Industry Systemic Risk Measurement Based on GARCH-EVT Method and Copula Function

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Abstract. The article uses data from the Shanghai and Shenzhen 300 Index and the Shenwanwan Industry Index from 2010 to 2021, constructs a dynamic weighted mixed Copula model based on GARCH EVT, analyzes the dependence between each industry and the market tail, and explores the systematic risk contribution of each industry based on marginal expected loss (MES). The empirical results indicate that industries such as agriculture, forestry, animal husbandry, and fishing, as well as non banking and finance, have relatively low tail dependence, while industries such as real estate and household appliances have relatively high tail dependence; The banking industry has the smallest contribution to systemic risk, while the construction materials industry has the largest contribution; During the 2015 "stock market crash", the tail dependence between industry indices such as real estate and mining and market indices increased, with the most significant increase in risk contribution from the defense, military, and chemical industries.

Keywords: GARCH EVT-Copula hybrid model; Systemic risk; Marginal expected loss; tail dependence.

1 Introduction

Systemic risk refers to the risk of financial service interruption or even serious impact on the real economy due to comprehensive or partial damage to the financial system. The global financial systemic risks caused by the US subprime mortgage crisis have spread to various countries, forcing market participants and regulators to recognize the harm of systemic risks. After the subprime crisis, China's financial market was hit by the stock market crash in 2015 and the COVID-19 in 2020. People from all walks of life have become more aware of the necessity and urgency of preventing financial market risks. In recent years, the Central Economic Work Conference has also conducted in-depth discussions and research on systemic risks, emphasizing repeatedly that preventing the occurrence of systemic financial risks is an eternal theme of financial work.

In recent years, domestic and foreign scholars have extensively explored systemic risks. Acharya et al. (2010) proposed MES (Marginal Expected Shortfa 11), which measures the expected return of a single institution or stock under the condition that the market return is less than or equal to a given threshold. Based on this, the corresponding systemic risk contribution can be obtained. This method has been widely used to measure risk spillover effects since its

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inception [1-4]. Adrian and Brunnermeier (2011) [5] proposed using the increase in tail dependency to define systemic risk and measuring it using CoVaR. A more popular method thereafter is SRISK [6], which is defined as a function of institutional size, leverage, and risk. The systematic risk contribution of the institution is obtained by ranking the function values. The CES (Com component Expected Shortfall) proposed by Banu1escu and Dumitrescu (2015) is similar to SRISK, but emphasizes its weight in the financial system, i.e. relative market value, when assessing the contribution of a certain institution to systemic risk. Research on tail dependence mostly focuses on risk spillovers in a single market [7-9]. Domestic research on tail risk spillovers within a single market started relatively late, but the results all indicate that when systemic risk is greater, the tail risk spillover effect is greater. In general, the previous literature on systematic risk and tail dependence mostly focused on the single model and the single market, and only partially considered the time-varying characteristics that are more in line with the market situation, and the use of time-varying parameters and mixed models between industries was slightly inadequate.

Therefore, in terms of theoretical models, this article constructs a GARCH EVT-Copula function hybrid model based on Gumbel Copula, Clayton Copula, and Generalized Autoregressive Score (GARCH EVT) models [10-14]. This model can mix different types of Copulas to more accurately capture the dependent structures of financial time series. At the same time, the GARCH EVT model is used to dynamically adjust the weights of the mixed Copulas, making it possible to describe the hidden information of the data more clearly and clearly. In addition, in order to improve the flexibility of the model, the model also mixes two asymmetric Copulas, which can describe the lower tail dependency and upper tail dependency of data in the same model. In terms of empirical application, this article is based on the GARCH EVT-Copula function mixed model and conducts empirical analysis on the daily data of the Shanghai Shenzhen 300 Index and the Shenwan level industry index from January 4, 2010 to November 20, 2021. It measures the tail dependence between China's stock market index and various industry indices in the market, and depicts the possibility of severe fluctuations in both industry and market indices under extreme circumstances; Estimate the MES values of various industries to analyze their contribution to systemic risk, in order to enable investors and regulatory agencies to understand which industries have the greatest impact or are more susceptible to systemic risk; Enable investors to allocate and diversify investments between departments in a reasonable manner, reducing losses; Enable regulatory agencies to target important industries in the financial market, effectively monitor and curb risk accumulation.

