Hindawi
Journal of Mathematics
Volume 2021, Article ID 9373614, 16 pages
https://doi.org/10.1155/2021/9373614

Research Article

Systemic Risk Contribution and Contagion of Industrial Sectors in China: From the Global Financial Crisis to the COVID-19 Pandemic

Jianxu Liu[1,2] **Yangnan Cheng**[2] **Yefan Zhou**[2] **Xiaoqing Li**[1] **Hongyu Kang**[3] **and Songsak Sriboonchitta**[2]

[1]*Shandong University of Finance and Economics, Faculty of Economics, Jinan 250000, China*
[2]*Chiang Mai University, Faculty of Economics, Chiang Mai 50200, Thailand*
[3]*Shandong University of Finance and Economics, School of International Trade and Economics, Jinan 250000, China*

Correspondence should be addressed to Yangnan Cheng; 706502056@qq.com

Received 10 August 2021; Revised 3 November 2021; Accepted 28 November 2021; Published 20 December 2021

Academic Editor: Alfred Peris

This paper investigates the risk contribution of 29 industrial sectors to the China stock market by using one-factor with Durante generator copulas (FDG) and component expected shortfall (CES) analyses. Risk contagion between the systemically most important sector and other sectors is examined using a copula-based ΔCoVaR approach. The data cover the 2008 global financial crisis and the beginning of the COVID-19 pandemic. The empirical results show that the banking sector contributed most to systemic risk before and during the global financial crisis. Nonbank finance became equally important in 2020, and the COVID-19 pandemic promoted the position of the computer and pharmaceuticals sectors. The spillover effect diminishes over time, but there remains risk contagion between sectors. The risk spillover trend is consistent with that of systemic risk.

1. Introduction

In finance, it is acknowledged that severe financial crises are inseparable from systemic risk, which is the risk of an entire market or financial system collapsing rather than the failure of individual parts. It is the risk of financial instability becoming so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially [1]. There are three main causes of systemic risk: macro shocks that negatively affect the financial market, contagion risk that spreads "horizontally" inside the financial system, and the consequences of imbalances that build up over time. The complexity and destructiveness of systemic risk raise a key question for policymakers: how to limit the build-up of systemic risk and contain crisis events when they happen. Over the past two decades, international financial markets have been extremely volatile, especially during the global financial crisis (GFC) in 2008 and the ongoing COVID-19 pandemic. As a major contributor to such crises, systemic risk has been studied intensively in the literature (e.g., Borri and Giorgio [2], Gavronski and Ziegelmann [3]). Both the GFC and the COVID-19 pandemic have been found to increase systemic risk in some of the most affected countries, and systemic risk has caused great damage to financial markets in those countries. Thus, it is of great importance for both investors and regulators to be able to identify and understand systemic risk and model its dynamics cross-sectionally and over time [4].

To gain a deeper understanding of systemic risk, empirical studies have usually focused on two aspects: the shock from systemically important financial institutions (SIFIs) and the cross-sectional contagion mechanism. SIFIs are institutions that contribute to a large proportion of systemic risk, and contagion increases the possibility that the failure of one institution will affect other institutions through bidirectional relationships and spread through the entire financial system. Some scholars have extended the concept of

SIFIs to cover systemically important sectors (SISs), which are sectors that account for large proportions of systemic risk. Identifying which sector is the most influential and how systemic risks spillover among sectors is essential for effective risk management and optimization of portfolios [5]. A thorough analysis of SISs, including their risk contribution and spillover effects, could help authorities monitor market trends and bubbles and take timely and effective action in response to crisis events, thus reducing the likelihood and severity of future financial crises.

In 2020, China, the world's second-largest economy and a developing country, accounted for about 18.34% of global gross domestic product (GDP). Although China's stock market has existed for only 30 years, it has developed rapidly. At the end of 2020, its trading volume was approximately 16.75 trillion shares. China's benchmark Shanghai Composite Index (SCI) was the third largest, with a market capitalization of USD 4.93 billion. Alongside this great success, owing to its immaturity, the stock market in China has gone through both international and domestic crises in the past two decades. During the GFC, the SCI plunged 72.8% from 2007 to 2008; its highest point is 6,124 and its lowest is 1,664. Market turbulence from 2015 to 2016 caused a loss of one-third of the value of A-shares on the Shanghai Stock Exchange within one month of the event. The statement is no longer maintained, and an updated version was published on June 29, 2020. In 2020, the sudden outbreak of COVID-19 significantly increased economic uncertainty [6]. To control the spread of the disease, on January 23, 2020, one day before the Lunar New Year, the city of Wuhan was locked down, and the Lunar New Year holiday was extended to February 2. Although the opening of the stock market on February 3 was expected to be a positive signal of economic conditions [7], the market was gloomy, with the SSE composite index at 2,746. However, this situation did not last long, and the stock market in China was not influenced severely. Although COVID-19 directly impacted volatility on stock markets worldwide, China seems to have contained the risk well [8].

Consideration of previous crises shows that the stock market in China responds differently to different types of crises. Unlike in the United States, in China, the COVID-19 pandemic has caused less damage to the stock market than the GFC did in 2008. The difference is more obvious from the perspective of individual sectors. Figures 1 and 2 show the stock index of three industrial sectors and the SSE composite index from 2006 to 2009 and 2019 to 2020. In Figure 1, the four indices show a similar trend before and during the GFC, reaching a peak around October 2007 and then falling dramatically in 2008. During the GFC, great fluctuations can be seen. However, the lines in Figure 2 are flatter, and the development trend varies from sector to sector. We can see similarities between the SSE composite index and the stock index of the banking sector, both of which decreased slightly in 2020. The stock indices of the pharmaceuticals and electronics sectors increased in 2019 and maintained an upward trend after a short period of decline during the COVID-19 period. Notably, the outbreak of COVID-19 fostered the development of some sectors, especially pharmaceuticals. Therefore, it is worth analyzing and comparing SISs in different periods, especially in relation to the two most influential recent global crises: the GFC and the COVID-19 pandemic.

Studies on systemic risk in China have been conducted from different perspectives. Some scholars have measured systemic risk in a single sector using institutional data (e.g., Xu et al. [9], Li et al. [10], Morelli and Vioto [11], Gong et al. [12]; Gong et al. [13]). Other researchers have used data from different industrial sectors. Wu [4] identified SISs from 11 industrial sectors in the post-GFC period from 2009 to 2018. The financial, industrial, and energy sectors were found to be the top contributors, and their contributions tended to change over time. Wu et al. [14] used data from 11 sectors for the period 2000 to 2018 to identify SISs and measure the risk spillovers across sectors over time. Their results show that the industrial sector played a critical role, followed by the consumer discretionary sector and that the spillover structure varied over the 18 years. Other studies focused on within-market risk spillover across sectors. Hao and He [15] measured the univariate dependence among the manufacturing, finance, and real estate sectors from 2000 to 2014 to generate an early warning signal for systemic risk. Feng et al. [16] used the three-tier industry indexes of the CSI for 25 sectors to examine the spillover effect among sectors from December 15, 2014, to January 27, 2017, excluding the data from August 10 to December 15, 2015. They found that the most influential and sensitive sectors differed for different time periods.

Following the outbreak of COVID-19, attention quickly turned to investigating its impact on the stock market (e.g., Huang et al. [7], Baker et al. [6], Ru et al. [17]) and on the stock market of China in particular (e.g., Shen et al. [18], Feng and Li [19], Apergis and Apergis [20]). Huo and Qiu [21] conducted their research at both the firm level and the industry level, dividing data from 28 industrial sectors from 22 January to 3 March 2020 into the event period and the postevent period to establish how China's stock market reacted to the sudden outbreak. They found that the overreactions in the Chinese stock market were mostly driven by industries and stocks that reacted positively to the announcement of the pandemic lockdown. Although some useful progress has been made, studies to date have not examined the systemic risk in China during the COVID-19 pandemic period, nor have they attempted to compare the GFC and the COVID-19 pandemic. Likewise, few studies have focused on industry-wide systemic risk measurement, which not only has macro implications for authorities but also provides portfolio management suggestions for investors.

