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Salience theory value spillovers between China's systemically important banks: evidence from quantile connectedness

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Abstract

Analyzing the interdependencies among financial institutions is critical for designing systemic risk monitoring mechanisms; however, most existing research focuses on the first moment of the return distribution, which falls into the conventional models of choice under risk. Previous literature has observed the scarcity of investors' attention and processing power, which makes the traditional theory of choice under risk more vulnerable and brings the salience theory that accommodates investors' cognitive limitations to our attention. Motivated by evidence of salience theory value (STV) containing unique information not captured by traditional higher-order moments, we employ a quantile connectedness approach to examine the STV interconnectedness of China's systemically important banks (C-SIBs). The quantile approach allows us to uncover the dynamic STV interconnectedness of C-SIBs under normal, bearish, and bullish market conditions and is well-suited to extreme risk problems. Our results show that the C-SIBs system is asymmetrically interconnected across quantiles and at higher levels under bullish than bearish market conditions. Principally, a bank's performance in the C-SIBs system depends on its systemic importance and market conditions. Furthermore, the comparative analysis indicates that STV could provide more information than higher-order moments in capturing the dynamic change in the C-SIBs system and detecting some market events more precisely. These results have important implications for policymakers and market participants to formulate regulatory policy and design risk management strategies.

Keywords: Salience theory value, Extreme spillovers, Quantile connectedness, China's systemically important banks

JEL Classification: C32, G11, G21, G41

Introduction

Systemic financial risk is always of great concern to regulators, policymakers, academics, market participants, and general consumers due to its significant role in maintaining financial stability and spurring socio-economic development. In the past few decades, financial crises, geopolitical tensions, United States (US)–China decoupling, and the COVID-19 pandemic have frequently exposed the international financial system to extreme risk and prompted the Chinese authorities to prioritize financial stability. In this context, reviewing reports on the work of the Chinese government in the last ten years indicates that the term systemic financial risk frequently appears, reflecting the Chinese authorities' growing emphasis on financial stability. The Chinese authorities significantly improved their financial supervision system in response to the global financial system's regulatory reform following the 2008 global financial crisis. In particular, given the importance of the banking sector in financial stability, the Chinese authorities published the first list of systemically important banks in October 2021. As a result, the study of China's systemically important banks (C-SIBs) has become critical for financial regulators in allocating regulatory resources and mitigating systemic financial risk.

Previous literature has emphasized that interdependencies among financial institutions can be vital for understanding the repercussions of systemic financial risk (Silva et al. 2017). Indeed, the network interconnectedness of financial institutions defines the characteristics and extent to which systemic financial risk spillovers occur (Billio et al. 2012). As a result, the nature of systemic financial risk has been shifting to the financial system as a whole rather than its components, making interconnectedness more relevant and critical in studying financial institutions. Several studies have demonstrated how widespread interconnectedness has become for academic research on financial institutions (Foglia and Angelini 2020; Fan et al. 2021; Roncoroni et al. 2021; Andries et al. 2022). Most of these studies rely on simple mean-based estimators, such as the Granger-causality methods (Billio et al. 2012) and the vector autoregression framework (Diebold and Yilmaz 2014), which fall short of accommodating heterogeneous effects across the size distribution of shocks. From the perspective of prudently supervising the financial system, network interconnectedness under extreme market conditions makes more sense than conventional average-based correlations (Betz et al. 2016). Therefore, "extreme risk connectedness" has inevitably drawn attention, which is critical to the financial system's stability despite adverse market conditions. Many studies have used return quantiles to assess extreme risk dependencies among financial institutions (Härdle et al. 2016; Yousaf et al. 2022).

Nonetheless, these previous studies have all derived their findings from the first moment of the return distribution, which falls into the conventional models of choice under risk, assuming that investors are rational and use all observable information presented in the decision frame. A large body of literature has observed the scarcity of investors' attention and processing power (Kahneman 1973; March 1982; Berger 1996), which makes the traditional theory of choice under risk more vulnerable. Accordingly, we should notice this when studying the extreme risk connectedness among financial institutions. Bordalo et al. (2012) propose a salience theory that assumes investors focus on stocks with the most unusual, salient payoffs to account for the cognitive limitations incompatible with the expected utility theory. On this basis, Cosemans and Frehen (2021) formulate a salience theory value (STV)[1] measure to capture the salience of past returns distributions with weights adjustment. The concept of STV is applied in other studies, including Cakici and Zaremba (2022), Chen et al. (2022b), Hu et al. (2023)

[1] Cosemans and Frehen (2021) state that a stock's salience theory value (STV) is defined as the degree to which an investor's return expectations are distorted by its salient thinking. A positive STV could be attained when the forecast of an investor with salient thinking exceeds the forecast associated with objective probabilities. Please refer to Section "Construction of banks' STV using high-frequency data" for how the STV is constructed.

and Sun et al. (2023). These studies show that the salience theory can effectively explain many empirical phenomena in the stock, fund, and cryptocurrency markets; however, they have all confined themselves to the asset pricing implications of salience theory but leave the connectedness implications untouched.

From the standpoint of salience theory, we must ask how financial institutions are interconnected. On the one hand, investors' mental accounting exerts a significant impact on their trading decisions and asset prices (Barberis and Huang 2001). On the other hand, following Barberis et al. (2016), investors with mental accounting may represent a stock by the distribution of its past returns that are salience-weight extrapolated as long as they engage in salient thinking. Through the key concept of mental accounting, investors' salient thinking plays an essential role in their trading behavior and the formation of stock prices. Furthermore, observing from the market perspective, the interconnectedness of financial institutions is well defined by their sentiment and trading behavior across time and space (Baruník and Křehlík 2018). Overall, to a certain extent, the interconnectedness of financial institutions can trace its origin to investors' salient thinking that the salience theory has been well formalized. In other words, salience theory may provide some theoretical arguments for the interconnectedness of financial institutions; however, as far as we know, no studies have examined the interconnectedness of financial institutions from the salience theory perspective.

To fill this gap in the literature, we compile empirical evidence on the quantile interconnectedness of C-SIBs from the salience theory perspective. The setting of employing a natural experiment in C-SIBs is appealing from an empirical standpoint. As the second largest economy in the world, China's financial system has also rapidly expanded and drawn growing global attention after proposing a series of liberalization policies since 2010. However, no matter how China's financial system is liberalized, the Chinese authorities have always put stability at the heart of their financial reform; therefore, they are concerned about the issue of "too interconnected to fail," enabling the investigation of the interconnectedness of C-SIBs to be more relevant. Basu et al. (2019) indicate that a key gradient in understanding the systemic risk of any economy is understanding the interconnectedness of its large institutions. Regarding the analyzing procedure, first, we follow Cosemans and Frehen (2021) to construct the STV for 15 C-SIBs stock returns from August 18, 2010 to June 30, 2022. Following Bordalo et al. (2012), we assume investors measure a bank's potential payoff by reviewing the distribution of its historical returns. The previous literature (Cosemans and Frehen 2021; Hu et al. 2023; Sun et al. 2023) considers daily returns to be the state space over the recent month or quarter. In contrast, we define a bank's high-frequency returns over the past 48 5-min intervals in one day as its state space because investors usually evaluate their trading performance over a much shorter period, i.e., intraday intervals. Investors with salient thinking are assumed to have limited attention (Cosemans and Frehen 2021), which makes it possible for them to project their future expectations on intraday returns. Second, we use the quantile-based connectedness approach of Ando et al. (2022) to uncover the dynamic STV interconnectedness of C-SIBs under normal, bearish, and bullish market conditions. Our study attempts to answer the following questions. Do market conditions matter for the STV interconnectedness of C-SIBs? Does a bank's systemic importance matter for its role as a net receiver or net transmitter of spillover? What are the differences between the STV and higher-order moment interconnectedness of C-SIBs? These research questions have been neglected in the existing literature, even if a sound analysis would enlighten policymakers and investors in formulating their regulatory mechanism and risk management.

This study's main contributions can be highlighted in several directions. First, to the best of our knowledge, this study is the first to investigate the STV interconnectedness, providing a new direction for understanding how financial institutions are interconnected. Based on the STV interconnectedness of C-SIBs, policymakers and investors can further improve the effectiveness of the supervision framework. Furthermore, we consider risk management strategy as investors' salient thinking. Second, as far as we know, this study is the first to examine the quantile interconnectedness of C-SIBs; thus, we shed new light on the time-varying and asymmetric interconnectivity of C-SIBs, which exposes the unsuitability of mean-based connectedness estimators. Considering the extreme risk interconnectedness of C-SIBs can help policymakers and investors design a better early warning system and risk response mechanism. Third, this paper is the first attempt to demonstrate how a bank performs in the C-SIBs system depending on its systemic importance and market conditions. Specifically, as the market conditions become increasingly bullish, a bank with lower systemic importance will transform from a net receiver of spillover to a net transmitter of spillover. In contrast, a bank with higher systemic importance will transform from a net transmitter of spillover to a net receiver of spillover. Finally, as a part of comparative analysis, this is the first time that the higher-order moment interconnectedness of C-SIBs is under consideration. This approach shows that STV could provide more information than higher-order moments in capturing the dynamic change in the C-SIBs system and detecting some market events more precisely. By employing a HAR-RV-X model, we also quantitatively corroborate the better predictive power of STV interconnectedness than higher-order moment interconnectedness in conveying information about future market development; however, the unique information embedded in the higher-order moment interconnectedness of C-SIBs makes it a helpful supplement to the STV interconnectedness of C-SIBs.[2] Nevertheless, the inherent economic implications of using STV interconnectedness relative to higher-order moment interconnectedness is how the C-SIBs system is interconnected from the standpoint of investors' salient thinking. This desirable feature cannot be inferred from the higher-order moment interconnectedness.

The structure of this paper is summarized as follows. Section "Literature review" presents the related literature, Section "Methodology" introduces the econometric methods, and Section "Data description" describes the dataset and preliminary statistics. Section "Empirical analysis" shows the empirical results, and Section "Conclusions and policy implications" presents some closing remarks and policy implications.

[2] The STV and higher-order moments consider different models of choice under risk. Therefore, we argue that the higher-order moment interconnectedness of C-SIBs contains unique information not captured by the STV interconnectedness of C-SIBs.

Literature review

The consequential costs and turbulence caused by the global financial crisis of 2007–2008 demonstrate that we should not regulate systemically important financial institutions (SIFI) in a business-as-usual manner. Public bail-outs, in the name of stabilizing economic and financial developments, prop up SIFI that fall into deep trouble. Unsurprisingly, the undesirable consequence of such actions may be that public funds are in jeopardy and an inevitable moral hazard problem.[3] To lift the global society from the threat of such blackmail, responsible regulatory bodies take concrete steps to improve financial regulations for banks that fall into trouble and may inflict severe costs on the financial system. Guided by these considerations, the global regulatory bodies proposed the term Global Systemically Important Bank (G-SIBs) after intensive deliberation, subjecting 29 "too-systemically-relevant to fail" banks[4] in November 2011 to the revamped regulation regimes. The four biggest banks in China[5] have always been included on the list of G-SIBs, indicating that the international community has recognized the achievements of financial reform in China and the importance of China's financial sector to the global financial system. Taking this as an opportunity, Chinese regulators gradually established the methodology and continuous evaluation framework of SIFI by combining the international standards and the characteristics of the Chinese banking industry. Marked by the list of 19 systemically important banks released on October 15, 2021, the regulatory framework for C-SIBs was implemented.

Which banks are designated as too systemically important to fail and why? Besides the cross-jurisdictional activity, size, substitutability, and complexity, Eisenberg and Noe (2001) indicate that network connections play a prominent role in determining SIFI. In line with this consideration, the Bank for International Settlements (2013) has recognized the interconnectedness of financial institutions as a critical factor when designating SIFI; however, Benoit et al. (2017) emphasize that the unobservability of the interconnectedness of financial institutions often induces the "hard-to-define-but-you-know-it-when-you-see-it" problem. Yellen (2013) also indicates that the complexity of the interconnectedness of financial institutions makes the financial system more vulnerable to sudden stops and further facilitates the spreading of idiosyncratic shocks. Dealing with this problem has become a priority for policymakers to stabilize financial systems and alleviate financial crises without preventing their outbreak (Liu et al. 2020). It is encouraging that the extensive attention from policymakers has promoted academic research on this issue, as evidenced by the rich literature on the interconnectedness of financial institutions (Diebold and Yilmaz 2014; Roncoroni et al. 2021; Andries et al. 2022).

In recent years, one strand of literature, i.e., physical networks, has attempted to solve this problem by comprehensively analyzing the transaction-level data of financial institutions. For instance, Allen and Gale (2000) define the interconnectedness of financial institutions as an equilibrium phenomenon with the higher level of interbank lending,

[3] Mariathasan et al. (2014) discuss the adverse consequences of bailing out SIFI with public funds.

[4] https://www.fsb.org/wp-content/uploads/r_111104bb.pdf?page_moved=1.

[5] The Bank of China, the Industrial and Commercial Bank of China, the Agricultural Bank of China, and the Construction Bank of China.

the higher the possibility of spillover. Krause and Giansante (2012) also show that a network of interbank lending may attenuate or exacerbate the spread of bank failure, indicating the insufficiency of regulating banking systems relying on balance sheet information. Affinito and Pozzolo (2017) adopt the social network analysis approach to better capture how Italian banks' interbank positions may impact each bank's network centrality and expose the adverse effect of excessive interconnectedness. With the help of an agent-based model approach, Liu et al. (2020) describe how interbank lending can transmit financial distress, thereby improving the understanding of network transitions in the US banking system.

Several research articles pinpoint how mutual asset exposure can transmit financial distress within physical networks. For example, Braverman and Minca (2014) suggest that as mutual asset exposure increases in size, the level of bank interconnectedness also increases, which reduces diversification opportunities and increases financial network fragility. Applying their proposed model to European banks, Greenwood et al. (2015) argue that propagating shocks from one bank to another may occur under the condition of banks holding common assets. Furthermore, Brunetti et al. (2019) propose a physical network to explore how the global financial crisis may impact bank interconnectedness due to shared asset credit. Barucca et al. (2021) find that forced fire sales of common holding assets may intensify the interconnectedness of multiple European financial institutions. Additionally, several papers have focused on modeling the interconnectedness of financial institutions due to derivative exposure (Markose et al. 2012), interbank liquidity management (Denbee et al. 2021), and geographic home lending, which are also part of physical networks. While the abundance of physical network literature has proven applicable for analyzing the interconnectedness of financial institutions, this strand of literature finds no escape path for data availability. Detailed information on proprietary balance sheets is often privately held and not publicly accessible. The comparative analysis conducted by Brunetti et al. (2019) emphasizes that the physical network is better equipped to analyze liquidity issues, while the information spillover network is more suitable for predicting systemic risk.

