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Analysis of The Stock Market Risk Spillover Effect of China's Insurance Industry Based on a GARCH-Copula-Covar Model

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Abstract: *The insurance fund operation requires consideration of prudence and security. Research on the risk spillover effect of the insurance industry in the stock market is of great significance. The study explored how to better assess the insurance industry's risk in the stock market and the spillover effects between the insurance industry and other different industries. Firstly, the ARMA-GARCH model was used to fit the logarithmic returns of six industries in China's A-share market, including insurance industry, pharmaceutical industry, public health, financial technology industry, green industry and blockchain industry. Then, each order model under the assumption residual of partial normal distribution was established respectively. Then the t-Copula connection function between the insurance industry and other industries was fitted. Finally, through the calculation of VaR and CoVaR, the risk spillover effects between each industry's own value at risk and the insurance industry were studied. The research provides a theoretical reference for the risk management of China' s insurance industry funds investing in the stock market.*

Keywords: *Insurance fund operation; risk spillover effect; GARCH-Copula-CoVaR model*

1. Introduction

The phenomenon of low operating rate and operating level of insurance funds still exists in China' s insurance industry [1]. The operation of insurance funds is not only related to the actual operating income of insurance companies, but also the guarantee of their good balance of assets and liabilities. Therefore, it is necessary to understand the risk spillover effects of various industries on the insurance industry.

The risk spillover effect refers to the fluctuation transmission mechanism between industries, that is, an industry will not only face risks from its own, but also be affected by risks from other industries. For the measurement of risk spillovers, many studies have conducted in-depth explorations [2-4].

The stock market is an important part of the investment of insurance funds in equity assets. In my country's stock market, which is still underdeveloped and immature, it is particularly important how to better evaluate the risk and spillover effect of the insurance industry in the stock market to make insurance funds realize the optimal allocation of assets in my country's stock market and reduce investment risks.

The research goal is to start from different industries in my country's A shares, several industries or emerging industries that are closely related to the insurance industry are selected as the research objects to study the risk spillover situation between them and the insurance market.

2. Introduction to the GARCH-Copula-CoVaR model

2.1. The ARMA-GARCH model

The autoregressive moving average (ARMA) model is one of the most common models used to characterize stationary time series.

If a time series $\{r_t\}$ satisfies equation (1):

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

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Where ε_t is the residual of the time series $\{r_t\}$ at time *t*, which is a sequence with zero mean and independent of each other.

Then $\{r_t\}$ is called the autoregressive moving average mixing process, and it is denoted as $ARMA(p,q)$.

The general autoregressive conditional heteroskedasticity (GARCH) model can better describe financial time series with the characteristics of aggregated volatility and sharp peaks and thick tails by considering the lagged residual square term. The $GARCH(1,1)$ model is effective and concise. The $GARCH(1,1)$ model is expressed as:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t \\ \varepsilon_t &= \sqrt{h_t}\xi_t \\ h_t &= \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \end{aligned} \tag{2}$$

Where h_t is the conditional variance and ξ_t is an independent sequence with zero mean.

The ARMA-GARCH model uses the ARMA model to describe the conditional mean distribution of the time series $\{r_t\}$, and uses the GARCH model to describe the conditional variance process. The $ARMA(p,q)-GARCH(1,1)$ model can be expressed as:

$$\begin{aligned} r_t &= \mu + \sum_{i=1}^{p}\phi_i r_{t-i} + \sum_{j=1}^{q}\varphi_j\varepsilon_{t-j} + \varepsilon_t \\ \varepsilon_t &= \sqrt{h_t}\xi_t \\ h_t &= \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \end{aligned} \tag{3}$$

2.2. Copula theory

Studies have shown that the t-Copula function can better describe the thick-tailed features of financial time series [5]. In this study, the Copula function of the ellipse family is chosen as the connection function.