In terms of research methods, popular techniques for identifying SIFIs, such as MES [22] and SRISK [23], have been widely used in the literature. However, dozens of applications have gradually revealed the drawbacks of these methods. For example, the marginal approach does not account for the level of the firm's characteristics (including size and leverage) in line with the Too Big To Fail paradigm, while methods that use SRISK are obliged to assume that the liabilities of the firm are constant over the period of crisis. In

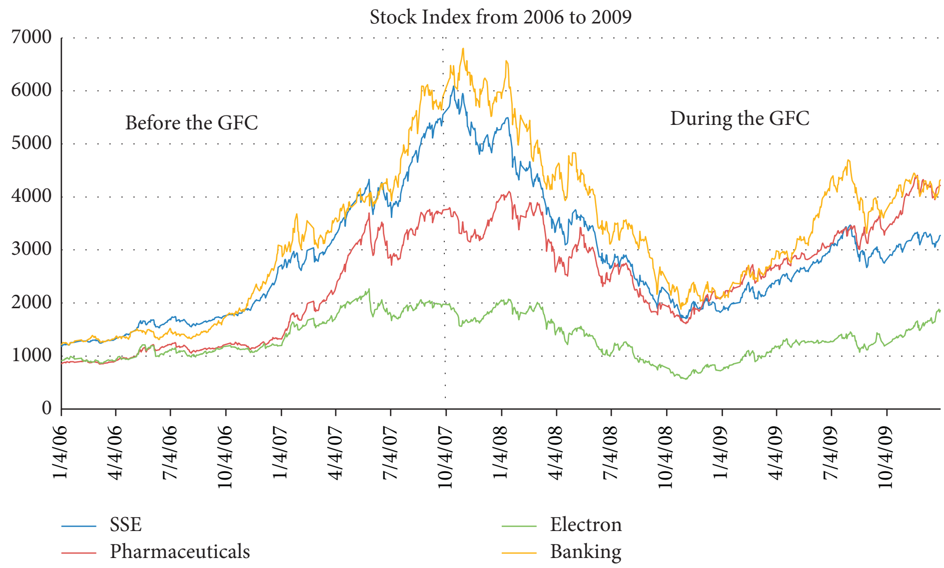

Figure 1: The stock index of the pharmaceuticals, electronics, and banking sectors, and the SSE composite index, 2006 to 2009.

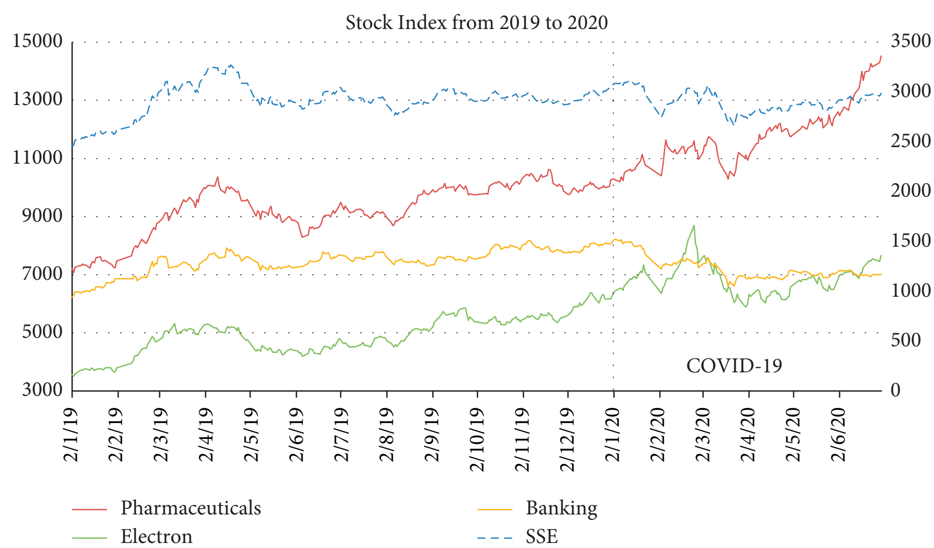

Figure 2: The stock index of the pharmaceuticals, electronics, and banking sectors, and the SSE composite index, 2019 to 2020.

2015, Banulescu and Dumitrescu [24] proposed a new systemic risk measure called component expected shortfall (CES), which performs better than MES and SRISK. In real applications, given the strong dependence that exists within the financial system, it is necessary to introduce copulas into the model. Copulas commonly used in high-dimensional applications include Archimedean copulas, nested Archimedean copulas, elliptical copulas, and pair-copula constructions and vines. Such copula models are either tractable or flexible, but rarely both. Accordingly, Mazo et al. [25] proposed the one-factor copula with Durante generators (the FDG copula) to cover all types of tail dependencies. In the present paper, we combine FDG copulas with CES to measure systemic risk and risk contribution accurately while understanding in detail the dependence structure between each pair of stocks.

This paper contributes to the literature in four ways. First, this study is the first to conduct a comprehensive measurement of systemic risk in China, including at the country level, the identification of SISs, and the spillover effect from SISs to other industrial sectors. The results will help supervision departments to monitor key sectors and the comovements of SISs and other sectors, enabling timely and effective measures to be taken to manage risk. They will also help investors better allocate their portfolios across different sectors. Second, this study divides the data into four periods (pre-GFC, GFC, post-GFC, and COVID-19), making it possible to see clearly the changes in SISs and their risk spillovers over time and analyze the impacts of different crisis events on systemic risk in China. Third, without precedent in the literature, the data are detailed into 29 industrial sectors. The more precise the industry classification, the more practical the policy suggestions. Finally, the method we propose (FDG copula-based CES) is shown to be ideal for purposes of risk contribution assessment and forecasting and to be well-suited for high-dimensional data.

The rest of this paper is organized as follows: Section 2 describes the data. We outline our methodology and computational process in Section 3. Section 4 presents the empirical results. Finally, conclusions are drawn in Section 5.

2. Data

We used the daily stock index of 29 sectors defined by China CITIC Bank covering 15 years from January 1, 2005, to June 30, 2020, a period that includes the 2007–2009 GFC and the early stages of the COVID-19 pandemic. According to Schmidt [26] and Jebran [27], the financial crisis started in October 2007, when the stock market in China crashed and lost about two-thirds of its total market value. Although the GFC and subsequent economic downturn greatly impacted the stock market, China's economy rebounded in 2010, with GDP growth of around 10%, outperforming all other major economies [28]. Some studies of the financial crisis in China, such as Gong et al. [12], Wang et al. [29], and Yu et al. [30], have taken December 2009 to be the end of the GFC period. Accordingly, we divided our data into four periods: pre-GFC (pre-September 2007), GFC (October 2007 to December 2009), post-GFC (January 2010 to December 2019), and COVID-19 (January 2020 onward). The rolling window method was used to calculate CES and ΔCoVar. Hence, a part of the data in each period was treated as out-of-sample and the rest as in-sample. For example, out of 665 observations in the pre-GFC period, 242 in the last year were out-of-sample data. Therefore, the window size was 423, and CES and ΔCoVar were calculated for the last 242 days. In the four periods, we computed CES and ΔCoVar from October 2006 to September 2007 (pre-GFC), January 2009 to December 2009 (GFC), and January 2009 to June 2020 (post-GFC). All data were transformed using $r_t = \ln R_t - \ln R_{t-1}$, where R_t is the stock index at day t. Since the computation process involved 29 sectors and 29 dimensions, our data can be characterized as high-dimensional.

Table 1 lists the 29 industrial sectors and shows the 5% value-at-risk of out-of-sample data in each period. Huge differences in value-at-risk among periods and in industries can be seen. The risk was higher in the pre-GFC and GFC periods because they had smaller value-at-risk. For most sectors under study, including coal, steel, computers, and real estate, the risk was higher during the COVID-19 pandemic than in the post-GFC period. The electronics sector had the highest risk in the GFC and COVID-19 periods, while media and computers were the riskiest in the pre-GFC and post-GFC periods. The industries with the lowest risks were different in each of the four periods. Table 1 shows the importance of identifying the SISs in different periods, as risks vary from sector to sector and different economic and financial backgrounds feature different risk levels.

3. Methodology

3.1. Model for Margins. To model the marginal distributions, we used the ARMA-GJR-GARCH model [31] to obtain the cumulative distribution function of each stock. This model performs better than others in the analysis of financial markets because of its ability to capture empirical phenomena that simple ARMA-GARCH models cannot capture, namely, that the negative impact from time $t-1$ to the variance of time t is greater than the positive impact.

The ARMA-GJR-GARCH model consists of ARMA (p, q) and GJR-GARCH (m, n) processes. The ARMA (p, q) is defined as

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \rho_j \varepsilon_{t-j} + \varepsilon_t, \tag{1}$$

where y_t is the conditional mean and ε_t denotes the error terms (return residuals, with respect to mean process). Here, ε_t is split into two parts, z_t, a random variable, and σ_t, the standard deviation. Thus,

$$\varepsilon_t = z_t \sigma_t, \tag{2}$$

where z_t are independent and identically distributed variables of standard innovation.

The GJR-GARCH (m,n) model is specified as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{n} \left[\alpha_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2\right] + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2, \tag{3}$$

where γ is the leverage effect that is only activated if the previous shock is negative, allowing the GJR-GARCH to consider the leverage effect and

$$I_{t-i} = \begin{cases} 0, & \text{if } \varepsilon_{t-i} \geq 0, \\ 1, & \text{if } \varepsilon_{t-i} < 0. \end{cases} \tag{4}$$

Since these cumulative distribution functions (CDFs) were to be treated as marginal distributions in FDG copulas, we standardized the error term using

$$\hat{z}_t = \frac{\hat{\varepsilon}_t}{\hat{\sigma}_t}, \tag{5}$$

ensuring that marginal distributions were uniformly distributed in [0, 1]. Given the nonnormality characteristics of the GARCH model residuals, we fitted the in-sample data with three possible distributions: skewed normal, skewed student t, and skewed generalized error distribution. Maximum likelihood values of each distribution for each series were thus obtained. Then, the best-fit distribution for each stock was selected using Bayesian information criteria (BIC).

