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An Empirical Study on the Systemic Risk Spillover Effect of Listed Securities Companies During the Epidemic

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Abstract: Based on the daily yield data from January 2, 2019 to December 31, 2020, this paper uses DCC-GJR-GARCH-CoVaR model to measure the systemic risk spillover effect among top 10 securities companies by market value in China. The conclusions are as follows: (1) There are asymmetric and bidirectional risk spillover effects among 10 securities companies, and effects are highly volatile in a short period of time. (2) The systematic risk spillover effect of securities companies has a stronger relationship with the sentiment of stock market than the market value. At last, we put forward suggestions.

Keywords: Loading Systemic Risk Spillover; Listed Securities Companies; DCC-GJR-GARCH-CoVaR.

1. Introduction

The occurrence of systemic financial risks can cause catastrophic damage to individual wealth and macroeconomics. However, because systemic financial risks are highly concealed and contagious, they are difficult to be accurately identified and measure. In addition, in recent years, China has continued to promote financial reforms and accelerate the pace of financial opening to the world. The number and harm of potential risk factors facing financial system are constantly increasing, and the possibility of systemic risks is also expanding.

Since the 1990s, China's capital market has developed rapidly. As of June 30, 2020, China's 164 securities companies have total assets of 8.03 trillion yuan, net assets of 2.09 trillion yuan, net capital of 1.67 trillion yuan, customer transaction settlement fund balance of 1.64 trillion yuan, and total entrusted management capital of 1.183 billion yuan. However, the overall scale of the securities industry is still small, and financing channels still need to be further expanded.At the same time, factors such as market environment and policy constraints still play a more or less inhibitory effect on the innovation of the securities industry. The main profitability of the securities industry is still limited to traditional businesses such as securities brokerage and proprietary securities. A single and simple business operation model makes the adverse effects of the financial market easy to spread to the securities industry. All these make China's securities industry very vulnerable when faced with risks [1,2]. As mentioned above, China's capital market will inevitably face more and more harmful risk factors in the process of increasing openness and deepening reform.

Systemic risk can be interpreted as a risk that can cause most market participants to suffer losses at the same time and spread rapidly in the market [3]. Compared with individual risk, systemic risk has five basic characteristics: complexity, suddenness, rapid contagion, wide spread and great harm [4]. Therefore, in order to better identify and control risks, many scholars are committed to preventing and reducing risk spillovers by scientifically monitoring and measuring systemic financial risks.

At present, the academic research methods for risk spillover effects can be summarized as follows: One is the financial network model proposed by Allen and Gale [5]. The core idea of the theory is to use the data of transactions between financial institutions to construct a financial network, and to study the contagion characteristics of financial risks by studying the structural characteristics of the financial network. The second is the Marginal Expected Shortfall (MES) method proposed by Acharya. The core idea of this method is to calculate the systemic risk contribution of a single individual to the entire market when the financial crisis breaks out, and to measure the loss that a single individual will face [6]. The third is the CoVaR model proposed by Adriany and Brunnermeier. The core idea of this model is to measure the possible losses of other institutions or markets when an institution or market already has risks [7]. Because the CoVaR method uses high-frequency data modeling, it can more sensitively capture the contagious characteristics of financial risks and measure financial risk spillover effects, so it has gradually become an important tool for analyzing financial risk spillover effects [8].