The expressions of the distribution function and density function of the t-Copula function for the binary random variable $(u_1,\ u_2)$ are as follows:

$$C(u_1,\ u_2;\ \rho,\ v) = \int_{-\infty}^{t_v^{-1}(u_1)}\int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi^2\sqrt{1-\rho^2}}\left(1+\frac{s^2+t^2-2\rho st}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} dsdt \tag{4}$$

$$c(u_1,\ u_2;\ \rho,\ v) = |\rho|^{-\frac{1}{2}}\frac{t(\frac{v+2}{2})t(\frac{v}{2})}{\left[t(\frac{v+1}{2})\right]^2}\times\frac{\left(1+\frac{1}{k}\xi'\rho^{-1}\xi\right)^{-\frac{v+2}{2}}}{\Pi_{i=1}^{2}\left(1+\frac{\xi_i^2}{v}\right)^{-\frac{v+1}{2}}} \tag{5}$$

Where ρ is the correlation coefficient and v is the degree of freedom.

2.3. The VaR and CoVaR models

Value at risk (VaR) is the value at risk of the variable itself. VaR_q^i refers to the maximum risk of loss *i* faces at a confidence level of 1-*q*, namely:

$$P\left(R^i \le VaR_q^i\right) = q \tag{6}$$

VaR is calculated using the ARMA-GARCH model, namely:

$$VaR_q^i(\alpha) = \hat{\mu}_i + \hat{\sigma}_i\xi_{i,q} \tag{7}$$

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Where $\hat{\mu}_i$ represents the predicted conditional mean of the model, $\hat{\sigma}_i$ represents the predicted conditional variance of the model, and $\xi_{i,q}$ represents the q quantile of the distribution of the standardized residual sequence in the GARCH model.

The volatility and uncertainty of the financial market led to a large correlation between various assets in the stock market, so CoVaR can be introduced to measure the risk spillover between the two assets. The following describes the conditional loss value of variable *j* when variable *i* reaches maximum loss of VaR_q^i at the 1-*q* confidence level as:

$$P\left(R^j \le CoVaR_q^{j|i},\ q\right) = q^2 \tag{8}$$

The Copula function is introduced, and $CoVaR_q^{j|i}$ can be obtained by connecting the ARMA-GARCH marginal distribution of the two variables R_i and R_j.

And there is:

$$CoVaR_q^{j|i} = \Delta CoVaR_q^{j|i} + VaR_q^j \tag{9}$$

Where $\Delta CoVaR_q^{j|i}$ represents the systematic risk spillover of variable R_j when the maximum risk loss of variable R_i occurs.

3. Research on the risk spillover effect of stock market in China's insurance industry

3.1. Preparation of data

One thousand six hundred and eighty daily closing price records were selected in this study as the original data for five insurance companies that have been listed on A-shares, including Ping an Insurance of China, China Life Insurance, New China Life Insurance, China Pacific Insurance and The People's Insurance of China. The final representative daily closing price of China's insurance industry was obtained by weighted their market capitalization. At the same time, the daily closing prices of the Shenzhen securities pharmaceutical, public health stock indices, fintech, carbon technology 30 and blockchain 50 that are closely related to the Chinese insurance industry were selected. The sample time span was from January 5, 2015 to November 26, 2021. Finally, their log-return time series is obtained using the following equation:

$$R_t = 100 \times ln\left(\frac{p_t}{p_{t-1}}\right) \tag{10}$$

Where P_t is the closing price of the stock index on day *t*. All data in this study come from the WIND database, and data processing is carried out in R language.

3.2. Verification of data

Before establishing the GARCH model, the ADF stationarity test, the Box-Lyung test, and the ARCH effect test need to be performed on each time series. The ADF stationarity test shows that the series were stationary. The Box-Lyung test shows that in the case of a lag of 12 orders, except for the Shenzhen Pharmaceutical and Carbon technology 30 industries, the return series of other industries have autocorrelations. The results of the ARCH effect test show that with a lag of 12, the return series of all industries have obvious conditional heteroscedasticity. Therefore, the ARMA-GARCH model with non-normal residual distribution is established for the return series of each industry to estimate the marginal distribution, which needs to be considered in the follow-up.

