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Two-Way Risk Spillover of Financial and Real Sectors in the Presence of Major Public Emergencies

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Abstract: In order to study the two-way risk spillovers between financial and real industries under major public emergencies in the Chinese market from 2007 to 2020, the sample period of major emergencies was determined based on the value at risk (VaR) time series, and it was found that the impact of major emergencies would lead to the rise of systemic risks in the financial industry. Secondly, the real sectors are taken as the main research object to measure the value of systemic risk spillover by using DCC-GARCH, and it shows that the industry with significantly systemic vulnerability from the overall financial risk spillover is the real estate industry, material industry, and energy industry. The results of subdividing financial sectors show that the banking sector has the most significant contribution to financial risk spillover in the real sectors. At the same time, identify the systemically important industries with high spillover risk to the financial industry, namely, utilities, consumer discretionary and industrials. Among the financial sub-industries, the risk spillover to the securities industry from the real sectors is the most significant. Finally, it was found that the system vulnerability and importance characteristics of the real entity industry depend on the nature of events and have certain rules.

Keywords: systemic financial risk; major public emergencies; conditional value at risk; DCC-GARCH

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Citation: Li, Y.; Zhang, Z.; Niu, T. Two-Way Risk Spillover of Financial and Real Sectors in the Presence of Major Public Emergencies. *Sustainability* **2022**, *14*, 12571. https://doi.org/10.3390/su141912571

Academic Editor: Francesco Tajani

Received: 3 September 2022
Accepted: 28 September 2022
Published: 2 October 2022

1. Introduction

The financialization and innovative business of the real entity industry have accelerated deep integration with the financial industry, and the inter-industry linkages have become increasingly close and complex, which has become an important source and spillover path of systemic financial risks. However, the way of defining the category of systemic financial risk in academic circles has not been unified. Based on the existing literature, we believe that systemic financial risk is the adverse impact of financial micro-individuals on themselves and external economies through their direct and indirect related businesses. It mainly reflects three characteristics: overall impact on the financial sector, correlations between institutions, and closely related to the operation of the macro economy. The root causes of systemic financial risks can be considered from internal and external factors. From the perspective of internal factors, the close and intricate connections within the financial industry and with the real entity industry, amplify the risk of agglomeration and form specific spillover paths. These paths include interbank transactions between financial institutions, derivatives transactions and payment systems, the credit and debt relationships between financial and entity institutions, to name a few. From the perspective of external factors, systemic risks can be linked to the financial market through foreign trade and investment channels, such as a decline in import demand, and shrinking overseas investment. In addition, the default event, debt crisis and governance of the enterprise itself can also affect systemic financial risks. Among these events, default events have the most direct impact [1–3], which may lead to an imbalance in the financial or economic sector, such as deterioration of financial conditions, and equity risk premium [4,5]. When the risk accumulates to a certain level, the price of financial assets will deviate, and the relationship between creditor's rights and debts between institutions will deteriorate. This may damage the financial system, stop its functions, or even cause a sharp economic recession in severe cases [6].

The existing theoretical research on the interaction mechanism between finance and the real economy has undergone a transition from separation to interaction theory, and then to interaction and crisis models. Although the two mechanisms are different under different theoretical frameworks, they are closely related. For one thing, changes in the financial industry and policy orientation are crucial to the stability of the real economy; for another, the development of the financial industry is also constrained by the real economy. The life cycle of the real entity industry, industrial upgrading and changes determine the financial industry lending preferences and capital flows. Therefore, systemic financial risks not only exist within the financial industry but may be transmitted from the real industry to the financial industry, repeating cycles.

The systemic risk of the market includes two aspects, namely risk exposure and risk contribution, which have opposite directions of risk transmission. Risk exposure refers to the risk that institutions will be seriously threatened and faced in the event of a crisis, which is generally expressed by system vulnerability. The risk contribution is that when these markets get into trouble during a crisis. It is the most dangerous for the financial system as a whole, and it is generally expressed as systemically important. In recent 10 years, China is facing a complex and changeable environment. Natural disasters, accidental disasters, social security, and major public health emergency events (hereafter referred to as the "major events"), have intensified the severity of the financial risk spillover between the entity industry, increasing the difficulty of major risk prevention. Previous "micro-prudential supervision" policies focused on individual risks of financial institutions and were insufficient to deal with major shocks. At present, China's financial regulatory policy is also in the transition to the "macro-prudential policy" to prevent and defuse systemic financial risks and adhere to the introduction of monetary policy and macro-prudential policy regulatory framework. The nature of market risk determines that different markets are corresponding to different policy instruments. However, current academic research mainly focuses on the discussion of one aspect of systemic risk, and rarely considers two-way spillovers which is the novelty of this paper. In-depth research on the classification of sub-markets is also lacking. Therefore, in-depth study of the characteristics and transmission paths of China's systemic financial risks, measurement of the risk spillover intensity between the financial and real sectors, and identification of systemically important and vulnerable industries have become meaningful topics to be studied urgently. Through identifying the systemically important and vulnerable industries in financial and entity spillovers and summarizing the market rules under major emergencies by using DCC-GARCH, this paper clarifies and summarizes the impact and rules of major events while also observing the two-way spillover channels and monitoring priorities of financial and entity industries. At the same time, it is of theoretical and practical significance for preventing and defusing major risks, ensuring financial stability and security, and improving the financial sector's support and service quality to the real economy.

The structure of the rest of this paper is arranged as follows. The second section provides a literature review about systemic financial risk. The third part is the research design, including the DCC-GARCH model and the ΔCoVaR measurement method, and the source of the sample data is explained. The fourth section contains the empirical research and results from the analysis, including the identification of systemically vulnerable industries and risk spillover analysis of financial sub-sectors to entity industries, as well as the identification of systemically important entity industries and risk spillover analysis to financial sub-sectors. The fifth part considers the risk spillover between financial and entity industries during major events. The sixth part discusses the robustness test. The final part summarizes the research conclusions and outlines policy recommendations.

2. Literature Review

The measurement index and method of systemic financial risk spillover are the core contents of systemic financial risk research. The existing literature is mainly developed along two paths: one is to build a risk spillover network model based on the financial data of financial institutions (such as capital structure, current assets, and leverage ratio) [7]. This method can intuitively identify risk transmission paths through financial data and determine the impact of risk spillovers on the daily operations of enterprises. However, due to the low frequency of data, it is only suitable for tracking and reflecting medium-term and long-term risk spillover changes. The second is to construct risk spillover indicators based on financial market transaction data [8–11]. Market transaction data contains investors' expectations for the market. Compared with financial data, it is more real-time information and is suitable for reflecting the short-term time-varying characteristics under the impact of major events, although it is difficult to reflect on actual business relationships. Representative papers based on the latter include: Diebold and Yilmaz [9] constructed a risk spillover indicator based on the variance decomposition results of the prediction error of the Vector Autoregression (VAR) model to reflect the tail dependence of transaction data on different financial markets; the conditional value-at-risk (ΔCoVaR) indicator proposed by Tobias and Brunnermeier [10] to describe the directional risk spillover between variables, which can be used to reflect causal relationship characteristics and tail distribution characteristics. At the same time, compared with the VaR (value at risk) which can only measure the value at risk of individual financial institutions, ΔCoVaR can also measure the risk spillover of a single institution to other institutions when the loss exceeds a certain threshold. As a result, ΔCoVaR is widely used in the measurement research of systematic financial risk spillover [12]. At present, the measurement methods of ΔCoVaR mainly include quantile regression and the Copula function method. However, the above methods struggle to describe complex and nonlinear risk relationships, nor can they describe the time-varying characteristics of systemic risk contributions. In contrast, the DCC-GARCH model has obvious advantages. It can effectively estimate the correlation coefficient matrix, express the nonlinear correlation between variables, and is good at capturing the time-varying systemic risk exposure of the financial industry (or institution) by fitting the dynamic correlation coefficient change process [13].