2 Construction of GARCH EVT-COPULA Function Hybrid Model

2.1 Basic Theory

The GARCH EVT-COPULA mixed function model is proposed by Acharya et al. (2010) on the basis of the method ES (Expected Shortfa11) for measuring individual stock risk. It is used to measure the expected return of a single stock under the condition that the market return is less than or equal to a predetermined threshold, in order to quantify the sensitivity of individual stocks to the market. From a risk measurement perspective, MES refers to the marginal contribution of individual stocks to market risk.

2.2 Definition and Properties of GARCH EVT Model

Usually, when analyzing econometric problems, we only focus on the impact of heteroscedasticity caused by cross-sectional data, and relax our vigilance against heteroscedasticity caused by time series data itself. Because in real life, many economic activities cannot satisfy the assumptions in the least squares method. In 1982, Professor Engel proposed and explored the possibility of heteroscedasticity in time series data, and ultimately proposed a method specifically for testing whether there is variance change in time series data - called the Autoregressive Conditionally Heteroscedastic Model. GARCH EVT type models typically consist of the following two equations:

$$r_t = \beta_0 + \beta_1 x + \cdots + u_t \sim N(0, \sigma^2) \tag{1}$$

$$\sigma^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_p \sigma_{t-p}^2 + v^2 \tag{2}$$

Among them, r_t is the dependent variable, x_t is the explanatory variable, u_t is the random perturbation term, a_i is the coefficient of the random perturbation term, and p is the order of the GARCH EVT process. The explanatory variable is the variance of the random perturbation term with a lag of one order to a lag of p order, while the dependent variable is the conditional variance of the random perturbation term. Assuming H_0: $a_1 = a_2 = a_3 = \ldots = a_p = 0$, there is homoscedasticity, and if at least one of H_1: $a_j (j = 1,2, \ldots p)$ is not zero, it is heteroscedasticity. However, the shortcomings of the GARCH EVT model are also extremely obvious - if the p-value is large (i.e. there are many lag periods), the conditional variance will depend on the variance before many times, and the number of parameters that need to be estimated will sharply increase.

2.3 Definition and Properties of GARCH Model

In 1986, "Bollerslev" proposed a generalized form to fully describe the volatility behavior of asset returns, called the Generalized Autoregressive Conditionally Heteroscedastic "Model", which can end in any specified order. However, "Hansen" and "Lunde" (2005) found through research that in daily life, it is difficult to find a higher-order generalized heteroscedasticity structure, and the results obtained will be better than the fitting results of (1,1) order. Therefore, in real life, we often use (1,1) order generalized difference structures. The GARCH (1,1) model process is as follows:

$$r_t = \beta_0 + \beta_1 x_t + u_t \sim N(0, \sigma^2) \tag{3}$$

$$\sigma_t^2 = a_0 + a_1 u_{t-1} + \gamma \sigma_{t-1}^2 + v_t \tag{4}$$

Among them, r_t is the dependent variable, x_t is the explanatory variable, u_t is the random perturbation term, a_1 is the coefficient of the first-order random perturbation term, and γ is the coefficient of the first-order variance term. The GARCH model can also be expressed as: the current conditional variance is equal to the weighted sum of past shocks plus its own autoregression.

3 Empirical analysis

3.1 Descriptives

Obtain the Shanghai Shenzhen 300 Index and Shenwanwan Industry Index from the Wind database, with a sample interval of 67256 data from January 4, 2010 to November 20, 2021, including 28 industry indices - mining, media, electrical equipment, electronics, real estate, textile and clothing, steel, utilities, chemicals, household appliances, building materials, building decoration, transportation, agriculture, forestry, animal husbandry and fishing, light industry manufacturing, commercial trade, food and beverage Leisure services, pharmaceuticals and biology, banking, non-ferrous metals, comprehensive, non banking and finance, national defense and military industry, mechanical equipment, computers, automobiles, and communication. The yield of the Shanghai and Shenzhen 300 Index is the market yield. The selection of sample intervals is mainly based on two reasons: starting from 2010, excluding the interference of the 2008 financial crisis; The sample interval includes the 2015 stock disaster, and in subsequent time series analysis, it is possible to specifically analyze the dependency structure between industries and markets in extreme situations. The Shanghai and Shenzhen 300 Index is composed of 300 constituent stocks with good liquidity in both the Shanghai and Shenzhen markets, which can comprehensively reflect the overall performance of China's A-share market. The Shenwan Industry Index is classified based on the main business income and profits of listed companies in the past two years, and selects constituent stocks from all stocks in the Shanghai and Shenzhen markets, with strong representativeness. The specific industry index is shown in Table 1.