In recent years, scholars have continued to expand and improve the CoVaR model, and reuse the improved model for systemic risk research. Li and Fan applied quantile regression to the estimation of the CoVaR value of seven Chinese banks.They found that the performance of state-owned banks on the systemic risk premium is more prominent than that of joint-stock commercial banks [9]. Gauthier, Lehar, and Soussi used the CoVaR model to study the relationship between Canadian banks with different capital allocation ratios and their systemic risk contributions. They found that while imposing macro-prudential requirements on bank capital, the stability of the financial system will also increase[10]. Bernardi et al. used the CoVaR model under Bayesian regression to explain the dynamic behavior of the tail of financial asset returns[11]. Lin et al. used the AR-GARCH-CoVaR model to calculate the systemic risk of Chinese insurance companies and found that China Life Insurance has the largest risk spillover effect [12]. Girardi and Ergun used the CoVaR value to measure the systemic risk of the U.S. financial industry, and the results show that there is no linear relationship between the scale of financial companies and the scale of systemic risk of financial companies[13]. Reboredo and Ugolini used the CoVaR-Copula model to study the different systemic risk characteristics of European sovereign debt markets before and after the outbreak of the Greek debt crisis. They found that after the crisis, the systemic risk of the crisis countries decreased, while the systemic risk of Greece to the crisis countries increased [14]. Harder et al. used generalized quantile regression to calculate the CoVaR value of American financial companies, and organically combined CoVaR with network technology. They found that the risk of acceptance and dissemination by depository institutions is greater, while insurance companies are the opposite [15].Xu, Wei, and Chen used quantile regression to estimate the CoVaR value of listed insurance companies in China. They found that the higher the proportion of non-traditional insurance in the insurance company's business, the greater the systemic risk. At the same time, effective supervision of the solvency of insurance companies has a significant role in restraining their risk spillovers [16]. Yuan and Wang found significant bidirectional asymmetric systemic risk spillovers between insurance companies, between insurance companies and the insurance industry[17]. Long et al. calculated the CoVaR and ΔCoVaR of the CSI 300 secondary industry index by constructing a time-varying t-copula function. They found that small-scale industries have a more prominent contribution to systemic risks than larger-scale industries [18]. Yang, Chen and Xie used the methods of VaR, MES, CoVaR and ΔCoVaR to measure the systemic risks of 56 Chinese listed companies. They found that the level of systemic risk spillovers in Chinese enterprises has increased year by year. In addition, in financial risk events such as "bank money shortage" and "stock market circuit breaker mechanism", the risk transmission center has also changed [19]. Wang and Yang used the EVT-Copula-CoVaR model to calculate the risk spillover effect of China’s stock market, and found that there is a bidirectional asymmetric risk spillover effect with the stock markets of countries along the “Belt and Road” [20]. Xu et al. used a risk network based on LASSO-CoVaR to study the changes in the systemic risks of Chinese financial institutions from 2010 to 2017. They found that the risks of financial institutions are time-varying [21]. Zhang and Xu used the ΔCoVaR method to measure the systemic risk of Chinese listed banks participating in derivatives transactions. They found that derivatives transactions increase the systemic risk of banks, and interest rate derivatives have a greater impact on systemic risks than foreign exchange derivatives [22]. Aviral Kumar Tiwari et al. used the ΔCoVaR and MES methods to measure the systemic risk of the G7 country's securities market, and found that the increase in market turbulence promoted the risk spillover level of oil price changes on the G7 country's securities market [23].

In summary, scholars are increasingly studying systemic financial risks, and the CoVaR model has been continuously expanded and improved in practical applications. However, the main results of the current research on risk spillover effects are mainly concentrated in the banking, insurance industry and other industries, with relatively little research on the securities industry. In addition, most of the existing research results of systemic risk spillovers in the securities industry still remain on the basic CoVaR and ΔCoVaR methods, which can no longer meet the needs of accurately capturing and fitting the characteristics of financial time series data.

Compared with the simple GARCH model, on the one hand, the GJR-GARCH model can more accurately and truly describe the asymmetry of volatility spillovers between markets[24];On the other hand, the DCC-GARCH model overcomes the shortcomings of the previous multivariate GARCH models that are difficult to estimate due to the large scale of the coefficient matrix, and can also be used to study the dynamic correlation of multiple assets under different periods and different influencing factors [25]. The DCC-GJR-GARCH model combines the advantages of the above DCC-GARCH model and GJR-GARCH model, making the fitting of financial time series more accurate and practical. The DCC-GJR-GARCH-CoVaR model is built on the basis of the DCC-GJR-GARCH model combined with the CoVaR method. The model uses the variance between the financial time series fitted by the DCC-GARCH model to calculate the risk spillover CoVaR value, and then measure the size of systemic risk spillovers.

In view of this, we use the DCC-GJR-GARCH-CoVaR model to study the characteristics of systemic risk spillover effects of listed securities companies in China.

2. Construction of DCC-GJR-GARCH-CoVaRModel

This section first introduces the basic definition of the CoVaR model, then introduces the specific method of the DCC-GJR-GARCH model to estimate the conditional variance of the return sequence, and finally introduces the estimation steps of the CoVaR value.