3.2. In-Sample Data Selection. To measure risk using the rolling window method, data were categorized as in-sample or out-of-sample. Here, because the out-of-sample period was fixed, the problem was deciding how many data should be treated as in-sample. Therefore, the mean squared prediction error (MSPE) was computed using

Table 1: Industrial sectors and their 5% value-at-risk.

Sector	5% quantile			
	Pre-GFC	GFC	Post-GFC	COVID
Banking	**−0.024**	−0.032	−0.028	−0.024
Coal	−0.048	−0.048	−0.020	−0.024
Nonferrous metals	−0.041	−0.053	−0.023	−0.030
Power and public utilities	−0.043	−0.033	−0.024	**−0.018**
Steel	−0.043	−0.046	−0.018	−0.022
Chemicals	−0.041	−0.043	−0.022	−0.029
Construction	−0.046	−0.032	−0.024	−0.023
Building materials	−0.041	−0.038	−0.020	−0.029
Media	**−0.053**	−0.042	−0.030	−0.034
Machinery	−0.040	−0.037	−0.024	−0.026
Electronics	−0.045	**−0.054**	−0.021	**−0.049**
Computers	−0.048	−0.047	**−0.032**	−0.047
Cars	−0.047	−0.037	−0.028	−0.025
Commercial and retail	−0.046	−0.040	−0.023	−0.022
Consumer services	−0.038	−0.044	−0.022	−0.034
Household appliances	−0.046	−0.037	−0.025	−0.029
Textiles and garments	−0.051	−0.044	−0.024	−0.026
Pharmaceuticals	−0.045	−0.036	−0.020	−0.025
Food and beverages	−0.035	**−0.031**	−0.027	−0.026
Agriculture, forestry, animal husbandry, and fishery	−0.044	−0.039	−0.025	−0.032
Petroleum and petrochemicals	−0.038	**−0.031**	**0.000**	−0.022
Nonbank finance	−0.039	−0.045	−0.019	−0.030
Real estate	−0.049	−0.043	−0.024	−0.027
Transportation	−0.036	−0.039	−0.023	−0.021
Electrical equipment and new energy	−0.039	−0.042	−0.021	−0.031
Communications	−0.046	−0.039	−0.029	−0.042
National defense and military	−0.042	−0.047	−0.024	−0.028
Light manufacturing	−0.042	−0.046	−0.026	−0.029
Other	−0.046	−0.040	−0.029	−0.022

$$\mathrm{MSPE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\widehat{\sigma}_{t+1}^{2} - r_{t+1}^{2}\right)}, \tag{6}$$

where $\widehat{\sigma}_{t+1}^{2}$ is the predicted value of variance at day $t+1$, r_{t+1} is the real return at day $t+1$, and N is the number of out-of-sample data. By taking different numbers of in-sample data, we obtained different values of $\widehat{\sigma}_{t+1}^{2}$ from the ARMA-GJR-GARCH model. For each period, the number of in-sample data that gave the smallest MSPE was selected as optimal.

3.3. FDG Copulas. A factor copula model is useful when the dependence in observed variables is based on a few unobserved variables. In a one-factor copula model, we assume there is one latent variable. More specifically, let $U = (U_1, \ldots, U_d)$ be the margins with $U_i \sim U(0,1)$. $U_1, \ldots, U_d$ are assumed to be conditionally independent given the latent variable U_0. Let C_{0i} be the joint distribution of (U_0, U_i) and $C_{i|0}(\cdot|u_0)$ the conditional distribution of U_i given $U_0 = u_0$ for $i = 1, \ldots, d$. Then, the one-factor copula is given by

$$C(u_1, \ldots, u_d) = \int_0^1 C_{1|0}(u_1|u_0), \ldots, C_{d|0}(u_d|u_0)\,du_0. \tag{7}$$

Note that

$$C_{i|0}(\cdot|u_0) = \frac{\partial C_{0i}}{\partial u_0}. \tag{8}$$

The copulas C_{0i} are called linking copulas because they link the factor U_0 to the variables of interest U_i. The class of FDG copulas is constructed by choosing appropriate linking copulas for the one-factor copula model. The class of linking copulas used to build the FDG copulas is referred to as the Durante class of bivariate copulas [32]. The Durante class takes the form

$$C(u,v) = \min(u,v) f(\max(u,v)), \tag{9}$$

where $f\colon [0,1] \longrightarrow [0,1]$, called the generator of C, is a differentiable and increasing function such that $f(1) = 1$ and $t \mapsto f(t)/t$ is decreasing. This model combines the advantages of a one-factor copula (such as nonexchangeability, parsimony, and easy data generation from the copulas) and Durante linking copulas. The integral in equation (7) can be calculated, and the resulting multivariate copula is nonparametric. Among the four examples of families given by Mazo et al. [25], the FDG-exponential requires a large sample size, and the FDG-sinus can be used only when Spearman's rho <0.37. Given the characteristics of our data, FDG-CA and FDG-F were employed along with their extreme value copulas.

3.3.1. FDG Copula with Cuadras–Augé Generators. In equation (9), let

$$f_i(t) = t^{1-\theta_i}, \quad \theta_i \in [0,1]. \tag{10}$$

A copula belonging to the Durante class with generator (10) gives rise to the well-known Cuadras–Augé copula with parameter θ_i [33].

Spearman's rho is given by

$$\rho_{ij} = \frac{3\theta_i\theta_j}{5-\theta_i-\theta_j}. \tag{11}$$

The lower and upper tail dependence coefficients are given by

$$\begin{aligned}\lambda_{ij}^{(L)} &= 0,\\ \lambda_{ij}^{(U)} &= \theta_i\theta_j.\end{aligned} \tag{12}$$

Kendall's tau is given by

$$\tau_{ij} = \begin{cases} \dfrac{\theta_i\theta_j\left(\theta_i\theta_j + 6 - 2\left(\theta_i+\theta_j\right)\right)}{\left(\theta_i+\theta_j\right)^2 - 8\left(\theta_i+\theta_j\right) + 15}, & \text{if } \theta_i+\theta_j \neq 1,\\[2ex] \dfrac{\theta(\theta-1)\left(\theta^2-\theta-4\right)}{8}, & \text{if } \theta = \theta_i = 1-\theta_j. \end{cases} \tag{13}$$

3.3.2. FDG Copula with Fréchet Generators. In equation (9), let

$$f_i(t) = \left(1-\theta_i\right)t + \theta_i, \quad \theta_i \in [0,1]. \tag{14}$$

A copula belonging to the Durante class with generator (14) gives rise to the well-known Fréchet copula with parameter θ_i [34]. Spearman's rho and the lower and upper tail dependence coefficients, respectively, are given by

$$\rho_{ij} = \lambda_{ij}^{(L)} = \lambda_{ij}^{(U)} = \theta_i\theta_j. \tag{15}$$

Kendall's tau is given by

$$\tau_{ij} = \frac{\theta_i\theta_j\left(\theta_i\theta_j+2\right)}{3}. \tag{16}$$

The Cuadras–Augé family allows upper but not lower tail dependence, and the Fréchet family allows both upper and lower tail dependence. Moreover, in the Fréchet case, the lower and upper tail dependence coefficients are equal.

To select the best-fit copula family for our data, we calculated the mean absolute percentage errors (MAPE) using

$$\text{MAPE}_r = \frac{1}{p}\sum_{i<j}\left|\frac{\hat{r}_{i,j} - r\left(\theta_i,\theta_j\right)}{r\left(\theta_i,\theta_j\right)}\right|, \tag{17}$$

where $\hat{\tau}_{i,j}$ is the empirical estimator of Kendall's tau calculated in EViews, $\tau(\hat{\theta}_i,\hat{\theta}_j)$ is Kendall's tau estimated by FDG copulas, and p is the number of variable pairs. In the rolling window process, θ_i was computed from in-sample data and used to generate simulations for the out-of-sample period.

3.4. Systemic Risk and Risk Contribution Measurement. The best-fit FDG copula family was used to generate 10,000 simulations of return residuals ε_{t+1} for each day of the out-of-sample period. Thus, we obtained 10,000 returns from the ARMA-GJR-GARCH functions using

$$r_{t+1} = c + \sum_{i=1}^{p}\varphi_i r_t + \sum_{j=1}^{q}\rho_j\varepsilon_t + \varepsilon_{t+1}. \tag{18}$$

In the previous equation, all the parameters are known from the marginal distribution function.

The systemic risk for each day of the out-of-sample period was then computed using

$$CES_{it+1} = w_{it}\frac{\partial ES_{m,t}(C)}{\partial w_{it}} = -w_{it}\mathbb{E}_t\left(r_{it+1}\mid r_{mt+1} < C\right), \tag{19}$$

where $w_{it} = \left(W_{it}/\sum_{i=1}^{n}W_{it}\right)$ is the weight of the i^{th} sector on day t calculated by the market capitalization of each sector, r_{it+1} is the simulated return of sector i at day $t+1$, and r_{mt+1} is the future aggregate return computed by

$$r_{mt+1} = \sum_{i=1}^{29} w_{it}r_{it+1}. \tag{20}$$

The risk contribution of sector i to the whole market is thus given by

$$\begin{aligned} CES\%_{it+1}(C) &= \frac{CES_{it+1}(C)}{ES_{m,t+1}(C)}\times 100\\ &= \frac{w_{it}\mathbb{E}_t\left(r_{it+1}\mid r_{mt+1}<C\right)}{\sum_{i=1}^{29}w_{it}\mathbb{E}_t\left(r_{it+1}\mid r_{mt+1}<C\right)}\times 100, \end{aligned} \tag{21}$$

where the threshold C in this paper is value-at-risk at 1% quantile.