The existing literature mainly focuses on the financial industry by discussing the formation mechanism, transmission channels, and important institutions of systemic financial risks from the perspective of time and space. The main points include: (1) The direct relationship between assets and liabilities of different types of financial institutions is the main channel for risk spillover, which is reflected in the transmission from the interbank market to the non-bank financial market. For example, the insurance industry risks mainly originate from the insurance assets directly held by banks and major insurance trigger events [14]. (2) The indirect correlation of the similarity of assets held by financial institutions can trigger risk spillover effects through asset prices and information contagion channels [15–17]. Risk changes in financial industries such as banking, securities, and insurance have synchronicity and obvious risk spillover capabilities, with asymmetric characteristics. Among them, the banking industry plays a leading role in the risk spillover, especially the large commercial banks located in the central link of the financial risk spillover network [18].

Systemic financial risks are not only transmitted within the financial industry, but also between real industries. Chiu et al. [19] used data from the US real and financial sector, showing that the financial industry has a net risk spillover effect on the real economy, and the performance is more pronounced during financial crisis. Some studies have found through the theory of financial frictions that the finance and the real economy share a pro-cyclical phenomenon of prosperity and recession [20]. In addition, finance and the real economy have business connections on various financial assets such as deposits and loans, bonds and stocks, and they have the conditions for multiple rounds of risk spillovers. Empirical tests have found that the coordinated changes in asset volatility across industries show highly nonlinear characteristics. Another study, examining the relationship between bank stability and the real economy and inflation in OECD countries, found that when the systemic risk level of the banking industry was relatively high, the negative impact on GDP was greater [4,21]. Besides, the pro-cyclical characteristics of the financial leverage of real enterprises have increased the intensity of systemic financial risks, and the mutual influence of corporate net value and loan interest rates has changed the network connection structure with banks through bank-enterprise lending relationships, affecting the path and method of risk contagion [22]. Government guarantees will also magnify the economic consequences of risks through the inter-industry risk linkage mechanism [23]. Therefore, for the banking industry and other financial industries, the leverage ratio, short-term debt ratio and other solvency indicators of entity enterprises with close business connections are the focus of monitoring [15].

Based on the above literature, existing studies have conducted in-depth research on the causes of systemic financial risks, the measurement of risk spillovers, the internal risk transmission of the financial industry, and the risk transmission with the real entity industry. However, there are few comprehensive descriptions of the characteristics and transmission mechanism of two-way risk spillovers between the financial and the real entity industry under major events. Si et al. [24] took the “COVID-19” pandemic event as an example and confirmed that the impact of the pandemic exacerbated the volatility of China’s energy market, and risk spillovers are mainly reflected in oil extraction, electricity, natural gas, coal, and petrochemical industries. The existing research focuses on the channel of systemic financial risk at the bank level. The systemic financial risk spillover needs to be considered by the whole industry. However, the existing research does not consider the two-way spillover of systemic risk in the financial and real industries, it rarely reflects the differences in contributions from the industries to the process of risk spillover, the impact of major events in particular is less systematically displayed. The impact and characteristics of risks between financial and real industries under the impact of major events.

Given this, we selected China’s financial industry (including 4 sub-sectors) and 10 real industries from 2007 to 2020, measured the conditional value at risk (ΔCoVaR) between the financial and real industries through the DCC-GARCH model, and compared the financial and real industries during major events. The characteristics of risk spillovers between real industries were identified, and on this basis, policy recommendations have been put forward. Different from previous studies, this study: (1) The conditional value at risk was measured by using the partial t-distribution assumption of return that could capture the “peak thick tail” characteristics of the return residual sequence and using the DCC-GARCH model to estimate the correlation coefficient matrix (ΔCoVaR), showing the two-way risk spillover characteristics of China’s financial and physical industries in the past decade. (2) Viewing the financial industry as a whole, its four financial sub-industries of banking, securities, insurance and diversified finance were selected to test the two-way risk spillover intensity from the financial industry and its sub-industries to 10 real industries. Among the financial industry and the real industry, the systemically important industries in the risk spillover and the systemically vulnerable industries in the risk reception were identified, respectively. (3) The changes of systematic risk two-way spillovers between financial and real industries during the subsample period of major events were measured, and a summary of the multi-sector, multi-channel and two-way feedback characteristics of risk spillovers between financial and real industries under the influence of different major events was produced.

3. Research Design

3.1. Model Setting

The empirical process mainly included two steps. First, use of the DCC-GARCH model to fit the logarithmic return series of the financial and real sector indices to obtain the dynamic correlation coefficient between industries. Secondly, the ΔCoVaR was obtained to identify the systemic vulnerable and important industries in the financial and real sectors.

3.1.1. DCC-GARCH Model

The GARCH model is based on the ARCH model and conditional heteroscedastic and conditional meanness assumptions, which are used to fit the forecast model of the return rate of a single financial market. However, the DCC-GARCH model proposed by Engle (2002) [25] is more suitable for further study of the correlation of returns among multiple markets. It improves the constant assumption of the traditional GARCH model and is suitable for describing the nonlinear risk correlation and agglomeration between financial and real industries, as well as measuring the contribution degree of risk spillover of financial sub-industries. The risk spillover proxy indicator is obtained by estimating the ΔCoVaR value of asset returns in the financial industry. Assuming that the financial time series formed by the industry's daily rate of return obeys the GARCH distribution, then the DCC setting is selected to capture the time-varying nature of systemic risk exposures. Suppose the logarithmic rate of return R_t of the industry obeys the following distribution, see Formula (1):

$$\begin{cases} r_1 \mid \Omega_{t-1} \sim N(0, H_t) \\ H_t = D_t R_t D_t \\ R_t = (\mathrm{diag}(Q_t))^{-1/2} Q_1 (\mathrm{diag}(Q_t))^{-1/2} \\ D_t = \mathrm{diag}\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \cdots, \sqrt{h_{NN,t}}\right) \end{cases} \tag{1}$$

Among them, Ω_{t-1} represents the information set in the period t, R_t represents the dynamic correlation coefficient matrix, D_t represents the conditional standard deviation consists of a diagonal matrix ($h_{NN,t}$, the conditional variance, is obtained by fitting a GARCH model of a single financial variable), and H_t represents the conditional covariance matrix.

The dynamic correlation coefficient matrix Rt satisfies the following conditions, see Formulas (2) and (3):

$$Q_t = (1 - \psi - \xi)\overline{Q} + \zeta Q_{t-m} + \psi \delta_{i,t-n} \delta_{j,t-n} \tag{2}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3}$$

Among them, Q_t represents the covariance matrix, $\overline{Q}$ represents the unconditional covariance matrix after standardization of residuals, ψ represents lag n standardized residual coefficients of order, and ξ, denotes the conditional variance coefficient of m order lag. ψ and ξ are both non-negative and satisfy $\psi + \xi < 1$.

The dynamic conditional correlation coefficient between finance and real industries under the DCC-GARCH (1, 1) model is shown in Formula (4):

$$\rho_{i,t} = \frac{(1 - \psi - \xi)\overline{q}_{ij} + \xi q_{i,t-1} + \psi \delta_{i,tt1} \delta_{j,t-1}}{\left[(1 - \psi - \xi)\overline{q}_{ii} + \xi q_{i,t-1} + \psi \delta_{i,t-1}^2\right]^{1/2} \left[(1 - \psi - \xi)\overline{q}_{jj} + \xi q_{jj,t-1} + \psi \delta_{j,t-1}^2\right]^{1/2}} \tag{4}$$

Among them, $q_{ij,t-1}$, $q_{ii,t-1}$ and $q_{jj,t-1}$ all represent the elements in the covariance matrix Q_t. Accordingly, $\overline{q}_{ij}, \overline{q}_{ii}, \overline{q}_{jj}$ all represent the elements in the unconditional covariance matrix $\overline{Q}$ after the normalization of residuals.

3.1.2. Conditional Value at Risk (ΔCoVaR)

According to the conditional value at risk (ΔCoVaRq) index (subscript q is the confidence level, set to 0.05) proposed by Adrian and Brunnermeier [11], we define the entity industry set $\overline{\overline{N}}$ = {1, 2, . . . , N}, and the financial sub-industry set $\overline{\overline{K}}$ = {1, 2, . . . , K }. i ∈ $\overline{\overline{N}}$ denotes the real entity industry, j denotes the financial sector, and k ∈ $\overline{\overline{K}}$ denotes the financial industries.

