



# Identifying systemically important financial institutions in China: new evidence from a dynamic copula-CoVaR approach

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Accepted: 17 June 2021 / Published online: 2 July 2021

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## Abstract

We examine the risk spillovers in the Chinese financial system by adopting a time-varying copula-CoVaR approach. We first identify the systemically important financial institutions for each industry group in China's financial sector in a dynamic context. We then find strong evidence of upside and downside risk spillovers between these key institutions and the financial system, by quantifying value at risk (VaR), conditional VaR (CoVaR) and delta CoVaR ( $\Delta$ CoVaR) through time-varying copulas. The empirical results further reveal asymmetric downside and upside risk spillover effects, indicating asymmetric hedging strategies for investors during market upturns and downturns.

**Keywords** Financial system · Systemically important financial institution · Risk spillovers · Copula · Delta CoVaR

## 1 Introduction

The issue of curbing systemic risk in the financial system has been central to regulatory and supervisory frameworks in various countries since the 2008 financial crisis. Compared to ex-post recovery and taxpayer bailouts, it is well realized that effective ex ante measures can curb systemic risk before it builds up and propagates across the system, thus sufficiently reducing the negative externalities and heavy social costs following a massive market meltdown (Acharya et al., 2012). Despite the fast-growing techniques and booming literature of modelling the sources of systemic risk and its various contagion trajectories,

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the definition of systemic risk is yet to gain a consensus among policy makers, regulators, market participants and academics, due to its complexity, fast evolution and fuzzy nature. Notwithstanding, as identified by the Financial Stability Board (FSB, 2009) and European Central Bank (ECB, 2010), there are two fundamental aspects of systemic risk: the distress of parts or the entire financial system, and a potential of material negative externalities to the rest of the economy and social welfare.

The concept of systemic risk can thus be regarded to involve both risks stemming from a particular source and the contagion as a result of interactions between agents (nodes) within a network structure. Regarding these two fundamental aspects of systemic risk, this study seeks to identify the financial institutions with systemic importance in China's financial system, and depict the time-varying risk spillovers between those key firms and the financial system. According to the Financial Stability Board (FSB, 2010), financial institutions whose disorderly failures contribute most significantly to financial instability and more widely economic disruption are identified as systemically important financial institutions (SIFIs). These institutions may only be a few, but due to their size, low level of substitutability, global scope, complexity and systemic interconnectedness (BCBS, 2013), their distress or collapses could be contagious and lead to a massive systemic failure (Billio et al., 2012; Sedunov, 2016). After the financial crisis, regulators not only pay attention to the risks of a single financial institution, but more importantly attempt to monitor the risk spillover dynamics between the financial system and individual institutions. This macro-prudential supervision seeks to identify the connectivity of a particular financial institution to determine its systemic importance and to further forecast or trace the possible contagion channels of risk and distress through a risk map. This is opposed to traditional micro-prudential supervision, which focuses on firm-level oversight through capital requirement, on-site examination, etc. Alongside with on-going policy updates, a growing body of academic research has emerged on how to measure and score SIFIs, both in a single country context (for example, Hmissi et al., 2017) and against a wider global backdrop.

On the other hand, there are voluminous studies focusing on the contagion effects of systemic risk. At the market level, Philippas and Siriopoulos (2013) argue that contagion occurs in the forms of increased cross-market linkages or transmission of shocks across markets in the wake of a systemic event. Both this study and Pragidis et al. (2015) use correlations of asset prices as systemic risk indicator and test time-varying volatility relationships between asset returns across the European Monetary Union economies during the European debt crisis. In addition, the many specifications of the multivariate GARCH model have been employed to measuring cross-market risk contagion (Mensi et al., 2017; Reboredo & Ugolini, 2015).

Our adoption of the dataset accounts for the growing importance of the fast internationalized and liberalized China's equity market on global financial stability (Glick & Hutchison, 2013; Yao et al., 2018; Zhang, 2017). Risk spillovers in developed economies, such as European (Ghulam & Doering, 2018; Shahzad et al., 2018) and US (Billio et al., 2012; Low, 2018) markets, have already drawn much attention. Sparse studies, however, have made efforts on exploring the Chinese market, despite the critical roles of the Chinese financial sector in fueling the country's economic growth and its international importance to systemic risk and financial stability in the global market.

Despite unprecedented economic growth in the past decades, China's economy has been facing perpetuating problems such as outside debt expansion, housing bubbles (Zhang & Fan, 2018; Zhang et al., 2017) and excess industrial capacity, and new challenges such as slowdown in growth and increasing economic policy uncertainties in the wake of the US-China trade war (Zhang et al., 2018). These have led to mounting anxiety and fear of a

financial calamity, which may not take the same course as, for example, the Lehman Brothers episode, due to China's unique political, economic and legal attributes, but can inflict no less damage on domestic economy and threaten global financial stability. Furthermore, compared to some previous studies focusing on a specific crisis, several recent market crises in the China market are covered by our sample period. Our empirical evidence shows that during these turmoil periods, risk spillover effects within the system were drastically amplified.

In this study, we test the bidirectional upside and downside risk spillovers between the SIFIs and their corresponding industry groups using VaR, CoVaR and  $\Delta$ CoVaR (Adrian & Brunnermeier, 2016) estimated by time-varying copulas. Institutions exhibiting the strongest spillover effects on their affiliated industry groups, as evidenced by the greatest value of CoVaR, are identified as SIFI in the financial system. To the best of our knowledge, this study is the first to apply the CoVaR-copula approach to detecting risk spillover effects in the Chinese financial system. Our adoption of time-varying copulas to estimate CoVaR well accounts for the time-varying characteristics of risk spillovers in the fast-evolving financial market (Zhang, 2017), and tackles the non-normally distributed characteristics of most financial data. Due to the advantages of copulas in measuring both average movements across marginal and extreme upward and downward joint movements, the copula-CoVaR methodology enables us to flexibly estimate the dynamic and asymmetric tail dependence between data (Patton, 2006), in our case, the upside and downside risk spillovers in the Chinese financial system. Compared to other methods used to estimate CoVaR in the literature, such as quantile regression (Fan et al., 2017), tail risk networks (Wang et al., 2018a), multivariate GARCH model (Huang et al., 2017), the combination of copula functions and CoVaR has many advantages (Bernardi et al., 2017; Mainik & Schaanning, 2014; Reboredo & Ugolini, 2015). By separately estimating the marginal distribution and dependence of the two groups of variables, it captures the nonlinear tail dependence between variables and makes the calculation of VaR and CoVaR more convenient.

By using this copula-CoVaR methodology, we also focus on the spillovers of extreme risks within a financial network. The importance of the spillovers of extreme risks is more highlighted than ever in the wake of the 2015 stock market crash in China (Fang et al., 2018; Wu, 2019). The financial crises and market crashes demonstrate that a tail event could rapidly propagate across the market and trigger system-wide disruption and malfunctioning, implying that extreme risk matters more than simple (mean) correlations, especially for financial surveillance and regulatory purposes (Betz et al., 2016). In recent studies, increasing emphasis has been placed on tail event driven network models, such as Hautsch et al. (2014) and Härdle et al. (2016). The latter describes the tail-driven spillover effects across US financial institutions by combining the CoVaR model and network dynamics. Fang et al. (2018) used relevant models to study the extreme risk spillover between financial institutions in China.

While most existing studies on the Chinese market focus on risk spillovers across firms (Fang et al., 2018; Wang et al., 2018a, 2018b) or sectors (Wu, 2019; Wu et al., 2019), we investigate the risk spillovers between the financial institutions and the subsectors they belong to, motivated by the current financial segregation in the Chinese financial system and the evidence in the literature. Though financial convergence has become increasingly popular in some developed economies, such as the US, the financial system in China is featured by business segregation arising from legal separation between businesses conducted by financial institutions. For example, the Law of the People's Republic of China on Commercial Banks imposes legal barriers between investment and commercial banking activities. In this framework, institutions in one financial sector cannot engage in businesses in other sectors. On the other hand, Zhang et al. (2020) depict the risk relationships across the financial institutions

in the Chinese financial markets from a network topology perspective and find that financial institutions within the same industrial group tend to be more interconnected. Motivated by this finding, we attempt to depict the risk transmission patterns from a within-industry perspective, based on the conjecture that risk spillovers tend to occur first across the firms within a sector and then ripple further out to firms in other sectors.

The contributions of our study are threefold: First, to the best of our knowledge, sparse studies in extant literature have tried to explore systemic risk spillovers in the Chinese financial system using the CoVaR-copula approach. This approach tackles the issue of identifying the source of and key contributors to systemic risk from a new perspective. It enables us to capture risk spillover patterns in a dynamic fashion. Based on CoVaR and  $\Delta$ CoVaR computed by time-varying copulas, we manage to address possible time variations in risk spillovers and identify the SIFI in this system by taking into account its own evolution and market dynamics. The information is highly relevant for financial investors when attempting to forecast the multivariate distributions of an asset portfolio to support investment decisions and risk management.

Second, this study investigates risk spillovers within the three subsectors in the Chinese financial system: commercial banks, insurance and diversified financials. The empirical evidence shows that Shanghai Pudong Development Bank (SPDB) is the SIFI in the Chinese banking industry, while Pacific Securities Co., Ltd. (PS) and Ping An Insurance (Group) Co. of China, Ltd. (PAI) are identified as SIFIs for diversified financials and insurance, respectively. According to the 2018 G-SIBs list released by the Financial Stability Board, China Construction Bank, Industrial and Commercial Bank of China, Bank of China and Agricultural Bank of China are recognized as global systemically important banks (FSB, 2018). The different rankings between our results and the G-SIBs implies that the systemic importance of an individual financial institution may differ significantly in the global and domestic contexts.

Third, we find evidence of strong bidirectional upside and downside risk spillovers, where downside and upside risk spillovers demonstrate asymmetric and time-varying patterns. These findings are of policy implications for regulators to diagnose systemic weakness and source of risk spillover during both bullish and bearish periods, so as to enhance resilience of the whole system and promote financial market governance. For stock market participants in the China market, they should bear in mind systemic risk of both SIFI and the sector/industry groups for effective risk management. The asymmetric upside and downside risk spillover effects within the financial system also imply that savvy investors should accordingly predict systemic risk and effectively adjust their hedging strategies and positions to protect portfolios from risk spillovers.

The remainder of the paper is organized as follows. In Sect. 2, we review relevant literature on risk spillovers within the Chinese financial system. In Sect. 3, we introduce the methodologies used in the empirical application. In Sect. 4, we present the data and discuss the empirical results. Section 5 summarizes our empirical results and concludes with policy and investment implications.

## 2 Literature review

Based on the manifold nature of systemic risk, models dedicated to measuring systemic risk are highly heterogeneous with focuses on capturing different facets of systemic risk. It is sometimes hard to distinguish models of measuring systemic risk versus detecting its contagion, as they tend to combine together (Wu, 2019). Traditionally, methods such as

correlation coefficient and copula functions are used to measure systemic risk by adopting low-frequency data, such as bilateral exposure data (Kanno, 2015) and supervision data (Glasserman & Young, 2015). One most notable limitation arising from low data frequency is that it is hard to timely capture the dynamic changes in the financial system or to conduct real-time detection and measurement of systemic risk. In recent years, a series of breakthroughs have been made in the methodologies of modelling systemic risk and its contagion. Some recently developed techniques rely on market available data to assess to what extent an individual bank contributes to the systemic risk in the financial system, namely, their marginal risk contribution to systemic risk, and vice versa. Prominent examples of market-data based measures from a portfolio perspective are conditional value-at-risk (CoVaR) (Adrian & Brunnermeier, 2016), marginal expected shortfall (MES) (Acharya et al., 2017), component shortfall (CES) (Banulescu & Dumitrescu, 2015), and SRISK (Brownlees & Engle, 2017).