3.5. Risk Spillover Measurement. Adrian and Brunnermeier [35] proposed CoVaR to measure the systemic risk and ΔCoVaR to capture the marginal contribution of a particular institution (in a noncausal sense) to the overall systemic risk or to that of another institution. In this paper, we computed $\Delta\text{CoVaR}^{j|i}$ to quantify the increase in the risk of individual institution j when institution i falls into distress.

Let r_{it} be the return for sector i and r_{jt} the return for sector j at time t. CoVaR, defined as the β-quantile of the conditional distribution of r_{it}, is as follows:

$$\Pr\left(r_{jt} \le \text{CoVar}_{\beta,t}^{j|i} \mid r_{it} = \text{VaR}_{\alpha,t}^{i}\right) = \beta, \tag{22}$$

where $\text{VaR}_{\alpha,t}^{i}$ is the VaR for sector i, measuring the maximum loss that sector i may experience for a confidence level $1-\alpha$ in a specific time horizon; that is,

$$\Pr\left(r_{it} \le \text{VaR}_{\alpha,t}^{i}\right) = \alpha. \tag{23}$$

As proved by Jianxu Liu [36],

$$\Pr\left(r_{jt+1} \le \mathrm{CoVar}^{j|i}_{\beta,t+1}, r_{it+1} = \mathrm{VaR}^{i}_{\alpha,t+1}\right) = \frac{\partial C(u,v)}{\partial v}, \quad (24)$$

where $C(u,v)$ is the copula function with $u = F_{r_{jt+1}}(\mathrm{CoVar}^{j|i}_{\beta,t+1})$ and $v = F_{r_{it+1}}(\mathrm{VaR}^{i}_{\alpha,t+1})$. Thus,

$$\Pr\left(r_{jt+1} \le \mathrm{CoVar}^{j|i}_{\beta,t+1}, r_{it+1} = \mathrm{VaR}^{i}_{\alpha,t+1}\right) = \frac{\partial C(u,v)}{\partial v} = \beta. \quad (25)$$

Since α, β, and v are given, the value of u can be obtained from equation (25). CoVaR can be obtained by r_{jt+1}: $\mathrm{CoVar}^{j|i}_{\beta,t+1} = F^{-1}_{r_{jt+1}}(u)$.

The spillover effect between sector i and j is thus defined as

$$\Delta\mathrm{CoVar}^{j|i}_{\beta,t} = \mathrm{CoVar}^{j|i}_{\beta,t} - \mathrm{CoVar}^{j|i,\alpha=0.5}_{\beta,t}, \quad (26)$$

which is the difference between the CoVaR of sector j conditional on the distress of sector i and the CoVaR of sector j conditional on the "normal" state of sector i. Hence, the higher the value of $\Delta\mathrm{CoVar}^{j|i}_{\beta,t}$, the higher the vulnerability of sector j and the greater the spillover risk of sector i.

With simulated returns, in this paper, the values of ΔCoVaR for each day in the out-of-sample period were calculated using the rolling window method after specifying $\alpha = \beta = 0.01$.

4. Empirical Results

4.1. Dependence. To select the best copula families to generate simulations, we first measured the dependence coefficients to compute MAPE. Table 2 shows the average values of Kendall's tau measured by the best-fit FDG copula family for each period. A higher value represents stronger dependence. The results indicate that, for all industries, dependence was strongest during the GFC and weakest in the COVID-19 period. In the GFC period, the strong correlation between sectors greatly increased the possibility of risk contagion and thus the failure of the entire stock market. Wide differences in dependence coefficients indicate that important events in different periods greatly impacted the dependence between sectors. Hence, it is reasonable and necessary to introduce the copula model into risk measurement.

4.2. Systemic Risk. CES can be used as a proxy of systemic risk. The higher the CES, the greater the systemic risk. Values of CES in the four periods are shown in Figure 3. Different periods had different development tendencies for systemic risk. Before the full-blown financial crisis, systemic risk showed an upward trend. During the GFC, systemic risk was higher and underwent bigger fluctuations than in the other two periods, ranging from 0.034 to more than 0.1. Systemic risk in the pre-GFC and GFC periods showed greater variation than in the other two periods. The curve of the post-GFC period was relatively flat, with a peak of only 0.066, which is much smaller than in the other periods. In the COVID-19 period, the curve rose suddenly on January 20, 2020, and then reduced after a slight fluctuation. Dramatic changes are found to be highly consistent with real-time events. For example, the sharp increase between July 29 and August 31, 2009, can be attributed to the slump of the Shanghai stock index. On January 20, 2020, the transmission of coronavirus between humans was first confirmed, and fear of a severe pandemic drove systemic risk to its highest level in that period. On January 23, 2020, Wuhan relaxed its two-month lockdown, bringing systemic risk down as confidence that the epidemic could be contained greatly increased. The accuracy of the CES results demonstrates the outstanding forecasting ability of the FDG copula-based CES method.

4.3. Risk Contribution. Figures 4–7 show the average risk contribution of the 29 sectors in the four periods. The top five contributors to systemic risk in each period are presented separately in the corresponding pie charts. The banking and nonbank finance sectors were systemically important over the 15 years. It is not surprising that nearly one-fourth of the risk came from the banking sector. Before the subprime crisis, China's commercial banks had bought a moderate number of mortgage-backed securities (MBS) and collateralized debt obligations (CDOs). According to a study by Henseng Bank, at the end of November 2007, Chinese commercial banks' total holdings of subprime-loan-related bonds was \$18.2 billion [37]. During the crisis, the most influential commercial banks in China, including Bank of China, China Construction Bank, and Industrial and Commercial Bank of China, suffered substantial losses because of their subprime MBS holdings. After the GFC, the banking sector lost its dominant position. The nonbank finance sector surpassed banking to become the most influential sector, and it was as important as the banking sector during the COVID-19 period. The rise of the nonbank finance sector in recent years is a sign of the higher quality of bank-related financial services, which often include risk pooling, contractual savings, market brokering, and general investments, as well as better allocation of surplus resources to individuals and companies with financial deficits. After years of effort by the Chinese government, a more mature financial market has been built.

The transportation sector maintained its importance from the pre-GFC to the GFC period since China was highly dependent on exports to stimulate its economic growth. In 2007, China overtook the United States to become the world's second-largest exporter of merchandise after the European Union (EU). China's net exports contributed to one-third of its GDP growth in that year. In January 2009, the total volume of foreign trade fell 29% compared with the previous year, and the losses from foreign trade impacted the transportation sector directly. The results show that it is unwise to rely heavily on exports and imports of foreign goods, even if they boost the economy to some extent. The benefits are accompanied by great potential risk, and loss of initiative will lead to the adoption of a passive position in international trade negotiations.

Table 2: Dependence coefficients of 29 industrial sectors in four periods.

Sector	Pre-GFC	GFC	Post-GFC	COVID
Banking	0.59	0.67	0.62	0.50
Coal	0.53	0.62	0.54	0.49
Nonferrous metals	0.58	0.72	0.60	0.51
Power and public utilities	0.68	0.79	0.68	0.44
Steel	0.57	0.70	0.58	0.55
Chemicals	0.73	0.80	0.73	0.50
Construction	0.70	0.77	0.65	0.61
Building materials	0.69	0.78	0.68	0.54
Media	0.70	0.79	0.71	0.48
Machinery	0.70	0.82	0.73	0.58
Electronics	0.68	0.77	0.72	0.60
Computers	0.58	0.69	0.56	0.51
Cars	0.69	0.82	0.71	0.42
Commercial and retail	0.72	0.81	0.70	0.53
Consumer services	0.65	0.72	0.63	0.47
Household appliances	0.68	0.75	0.59	0.42
Textiles and garments	0.70	0.81	0.72	0.44
Pharmaceuticals	0.72	0.76	0.62	0.44
Food and beverages	0.60	0.72	0.50	0.36
Agriculture, forestry, animal husbandry and fishery	0.69	0.70	0.66	0.38
Petroleum and petrochemicals	0.50	0.58	0.33	0.29
Nonbank finance	0.49	0.58	0.49	0.42
Real estate	0.63	0.67	0.57	0.54
Transportation	0.64	0.79	0.66	0.45
Electrical equipment and new energy	0.60	0.77	0.67	0.52
Communications	0.59	0.67	0.67	0.46
National defense and military	0.63	0.75	0.63	0.49
Light manufacturing	0.55	0.75	0.62	0.49
Other	0.69	0.79	0.68	0.51