Table 2 on the next page shows the basic statistical information of the sample data. It can be found that the expected returns of the market and industry indices are close to 0, and the standard deviation of each industry index is greater than the market standard deviation, indicating that the fluctuation of the industry index is greater than that of the market index. The kurtosis of each sequence are greater than 3, and the skewness is less than 0, presenting a "peak thick tail" characteristic, consistent with the JB test results. In addition, according to the ADF test results, it is known that all sequences are stable.

3.2 Edge distribution fitting

Table 1. Shenwanwan Industry Index

Index codeIndex	Industry index name	Index code	Industry index name
801020.SI	digging	801010.SI	Agriculture
801030.SI	chemical industry	801120.SI	food and beverage
801040.SI	steel	801210.SI	leisure services
801050.SI	nonferrous metal	801150.SI	medical biology
801710.SI	construction material	801160.SI	public utility
801720.SI	architectural	801170.SI	traffic
801730.SI	electric accessory	801180.SI	real estate
801890.SI	mechanical	801080.SI	electron
801740.SI	defense military	801750.SI	computer
801880.SI	automobile	801760.SI	media
801110.SI	domestic appliance	801770.SI	communication

Index codeIndex	Industry index name	Index code	Industry index name
801130.SI	textile clothing	801780.SI	bank
801140.SI	light manufacturing	801790.SI	non-bank finance
801200.SI	commercial trade	801230.SI	synthesize

As can be seen from the previous text, each sample sequence is stationary and the residuals refuse to follow the original assumption of a normal distribution. Therefore, this article chooses the ARMA (1,1) - GARCH (1,1) - t model to fit it. The first, median, and third quantiles of all estimated results are shown in Table 3 on the following page (only partial estimated results are listed). The estimated results indicate that the median degree of freedom of the model is 5.6747, further confirming the results of the Jarque Bera test. The sum of parameters a and 0 in the GARCH model is close to 1, indicating the existence of wave aggregation in each sequence, which is consistent with the research conclusions of Avdulaj and Ba runik (2015).

Table 2. Descriptive statistics of logarithmic returns of each index

	[Count] mean value	Standard deviation	Min	Max	Skewness	Kurtosis	JB		ADF	
Shanghai and Shenzhen300	0.0000	0.0147	-0.0915	0.0650	-0.6627	7.8302	2497.42	***	-47.76	***
Digging	-0.0004	0.0187	-0.0922	0.0839	-0.4361	6.2350	1116.98	***	-46.92	***
Media	0.0000	0.0192	-0.0872	0.0631	-0.5003	4.9408	474.31	***	-45.85	***
Electric accessory	-0.0001	0.0178	-0.0916	0.0734	-0.7644	6.0987	1188.61	***	-45.16	***
Electron	-0.0002	0.0196	-0.0911	0.0924	-0.4709	5.4288	675.10	***	-46.47	***
Realty	0.0000	0.0180	-0.0902	0.0628	-0.5940	5.9369	998.89	***	-47.29	***
Textile clothing	-0.0001	0.0166	-0.0884	0.0666	-0.9345	6.9478	1899.68	***	-43.71	***
Iron	-0.0003	0.0177	-0.0898	0.0718	-0.5956	6.1359	1119.90	***	-47.86	***
Utility	-0.0001	0.0150	-0.0808	0.0640	-0.8723	7.8705	2664.95	***	-46.09	***
Chemical industry	-0.0001	0.0166	-0.0871	0.0675	-0.8649	6.4449	1479.56	***	-45.12	***
Domestic appliance	0.0005	0.0173	-0.0923	0.0732	-0.3676	5.5916	721.83	***	-47.46	***
Construction material	0.0001	0.0187	-0.0902	0.0722	-0.6375	5.6533	862.49	***	-45.61	***
Architectural ornament	0.0000	0.0173	-0.0932	0.0713	-0.5608	7.4217	2071.33	***	-45.53	***
Traffic	-0.0001	0.0158	-0.0882	0.0655	-0.7478	7.5244	2260.61	***	-45.25	***
Agriculture	0.0002	0.0178	-0.0934	0.0662	-0.6451	5.8693	985.08	***	-44.00	***
Light manufacturing	0.0000	0.0161	-0.0806	0.0511	-0.8959	5.8628	1135.88	***	-44.86	***
Commercial trade	-0.0001	0.0170	-0.0927	0.0674	-0.9018	6.8811	1823.75	***	-44.98	***
Food and beverage	0.0005	0.0160	-0.0860	0.0673	-0.3239	5.3640	597.51	***	-47.43	***
Leisure services	0.0003	0.0170	-0.0886	0.0669	-0.6089	5.9514	1014.50	***	-45.16	***
Medical biology	0.0003	0.0166	-0.0873	0.0631	-0.6218	5.9788	1037.06	***	-45.10	***
Bank	0.0001	0.0150	-0.1051	0.0785	0.0436	9.4495	4141.59	***	-49.69	***
Nonferrous metal	-0.0002	0.0196	-0.0911	0.0924	-0.4709	5.4288	675.10	***	-46.47	***
Nonferrous metal	0.0000	0.0172	-0.0798	0.0566	-0.8882	5.5033	938.39	***	-43.82	***
Non-bank finance	0.0001	0.0199	-0.1020	0.0915	-0.0209	6.7637	1409.53	***	-48.05	***
Defense and military industry	0.0000	0.0221	-0.1023	0.0894	-0.5079	6.3941	1249.06	***	-44.98	***
Mechanical installation	0.0000	0.0177	-0.0930	0.0696	-0.8054	6.4154	1419.74	***	-45.43	***
Computer	0.0004	0.0208	-0.0945	0.0715	-0.4520	4.8702	429.20	***	-45.10	***
Automobile	-0.0001	0.0172	-0.0940	0.0717	-0.6859	6.4437	1367.79	***	-46.31	***
Communication	0.0000	0.0188	-0.0952	0.0657	-0.6400	5.6891	882.80	***	-46.00	***

