47*** | 0.447*** | 0.312*** | 0.3*** | 0.237*** | 0.29*** | 0.277*** | 0.335*** | 0.296*** | 0.289*** | 0.246*** | 0.28*** | 0.295*** | 0.347*** |
| | | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 | -0.004 | -0.005 | -0.004 | -0.005 |
| 50 | Date_COVID | 0.117*** | 0.07 | -0.141** | 0.049 | -0.106 | 0.327*** | 0.203** | 0.271*** | -0.083* | 0.178** | 0.118 | 0.381*** | 0.308*** | 0.297*** | -0.065 | 0.217** | 0.109 | 0.428*** |
| | | -0.04 | -0.063 | -0.055 | -0.068 | -0.077 | -0.045 | -0.094 | -0.055 | -0.045 | -0.079 | -0.102 | -0.07 | -0.102 | -0.064 | -0.041 | -0.086 | -0.098 | -0.048 |
| 50 | Date_Ukraine | -0.322*** | -0.092*** | -0.179*** | -0.101*** | -0.103*** | -0.066*** | -0.204*** | -0.249*** | -0.114*** | -0.178*** | -0.217*** | 0.02*** | -0.15*** | -0.191*** | -0.048*** | -0.145*** | -0.125*** | -0.001 |
| | | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 | -0.004 | -0.005 | -0.004 | -0.005 |
| 50 | Date_Evergrande | -0.199*** | -0.158*** | -0.213** | -0.188*** | -0.063* | -0.14 | -0.128*** | -0.12 | -0.148*** | -0.138*** | -0.151*** | -0.129*** | -0.111*** | -0.114** | -0.128*** | -0.115*** | -0.069** | -0.09 |
| | | -0.046 | -0.027 | -0.099 | -0.019 | -0.037 | -0.109 | -0.036 | -0.082 | -0.017 | -0.035 | -0.028 | -0.047 | -0.04 | -0.056 | -0.021 | -0.033 | -0.033 | -0.064 |
| 95 | (Intercept) | 0.76*** | 0.792*** | 0.782*** | 0.729*** | 0.759*** | 0.754*** | 0.719*** | 0.708*** | 0.704*** | 0.696*** | 0.702*** | 0.745*** | 0.685*** | 0.65*** | 0.65*** | 0.719*** | 0.703*** | 0.675*** |
| | | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| 95 | Date_COVID | -0.039 | -0.02 | -0.083*** | -0.023 | -0.123** | 0.016 | -0.024 | -0.007 | -0.039 | -0.027 | -0.112 | 0.015 | 0.001 | 0.002 | -0.012 | -0.008 | -0.078 | 0.044** |
| | | -0.026 | -0.018 | -0.007 | -0.016 | -0.056 | -0.016 | -0.044 | -0.038 | -0.03 | -0.026 | -0.079 | -0.028 | -0.036 | -0.03 | -0.025 | -0.03 | -0.067 | -0.021 |
| 95 | Date_Ukraine | -0.016*** | -0.027*** | -0.031*** | -0.023*** | 0.014*** | -0.036*** | -0.007*** | -0.08*** | -0.032*** | -0.066*** | -0.024*** | -0.066*** | 0.003*** | -0.041*** | -0.005*** | -0.034*** | -0.018*** | -0.043*** |
| | | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| 95 | Date_Evergrande | -0.05*** | -0.045*** | -0.034* | -0.043* | -0.033** | -0.038** | -0.001 | -0.01 | 0.006 | -0.012 | -0.005 | -0.018*** | 0.023 | -0.001 | 0.018 | -0.008 | 0.007 | -0.001 |
| | | -0.014 | -0.015 | -0.019 | -0.025 | -0.014 | -0.018 | -0.025 | -0.028 | -0.016 | -0.025 | -0.021 | -0.005 | -0.025 | -0.013 | -0.013 | -0.012 | -0.02 | -0.009 |