2.1 Introduction to CoVaR Model

Adrian and Brunnermeier proposed CoVaR based on *VaR* [26]. *CoVaR*is defined as when the loss X^i of financial institutions isVaR_q^i, under the confidence level of q, the VaR faced by financial institution *j*. That is:

$$\Pr ob(X^{j} \leq CoVaR_q^{j|i} \left| X^{i} = VaR_q^{i}\right.) = q \quad (1)$$

Thus, the systemic risk spillover value (△CoVaR) of financial institution i to financial institution j can be expressed as follows:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|i} - VaR_q^{j} \quad (2)$$

Among them, VaR_q^j is the value at risk faced by financial institution i under normal conditions.

2.2 Fitting Conditional Variance of DCC-GJR-GARCH Model

The GARCH model can effectively explain the heteroscedasticity effect and volatility aggregation that are common in financial time series.In addition, Engel's research found that the DCC-GARCH model, by allowing the conditional correlation coefficients to be variable, effectively solves the difficulty of the previous multivariate GARCH models with too many parameters that are difficult to estimate. At the same time, it more truly describes the time-varying characteristics of the degree of influence between financial time series [27]. The GJR-GARCH model proposed by Glosten et al., through the introduction of dummy variables, makes the parameters in the GARCH model negative [28], and more truly describes the asymmetric response of financial time series to different information.Therefore, this article uses the DCC-GJR-GARCH model introduced by scholars such as Glosten to estimate the conditional variance of financial time series.

We assume that the residual series e_t of financial institutions' return series is white noise series, the covariance matrix is H_t, v is the degree of freedom of multivariate joint t distribution.

$$e_t|\Omega_{t-1} \sim T(0,\ H_t,\ \nu). \quad (3)$$

Where Ω_{t-1} represents the previous information set.

H_t is the covariance matrix, which can be expressed as:

$$H_t = D_t R_t D_t. \quad (4)$$

D_t of equation (4) is the variance matrix of the residual error e_t, it can be shownas follows:

$$\mathrm{D_t} = \mathrm{diag}\ (\sqrt{\mathrm{h_{11,\ t}}},\ \cdots,\ \sqrt{\mathrm{h_{nn,\ t}}}) \ . \quad (5)$$

Among them, $h_{ii,\ t}$ is the conditional variance of the residual error e_t, it is characterized by GARCH (1,1). That is:

$$h_{ii,\ t} = w_i + \alpha_i e_{i,\ t-1}^2 + \beta_i h_{ii,\ t-1} + g I_{t-1} e_{i,\ t-1}^2. \quad (6)$$

The expression of schematic function I_{t-1} of equation (6) is as follows:

$$I_{t-1} = \begin{cases} 1, e_{i,t-1} < 0 \\ 0, e_{i,t-1} \geq 0 \end{cases}. \quad (7)$$

When there is good news in the market ($e_{i,\ t-1} \geq 0$), the variance $h_{ii,\ t}$ is affected by

α_i. When the market appears bad news ($e_{i,\ t-1} < 0$), the variance $h_{ii,\ t}$ is affected by($\alpha_i + g$).

R_t of equation (4) is the dynamic correlation coefficient matrix. The expression is as follows:

$$R_t = \mathrm{diag}\left(1/\sqrt{\mathrm{q}_{11,\ t}},\ \cdots,\ 1/\sqrt{q_{nn,\ t}}\right) {*} Q_t {*} \mathrm{diag}\left(1/\sqrt{\mathrm{q}_{11,\ t}},\ \cdots,\ 1/\sqrt{q_{nn,\ t}}\right). \tag{8}$$

Where, $\mathrm{q}_{nn,\ t}$ is the conditional variance of standardized residuals.Therefore, the dynamic correlation coefficient ($\rho_{ij,\ t}$) in R_t is as follows: $\rho_{ij,\ t} = q_{ij,\ t} / \sqrt{q_{ii,\ t} q_{jj,\ t}}$.

Q_t of equation (8) can be expressed as:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{`} + \beta Q_{t-1}. \tag{9}$$

Where $\bar{Q}$ is the unconditional variance matrix of standardized residuals ε_t and $\varepsilon_t = D_t^{-1} e_t$ is the vector normalized residuals.

For the positive definiteness of H_t, only $\alpha + \beta < 1$ is required [29].