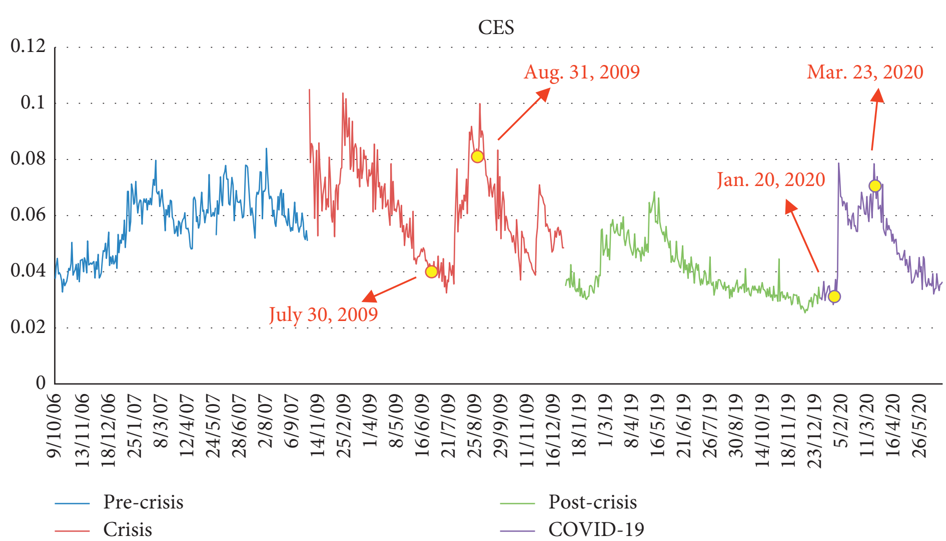

Figure 3: CES in four periods.

During the GFC, the petroleum and petrochemicals sector was highly significant because of drastic fluctuations in oil prices. Shortly before the GFC, West Texas Intermediate (WTI) prices rose by nearly 287%, from USD 52.51 to USD 145.31 per barrel. The main drivers behind this rise were supply-demand imbalances, depreciation of the US dollar, and speculation. However, after July 2008, WTI prices fell by about 80% from their peak to USD 30.28 per barrel for five months [38]. This is because after the outbreak of the GFC, there was a sharp decrease in speculative money. This quickly drove down oil prices. In recent financial crises, crude oil has shown more of the characteristics of a financial

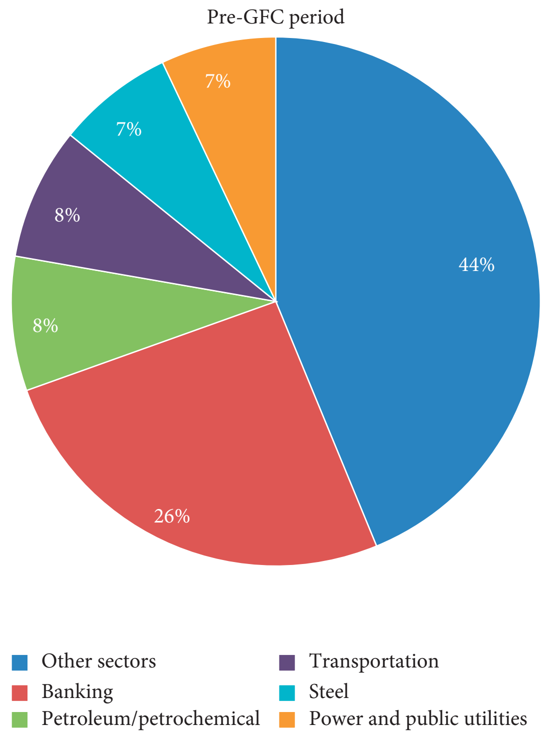

Figure 4: CES in the pre-GFC period (%).

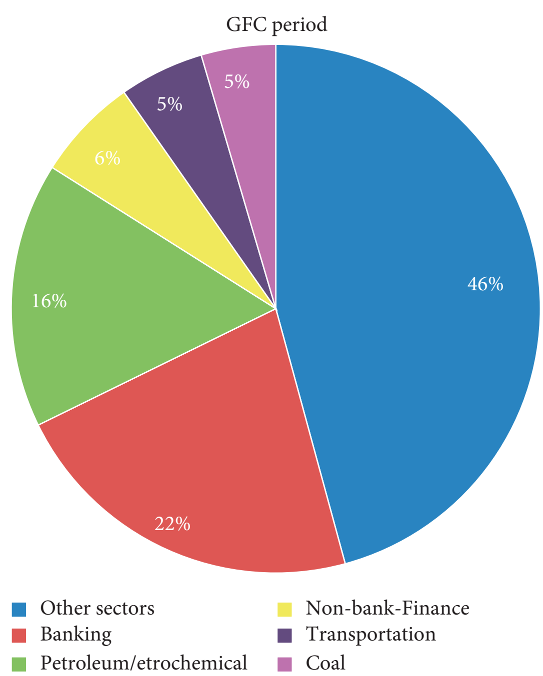

Figure 5: CES in the GFC period (%).

product than of a commodity in that it is easily affected by factors including exchange rate fluctuation, market intervention, and short-term flow of funds in international capital markets. These factors impact oil prices by affecting the supply and demand relationship or by changing investors' expectations of that relationship in the short term.

Since the GFC, the petroleum and petrochemicals and transportation sectors have become much less important. In contrast, electronics, machinery, pharmaceuticals, and computers have gradually increased their influence in the stock market. In both the post-GFC and the COVID-19 periods, the electronics sector has been the largest

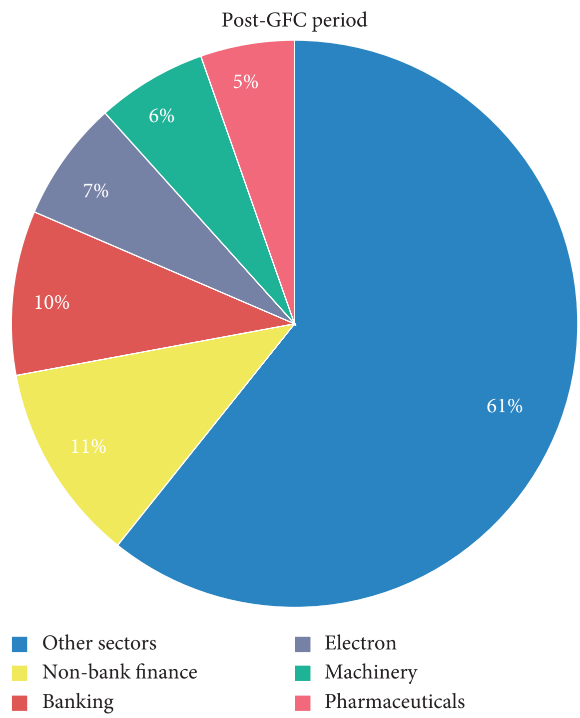

Figure 6: CES in the post-GFC period (%).

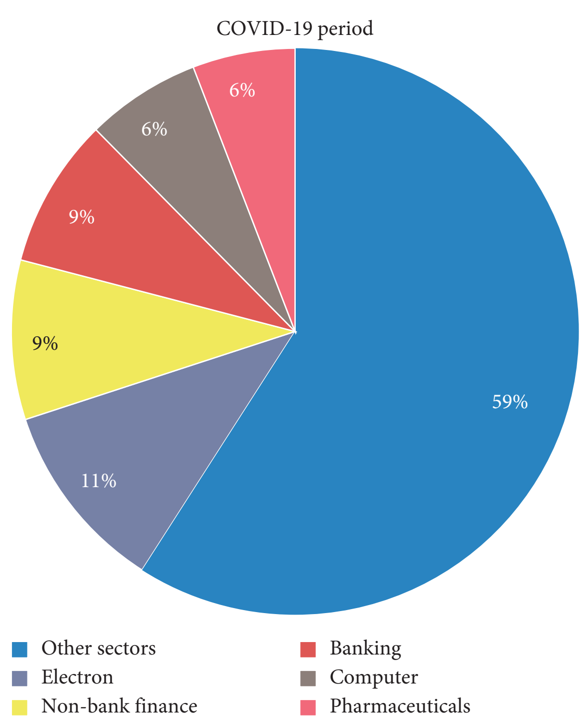

Figure 7: CES in the COVID-19 period (%).

contributor to systemic risk. It is one of the fastest-growing industries in China, with developments in 5G, artificial intelligence (AI), virtual reality (VR), and new-energy automobiles stimulating its growth. China is not only the producer but also the exporter of many electronic products, not least mobile phones and computers. The COVID-19 pandemic is notable for having fostered growth in the pharmaceuticals and computer sectors. High demand for medical equipment increased the importance of the pharmaceuticals sector, while pandemic-related home office/

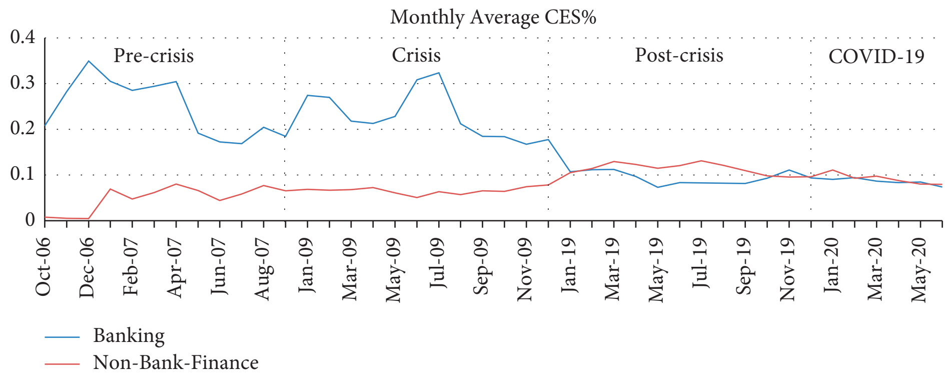

Figure 8: CES of the banking and nonbank finance sectors in four periods (%).