A second strand of research, i.e., correlation networks, analyzes the interconnectedness of financial institutions relying on publicly traded market data. In this literature, asset return correlations are the building block of interconnectedness (Billio et al. 2012), while agent choices, i.e., interbank lending and common assets holding, as in Affinito and Pozzolo (2017), determine the degree of interconnectedness in physical networks. Cai et al. (2010) propose a correlation-based weighted complex network to uncover the interactional mechanism of financial markets. The empirical findings of Patro et al. (2013) show that the correlation network, built on stock return correlations among the US 22 largest financial institutions, is a useful analytical tool for timely detecting systemic risk and understanding financial interconnectivity. Hui et al. (2013) claim that interconnectedness is a function of the implied correlation derived from publicly traded options on Europe CDS indexes, highlighting interdependence among financial institutions. Furthermore, Fan et al. (2021) claim that the interconnectedness of China's financial institutions will amplify the impact of financial shocks, measuring linkages among financial institutions, such as the stock return correlation, public sentiment correlation, and the degree of risk correlation. When estimating the interconnectedness of financial institutions, correlation networks take full advantage of publicly traded market data, i.e., high data frequency and easy availability; thus, they explore a wide range of interconnectivity. This exploration is forward-looking as the underlying dataset reflects investors' expectations for the future performance of financial institutions. Undeniably, correlation networks cannot separate common exposures from transmission among financial institutions. Likewise, correlation networks cannot identify the direction and channels of transmission, which is desirable for policymakers to take preventive actions for financial stability.

Another burgeoning strand of literature, i.e., information spillover networks, examines information transmission and interconnectedness of financial institutions similar to the correlation networks in that they rely heavily on publicly traded market data. Unlike correlation networks, information spillover networks can detect the direction and channels of information transmission, which is desirable from a policy perspective. Several studies also corroborate the popularity and effectiveness of information spillover networks as far as quantifying the interconnectedness of financial institutions (Wang et al. 2018a; Liang et al. 2020). Information spillover networks generally fall into three categories: mean spillover network, volatility spillover network, and risk spillover network. For instance, from the perspective of the mean spillover network based on the Granger-causality method, Billio et al. (2012) document that the US 100 financial institutions appear highly interrelated over the past decade. Furthermore, Baruník and Křehlík (2018) argue that how the interconnectedness dynamizes in the frequency domain is crucial to understanding the sources of interconnectedness; institution-specific factors may exert a differential influence on the future performance of financial institutions than market factors. Therefore, Wang et al. (2021b) expand the Granger-causality mean spillover network into the frequency domain that shows system- and individual-level interconnectedness concentrates on different frequencies, which is significantly affected by major financial events and macroeconomic situations.

Regarding the volatility spillover network, Diebold and Yilmaz (2014) make a seminal contribution to defining interconnectedness in financial markets, presenting a theoretical framework (i.e., the DY spillover index) based on variance decompositions to show that the interconnectedness of major US financial institutions is a consequence of network structure. In their work, the defined DY spillover index extracts the most attractive information and simplifies the complex financial system to a financial network, providing a graphical and insightful description of interconnectedness. Diebold and Yilmaz (2015) further explore how volatility connectedness evolves in major financial institutions in American and European markets. Similarly, Demirer et al. (2018) estimate a high-dimensional network structure, showing that the world's largest 150 banks illustrate a significant geographic clustering, and the interconnectedness index increases dramatically during the global financial crisis. Demirer et al. (2018) conclude that improved interconnectedness results from fluctuations in cross-country linkages, not within the country. Wang et al. (2018b) take the same approach, emphasizing that the banking system in China is interlinked from the perspective of volatility transmission, and non-state-owned banks contribute more to volatility connectedness than state-owned banks. Similar to Wang et al. (2021b), Baruník and Křehlík (2018) borrow the principle of the DY spillover index and develop a frequency interconnectedness model based on the spectral representation of variance decompositions that documents abundant frequency dynamics of volatility interconnectedness in US financial sector. Liang et al. (2020) utilize the frequency connectedness approach to investigate how financial institutions in China are interlinked at the frequency domain, indicating that market risk is the source of high-frequency interconnectedness and business interaction among financial institutions is the source of low-frequency interconnectedness.

Some works consider that mean and volatility spillover networks are insufficient to capture the interconnectedness between financial agents in extreme market conditions (Bali 2000; Longin 2000). In practice, the more frequent outbreak of financial crises and geopolitical events inspires exploration of the dynamics of interconnectedness under extreme market conditions. For example, Betz et al. (2016) extend the tail risk network of Hautsch et al. (2015) to accommodate the high-dimensional financial system, showing how the interconnectedness between European financial institutions and sovereigns evolves. After concurrently considering the tail event and network dynamics, Härdle et al. (2016) present a tail-event-driven network (TENET) based on conditional value-at-risk that captures the tail interconnectedness of US financial institutions, simultaneously bringing the issue of "too big to fail" and "too big to interconnected" into consideration. Foglia and Angelini (2020) and Pacelli et al. (2022) also employ the TENET approach to measure the interconnectedness of European financial institutions. Wang et al. (2017) highlight an extreme risk spillover network based on the conditional autoregressive value-at-risk mode of Engle and Manganelli (2004) and the Granger-causality risk test of Hong et al. (2009) to discover the interconnectedness of the US financial institutions. Wang et al. (2021a) argue that mapping financial systems into a multilayer network structure is more suitable for identifying the channels of information transmission and interconnectedness of financial institutions. They design a novel multilayer information spillover network consisting of return, volatility, and extreme risk spillover layers to review the interconnectedness of 30 Chinese financial institutions. From the quantile perspective, Li et al. (2020) propose a novel extreme risk network based on the Granger-causality test across quantiles of Candelon and Tokpavi (2016) and the network density of Billio et al. (2012) to investigate the interconnectedness between US financial and FinTech institutions. In a recent paper, Foglia et al. (2022) apply this approach to compare how the Eurozone financial system is interconnected under bearish and bullish markets.

In summation, the interconnectedness of financial institutions has been widely studied through physical networks, correlation networks, and information spillover networks, providing a diversified and abundant perspective on the dynamic and complex linkage among financial institutions. Considering heteroscedasticity in economic conditions and firm-specific factors, it might be better for academics to approach this study from different angles. Methodologically, Ando et al. (2022) propose a theoretical model based on quantile regression and the DY spillover index to investigate how credit risk is interlinked among 18 sovereign countries. Abundant application of this model has been found in the literature (Chen et al. 2022a; Billah et al. 2022; Yousaf et al. 2022; Rehman et al. 2023; Ghosh et al. 2023). The quantile connectedness approach offers a rich framework for studying the interconnectedness of financial institutions under different market conditions, as well as highlighting how tail events affect the dynamics and magnitude of the interconnectivity of financial institutions. This approach can capture the relative dependencies of the quantiles and other extreme spillovers that cannot be attained by the remaining information spillover networks, which is sufficient for policymakers to understand the information transmission mechanism when economic conditions are not helpful. To the best of our knowledge, we are the first to study the interconnectedness of financial institutions using the quantile connectedness approach, which complements the existing research.

We now examine the key concept of salience theory that forms the foundation of this study. Li and Camerer (2022) define the concept of salience as the features of an attention-grabbing stimulus. In the past decade, as part of a growing body of behavioral economics, salience has attracted the attention of many researchers when exploring individuals' decision-making processes.[6] Bordalo et al. (2012) propose a novel framework (salience theory) to accommodate investors' cognitive limitations, including inattention and shortage of processing power. Their approach assumes investors focus on stocks with the most unusual—or salient—payoffs, and they formalize how investors' salient thinking will impact their choice under risk. Bordalo et al. (2012) indicate that salience allows for a theory of context-dependent choice consistent with a broad range of evidence, which distinguishes the salience theory from the cumulative prospect theory of Tversky and Kahneman (1992), enabling it to accommodate many violations of traditional theory of choice under risk. Salience theory has been applied in various areas, including asset pricing (Bordalo et al. 2013a; Cosemans and Frehen 2021; Cakici and Zaremba 2022; Chen et al. 2022b; Sun et al. 2023), consumer choice (Bordalo et al. 2013b), judicial decision (Bordalo et al. 2015), corporate cash holdings (Dessaint and Matray 2017), investor skewness preference (Dertwinkel-Kalt and Koster 2020), asset allocation (Alok et al. 2020), stock trading models (Huang et al. 2018; Frydman and Wang 2020; Sim and Kim 2022), and mutual fund flows (Hu et al. 2023).

Following Bordalo et al. (2012), Cosemans and Frehen (2021) assume that investors' salient thinking may impact how they evaluate a stock's representation. Consequently, they formulate a salience theory value (STV) measure to capture the salience of past returns distributions with weights adjustment. They empirically examine the predictive power of the salience-based asset pricing model of Bordalo et al. (2013a) with the key premise of making choices in context. Their study shows that a negative salient return effect occurs in the US stock market in the context of salient thinking. Likewise, Sun et al. (2023) confirm a similar phenomenon in the Chinese stock market even after considering its unique features in structures of investors, private-information preferences, and institutional arrangement (Song and Xiong 2018). Hu et al. (2023) show that Chinese investors also make choices under risk among mutual funds in the context of salient thinking. Under the guidance of salience theory, Sim and Kim (2022) propose an enhanced momentum strategy that is more profitable than the traditional momentum strategy. Furthermore, Chen et al. (2022b) show the presence of salience-induced behavioral biases in the cryptocurrency market. These studies indicate the broad application of STV measures in understanding many empirical phenomena in the stock, fund, and cryptocurrency markets; however, they have all confined themselves to the asset pricing

[6] Notable contributions related to salience include salience theory (Bordalo et al. 2012, 2013a, 2013b), dynamic inattention (Schwartzstein 2014), and theories of rational (Caplin and Dean 2015; Caplin et al. 2019; Caplin et al. 2020).

implications of salience theory but leave the connectedness implications untouched. This study attempts to extend the application of salience theory to the interconnectedness of financial institutions. We believe that investors' salient thinking impacts their trading behavior as measured by the STV of Cosemans and Frehen (2021) and affects the interconnectedness of financial institutions from the market perspective.[7] Therefore, we are the first to thoroughly investigate the implications of salience theory for the interconnectedness of financial institutions, which extends the application of salience theory and highlights this study's novelty.

Methodology

Construction of banks' STV using high-frequency data

We follow the guidance of Cosemans and Frehen (2021) to define the STV on banks' return attribute and investigate the interconnectedness of C-SIBs from the salience theory perspective.[8] For compatibility with the initial parameterization proposed by Bordalo et al. (2012), we first transform five-minute returns into daily returns.[9] We then employ the salience function to calculate the salience of each bank's five-minute returns in a given state, s, and day, t, as follows:

$$\sigma\left(r'_{i,s;t}, \overline{r}'_{s;t}\right) = \frac{\left|r'_{i,s;t} - \overline{r}'_{s;t}\right|}{\left|r'_{i,s;t}\right| + \left|\overline{r}'_{s;t}\right| + \theta}, \tag{1}$$

where $\overline{r}'_{s;t}$ is the benchmark index return for the corresponding state space. Following Cosemans and Frehen (2021), the salience parameter (θ) is assumed to equal 0.1 and measures the relative deviation of the returns from the whole state space. The state returns of bank i are subsequently ranked from most to least salient, with a value assignment of 1 to S_t. The total number of state spaces (S_t) is 48 in a given day t. We next define the salience weights for the returns in a given day as follows:

$$\tilde{\omega}_{i,s;t} = \frac{\delta^{rank_{i,s;t}}}{\sum_{s'} \delta^{rank_{i,s';t}} \pi_{i,s';t}} \cdot \pi_{i,s;t} \tag{2}$$

where $\delta^{rank_{i,s;t}}$ represents the salience rank of return, $r'_{i,s;t}$, and $\pi_{i,s;t}$ is the objective probability with a value of $1/S_t$. The parameter, $\delta \in (0, 1]$, defines how much the salience of returns distorts the decision weights from the objective probabilities. As the value of δ approaches zero, the salience status becomes increasingly prominent. We follow Cosemans and Frehen (2021) to set $\delta = 0.7$. The normalization process of Eq. (2) ensures the presence of $E\left(\tilde{\omega}_{i,s;t}\right) = E\left(\pi_{i,s;t}\right) = 1$, which indicates the sum of expected distortion equals zero. Finally, the STV for bank i in a given day t is defined as:

[7] Please refer to paragraph four of Section "Introduction" for a detailed explanation of financial institutions' interconnectedness from the salience theory perspective.

[8] Section "Introduction" summarizes why we consider the state space from the high-frequency perspective.

[9] The transformation process considers the following formula: $r'_{i,s;t} = \left(1 + r_{i,s;t}\right)^{48} - 1$, in which $r_{i,s;t}$ is the five-minute return in a given interval s and day t and $r'_{i,s;t}$ is the transformed version on a daily basis.

$$STV_{i;t} \equiv \mathrm{cov}\left(\tilde{\omega}_{i,s;t}, r'_{i,s;t}\right) = \sum_{S}^{S_t} \tilde{\omega}_{i,s;t} \cdot r'_{i,s;t} - \sum_{S}^{S_t} \pi_{i,s;t} \cdot r'_{i,s;t}. \tag{3}$$

By definition, $STV_{i;t}$ measures the deviation between salience-adjusted and equal-weighted bank returns; therefore, as the value of $STV_{i;t}$ increases, the salience status of bank i becomes increasingly prominent.