3.3. Estimation of models

3.3.1. Estimation of marginal distribution in the ARMA-GARCH model

The ARMA (1,1)-GARCH (1,1)-snorm model fitting of logarithmic return rate of Chinese insurance industry

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The ARMA model was fitted by the time series conditional mean of the logarithmic return rate of China's insurance industry, and the ARMA (1,1) model was established according to the AIC criterion. By changing the residual distribution and the corresponding order of the ARMA-GARCH model, the fitting parameters of the ARMA (1,1)-GARCH (1,1) model could be obtained. when ξ_t obeyed the skewed normal distribution, the ARMA (1,1)-GARCH (1,1)-snorm model was developed for the logarithmic return rate of China's insurance stock market after analyzing each parameter.

$$
\begin{aligned}
r_t &= -0.8904 r_{t-1} + \varepsilon_t + 0.9085\varepsilon_{t-1} \\
\varepsilon_t &= \sqrt{h_t}\xi_t \\
h_t &= 0.0386 + 0.0655\varepsilon_{t-1}^2 + 0.9263 h_{t-1}
\end{aligned} \tag{11}
$$

Where ξ_t is independent and identically distributed in a standard skewed normal distribution with a skewness coefficient of 1.1003.

The Box-Lyung test and the ARCH effect test on the residual of the model shows that the model fits the logarithmic return series of the Chinese insurance stock market well.

Model fitting of logarithmic returns in other industries

In the same way, the logarithmic returns of stock markets such as Shenzhen Securities Pharmaceuticals, Public Health, Fintech, Carbon technology 30 and Blockchain 50 were modeled. After selecting the optimal model for them respectively, there were obtained: the residual sequences of the built models adopted the assumption that they conformed to the skewed normal distribution. In addition, from the fitting results for the logarithmic return rate's parameters of various industries, the average constant term of the logarithmic return rate of each industry was not significant. Therefore, models with a constant zero were established after modifying these models. The estimation of those parameters of the models showed significant p-values for almost all parameters.

3.3.2. Estimation of Copula Parameters

This part takes the estimation of t-Copula function parameter of the logarithmic return for China's insurance industry and financial technology as an example, and the estimation results of parameter for other industries are presented in tabular form. Firstly, R_j and R_i were extracted, and the residual sequence was standardized after fitting by ARMA-GARCH model, and then transformed into two uniformly distributed sequences (u_1, u_2) that obeyed the (0,1) interval after probability transformation.

The estimated results of t-Copula function parameters between the logarithmic returns of China's insurance industry and various industries are shown in Table 1.

Table 1: Fitting values of parameters of t-Copula function between China's insurance industry and various industries

	Parameters	Estimated values
Shenzhen medicine	ρ	0.38
	v	5.01
Public health	ρ	0.34
	v	6.13
fintech	ρ	0.38
	v	5.38
Carbon technology 30	ρ	0.28
	v	5.07
Blockchain 50	ρ	0.45
	v	4.62

3.4. Result analysis of the risk spillover effect of China's insurance industry stock market

3.4.1. Estimation of Copula Parameters

The VaR sequences were obtained by using the relevant parameters of the GARCH model to measure various industries. VaR under conditional mean and conditional variance was obtained by calculating the mean and median of the VaR series. In addition, the VaR under the unconditional variance was also

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calculated.

By comparing the VaR of the logarithmic return of rate these industries at the 5% level, it was found that the VaR of the insurance industry was close to that of the pharmaceutical and health industries; these two industries were more consistent with the nature of the insurance industry, and their life insurance Premium income accounted for a large proportion of insurance funds. Therefore, the reason for guessing the consistency may be that, the pharmaceutical industry and the health industry have a greater impact on life insurance premium income relative to other industries.