**Table 3D**

Pariwise Connectedness Spillovers on Volatilites

| Quantile | Variable | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP | US | EU | IN | UK | CA | JP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Hong Kong | | | | | | Shenzhen | | | | | | Shanghai | | | | | |
| 5 | (Intercept) | 0.593*** | 0.668*** | 0.624*** | 0.643*** | 0.684*** | 0.648*** | 0.65*** | 0.701*** | 0.562*** | 0.689*** | 0.704*** | 0.645*** | 0.696*** | 0.623*** | 0.66*** | 0.554*** | 0.745*** | 0.795*** |
| | | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 |
| 5 | Date_COVID | 0.056*** | 0.039*** | 0.035* | 0.033 | 0.011 | 0.051*** | 0.087*** | 0.052* | 0.041*** | 0.055*** | 0.032 | 0.028 | 0.07** | 0.02 | -0.011 | -0.014 | 0.031 | 0.028* |
| | | -0.021 | -0.014 | -0.021 | -0.029 | -0.015 | -0.006 | -0.021 | -0.03 | -0.011 | -0.015 | -0.033 | -0.03 | -0.034 | -0.042 | -0.049 | -0.049 | -0.025 | -0.017 |
| 5 | Date_Ukraine | 0.053*** | 0.054*** | 0.009*** | 0.025*** | 0.036*** | 0.051*** | 0.071*** | -0.02*** | 0.03*** | 0.07*** | 0.009*** | -0.025*** | 0.053*** | 0.118*** | -0.003 | 0.078*** | 0.074*** | 0.044*** |
| | | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 |
| 5 | Date_Evergrande | 0.072*** | -0.028 | 0.015 | 0.063*** | 0.059** | 0.009 | 0.074* | 0.01 | 0.04 | 0.055 | 0.026 | 0.063* | 0.083*** | 0.002 | 0.027 | 0.057*** | 0.035 | 0.006 |
| | | -0.028 | -0.048 | -0.035 | -0.024 | -0.023 | -0.023 | -0.041 | -0.013 | -0.028 | -0.034 | -0.016 | -0.034 | -0.023 | -0.044 | -0.033 | -0.011 | -0.03 | -0.019 |
| 50 | (Intercept) | 0.274*** | 0.248*** | 0.238*** | 0.282*** | 0.585*** | 0.487*** | 0.279*** | 0.249*** | 0.458*** | 0.373*** | 0.344*** | 0.368*** | 0.27*** | 0.307*** | 0.208*** | 0.215*** | 0.489*** | 0.714*** |
| | | -0.003 | -0.004 | -0.004 | -0.004 | -0.005 | -0.004 | -0.004 | -0.004 | -0.005 | -0.004 | -0.005 | -0.005 | -0.004 | -0.004 | -0.003 | -0.004 | -0.004 | -0.003 |
| 50 | Date_COVID | 0.189 | 0.206 | -0.001 | -0.099*** | 0.111 | 0.301*** | 0.153 | 0.124 | -0.191 | -0.17* | 0.27 | 0.361*** | 0.48*** | 0.395** | 0.303 | 0.395* | 0.233 | 0.212*** |
| | | -0.151 | -0.134 | -0.064 | -0.015 | -0.156 | -0.045 | -0.154 | -0.24 | -0.13 | -0.09 | -0.218 | -0.061 | -0.154 | -0.181 | -0.223 | -0.206 | -0.206 | -0.023 |
| 50 | Date_Ukraine | 0.33*** | 0.231*** | 0.019*** | -0.204*** | 0.05*** | 0.203*** | -0.219*** | -0.038*** | 0.183*** | 0.09*** | -0.15*** | -0.336*** | 0.332*** | 0.048*** | -0.151*** | -0.187*** | 0.088*** | 0.158*** |
| | | -0.003 | -0.004 | -0.004 | -0.004 | -0.005 | -0.004 | -0.004 | -0.004 | -0.005 | -0.004 | -0.005 | -0.005 | -0.004 | -0.004 | -0.003 | -0.004 | -0.004 | -0.003 |
| 50 | Date_Evergrande | 0.049 | 0.003 | -0.065 | -0.043 | -0.123*** | -0.062 | -0.192*** | -0.098 | -0.024 | -0.053 | -0.209*** | -0.14 | 0.015 | 0.013 | -0.048** | 0.049 | -0.07* | 0.057 |
| | | -0.114 | -0.091 | -0.043 | -0.063 | -0.042 | -0.041 | -0.014 | -0.062 | -0.073 | -0.073 | -0.014 | -0.094 | -0.087 | -0.089 | -0.024 | -0.059 | -0.043 | -0.085 |
| 95 | (Intercept) | 0.531*** | 0.561*** | 0.538*** | 0.571*** | 0.677*** | 0.565*** | 0.56*** | 0.545*** | 0.581*** | 0.542*** | 0.598*** | 0.567*** | 0.572*** | 0.59*** | 0.565*** | 0.558*** | 0.638*** | 0.607*** |
| | | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 |
| 95 | Date_COVID | -0.01 | -0.006 | -0.182*** | -0.162*** | -0.024* | -0.028*** | -0.024 | -0.097 | 0.011 | -0.007 | -0.141*** | -0.036*** | 0.001 | 0.001 | -0.247*** | -0.164*** | -0.043*** | -0.019 |
| | | -0.019 | -0.008 | -0.061 | -0.051 | -0.013 | -0.01 | -0.119 | -0.071 | -0.076 | -0.051 | -0.054 | -0.012 | -0.031 | -0.005 | -0.071 | -0.064 | -0.013 | -0.043 |
| 95 | Date_Ukraine | 0.076*** | 0.002 | -0.161*** | 0.036*** | 0.042*** | 0.003*** | 0.015*** | 0.043*** | 0.02*** | 0.1*** | -0.081*** | -0.035*** | 0.095*** | 0.019*** | 0.032*** | 0.044*** | 0.063*** | 0.023*** |
| | | -0.002 | -0.001 | -0.002 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.001 |
| 95 | Date_Evergrande | -0.035 | 0.013 | -0.013 | 0.052** | -0.034* | 0.078* | -0.049 | 0.019 | 0 | 0.036*** | 0.007 | 0.029 | 0.009 | -0.034 | -0.016 | -0.001 | -0.001 | -0.047 |
| | | -0.048 | -0.015 | -0.012 | -0.024 | -0.019 | -0.043 | -0.063 | -0.015 | -0.039 | -0.011 | -0.031 | -0.029 | -0.016 | -0.04 | -0.039 | -0.044 | -0.025 | -0.043 |


**Fig. A.4.** Dynamic cumulative returns from portfolio analysis.

## Data availability

Data will be made available on request.

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