Among existing literature focusing on measuring systemic risk and identifying the network structure in the Chinese financial system, the Diebold and Yilmaz (2014) method is employed to find evidence of strong interconnectedness in the commercial banking sector in China (Wang et al., 2018b). Gang and Qian (2015) measure systemic risk of financial institutions by marginal expected shortfall (Acharya et al., 2017), while several others focusing on China's banking sector (Fan et al., 2017; Huang et al., 2017; Xu et al., 2018) adopt MES, CoVaR, VI and SII as systemic risk measures. In this study, we measure systemic risk and capture its spillover effects in the Chinese financial system by dynamic copula-CoVaR models. Using this approach, we manage to analyse the bidirectional risk spillovers between individual institutions and the financial sector. By measuring the system's VaR conditional on a single firm being in distress, we detect the transmission of extreme risk from a bottom-up perspective, which is different from other top-down models such as MES, CES and SRISK, which examine the extent to which firms are exposed when the system is in distress. Notably, these directions of risk transmission do not reveal any causal relationship but only tail risk dependence.

While existing China-related studies quantifying CoVaR by, for example, quantile regression (Fan et al., 2017), tail risk networks (Wang et al., 2018a) or multivariate GARCH model (Huang et al., 2017), we use CoVaR and  $\Delta$ CoVaR characterized and estimated by time-varying copulas to capture risk spillover patterns in the Chinese financial system. To the best of our knowledge, this CoVaR-copula approach has not been used in the existing literature to detect risk spillover effects in the Chinese financial system.

Within the framework of copula, Patton (2006) is a pioneering study adopting time-varying copulas to studying the dynamics of asymmetric dependence structure of exchange rates. Detailed reviews of the copula families can be found in Joe (1997), Nelsen (2006) and Patton (2012). With its strength in detecting dependence structure and its evolution, the copula approach has gained increasing popularity in empirical finance research (see for example, Reboredo & Ugolini, 2015; Liu et al., 2017; Mensi et al., 2017; Ji et al., 2018).

Mainik and Schaanning (2014) first propose to use copula to represent CoVaR. The extant literature has shown that the calculation of CoVaR can benefit from using copulas (Bernardi et al., 2017; Patton, 2006). Copula has its advantages in capturing the non-normal characteristics of the joint distributions present in many common economic variables (Patton, 2006). By separately modelling marginal distribution and dependence, copula models render the flexibility to obtain different dependence measures with varied tail dependence features which linear correlation coefficients fail to capture, thus facilitating the computation of VaR and CoVaR. Furthermore, the various model specifications of time-varying copulas allow for time variation in the associated dependency parameters,

making it possible to detect the dynamics of the market network structure. Drawn on the advantages of copulas in measuring both average movements across marginal and extreme upward and downward joint movements, the copula-CoVaR methodology enables us to flexibly and fully estimate both upside and downside risk spillovers in the Chinese financial system, which helps to build an effective early warning system and emergency risk management system.

In terms of the regulatory frameworks, the FSB identifies the G-SIBs by an indicator-based assessment methodology published by the BCBS in 2013 (FSB, 2018). In this framework, the systemic importance of an individual bank is scored based on five equally weighted indicators including a bank's size, interconnectedness, substitutability, the level of global activity and complexity (BCBS, 2013). The bank is then allocated to one of the four equally sized buckets based on its score of systemic importance and is subject to the loss absorbency requirement specifically applicable to that bucket. Both the systemic importance score and bucket allocation are subject to annual review.

Compared to the indicator-based method proposed by the BCBS, there are some advantages of the copula-CoVaR approach adopted in this study. By equally weighing the significance of these five indicators, the indicator-based approach cannot address the potentially greater impact of a particular indicator on a bank's systemic importance and may potentially cause bias on the evaluation of firm-level systemic importance. The copula-CoVaR method avoids this problem, as it captures the tail dependence across financial institutions without having to make prior assumption of the weight of any firm-level contributor to the systemic importance. Another drawback of the indicator-based approach is the lags in the risk measure arising from constructing the indicators of a current year by the accounting data of the previous fiscal year. By contrast, using market asset prices can convey forward-looking information to facilitate the detecting of early warning signals and ex ante regulating. Moreover, the indicator-based method measures a bank's level of interconnectedness mainly by interbank exposure arising from lending and borrowing positions in the interbank market, which in many cases are firm-level private information and are not available to the public. Using the copula-CoVaR approach does not require us to acquire the exact cross-positions between financial institutions, or to assume time-invariant assets or liabilities over the given period (Wu, 2019).

### 3 Methodology

There are three steps in the analysis. We first adopt the ARMA-GARCH models to estimate the marginal distribution for each return series. We then apply the time-varying copulas to characterize the joint distributions of the return series and tail dependence, allowing the dependence parameters to change over time (Mensi et al., 2017). Following Reboredo and Ugolini (2015) and Reboredo et al. (2016), we estimate the downside and upside CoVaRs by the time-varying copula functions to measure the risk relationship between two variables.

#### 3.1 The marginal distribution model

Our starting point is to estimate marginal distributions/densities of each return series in the full sample, which is characterized by an ARMA( $p, q$ )-GARCH( $m, n$ ) specification:

$$r_{i,t} = \varphi_0 + \sum_{j=1}^p \varphi_j r_{i,t-j} + \varepsilon_{i,t} - \sum_{i=1}^q \theta_i \varepsilon_{i,t-j} \tag{1}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t} \tag{2}$$

where  $r_{i,t}$  is the return of institution  $i$  at time  $t$ ;  $\varphi_0$  is a constant;  $p$  and  $q$  are the number of lags, which are non-negative integers;  $\varphi_j$  and  $\theta_i$  are the autoregressive (AR) and moving average (MA) parameters, respectively; and  $\sigma_{i,t}^2$  is the conditional variance with its dynamics given by a GARCH model:

$$\sigma_{i,t}^2 = \omega_0 + \sum_{h=1}^m \alpha_h \varepsilon_{i,t-h}^2 + \sum_{k=1}^n \beta_k \sigma_{i,t-k}^2 \tag{3}$$

where  $\omega_0$  is a constant;  $n$  and  $m$  are the number of lags, which are non-negative integers;  $\varepsilon_{i,t-h}^2$  and  $\sigma_{i,t-k}^2$  are the ARCH and GARCH components, with  $\alpha_h$  and  $\beta_k$  being the parameters, respectively. The numbers of lags ( $p$ ,  $q$ ,  $m$  and  $n$ ) are decided by Akaike information criteria.

Considering non-normality characteristics of the GARCH model residuals (Bollerslev & Wooldridge, 1992), and possible time-varying parameters of the error distribution, we build our univariate margin model based on Hansen’s skewed Student- $t$  distribution (Hansen, 1994) to allow for a control of asymmetry and fat-tailedness of the return series and to obtain time-varying higher moments (Liu et al., 2017; Reboredo et al., 2016). Hansen’s model is specified as:

$$f(z_{i,t}; v, \eta) = \begin{cases} bc \left( 1 + \frac{1}{v-2} \left( \frac{bz_{i,t}+a}{1-\eta} \right)^2 \right)^{-(v+1)/2} & \text{if } z_{i,t} < -a/b \\ bc \left( 1 + \frac{1}{v-2} \left( \frac{bz_{i,t}+a}{1+\eta} \right)^2 \right)^{-(v+1)/2} & \text{if } z_{i,t} \geq -a/b \end{cases} \tag{4}$$

where  $f(z_{i,t}; v, \eta)$  is the density function for the random variable  $Z$ ;  $v$  is the degree-of-freedom parameter;  $\eta$  is the symmetric parameter; the intervals for the distribution parameters are  $2 < v < \infty$ ,  $-1 < \eta < 1$ ;  $a$ ,  $b$  and  $c$  are defined as  $a \equiv 4\eta c \left( \frac{v-2}{v-1} \right)$ ,  $b^2 \equiv 1 + 3\eta^2 - a^2$ , and  $c \equiv \Gamma\left(\frac{v+1}{2}\right) / \sqrt{\pi(v-2)} \Gamma\left(\frac{v}{2}\right)$ , respectively.

### 3.2 Time-varying copula models

In the family of copulas, there are diverse specifications able to capture complex patterns of dependence in tails. To address its non-linear, asymmetric and dynamic characteristics of the market dependence structure, we employ seven well-known and widely adopted time-varying copula models to characterize and compute the risk measures (Mensi et al., 2017; Patton, 2006).

Let  $C(u, v)$  denote the basic form of static copula, and  $F_X(x)$  and  $F_Y(y)$  denote the continuous marginal distributions of random variables  $x$  and  $y$ , respectively. The bivariate joint cumulative distribution function (*c.d.f.*) of  $x$  and  $y$  is decomposed as:

$$F_{XY}(x, y) = C(u, v) = C(F_X(x), F_Y(y)) \tag{5}$$

where the copula function  $C(u, v)$  couples together the marginal distributions of  $x$  and  $y$  and form a bivariate joint distribution of  $x$  and  $y$ ,  $F_{XY}(x, y)$ . The bivariate joint probability density function (*p.d.f.*) of  $x$  and  $y$ ,  $f_{XY}(x, y)$ , is decomposed as:

$$f_{XY}(x, y) = c(u, v)f_X(x)f_Y(y) \tag{6}$$

where  $c(u, v) = \partial^2 C(u, v) / \partial u \partial v$ ;  $f_X(x)$  and  $f_Y(y)$  are the marginal probability density functions for  $x$  and  $y$ , respectively. Using copula models, we can characterize the joint distributions of return series and quantify their tail dependence.

Much evidence shows that conditional correlations between financial asset returns fluctuate through time, and it is necessary to consider the potential time variation of the copula functions. Drawn on Patton (2006, 2012), Mensi et al. (2017), Liu et al. (2017) and Ji et al. (2018), we construct seven time-varying copula models in this study, derived from their static counterparts using specific evolution equations to allow the model parameters to evolve over time while keeping the functional form of copula fixed during the sample period.<sup>1</sup> The seven copula specifications are time-varying Gaussian, Clayton, Rotated Clayton, Gumbel, Rotated Gumbel, SJC and Student-t. Following Patton (2006) and Liu et al. (2017), the evolution equations for the dependence parameters in each copula are specified as follows. To estimate the copula model parameters, we adopt maximum likelihood, while the most fitting copula is selected by minimizing the AIC value.

For the Gaussian and Student-t copulas, the evolution of the dependence parameter  $\rho_t$  is assumed to follow an ARMA (1, q)-type process:

$$\rho_t = \Lambda \left( \psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q} \sum_{j=1}^q \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j}) \right) \tag{7}$$

where  $\Lambda(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$  is the modified logistic transformation that retains  $\rho_t$  in  $(-1, 1)$ ;  $\Phi^{-1}(x)$  is the normal distribution quantile function. For the Student-t copula, the dynamics for  $\rho_t$  is characterized by the same specification, only that  $\Phi^{-1}(x)$  is substituted by  $t_n^{-1}(x)$ , which is the quantile function of the univariate Student-t distribution with degree-of-freedom  $n$ .

The evolution of the dependence parameters of Clayton, Gumbel and their rotated versions is also assumed to follow an ARMA (1, q)-type process:

$$\delta_t = \Lambda \left( \omega + \beta \delta_{t-1} + \alpha \frac{1}{q} \sum_{j=1}^q |u_{t-j} - v_{t-j}| \right) \tag{8}$$

where for time-varying Clayton and Rotated Clayton,  $\Lambda(x) = x^2$  to retain  $\delta_t$  in  $(0, +\infty)$ ; for time-varying Gumbel and Rotated Gumbel,  $\Lambda(x) = 1 + x^2$  so that  $\delta_t$  is kept in  $(1, +\infty)$ .