Note: * * * indicates significant at the 1% level.

Table 3. RMA (1,1) - GARCH (1,1) - t parameter estimation results

	ARMA(1,1)			GARCH(1,1)			freedom
	c	(p	0		a	[J	dof
1stquartile	1.65E-04	-8.04E-01	4.79E-01	2.16E-06	5.50E-02	9.26E-01	5.08
Median	6.95E-04	-6.43E-01	6.57E-01	2.95E-06	5.94E-02	9.29E-01	5.67
3rdquartile	1.07E-03	-5.15E-01	7.73E-01	4.15E-06	6.50E-02	9.38E-01	6.11

3.3 Systematic Risk Analysis Based on DMC-MES

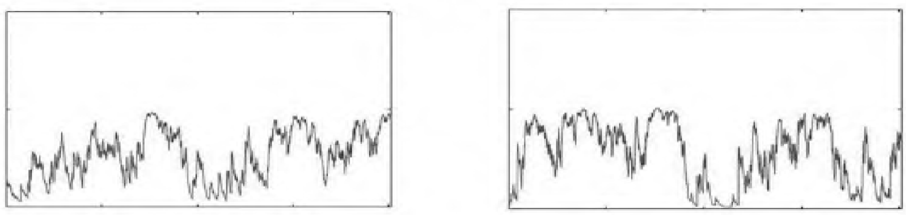
3.3.1 Tail Dependency Analysis Based on Weighted time-varying Hybrid Copula

The mixed model of GumbelCopula and ClaytonCopula with time-varying weights was used to fit the Shanghai Shenzhen 300 Index and the Shenwanwan Industry Index. The median results of parameter estimation are shown in Table 4.

Table 4. Copula estimation results

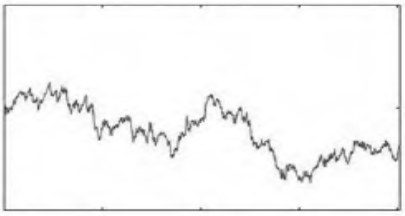
	GARCH EVT(1,1)			^{0}1	^{0}2
	3	A	B		
1stquartile	0.0123	0.0214	0.9676	2.1953	1.2927
Median	0.0296	0.0549	0.9852	2.8762	1.7292
3rdquartile	0.1032	0.0932	0.9891	3.3568	3.3633

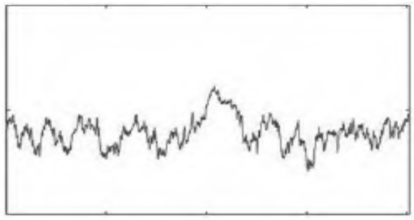
To more intuitively describe the daily tail risk situation between the Shanghai and Shenzhen 300 Index and the industry index, this article uses the estimated results to calculate the bottom tail dependency coefficient. By combining the lower tail dependency coefficients of GumbelCopula and ClaytonCopula, the lower tail dependency coefficients of the time-varying mixed Copula in this paper are obtained. Due to space constraints, only a partial time series diagram of the bottom dependence coefficients between the Shanghai and Shenzhen 300 indices and various industry indices is listed, as shown in Figure 1.