According to the above assumptions, $\Delta CoVaR_q^{i|j}$ measures the risk spillover of financial sector j to real sector i, and $\Delta CoVaR_q^{i|k}$ measures the risk spillover of financial industry k to real entity industry i. Similarly, the risk spillover from the real entity industry i to the financial sector is $\Delta CoVaR_q^{j|i}$, and the risk spillover from real entity industry i to financial industry k is $\Delta CoVaR_q^{k|i}$. $\Delta CoVaR_q^{i|j}$, $\Delta CoVaR_q^{j|i}$, $\Delta CoVaR_q^{i|k}$ and $\Delta CoVaR_q^{k|i}$ have a similar calculation method. As $\Delta CoVaR_q^{i|j}$ for example, see Formula (5):

$$\Delta \mathrm{CoVaR}_{q,t}^{i|j} = \mathrm{CoVaR}_t^{i|VaR_q^j} - \mathrm{CoVaR}_t^{i|VaR_{0.5}^j} \tag{5}$$

Among them, $\Delta CoVaR_q^{i|j}$ represents risk spillover value of the real industry i to the financial industry j. VaR_q^j, the value at risk, determined by Pr (R j $\leq -VaR_q^j$) = 1 − q, represents the maximum daily loss rate of the financial industry j under the given confidence level q (R j represents the daily logarithmic rate of return of the financial industry), which also reflects the risk level of financial industry j under stress. $VaR_{0.5}^j$ is the maximum daily loss rate of the financial industry j under the 50% confidence level, indicating that the industry is in a normal state. $\Delta CoVaR_{q,t}^{i|j}$ represents the difference in the value at risk of the entity industry i between the financial stress state and the normal state, reflecting the risk spillover of the financial industry to the entity industry. $CoVaR_t^{i|VaR_q^j}$ represents the value at risk of the real entity industry i when the financial industry is under stress; $CoVaR_t^{i|VaR_{0.5}^j}$ represents the value at risk of the real entity industry i when the financial industry is in a normal state.

Let Q(q) be the q quantile value of the distribution that the return rate of the entity industry i obeys when the confidence level is 1- q, and the dynamic correlation coefficient is obtained through the DCC function to infer $CoVaR_{q,t}^{i|j}$. The dynamic correlation coefficient and the expressions of VaR and CoVaR have been obtained under the framework of DCC-GARCH, see Formulas (6) and (7):

$$V_{q,t}^i = \hat{u}_t^i - Q(q)\hat{h}_t^i \tag{6}$$

$$\mathrm{CoVaR}_{q,t}^{i|j} = \gamma_t^{i|j}\mathrm{VaR}_{q,t}^i \tag{7}$$

From Formula (5), we get:

$$\Delta\mathrm{CoVaR}_{q,t}^{i|j} = \gamma_t^{i|j}\left(\mathrm{VaR}_{q,t}^i - \mathrm{VaR}_{0.5,t}^i\right) \tag{8}$$

$$\gamma_t^{i|j} = \rho_{ij,t}\sigma_{i,t}^2/\sigma_{j,t}^2 \tag{9}$$

Perform de-dimensioning processing on $CoVaR_{q,t}^{i|j}$ to obtain the conditional risk spillover degree (%Δ CoVaR), see Formula (10):

$$\%\Delta\mathrm{CoVaR}_{q,t}^{i|j} = \Delta\mathrm{CoVaR}_{q,t}^{i|j}/\mathrm{VaR}_{q,t}^i * 100\% \tag{10}$$

3.2. Data Sources and Processing

11 Wind primary industry indices in the financial industry and the real entity industry were selected. The sample interval was from 4 January 2007 to 22 October 2020, including 3356 groups of observations. The first-order logarithmic difference processing of the daily closing price of the selected index was performed to obtain the logarithmic return. Descriptive statistics are shown in Table 1.

From Table 1, the average logarithmic rate of return of the sample industry was around 0, and the kurtosis coefficient of the return series was significantly higher than the kurtosis of the normal distribution 3, showing a typical "peak and thick tail" distribution characteristic. The results of the stationarity test show that the series of returns of various industries had good stationarity at the 1% significance level. Among them, the health care, information technology, and consumer staples industries had higher average income levels;

the telecommunication services, information technology, and real estate industries had large standard deviations, that is, the return fluctuations were relatively large, while the public consumption and daily consumption industries had relatively small return fluctuations.

Table 1. Descriptive statistics of industry index logarithmic return.

Industry	Mean	Standard Deviation	Skewness	Kurtosis	ADF	ADF-*p* Value
Financials	0.0003	0.0190	−0.2744	3.9828	−14.704	0.01
Energy	0.0001	0.0198	−0.4420	3.8532	−13.631	0.01
Materials	0.0003	0.0210	−0.7322	3.3813	−13.642	0.01
Industrials	0.0003	0.0200	−0.7753	4.1845	−13.829	0.01
Consumer Discretionary	0.0005	0.0200	−0.7875	3.9599	−13.641	0.01
Consumer Staples	0.0006	0.0184	−0.6276	3.6267	−14.058	0.01
Health Care	0.0007	0.0194	−0.6215	3.5366	−13.899	0.01
Information Technology	0.0006	0.0228	−0.6559	3.6367	−14.168	0.01
Telecommunication Services	0.0001	0.0236	−0.2112	3.4398	−14.164	0.01
Utilities	0.0003	0.0182	−0.8215	5.7108	−13.888	0.01
Real Estate	0.0003	0.0224	−0.5238	3.8535	−14.571	0.01

4. Analysis of Empirical Results

4.1. Systemic Financial Risk Measurement and Identification of Major Event Periods

This part aimed to explore whether there was cyclical variability in systemic financial risk spillovers, and the evolutionary characteristics of financial risk spillovers when impacted by major events. With reference to historical data and the VaR measurement value, starting from the event outbreak period (set the absolute value of VaR higher than 6 for the first time) and based on the entire high-risk fluctuation period after the event, the major event period was identified. After determining the data stationarity, the ARMA model was used to fit the time series data of financial industry index returns, and the optimal order was ARMA (5, 5) considering the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) comprehensively. Secondly, the Ljung-Box test was performed on the residual series, which showed that the financial industry index return time series had an ARCH effect, so the ARMA-GARCH family model could be used to fit it, and the VaR time series (absolute value) could be obtained. See Figure 1.

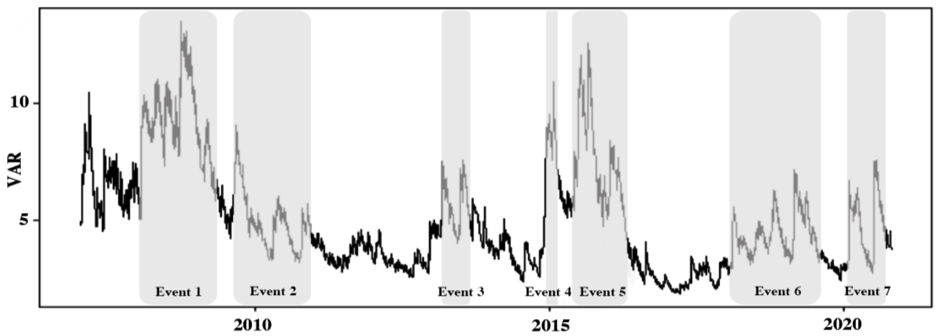

Figure 1. Risk change trend of the financial industry (2007–2020). Notes: (1) Event 1: Global Financial Crisis (2008.01~2009.05); Event 2: European Debt Crisis (2009.10~2011.02); Event 3: "Money Crunch" (2013.06~2013.11); Event 4: A—share Soaring (2014.11~2015.01); Event 5: stock market crash (2015.05~2016.03); Event 6: Sino-US trade friction (2018.02~2019.04); Event 7: COVID-19 pandemic (2020.02~2020.08). (2) The event names are all taken from the literature, not strictly defined and not the focus of this research.