2.3 Estimation Steps of CoVaR

According to 2.1 and 2.2, we can estimate the CoVaR value and ΔCoVaR value of financial time series. The specific estimation steps are as follows:

The first step is to establish a GARCH(p,q) model based on the time series data of financial institutions to measure the volatility of their return series.

$$r_{i,t} = \beta_i + \beta_{i,p} A_p(L) r_{i,t-1} + B_p(L) e_{i,t}. \tag{10}$$

$$h_{i,t}^2 = \gamma_i + \delta_i e_{i,t-1}^2 + \theta_i h_{t-1}^2. \tag{11}$$

Among them, $r_{i,t}$ is the yield of financial institution *i* in period *t*, $h_{i,t}^2$ is the variance of the residual error $e_{i,t}$ in t period, $e_{i,t-1}^2$ is the square of the residual error $e_{i,t}$ in t-1 period, namely ARCH term; h_{t-1}^2 denotes GARCH term, dummy variable I_{t-1} represents the asymmetric effect of new information. β_i and γ_i areconstant terms, $A_p(L)$ and $B_p(L)$ arelagging operators.

In the second step, estimate the VaR_i valueof financial institutions. The formula is as follows:

$$VaR_{i,t} = -\widehat{r_{i,t}} + F^{-1}(q)\widehat{h_{i,t}}. \tag{12}$$

Among them, $\widehat{r_{i,t}}$ is the one-step forward estimate of the return rate of financial institutions i obtained by GARCH model, and $\widehat{h_{i,t}}$ is the one-step forward estimation value of $h_{ii,\ t}$. $F^{-1}()$ is the inverse function of the distribution function of t distribution, and q is the confidence level [30].

In the third step, using the DCC-GJR-GARCH model and the results of the previous step, calculate the CoVaR of financial institution j under the influence of financial institution i. The formula is as follows:

$$r_{j,t}=\beta_i+\beta_{j,p}A_p(L)r_{j,t-1}+\theta_{j|i}r_{i,t}+B_p(L)e_{i,t}. \tag{13}$$

$$h_{j,t}^2=\gamma_j+\delta_j e_{j,t-1}^2+\theta_j h_{t-1}^2+gI_{t-1}e_{j,t-1}^2. \tag{14}$$

Where, $r_{j,t}$ is the yield of financial institution *j*, $r_{i,t}$ and $r_{m,t-1}$ represent the impact of financial institution i and macro situation on financial institution *j* respectively. $A_p(L)$ and $B_p(L)$ are lag operators, and $\theta_{j|i}$ is the regression coefficient of financial institution i in the formula.Introducing $r_{i,t}=VaR_{i,t}$ into the mean value equation, the following formula is obtained:

$$r_{j,t}=\beta_i+\beta_{j,p}A_p(L)r_{j,t-1}+\theta_{j|i}VaR_{i,t}+\varphi_j r_{m,t-1}+B_p(L)e_{i,t}. \tag{15}$$

According to the mean value $\widehat{r_{j,t}}$ and the conditional variance $\widehat{h_{j,t}}$, the CoVaR and ΔCoVaR of financial institution j are obtained. The formula is as follows:

$$CoVaR_{j|i,q,t}=-\widehat{r_{j.t}}+F^{-1}(q)\widehat{h_{j.t}}. \tag{16}$$

$$\Delta CoVaR_{j|i,q,t}=CoVaR_{j|i,q,t}-VaR_{i,q,t}. \tag{17}$$

Where, $VaR_{i,q,t}$ is the same as the VaR_i value of financial institution i calculated by formula (12).

3. Empirical Analysis

3.1 Data Selection and Processing

This paper uses the stock price index of the top 10 securities companies with total market value which listed in China's A-share market before January 1, 2019. They areGF Securities Co., Ltd.(000776.SZ), GuotaiJunan Securities Co., Ltd.(601211.SH), Guosen Securities Co., Ltd.(002736.SZ), Haitong Securities Co., Ltd.(600837.SH), Huatai Securities Co., Ltd.(601688.SH), ShenWanHongYuan Securities Co., Ltd.(000166.SZ), China Galaxy Securities Co.,Ltd.(601881.SH), China Merchants Securities Co.,Ltd.(600999.SH), China Securities Co., Ltd.(601066.SH) and Citic Securities Co., Ltd.(600030.SH)), and this paperchooses the closing priceon each trading day as the original data. The data selection time limit is from January 2, 2019 to December 31, 2020, excluding daily data with missing data, all data comes from the CSMAR database.