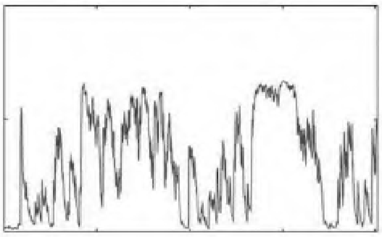
(1) Agriculture, Forestry, Animal Husbandry and Fish

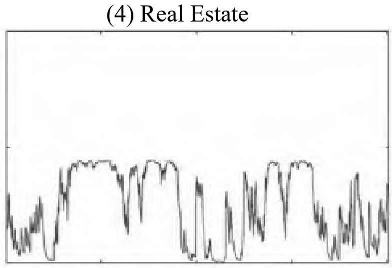
(2) Medical Biology





(3) Mining (4) Real Estate





(5) Transportation (6) Media

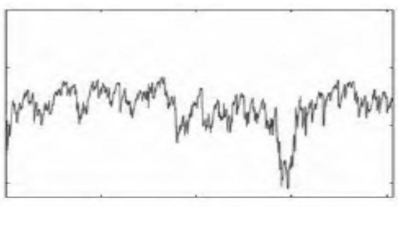
Fig. 1. Time series of tail dependence coefficients between some industry indices and the market

Observing the entire sample period, it can be found that the tail dependence coefficient of the agricultural, forestry, animal husbandry, and fishery, pharmaceutical and biological industry indices is relatively small. Although there is some fluctuation throughout the entire sample period, the overall range remains relatively low. Industries such as agriculture, forestry, animal husbandry, fishing, medicine, and biology are recognized as defensive and countercyclical industries. These industries have relatively stable income, lack short-term explosive profits and development, and are less attractive to hot money. They do not have a sense of participation in the market's general upward phase, but they can maintain relative stability during periodic upward and downward movements, not in line with market fluctuations. The tail dependence coefficient of mining, automotive industry, and textile and clothing index gradually decreases, with a value of around 0.5 before 2014 and gradually dropping to around 0.25 thereafter. This phenomenon may be related to the supply side structural reform that began in 2015. This policy has led to the gradual transition of traditional overcapacity industries from extensive development to refined development. During the transformation process, it is inevitable to encounter problems such as reduced profitability and market influence caused by reforms, leading to weakened linkage with the stock market.

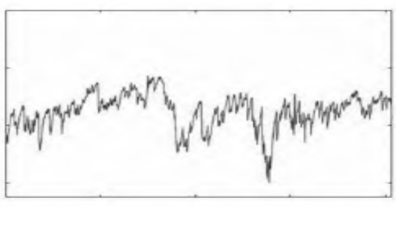
In addition, there are also some observations on the tail index during the 2015-2016 stock market crash. This year's market-oriented reform injected new vitality into the stock market, and investors also held optimistic expectations, driving the stock market to soar. However, the result was to forget the risk accumulation caused by the influx of highly leveraged funds. Subsequently, the regulatory authorities launched the supervision of OTC financing, which triggered the decline of the stock market, escalated the market panic and burst the market foam. Specifically, during this stage, the correlation between industry indices such as mining, real estate, and mechanical equipment and market indices has increased, while the correlation between industry indices such as chemicals, transportation, and food and beverage has decreased. There has been no significant change in the correlation between industry indices such as household appliances, light industry manufacturing, and non banking finance and market indices. Secondly, near January 2016, the probability of the real estate, textile and clothing, household appliances, and electrical equipment industry indices falling simultaneously with the market index reached its highest point. At the same time, the probability of the index of chemical, transportation, food and beverage, media, agriculture, forestry, animal husbandry, fishing, leisure services, commercial trade, and communication industries falling simultaneously with the market index first bottoms out and then sharply rebounds. The transportation and non-ferrous metal industry index showed similar trends after January 2016, while the mechanical equipment and computer industry index showed consistent trends throughout the entire observation period.