3.4.2. Calculation of CoVaR

Using the ARMA-GARCH model to fit the t-Copula function of the insurance industry and other industries in the stock market and calculate the VaR, the risk spillover effects of other industries on the insurance industry and the insurance industry on each industry were studied respectively. Table 2 below shows the risk profile of the insurance industry's highest risk loss reaching, respectively, under the condition that the highest risk loss in the five industries is VaR.

Table 2: Risk spillover effects of various industries on the insurance industry

Industry	Conditional mean and conditional variance			Unconditional mean and unconditional variance		
	$CoVaR_q^{j\|i}$	$\Delta CoVaR_q^{j\|i}$	Rank	$CoVaR_q^{j\|i}$	$\Delta CoVaR_q^{j\|i}$	Rank
Shenzhen medicine	-4.65	-1.60	3	-5.27	-1.81	3
Public health	-4.54	-1.50	4	-5.15	-1.70	4
Fintech	-4.65	-1.61	2	-5.28	-1.82	2
Carbon technology 30	-4.49	-1.45	5	-5.10	-1.64	5
Blockchain 50	-4.75	-1.70	1	-5.38	-1.92	1

The results show that the risk spillover effects of various industries on the insurance industry are consistent under the conditional and the unconditional mean and variance. Specifically, the blockchain industry has the largest risk spillover effect on the insurance industry, followed by the financial technology and pharmaceutical industries, and the risk spillover effect is close. Public health and carbon technology 30 have less risk spillover effect on the insurance industry.

Table 3: Risk spillover effects of insurance industry on various industries under unconditional mean and unconditional variance

Industry	$CoVaR_q^{j\|i}$	$\Delta CoVaR_q^{j\|i}$	$\%\Delta CoVaR_q^{j\|i}$	Rank
Shenzhen medicine	-5.59	-2.09	59.88	1
Public health	-5.21	-1.86	55.50	2
Fintech	-5.96	-2.18	57.60	4
Carbon technology 30	-5.82	-2.00	52.29	5
Blockchain 50	-4.99	-1.90	61.45	3

Table 3 shows that the risk spillover effect of the insurance industry on the blockchain is the largest among the five industries. This strong correlation illustrates the synergy between the insurance industry and the blockchain industry in the stock market.

On the whole, the interdependence between the blockchain industry and the insurance industry is high, and the mutual risk spillover effect between the financial technology and pharmaceutical industries and the insurance industry is also strong.

4. Conclusion and suggestion

As a risk management industry, the development of the insurance industry can effectively enhance the ability of the whole society to resist risks. At the same time, the insurance industry is also an important part of the financial industry. The research used the GARCH-Copula-CoVaR model to measure the stock market risk spillover effects of China’ s insurance industry industry in the A-share market, and drew the following conclusions and suggestions:

(1) Judging from the VaR calculation results of various industries, whether under the conditional mean and variance or the unconditional mean and variance, the VaR of China’ s insurance industry industry is similar to that of the pharmaceutical industry, and its risk is at a medium level. Compared with emerging industries such as fintech and carbon technology 30, the VaR value of traditional industries is relatively small.

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(2) After considering the risk spillover effect, it is found that the industry with higher VaR does not necessarily have a higher stock market risk spillover effect on the insurance industry. The blockchain industry has the largest risk spillover effect on the insurance industry, and its own VaR is the smallest among the five industries. This industry needs to be considered as a highly correlated industry with large systemic risks. The carbon technology 30 industry with the highest VaR has the lowest CoVaR among the five industries, indicating that the green industry has less risk spillover to the insurance industry and can be used as an industry to diversify investment risks.

(3) The risk spillover effects of the insurance industry on other industries are consistent with the risk spillover effect of other industries on it. The pharmaceutical industry and the public health industry have a strong dependence on the insurance industry, and the systemic risks of the insurance industry have a greater impact on these two industries.

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