From Figure 1, the systemic risk in China's financial industry does not show obvious periodicity, and the trend is complex and changeable. The maximum value of VaR occurred in event 1, that is, during the global financial crisis in 2008; and during events 4 and 5, the VaR fluctuated the most, which showed that the stock market volatility in 2014 and 2015 was closely related to systemic risk. During Event 7, VaR continued to fluctuate at a high level, indicating that the Sino-US trade friction in 2018 and the COVID-19 in 2020 both caused systemic financial risks to rise to varying degrees. The above results show that the period of major events selected based on VaR is basically consistent with the facts, and the risk of the financial industry increases under the impact of major events. In terms of event types, consistent with the study of Wang et al. (2021) [26], shocks in China's internal financial market generally have a deeper impact on the systemic risk of China's financial market than shocks in the international market. However, in the contemporary era of frequent shocks in the international market, the financial market of a single country is not immune from them, and the internal market will also be affected to some extent.

4.2. Risk Spillover from the Financial Industry to the Real Entity Industry

4.2.1. Identification of System Vulnerability Entity Industries

In order to explore the extent to which the real entity industry is affected by the risk spillover of the financial industry, the % ΔCoVaR indicator is calculated and used to identify the system vulnerability of the real entity industry. First, ARMA ordering was performed on the time series data of the financial industry and the real entity industry to construct a single-sequence ARMA-GARCH model. Secondly, the Bayesian DCC-GARCH method was used to fit the time series of the financial industry and a certain real entity industry respectively and ten groups of dynamic correlation coefficient sequences were obtained. Then the DCC function was to calculate the dynamic correlation coefficient and obtain the conditional risk spillover value CoVaR. ΔCoVaR sequence reflects the dynamic change of risk spillover from the financial industry to the real entity industry. See Figure 2.

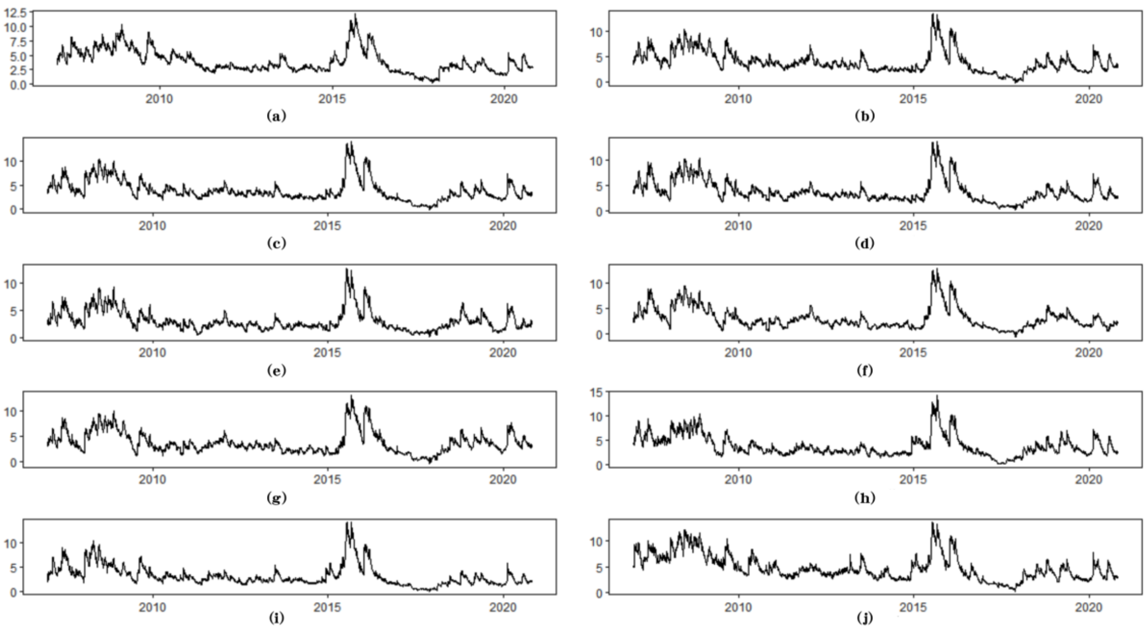

Figure 2. Risk spillover from the financial sector to the real industries: (**a**) Energy; (**b**) Materials; (**c**) Industrials; (**d**) Consumer Discretionary; (**e**) Consumer Staples; (**f**) Health Care; (**g**) Information Technology; (**h**) Telecommunication Services; (**i**) Utilities; (**j**) Real Estate.

From Figure 2, we can find the changing characteristics of the risk spillover from the financial industry to the real industries through observation: (1) The changing trend of the risk spillover from the financial industry to the real entity industry is essentially the same, which is consistent with the conclusion in Figure 1, and the risk spillover value during major events increases significantly. (2) During the period of event 5, the risk spillover value reached the largest value, and the risk spillover value of the financial industry to the telecommunication services, utilities, and industrials all exceeded 14, which were 14.300, 14.260, and 14.225 respectively. Among the above-mentioned major events, during the "stock market crash," the financial industry had the largest risk spillover to the real entity industry. More specifically, the risk spillover to the telecommunications service industry was the most apparent, and the risk spillover to the industrials was the most unstable.

The ΔCoVaR was de-dimensionalized to obtain the conditional risk spillover degree (%ΔCoVaR), which was used as the basis for the identification of the systemically vulnerable entity industry. See Table 2.

Table 2. Risk spillover effects of the financial industry on the real industries.

Industry	CoVaR		ΔCoVaR		%ΔCoVaR	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Energy	−3.887	−3.342	−3.960	−3.391	78.78%	78.22%
Materials	−3.948	−3.518	−4.017	−3.577	80.55%	80.39%
Industrials	−3.835	−3.306	−3.902	−3.357	77.54%	76.71%
Consumer Discretionary	−3.761	−3.194	−3.827	−3.235	76.27%	76.37%
Consumer Staples	−3.058	−2.539	−3.112	−2.563	61.70%	61.37%
Health Care	−2.945	−2.372	−3.000	−2.399	58.41%	57.80%
Information Technology	−3.663	−3.177	−3.724	−3.222	75.20%	74.64%
Telecommunication Services	−3.839	−3.264	−3.911	−3.309	70.60%	70.16%
Utilities	−3.177	−2.647	−3.238	−2.685	62.37%	61.28%
Real Estate	−4.809	−4.309	−4.901	−4.380	97.20%	96.31%

From Table 2, the top three real industries in terms of %ΔCoVaR are the real estate, materials, and energy industries, which are most affected by the risk spillover from the financial industry. The real estate industry is the most affected, with a risk spillover value of −4.901 and a spillover degree of 97.20%. The materials industry was followed, with a risk spillover value of −4.901 and a spillover degree of 80.55%. The energy industry ranked third with a risk spillover value of −3.960 and a spillover degree of 78.78%. Analysis of the main reasons: (1) There is a close capital business relationship between the real estate industry and the financial industry, with real estate loans accounting for a large proportion of the total bank loans. The real estate industry has strong pro-cyclicality, and the real estate industry becomes the "habitat" of excess social funds during the economic upswing. Since 1998, with the cancellation of China's welfare housing allocation system and the implementation of the personal housing mortgage loan policy, real estate loans have become the fastest-expanding business of commercial banks. China's real estate-related loans account for about 39% of the total banking sector loans, and a large number of bonds, financing equity, trust, other shadow banking funds and various off-balance-sheet loans have entered this industry. Since the Central Economic Work Conference at the end of 2016, China proposed to promote the stable and healthy development of the real estate market and adhere to the positioning of "houses are for the living, not for speculation" at first time, which has promoted the stable and healthy development of the real estate market. With the gradual implementation of the strict credit control policy in recent years, the problem that the real estate industry is affected by the constraints of exogenous financing has emerged. (2) According to Wind data, in 2020, the asset-liability ratio of the base metal industry in the materials industry was about 54%, the precious metal industry was about 53% and the steel industry was about 56%. The material industry has the characteristics of high debt and has a high degree of risk correlation with the financial industry. The chemical industry, building products, metal, non-metal mining and other sub-sectors included in the material industry are generally in the middle and upper reaches of the industrial chain. Under the impact of major events, it is vulnerable to the two-way squeeze from the upstream raw material supply side and the downstream application field demand side, resulting in the negative impact of rising costs and declining demand. (3) The energy industry has the characteristics of large investment amount and long turnover period and is easily affected by the financing constraints of the financial industry. In addition, the derivatives market built around energy product transactions makes energy products have the dual attributes of general commodities and financial products, which is greatly affected by the investment and asset allocation needs of market participants. To sum up, financial market hedging, arbitrage, and other transaction behaviors may all impact the operation and stock price of the energy industry.