3.3.2 Analysis of systematic risk contribution by various industries

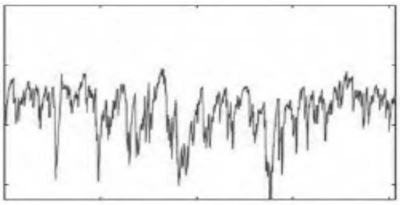
On the basis of time-varying mixed Copula, the GARCH EVT-COPULA function mixed model is used to estimate the risk contribution of the 28 industry indices selected in this article, with a market threshold of -2%. The specific MES values of various industry indices are shown in Table 5. If the estimated industry index MES value is larger, it indicates that the industry's risk contribution is smaller. From Table 5, it can be seen that the systematic risk contribution exhibits significant industry heterogeneity, with the banking industry having the smallest risk contribution and the building materials industry having the largest. In addition, the four industries with the lowest contribution to systemic risk are banking, public utilities, pharmaceutical biology, and food and beverage industries. In China, the banking and public utility industries have strong state-owned enterprise attributes, supported by strong financial funds, and are not easily affected by hot money. The estimation of their risk contribution is in line with the reality. The pharmaceutical and food and beverage industries both belong to the basic needs of residents' lives in terms of demand elasticity, and their risk contributions are relatively low with a difference of less than 0.01%, which is also consistent with reality. The four industries with the highest contribution to systemic risk are construction materials, national defense and military industry, electronics, and non-ferrous metal industry, with similar risk contributions from the electronics and non-ferrous metal industries. In addition, there is little difference in systemic risk contribution between the electrical equipment and media industries, as well as the automotive and mechanical equipment industries. In summary, risk averse investors should try to avoid investing in industries such as construction materials, and prioritize investments in industries such as banking, utilities, and pharmaceutical biology in their investment portfolios. Moreover, when constructing investment portfolios, industries with similar systemic risk contributions cannot effectively diversify risks.



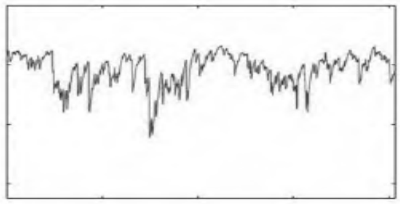
(1) Electronic



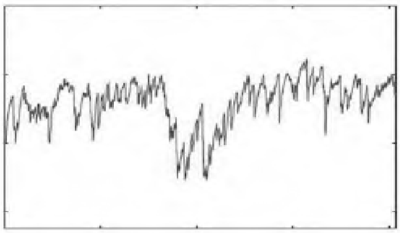
(2) Building Materials



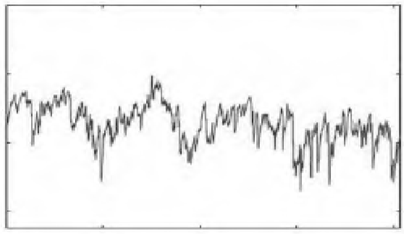
(3) National Defense and Military Industry



(4) Bank



(5) Textile and Clothing



(6) Communication

Fig. 2. MES time series of some industry indices

Table 5. Average MES of various industry indices during the sample period (unit:%)

Trade	MES	Trade	MES
Bank	-2.1324	Realty	-3.0352
Public utility	-2.4402	Digging	-3.0410
Medical biology	-2.6833	Automobile	-3.0753
Food and beverage	-2.6900	Mechanical-installation	-3.0766
Leisure services	-2.7460	Synthesize	-3.0799
Iron and Steel	-2.7677	Architectural ornament	-3.0857
Textile clothing	-2.8190	Commercial trade	-3.1015
Light manufacturing	-2.8642	Chemical industry	-3.1432
Computer	-2.8795	Non-bank finance	-3.2751
Agriculture	-2.8910	Communication	-3.3522
Traffic	-2.9260	Nonferrous metal	-3.3581
Domestic appliance	-2.9700	Electron	-3.3624
Electric accessory	-3.0171	Defense and military industry	-3.4018
Media	-3.0187	Building materials	-3.5595

Note: Arrange in descending order of MES values.