Interconnectedness analysis at various quantiles

We employ the quantile connectedness approach of Ando et al. (2022) to conduct the interconnectedness analysis of C-SIBs at various quantiles.[10] Following Koenker and Bassett (1978), we adopt a quantile regression to investigate the dependence of y_t on x_t at each quantile $\tau(\tau \in (0,1))$ of the conditional distribution of y_t/x_t, which can be denoted as:

$$Q_\tau\left(y_t|x_t\right) = x_t\beta(\tau) \tag{4}$$

where Q_τ is designated as the function of y_t at the quantile τ. Furthermore, x_t is a vector of dependent variables, and $\beta(\tau)$ defines the dependence structure between x_t and y_t at the quantile τ. The estimation of the parameter vector of $\beta(\tau)$ is expressed as:

$$\hat{\beta}(\tau) = \arg\min_{\beta(\tau)} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < x_t\beta(\tau)\}}\right) \left|y_t < x_t\beta(\tau)\right|. \tag{5}$$

Subsequently, a quantile vector autoregression with p lags is constructed as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \varphi_j(\tau) y_{t-j} + u_t(\tau). \tag{6}$$

Here, y_t and y_{t-j} are endogenous $k \times 1$ dimensional vectors representing the matrices for the STV of C-SIBs. $\mu(\tau)$ represents the $k \times 1$ dimensional intercept term at quantile τ. $\varphi_j(\tau)$ signifies the lagged coefficient matrix with k dimensions at quantile τ, and $u_t(\tau)$ displays a N-dimensional error vector at quantile τ. The estimated values of $\varphi_j(\tau)$ and $\mu(\tau)$ are defined as $\hat{\varphi}_j(\tau)$ and $\hat{\mu}(\tau)$ respectively; these are obtained by assuming that the error term $u_t(\tau)$ satisfies the population quantile restriction $Q_\tau\left(u_t(\tau)\middle|y_{t-1}, ..., y_{t-p}\right) = 0$. The population τ_{th} conditional quantile of response y is defined as:

$$Q_\tau\left(u_t(\tau)\middle|y_{t-1}, \ldots, y_{t-p}\right) = \hat{\mu}(\tau) + \sum_{j=1}^{p} \hat{\varphi}_j(\tau) y_{t-j}. \tag{7}$$

Following Ando et al. (2022), Eq. (7) can be estimated on an equation-by-equation at the quantile τ. Its moving average representation is given as:

[10] The full implementation of this analysis is based on David Gabauer's open-source code of the R program, which is available at: https://sites.google.com/view/davidgabauer/econometric-code.

$$y_t = \mu(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau) u_{t-i}(\tau) \tag{8}$$

where y_t is defined by the sum of the errors $u_t(\tau)$.

We invoke the generalized variance decomposition function of Koop et al. (1996) and Pesaran and Shin (1998). We calculate a standard decomposition with an H-step forward horizon, given as:

$$\psi_{ij}^{g}(\tau) = \frac{\sum(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \psi_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \psi_h(\tau) \sum(\tau) \psi_h(\tau)' e_i\right)^2} \tag{9}$$

where e_j signifies a vector with a value of 1 for the j-th variable and 0 for others, and $\psi_{ij}^{g}(\tau)$ defines the extent of a shock in variable j on variable i at quantile τ. Consequently, we follow the normalization approach and obtain the normalized version of Eq. (9) as:

$$\tilde{\psi}_{ij}^{g}(\tau) = \frac{\psi_{ij}^{g}(\tau)}{\sum_{j=1}^{k} \varphi_{ij}^{g}(\tau)} \tag{10}$$

where $\sum_{j=1}^{k} \tilde{\psi}_{ij}^{g}(\tau) = 1$ and $\sum_{i,j=1}^{k} \tilde{\psi}_{ij}^{g}(\tau) = k$.

Following Diebold and Yilmaz (2012, 2014), the "TO" directional connectedness index, which measures the influence of variable i on all variables j at the quantile τ, is defined as:

$$C_{i \to j}^{g}(\tau) = \sum_{j=1, j \neq i}^{k} \tilde{\psi}_{ij}^{g}(\tau) \times 100. \tag{11}$$

Conversely, the "FROM" directional connectedness index, which quantifies the influence of all variables j on variable i at the quantile is τ, is given as:

$$C_{i \leftarrow j}^{g}(\tau) = \sum_{j=1, j \neq i}^{k} \tilde{\psi}_{ji}^{g}(\tau) \times 100. \tag{12}$$

The "NET" directional connectedness index measures how the variable i influences the whole network at the quantile τ. NET is obtained after comparing the "TO" and "FROM" directional connectedness indices; it is defined as:

$$C_{i}^{g}(\tau) = C_{i \to j}^{g}(\tau) - C_{i \leftarrow j}^{g}(\tau). \tag{13}$$

A positive (negative) sign for $C_{i}^{g}(\tau)$ signifies a net transmitter (receiver). Finally, the total connectedness index at the quantile τ, which is a common way to illustrate the total connectedness effect in the entire system at the quantile τ, is given as:

$$TCI(\tau) = \frac{\sum_{i,j=1, j \neq i}^{k} \tilde{\psi}_{ij}^{g}(\tau)}{k}. \tag{14}$$

Table 1 Bank information

Code	Institution	Abbreviation	Group
000001.SZ	Ping An Bank	PAB	G5
002142.SZ	Bank of Ningbo	BON	G5
600015.SH	Huaxia Bank Co., Ltd	HXB	G5
600016.SH	China Minsheng Banking Corp., Ltd	CMBC	G5
601169.SH	Bank of Beijing	BOB	G5
601818.SH	China Everbright Bank	CEB	G5
600000.SH	Shanghai Pudong Development Bank	SPD	G4
601998.SH	China CITIC Bank	CITIC	G4
600036.SH	Chin Merchants Bank	CMB	G3
601166.SH	Industrial Bank	CIB	G3
601328.SH	Bank of Communications	BoCom	G3
601288.SH	Agricultural Bank of China	ABC	G2
601398.SH	Industrial and Commercial Bank of China	ICBC	G2
601939.SH	China Construction Bank	CCB	G2
601988.SH	Bank of China	BOC	G2

Data description

Our sample comprises 15 commercial banks included in the list of systemically important banks published by China's supervisory authorities and traded in China's A-share market, ensuring the availability of price information. Table 1 shows an overview of banks' codes, institutions, abbreviations, and groups. The 15 C-SIBs fall into four groups. The second group (G2) is the most systemically important, whereas the fifth group (G5) is the least. This study deploys a high-frequency price series from August 18, 2010, to June 30, 2022, to gauge the STV interconnectedness of C-SIBs.[11] Based on previous studies (Corsi et al. 2008; Kumar 2017), we believe that a sample interval of five minutes attains a reasonable trade-off between measurement accuracy and microstructure noise due to asynchronous trading, infrequent trading, price discreteness, and bid-ask bounce. All the data is from the RESSET Financial Terminal on a 4-h basis; we obtain 48 5-min intervals with matched date/time information set at Beijing time per trading day. We calculate the 5-min price returns of each bank as the first logarithmic closing price difference in two consecutive intervals and use them to estimate STVs.

Table 2 presents the descriptive statistics and test results for the STV of C-SIBs, showing that all C-SIBs report positive mean STV, indicating the presence of investors' salient thinking. The significant difference among all C-SIBs' mean STV, highlighted by the highest and lowest values recorded by BON and BoCom, suggests that the extent to which investors' salient thinking preference varies across C-SIBs. The reported variance still fluctuates across all C-SIBs, implying BON and BoCom have the highest and lowest volatility among all C-SIBs, respectively. Another descriptive statistic is skewness. All C-SIBs represent positive values, indicating that the frequency of positive STVs is higher than negative ones in reverse. For the kurtosis statistic, total STVs follow a leptokurtic

[11] Initially, there were 19 commercial banks included in the list of systemically important banks published by China's regulatory bodies. We preselect 15 of 19 C-SIBs due to the consideration that restricts them to those in existence as of August 18, 2010. Regarding the benchmark index for composing the state space, we consider the representative stock index for China's stock market, i.e., the SSEC stock index.

Table 2 Descriptive statistic and test results

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	Q(20)	Q2(20)
PAB	0.060	0.016	2.434***	9.745***	14,249.428***	− 4.821***	916.423***	671.366***
BON	0.079	0.023	2.596***	10.609***	16,752.234***	− 18.965***	350.067***	98.751***
HXB	0.033	0.008	2.325***	8.991***	12,304.131***	− 15.230***	346.383***	237.195***
CMBC	0.034	0.009	3.124***	16.014***	35,482.284***	− 9.712***	690.272***	850.364***
BOB	0.032	0.008	2.317***	9.282***	12,925.623***	− 16.568***	513.668***	714.793***
CEB	0.065	0.016	3.417***	19.615***	51,808.952***	− 1.357	335.478***	420.251***
SPD	0.032	0.010	2.809***	11.980***	21,026.140***	− 8.597***	2137.595***	4914.244***
CITIC	0.073	0.033	4.564***	28.589***	108,154.388***	− 15.062***	1082.575***	548.402***
CMB	0.035	0.007	1.124***	2.511***	1363.437***	− 20.814***	132.324***	312.093***
CIB	0.034	0.008	1.831***	6.118***	6105.000***	− 9.635***	413.477***	508.503***
BoCom	0.028	0.007	2.947***	16.981***	38,798.081***	− 10.016***	235.360***	468.482***
ABC	0.052	0.006	0.332***	0.630***	100.578***	− 19.916***	189.884***	329.293***
ICBC	0.029	0.006	2.029***	10.548***	15,337.333***	− 11.417***	334.839***	1496.611***
CCB	0.030	0.006	1.446***	4.713***	3671.491***	− 18.907***	221.709***	794.043***
BOC	0.049	0.008	2.275***	13.277***	23,652.027***	− 16.557***	213.961***	712.953***

The Jarque–Bera statistic is used to test the null hypothesis that the STV series is normally distributed. ERS is the Elliott, Rothenberg, and Stock statistic that is used to test the null hypothesis that the STV series has a unit root. Q(20) and Q2(20) are the Fisher and Gallagher statistics for time series goodness of fit testing. *** denotes the statistical significance of the estimates at the 1% level

distribution. Furthermore, all JB statistics significantly differ from 0, indicating that normal distribution is unsuitable for all C-SIBs. According to the Elliott, Rothenberg, and Stock unit root test, on the whole, the STVs of C-SIBs show stationary characteristics. Finally, the Fisher and Gallagher statistics confirm the presence of significant autocorrelation for the STVs of C-SIBs.

Empirical analysis

Static quantile interconnectedness of C-SIBs

This study employs the quantile connectedness approach of Ando et al. (2022) to investigate the interconnectedness of C-SIBs under various market conditions. Before conducting the related analysis, we determine an optimal lag length of order one and a 10-step-ahead forecast horizon based on the AIC.

We start our empirical analysis by investigating the static interconnectedness mechanism in C-SIBs under normal market conditions and report all related results in Table 3.[12] As shown in Table 3, the total STV interconnectedness of C-SIBs is 45.57%, implying that the C-SIBs system exhibits moderate spillover effects under normal market conditions. When analyzing the interconnectedness of China's financial institutions, including commercial banks, security firms, and insurance companies, Liang et al. (2020) report a total connectedness of 88.66, significantly higher than our empirical finding. However, their results are derived from the return series of financial institutions rather than the STV of financial institutions. Nevertheless, the spillover effects could explain almost half of the forecast error in the C-SIBs system, providing solid evidence of the interconnected status of C-SIBs. This phenomenon could be interpreted as market shocks simultaneously affecting commercial banks with similar or related fundamentals

[12] This study defines $\tau = 0.05$, $\tau = 0.50$, and $\tau = 0.95$ as bearish, normal, and bullish market conditions, respectively.

Table 3 Static STV interconnectedness at the conditional median ($\tau = 0.5$)

	PAB	BON	HXB	CMBC	BOB	CEB	SPD	CITIC	CMB	CIB	BoCom	ABC	ICBC	CCB	BOC	FROM
PAB	51.45	5.92	4.03	3.16	2.82	2.68	5.04	4.68	4.31	6.50	2.04	1.03	1.49	2.79	2.05	48.55
BON	5.88	47.71	4.96	2.67	4.08	3.89	4.75	5.87	4.27	5.38	3.28	1.26	1.34	2.79	1.88	52.29
HXB	3.91	5.19	48.24	4.52	4.14	3.26	5.41	5.02	3.62	6.19	2.44	1.52	1.84	2.78	1.91	51.76
CMBC	3.19	2.83	5.01	54.86	3.82	2.54	4.74	4.28	3.64	4.79	2.50	1.53	1.80	2.29	2.18	45.14
BOB	2.91	4.77	4.56	3.74	51.38	3.10	5.47	5.11	2.83	4.23	2.53	1.39	1.78	3.44	2.76	48.62
CEB	3.07	4.21	3.78	2.48	3.18	54.37	4.03	7.15	1.53	3.65	3.34	2.08	2.08	2.25	2.78	45.63
SPD	4.93	4.96	4.96	3.73	4.45	3.21	49.09	3.93	3.48	7.34	2.04	1.56	1.73	2.76	1.83	50.91
CITIC	4.17	5.52	5.19	3.81	4.11	6.62	4.36	50.06	2.05	4.47	3.08	1.09	1.59	2.34	1.53	49.94
CMB	4.80	5.26	4.30	4.24	3.13	2.06	4.45	2.76	53.89	5.09	2.08	1.65	1.86	3.11	1.32	46.11
CIB	6.24	5.29	5.90	3.89	3.84	3.36	7.18	4.30	4.26	45.43	2.75	0.93	2.05	2.82	1.76	54.57
BoCom	2.55	4.68	2.90	2.49	2.79	4.05	2.81	3.50	2.28	3.46	57.29	2.50	2.70	2.73	3.26	42.71
ABC	1.64	1.92	2.14	2.15	1.86	2.79	1.89	1.46	1.56	1.66	2.81	67.53	3.76	3.22	3.59	32.47
ICBC	1.89	1.96	2.66	2.26	2.06	2.41	2.29	2.29	2.25	2.80	2.99	3.56	63.52	4.13	2.94	36.48
CCB	2.66	3.50	2.96	2.80	3.28	2.64	3.06	2.64	2.91	2.99	2.77	3.08	3.31	59.01	2.38	40.99
BOC	2.49	3.05	2.59	2.42	2.75	3.00	2.15	1.93	1.67	2.40	3.79	3.06	3.35	2.69	62.67	37.33
TO	50.32	59.06	55.95	44.36	46.31	45.61	57.62	54.92	40.65	60.97	38.45	26.26	30.68	40.14	32.18	**TCI**
NET	1.77	6.76	4.19	− 0.77	− 2.30	− 0.02	6.71	4.98	− 5.45	6.40	− 4.27	− 6.21	− 5.79	− 0.84	− 5.15	45.57%

Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (based on the AIC criterion) and a 10-step-ahead generalized forecast error variance decomposition

such that one bank's changes will be relevant to others. SPD and CIB record the most significant spillover effect (7.18%), whereas ABC and CIB exhibit the least prominent spillover effect (0.93%). The "TO" values in Table 3 confirm that CIB and ABC are the strongest and weakest spillover transmitters, respectively. Similarly, the "FROM" values in Table 3 also suggest that CIB and ABC could be labeled as the largest and smallest spillover receivers, respectively. This finding is roughly in line with the observation of Mensah and Premaratne (2017); a bank's size and systemic importance matter for its role in the interconnectedness, i.e., the smaller the market capitalization, the more prominent the directional STV interconnectedness. Notably, a positive relationship exists between a systemically important bank's STV "FROM" and "TO" connectedness. This finding indicates that information spillover is bidirectional, albeit the to-connectedness is more significant than the from-connectedness as measured by their values.[13] Our findings are also consistent with Yousaf et al. (2022), who find that investors' sentiment significantly affects the interconnectedness of financial markets. In other words, evidence shows that investors' salient thinking influences risk connectedness.