For the SJC copula, the evolution of the two dependence parameters is assumed to follow:

<sup>1</sup> It should be mentioned that there are several alternative methods when estimating the time-varying parameters of the copula models. On the other hand, the regime switching copulas allow the changes of functional forms of couples over time. A detailed review can be found in Manner and Reznikova (2012). The detailed description of these approaches, however, is beyond the scope of this study.



$$\tau_t^U = \Lambda \left( \omega_U + \beta_U \tau_{t-1}^U + \alpha_U \frac{1}{q} \sum_{j=1}^q |u_{t-j} - v_{t-j}| \right) \quad (9)$$

$$\tau_t^L = \Lambda \left( \omega_L + \beta_L \tau_{t-1}^L + \alpha_L \frac{1}{q} \sum_{j=1}^q |u_{t-j} - v_{t-j}| \right) \quad (10)$$

where  $\Lambda(x) = (1 + e^{-x})^{-1}$  is the logistic transformation to retain  $\tau_t^U$  and  $\tau_t^L$  in  $(0, 1)$ .

### 3.3 Testing structural breaks in dependence

As the sample period covers several prominent systemic events, such as the global financial crisis and the stock market turbulence during 2014 and 2015, it is a natural concern that there might exist structural changes through time in the copula dependence between the financial institutions and the financial system.<sup>2</sup> While the time-varying copula functions introduced above capture the temporal variation of the copula dependence over time, it may not directly reveal substantial structural changes of the dependence relationships (Ji et al., 2019). To address this concern, we follow the method of Dias and Embrechts (2009), Liu et al. (2017) and Ji et al. (2019) to detect if there are any structural breaks of the dependence by the following steps.

For a random vector  $U_t = (U_{1t}, U_{2t})$  in  $[0, 1]^2$  with univariate uniformly distributed margins and copula  $C(u; \theta_t)$ , where  $\theta_t \in \Theta \subseteq R^n$ , the following hypothesis is proposed to test the existence of structural changes of the copula function parameter series:

$$H_0 : \theta_1 = \theta_2 = \dots = \theta_T \text{ VS. } H_A : \theta_1 = \dots = \theta_{k^*} \neq \theta_{k^*+1} = \dots = \theta_T \quad (11)$$

If the null hypothesis  $H_0$  is rejected by the test results, there is evidence at a given level of significance that a structural change of the copula parameter series occurs at time  $k^*$ . The likelihood ratio statistic is constructed as:

$$\Lambda(k) = \frac{\sup_{(\theta', \theta'') \in \Theta \times \Theta} \prod_{1 \leq t \leq k} c(u_t, \theta') \prod_{k \leq t \leq T} c(u_t, \theta'')}{\sup_{\theta \in \Theta} \prod_{1 \leq t \leq T} c(u_t, \theta)} \quad (12)$$

Given  $L(\theta', \theta'') = \sum_{1 \leq t \leq k} \log(c(u_t, \theta')) + \sum_{k \leq t \leq T} \log(c(u_t, \theta''))$  and  $L_0(\theta) = \sum_{1 \leq t \leq T} \log(c(u_t, \theta))$ , we then have:

$$2 \log \Lambda(k) = 2 \left( \sup_{(\theta', \theta'') \in \Theta \times \Theta} L(\theta', \theta'') - \sup_{\theta \in \Theta} L_0(\theta) \right) \quad (13)$$

The value of  $2 \log \Lambda(k)$  is estimated by the maximum log-likelihood method. The null hypothesis  $H_0$  will be rejected if the value of  $2 \log \Lambda(k)$  is high enough at a given level of significance  $\alpha$ . The structural change point is identified by the statistic  $Z_T = \max_{1 \leq k \leq T} 2 \log \Lambda(k)$ , where the distribution of  $Z_T^{1/2}$  is:

<sup>2</sup> We thank an anonymous reviewer for this comment.

$$\Pr\left(Z_T^{1/2} \geq x\right) \approx \frac{x^n \cdot \exp\left(-\frac{x^2}{2}\right)}{2^{\frac{n}{2}} \cdot \Gamma\left(\frac{n}{2}\right)} \cdot \left(\log \frac{(1-h)(1-l)}{hl}\right) + \frac{4}{x^2} + o\left(\frac{1}{x^4}\right) \cdot x \rightarrow \infty \quad (14)$$

where  $h = l = \log T^{3/2} / T$ , Given a significance level  $\alpha$  and the statistic's value  $z_T^{1/2}$ , the null hypothesis will be rejected if  $\Pr\left(Z_T^{1/2} \geq z_T^{1/2}\right) \leq \alpha$ , and the location of the structural change point is then detected by:

$$\hat{k} = \min\left(1 \leq k < T : 2 \log \Lambda(k) = z_T\right) \quad (15)$$

If a structural break is detected, we then divide the full sample into subperiods using the time point of the structural change, and then test the null hypothesis in each of the subperiods. We continue this segmentation process until no further structural changes are detected in the subsamples.

### 3.4 Risk spillovers and CoVaR

To investigate risk spillovers in the Chinese financial system, we adopt three risk measures: value at risk (VaR), conditional value at risk (CoVaR), and delta conditional value at risk ( $\Delta$ CoVaR), which are to be characterized and computed by copulas. The standard firm-level risk measure VaR quantifies the maximum possible loss of a given portfolio within a set time horizon at a given confidence level, assuming normal market conditions and no trading in the portfolio. The given significance level  $\alpha$  indicates that the probability of a loss greater than the VaR is less than or equal to  $\alpha$ . The VaR measure is related to downside risk (the lower tail of the return's distribution) for an investor holding a long position, or upside risk (the upper tail) for an investor holding a short position. The CoVaR measure proposed by Adrian and Brunnermeier (2016) is then constructed based on the VaRs of any two components in the financial system.

The downside  $VaR_{i,t}^\alpha$  and upside  $VaR_{i,t}^{1-\alpha}$  for returns of institution  $i$  at time  $t$  are defined as:

$$P\left(r_{i,t} \leq VaR_{i,t}^\alpha\right) = P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha \quad (16)$$

Further, the downside and upside VaRs are computed as:

$$VaR_{i,t}^\alpha = \mu_{i,t} + t_{v,\eta}^{-1}(\alpha)\sigma_{i,t} \quad (17)$$

$$VaR_{i,t}^{1-\alpha} = \mu_{i,t} + t_{v,\eta}^{-1}(1-\alpha)\sigma_{i,t} \quad (18)$$

where  $\mu_{i,t}$  and  $\sigma_{i,t}$  are the conditional mean and standard deviation of returns, computed based on results from Eqs. (1) and (3), respectively;  $t_{v,\eta}^{-1}(\alpha)$  and  $t_{v,\eta}^{-1}(1-\alpha)$  are  $\alpha$  and  $1-\alpha$  quantiles of a skewed- $t$  distribution in Eq. (4).

While VaR measures a single asset/firm's risk in isolation, the CoVaR measure considers losses in total assets/all firms. Drawn from the definition of CoVaR in Adrian and Brunnermeier (2016), the conditional value-at-risk (CoVaR) of a financial institution  $i$  relative to another financial institution  $j$  is defined as the VaR of  $j$ , conditional on  $i$  being in distress as measured by its VaR (namely, when  $i$ 's return is less than the  $\alpha$ -quantile).

More generally, when CoVaR adopts a conditional change in VaR in the financial system and estimates the potential financial system losses conditional on the extreme movements of a particular financial institution, it depicts marginal risk contribution of the individual institution to the wider system, and vice versa. Considering the focus of this study, CoVaR is an informative tool to serve our purpose.

The downside  $CoVaR_{j,t}^\beta$  and upside  $CoVaR_{j,t}^{1-\beta}$  are defined by the  $\beta$  quantile of the conditional probability distribution of  $r_{j,t}$ :

$$P\left(r_{j,t} \leq CoVaR_{j,t}^\beta | r_{i,t} \leq VaR_{i,t}^\alpha\right) = P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta} | r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \beta \tag{19}$$

Computing CoVaR thus requires determination of the quantile of a conditional distribution. Equation (19) can be expressed as an unconditional bivariate distribution:

$$\frac{P\left(r_{j,t} \leq CoVaR_{j,t}^\beta, r_{i,t} \leq VaR_{i,t}^\alpha\right)}{P\left(r_{i,t} \leq VaR_{i,t}^\alpha\right)} = \frac{P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta}, r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right)}{P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right)} = \beta \tag{20}$$

Given by Eq. (16) that  $P\left(r_{i,t} \leq VaR_{i,t}^\alpha\right) = P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha$ , Eq. (20) is transformed to:

$$P\left(r_{j,t} \leq CoVaR_{j,t}^\beta, r_{i,t} \leq VaR_{i,t}^\alpha\right) = P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta}, r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha\beta \tag{21}$$

In this study we follow Reboredo and Ugolini (2015) and several others to compute CoVaR by copulas. The joint probability in Eq. (21) can then be rewritten as:

$$C\left(F_{r_{j,t}}\left(CoVaR_{j,t}^\beta\right), F_{r_{i,t}}\left(VaR_{i,t}^\alpha\right)\right) = \alpha\beta \tag{22}$$

$$C\left(F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right), F_{r_{i,t}}\left(VaR_{i,t}^{1-\alpha}\right)\right) - F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right) - F_{r_{i,t}}\left(VaR_{i,t}^{1-\alpha}\right) + 1 = \alpha\beta \tag{23}$$

where  $CoVaR_{j,t}^\beta$  and  $CoVaR_{j,t}^{1-\beta}$  denote the downside and upside CoVaRs;  $F_{r_{j,t}}$  and  $F_{r_{i,t}}$  are the marginal distribution functions of returns of institutions  $i$  and  $j$ . Using a two-step approach in Reboredo and Ugolini (2015) and Reboredo et al. (2016), we first calculate the value of  $F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right)$  by solving Eqs. (22) and (23), based on the given significance levels  $\alpha$  and  $\beta$  and the selected copula function form. Then by computing  $F^{-1}\left(F_{r_{j,t}}\right)$ , the values of downside and upside CoVaRs can be obtained.

$\Delta CoVaR$  is further used to captures the part of systemic risk in institution  $j$  that can be attributed to institution  $i$ 's risk, and thus can measure tail-dependence between the two institutions. It is calculated as the change in CoVaR of  $j$ , conditional on  $i$ 's return shifting from its median state (i.e., 50% quantile with  $\alpha = 0.5$ ) to a distressed state (i.e., adverse  $VaR_{i,t}^\alpha$ ):

$$\Delta CoVaR_{j|i,t}^\beta = \frac{\left(CoVaR_{j|i,t}^\beta - CoVaR_{j|i,t}^{\beta|\alpha=0.5}\right)}{CoVaR_{j|i,t}^{\beta|\alpha=0.5}} \tag{24}$$

In Eqs. (20)–(24),  $i$  and  $j$  can be generalized from representing an individual institution to representing an industry group or the whole financial sector, equivalent to a portfolio composed of all financial institutions in that group or sector.

## 4 Empirical results

### 4.1 Sample analysis

The dataset employed in our empirical study is collected from WIND financial database. It consists of daily returns of 22 publicly traded financial institutions from 2 January 2008 to 20 August 2018. The financial institutions in our sample are categorized into three financial industry groups based on the four-level industrial structure defined in WIND. These industry groups are banks, diversified financials, and insurance II, with each group's index provided by WIND to represent group returns. All three industry groups belong to the financials sector. Table 1 lists the trading codes, full names and abbreviations of the 22 financial institutions and three industry groups within the financial system in China.

Prior to 2008, many financial institutions in China had not been listed, including several important ones such as China Construction Bank, China CITIC Bank, Industrial Bank, Bank of Beijing, Bank of Nanjing, and Bank of Ningbo. Taking into account the complexity and importance of these financial institutions, our sample period starts from the beginning of 2008. In addition, our sample period covers a period of over ten years. Several systemic events inflicting stock market turbulence and crashes in the recent decade are covered by the time span (Wu, 2019).