After obtaining the daily closing price data, calculate the daily return rate of each stock according to the following formula:

$$r_t=100*\ln(P_t/P_{t-1}). \tag{18}$$

Among them, P_t is the closing price of the stocks on day *t*.

3.2 Descriptive Statistics of Data

At the beginning of the analysis, we conducted descriptive statistics on the daily return rate series of samples. See Table 1 for details.

Table 1. Descriptive Statistics of the yield series of securities companies stocks.

Company	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	JBstatistics	Probability
C1	0.0753	< 0.0001	9.5537	-10.5286	2.1734	0.1147	8.4926	593.1025	< 0.0001
C2	0.0341	-0.0615	9.5310	-10.5550	2.0356	0.2070	8.5519	608.2802	< 0.0001
C3	0.1121	<0.0001	9.5664	-10.5361	2.3889	0.6947	6.9161	338.8516	< 0.0001
C4	0.0884	-0.0730	9.5667	-10.5520	2.3742	0.6039	7.0814	355.5272	< 0.0001
C5	0.0220	-0.0986	9.5534	-10.5361	2.2784	0.1316	7.8838	469.4454	< 0.0001
C6	0.0665	< 0.0001	9.5479	-10.4900	2.0494	0.3017	9.7053	889.5073	< 0.0001
C7	0.1365	< 0.0001	9.5882	-10.5163	2.8210	0.3983	5.6374	148.9615	< 0.0001
C8	0.1572	0.0483	9.5517	-10.5064	2.4371	0.6029	7.3751	404.1900	< 0.0001
C9	0.3088	-0.1322	9.5614	-10.5551	3.6590	0.3767	4.2529	41.9494	< 0.0001
C10	0.1367	-0.0862	9.5450	-10.5527	2.3708	0.3840	7.9267	487.9154	< 0.0001

Note: C1 , C2, …, C10 representGF Securities Co., Ltd., GuotaiJunan Securities Co., Ltd., Guosen Securities Co., Ltd., Haitong Securities Co., Ltd., Huatai Securities Co., Ltd., Shen Wan Hong Yuan Securities Co., Ltd., China Galaxy Securities Co.,Ltd., China Merchants Securities Co.,Ltd., China Securities Co., Ltd., and Citic Securities Co., Ltd., respectively. C1 , C2, …, C10 in all tables below have the same meaning as this table. According to Table 1, the average daily return rate of 10 securities company stocks are all greater than 0. Among them, the largest average yield is China Securities Co., Ltd., which reaches 0.3088; the smallest is Huatai Securities Co., Ltd., which is 0.0220. The standard deviation of the stock daily return sequence is generally more than 2 units larger than its mean, and the difference in the return of the same stock can reach 20%, which shows that the stock return sequence has fluctuated during the observation period. In addition, we can observe that the kurtosis of the stock return sequence of all securities companies is greater than 3, showing a certain degree of right deviation. The JB statistics are all very large, and the P values are all less than 0.01, showing the peak and thick tail characteristics of financial time series.In order to adapt to the data characteristics of the return rate data itself, this paper chooses the t distribution to describe the stock return rate sequence.

3.3 Stability Test

When the observation object is time series data, it is necessary to perform stability test to avoid the pseudo regression phenomenon that may appear in regression analysis, so as to prevent wrong conclusions. Here, we conduct an ADF test on the daily return rate series of 10 securities company stocks during the test period. See Table 3 and Table 4 for details.

Table 2. ADF test of stock yield series of securities companies.

Company	Obs	Prob	Lag	Max Lag
C1	471	<0.0001	0	17
C2	471	<0.0001	0	17
C3	471	<0.0001	0	17
C4	471	<0.0001	0	17
C5	471	<0.0001	0	17
C6	471	<0.0001	0	17
C7	471	<0.0001	0	17
C8	471	<0.0001	0	17
C9	471	<0.0001	0	17
C10	471	<0.0001	0	17

According to Tables 3 and 4, the data of the stock return rate series of securities companies during the observation period have passed the ADF test. The original hypothesis that the yield series have unit root is rejected by all results at the 1% significance level.

3.4 Autocorrelation Test

When autocorrelation occurs in the random error term in the time series data, the true variance of the parameter estimate is underestimated, which leads to the overestimation of the value of t statistic, which enhances the reliability of the parameter estimate, and may be eliminated. The explanatory variable of is incorrectly retained, which ultimately leads to a decrease in the accuracy of the model's prediction. With the help of Eviews software, we have investigated the ACF and PACF values of 10 securities companies' stock returns series. The results show that at the 5% significance level, the null hypothesis that the rate of return series has autocorrelation is rejected.