4.2.2. Identification of Systemically Important Financial Sectors

First, according to the Shenwan secondary industry classification, the financial industry was divided into 4 sub-industries: banking, securities, insurance, and multi-finance (including trust, futures, leasing, financial information, and asset management companies). The daily data in the bank index, brokerage index, insurance index, and multi-financial index in the secondary industry index were used to conduct the ADF unit root tests, residual squared sequence autocorrelation test, and ARCH effect test on the return rate series of the four financial sub-sectors in turn, all rejecting the null hypothesis. Secondly, the Ljung-Box statistic was used to calculate the test results of the square lag of 1–6 periods of return and residual terms, which showed that the ARCH effect exists, and was suitable for building a GARCH model. Thirdly, the standard residual sequence DCC model was used and the time-varying correlation coefficient was obtained, followed by the risk spillover value CoVaR and the systemic risk spillover degree %ΔCoVaR. See Table 3.

Table 3. Risk spillover from financial industries to real industries.

Industry	Bank		Securities		Insurance		Diversified Finance	
	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR
Energy	−3.230	68.50%	−5.479	50.33%	−4.062	52.33%	−5.076	57.56%
Materials	−2.999	63.89%	−5.908	54.58%	−4.443	51.20%	−6.140	69.70%
Industrials	−2.883	61.05%	−5.729	52.47%	−3.808	49.38%	−6.026	67.93%
Consumer Discretionary	−2.769	59.04%	−5.470	49.85%	−3.791	49.32%	−5.811	64.96%
Consumer Staples	−2.273	48.23%	−4.411	40.03%	−3.251	42.33%	−4.671	51.93%
Health Care	−2.062	42.91%	−4.461	39.99%	−2.945	38.02%	−4.910	54.10%
Information Technology	−2.516	53.87%	−5.786	54.25%	−3.536	46.74%	−6.388	73.11%
Telecommunication Services	−3.140	65.87%	−5.473	50.50%	−3.992	51.94%	−5.435	61.62%
Utilities	−2.473	50.84%	−4.693	41.61%	−3.226	40.81%	−4.905	53.37%
Real Estate	−3.702	77.47%	−6.249	56.82%	−4.586	58.98%	−6.080	67.85%

From Table 3, the comparison of the risk spillover degree of the financial sub-sectors showed that the banking industry had the most obvious risk spillover effect on the real sector, while the securities industry had the lowest risk spillover degree. On the one hand, the banking industry's spillover rate to the real estate industry was 77.47%, and the spillover degree to the energy and telecommunications service industries exceeded 65%. The overall risk spillover from the bank to the real entity industry was relatively large. The spillover degree from the securities industry to the consumer staples, health care and utilities industries was less than 45% which showed a relatively low overall risk spillover degree to the real entity industry. Besides, the risk spillover degree of the insurance industry and the diversified financial industry is in the middle position. The above results show that: (1) China's banking industry plays a central role in the process of risk transmission to the real entity industry. Due to the large demand for credit funds in industries such as real entity and energy, risks originating from the banking industry are easily transmitted to the above industries. In addition, the banking industry and other financial institutions form complex network relationships through multiple channels such as assets, liabilities, and intermediary business. The liquidity risk of the banking industry may also be transmitted to other financial industries through the above-mentioned business-related channels, and indirectly affect the real entity industry. (2) The risk transmission mechanism of the insurance industry to the real entity industry is mainly manifested in the participation or holding of real enterprises through equity investment. The insurance industry is operating based on liability, and the nature of its operation determines the term structural characteristics of the use of insurance funds. From the perspective of the asset allocation structure of insurance funds, the proportion of equity assets is less than 20%, so the risk transmission to the real economy is relatively limited. This is also consistent with the research of Cummins and Weiss (2014) [27] on the American insurance industry, that is, the core business of the insurance industry does not constitute a systemic risk. (3) Securities industry and diversified financial industry are mainly related to securities trading, trust, futures, leasing, financial information services, asset management, and other businesses. Through diversified financial servicing for the real economy, those industries mainly use the financial market to achieve resource allocation, financial risk management, and control, indirectly forming a risk linkage with the real entity industry. As a result, the risk spillover to the real entity industry is weak.

4.3. Risk Spillover from the Real Entity Industry to the Financial Industry

4.3.1. Identification of Systemically Important Entity Industries

In order to explore the strength of the impact of the real entity industry on financial risk spillover on the financial industry. The %ΔCoVaR indicator was used to identify the systemically important entity industry. The ΔCoVaR time series represented the time-varying situation of systemic risk spillovers from the real entity industry to the financial industry, see Figure 3.

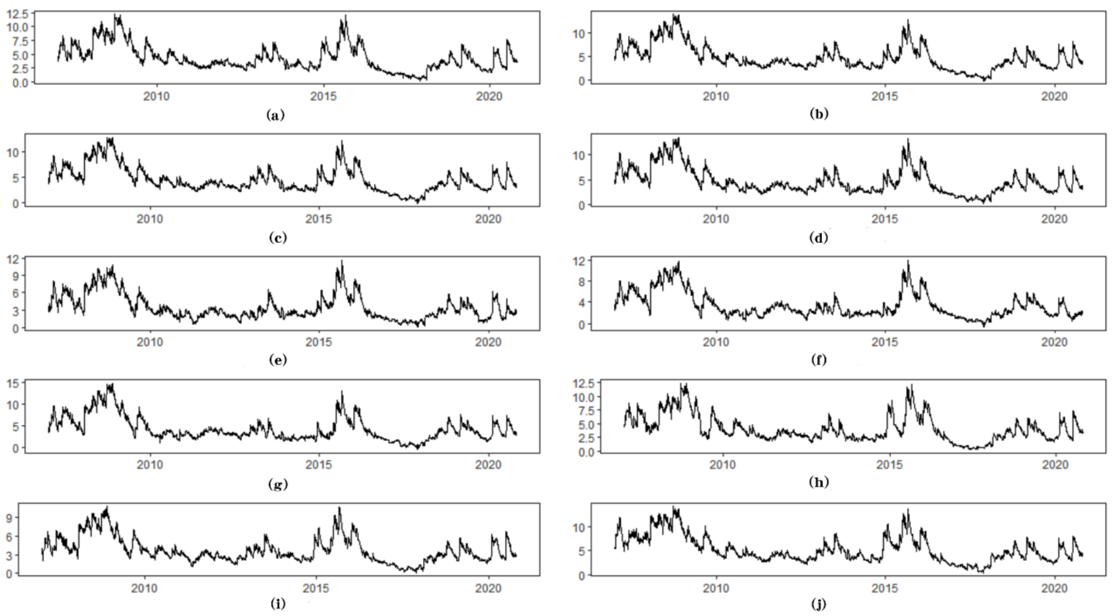

Figure 3. Risk spillovers from the real entity industries to the financial sector: (**a**) Energy; (**b**) Materials; (**c**) Industrials; (**d**) Consumer Discretionary; (**e**) Consumer Staples; (**f**) Health Care; (**g**) Information Technology; (**h**) Telecommunication Services; (**i**) Utilities; (**j**) Real Estate.

From Figure 3, the characteristics of the risk spillover changes from the real entity industry to the financial industry were obtained: (1) The risk spillover trend of the entity industry was generally consistent, and the risk spillover value of the entity to the financial industry increased significantly during the major events. (2) The risk spillover degree of the real entity industry was the largest during the event 1 (2008–09 global financial crisis), and the risk spillover value was generally high and fluctuated sharply. Among them, the information technology, real estate, and materials industries had higher risk premiums to the financial industry than the other industries, which were 14.757, 14.240 and 14.011, respectively. (3) During Event 5 (2015–2016 "stock market crash"), the risk spillover from the real entity industry to the financial industry fluctuated the most, among which the information industry had the most obvious risk spillover to the financial industry, with a variance value of 5.098.