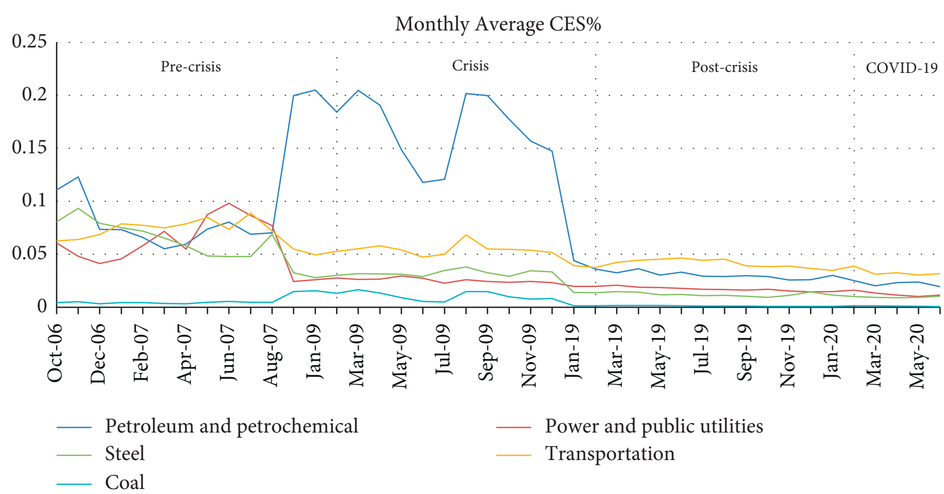

Figure 9: CES of the petroleum and petrochemicals, power and public utilities, steel, and transportation sectors in four periods (%).

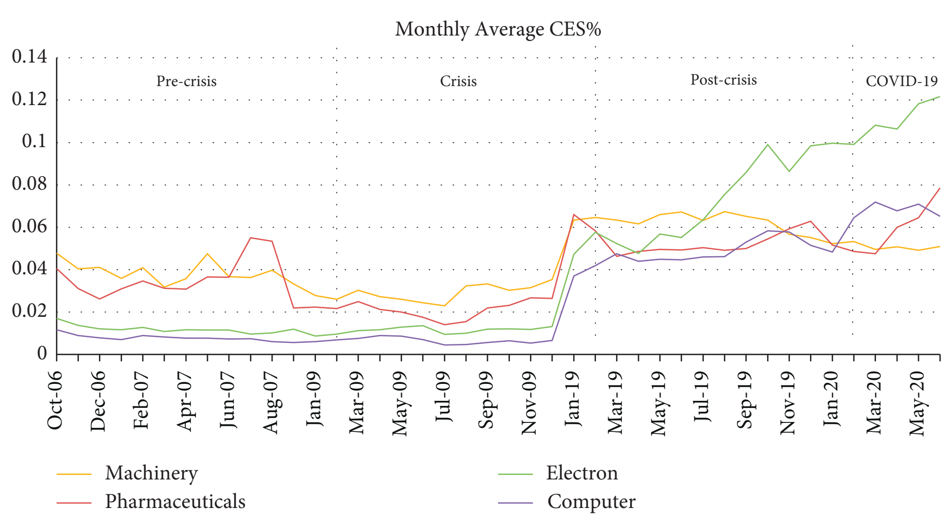

Figure 10: CES of the machinery, pharmaceuticals, electronics, and computer sectors in four periods (%).

education/entertainment and consumption stimulus policies stimulated demand for computers. In terms of the stock market, the higher risk of investing in these industries is accompanied by higher returns. If close attention is paid to these sectors, systemic risk can be foreseen and curbed in a timely and effective manner.

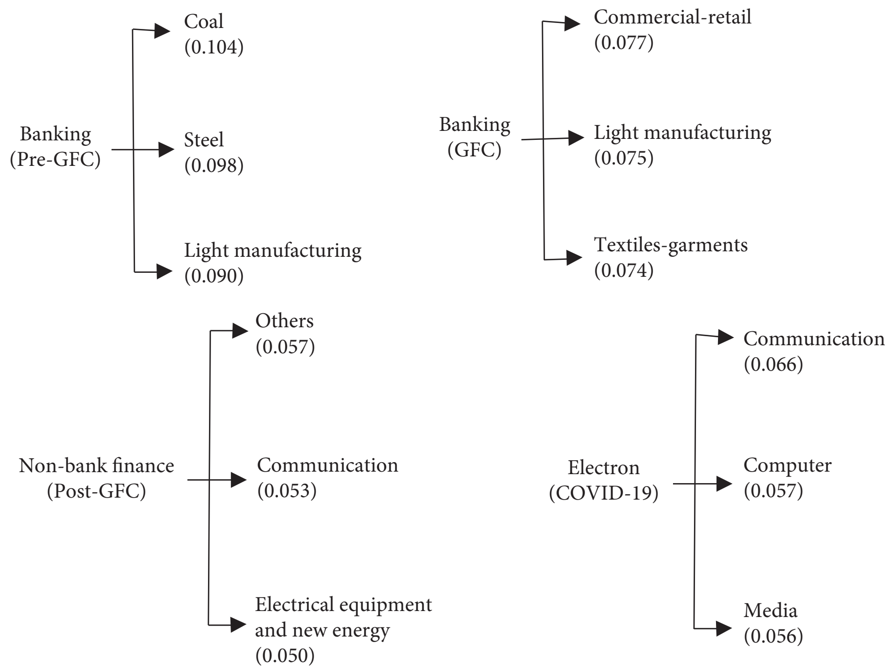

Figure 11: The three sectors that received the largest risk from the systemically most important sectors in four periods.

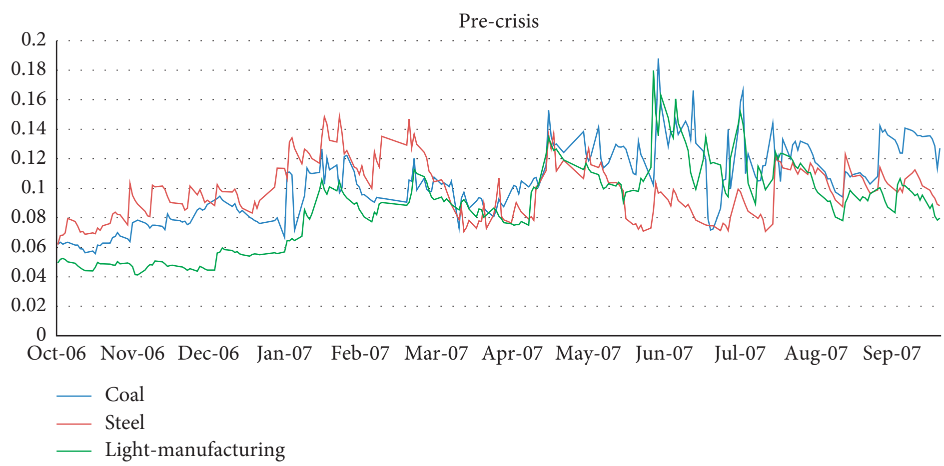

Figure 12: ΔCoVaR of the coal, steel, and light manufacturing sectors in the pre-GFC period.

It is also clear that systemic risk became more dispersed and more widely distributed across sectors in the post-GFC period. From the pre-GFC to the post-GFC period, the CES of all SISs reduced from 56% to 39%, although it increased slightly to 41% in the COVID-19 period. The tendency toward risk diversification implies a reduction in the initial shock from a single sector, which increases the difficulty of supervision, and the COVID-19 pandemic increased the importance of some sectors.

Individual sectors that appear to be systemically important at different times can be divided into three categories. Banking and nonbank finance have maintained their importance. Figure 8 shows the monthly average CES. Figure 9 shows that some sectors have gradually lost their influence on risk, whereas some previously unimportant sectors now occupy critical positions. From 2006 to 2009, the CES of the banking sector has been significantly higher than that of the nonbank finance sector. It is surprising that, in 2006, nonbank finance contributed almost zero to systemic risk. Even though the sector became more important thereafter, its contribution remained at a level no higher than 10% until it surpassed that of the banking sector in 2019. Thus, its dominant position did not last long, as shown by the tangling of the two lines on the right of Figure 8, and since the end of 2019, these two sectors have contributed almost equally to systemic risk. Nevertheless, it is encouraging to note that this balance has not been disturbed by the COVID-19 pandemic, which indicates that the financial industry is relatively stable in the face of a global shock.