From the group perspective, G4 is the smallest spillover transmitter (32.32%) and receiver (36.82%), whereas G2 is the largest spillover transmitter (56.27%) and receiver (50.43%).[14] As a bank's systemic importance becomes more prominent, i.e., ascending from G5 to G2, its status as a spillover transmitter or receiver decreases. Focusing on the net spillover effect, BON and ABC report the strongest spillover effects with positive (6.76%) and negative (−6.21%) directions, respectively, indicating their status as the largest net transmitter of spillover and net receiver. From the group perspective, G4 is the largest net transmitter of spillover (5.85%), whereas G2 is the largest receiver of spillover (−4.50%). Generally, the more prominent a bank's systemic importance becomes, i.e., moving up from G5 to G2, the more significant its role as a net receiver of spillover becomes, i.e., gradually transforming from a net transmitter of spillover to a net receiver of spillover.[15]

Tables 4 and 5 summarize how C-SIBs entertain their static interconnectedness mechanism under extreme market conditions. Excessive spillover effects are recorded under extreme market conditions. The total STV interconnectedness of C-SIBs is 86.32% (91.09%) under bearish (bullish) market conditions, significantly higher than the total STV interconnectedness of C-SIBs under normal market conditions. This finding indicates that unexpected events tend to have a more significant impact when the market is in extreme conditions. The extent to which shocks impact the interconnectedness of C-SIBs depends on market conditions and justifies our choice of the quantile connectedness approach of Ando et al. (2022) to reveal the evolving connectedness at different market states. The higher total STV interconnectedness measured under extreme market conditions is reminiscent of how tailed or extreme shocks exert a higher impact on the connectedness. This finding is consistent with the observation of Umar et al. (2023),

[13] Due to space limitations, the summary statistics of C-SIBs' market capitalization are not presented here and are available upon request.

[14] Calculated from the value of "TO" in Table 3, G5 to G2 report the spillover effect of 50.27%, 56.27%, 46.69%, and 32.32%, respectively. Similarly, calculated from the value of "FROM" in Table 3, G5 to G2 report the spillover effect of 48.67%, 50.43%, 47.80%, and 36.82%, respectively.

[15] Calculated from the value of "NET" in Table 3, G5 to G2 report the net spillover effect of 1.61%, 5.85%, −1.11%, and −4.50%, respectively.

Table 4 Static STV interconnectedness at the extreme lower quantile ($\tau = 0.05$)

	PAB	BON	HXB	CMBC	BOB	CEB	SPD	CITIC	CMB	CIB	BoCom	ABC	ICBC	CCB	BOC	FROM
PAB	14.06	6.60	6.31	6.03	5.78	5.99	6.52	5.77	6.63	6.97	5.75	5.92	5.56	6.11	6.01	85.94
BON	6.62	14.24	6.48	5.53	6.44	6.24	6.39	5.91	6.44	6.67	6.21	5.77	5.37	5.89	5.80	85.76
HXB	6.02	6.11	13.19	6.41	6.53	6.14	6.60	5.73	6.31	6.74	5.95	6.15	5.92	6.20	6.00	86.81
CMBC	6.08	5.52	6.86	13.88	6.42	5.90	6.48	5.71	6.57	6.45	5.97	6.16	5.69	6.14	6.16	86.12
BOB	5.61	6.18	6.61	6.12	13.48	6.15	6.61	5.80	6.21	6.32	6.03	6.24	6.02	6.37	6.26	86.52
CEB	5.87	6.08	6.25	5.74	6.19	13.74	6.42	6.37	5.81	6.24	6.26	6.47	6.08	6.14	6.35	86.26
SPD	6.28	6.09	6.65	6.20	6.51	6.24	13.25	5.54	6.43	7.05	5.99	6.06	5.67	6.11	5.93	86.75
CITIC	6.20	6.24	6.56	6.08	6.43	7.01	6.22	15.18	5.53	6.28	6.12	5.29	5.45	5.81	5.61	84.82
CMB	6.40	6.22	6.43	6.35	6.21	5.76	6.52	5.03	13.42	6.65	6.12	6.49	5.93	6.49	5.98	86.58
CIB	6.65	6.24	6.76	6.19	6.16	6.03	7.01	5.56	6.53	13.19	6.08	5.90	5.76	6.02	5.92	86.81
BoCom	5.62	5.96	6.11	5.85	6.07	6.30	6.00	5.56	6.13	6.21	13.58	6.78	6.51	6.47	6.85	86.42
ABC	5.70	5.57	6.18	5.97	6.27	6.36	5.92	4.77	6.45	5.97	6.57	13.26	6.99	6.90	7.12	86.74
ICBC	5.59	5.38	6.27	5.79	6.12	6.27	5.84	5.08	6.13	6.05	6.54	7.28	13.8	6.90	6.95	86.20
CCB	5.83	5.61	6.28	5.97	6.35	6.06	6.01	5.25	6.45	6.10	6.39	6.97	6.63	13.42	6.68	86.58
BOC	5.76	5.56	6.12	5.99	6.24	6.35	5.93	5.06	5.96	5.98	6.80	7.25	6.80	6.67	13.53	86.47
TO	84.21	83.35	89.89	84.24	87.72	86.80	88.47	77.13	87.58	89.7	86.76	88.73	84.37	88.20	87.63	**TCI**
NET	− 1.73	− 2.42	3.08	− 1.88	1.20	0.54	1.72	− 7.69	1.00	2.89	0.35	1.98	− 1.83	1.62	1.16	86.32%

Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (based on the AIC criterion) and a 10-step-ahead generalized forecast error variance decomposition

Table 5 Static STV interconnectedness at the extreme upper quantile ($\tau = 0.95$)

	PAB	BON	HXB	CMBC	BOB	CEB	SPD	CITIC	CMB	CIB	BoCom	ABC	ICBC	CCB	BOC	FROM
PAB	9.28	6.57	6.88	6.70	6.55	6.46	6.81	7.97	6.38	6.52	5.96	5.86	5.85	6.28	5.94	90.72
BON	7.24	8.67	6.90	6.60	6.51	6.43	6.84	8.08	6.45	6.48	6.09	5.83	5.82	6.25	5.81	91.33
HXB	6.97	6.52	9.00	6.68	6.78	6.49	6.75	8.04	6.21	6.51	5.92	6.02	5.83	6.25	6.05	91.00
CMBC	7.13	6.31	6.88	8.86	6.60	6.66	6.85	8.52	6.14	6.22	6.10	6.03	5.72	6.06	5.92	91.14
BOB	6.74	6.41	6.91	6.73	8.81	6.55	6.67	8.49	6.17	6.22	6.11	5.95	5.83	6.37	6.04	91.19
CEB	6.96	6.43	6.78	6.61	6.56	8.89	6.83	8.06	6.12	6.36	6.13	5.96	5.88	6.29	6.14	91.11
SPD	6.91	6.42	6.95	6.67	6.67	6.56	8.86	8.21	6.18	6.56	6.09	5.78	5.87	6.27	6.00	91.14
CITIC	7.03	6.47	6.87	6.84	6.66	6.80	6.91	10.59	6.05	6.24	6.06	5.82	5.71	6.20	5.76	89.41
CMB	7.08	6.53	6.77	6.68	6.62	6.30	6.70	7.79	8.53	6.55	6.19	5.95	5.91	6.46	5.93	91.47
CIB	7.03	6.44	6.91	6.53	6.56	6.45	6.89	7.99	6.37	8.43	6.13	5.85	5.96	6.44	6.02	91.57
BoCom	6.88	6.28	6.77	6.66	6.70	6.49	6.69	8.33	6.08	6.19	8.52	6.02	5.93	6.24	6.21	91.48
ABC	6.82	6.13	6.78	6.58	6.53	6.50	6.51	7.79	6.09	6.20	6.33	8.92	6.14	6.46	6.23	91.08
ICBC	6.63	6.17	6.85	6.60	6.46	6.47	6.47	7.85	6.26	6.44	6.21	6.15	8.67	6.49	6.28	91.33
CCB	6.88	6.50	6.84	6.41	6.39	6.63	6.61	7.78	6.15	6.62	6.25	6.04	6.13	8.54	6.23	91.46
BOC	6.74	6.20	6.90	6.54	6.59	6.67	6.52	7.85	5.95	6.21	6.38	6.03	6.08	6.32	9.01	90.99
TO	97.04	89.37	96.01	92.83	92.17	91.46	94.05	112.8	86.61	89.33	85.95	83.28	82.65	88.38	84.56	**TCI**
NET	6.31	− 1.96	5.00	1.69	0.99	0.35	2.91	23.34	− 4.86	− 2.24	− 5.53	− 7.81	− 8.68	− 3.08	− 6.42	91.09%

Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (based on the AIC criterion) and a 10-step-ahead generalized forecast error variance decomposition

who focus on the commodity and exchange markets. The more volatile the market conditions become, the more prominent the interconnectedness of C-SIBs will be. This phenomenon aligns with investors' preference for flight to quality under more volatile market conditions. Furthermore, investors' speculation on the changes in one C-SIB will lead to more information diffusion to other C-SIBs if market conditions become more volatile, which results in the more prominent interconnectedness of C-SIBs. In other words, when the C-SIBs system is affected by extreme shocks, both interconnectedness and risk spread between C-SIBs increase. This finding also corroborates previous contagion literature that illustrates how extreme shocks spill over under extreme market conditions (Londono 2019).

Focusing on the group perspective, when the market becomes more bearish, G4 is still the smallest spillover transmitter (82.80%) and receiver (85.79%), whereas G3 is the largest spillover transmitter (88.01%) and receiver (86.60%).[16] Similarly, under more bullish market conditions, G2 and G4 are the smallest spillover transmitters (84.72%) and receivers (90.23%), respectively, whereas G4 and G3 are the largest spillover transmitters (103.43%) and receivers (91.51%), respectively.[17] Moreover, the difference between the largest and smallest spillover transmitter (receiver) is significantly lower under bearish or bullish market conditions than under normal market conditions, suggesting that a bank's systemic importance becomes less relevant under extreme market conditions. When examining the net spillover effect, under bearish market conditions, G3 is the largest net transmitter of spillover (1.41%), whereas G4 is the largest receiver of spillover (−2.99%). Roughly speaking, increasing a bank's systemic importance will turn it from a net receiver of spillover to a net transmitter of spillover, which is the direct opposite of the C-SIBs system experiences under normal market conditions.[18] By comparison, under bullish market conditions, G4 is the largest net transmitter of spillover (13.13%), whereas G2 is the largest receiver of spillover (−6.50%). The gradual strengthening of a bank's systemic importance will transform it from a net transmitter of spillover to a net receiver of spillover, consistent with what will happen when the market is under normal conditions.[19] Overall, as market conditions become increasingly bullish, i.e., from extreme lower quantile to extreme upper quantile, a bank with lower systemic importance, i.e., G5, will transform from a net receiver of spillover to a net transmitter. In contrast, a bank with higher systemic importance, i.e., G2, will transform from a net transmitter of spillover to a net receiver. From a policymaker's perspective, C-SIBs with higher systemic importance should be assigned more attention when the market is under bullish conditions since they dominate the C-SIBs system as the net transmitter of spillover. In contrast, policymakers should allocate more regulatory resources to C-SIBs with lower

[16] Calculated from the value of "TO" in Table 4, G5 to G2 report the spillover effect of 86.04%, 82.80%, 88.01%, and 87.23%, respectively. Similarly, calculated from the value of "FROM" in Table 4, G5 to G2 report the spillover effect of 86.24%, 85.79%, 86.60%, and 86.50%, respectively.

[17] Calculated from the value of "TO" in Table 5, G5 to G2 report the spillover effect of 93.15%, 103.43%, 87.30%, and 84.72%, respectively. Similarly, calculated from the value of "FROM" in Table 5, G5 to G2 report the spillover effect of 91.08%, 90.28%, 91.51%, and 91.22%, respectively.

[18] Calculated from the value of "NET" in Table 4, G5 to G2 report the net spillover effect of –0.20%, –2.99%, 1.41%, and 0.73%, respectively.

[19] Calculated from the value of "NET" in Table 5, G5 to G2 report the net spillover effect of 2.06%, 13.13%, −4.21%, and −6.50%, respectively.