The conditional risk spillover (%ΔCoVaR) was obtained by de-dimensionalizing ΔCoVaR. See Table 4.

Table 4. Risk spillover effects of the real entity industry on the financial industry.

Industry	CoVaR		ΔCoVaR		%ΔCoVaR	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Energy	−4.349	−3.777	−4.368	−3.815	71.11%	71.14%
Materials	−4.552	−3.962	−4.781	−4.189	66.62%	66.18%
Industrials	−4.358	−3.786	−4.561	−3.974	72.02%	71.62%
Consumer Discretionary	−4.365	−3.699	−4.624	−3.917	72.24%	71.09%
Consumer Staples	−3.267	−2.603	−3.476	−2.793	66.05%	64.25%
Health Care	−3.180	−2.408	−3.375	−2.549	55.69%	56.18%
Information Technology	−4.117	−3.325	−4.337	−3.515	49.57%	47.07%
Telecommunication Services	−4.094	−3.422	−4.123	−3.444	47.89%	48.35%
Utilities	−3.615	−3.140	−3.736	−3.236	83.39%	81.95%
Real Estate	−5.137	−4.427	−5.256	−4.532	67.59%	68.36%

From Table 4, the real sector generally had risk spillover effects on the financial industry, and the top three industries in terms of risk spillovers were utilities, consumer discretionary and industrials, showing obvious systemic importance. Among them, the risk spillover value of the utilities to the financial industry ranked first, which was at −3.736, with a spillover degree of 83.39%. The consumer discretionary followed, with a risk spillover value of −4.624 and a spillover degree of 72.24%. The industrials ranked third, with a risk spillover value of −4.561, and a spillover degree of 72.02%. The shock of major events may expand in the real economy and financial system through the credit market and capital market, therefore, specific reasons were analyzed. (1) Utilities have the characteristics of capital-intensive industries, that is, the scale of assets is large, the turnover time of special-purpose assets is long, and the ability to convert into funds is poor. Assets in China's utilities industry are more than 6 trillion yuan in total, thus the impact of major events on utilities has increased default risk and exacerbated the tightening of credit markets. (2) Affected by the impact of major events, it takes a certain buffer time for the consumer industry to usher in recovery. On the supply side, companies may face many pressures such as difficulties in cargo delivery, increasing transaction costs and the shortage of cash flow; on the demand side, different from the consumer staples industries represented by food and beverage, clothing, and daily necessities, the consumer discretionary industries represented by luxury goods and tourism are more prone to problems such as lower consumer confidence and lower consumption willingness, while the decline in retail performance may be transmitted to the stock market through the industrial chain, supply chain and capital chain. (3) The risk spillover degree of the industrials to the financial industry is relatively high. The proportion of overcapacity in Chinese industrial enterprises exceeding 10% and 20% is about 61% and 25%, respectively. With the continuous advancement of the current supply-side structural reform, the production and operation activities of industrial enterprises with overcapacity will be affected. It will be easy to create credit risk of liquidity shortages and difficulties in repaying bank loans.

4.3.2. Identification of Systemic Vulnerabilities in the Financial Industry

In order to explore the strength of the impact of the real entity industry on the financial risk spillover of the financial sub-industry, the %ΔCoVaR indicator was used to identify and determine the systemically vulnerable industries of the financial industry. Table 5 shows the risk spillover from the real sector to the financial sub-sector.

Table 5. Risk spillovers from the real entity industry to the financial sub-sector.

Industry	Bank		Securities		Insurance		Diversified Finance	
	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR	ΔCoVaR	%ΔCoVaR
Energy	−3.680	59.84%	−5.941	99.40%	−4.446	74.15%	−5.044	84.25%
Materials	−3.712	51.62%	−6.867	98.39%	−4.666	66.36%	−6.526	91.81%
Industrials	−3.500	55.14%	−6.585	97.95%	−4.417	71.48%	−6.309	91.28%
Consumer Discretionary	−3.466	54.13%	−6.492	99.42%	−4.570	73.95%	−6.306	99.11%
Consumer Staples	−2.619	49.72%	−4.814	93.66%	−3.605	71.40%	−4.687	89.33%
Health Care	−2.399	39.23%	−4.925	84.60%	−3.279	56.47%	−5.008	85.02%
Information Technology	−3.085	35.24%	−6.547	77.48%	−4.099	48.51%	−6.638	76.86%
Telecommunication Services	−3.429	39.53%	−5.667	68.79%	−4.170	50.10%	−5.132	61.00%
Utilities	−2.943	65.47%	−5.339	96.37%	−3.670	84.18%	−5.057	94.72%
Real Estate	−4.107	52.26%	−6.577	87.08%	−4.899	64.86%	−5.858	76.22%

From Table 5, the level of risk spillover from the real entity industry in the securities industry was relatively high, among which the energy, materials, industrials, consumer discretionary and utilities industries had significant risk spillovers to the securities industry, with %ΔCoVaR reaching more than 95%. The banking industry suffered from a low degree of risk spillover from the real entity industry, among which the risk spillover degree of the health care, information technology, and the telecommunication service industries was less than 40%, indicating that the banking industry played a "stabilizer" role in the systemic financial risk spillover network. The insurance industry and the diversified financial industry are in the middle of the risk spillover degree of the real entity industry. The specific analysis of the data is as follows: (1) The securities industry is vulnerable to market fluctuations in the real sector. The securities industry has effectively promoted capital flow and resource integration by helping enterprises carry out investment and financing, merger and reorganization by diversified financial means, and other business activities. This allows for the investment, financing and industrial upgrading needs of real enterprises and the capital appreciation needs of their diversified financial development are met. The securities brokerage, securities market investment advisory services, securities underwriting and sponsorship, asset management, corporate mergers and acquisitions and other businesses in the securities market are closely related to the financial assets such as stocks, bonds and funds, while the operating conditions of the real industry determine the income status of the financial assets held. Besides, due to the small proportion of institutional investors in the securities industry and a large number of high-indebted investors, the securities industry is unable to accurately price the financial market, and the risk acceptance ability is insufficient. It is easy to form a herd effect when it is impacted, and financial risks are affected by fear and spread rapidly. (2) The banking industry is not only the main body that affects the stability of the overall financial system but also the focus of macro-prudential supervision of the financial system. Therefore, when the systemic risk rises, the banking industry instead acts as a stabilizer and is less affected by the risk spillover from the real entity industry. This is mainly because in the period of rising systemic risks, state-owned banking institutions are the main way for the central bank to use monetary policy to achieve national macroeconomic control and risk diversification. In addition, the banking industry is more strictly supervised than other institutions, so it plays the role of "main channel" in preventing and defusing systemic risks. (3) The risk spillover from the real entity industry to the insurance industry is mainly caused by risk transmission through insurance business loss compensation and insurance investment capital utilization losses. Since China's insurance industry accounts for only 6.46% of the total assets of the financial industry, it is far lower than the global insurance market's share of 17.8%. Compared with the structure, the use of insurance funds is strictly regulated by Chinese industry regulators, so the impact is limited. At the same time, the premium income of China's insurance industry accounts for only 4.6% of the total GDP, and the insurance loss on industry level in response to major risk events is about 10%. Due to the lack of pertinence and diversity of insurance types in the insurance industry, there is still much room for improvement in the level of risk protection, so the risk spillover effect of the real entity industry on the insurance industry is limited.

In general, although the spillover of the securities industry to the real industry is low, the risk spillover received from the real industry is the highest among the financial sub-industries. On the contrary, the banking sector has the highest risk spillover to the real sector due to credit and financing constraints, but because of the nature of "financial stabilizers," it is less affected by risk spillover from the real sector. Traditional theory holds that the center of China's financial system is the bank rather than the securities market (Chan, 2007) [28]. But this idea is limited to considering only risk spillovers, rather than considering the nature of risk in the industry from the perspective of two-way spillovers. Other financial subsectors have intermediate levels of risk spillover and acceptance due to business scope and regulatory constraints.

5. Discussion on Sub-Samples of Major Events

In order to explore the differences in risk spillovers between the entities and financial industry under different types of major events, representative major events were selected for sub-sample analysis. Three representative major economic emergencies (Event 1, Event 5 and Event 6) and one public health event (Event 7) were selected as sub-samples, and the two-way ΔCoVaR values between the financial and real industries was solved through the DCC-GARCH model. See Table 6.