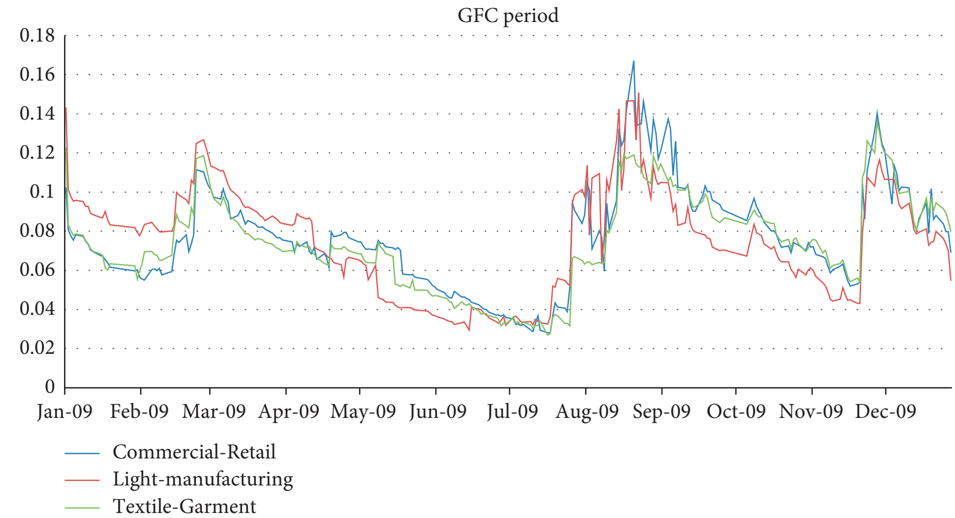

Figure 13: ΔCoVaR of the commercial-retail, light manufacturing, and textiles-garments sectors in the GFC period.

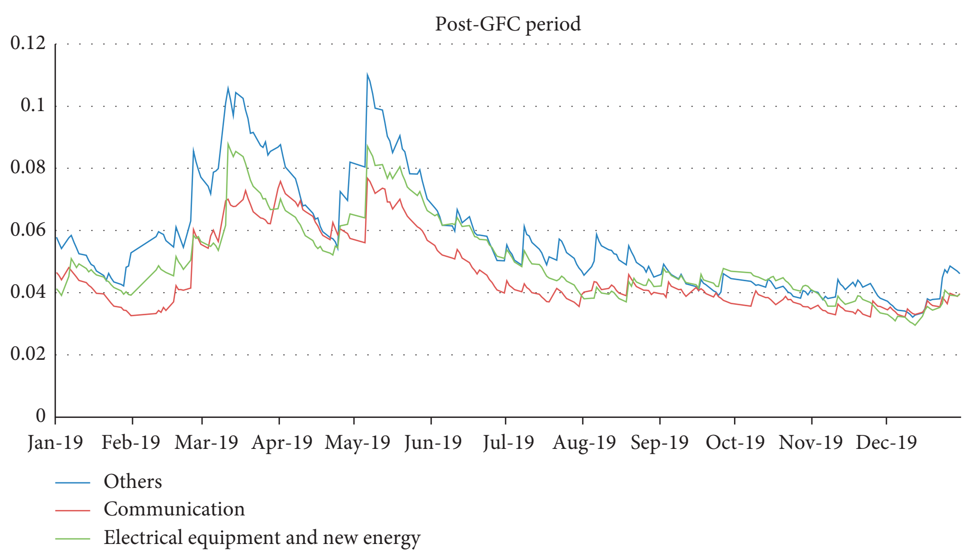

Figure 14: ΔCoVaR of the communications, other, and electrical equipment and new energy sectors in the post-GFC period.

Aside from banking and nonbank finance, five sectors appear to be systemically important in the pre-GFC and GFC periods, namely, petroleum and petrochemicals, power and public utilities, steel, transportation, and coal. Figure 9 shows the winding paths of the five lines before the GFC. Thereafter, four of these sectors contribute less, with the exception of petroleum and petrochemicals, which experienced a dramatic rise during the GFC. From 2019 to 2020, the rankings among the five sectors did not change, even during the COVID-19 period. In the post-GFC and COVID-19 periods, there were four SISs (excluding banking and nonbank finance), and their CES values are given in Figure 10. Unexpectedly, these four sectors had the lowest CES in the GFC period, unlike the SISs shown in Figures 8 and 9. From June 2019, the contribution of the electronics sector rose sharply, from 5% to 12% in a single year. Computers and pharmaceuticals also increased their influence, whereas the machinery sector became less significant.

It is worth noting that computers and pharmaceuticals were more affected by the COVID-19 pandemic, undergoing greater fluctuations in CES, than machinery and electronics, which maintained their downward and upward tendency, respectively. This is because the epidemic stimulated demand for pharmaceuticals across the whole of society, and months of lockdown increased sales of computers to meet people's home entertainment, education, and work needs. Although these four sectors appear to have been systemically important during the COVID-19 period, we do not know whether this situation will continue after the pandemic.

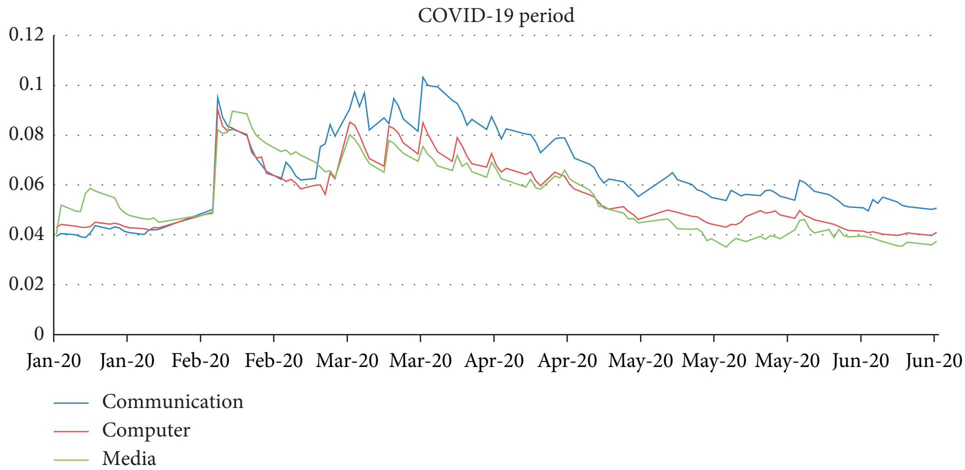

Figure 15: ΔCoVaR of the communications, computer, and media sectors in the COVID-19 period.

4.4. Spillover Effect. Following our analysis of CES, we measured the spillover effect between the most influential sector and other sectors. Figure 11 shows the three sectors with the greatest unidirectional spillover effect in each period. The value of ΔCoVaR (given in parentheses) shows the increase in CoVaR at a 1% level of significance when the former moves from its normal state to a distressed state. For example, in the pre-GFC period, the distress of the banking sector caused an increase of 0.104 in the CoVaR of the coal sector. This means that if USD 100 was invested in the coal sector, there was a 99% chance that the maximum loss in that sector would increase (USD $100 \times 0.104 =$ USD 10.4). Taking the value of ΔCoVaR given in Figure 11, we find that the spillover effect was at its strongest before the GFC and that it decreased over time until COVID-19 drove it up. This means that even a crisis that does not originate from the financial industry will increase the spillover effect between sectors, and a strong spillover effect in the pre-GFC period could have been taken as an early warning of a severe crisis. In the GFC period, the top receivers of risk were commercial and retail, light manufacturing, and textiles and garments. These three sectors are closely related to export, and products from them account for a large proportion of exported goods. Overreliance on exports therefore brought high risk contagion from the banking sector to these sectors.

During the COVID-19 pandemic, the electronics sector transmitted more than 5% risk to the communications, computer, and media sectors. One of the main products in the electronics sector, semiconductors, are an important raw material for products in those other sectors. This result indicates that the copula-CoVaR method is accurate, as electronics is strongly connected with these three sectors regardless of which period is under consideration. It is hard to tell whether the COVID-19 pandemic has strengthened the correlations between them. If we combine the results for risk spillovers with the results for SISs, we see that only steel and computers appear to be both systemically important and vulnerable in the same period. This means that the most important sector is not very influential on other SISs and, specifically, that less important sectors are more vulnerable to contagion risk. The substantial differences between the top risk receivers in different periods reflects the complexity and volatility of linkage between industrial sectors.

To take a closer look at the risk spillover throughout the four periods, we considered the values of ΔCoVaR for the top three vulnerable sectors, shown in Figures 12–15. Notably, the three lines show similar trends to each other in each period. A comparison of these figures with Figure 3 shows that, regardless of the period, the spillover effect fluctuates in a similar way to systemic risk. This means that higher systemic risk brings a stronger spillover effect. It should also be noted that the systemic risk and spillover effects were measured using different methods (FDG-based CES and ΔCoVaR), which indicates that the models we used are both robust and practical.