Table 2 reports the descriptive statistics of the returns of each individual financial institution and indices of the industry groups. Seen in the table, mean returns for all series are positive during the sample period, except the Pacific Securities Co., Ltd. (PS) and China Life Insurance Co., Ltd. (CLI). Anshan Trust and Investment Co., Ltd. (ATI) has the highest mean returns among all. All series appear to be leptokurtic with kurtosis exceeding three as in a normal distribution, indicating excess kurtosis and fat tails in all series. The non-normality features are further corroborated by the Jarque–Bera statistics which significantly reject the null hypothesis of normality at 1% level for all series, thus validating our choice of Hansen's model for specifying marginal distributions. The return series are shown to be stationary and autocorrelated with the presence of the ARCH effect, all at the 1% significance level, according to the ADF, Ljung-Box and ARCH effect statistics, respectively.

### 4.2 Marginal model results

The results of marginal model estimates are reported in Table 3, using Eqs. (1)–(3) in Sect. 3.1. The lag values of  $p$  and  $q$  are considered ranging from zero to a maximum of three, while  $m$  and  $n$  range from zero to a maximum of two. These lag values are then selected so as to minimize the AIC values. The return series tend to have different best ARMA fits, and the selections of  $p$  and  $q$  vary across series. For example, ARMA (1,1) is the best fitting model for Bank of Ningbo (BNB), while ARMA (1, 3) is the best fit for Shanghai Pudong Development Bank (SPDB). For the GARCH model specification,  $m$  and  $n$  are selected as one, with GARCH (1,1) being the best fitting model for all series. Several

**Table 1** Sample description

Code	Name	Abbreviations
<i>Panel A: banks</i>		
000001	Ping An Bank Co Ltd	PAB
002142	Bank of Ningbo	BNB
600000	Shanghai Pudong Development Bank	SPDB
600015	Hua Xia Bank co., Limited	HXB
600016	China Minsheng Banking Corporation	CMBC
600036	China Merchants Bank Co Ltd	CMB
601009	Bank of Nanjing	BNJ
601166	Industrial Bank Co Ltd	IBC
601169	Bank of Beijing Co Ltd	BB
601328	Bank of Communications Co. Ltd	BCM
601398	Industrial & Commercial Bank of China (the)— ICBC	ICBC
601939	China Construction Bank Corporation Joint Stock Company	CCB
601988	Bank of China Limited	CB
601998	China CITIC Bank Corporation Limited	CITIB
<i>Panel B: diversified financials</i>		
600030	CITIC Securities Company Limited	CITIS
601099	The Pacific Securities Co., Ltd	PS
000563	Shaanxi International Trust Co., Ltd	SIT
600643	Shanghai AJ Group Co., Ltd	SAJ
600816	Anshan Trust and Investment Co., Ltd	ATI
<i>Panel C: insurers</i>		
601318	Ping An Insurance (Group) Co. of China, Ltd	PAI
601601	China Pacific Insurance (Group) Co., Ltd	CPI
601628	China Life Insurance (Group) Co., Ltd	CLI
<i>Panel D: Industrial group indices</i>		
882115	Banks industry group index	Banks
882116	Diversified financials industry group index	Diversified financials
882117	Insurance industry group index	Insurance

The table reports the basic information including trading codes, full names and abbreviations of the 22 financial institutions and the three industry groups (Banks, Diversified financials, and Insurance) as defined by WIND database in our sample

goodness-of-fit tests are conducted and the results are reported in the last few columns in Table 3. Marginal distributions for most return series exhibit asymmetry, evidenced by the significantly positive symmetry parameter  $\lambda$  at 5% level, except for PS and SIT. The Ljung–Box and Engle’s LM test statistics cannot reject the null hypotheses of no serial correlation or ARCH effects in the standardized residuals and squared standardized residuals, each taking 10 lags. The  $p$  values of the Kolmogorov–Smirnov (KS) test (Abadie, 2002) cannot reject the null hypothesis of the correct specification of the marginal distribution model at the 5% significance level (Bernal et al., 2014). These tests verify the adequacy of the skewed Student-t distribution and rules out the possibility of model misspecification.

**Table 2** Descriptive statistics

	Mean	Max	Min	SD	Skewness	Kurtosis	Jarque–Bera	ADF	Q (20)	Q <sup>2</sup> (20)	ARCH (20)
PAB	0.027	10.042	-10.020	2.459	0.262	6.650	1466.563***	-49.944***	31.107*	880.502***	281.758***
BNB	0.043	10.073	-10.016	2.418	0.129	6.217	1123.835***	-52.741***	53.126***	604.539***	224.796***
SPDB	0.031	10.031	-10.026	2.313	0.244	7.471	2181.838***	-50.452***	37.016*	1483.962***	373.390***
HXB	0.026	10.070	-10.048	2.344	0.091	6.807	1567.191***	-51.789***	32.604**	1444.314***	371.781***
CMBC	0.028	10.101	-10.000	2.116	0.312	7.663	2387.826***	-50.150***	45.161***	998.211***	305.603***
CMB	0.036	10.026	-10.007	2.203	0.242	7.066	1808.232***	-50.540***	35.759**	1388.630***	379.127***
BNJ	0.050	10.065	-10.013	2.278	0.157	6.996	1733.566***	-51.594***	42.919***	936.896**	357.271***
IBC	0.033	10.053	-10.020	2.376	0.181	6.810	1579.656***	-49.951**	43.428***	1267.930***	338.191***
BB	0.020	10.054	-10.013	2.166	0.245	7.560	2269.061***	-53.552***	37.711***	977.550***	340.305***
BCM	0.002	10.103	-10.058	2.019	0.178	9.285	4274.266***	-48.990***	65.222***	1470.091***	447.457***
ICBC	0.018	10.053	-10.043	1.635	0.080	10.606	6242.737***	-49.704***	61.514***	921.439***	346.156***
CCB	0.022	10.039	-10.094	1.815	0.234	9.339	4358.556***	-50.067***	62.502***	1535.334***	473.934***
CB	0.010	10.164	-10.040	1.655	0.582	11.660	8236.389***	-50.614***	48.616***	1363.682***	422.346***
CITIB	0.018	10.090	-10.025	2.300	0.357	7.189	1947.863***	-50.690***	42.459***	816.881**	271.675***
CITIS	0.024	10.043	-10.016	2.804	0.155	5.801	856.420***	-48.667***	38.860***	1263.549***	359.239***
PS	-0.025	10.095	-10.030	3.039	0.038	5.560	707.798***	-51.292***	40.089***	2557.895***	551.242***
SIT	0.033	10.061	-10.043	3.219	-0.033	5.074	464.282***	-51.272***	21.091	908.349***	274.993***
SAJ	0.036	10.066	-10.030	3.005	0.130	5.670	776.534***	-49.095***	37.306**	1338.829***	371.140***
ATI	0.063	10.044	-10.024	3.057	0.115	5.668	773.755***	-49.927***	41.074***	1291.298***	348.047***
PAI	0.038	10.017	-10.004	2.412	0.045	6.097	1035.631***	-50.134***	43.637***	1110.339***	344.566***
CPI	0.025	10.033	-10.007	2.512	0.139	5.215	537.367***	-50.757**	50.212***	735.439***	260.102***
CLI	-0.001	10.036	-10.007	2.429	0.382	6.296	1234.945***	-50.278***	63.398***	1394.995***	386.973***
Banks	0.019	10.021	-9.971	1.858	0.136	8.418	3174.747***	-51.019***	53.064***	1582.417***	407.219***
Diversified Financials	0.009	10.026	-10.000	2.683	0.062	5.708	792.995***	-49.261***	36.583**	1681.263***	420.265***
Insurance	0.025	10.014	-10.000	2.317	0.115	5.961	951.549***	-50.749***	57.967***	1200.778***	362.142***

The table reports the descriptive statistics for the returns of the 22 financial institutions and three industry group indices at daily frequency from 2 January 2008 to 20 August 2018 (denominated in CNY). Jarque–Bera denotes the Jarque–Bera test statistics for normality. ADF denotes the statistics of the augmented Dickey–Fuller test. Q (20) and Q<sup>2</sup> (20) denote the statistics of Ljung–Box test for autocorrelation in returns and squared returns, respectively, where lag = 20. ARCH (20) is the statistics of the ARCH effect test with lag = 20. \*, \*\*, and \*\*\* indicate rejection of the null hypothesis at 1%, 5% or 10% levels, respectively

**Table 3** Parameter estimates for ARMA-GARCH marginal models of returns

	Phi0	Phi1	Phi2	Phi3	Theta1	Theta2	Theta3	w	Alpha
PAB	0.026 (-0.035)							0.017*** (-0.002)	0.946*** (-0.003)
BNB	0.013 (-0.011)	0.807*** (-0.120)			-0.836*** (-0.111)			0.068*** (-0.008)	0.929*** (-0.005)
SPDB	0.019 (-0.053)	-0.660* (-0.370)			0.661* (-0.373)	0.021 (-0.026)	0.012 (-0.021)	0.023*** (-0.004)	0.927*** (-0.003)
HXB	0.012 (-0.034)							0.030*** (-0.004)	0.927*** (-0.003)
CMBC	0.039 (-0.114)	-1.293*** (-0.363)	-1.210*** (-0.371)	-0.253 (-0.323)	1.301*** (-0.366)	1.218*** (-0.381)	0.248 (-0.333)	0.030*** (-0.004)	0.898*** (-0.005)
CMB	0.02 (-0.012)	1.565*** (-0.042)	-0.921*** (-0.054)	-0.008 (-0.022)	-1.555*** (-0.036)	0.912*** (-0.039)		0.025*** (-0.004)	0.945*** (-0.004)
BNJ	0.047 (-0.036)							0.038*** (-0.006)	0.931*** (-0.004)
IBC	0.044 (-0.031)							0.012*** (-0.002)	0.942*** (-0.004)
BB	0.018 (-0.032)	-0.983*** (-0.225)	0.385 (-0.399)	0.731*** (-0.228)	0.965*** (-0.220)	-0.414 (-0.388)	-0.733*** (-0.221)	0.012*** (-0.002)	0.955*** (-0.002)
BCM	-0.001 (-0.010)	0.096 (-0.404)	0.516 (-0.365)		-0.069 (-0.400)	-0.509 (-0.364)	-0.043** (-0.020)	0.052*** (-0.005)	0.869*** (-0.005)
ICBC	0.004 (-0.005)	-0.052 (-0.062)	0.933*** (-0.064)	0.003 (-0.022)	0.044 (-0.059)	-0.946*** (-0.058)		0.018*** (-0.003)	0.902*** (-0.004)
CCB	0.1 (-0.061)	-0.454*** (-0.002)	-0.992*** (-0.002)		0.476*** (-0.022)	1.004*** (-0.010)	0.027 (-0.021)	0.036*** (-0.004)	0.886*** (-0.006)
CB	0.022 (-0.035)	0.299*** (-0.030)	-0.937*** (-0.026)	-0.006 (-0.021)	-0.310*** (-0.021)	0.958*** (-0.019)		0.028*** (-0.003)	0.890*** (-0.004)
CITIB	0.009 (-0.020)	0.994** (-0.415)	-0.041 (-0.667)	-0.533 (-0.413)	-1.001** (-0.423)	0.052 (-0.675)	0.501 (-0.414)	0.081*** (-0.010)	0.901*** (-0.006)
CITIS	0.044 (-0.043)	0.021 (-0.019)						0.026*** (-0.005)	0.952*** (-0.003)

Table 3 (continued)