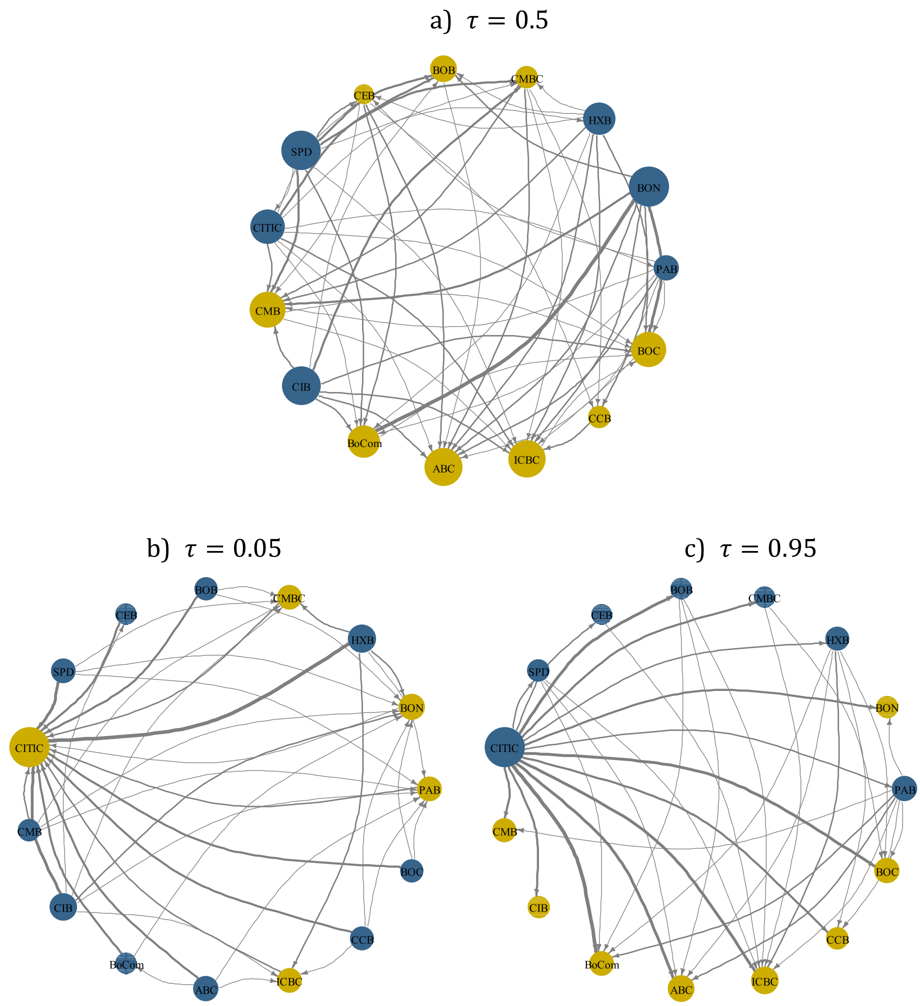

Fig. 1 Net pairwise directional STV interconnectedness network at different quantiles over the full-sample period. **a**–**c** Present results of net pairwise directional STV interconnectedness at median ($\tau = 0.5$), lower ($\tau = 0.05$) and upper ($\tau = 0.95$) quantile conditions. The size of the nodes signifies the extent of the spillover effect, and the color of the nodes specifies whether a C-SIB is a net transmitter (steel blue) or receiver (gold) of spillovers. The thickness of the edges represents the strength of spillover towards other C-SIBs, while the direction of the arrows specifies the direction of pairwise spillovers. Note: Results are based on a 200-days rolling-window QVAR model with a lag length of order one (based on the AIC criterion) and a 10-step-ahead generalized forecast error variance decomposition

systemic importance when the market is under bearish conditions since they are now the net transmitters of spillover.

Figure 1 illustrates the network visualization of net pairwise directional STV interconnectedness under normal, bearish, and bullish market conditions. The node's size signifies the extent of the spillover effect, and node colors specify whether a C-SIB is a net transmitter (steel blue) or receiver (gold) of spillovers. The thickness of the edges represents the strength of spillover toward other C-SIBs, while the direction of the arrows specifies the direction of pairwise spillovers. Figure 1a vividly depicts a dense and robust STV interconnectedness structure of C-SIBs under normal market conditions. Most C-SIBs are the net receivers of spillovers under normal market conditions. From the group perspective, half the members of G5, i.e., PAB, BON, and HXB, are net transmitters of spillovers, whereas the remaining members, i.e., CMBC, BOB, and CEB, are net receivers of spillovers. Due to the opposite roles played by G5 members, its status as a net transmitter of spillovers is relatively weak. In contrast, all the members of G4, i.e., SPD and CITIC, are the net transmitters of spillovers; therefore, as a net transmitter of spillovers, G4 plays a relatively major role in the C-SIBs system. CMB and BoCom, as net receivers of spillovers, dominate CIB as the net transmitter of spillovers in G3, weakening G3's status as a net receiver of spillovers. Last, all members of G2, i.e., ABC, ICBC, CCB, and BOC, are the net receiver of spillovers, implying that the strength of G2 as a net receiver of spillover is comparatively strong. Overall, within the dense and robust STV interconnectedness structure of C-SIBs, a bank's increasing systemic importance is usually associated with transforming from a net transmitter of spillover to a net receiver of spillover.

Likewise, contrary to the dense and robust STV interconnectedness structure of C-SIBs under normal market conditions, Fig. 1b and c illustrate a relatively sparse but stronger STV interconnectedness structure of C-SIBs under bearish and bullish market conditions, respectively. Under extreme market conditions, the intensity of net spillovers between the C-SIBs is more pronounced, as illustrated by the thicker arrows, which indicates that large shocks propagate considerably more forcefully than weaker shocks (Ando et al. 2022). Compared to normal market conditions, most C-SIBs are the net transmitters of spillovers under bearish market conditions, whereas the C-SIBs are roughly split between the net transmitter of spillovers and the net receiver of spillovers under bullish market conditions. Furthermore, as a bank becomes more systemically important, it will gradually transform from a net receiver of spillover to a net transmitter of spillover under bearish market conditions and take an opposite transformation under bullish market conditions. Combining previous analysis, we conclude that the extent of spillover among the C-SIBs system varies considerably under different market conditions, which aligns with Li et al. (2019). Moreover, a bank with lower systemic importance will transform from a net receiver of spillover to a net transmitter of spillover, and a bank with higher systemic importance will experience an opposite transformation as market conditions become increasingly bullish. The graphical visualization illustrated in Fig. 1 is consistent with the empirical results summarized in Table 3, 4 and 5.

We plot the total and directional net STV interconnectedness index at different quantiles to further examine how the STV interconnectedness of C-SIBs varies across various quantiles. The first plot of Fig. 2 shows that the total STV interconnectedness index exhibits a distinct U-shaped characteristic with the lowest points around the median and the highest points at the upper and lower quantiles. The total STV interconnectedness index change between the extremes of the lower and upper quantiles appears to follow a symmetrical pattern. This observation is consistent with prior research on contagion and indicates that extreme occurrences have a roughly equal possibility of spreading to higher and lower quantiles (Londono 2019). This result again shows that the STV interconnectedness of C-SIBs tends to increase significantly under extreme market conditions and further corroborates the necessity of considering the quantile-based connectedness method, as the mean-based connectedness method cannot capture this critical feature. This finding follows Betz et al. (2016) and Mensi et al. (2023); network interconnectedness under extreme market conditions makes more sense than

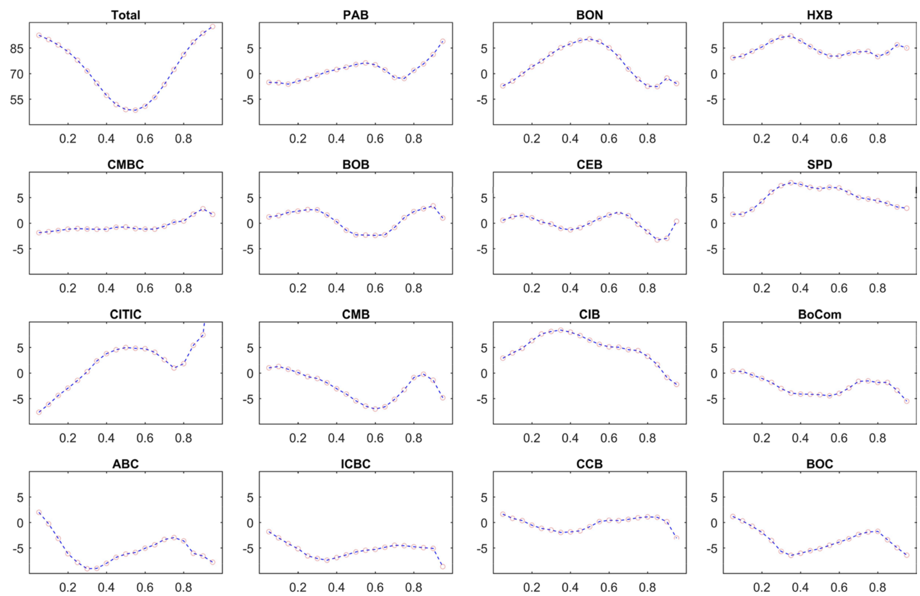

Fig. 2 Variation in the STV interconnectedness across various quantiles. Notes: The first panel reports the value of the total STV interconnectedness index at the τth conditional quantile. The remaining panels report the value of the net directional STV interconnectedness index at the τ^{th} conditional quantile. Note: Please refer to Fig. 1

conventional average-based correlations in terms of adequately supervising the financial system as the usage of mean-based connectedness measures does not provide accurate results. Notably, this conclusion is also consistent with other scholars investigating stock markets (Wang et al. 2023), cryptocurrency markets (Mensi et al. 2023), and commodity markets (Asadi et al. 2023). Furthermore, the remaining plots of Fig. 2 indicate that the intensity of STV interconnectedness still varies across various quantiles even if the U-shaped curve does not apply to the directional net STV interconnectedness index, which justifies the choice of the quantile-based connectedness method.

Dynamic quantile interconnectedness of C-SIBs

As summarized in Table 3, 4 and 5, the previous static quantile interconnectedness analysis reveals the variation of the STV interconnectedness of C-SIBs under different market conditions; however, the static analysis sheds no light on the evolutionary characteristics of STV interconnectedness of C-SIBs. Moreover, Ang and Bekaert (2002) suggest that the intensity of market linkages is stronger under turbulent market conditions than in normal market conditions, indicating the necessity of time-varying analysis. Therefore, to better understand how the STV interconnectedness of C-SIBs fluctuates during the sample period, we consider a 200-day rolling-window quantile vector autoregressive model with a lag length of order one and a 10-step-ahead forecast horizon based on the AIC. Figure 3 illustrates the trajectory of dynamic STV interconnectedness of C-SIBs under different market conditions.

The first plot of Fig. 3 shows that for normal market conditions, the STV interconnectedness of C-SIBs varies considerably between 35 and 65%, with a clear trough recorded in 2012. This short-term trough is categorized as the post-European debt crisis period. From the beginning of 2013, the STV interconnectedness of C-SIBs sharply bounced

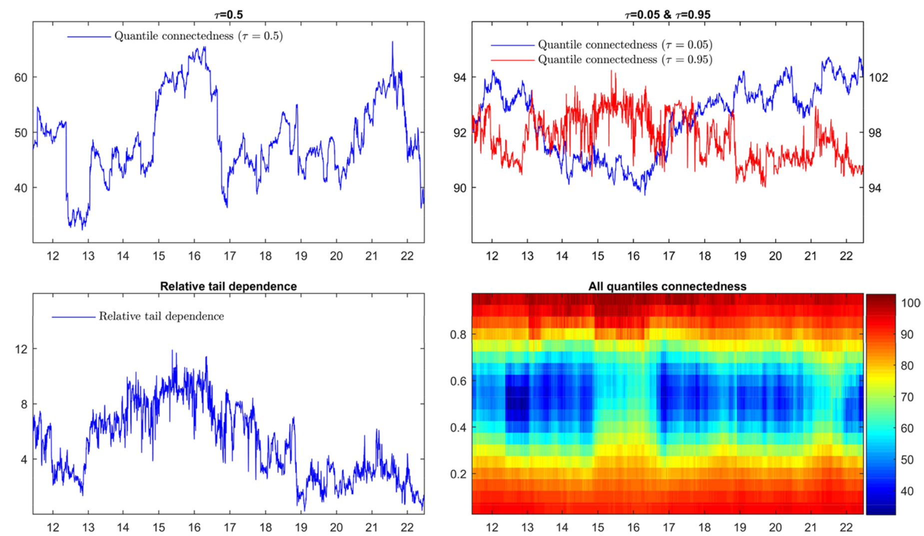

Fig. 3 Dynamic total STV interconnectedness at different quantiles. Relative tail dependence is defined as the difference between the total STV interconnectedness at the 95th quantile and the total STV interconnectedness at the 5th quantile. A negative (positive) value indicates a strong dependence at the lower (upper) quantile. The strength of the total STV interconnectedness at all quantiles is shown by the colored bar with warm (red) shade refers to higher total STV interconnectedness and cold (blue) shade denotes lower total STV interconnectedness. Note: Please refer to Fig. 1

back to approximately 45%, exhibiting some small fluctuations around this level until the end of 2014. Subsequently, the STV interconnectedness of C-SIBs experienced a sharp increase and stayed at a high level of roughly 60% from 2015 to 2016, categorized by the Chinese stock market turbulence. The waning influence of the Chinese stock market turbulence enabled the STV interconnectedness of C-SIBs to experience a sharp decline and keep a low level until the end of 2019. Following the outbreak and deterioration of the COVID-19 pandemic, the STV interconnectedness of C-SIBs gradually ascended to approximately 60% but fell to about 35% at the end of the first half of 2022. The quick reversion could be attributed to the expansionary nature of monetary and fiscal policies (Umar et al. 2023), partly contributing to easing financial hardships and market volatility (Antonakakis et al. 2023). Thus, the STV interconnectedness of C-SIBs fluctuates widely over time and witnesses two spikes, consistent with two turbulence periods, implying the time-varying characteristics of STV interconnectedness of C-SIBs. This outcome also supports the argument proposed by Andries et al. (2022) that the interconnectedness between systemically important institutions will experience a significant increase when unexpected shock occurs. The increased interconnectedness may hurt financial stability by amplifying C-SIBs' mistakes of underestimating risk. This observation is consistent with the empirical findings summarized by Chen (2022) that build a network model to examine the relationship between financial stability and interconnectedness among banks.

A natural question is whether the STV interconnectedness of C-SIBs evaluated under normal market conditions shares typical dynamics with the STV interconnectedness of C-SIBs evaluated under extreme market conditions. Observing the evolutionary nature of the STV interconnectedness of C-SIBs under extreme market conditions will provide invaluable information for investors to design their investment strategy promptly. The second plot of Fig. 3 illustrates the STV interconnectedness of C-SIBs under both bearish and bullish market conditions. This finding conveys that common dynamics are not the case for the STV interconnectedness of C-SIBs evaluated under different market conditions. On the one hand, the STV interconnectedness of C-SIBs is much stronger under extreme market conditions than in normal market conditions. On the other hand, unlike under normal market conditions, the STV interconnectedness of C-SIBs fluctuates within a smaller boundary of 88–102% under extreme market conditions, indicating a moderate time-varying characteristic.