5. Conclusions

In this study, daily stock index data for 29 sectors were used to measure systemic risk and risk contribution in China using the FDG copula-based CES method. We show that the banking sector contributed most to systemic risk in the pre-GFC and GFC periods. In 2009, the nonbank finance sector took first place, reflecting the maturing of the financial system in China. In the first half of 2020, which saw the beginning of the COVID-19 pandemic, the electronics sector appeared to be the largest contributor to systemic risk. Some sectors, including computers and pharmaceuticals, were made systemically important by the pandemic. Following our risk contribution assessment, we investigated the risk spillover effect between the most systemically important sector and other sectors using bivariate copula-based ΔCoVaR. As expected, the COVID-19 pandemic increased risk contagion, and there is evidence of a strong positive correlation between systemic risk and risk spillover. It is not enough to focus on the risk contribution of individual sectors, as some sectors are sensitive to an increase in risk in the systemically most important sector. Risk contagion between sectors must also be considered to ensure timely and efficient risk management.

Our results yield a number of practical implications. For the government, SISs should be monitored closely so that favorable policies at the macro level can be implemented in a timely manner to control the influence of certain industries and thus maintain market stability. It is equally important for supervision departments to focus on comovements and linkages between the most influential sector and sectors that are vulnerable and/or weak. An increase in risk spillover can be taken as a sign of an increase in systemic risk. Beyond the banking and nonbank finance sectors, investors should pay more attention to emerging sectors, such as pharmaceuticals, electronics, and computers, the development of which has been fostered by the COVID-19 pandemic. Investors could profit from these sectors, as the COVID-19 pandemic may last for several years. For future studies, the FDG copula-based CES approach has been shown to be suitable and accurate in high-dimensional applications. This method could therefore be applied to both the assessment and forecasting of systemic risk.

Data Availability

The daily data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the Faculty of Economics and the Centre of Excellence in Econometrics at Chiang Mai University, the China–ASEAN High-Quality Development Research Center in Shandong University of Finance and Economics, and the Education Plan of the Youth and Creative Talents in Shandong Higher Education Institutions.

References

[1] European Central Bank, *Financial Stability Review*, 2009, https://www.ecb.europa.eu/pub/pdf/fsr/financialstabilityreview200912en.pdf.

[2] N. Borri and G. D. Giorgio, "Systemic risk and the COVID challenge in the European banking sector," *Journal of Banking & Finance*, 2021, in Press.

[3] P. G. Gavronski and F. A. Ziegelmann, "Measuring systemic risk via GAS models and extreme value theory: revisiting the 2007 financial crisis," *Finance Research Letters*, vol. 38, 2021.

[4] F. Wu, "Sectoral contributions to systemic risk in the Chinese stock market," *Finance Research Letters*, vol. 31, pp. 386–390, 2019.

[5] W. Zhang, X. Zhuang, J. Wang, and Y. Lu, "Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network," *The North American Journal of Economics and Finance*, vol. 54, 2020.

[6] S. R. Baker, N. Bloom, S. J. Davis, and S. J. Terry, "COVID-induced economic uncertainty," *NBER Working Paper Working Paper 26983*, 2020, in Press.

[7] Y. Huang, L. Chen, P. Wang, and Z. Xu, "Saving China from the Coronavirus and economic meltdown: experiences and lessons," *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever it Takes*, 2020.

[8] D. Zhang, M. Hu, and Q. Ji, "Financial markets under the global pandemic of covid-19," *Finance Research Letters*, vol. 36, Article ID 101528, 2020.

[9] Q. Xu, M. Li, C. Jiang, and Y. He, "Interconnectedness and systemic risk network of Chinese financial institutions: a LASSO-CoVaR approach," *Physica A: Statistical Mechanics and its Applications*, vol. 534, 2019.

[10] X. Li, H. Yu, L. Fang, and C. Xiong, "Do firm-level factors play forward-looking role for financial systemic risk: evidence from China," *Pacific-Basin Finance Journal*, vol. 57, 2019.

[11] D. Morelli and D. Vioto, "Assessing the contribution of China's financial sectors to systemic risk," *Journal of Financial Stability*, vol. 50, 2020.

[12] X. L. Gong, X. H. Liu, X. Xiong, and W. Zhang, "Financial systemic risk measurement based on causal network connectedness analysis," *International Review of Economics & Finance*, vol. 64, pp. 290–307, 2019.

[13] X. L. Gong, X. H. Liu, X. Xiong, and W. Zhang, "Research on China's financial systemic risk contagion under jump and heavy-tailed risk," *International Review of Financial Analysis*, vol. 72, 2020.

[14] F. Wu, D. Zhang, and Z. Zhang, "Connectedness and risk spillovers in China's stock market: a sectoral analysis," *Economic Systems*, vol. 43, no. 3–4, 2019.

[15] J. Hao and F. He, "Univariate dependence among sectors in Chinese stock market and systemic risk implication," *Physica A: Statistical Mechanics and its Applications*, vol. 510, pp. 355–364, 2018.

[16] S. Feng, S. Huang, Y. Qi, X. Liu, Q. Sun, and S. Wen, "Network features of sector indexes spillover effects in China: a multi-scale view," *Physica A: Statistical Mechanics and its Applications*, vol. 496, pp. 461–473, 2018.

[17] H. Ru, E. Yang, and K. Zou, "Combating the COVID-19 pandemic: the role of the SARS imprint (january 19, 2021)," *Management Science*, vol. 67, no. 9, pp. 5606–5615, 2020.

[18] H. Shen, M. Fu, H. Pan, Z. Yu, and Y. Chen, "The Impact of the COVID-19 pandemic on firm performance," *Emerging Markets Finance and Trade*, vol. 56, no. 10, pp. 2213–2230, 2020.

[19] Y. Feng and X. Li, "Causal estimation of COVID-19 and SARS on China's stock market: evidence from a time series counterfactual prediction," *Economic Research-Ekonomska Istraživanja*, pp. 1–17, 2021.

[20] N. Apergis and E. Apergis, "The role of covid-19 for Chinese stock returns: evidence from a GARCHX model," *Asia-Pacific Journal of Accounting & Economics*, pp. 1–9, 2020.

[21] X. Huo and Z. Qiu, "How does China's stock market react to the announcement of the COVID-19 pandemic lockdown?" *Economic and Political Studies*, vol. 8, no. 4, pp. 436–461, 2020.

[22] V. Acharya, L. Pedersen, T. Philippe, and M. Richardson, "Measuring systemic risk," Technical Report, Department of Finance, NYU, New York, NY, USA, 2010.

[23] T. C. Brownlees and R. F. Engle, "Volatility, correlation and tails for systemic risk measurement," Work Paper, SSRN 1611229, New York University, New York, NY, USA, 2012.

[24] G. D. Banulescu and E. I. Dumitrescu, "Which are the SIFIs? a component expected shortfall approach to systemic risk," *Journal of Banking & Finance*, vol. 50, pp. 575–588, 2015.

[25] G. Mazo, S. Girard, and F. Forbes, "A flexible and tractable class of one-factor copulas," *Statistics and Computing*, vol. 26, no. 5, pp. 965–979, 2016.

[26] D. Schmidt, "The financial crisis and its impact on China," *Economics Research International*, vol. 67, 2009.
[27] K. Jebran, "Volatility spillover between stock and foreign exchange market of China: evidence from subprime Asian financial crisis," *Journal of Asia Business Studies*, vol. 12, no. 2, pp. 220–232, 2018.
[28] L. Li, T. D. Willett, and N. Zhang, "The effects of the global financial crisis on China's financial market and macroeconomy," *Economics Research International*, vol. 2012, Article ID 961694, 6 pages, 2012.
[29] G. J. Wang, C. Xie, M. Lin, and H. E. Stanley, "Stock market contagion during the global financial crisis: a multiscale approach," *Finance Research Letters*, vol. 22, pp. 163–168, 2017.
[30] H. Yu, L. Fang, B. Sun, and D. Du, "Risk contribution of the Chinese stock market to developed markets in the post-crisis period," *Emerging Markets Review*, vol. 34, pp. 87–97, 2018.
[31] L. R. Glosten, R. Jagannathan, and D. E. Runkle, "On the relation between the expected value and the volatility of the nominal excess return on stocks," *The Journal of Finance*, vol. 48, no. 5, pp. 1779–1801, 1993.
[32] F. Durante, "A new class of symmetric bivariate copulas," *Journal of Nonparametric Statistics*, vol. 18, no. 7-8, pp. 499–510, 2006.
[33] C. M. Cuadras and J. Augé, "A continuous general multivariate distribution and its properties," *Communications in Statistics—Theory and Methods*, vol. 10, no. 4, pp. 339–353, 1981.
[34] M. Fréchet, "Remarques au sujet de la note précédente," *Comptes Rendus de l'Académie des Sciences Sér. I Math*, vol. 246, pp. 2719-2720, 1958.
[35] T. Adrian and M. K. Brunnermeier, "CoVaR," *American Economic Review*, vol. 106, no. 7, pp. 1705–1741, 2016.
[36] J. Liu, *Applications of Copula Econometrics to Analyses of Some Economic Issues*, Chiang Mai University, Chiang Mai, Thailand, 2013.
[37] Y. Yu, "The impact of the global financial crisis on the Chinese economy and China's policy responses," *TWN Global Economy Series No. 25*, Third World Network, Jalan Macalister, Malaysia, 2010.
[38] K. Joo, J. H. Suh, D. Lee, and K. Ahn, "Impact of the global financial crisis on the crude oil market," *Energy Strategy Reviews*, vol. 30, 2020.