	Phi0	Phi1	Phi2	Phi3	Theta1	Theta2	Theta3	w	Alpha
PS	-0.035 (-0.063)	-0.316 (-0.688)	-0.008 (-0.028)	0.003 (-0.021)	0.293 (-0.688)			0.105*** (-0.012)	0.914*** (-0.005)
SIT	0.021 (-0.053)							0.111*** (-0.016)	0.947*** (-0.005)
SAJ	0.302*** (-0.097)	-1.930*** (-0.021)	-0.955*** (-0.041)	0.021 (-0.021)	1.952*** (-0.002)	0.996*** (-0.002)		0.178*** (-0.011)	0.903*** (-0.005)
ATI	0.044 (-0.048)				0.011 (-0.021)	-0.016 (-0.022)	-0.017 (-0.021)	0.063*** (-0.002)	0.920*** (-0.002)
PAI	0.009* (-0.005)	1.831*** (-0.023)	-0.973*** (-0.040)	0.012 (-0.020)	-1.830*** (-0.010)	0.964*** (-0.010)		0.034*** (-0.005)	0.929*** (-0.005)
CPI	0.001 (-0.001)	-0.175*** (-0.051)	0.307*** (-0.042)	0.859*** (-0.046)	0.193*** (-0.043)	-0.290*** (-0.036)	-0.903*** (-0.039)	0.019*** (-0.006)	0.954*** (-0.004)
CLI	0.018 (-0.116)	-0.971*** (-0.031)	-0.906*** (-0.028)	-0.033 (-0.022)	0.980*** (-0.024)	0.920*** (-0.021)		0.064*** (-0.009)	0.924*** (-0.006)
Banks	0.032 (-0.025)	0.938*** (-0.017)	-0.955*** (-0.016)		-0.939*** (-0.015)	0.966*** (-0.014)		0.014*** (-0.002)	0.929*** (-0.004)
Diversified Financials	0.009 (-0.060)	0.332 (-0.293)	-0.038 (-0.336)	-0.772*** (-0.279)	-0.322 (-0.287)	0.033 (-0.329)	0.787*** (-0.275)	0.019*** (-0.004)	0.952*** (-0.003)
Insurance	0.153 (-0.105)	-0.967*** (-0.026)	-0.957*** (-0.023)	-0.027 (-0.021)	0.971*** (-0.016)	0.952*** (-0.013)		0.021*** (-0.005)	0.940*** (-0.005)
		Beta	v	λ	logL	LB(10)	LB <sup>2</sup> (10)	ARCH(10)	K-S
PAB		0.054*** (-0.003)	3.904*** (-0.233)	0.070*** (-0.017)	5582.836	0.189	0.043	0.09	0.46
BNB		0.060*** (-0.005)	4.357*** (-0.250)	0.063*** (-0.021)	5707.398	0.216	0.51	0.433	0.891
SPDB		0.072*** (-0.004)	3.878*** (-0.231)	0.075*** (-0.018)	5313.319	0.782	0.337	0.274	0.154



Table 3 (continued)

	Beta	$\nu$	$\lambda$	logL	LB(10)	LB <sup>2</sup> (10)	ARCH(10)	K-S
HXB	0.069*** (-0.004)	4.357*** (-0.295)	0.063*** (-0.020)	5421.677	0.511	0.222	0.147	0.222
CMBC	0.102*** (-0.006)	4.091*** (-0.256)	0.072*** (-0.017)	5119.566	0.111	0.081	0.068	0.082
CMB	0.050*** (-0.004)	4.576*** (-0.291)	0.100*** (-0.020)	5316.131	0.763	0.895	0.908	0.65
BNJ	0.063*** (-0.004)	4.337*** (-0.265)	0.061*** (-0.020)	5457.476	0.904	0.415	0.37	0.185
IBC	0.058*** (-0.004)	4.464*** (-0.320)	0.090*** (-0.017)	5371.097	0.023	0.076	0.089	0.057
BB	0.043*** (-0.002)	4.084*** (-0.287)	0.055*** (-0.018)	5204.061	0.282	0.109	0.122	0.223
BCM	0.126*** (-0.006)	3.940*** (-0.194)	0.049*** (-0.020)	4899.556	0.072	0.835	0.825	0.975
ICBC	0.097*** (-0.005)	4.404*** (-0.281)	0.059*** (-0.020)	4395.071	0.144	0.372	0.55	0.308
CCB	0.107*** (-0.007)	4.450*** (-0.268)	0.058*** (-0.022)	4631.014	0.004	0.736	0.804	0.341
CB	0.103*** (-0.005)	4.198*** (-0.237)	0.067*** (-0.021)	4317.745	0.25	0.985	0.985	0.852
CITIB	0.086*** (-0.006)	4.132*** (-0.272)	0.086*** (-0.019)	5480.358	0.012	0.976	0.987	0.507
CITIS	0.046*** (-0.003)	4.241*** (-0.266)	0.080*** (-0.023)	6002.102	0.223	0.294	0.303	0.729
PS	0.074*** (-0.005)	4.724*** (-0.400)	0.033 (-0.022)	6136.979	0.362	0.864	0.849	0.663
SIT	0.041*** (-0.004)	4.082*** (-0.297)	-0.027* (-0.016)	6468.432	0.758	0.952	0.953	0.104

Table 3 (continued)

	Beta	$\nu$	$\lambda$	logL	LB(10)	LB <sup>2</sup> (10)	ARCH(10)	K-S
SAJ	0.077*** (-0.005)	3.623*** (-0.272)	0.004** (-0.002)	6201.084	0.479	0.633	0.667	0.069
ATI	0.078*** (-0.003)	3.218*** (-0.193)	0.044*** (-0.012)	6146.083	0.172	0.949	0.957	0.396
PAI	0.067*** (-0.005)	4.705*** (-0.368)	0.060*** (-0.019)	5583.395	0.122	0.627	0.584	0.245
CPI	0.044*** (-0.004)	6.026*** (-0.622)	0.051** (-0.021)	5788.121	0.164	0.858	0.913	0.251
CLI	0.064*** (-0.006)	5.496*** (-0.493)	0.095*** (-0.022)	5615.5	0.165	0.328	0.335	0.929
Banks	0.069*** (-0.005)	4.232*** (-0.249)	0.092*** (-0.019)	4671.127	0.037	0.029	0.034	0.523
Diversified Financials	0.046*** (-0.004)	4.558*** (-0.308)	0.070*** (-0.021)	5821.635	0.252	0.691	0.718	0.746
Insurance	0.057*** (-0.005)	5.563*** (-0.490)	0.069*** (-0.022)	5480.176	0.084	0.511	0.425	0.417

The table presents parameter estimates for the marginal models described in Eqs. (1)–(3), with z statistics shown under the estimates. LogL is the log-likelihood value; LB(10) denotes the Ljung-Box statistics for serial correlation in the residual model calculated with 10 lags; LB<sup>2</sup>(10) is the Ljung-Box statistics for serial correlation in the squared residual model calculated with 10 lags. ARCH(10) denotes the Engle's LM test for ARCH effects in the residuals up to tenth order. K-S denotes the p values of the Kolmogorov-Smirnov test for adequacy of the skewed Student-t distribution mode

\*\*\*, \*\* and \*Indicate rejection of the null hypothesis at 1%, 5% or 10% levels, respectively

### 4.3 Time-varying copula results

Considering the time-varying market conditions and internal structure, we estimate time-varying versions of copula models where dependence parameters are allowed to be rendered time-varying. The evolution equations for copula parameters are shown in Sect. 3.2. Model parameters are estimated using maximum likelihood. The best copula fit for each pair composed of a financial institution and its affiliated industry group is selected based on minimum AIC values. Table 4 shows the coefficient estimates of the best time-varying copula fits for pairwise returns. Among totally 22 pairs, the best fitting model for 12 pairs is the time-varying Student-t copula (54.5%). The time-varying SJC is the best fit for 6 pairs (27.3%), while it is Gumbel for 3 pairs and Rotated Gumbel for 1 pair.

Compared to static copulas, time variations of the dependence are heeded by the time-varying copulas. We thereby circumvent the problem of possible one-time changes, or structural breaks, in the copula at some time in the sample period. To test the robustness of our main results based on time-varying copulas, we test the structural changes of the pairwise dependence in the static copula framework, which is discussed in Sect. 6.1.

### 4.4 CoVaR and $\Delta\text{CoVaR}$ results

#### 4.4.1 Determining SIFI by $\Delta\text{CoVaR}$

As larger magnitudes of  $\Delta\text{CoVaR}$  indicate higher risk spillover effects, the financial institution with the largest temporal  $\Delta\text{CoVaR}$  value should be identified as the temporal SIFI. Based on this logic, we use the best time-varying copula fits shown in Table 4 to compute temporal  $\Delta\text{CoVaRs}$  of each financial institution to its affiliated industry group, which determines the institution's risk contribution to the system at each time point.<sup>3</sup> We then rank the financial institutions within each industry group based on the magnitudes of their temporal  $\Delta\text{CoVaRs}$ . Those with the highest  $\Delta\text{CoVaRs}$  are identified as the top risk contributor at that particular time point. The dynamics of top risk contributors in each industry group are shown in Fig. 1.

Seen in Fig. 1, the financial institutions exhibiting the largest risk spillovers tend to vary over time. With the presence of time variation in top risk contributors, conclusions on which is the SIFI cannot be drawn by simply comparing temporal risk contributions across institutions but ignoring the time dimension. A more convenient way is to compare the frequency of each financial institution appearing as the top risk emitter in its industry group during the whole sample period. Figure 2 shows the ranking of financial institutions in each industry group in a descending order, according to their frequency of exhibiting temporal highest risk spillovers. The left panel reveals that among all banks, SPDB has the highest frequency of being the top emitter in banks sector (46.3% of the sample period), and thus is identified as the most systemically important bank. Similarly, shown in the right upper and lower panels, we manage to identify PS and PAI as SIFIs in diversified financials and insurance, with 49.8% and 62% frequencies, respectively.

Given that the three financial institutions, SPDB, PS and PAI, are identified as the SIFIs in their own affiliated industry groups based on findings of the copula- $\Delta\text{CoVaR}$  method,

<sup>3</sup> The empirical analysis is based on the 5% VaR. When using the 1% VaR, our main findings remain robust. For brevity, the results using the 1% VaR are not reported here but can be provided upon request.