3.5 ARCH Effect Test

The existence of heteroscedasticity effect directly determines whether the variance of the return rate series is suitable for GARCH model modeling. Engle proposed a method to test whether there is heteroscedasticity in a time series, that is, the ARCH test method [31]. We assume that the number of lag periods for the ARCH test is 1, and perform the ARCH effect test on the daily return sequence of 10 securities company stocks during the test period. See Tables 5 and 6 for details.

Table 3. ARCH test of stock yield series of securities companies.

Company	F-statistic	Prob.F	Obs*R-squared	Prob. Chi-Square(1)
C1	14.9449	0.0001	14.5443	0.0001
C2	33.7323	<0.0001	31.5989	<0.0001
C3	10.3583	0.0014	10.1773	0.0014

C4	10.6437	0.0012	10.4515	0.0012
C5	16.3962	0.0001	15.9089	0.0001
C6	39.0690	<0.0001	36.2129	<0.0001
C7	4.0942	0.0436	4.0760	0.0435
C8	15.5067	0.0001	15.0735	0.0001
C9	52.9810	<0.0001	47.7965	<0.0001
C10	8.5823	0.0036	8.4638	0.0036

Note:"1" inProb. Chi-Square(1) represents the degrees of freedom of the chi-square distribution, and also represents the number of lag periods assumed in the ARCH test. It has the same meaning in Table6.

According to Table 5,the p value of the n*R-squared statistic of the stock yield series of ten securities companies are all below 0.05, that is, the original hypothesis that the random error term of the yield series have no heteroscedasticity is rejected at the significance level of 5%. This also shows that under the assumption that the random error term lags by one period, the daily yield series have an ARCH effect.

3.6 Analysis of Systemic Risk Spillover Effect Among Securities Companies

We analyze the size of the systemic risk spillover effect of securities companies according to the following steps: First, use equation (18) to calculate the stock returns of 10 sample companies.Second, use formula (10) and formula (11) to fit the mean and variance of the return series of 10 stocks to obtain the degrees of freedom of the t distribution.Third, predict the mean forecast value $\widehat{r_{i,t}}$ and variance forecast value $\widehat{h_{i,t}}$ by the estimation formula one step forward, and substitute the degree of freedom of t distribution and the 95% confidence level into equation (12) to calculate theVaR_ivalue of 10 stock return series at 95% confidence level.Fourth, use the DCC-GJR-GARCH(1,1) model of Student t distribution to fit the mean and variance of the stock return sequence of each sample securities company under the influence of the remaining nine sample securities companies.Get the following two formulas:

$$r_{j,t} = \beta_i + \beta_{j,p} A_p(L) r_{j,t-1} + \theta_{j|i} r_{i,t} + B_p(L) e_{i,t}. \quad (19)$$

$$h_{j,t}^2 = \gamma_j + \delta_j e_{j,t-1}^2 + \theta_j h_{t-1}^2 + g I_{t-1} e_{j,t-1}^2. \quad (20)$$

Fifthly,predict the mean $\widehat{r_{j,t}}$ and the conditional variance$\widehat{h_{j,t}}$ by the estimation formula one step forward, and substitute the degree of freedom of t distribution and 95% confidence level into equation (16), and calculate the $CoVaR_{j|i}$ value of each securities company at 95% confidence level.

Sixth, substitute $CoVaR_n$ and VaR_n into equation (17) to get $\Delta CoVaR_{j|i}$ values.The results are shown in Table 4.

Table 4. Systemic risk spillover effect among securities companies.