Notably, the STV interconnectedness of C-SIBs under bearish market conditions negatively correlates to the STV interconnectedness of C-SIBs under bullish market conditions. This result suggests that changes under bearish market conditions synchronize somewhat with oppositely-signed changes under bullish market conditions. At this stage, a prolonged downward drift is observed in the STV interconnectedness of C-SIBs under bearish market conditions, signaling a weakened appetite for transmitting good news. Meanwhile, a sustained peak is illustrated in the STV interconnectedness of C-SIBs under bullish market conditions, indicating a pronounced increase in investors' sensitivity to bad news. Furthermore, during the COVID-19 period, a similar but moderate comparison arises between the STV interconnectedness of C-SIBs under bearish and bullish market conditions. The comparison could be attributed to investors' aggregate behavior if bad news associated with adverse shocks prompts a non-trivial proportion of investors to disproportionately fix their attention on subsequent bad news while focusing less on good news (Ando et al. 2022). Take the post-European debt crisis period as an example of beneficial shock. A significant reduction is recorded in the STV interconnectedness of C-SIBs under bullish market conditions, and a sustained increase is illustrated in the STV interconnectedness of C-SIBs under bearish market conditions. The opposite comparison manifests that investors' optimism is gaining ground, and, as good news, improving the economic situation can stimulate a significant intensification of stabilizing beneficial spillovers. Overall, it is intuitive to infer that periods of increasing fragility, characterized by the propensity for spreading adverse shocks, are also periods of intensively spreading positive shocks, and vice versa. The observation derived from the quantile connectedness aligns with those of Bouri et al. (2021) and Umar et al. (2023). It has been extensively reviewed that major economic and social events tend to increase the connectedness of financial markets (Aharon et al. 2022; Umar et al. 2023). Our findings infer that these dynamics are much more intense and observable under extreme market conditions than in normal market conditions; hence, the quantile-based connectedness is relevant to discovering the hidden reality behind C-SIBs' linkages in periods of heightened turbulence and widespread uncertainty.

Thus far, our findings indicate that major adverse events, i.e., the Chinese stock market turbulence and the COVID-19 pandemic, coincide with a significant and sustained increase in average interconnectedness of C-SIBs; however, their effects on the tails vary sharply. These findings support Ando et al. (2022) and Chen et al. (2022a) that traditional mean-based estimators are unsuitable for analyzing extreme risk propagation across markets. Against this backdrop, we follow Ando et al. (2022) to investigate the relative tail dependence (RTD) that measures the difference between the STV interconnectedness of C-SIBs under bullish market conditions and the STV interconnectedness

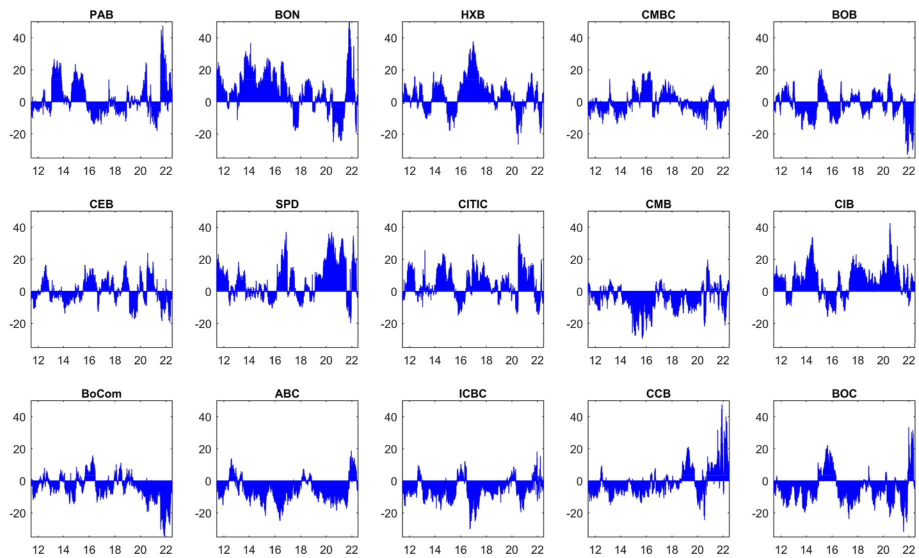

Fig. 4 Dynamic net directional STV interconnectedness at the median ($\tau = 0.05$) condition. Note: Please refer to Fig. 1

of C-SIBs under bearish market conditions. A positive (negative) value indicates a strong dependence at the upper (lower) quantile. The graphical illustration of RTD is presented in the third plot of Fig. 3. The RTD noticeably fluctuates within a 1–12% boundary, highlighting that the C-SIBs system is asymmetrically interconnected across quantiles and at higher levels under bullish than bearish market conditions. The asymmetry may be attributed to the amplification of market volatility during the crisis periods (Kocaarslan and Soytas 2019; Rehman et al. 2023). The time-varying characteristic of the RTD implies how effectively forecasting market movements and the occurrence of significant events is critical for policymakers and market participants in terms of effective policymaking and risk management. During the Chinese stock market turbulence and the COVID-19 pandemic periods, the RTD increased significantly. This result extends the study by Ando et al. (2022) that the increase in RTD provides evidence of the rising financial fragility of the C-SIBs system during these periods.

The heatmap, presented as the last plot of Fig. 3, graphs the dynamic STV interconnectedness of C-SIBs across a quantile range of 0.05–0.95, with warm (red) and cold (blue) shades referring to the strong and weak STC interconnectedness of C-SIBs, respectively. Interconnectedness is strong under bearish (below the 25% quantile) and bullish (above the 75% quantile) market conditions; however, the C-SIBs system is asymmetrically interconnected as shocks in the upper quantiles impact the system of interconnectedness more than shocks estimated at the lower quantiles. Furthermore, the STC interconnectedness of C-SIBs under normal market conditions, associated with the 50% quantile, presents more volatile and frequent changes in color shades, indicating its dynamic characteristics. During some specific periods, i.e., the Chinese stock market turbulence and the COVID-19 pandemic, significant values are recorded for the STC interconnectedness of C-SIBs under normal market conditions. This finding indicates the cyclical pattern and event-driven feature of STV interconnectedness of C-SIBs.

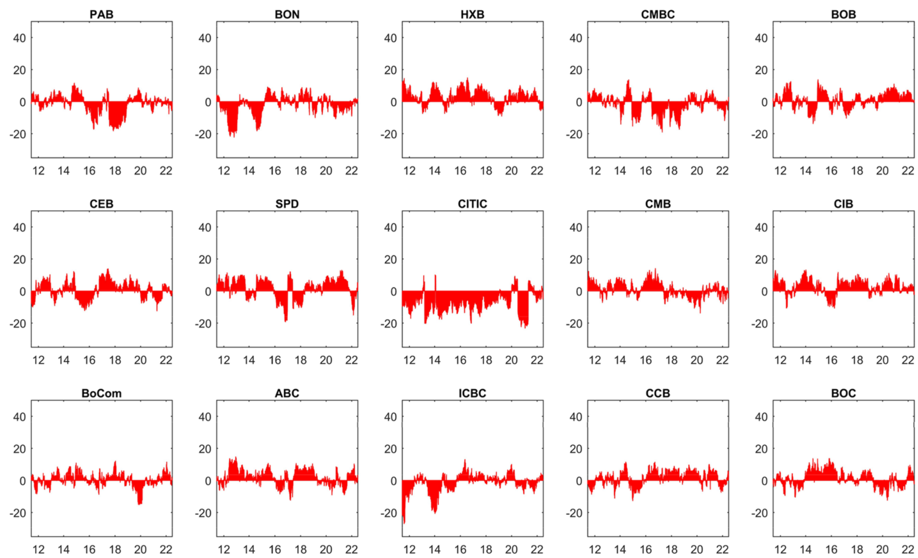

Fig. 5 Dynamic net directional STV interconnectedness at the extreme lower ($\tau = 0.05$) quantile condition. Note: Please refer to Fig. 1

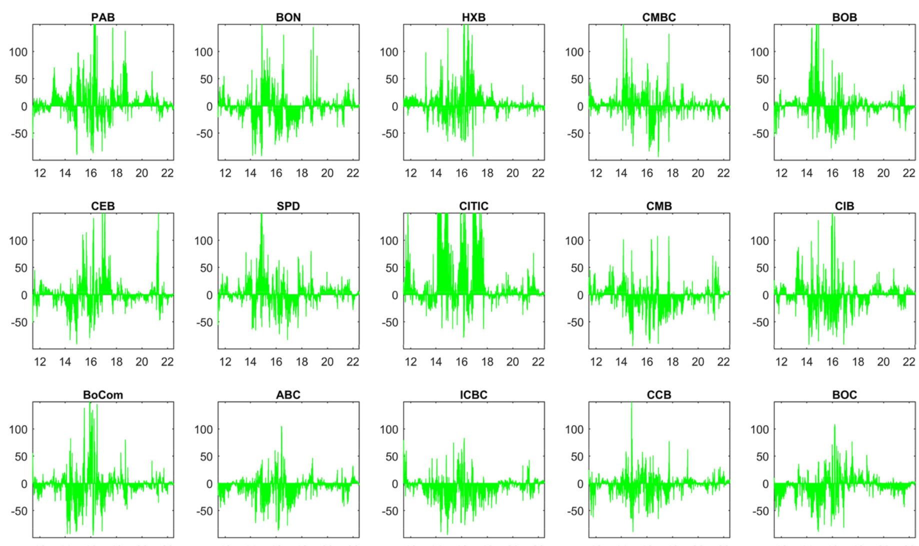

Fig. 6 Dynamic net directional STV interconnectedness at the extreme upper ($\tau = 0.95$) quantile condition. Note: Please refer to Fig. 1

We next analyze the net spillover effects of each C-SIB by observing each S-SIB's position in the whole C-SIB system under different market conditions. Figures 4, 5 and 6 illustrate the dynamic net directional STV interconnectedness of C-SIBs under normal, bearish, and bullish market conditions. From the group perspective, there are two modes of net spillovers in Fig. 4. The first includes G5 and G4, which are the transmitters of spillover because their net spillovers are mainly positive during the sample period. The second mode comprises G3 and G2, whose net spillovers are predominantly negative over the sample period, implying their role as net receivers of spillover. As a net transmitter of spillover, G4 plays a more significant role than

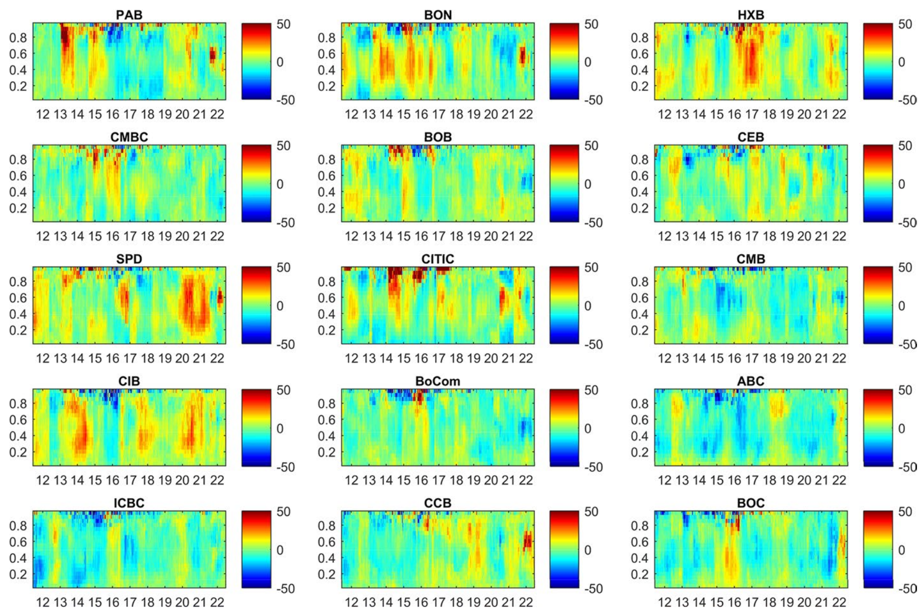

Fig. 7 Dynamic net directional STV interconnectedness at all quantile conditions. Note: Please refer to Fig. 1

G5, which is also the case of G2 compared to G3 as a net receiver of spillover. This finding implies that the role of C-SIBs has changed from a net transmitter of spillover to a net receiver of spillover in the wake of the gradual increase of their systemic importance. At the same time, the plots in Fig. 5 depict a different picture. G5 and G4 could be classified as net receivers of spillover, whereas G3 and G2 fall into the mode of the net transmitter of spillover. The general pattern from this finding suggests that under bearish market conditions, C-SIBs will transform from a net receiver of spillover to a net transmitter of spillover following the increase of their systemic importance. In contrast, Fig. 6 indicates a similar but enhanced pattern to that presented under normal market conditions. Overall, we again conclude that the role played by a C-SIB with different systemic importance depends on changes in market conditions. As market conditions gradually improve, i.e., turning from bearish to bullish, a C-SIB will transform from a net receiver of spillover to a net transmitter of spillover if its systemic importance is labeled "low." In contrast, a C-SIB will transform from a net transmitter of spillover to a net receiver if its systemic importance is labeled "high."

To better understand how sensitive the net spillover effects of C-SIBs are to market conditions, we visualize the dynamic net interconnectedness of C-SIBs across a broad spectrum of quantiles spanning from 0.05 to 0.95. Figure 7 illustrates the results in heatmap matrices, with warmer shades indicating a net transmitter of spillover and colder shades representing a net receiver of spillover. Figure 7 shows that the net spillover effects of C-SIBs are relatively sensitive to market conditions. In the context of market conditions becoming more bullish, a C-SIB with a lower level of systemic importance has more potential to act as a net transmitter of spillover than a net receiver of spillover. In contrast, a C-SIB with a higher level of systemic importance has more potential to act as a net receiver of spillover than a net transmitter. Furthermore, the warmer shades are more significant in the heatmaps for the C-SIBs with a lower level of systemic importance, indicating they predominantly act as the net transmitter of spillover. In comparison, the C-SIBs with a higher level of systemic importance play the net receiver of spillover more constantly, as shown by more pronounced colder shades in the heatmaps. Overall, the general findings of Figs. 4, 5, 6 and 7 corroborate those discussed in Section "Static quantile interconnectedness of C-SIBs"/these results provide policymakers and market participants guidelines for scrutinizing the dynamic changes of spillover effects of C-SIBs depending on their systemic importance and market conditions.