**Table 4** Coefficients estimates of the optimal time-varying copulas

	Optimal copula	Phi1	Phi2	Phi3	Phi4	Phi5	Phi6	logL	AIC
PAB-banks	TVP-SJC	1.597*** (0.001)	-6.851*** (0.023)	0.001*** (0.000)	3.681*** (0.021)	-12.646*** (0.053)	-2.084*** (0.012)	1699.353	-3392.71
BNB-banks	TVP-student-t	-1.751*** (0.250)	0.034*** (0.013)	4.904*** (0.323)	5.510*** (0.673)			1465.256	-2924.51
SPDB-banks	TVP-SJC	0.886*** (0.000)	-8.757*** (0.001)	1.420*** (0.001)	3.829*** (0.001)	-8.807*** (0.004)	-2.494*** (0.001)	2058.715	-4111.43
HXB-banks	TVP-SJC	-0.580*** (0.000)	-2.869*** (0.001)	2.566*** (0.000)	1.885*** (0.000)	-10.283*** (0.004)	0.229*** (0.000)	1863.811	-3721.62
CMBC-banks	TVP-student-t	-1.837 (7.190)	0.093 (0.544)	5 (9.262)	5.295** (2.479)			1818.931	-3631.86
CMB-banks	TVP-student-t	-1.653* (0.864)	0.027 (0.034)	5.000*** (1.024)	4.457*** (0.597)			2090.874	-4175.75
BNJ-banks	TVP-student-t	1.371 (4.092)	0.017 (0.029)	1.198 (4.863)	4.063*** (0.372)			1620.07	-3234.14
IBC-banks	TVP-student-t	-1.618 (5.432)	0.046 (0.045)	5 (6.116)	4.849*** (0.634)			2228.09	-4450.18
BB-banks	TVP-student-t	-1.816*** (0.403)	0.045** (0.022)	5.000*** (0.515)	4.413*** (0.486)			1643.164	-3280.33
BCM-banks	TVP-student-t	1.451 (4.802)	0.005 (0.004)	1.505 (5.433)	5.474*** (0.699)			2036.462	-4066.92
ICBC-banks	TVP-SJC	3.857*** (0.201)	-11.756*** (1.150)	-2.437*** (0.168)	2.681*** (0.135)	-9.521*** (0.227)	-1.187*** (0.018)	1724.911	-3443.82
CCB-banks	TVP-student-t	-1.815*** (0.498)	0.055** (0.025)	5.000*** (0.622)	5.204*** (0.720)			1691.754	-3377.51
CB-banks	TVP-student-t	-1.832*** (0.000)	0.062*** (0.002)	4.998*** (0.000)	5.482*** (0.660)			1639.251	-3272.5
CITIB-banks	TVP-student-t	5.000*** (1.570)	-0.099 (0.087)	-3.014* (1.757)	4.594*** (0.546)			1560.586	-3115.17
CITIS-diversified financials	TVP-Gumbel	1.321*** (0.069)	0.175*** (0.007)	-3.007*** (0.377)				3169.545	-6333.09

**Table 4** (continued)

	Optimal copula	Phi1	Phi2	Phi3	Phi4	Phi5	Phi6	logL	AIC
PS-diversified financials	TVP-student-t	-1.798*** (0.528)	0.038 (0.024)	5.000*** (0.665)	3.340*** (0.297)			1731.953	-3457.91
SIT-diversified financials	TVP-rotated Gumbel	0.419*** (0.056)	0.351*** (0.016)	-0.801*** (0.153)				934.9506	-1863.9
SAJ-diversified financials	TVP-SJC	0.566 (0.635)	-7.076** (3.266)	-0.127 (0.079)	2.604*** (0.670)	-11.241*** (2.242)	-1.651* (0.888)	553.5424	-1101.08
ATI-diversified financials	TVP-SJC	0.659 (0.415)	-7.907*** (2.234)	0.023*** (0.008)	-1.922*** (0.033)	-0.457*** (0.139)	4.003*** (0.047)	537.4421	-1068.88
PAI-insurance	TVP-Gumbel	1.538*** (0.054)	0.157*** (0.004)	-4.664*** (0.455)				3703.426	-7400.85
CPI-insurance	TVP-student-t	5.000 (42.873)	(0.051)	(2.352)	5.167*** (0.624)			2075.079	-4144.16
CLI-insurance	TVP-Gumbel	1.109*** (0.047)	0.205*** (0.006)	-2.823*** (0.292)				2262.903	-4519.81

This table reports coefficients estimates of the optimal time-varying parameter (TVP) copulas for each pair composed of a financial institution and its affiliated industry group  
 \*\*\*, \*\* and \*Indicate rejection of the null hypothesis at 1%, 5% or 10% levels, respectively

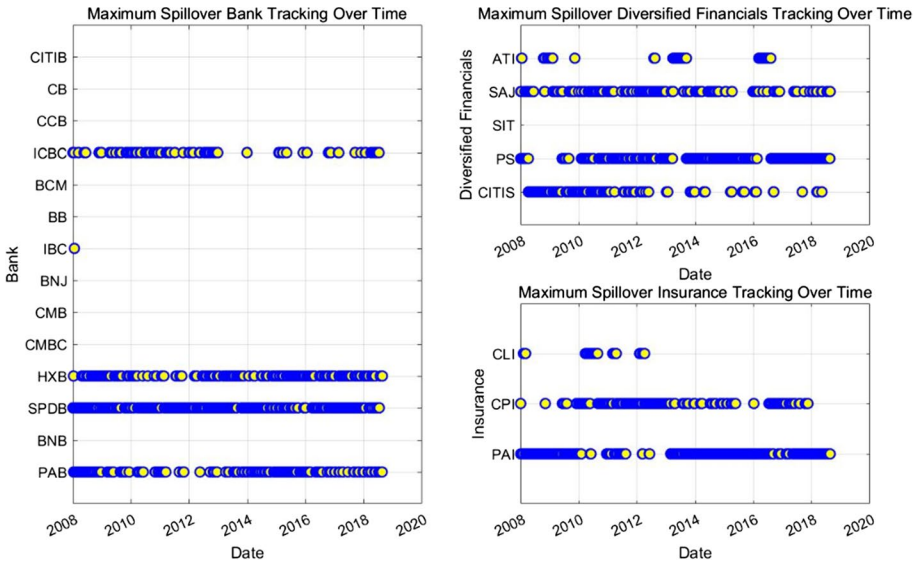


Fig. 1 Tracking top risk contributors by industry groups

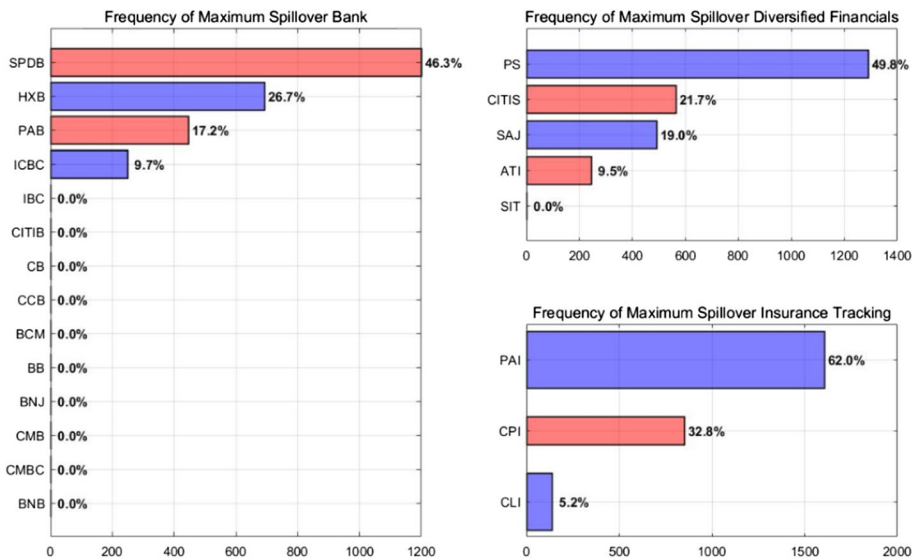


Fig. 2 Frequency of financial institutions being the top risk contributor

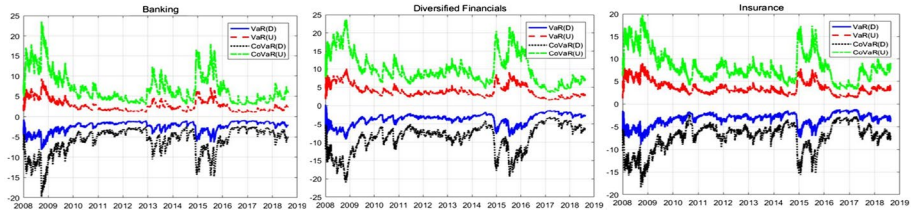
we proceed to analyze bidirectional risk spillover effects between the SIFIs and their affiliated industry groups. We couple each SIFI to its industry group and form three pairs, and quantify upside and downside VaRs, CoVaRs and  $\Delta$ CoVaRs to evaluate bidirectional downside and upside risk spillovers in each pair.

**Table 5** Summary statistics for the VaRs, CoVaRs and  $\Delta$ CoVaRs calculated by optimal time-varying copulas

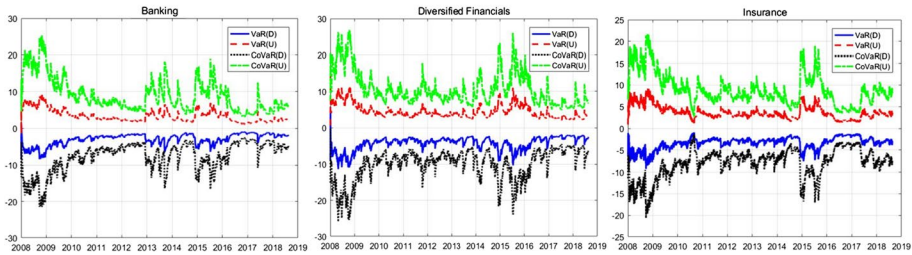
	Downside			Upside		
	VaR	CoVaR	$\Delta$ CoVaR	VaR	CoVaR	$\Delta$ CoVaR
<i>Panel A: VaR of financial system returns, CoVaR and <math>\Delta</math>CoVaR from SIFI to financial system</i>						
Banks $\leftarrow$ SPDB	-2.395 (1.300)	-5.878 (3.146)	0.925 (0.055)	2.650 (1.417)	6.947 (3.713)	1.007 (0.059)
Diversified financials $\leftarrow$ PS	-3.697 (1.579)	-8.749 (3.679)	0.875 (0.118)	3.961 (1.680)	9.903 (4.153)	0.941 (0.053)
Insurance $\leftarrow$ PAI	-3.282 (1.357)	-7.236 (2.972)	0.758 (0.081)	3.533 (1.436)	8.209 (3.289)	0.826 (0.056)
<i>Panel B: VaR of SIFI returns, CoVaR and <math>\Delta</math>CoVaR from financial system to SIFI</i>						
Banks $\rightarrow$ SPDB	-3.002 (1.537)	-7.787 (3.941)	1.001 (0.414)	3.302 (1.652)	8.989 (4.528)	1.063 (0.244)
Diversified financials $\rightarrow$ PS	-4.277 (1.802)	-10.092 (4.241)	0.861 (0.045)	4.360 (1.855)	10.629 (4.485)	0.904 (0.046)
Insurance $\rightarrow$ PAI	-3.364 (1.402)	-7.941 (3.283)	0.854 (0.092)	3.628 (1.476)	8.960 (3.602)	0.918 (0.062)

This table reports the average values of the temporal bidirectional downside and upside VaR, CoVaR and  $\Delta$ CoVaR of the SIFIs and corresponding industry groups, based on the 5% VaR. Panel A reports the risk spillovers from SIFIs to their affiliated industry groups, while Panel B reports risk spillovers from the opposite direction

Panel A: Upside and downside VaRs of industrial indices and CoVaRs from SIFIs to affiliated industry groups



Panel B: Upside and downside VaRs of SIFI returns and CoVaRs from industry groups to corresponding SIFIs



**Fig. 3** Upside and downside VaRs and CoVaRs between SIFIs and the financial system. Panel A: Upside and downside VaRs of industrial indices and CoVaRs from SIFIs to affiliated industry groups, Panel B: Upside and downside VaRs of SIFI returns and CoVaRs from industry groups to corresponding SIFIs

Summary statistics of average values of bidirectional upside and downside VaR, CoVaR and  $\Delta$ CoVaR are reported in in Table 5, with standard errors shown in the parentheses. Panel A reports risk spillovers from SIFIs to their corresponding industry groups, while Panel B reports risk spillovers from the opposite direction.

#### 4.4.2 Risk spillovers from SIFI to the financial system

For more in-depth analysis on risk spillovers, we examine directional risk spillovers from SIFIs to the financial system. Specifically, it is measured by risks transmitted from SIFIs to their corresponding industry groups. Panel A in Fig. 3 depicts the dynamics of upside and downside VaRs and CoVaRs for all three pairs during the sample period. Noticeably, all exhibit that downside CoVaRs are systemically below downside VaRs during the entire sample period. We corroborate this finding by the KS test, as these differences are reported as significant by the test in all cases, shown in column 2 of Panel A in Table 6. This indicates that extreme downward movements in SIFIs’ returns have spillover effects on their corresponding industrial indices, whose VaRs drop by significant amounts following extreme downturns of SIFI returns, although to different extents (measured by magnitudes) across industry groups.