Table 6. Two-way risk spillover effects of financial and real industries during the sub-sample period of major events.

(1) Risk Spillover from the Financial Industry to the Real Entity Industry								
Event Name	**Event 1 Global Economic Crisis**		**Event 5 Stock Market Crash**		**Event 6 Sino-US Trade Friction**		**Event 7 COVID-19 Pandemic**	
Industry	**ΔCoVaR**	**%ΔCoVaR**	**ΔCoVaR**	**%ΔCoVaR**	**ΔCoVaR**	**%ΔCoVaR**	**ΔCoVaR**	**%ΔCoVaR**
Energy	−8.811	95.49%	−8.679	97.43%	−3.926	88.65%	−4.576	92.42%
Materials	−7.063	76.62%	−8.788	98.00%	−3.015	67.75%	−4.216	84.79%
Industrials	−7.054	76.91%	−8.293	91.69%	−3.238	73.17%	−4.286	85.87%
Consumer Discretionary	−6.962	75.55%	−8.427	93.39%	−3.130	70.73%	−4.196	85.07%
Consumer Staples	−6.851	73.58%	−8.141	89.69%	−3.654	82.37%	−4.510	90.16%
Health Care	−6.844	74.69%	−7.917	88.38%	−3.095	70.88%	−3.723	75.74%
Information Technology	−6.647	72.10%	−8.351	93.86%	−3.455	77.91%	−4.950	87.16%
Telecommunication Services	−5.843	63.18%	−8.280	90.57%	−2.198	49.11%	−2.849	56.86%
Utilities	−5.801	62.57%	−7.882	86.65%	−2.746	61.93%	−2.275	48.01%
Real Estate	−5.799	62.73%	−7.153	76.06%	−3.006	68.14%	−3.429	68.74%
(2) Risk spillover from the Real Entity Industry to the Financial Industry								
Energy	−8.655	88.35%	−7.543	69.69%	−3.650	73.99%	−4.623	84.88%
Materials	−9.981	92.30%	−7.957	60.85%	−4.076	70.45%	−5.255	78.92%
Industrials	−9.523	96.11%	−7.676	61.34%	−3.808	75.77%	−5.064	86.12%
Consumer Discretionary	−9.577	91.82%	−7.920	64.47%	−4.066	76.43%	−5.058	81.52%
Consumer Staples	−7.612	97.21%	−6.901	78.42%	−3.008	61.66%	−3.497	63.16%
Health Care	−7.989	91.72%	−7.058	63.31%	−2.824	49.18%	−2.567	46.06%
Information Technology	−10.153	86.40%	−7.571	46.08%	−3.752	47.39%	−4.824	49.33%
Telecommunication Services	−8.460	65.08%	−7.738	55.51%	−3.516	44.61%	−4.566	53.30%
Utilities	−7.672	97.56%	−6.632	68.02%	−3.126	96.18%	−4.331	97.02%
Real Estate	−10.366	81.79%	−8.454	65.73%	−4.488	72.82%	−5.316	77.76%

From Table 6, compared with the full sample, the two-way spillover effects of the financial and real industries during major events were obvious. Among them, the risk spillover degree of the financial industry to the real entity industry during the Event 5 was the highest, while the risk spillover degree of the real entity industry to the financial industry during the Event 1 was the highest. The systemically vulnerable and systemically important industries displayed during the outbreak of different major events had both commonalities and differences: the commonality was that the financial industry ranks first in the risk spillover to the energy industry, while the risk spillover degree of public utilities to the financial industry ranked first in events 1, 6 and 7. The differences were reflected in the fact that the second most systemically vulnerable industries in terms of risk spillover during events 1, 5, 6 and 7 were the industrials, materials, information technology, and consumer staples while the second most systemically important industries were the consumer staples, energy, consumer discretionary and industrials.

The energy industry mostly shows systemic vulnerability, and the utilities industry shows systemically important characteristics. The risk spillover degree of the financial industry to the energy industry during the Event 1, 5, 6, and 7 is as high as 95.49%, 97.43%, 88.65% and 92.42% respectively, and the energy industry showed systemic vulnerability. This is closely related to the asset-heavy nature of the energy industry. The high financing dependence brought about by the long capital turnover cycle makes the energy industry suffer from obvious risk spillovers when major events impact the financial system. The risk spillover degree of public utilities to the financial industry during events 1, 6, and 7 is 97.56%, 96.18% and 97.02% respectively, showing systemic importance. The utility industry is different from other real entity industries. The pricing and implementation of power generation, power supply, water supply, gas supply and other projects are strictly guided by the government, so the utility industry is dependent on government subsidies. The impact of the policy is faster and more obvious, and the shock is more easily transmitted into the capital market, which in turn affects the financial system.

Event 1: The 2008–2009 global financial crisis. The risk spillover degree of the financial industry to the real sector is quite differentiated, of which the risk spillover degree of the energy industry has reached 95.49%, followed by the industrials at 76.91%, while the public utility is only 62.57%. As a capital-intensive industry, assets in the industrial industry are large in scale, while special-purpose assets have a long turnaround time with poor liquidity. Under the influence of external shocks, the risk spillover between financial industry and industrials with the help of the credit market and capital market circular expansion leads to the systemic vulnerability of the industrials industry. The risk spillover degree of the real entity industry to the financial industry is very high, of which the conditional risk spillover degree of daily consumption to the financial industry exceeds 95%. The purchasing power of China's domestic market and major trading partners such as the United States, the European Union and Japan has decreased, resulting in shrinking demand in the daily consumption market and sluggish export. This result is also similar to the research findings of Barunik (2016) [29] on the US market, in which energy and consumer industries are the main exposure and contributors of risks during the global financial crisis.

Event 5: The 2015 stock market crash. In the first half of 2015, the stock market was in a state of "mad". There were great hidden risks behind the irregular prosperity of the stock market. Excessive market liquidity caused most industries to hold common risk exposures. The excess liquidity in the market leads to the common risk exposure of most industries, the potential risk contagion channels between financial and real industries are rapidly expanding, and the economic system is increasingly fragile. The risk spillover degree of the financial industry to the materials industry has reached 98%. The ethos of "highly leveraged capital allocation" leads to the accumulation of risks. Driven by policy adjustments, investors are easily affected by domestic market sentiment and irrationally get on the bandwagon. For one thing, equity funds have withdrawn too much, and financial institutions have cut prices to sell, thus forming a negative feedback effect of lower and lower stock prices and more selling. For another, the phenomenon of irrational selling of stocks has prompted the spread of the "herd effect" and "information asymmetry" effect in the financial market. Although Yin et al. (2020) [30] pointed out that the industrial restructuring after the stock market disaster led to a significant increase in the level of industrial risk net spillover, the decline in stock prices itself affected the efficiency of financial resources allocated to the real industry, and the material industry showed systemically vulnerable. Energy plays a pivotal role in the real economy, with a risk spillover rate of 69.69% to the financial industry. Energy price fluctuations caused by the stock market crash will affect the prices of downstream industries and energy derivatives. By this way, the risk spillover effect from the energy industry to the financial industry has been further amplified.

Event 6: The Sino-US trade friction in 2018. The United States issued a seven-year ban on the sale of telecommunications service equipment manufacturer ZTE and subsequently banned American operators from subsidizing the purchase of the ZTE and Huawei communication equipment, which had a greater adverse impact on the information technology industry. In addition, software and hardware services provide strong support for the daily operations of the financial industry and maintain a high degree of correlation with the financial industry. Under the influence of Sino-US trade friction, the risk linkage has been further enhanced, and the risk spillover degree of the financial industry to the information technology industry has reached 77.91%, showing systemic fragility. Increasing tax and trade barriers have led to a decline in external demand, and the consumer discretionary industry related to export demand has transmitted risks to the financial system, with a risk spillover rate of 76.43%, showing systemic importance.