The comparison between STV and higher-order moments interconnectedness of C-SIBs

The previous two subsections provided a thorough analysis of the STV interconnectedness of C-SIBs, which significantly expands the sphere of application of the salience theory proposed by Bordalo et al. (2012). Notably, from the salience theory perspective, we effectively confirm that the interconnectedness between systemically important institutions will experience a significant increase when unexpected shock occurs. At this stage, an obvious question arises: does this confirmation hold if the interconnectedness of C-SIBs is measured from the return, volatility, or higher-order moments perspective?[20] Specifically, we attempt to answer the following critical question. What are the differences between STV interconnectedness and higher-order moment interconnectedness? This research question has never arisen in the existing studies; however, it is of practical importance for policymakers and market participants in formulating their regulatory strategies and risk management.

Figures 8, 9, 10 and 11 compare the dynamic STV and higher-order moment interconnectedness of C-SIBs under different market conditions.[21] In general, the graphical evidence illustrates that the interconnectedness of C-SIBs prominently varies with the order of the moments, and a significant difference exists between the higher-order and STV interconnectedness of C-SIBs. Specifically, as the first plot of Figs. 8, 9, 10 and 11 shows for the normal market conditions, the higher-order moment interconnectedness of C-SIBs is higher than the STV interconnectedness of C-SIBs; however, the STV interconnectedness of C-SIBs has been more accurate and robust in responding to significant market events, i.e., the Chinese stock market turbulence and the COVID-19 pandemic. This result could be explained by the fact that compared to the higher-order moment estimators, the STV estimator contains more information about investors' expectations for the future performance of C-SIBs in reaction to the outbreak of significant market events. Moreover, the STV interconnectedness of C-SIBs illustrates a more obvious fluctuating characteristic, making the trajectory steeper. Although the initial confirmation has been upheld from the higher-order moments perspective, we should acknowledge

[20] Numerous studies of the interconnectedness of financial institutions have appeared in the literature (Billio et al. 2012; Diebold and Yilmaz 2014; Demirer et al. 2018; Wang et al. 2018a; Liang et al. 2020). These existing studies have all confined themselves to the return and volatility interconnectedness. Scant attention has been paid to the higher-order moment interconnectedness of financial institutions. In this sense, this study is the first to present the higher-order moment interconnectedness of financial institutions.

[21] $r_{i,s;t}$ is the 5-min return in a given interval *s* and day *t* for bank i, and the daily realized return $RR_{i,t}$ is defined as: $RR_{i,t} = \sum_S^{S_t} r_{i,s;t}$. Inspired by Andersen and Bollerslev (1998) and Amaya et al. (2015), we further construct the daily realized volatility $RV_{i,t} = \sum_S^{S_t} r_{i,s;t}^2$, skewness $RS_{i,t} = \sqrt{S_t} \sum_S^{S_t} r_{i,s;t}^3 / RV_{i,t}^{3/2}$, and kurtosis $RK_{i,t} = S_t \sum_S^{S_t} r_{i,s;t}^4 / RV_{i,t}^2$.

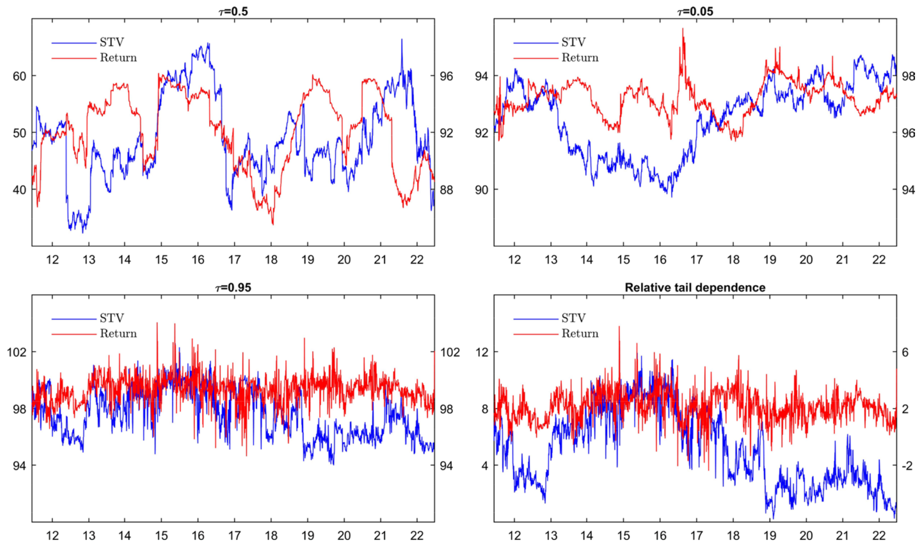

Fig. 8 Comparison of dynamic STV and Return interconnectedness at different quantiles. Relative tail dependence is defined as the difference between the STV (Return) interconnectedness at the 95th quantile and the STV (Return) interconnectedness at the 5th quantile. Note: Please refer to Fig. 1

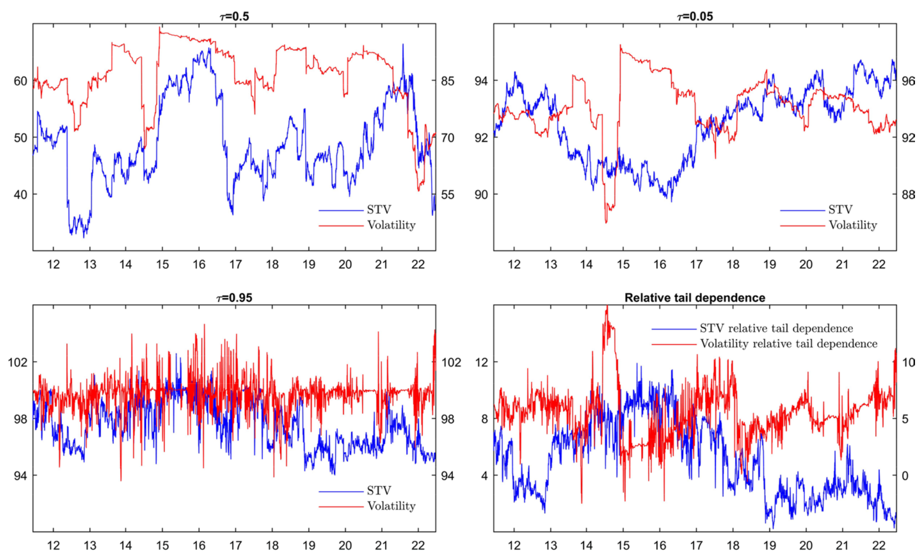

Fig. 9 Comparison of dynamic STV and Volatility interconnectedness at different quantiles. Relative tail dependence is defined as the difference between the STV (Volatility) interconnectedness at the 95th quantile and the STV (Volatility) interconnectedness at the 5th quantile. Note: Please refer to Fig. 1

that STV could provide more information than higher-order moments in capturing the dynamic change in the C-SIBs system and detecting some market events more precisely.

The second plot of Figs. 8, 9, 10 and 11 compares STV and higher-order moments interconnectedness of C-SIBs under bearish market conditions. Besides the kurtosis interconnectedness of C-SIBs, the remaining higher-order moment interconnectedness of C-SIBs is relatively higher than the STV interconnectedness of C-SIBs. Like STV interconnectedness, the higher-order moment interconnectedness reflects the impact of the Chinese stock market turbulence in a pronounced manner. Furthermore, during the

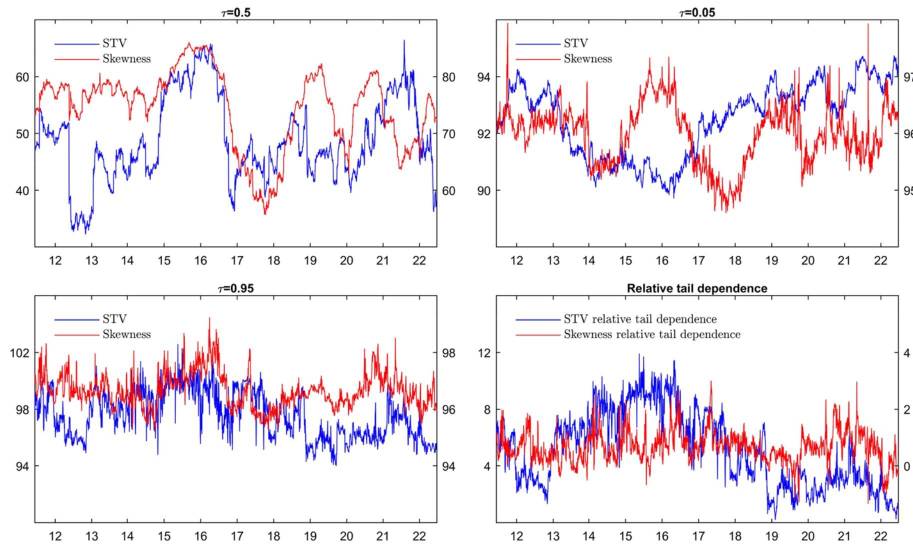

Fig. 10 Comparison of dynamic STV and Skewness interconnectedness at different quantiles. Relative tail dependence is defined as the difference between the STV (Skewness) interconnectedness at the 95th quantile and the STV (Skewness) interconnectedness at the 5th quantile. Note: Please refer to Fig. 1

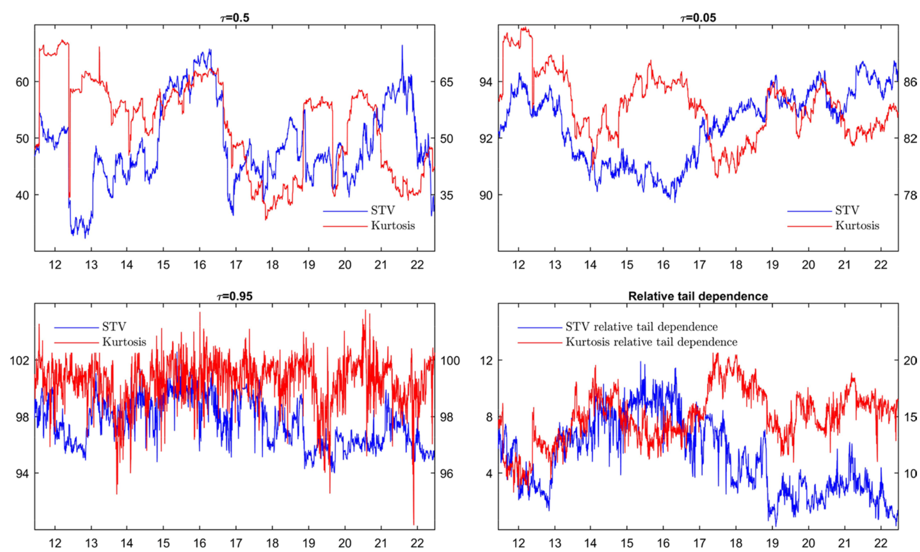

Fig. 11 Comparison of dynamic STV and Kurtosis interconnectedness at different quantiles. Relative tail dependence is defined as the difference between the STV (Kurtosis) interconnectedness at the 95th quantile and the STV (Kurtosis) interconnectedness at the 5th quantile. Note: Please refer to Fig. 1

COVID-19 period, a similar but moderate comparison arises between the STV interconnectedness of C-SIBs and the higher-order moment interconnectedness of C-SIBs. Overall, compared to the sharp changes observed in higher-order moment interconnectedness, the responses of STV interconnectedness to important market events are sustained and forward-looking. The forward-looking merit is essential for policymakers and market participants attempting to forecast crisis events in advance. We can draw the same conclusion after graphically visualizing the comparison between STV and higher-order moments interconnectedness of C-SIBs under bullish market conditions as presented in the third plot of Figs. 8, 9, 10 and 11. This finding's credibility is also supported by the last plot of Figs. 8, 9, 10 and 11; the STV interconnectedness of C-SIBs records more significant changes of relative tail dependence than the higher-order moment interconnectedness of C-SIBs could in responding to the Chinese stock market turbulence, and the COVID-19 pandemic. However, capturing the higher-order moment interconnectedness of C-SIBs is still worthwhile, as they contain information about market risk and consequently become a helpful supplement to the STV interconnectedness of C-SIBs. This finding corroborates Fengler and Gisler (2015); the analysis of spillovers should extend to higher-order moments. Finally, the comparative analysis extends the studies of Adekoya and Oliyide (2021) and Cui and Maghyereh (2023) that cover the higher-order moment risk spillover transmissions across oil and commodity markets.

We next focus on the quantitative evidence supporting the superior predicting performance of STV interconnectedness. As interconnectedness jumps whenever the financial market experiences distress, which could be measured as significant volatility fluctuations, we expect that the interconnectedness of financial institutions will convey information regarding future volatility and exhibit a certain degree of predictive power for significant market events, i.e., the Chinese stock market turbulence and the COVID-19 pandemic. We start from the in-sample estimation, employing the HAR-RV-X[22] model:

$$\begin{aligned}\log\left(RV_t^M\right) &= w_0 + w_1 \log\left(RV_{t-s}^M\right) + w_2\left(5^{-1}\sum_{k=1}^{5}\log\left(RV_{t-s-k}^M\right)\right)\\ &+ w_3\left(22^{-1}\sum_{k=1}^{22}\log\left(RV_{t-s-k}^M\right)\right)\\ &+ w_4 IV_{t-s}^X + w_5\left(5^{-1}\sum_{k=1}^{5} IV_{t-s-k}^X\right)\\ &+ w_6\left(22^{-1}\sum_{k=1}^{22} IV_{t-s-k}^X\right) + \varepsilon_t\end{aligned} \tag{15}$$

where RV_t^M is the daily realized volatility of China's stock market, represented by the SSE Composite Index. IV^X denotes the STV interconnectedness of C-SIBs or one of the higher-order moment interconnectedness of C-SIBs. We consider s-days ahead forecasts for $s = 1, 22$, equivalent to one-day and one-month forecasting horizons, respectively. ε_t represents white noise. The initial sample period is $\tilde{T} = 726$ days to ensure a large sample size for estimating the Eq. (15). The initial sample period is used to obtain the first out-of-sample forecasts for 1 day and 22 days ahead. We consider a rolling-window approach for each subsequent forecast, with a fixed length of 726 days. Two well-known evaluation functions, i.e., the mean squared predicted error (MSE) and the mean absolute predicted error (MAE), are employed to evaluate the forecasting accuracy of Eq. (15).

Table 6 summarizes the MAE and MSE ratios of the HAR-RV-X model with higher-order moment interconnectedness as exogenous variables to the HAR-RV-X model with

[22] Degiannakis and Filis (2017) indicate that the heterogeneous autoregressive model (HAR) by Corsi (2009) is considered the most suitable method for modeling and forecasting asset price volatility.