Similarly, the average upside CoVaR values are systemically greater than the average upside VaR values though with different magnitudes, also corroborated by the KS statistics reported in column 3 of Panel A in Table 6. It provides evidence of upside risk spillovers from SIFIs to the financial system, meaning that extreme upward movements of SIFIs’ returns have significant positive impacts on the returns of the financial system.



**Table 6** Risk spillovers and asymmetric downside and upside effects based on time-varying copulas

	Downside	Upside		
	H0: CoVaR = VaR	H0: CoVaR = VaR	H0: CoVaR/ VaR(Down) = CoVaR/ VaR(Up)	H0: DeltaCoVaR (Down) = DeltaC oVaR(Up)
	H1: CoVaR < VaR	H1: CoVaR > VaR	H1: CoVaR/ VaR(Down) < CoVaR/ VaR(Up)	H1: DeltaCoVaR (Down) < DeltaC oVaR(Up)
<i>Panel A: VaR of financial system returns, CoVaR and ΔCoVaR from SIFI to financial system</i>				
Banks ← SPDB	0.657*** (0.000)	0.692*** (0.000)	0.662*** (0.000)	0.686*** (0.000)
Diversified finan- cials ← PS	0.688*** (0.000)	0.713*** (0.000)	0.634*** (0.000)	0.654*** (0.000)
Insurance ← PAI	0.686*** (0.000)	0.718*** (0.000)	0.419*** (0.000)	0.456*** (0.000)
<i>Panel B: VaR of SIFI returns, CoVaR and ΔCoVaR from financial system to SIFI</i>				
Banks → SPDB	0.664*** (0.000)	0.693*** (0.000)	0.915*** (0.000)	0.929*** (0.000)
Diversified finan- cials → PS	0.746*** (0.000)	0.759*** (0.000)	0.738*** (0.000)	0.755*** (0.000)
Insurance → PAI	0.720*** (0.000)	0.737*** (0.000)	0.367*** (0.000)	0.406*** (0.000)

This table reports the Kolmogorov–Smirnov statistics for testing bidirectional downside and upside risk spillovers, as well as symmetry of upside and downside CoVaRs and ΔCoVaRs, based on the 5% VaR and the optimal time-varying copulas. Panel A reports test results for risk spillovers from SIFIs to their affiliated industry groups, while Panel B reports results for the opposite direction

\*\*\*Indicates rejection of the null hypothesis at the 1% significance level

### 4.4.3 Risk spillovers from the financial system to SIFI

Considering risk spillovers from the financial system to SIFIs, the movements of VaRs and CoVaRs again exhibit similar trends in both downside and upside cases during the sample period based on the graphic evidence. Overall, SIFIs’ returns are significantly affected by risk spillovers from the financial system. Considering downside risk spillovers, downside VaR values are above the downside CoVaR values in a systematical and significant fashion for all three pairs, corroborated by the KS statistics reported in column 2 of Panel B in Table 6. The finding of significant downside risk spillovers from industrial groups to the SIFIs implies that extreme downturns in the industrial indices have significant negative systemic impacts on SIFIs’ returns.

With regard to upside risk spillovers, the average values of upside CoVaR are systematically and significantly higher than upside VaR, as confirmed by the KS test results in column 3 of Panel B in Table 6. This indicates that extreme upward movements in sectoral and industrial returns are accompanied by a significant increase in SIFIs’ returns, proving existence of upside risk spillover effects from the financial system to SIFIs. The extreme upward movements in industrial returns have positive impacts on SIFIs’ returns.

#### 4.4.4 Asymmetric risk spillovers

In addition, upside and downside risk spillover effects are shown to be asymmetric in bidirectional risk spillover cases. We confirm this asymmetry by testing the significant differences between the downside CoVaRs normalized by the downside VaRs and the upside CoVaRs normalized by the upside VaRs. The KS test results are summarized in column 4 in Table 6. The KS statistics provide evidence that there exists significant asymmetry between normalized downside and upside CoVaRs, suggesting asymmetric downside and upside risk spillover effects from SIFIs to the financial system and vice versa.

Considering risk spillovers from SIFIs to the financial system, the results in Panel A in Table 6 imply that SIFIs' downward systemic impacts on the financial system are lower than its upward systemic impacts, and market participants may be more susceptible to upside risk than downside risk passing down following SIFIs' extreme movements.

Likewise, in the cases of risk spillovers from the financial system to SIFIs, downside risk spillovers are lower than upside risk spillovers, corroborated by the KS statistics shown in Panel B in Table 6. Empirical results imply that capital outflows following extreme sectoral downturns can affect SIFIs' returns to a lower extent than capital inflows following a soaring sectoral index.

#### 4.4.5 $\Delta$ CoVaR analysis

The average values of upside and downside  $\Delta$ CoVaRs for bidirectional spillovers are reported in Table 5. Average downside  $\Delta$ CoVaR values are shown to be lower than average upside  $\Delta$ CoVaR values in all cases. These significant differences between upside and downside  $\Delta$ CoVaR are corroborated by KS tests reported in column 5 in Table 6. These findings of asymmetric downside and upside  $\Delta$ CoVaRs are consistent with our previous results obtained by quantifying bidirectional CoVaRs.

## 5 Discussion

Our empirical analysis shows that Shanghai Pudong Development Bank (SPDB) is the most systemically important financial institution in China's Banking industry, as it exhibits the strongest risk spillover effects on the banking industry over the sample period. While from a global perspective, CB, ICBC, Agricultural Bank of China and CCB are identified as G-SIBs (FSB, 2018), our analysis find evidence that within the banking sector in China, SPDB exhibits highest systemic importance. This difference may be attributed to different business focuses and expansion modes between the G-SIBs and the domestic SIFI, which can be of further research interest. Similarly, Pacific Securities Co., Ltd. (PS) and Ping An Insurance (Group) Co. of China, Ltd. (PAI) are identified as SIFIs for diversified financials and insurance, respectively. The latter is consistent with the findings in the 2016 G-SIIs list (FSB, 2016), implying PAI's systemic importance in both local and global contexts.

Based on the strong evidence of bidirectional downside and upside risk spillovers between these SIFIs and their industrial groups, the risk spillover effects are noticeably stronger during the 2008 global financial crisis, indicating risk influence from the global market to Chinese market as a consequence of increasing integration of China's

economy into world's economy. Also, during the Chinese stock market turbulence periods in 2009, 2013 and 2015, systemic risk spillovers are shown to be remarkably stronger than calm periods, implying increased risk flows between the stock market and the financial sector.

The extreme risk spillovers from the financial system to the SIFIs can be explained by the phenomenon that substantial reduction in industrial indices triggers low market valuations and investors' expectation of a bearish trend. Due to the flight-to-quality effect (Bernanke et al., 1996), capital flees out from the financial sector, leading to a considerable drop in stock price and returns of SIFIs.

Regarding downside risk spillovers from SIFIs to the financial system, portfolios composed of assets diversified across financial industry groups may still be highly susceptible to systemic risk contributed largely by SIFIs. Simply holding portfolios composed of non-SIFI stocks is rarely sufficient to protect portfolios against downside risk transmitted from SIFIs to the financial sector. Investors should consider downside risks of both SIFIs and those affected industry groups and take short positions on SIFIs' returns, to hedge downside risk spillovers. For upside risk spillovers, the practical implications are similar, but considering taking long rather than short positions on SIFIs' returns.

Notably, both CoVaR and  $\Delta$ CoVaRs asymmetries demonstrate that upside systemic impacts exceed downside systemic impacts in all industrial groups, irrespective of the direction of risk spillovers. To take the higher level of the upside spillovers than the downside spillovers from the SIFIs to the financial system as an example, a plausible explanation can be the asymmetric reactions by investors to upward and downward extreme conditions when formulating momentum investing strategies. Given upside risk spillovers, excessively high SIFI returns cause capital inflows into its affiliated industry due to the trend-chasing effect, boosting a bullish market and an overall upward movement of sectoral returns. In an opposite scenario, investors perceive high risks signaled by abruptly declined SIFI returns, leading to capital outflows from SIFIs and the wider system due to the flight-to-quality effect and pessimistic sentiment among investors, pushing down the market to a bearish status.

Our findings thus support the argument in extant literature that besides market fundamentals, other factors such as investors' sensitivities to news and their sentiments can affect and enhance risk spillovers patterns (for example, Mensi et al., 2017; Reboredo et al., 2016). While several other studies find evidence of stronger market reaction to bearish news (Jin, 2018; Reboredo et al., 2016), we find that investors in the China market also exhibit more sentiment to market upturns than downturns and react more to good news than to bad news. These differed reactions thus make the whole system more sensitive to extreme upturns (upside risk) than downturns (downside risk).

To sum up, we provide evidence that changes in capital flows in the stock market and investors' expected returns reinforce upside risk spillovers to a greater extent than downside spillovers in the Chinese financial system. This suggests a stronger trend-chasing effect than the flight-to-quality effect, and the latter is possibly offset by the disposition effect among China's market participants. Based on the above evidence of significant asymmetric downside and upside risk spillovers from both directions, stock market investors can assess to what extent the portfolio might be affected by extreme movements in the sectoral/industrial indices by looking at the downside and upside VaR and CoVaR measures, or how the extreme loss/gain of a SIFI's stock tends to spread across the sector, thus enabling better asset allocation across sectors and industry groups.

**Table 7** Structural change tests for dependence between SIFIs and the industrial groups

Pairs	Gaussian	Clayton	Rot Clayton	Gumbel	Rot Gumbel	SJC	Student-t
<i>Panel A: optimal copula selection (by minimizing AIC values)</i>							
Banks-SPDB	-3790.1	-3147	-3108.6	-3786.1	-3818.1	-3901.3	<b>-4057.4</b>
Diversified financials-PS	-3064.9	-2716.5	-2397.8	-3069.1	-3255.4	-3197.1	<b>-3448.8</b>
Insurance-PAI	-6575.3	-5721.9	-5837.4	<b>-6787.6</b>	-6744.9	-6743	-6656.6
Period	p	T	$Z_T^{1/2}$	$\Pr\left(Z_T^{1/2} \geq z_T^{1/2}\right)$	$H_0$ (0.95)	Time point of change	
<i>Panel B: structural change tests</i>							
Banks-SPDB (best-fitting copula) I: 2 Jan 2008–20 Aug 2018							
I	2	2589	5.452	0.000	Reject	1 September 2015	
II <sub>1</sub>	2	1866	3.413	0.134	Not reject	–	
II <sub>2</sub>	2	723	3.343	0.136	Not reject	–	
Diversified Financials—PS I: 2 Jan 2008–20 Aug 2018							
I	2	2589	2.964	0.424	Not reject	–	
Insurance-PAI I: 2 Jan 2008–20 Aug 2018							
I	1	2589	2.305	0.548	Not reject	–	

The optimal static copula functions identified by minimizing the AIC values are shown in bold numbers in Panel A

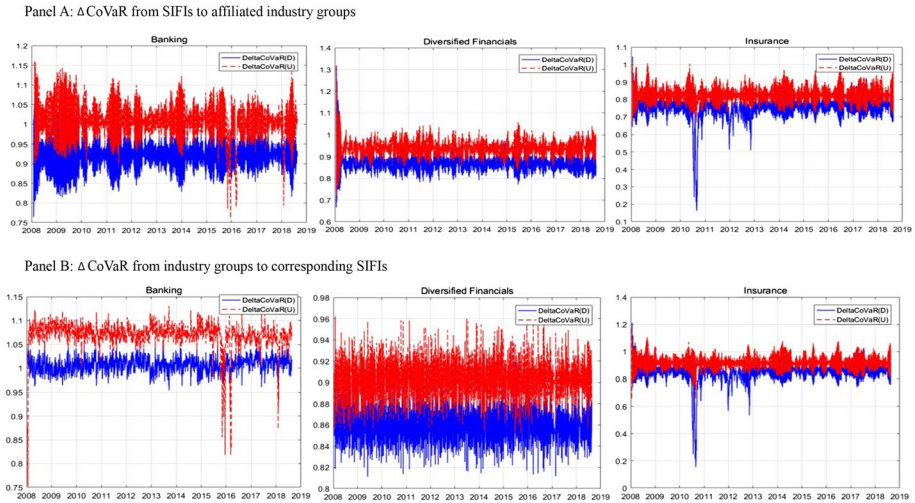
## 6 Robustness analysis

In this section, a structural change test is applied to identifying and locating any breaking points of the pairwise dependence relationships. The whole sample is then divided into subsamples by the breaking points, for which all the modeling process and calculation are then repeated to test the robustness of the main results. We also use second best time-varying copulas to test if the main conclusions still hold.