Event 7: The "COVID- 19" pandemic in 2020. On the supply side of China, there are phenomena such as obstruction of corporate logistics and transportation, increased trade costs, and shortage of cash flow, while consumer confidence and willingness to spend are weakened on the demand side. For one thing, the risk exposure of the financial industry to the consumer staples industry has increased with a spillover degree of 90.16%, thus it has shown systemic fragility. For another, the supply of manufactured goods has weakened, market expectations have deteriorated, market volatility has increased, and the systemic risk of the industry has increased. The risk spillover rate to the financial industry has reached 86.12%, showing systemic importance.

According to the above results, the systemically vulnerable industries and systemically important industries during major events are summarized, as shown in Table 7.

Table 7. Systemically vulnerable and important entity industries during major events.

Event	Systemic Vulnerability	Systemic Importance
Event 1: Global Financial Crisis	Energy, Industrials	Utilities, Consumer Staples
Event 5: Stock Crash	Energy, Materials	Consumer Staples, Energy
Event 6: Sino-US trade friction	Energy, Information Technology	Utilities, Consumer Discretionary
Event 7: COVID-19 Pandemic	Energy, Consumer Staples	Utilities, Industrials

6. Robustness Test

In order to ensure the robustness of the empirical results, the measurement method of the main indicator CoVaR was replaced. In the quantile test step of CoVaR, the VaR and quantile results at the 5% significance level were replaced with 1%, and the risk spillover value of the financial industry to the real entity industry was re-measured. The relevant results reported in Table 8 show that the risk spillover effect on the real estate industry was the highest among the ten real industries, with a risk spillover value of −9.908 and a spillover degree of 96.35%; the material industry followed, with a risk spillover value of −8.121 and a spillover degree of 79.91%; the energy industry ranked third, with a risk spillover value of -8.005 and a spillover degree of 78.09%. There was a difference in the risk spillover value with the results in Table 2, but the results of the de-dimensioned treatment %ΔCoVaR are consistent, indicating that the aforementioned empirical results are robust.

Table 8. Risk spillovers from the financial industry to the real entity industry (1% significance level).

Industry	CoVaR		ΔCoVaR		%ΔCoVaR	
	Mean	Median	Mean	Median	Mean	Median
Energy	−7.933	−6.856	−8.005	−6.856	78.09%	77.65%
Materials	−8.053	−7.183	−8.121	−7.231	79.91%	79.69%
Industrials	−7.821	−6.753	−7.888	−6.786	76.93%	75.81%
Consumer Discretionary	−7.672	−6.495	−7.737	−6.541	75.65%	75.73%
Consumer Staples	−6.237	−5.153	−6.291	−5.181	61.20%	60.86%
Health Care	−6.010	−4.821	−6.064	−4.850	57.91%	57.25%
Information Technology	−7.836	−6.648	−7.908	−6.689	76.92%	77.10%
Telecommunication Services	−7.468	−6.471	−7.528	−6.513	74.63%	73.80%
Utilities	−6.542	−5.417	−6.604	−5.435	62.28%	61.10%
Real Estate	−9.816	−8.799	−9.908	−8.854	96.35%	95.58%

7. Conclusions and Recommendations

7.1. Conclusions

Through the above analysis, the main conclusions are as follows: (1) China's systemic financial risk has no obvious cyclical characteristics in the past ten years and has been significantly affected by the impact of major events. The peak of risk occurred during the financial crisis in 2008, and the systemic risk volatility was the severest during the 2015 stock market crash. (2) The financial industry has significant risk spillovers to the real estate, materials, and energy industries. Factors such as the pro-cyclicality of the real entity industry, the material industry being in the middle and upper reaches of the industrial chain, and the "financialization" of the energy industry may lead to systemic vulnerabilities. In the financial industry, the banking industry has the highest risk spillover from the real entity industry, and the securities industry has the lowest, reflecting the centrality of the banking industry in risk transmission. (3) The risk spillover effect of utilities, consumption discretionary and industrials on the financial industry is significant. Among the financial industry, the securities industry has the highest risk spillover degree, and the banking industry has the lowest risk spillover degree. (4) Through the analysis of the sub-sample period of major events, it is found that the entity industry presents different characteristics of systemic vulnerabilities and importance. Despite being affected by different major events, the financial industry has the largest risk spillover to the energy industry while the utilities industry has the highest risk spillover to the financial industry. Other system vulnerability and importance characteristics, such as industry, materials, information technology, daily consumption, and optional consumption, to name a few, differ from the differences in major events.

7.2. Recommendations

Based on the above conclusions, it can be observed that the two-way risk spillover effect of China's systemic financial risks under major events is obvious, and the impact of different events has both commonalities and differences. In addition, China's two-way spillovers are not isolated. Other countries with developed economic systems have similar spillovers. For example, the trade war between China and the United States and the epidemic have similar risk impacts on financial sub-industries and real industries in China and the United States (Choi, 2022) [31]. However, in view of the particularity of China itself, such as government-affiliated equity and imperfect stock market (Yang et al., 2014) [32], this paper puts forward the following policy suggestions on preventing and resolving major risks in the financial system, mainly in view of China's national conditions:

First, China needs to pay attention to the risk management of the system vulnerability industry. Standardize the financing behavior of industries with system vulnerabilities, appropriately expand financing channels for industries with system vulnerabilities, adjust the financing concentration of such industries, and moderately reduce their dependence on banks. The scale of shadow banking businesses such as financial products issued by financial institutions purchased by relevant enterprises in the system vulnerability industry should be appropriately controlled to avoid the phenomenon of "idling" of funds caused by multi-layer nesting, and the length of the credit chain should be controlled. Finally, for the real estate industry, emphasis is placed on the supervision of new real estate financialization models represented by real estate investment trusts, real estate equity and real estate bonds. Pay attention to policy consistency and prevent the inflation of housing price bubbles, so as to maintain the safe and stable development of the financial market.

Second, strengthen the supervision of risk transmission channels in systemically important industries. First, for systemically important industries, limit banks' industry loan scale, monitor industry default rates, debt scale, debt structure, asset liquidity, solvency and other indicators in real-time, and establish a risk contagion isolation mechanism. Second, attach importance to the supervision of financial investment in real enterprises in systemically important industries, and reasonably guide funds to flow into the real economy. The government needs to develop the equity financing market in an orderly manner, enhance enterprises' ability to absorb risks, optimize capital structure, offset or weaken the impact of financialization on capital structure, and prevent a vicious rise in leverage ratios. Finally, in the non-bank financial sector, the securities industry, which is significantly affected by the risk spillover of the real entity industry, should be concerned by the regulatory authorities. Further promoting the financial supply-side reform will help securities companies comprehensively transform their businesses and improve the quality and efficiency of their services to the real economy.

Third, improve the risk emergency management and prevention and control system according to the types of major events and industry characteristics. Different types of major events have different impact processes and degrees on the industries. It is necessary to monitor the dynamic changes of risks in various industries under the influence of major events in time and build a whole-process dynamic risk prevention and control system that covers the identification, assessment, monitoring, control and disposal of risks. Research shows that under major events, the finance and energy, utilities, industrials, materials, information technology, consumer staples, consumer discretionary and other industries are strongly correlated. Therefore risk monitoring indicators such as leverage ratio, return on total assets, loan cost and industry scale should be established according to the characteristics of the industry to prevent and defuse the impact of two-way risk spillovers in a timely manner.

7.3. Limitation and Future Work

This study identifies the systemic vulnerability and systemic importance characteristics of the real entity industry in the process of two-way risk spillover with the financial industry under major events, which has certain implications both theoretically and practically. It should be pointed out that this study is based on stock market transaction data, but there may be "superimposed" effects of other events during the major event period of the sample, which are difficult to eliminate, so it is difficult to clearly and accurately reflect the impact of a single major event in the selected sample. Besides, because the risk spillover channels between industries are complex, there may be the impact of industry financing concentration, leverage and other factors on the risk spillover effect between the financial and the real industries, which need to be further explored.

Author Contributions: Conceptualization, Y.L.; Methodology, Y.L. and Z.Z.; Software and programming, Z.Z.; Validation, Y.L.; Data Analysis, Z.Z. and T.N.; Writing, Z.Z. and T.N.; Review and Editing, T.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received funding support from Humanities and Social Science Fund of Ministry of Education of the People's Republic of China (No. 22YJA790033).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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