Company	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	—	-12.7570	-13.1343	-12.9146	-12.8300	-12.8210	-13.1502	-12.1298	-11.8152	-13.8192
C2	-10.7950	—	-11.0524	-10.8471	-10.7647	-10.8162	-11.1778	-10.0634	-9.7183	-11.8143
C3	-19.5784	-19.4586	—	-19.5853	-19.5958	-19.4815	-19.7950	-18.8930	-18.6136	-20.3539
C4	-16.9534	-16.8480	-17.1801	—	-16.9171	-17.0295	-17.2458	-16.4005	-15.8975	-17.8309
C5	-15.9970	-15.8973	-16.3188	-16.0453	—	-16.0311	-16.2854	-15.3746	-14.8554	-16.8518
C6	-12.0308	-11.9881	-12.2473	-12.2005	-12.0739	—	-12.2998	-11.2644	-11.1012	-13.0421
C7	-24.0920	-24.0816	-24.2927	-24.1487	-24.0602	-16.5501	—	-23.5581	-23.1421	-24.8172
C8	-23.9848	-23.8962	-24.2304	-24.1597	-24.0285	-16.4658	-24.3605	—	-23.0264	-24.9682
C9	-31.2600	-31.1489	-31.5316	-31.2955	-31.1524	-16.3601	-31.5607	-30.5396	—	-32.0801
C10	-25.5327	-25.4899	-25.6234	-25.5056	-25.3983	-17.1208	-25.5889	-25.0910	-24.5556	—

It can be seen from Table 4 that each securities company has a certain risk spillover effect on other securities companies, and the risk spillover characteristics of different companies are very different.

In terms of the spread of systemic risks,horizontally, we can observe that the risk spillover effect of China Securities Co., Ltd. on other securities companies is very significant, and its spread ΔCoVaR value is generally 5-6 units higher than the second place; on the contrary, the risk spillover effect of Shen Wan Hong Yuan Securities Co., Ltd., GF Securities Co., Ltd., Guotai Junan Securities Co., Ltd. on other securities companies is not significant, and its diversified ΔCoVaR value is about 20 units lower than that of China Securities. The ΔCoVaR values of other securities companies are among the above-mentioned securities companies, and the systemic risk spillover effect is moderate. This shows that due to the larger business volume of larger securities companies, their business connections with other securities companies are also closer, and they have a greater impact on other securities companies. Therefore, they play an important role in spreading systemic risks into the securities system.

In addition, in terms of systemic risk acceptance, vertically, we can observe that Citic Securities Co., Ltd. accepts a greater risk spillover effect, and its accepted ΔCoVaR value is about 1 unit higher than the normal level; on the contrary, the probability of Shenwan Hongyuan Securities Co., Ltd. accepting the risk is very small, and the ΔCoVaR value that it accepts from major securities companies such as China Securities Co., Ltd. remains at a normal level. The ΔCoVaR values accepted by the remaining securities companies are between the two companies, and the possibility of accepting systemic risk spillovers is medium. This shows that Shen Wan Hong Yuan Securities Co., Ltd. has a relatively high level of risk management, while Citic Securities Co., Ltd. does poorly in risk management.

By comparing the differences in risk diffusion and risk acceptance of different securities companies, it is not difficult to find that the risk spillover effects between securities companies are asymmetric. For example, the ΔCovar value of China Galaxy Securities Co., Ltd. to other securities companies is significantly higher than the ΔCovar value it accepts, which is generally 5 units higher. On the contrary, the risk spillover value accepted by Guotai Junan Securities Co., Ltd. is higher than the spread risk spillover value, which is about 10 units higher. We also found that there is no direct correlation between the size of the company's market capitalization and the risk spillover effects between securities companies. For example, as the two securities companies with the largest market capitalization in the industry, the ΔCovar values accepted by China Securities Co., Ltd. and Citic Securities Co., Ltd. from other securities companies are at a normal level or even smaller.

4. Conclusions and Suggestions

This paper selects the top 10 securities company stocks in China's stock market by market capitalization as the research object, uses the DCC-GJR-GARCH model to calculate the risk spillover value, and draws a time series diagram of the systematic risk spillover of each securities company based on the research results to study my country's securities companies The changing law of systemic risk spillover effects. The conclusions reached are: (1) There are risk spillover effects among 10 securities companies which are asymmetric and bidirectional, and highly volatile in a short period of time. (2) There is no direct relationship between the systemic risk spillover effects of securities companies and the market value of securities companies. (3) The trend of systemic risk spillover effects of securities companies is closely related to the trend of Shanghai stock index. When the trend of Shanghai stock index fluctuates on a large scale, the systemic risk spillover effects of securities companies also increase.

Based on this, we put forward the following suggestions: (1) Implement differentiated risk supervision measures for different securities companies to improve the flexibility of risk supervision. (2) Steadily advance the reform of the securities industry and stabilize the fluctuation of market trading sentiment. (3)Improve the accuracy of risk measurement and enhance risk identification capabilities.

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