### 6.1 Structural breaks of dependence

As discussed in Sect. 3.3, potential structural changes of the copula dependence may exist during the sample period. We thus test the existence of any structural breaks in the dependence by the method of Dias and Embrechts (2009), Liu et al. (2017) and Ji et al. (2018) shown in Sect. 3.3. To the best of our knowledge, potential structural breaks of dependence can only be tested using a single copula (Liu et al., 2017). To avoid the disturbance of using different copulas to run the tests, the dependence over the full sample is estimated by seven static copula candidates corresponding to their time-varying counterparts introduced in Sect. 3.4. The test results are reported in Table 7. Penal A reports the best fitting copula functions for each pair of SIFI and the industrial group,<sup>4</sup> selected by minimizing the value of AIC. The full-sample optimal copula functions for the banks-SPDB and diversified financials-PS are static Student-t copula, while it is static Gumbel for insurance-PAI.

<sup>4</sup> The SIFIs identified for each of the three industrial groups using the static copula-CoVaR approach are the same institutions as identified by the time-varying copula CoVaR approach, namely, SPDB, PS and PAI for banks, diversified financials and insurance, respectively. The estimation process is not shown here for brevity.



**Fig. 4** Upside and downside  $\Delta$ CoVaR between SIFIs and the financial system. Panel A:  $\Delta$ CoVaR from SIFIs to affiliated industry groups, Panel B:  $\Delta$ CoVaR from industry groups to corresponding SIFIs

The test results of structural changes of the copula dependence are reported in Panel B of Table 4. The null hypothesis of no structural changes of the dependence is not rejected for both the diversified financials and insurance pairs, while rejected for the banks-SPDB pair at the 5% significance level, where the only structural break is identified to be 1 September 2015 for the full sample. We then divide the whole sample periods into two subperiods, and test for structural changes for each subsample. The tests cannot reject the null hypothesis of no structural changes in each of the subsamples, as shown in Panel B of Table 7. Notably, for each subsample, we opt for applying the Student-t copula function as for the full sample to make the results comparable.

This structural break corresponds to the major crash of the Chinese stock market in the summer of 2015 starting from June. The benchmark Shanghai Stock Exchange (SSE) Composite Index plunged from a peak on 12 June to over 40% of loss by the end of August. The steep market decline triggered severe market turbulences, extreme volatility and rattled market sentiment (Wu, 2019), despite the various measures taken by the Chinese government including imposing a lock-up period, reining in short-sellers, and installation of circuit breakers, etc. It is thus not surprising that a structural break of the dependence transpires at the time close to the end of the biggest market crash during the sample period, significantly changing the dependence mechanism between the banking sector and the sectoral SIFI (Fig. 4).

To test the robustness of the main results based on time-varying copula models, we calculate VaR, CoVaR and  $\Delta$ CoVaR by the optimal static copula models shown in Table 7. For the dependence between diversified financials and PS or insurance and PAI, no structural changes are identified and the optimal copula models are identical in the dynamic and static contexts (being Student-t and Gumbel for each pair respectively). The robustness of

**Table 8** Risk spillovers and asymmetric downside and upside effects for banks-SPDB over subperiods

	Downside		Upside	
	VaR	CoVaR	ΔCoVaR	CoVaR
<i>Panel A: summary statistics for VaR, CoVaR and ΔCoVaR</i>				
Panel A1: subperiod II <sub>1</sub> (2 January 2008–1 September 2015)				
Banks ← SPDB	-2.665 (1.373)	-6.538 (3.315)	0.925 (0.062)	2.944 (1.496)
Banks → SPDB	-3.381 (1.572)	-8.769 (4.023)	0.998 (0.488)	3.713 (1.689)
Panel A2: subperiod II <sub>2</sub> (2 September 2015–20 August 2018)				
Banks ← SPDB	-1.700 (0.723)	-4.174 (1.750)	0.925 (0.034)	1.892 (0.786)
Banks → SPDB	-2.023 (0.872)	-5.253 (2.221)	1.010 (0.015)	2.241 (0.920)
Downside				
	H0: CoVaR = VaR		H0: CoVaR = VaR	
	H1: CoVaR < VaR		H1: CoVaR > VaR	
Upside				
			H0: CoVaR/VaR(D) = CoVaR/VaR(U)	H0: ΔCoVaR (D) = ΔCoVaR (U)
			H1: CoVaR/VaR(D) < CoVaR/VaR(U)	H1: ΔCoVaR (D) < ΔCoVaR (U)
<i>Panel B: tests of risk spillovers and asymmetric downside and upside spillover effects</i>				
Panel B1: subperiod II <sub>1</sub> (2 January 2008–1 September 2015)				
Banks ← SPDB	0.614*** (0.000)	0.655*** (0.000)	0.667*** (0.000)	0.689*** (0.000)
Banks → SPDB	0.682*** (0.000)	0.709*** (0.000)	0.955*** (0.000)	0.963*** (0.000)
Panel B2: subperiod II <sub>2</sub> (2 September 2015–20 August 2018)				
Banks ← SPDB	0.534*** (0.000)	0.887*** (0.000)	0.724*** (0.000)	0.690*** (0.000)
Banks → SPDB	0.795*** (0.000)	0.826*** (0.000)	0.815*** (0.000)	0.841*** (0.000)

Panel A reports the summary statistics for VaR, CoVaR and ΔCoVaR by the optimal static copulas for each subperiod; Panel B reports the Kolmogorov–Smirnov statistics for testing bidirectional downside and upside risk spillovers, as well as symmetry of upside and downside CoVaRs and ΔCoVaRs for each subperiod  
 \*\*\*indicates rejection of the null hypothesis at the 1% significance level

**Table 9** Tests of the risk spillover and asymmetric effects by suboptimal time-varying copulas

	Downside		Upside		H0: $\Delta\text{CoVaR}(D) = \Delta\text{CoVaR}(U)$	H1: $\Delta\text{CoVaR}(D) < \Delta\text{CoVaR}(U)$
	H0: $\text{CoVaR} = \text{VaR}$	H1: $\text{CoVaR} < \text{VaR}$	H0: $\text{CoVaR} = \text{VaR}$	H1: $\text{CoVaR} > \text{VaR}$		
<i>Panel A: VaR of financial system returns, CoVaR and <math>\Delta\text{CoVaR}</math> from SIFI to financial system</i>						
Banks $\leftarrow$ SPDB	0.654*** (0.000)	0.691*** (0.000)	0.702*** (0.000)	0.727*** (0.000)		
Diversified financials $\leftarrow$ PS	0.643*** (0.000)	0.718*** (0.000)	0.915*** (0.000)	0.955*** (0.000)		
Insurance $\leftarrow$ PAI	0.686*** (0.000)	0.718*** (0.000)	0.416*** (0.000)	0.455*** (0.000)		
<i>Panel B: VaR of SIFI returns, CoVaR and <math>\Delta\text{CoVaR}</math> from financial system to SIFI</i>						
Banks $\rightarrow$ SPDB	0.660*** (0.000)	0.690*** (0.000)	0.973*** (0.000)	0.980*** (0.000)		
Diversified financials $\rightarrow$ PS	0.684*** (0.000)	0.764*** (0.000)	0.968*** (0.000)	0.987*** (0.000)		
Insurance $\rightarrow$ PAI	0.719*** (0.000)	0.737*** (0.000)	0.365*** (0.000)	0.404*** (0.000)		

This table reports the Kolmogorov–Smirnov statistics for testing bidirectional downside and upside risk spillovers, as well as symmetry of upside and downside CoVaRs and  $\Delta\text{CoVaRs}$ , based on the 5% VaR and suboptimal time-varying copulas. The suboptimal time-varying copulas are Student-t for Banks-SPDB and Rotated Gumbel for both Diversified Financials-PS and Insurance-PAI. Panel A reports test results for risk spillovers from SIFIs to their affiliated industry groups, while Panel B reports results for the opposite direction

\*\*\*Indicates rejection of the null hypothesis at the 1% significance level

the main results remains for those two pairs.<sup>5</sup> As one structural break is detected for the dependence between banks and SPDB, the full sample is divided into two subperiods by 1 September 2015. The summary statistics of CoVaR and  $\Delta\text{CoVaR}$  for each subperiod are reported in Panel A of Table 8, while the tests of risk spillovers and asymmetric downside and upside spillover effects are reported in Panel B. Comparing the results in Table 8 to those in Tables 5 and 6, the general trends and asymmetric downside and upside spillover effects of the main analysis remain robust in both subsamples.

It is worth mentioning that the AIC values of the optimal time-varying copulas for all the three pairs composed of the SIFIs and the industrial groups (shown in Table 4) are universally smaller than those of the optimal static copulas shown in Table 7. This further corroborates our application of the time-varying copula specifications in the main analysis to calculating VaR, CoVaR and  $\Delta\text{CoVaR}$ .

## 6.2 Estimating risk spillovers by suboptimal time-varying copulas

The suboptimal time-varying copulas are Student-t for banks-SPDB and Rotated Gumbel for both diversified financials-PS and insurance-PAI. We use these second-best copulas to estimate VaR, CoVaR and  $\Delta\text{CoVaR}$  to test if the main conclusions still hold. The results are reported in Table 9 and are consistent with the findings using the best fitting time-varying copulas.

## 7 Conclusion

In this study, we first attempt to identify the systemically important financial institution (SIFI) in China based on CoVaR values of firms to their corresponding industries, and further examine upside and downside risk spillovers between SIFI and the financial system as a whole. We find strong evidence of bidirectional downside and upside risk spillovers between SIFIs and the financial system, which are noticeably stronger during market turbulences. Our findings are consistent with the fact that while SIFIs are individual institutions, their returns tend to co-move with the sectoral/industrial trend. Due to their systemic importance, their own extreme movements can also trigger market reactions and significantly affect sectoral returns.

Our results further reveal that downside and upside risk spillovers are asymmetric, with upside spillover effects stronger than downside counterparts in all cases. Market participants should take into account the asymmetric patterns of risk spillovers and accordingly hedge and adjust their positions to reduce risk exposure of portfolios.

From the regulatory and supervisory perspectives, identifying SIFI and the risk spillover trajectories is also of great importance. First, it can help policy practitioners precisely locate the most influential risk elements in the financial sector, who act as the bellwether dominating systemic risk flows and leading the trend of movements of many others and the entire system at large. Second, policies and regulations will be able to target the riskiest parts of the system and take preemptive actions before systemic risk escalates to impair the functioning of the financial system. Our findings hope to help regulators improve the

<sup>5</sup> For brevity, the results of risk spillover and tests of asymmetric effects for diversified financials-PS and insurance-PAI are not reported here.



governance of the financial sector and impose more proper macro-prudential regulations to bolster financial stability.

**Acknowledgements** Supports from the National Natural Science Foundation of China under Grant Nos. 72022020, 71974159, 71974181 and the 111 Project (Grant No.: B16040) are acknowledged.

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