3.3.3 Time series analysis of the contribution of systemic risks in various industries

Figure 2 shows the time series of the contribution of systemic risks in various industries. Observing the entire sample period, it can be seen that there are significant differences in the MES fluctuations of various industry indices, with the minimum MES values of media, electronics, building materials, building decoration, non-ferrous metals, and defense and military industry indices significantly exceeding -5%, and their MES values fluctuate significantly. Affected by the domestic and foreign economic environment, these industries located upstream in the industrial chain have long been in an important position in economic development, becoming key nodes in the contribution of systemic risks when they occur. The MES fluctuations of the public utilities, pharmaceutical biology, and banking industry indices are relatively small, and their MES values are higher compared to other industry indices, indicating a lower risk contribution and a risk hedging effect in market crises. Market participants can fully leverage the comparative advantages of these industries, upgrade their investment and financing portfolios in a targeted manner, and enhance their overall risk resistance ability.

In addition, during the 2015 stock market crash, the MES values of most industry indices decreased to a certain extent, with the MES values of textile and clothing, non banking and finance, and defense and military industry indices showing the most significant decline, indicating a rapid increase in the contribution of systemic risks to the industry in a short period of time. In addition, the risk contribution level of the banking industry has always been at a relatively low level during the stock market crash, which indirectly confirms the ability of the banking industry as a "stabilizer" and to some extent reflects the role of the banking industry in effectively allocating financial resources by providing credit funds, promoting the good development of the industry and the stock market. Since October 2017, the MES values of industries such as nonferrous metals, steel, electronics, and communication have decreased to some extent, and the risk contribution has continued to rise, which may be related to the fermentation of trade frictions between China and the United States. This trade war has seriously damaged the international trade between the two countries, causing a huge impact on industries that are highly sensitive to exports, and increasing their contribution to market systemic risks in such industries. The MES time series of some industry indices is shown in Figure 2.

The empirical results show that regulatory authorities should closely monitor the systemic contributions of the aforementioned industries, regulate the financial industry, and intervene in policies in other industries to leverage the risk transmission and dispersion functions of different industries and prevent systemic risk linkage. The industry itself can achieve industrial transformation and upgrading by improving innovation capabilities, maintaining stable market value growth, and enhancing its ability to resist risks. For investors, analyzing the risk contribution of the industry can effectively predict the future trend of the market, which is helpful for their asset allocation and investment decisions.

4 Conclusions

This article constructs a weighted time-varying GARCH EVT-COPULA function hybrid model based on mixed Copula and GARCH EVT, measures the tail dependence of China's stock market index and different industry indices in the market, and estimates the degree of systemic risk contribution of each industry. It is found that there is significant heterogeneity in tail dependence and risk contribution. The specific conclusions are as follows:

(1) By constructing a time-varying weight mixed Copula model based on GARCH EVT, not only can the upper and lower tail dependent structures be distinguished, but also the time-varying weight can be used to dynamically describe the data dependent structures more intuitively, achieving capture and analysis of the real market with lower difficulty.

(2) Throughout the entire sample period, the tail dependence between the agricultural, forestry, animal husbandry, fishery, pharmaceutical, biological, non banking and financial, defense and military industry indices and market indices is relatively small, and the overall volatility remains

relatively low; The tail dependence coefficient between industry indices such as real estate, household appliances, and mechanical equipment is relatively high, indicating that these industries have relatively consistent fluctuations with the market. During the 2015 stock market crash, the tail dependence of industries such as mining, real estate, and mechanical equipment increased, while the dependence of industries such as chemical, transportation, and food and beverage decreased. There was no significant change in the dependence of industry indices such as household appliances, light industry manufacturing, and non banking finance on market indices.

(3) Throughout the entire sample period, there were significant differences in the average systemic risk contributions of various industries, with banks, public utilities, and pharmaceutical and biological industries having relatively small average risk contributions, while electronics, defense and military industries, and building materials industries having relatively large risk contributions. During the 2015 stock market crash, the contribution of systemic risks in most industries increased to a certain extent, with textile and clothing, non banking and finance, and defense and military industries showing the most significant increase in contribution. The risk contribution level of the banking industry has always been at a relatively low level during the stock market crash, which indirectly confirms the role of the banking industry as a "stabilizer". In addition, since August 2017, the risk contribution level of industries such as non-ferrous metals, steel, electronics, and communication has continued to increase, possibly due to the impact of trade frictions between China and the United States.

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