Table 6 MAE and MSE ratios on the real out-of-forecasts

	Return_T	Return_S	Return_C	VolatilityT	VolatilityS	Volatility_C	Skewness_T	Skewness_S	Skewness_C	Kurtosis_T	Kurtosis_S	Kurtosis_C
MAE, 1 day ahead												
$\tau=0.05$	1.0152	1.0277	0.9931	1.0158	1.0305	1.0147	1.0021	1.0002	0.9938	1.0051	1.0084	1.0001
$\tau=0.50$	1.0208	1.0407	1.0014	1.0034	1.0061	0.9989	0.9942	0.9883	1.0022	0.9942	0.9926	0.9972
$\tau=0.95$	1.0156	1.0142	0.9987	1.0162	1.0183	0.9981	1.0095	1.0059	1.0194	1.0071	1.0006	0.9960
MAE, 22 days ahead												
$\tau=0.05$	1.0242	1.0435	0.9655	1.0690	1.1006	0.9939	1.0195	1.0337	0.9734	1.0393	1.0740	0.9512
$\tau=0.50$	0.9769	0.9608	1.0022	1.0199	1.0131	1.0158	0.9720	0.9458	1.0271	0.9792	0.9652	1.0022
$\tau=0.95$	1.0079	1.0156	0.9906	1.0346	1.0476	1.0032	1.0245	1.0269	1.0463	1.0083	1.0002	0.9966
MSE, 1 day ahead												
$\tau=0.05$	0.9999	1.0093	1.0397	1.0183	1.0426	1.0458	0.9813	0.9750	1.0180	0.9965	0.9983	1.0366
$\tau=0.50$	1.0432	1.0711	1.0018	1.0184	1.0232	0.9467	0.9610	0.9457	1.0095	1.0049	1.0004	1.0177
$\tau=0.95$	1.0172	1.0065	0.9820	1.0114	1.0145	1.0034	1.0051	1.0028	1.0245	0.9877	0.9815	0.9902
MSE, 22 days ahead												
$\tau=0.05$	1.0966	1.0999	1.0319	1.1691	1.1744	1.1007	1.0832	1.0861	1.0296	1.1320	1.1390	1.0186
$\tau=0.50$	0.9384	0.9345	0.9897	1.0457	1.0475	0.9951	0.8811	0.8727	1.0026	0.9873	0.9853	1.0101
$\tau=0.95$	1.0443	1.0447	1.0033	1.0334	1.0314	1.0170	1.0192	1.0186	1.0072	1.0055	1.0017	0.9800

T refers to the whole sample period; S refers to the subsample period corresponding to the Chinese stock market turbulence between January 1, 2015 and December 31, 2016; C refers to the subsample period corresponding to the COVID-19 pandemic between January 1, 2020 and June 30, 2022. Values represent ratios of HAR-RV-X model with higher-order moment interconnectedness as exogenous variables to HAR-RV-X models with STV interconnectedness as exogenous variables. A ratio above 1 suggests that the MAE/MSE of the HAR-RV-X model with STV interconnectedness as exogenous variable outperform those of the HAR-RV-X models with higher-order moment interconnectedness as exogenous variables

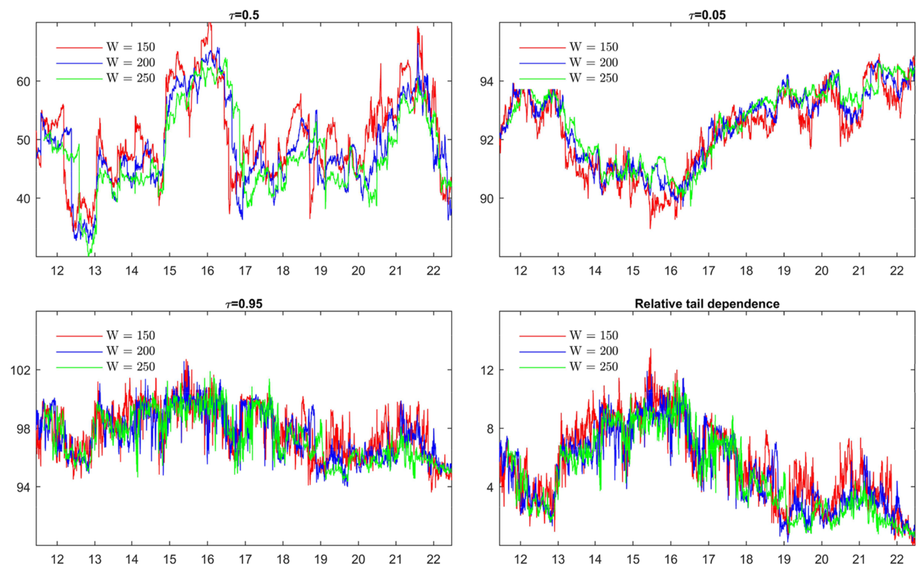

Fig. 12 Robustness to the selections of rolling window lengths at different quantiles. Relative tail dependence is defined as the difference between the STV interconnectedness at the 95th quantile and the STV interconnectedness at the 5th quantile. Note: Results are based on 150-, 200-, and 250-days rolling-window QVAR models with lag length of order one (based on the AIC criterion) and a 10-step-ahead generalized forecast error variance decomposition

STV interconnectedness as exogenous variables. A ratio above 1 suggests that the MAE/MSE of the HAR-RV-X model with STV interconnectedness as an exogenous variable outperforms those of the HAR-RV-X models with higher-order moment interconnectedness as exogenous variables. Table 6 shows that in most cases, STV interconnectedness provides more predictive power than higher-order interconnectedness. This result may quantitatively corroborate the effectiveness of STV interconnectedness in conveying information about future market development; however, the main idea of this study is not to identify out-of-sample forecasting but to use it for economic inference. Nevertheless, compared to Fengler and Gisler (2015), we conclude that the analysis of spillovers should be extended to other higher-order moments.

Robustness analysis

To ensure the robustness of our empirical results, we conduct the sensitivity analysis with two alternative settings. Figure 12 shows the robustness of our empirical results to the selections of rolling-window lengths at different quantiles. The selection of rolling-window length affects the level of the interconnectedness index under normal market conditions, with shorter window lengths yielding relatively higher values. This basic feature is also apparent under bearish and bullish market conditions, although with greater noise; however, the time-varying characteristics of the STV interconnectedness, our primary concern, are largely unaffected by the selection of rolling-window length. This finding holds even if the relative tail dependence is under consideration, as shown in the last plot of Fig. 12. Second, we test the robustness of our empirical results under different forecast horizons. The first two plots of Fig. 13 show that the forecast horizon selection does not exert a discernable effect on the STV interconnectedness under normal and bearish market conditions. Moreover, the last two plots of Fig. 13 illustrate that the

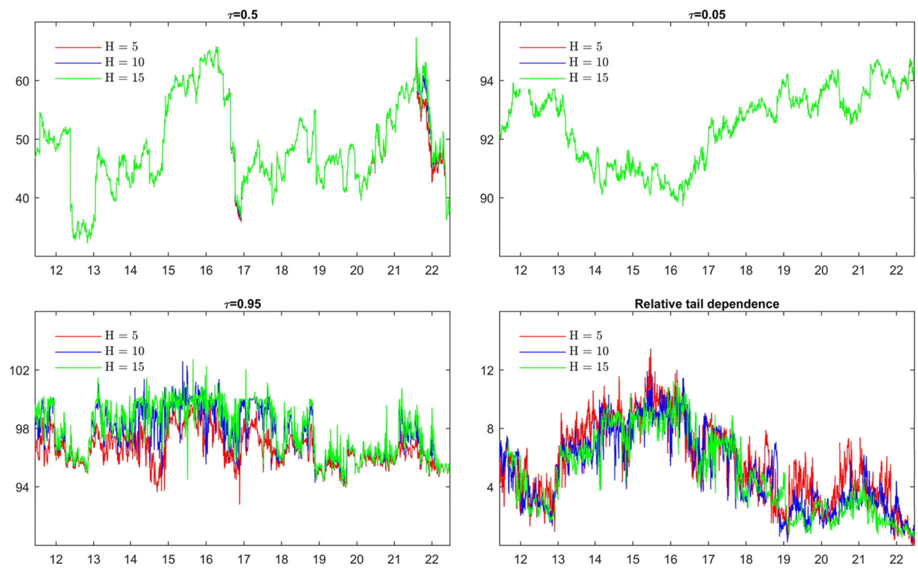

Fig. 13 Robustness to the selections of forecasting horizons at different quantiles. Relative tail dependence is defined as the difference between the STV interconnectedness at the 95th quantile and the STV interconnectedness at the 5th quantile. Note: Results are based on a 200-days rolling-window QVAR models with lag length of order 1 (based on the AIC criterion) and 5-, 10-, and 15-step-ahead generalized forecast error variance decompositions

time-varying trend of STV interconnectedness and relative tail dependence is consistent under different forecast horizons. Therefore, we conclude that the choice of rolling-window length and forecast horizon does not influence our empirical results, confirming the robustness of our empirical findings.[23]

Conclusions and policy implications

This paper contributes to the existing literature on the spillover property of financial institutions by exploring the interconnectedness of C-SIBs under different market conditions from the salience theory perspective. As far as we know, this is a unique study where the analysis considers the STV. Building on Cosemans and Frehen (2021), we construct the STV for C-SIBs stock high-frequency returns and apply the quantile-based connectedness method proposed by Ando et al. (2022) to examine the STV interconnectedness of C-SIBs under different market conditions from 2010 to 2022. Our primary motivation is twofold. On the one hand, STV may contain unique information not captured by traditional higher-order moments, i.e., return, volatility, skewness, and kurtosis, which makes the spillover analysis more attractive and enlightening. On the other hand, the mean-based interconnectedness of C-SIBs may not share the same features as those appearing under extreme market conditions, indicating the need for a more refined model of STV interconnectedness to uncover the complexity in the time-varying connectivity of C-SIBs.

[23] We also investigate the robustness of our empirical results on selecting the remaining combinations of rolling-window length and forecast horizon. The test results also show the robustness of our empirical results. Due to space limitations, the detailed graphical visualizations of these test results are not presented here and are available from the author upon request.

Our empirical analysis summarizes convincing evidence for several significant results. First, our findings suggest stronger time-varying STV interconnectedness of C-SIBs under extreme market conditions compared to normal market conditions. Furthermore, evidence suggests that the C-SIBs system is asymmetrically interconnected across quantiles and at higher levels under bullish than bearish market conditions. Accordingly, applying the quantile-based connectivity approach explains the asymmetric tail risk dispersion in the C-SIBs system, which could be masked by only considering mean-based connectedness measures. Second, we show that a bank's performance in the C-SIBs system depends on its systemic importance and market conditions. As market conditions become increasingly bullish, a bank with lower systemic importance will transform from a net receiver of spillover to a net transmitter of spillover. In contrast, a bank with higher systemic importance will transform from a net transmitter of spillover to a net receiver of spillover. Finally, this study provides clear evidence that STV could provide more information than higher-order moments in capturing the dynamic change in the C-SIBs system and detecting some market events more precisely. Our empirical findings in this study are crucial for policymakers and market participants to formulate regulatory policy and design risk management strategies. For policymakers, evidence of asymmetrical interconnectedness under extreme market conditions provides a nuanced understanding of the importance of extreme risk transmission within the C-SIBs system. This information makes the quantile-based method essential to a sound early warning system and a risk response mechanism. By extending our knowledge regarding the dynamic changes of spillover effects of C-SIBs in response to their systemic importance and market conditions, policymakers should pay more attention to C-SIBs with higher (lower) systemic importance under bullish (bearish) market conditions. Otherwise, focusing only on systemic importance or market conditions within the interconnectedness of C-SIBs will likely lead to the misallocation of valuable supervision resources and the application of inappropriate policy tools and surveillance mechanisms. For instance, most regulatory efforts are allocated to large state-owned commercial banks due to their higher systemic importance; however, we show that small and medium-sized commercial banks matter to the stability of the interconnectedness of C-SIBs, especially under bearish market conditions, even if their systemic importance is relatively low. Regarding market participants, our empirical analysis may help them refine their decision-making procedure under extreme market conditions and improve risk management effectiveness. The results concerning dynamic and asymmetric interconnectedness have helpful implications for market participants designing investment strategies. Furthermore, the foresight of the STV indicator can help market participants effectively predict future market events and promptly adjust their investment decisions. It is also helpful for policymakers to construct an STV-based surveillance mechanism with higher-order moment-based tools to more effectively predict systemic risk arising from the interconnectedness of C-SIBs under extreme market conditions. Last, this paper provides a possible framework or reference for C-SIBs to implement internal risk management. Based on the quantile interconnectedness approach, C-SIBs can manage their internal risk from the perspective of market conditions, investors' salient thinking, and risk-return preference. C-SIBs especially should behave carefully under bearish and bullish market conditions as investors' salient thinking and risk-return preference could be affected by market conditions.

Nonetheless, our study does not address whether the empirical finding is reliable if other intraday frequencies are considered, e.g., 10-, 15-, and 30-min intervals. The robustness of our empirical findings should be further examined by following the path of Cosemans and Frehen (2021) to formulate a salience theory value based on daily frequency. By pursuing this direction, we will have the opportunity to examine the robustness of this study to data frequency. Furthermore, our proposed STV interconnectedness only focuses on C-SIBs. It can be extended to global systemically important banks in future studies to depict a clear picture concerning the interconnectedness of global systemically important banks with the consideration of investors' salient thinking and risk-return preference as well as market conditions. Moreover, with the help of Baruník and Křehlík (2018) and Chatziantoniou et al. (2022), this study can be extended to analyze the STV interconnectedness of C-SIBs from the frequency perspective. By addressing these limitations, future research can build upon our empirical findings and contribute to a deeper understanding of how China's systemically important banks are affected by the interaction among market conditions, investors' salient thinking, and their risk-return preference.

Abbreviations

STV	Salience theory value
C-SIBs	China's systemically important banks
G-SIBs	Global Systemically Important Bank
SIFI	Systemically important financial institutions
TENET	Tail-event-driven network
AIC	Akaike information criterion
US	United States

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XJ: Conceptualization, data curation, methodology, software, formal analysis, project administration, roles/writing—original draft; writing—review and editing. The author has read and approved the final version of the manuscript.

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Availability of data and materials
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Declarations

Competing interests
The author whose name is listed immediately below certify that there is no form of competing interests with any kind of organization or entity.

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