Research on Integrated Risk of Insurance Company in My Country Based on R-vine Copula Model

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Abstract: In today's rapid development of financial integration and economic globalization, my country's insurance companies are faced with a large number and complex types of risks. At the same time, the insurance industry occupies a position that cannot be ignored in the financial field. Its response to risks directly affects the development of the entire financial field. Therefore, it is important to study the internal relationship between the risks faced by insurance companies in my country and how to reduce the overall risk of the industry. This paper selects three indicators: the overall monthly loss ratio of the insurance industry, the monthly yield of the Shanghai Stock Exchange Treasury Bond Index, and the monthly yield of the Shanghai Composite Index to measure the three main risks faced by insurance companies in my country: insurance risk, credit risk and market risk. After a series of data processing and testing, the GARCH model and the R-vine Copula model were established, and the VaR values of the three indicators were calculated. The study found that the R R-vine copula model can accurately describe the relationship between the three risks, and various risks are related to each other in a standardized R-vine copula structure. Appropriate strategies are needed to reduce such risks.

Keywords: Integrated Risk; GARCH Model; R-Vine Copula Model

1. Introduction

The ancients' understanding of risk management has reached a higher level, from the Confucian "born in distress, and died in peace" to the Taoist "adversity and fortune depend on, and fortune and misfortune lie in", and then to the Legalist theory. "The strong follower of the law will make the country strong", all of which contain the concept of risk management. With the continuous improvement of my country's socialist market economic system and the deepening of financial system reform, risk management has become a key topic for Chinese enterprises to discuss when establishing their own comprehensive capital management framework. In the high-risk financial industry, risk management is particularly important. On the one hand, high-level risk management achieves good internal control and reduces operating costs. On the other hand, it reduces the risk of companies using funds externally, thereby enhancing the competitiveness of the company. As an important part of the financial industry, insurance companies have a huge business scale, complex business types, and a special type of debt management company. complex risks [1]. Then, it is of great significance to the internal and external management of insurance companies to analyze what risks the insurance companies are facing and the interrelationships between them.

From the perspective of integrated risk, this paper analyzes the three main risks of insurance risk, credit risk and market risk faced by insurance companies in my country. The three indicators of yield are quantified. After a series of processing and testing of the data, the GARCH model and the R-vine Copula model are established, and the VaR value of the three indicators is calculated to visually and clearly show the proportion of the three types of risks and the difference. The internal relationship between them provides a feasible idea for the risk measurement and capital allocation of Chinese insurance companies.

2. Literature Review

2.1 Literature Review of Integrated Risk Management

The concept of integrated risk management was first put forward by Scott in 1996 [2-3]. Through his research on the risk management of Bank of America, he found that the different risks faced by banks

are interrelated, and through this correlation, risks can be integrated. In the "New Basel Capital Accord" announced in 2004, the framework and process of risk management were proposed. Xeni and Kjersti put forward an integrated risk measurement model through empirical research on the capital allocation problem of Norwegian Financial Holding Group, and found that the method of integrated risk measurement can effectively reduce the total risk faced by banks [4]. Rosenberg further quantified the risks that financial institutions can reduce by integrated risk management through his research on the risk management issues of the Federal Reserve Bank of the United States. For banks, integrated risk management can effectively reduce the total risk by 15%, and for insurance companies 20%-25%, and 5%-15% for financial holding companies [5].

In China, in his article "Establishing a Comprehensive Risk Management Model", Zhang Enzhao described in detail the methods of establishing a comprehensive risk management system from both internal and external aspects, including using internal evaluation as supervision and establishing corporate alliances [6]. Zeng Zhongdong made a preliminary discussion on how to establish a comprehensive risk management system for insurance companies from the perspective of system framework construction, and pointed out that comprehensive risk management is an inevitable trend in the development of modern financial risk management [7]. Xiu Guoyi and Wang Fangfei compared the comprehensive risk management of my country's commercial banks with those of foreign countries, and found some problems that need to be solved in terms of the organizational structure of my country's commercial banks and the methods and means of risk management. Sexual recommendations [8]. Combining the background of my country's economic development from "speed" to "quality", Gao Xueli introduced the lag and limitations of my country's commercial banks under this background, and proposed how to flexibly change and establish a comprehensive risk management system for my country's commercial banks. Some constructive countermeasures have been developed [9].

Combining domestic and foreign literatures on integrated risk management research, this paper finds that integrated risk management in commercial banks can effectively reduce the total risk faced by banks, and insurance companies, like commercial banks, are members of the financial industry and face Credit risk and market risk are also similar to commercial banks. Therefore, this paper analyzes the three main types of risks faced by insurance companies in our country from the perspective of integrated risk, in order to provide some suggestions for reducing the overall risk of insurance companies in our country.

2.2 Literature Review of Copula Theory

Copula theory was first proposed by Sklar in 1959 [10]. Due to its unique nature, it attracted the attention of the risk control department once it was proposed. After a period of attempts and experiments, Embrechts formally introduced the Copula method into the field of financial risk management in 1999 [11]. In 2002, Patton applied Copula theory to financial econometric models and achieved good results [12]. Nelsen focused on theoretical research, he systematically summarized the Copula method, constructed the Copula function and introduced its properties and application scenarios in detail [13]. In 2011, Shamiri et al. combined two Copula functions to construct a hybrid Copula model, which has a good effect on the study of tail correlation [14]. Chuanqi, Khan, and Imtiaz constructed a Copula-based Bayes network model that overcomes the challenge of nonlinear relationships and describes the joint probability density of network nodes in BN [15]. Aas et al. constructed the Pair-Copula function in order to reduce the joint distribution of high-dimensional variable data, which better solved the problem of errors caused by too many dimensions. basis [16]. Mendes, Accioly, etc. conducted research and analysis on multiple financial time series based on the vine Copula model [17]. Based on the D-vine Copula structure, Czado et al. conducted research and analysis on the interdependence of financial assets [18].

The domestic research on the Copula model is relatively late, but it has also made long-term development so far. Zhang Yaoting introduced the Copula method to us in an easy-to-understand language, and conducted an in-depth discussion on the feasibility of the application of the Copula method in the field of financial risk analysis, which later became the theoretical basis for the application of the Copula method in my country [19]. In 2004, Wei Yanhua and Zhang Shiying conducted a detailed review of the origin and development of Copula theory, and collected specific data in the financial field to discuss the correlation of financial asset variables, which enabled us to have a better understanding of Copula theory. [20]. Wu Zhenxiang, Chen Min, etc. constructed several general models based on Copula theory, and combined them with specific financial risk analysis cases, which clearly introduced the practicality of Copula theory to us [21]. By analyzing two different stock data, Dong Zhiqian, Li Xingye and others put forward a model that can accurately analyze the tail

correlation of portfolio asset variables in the financial field based on the existing Copula model, which makes the application of the Copula model further. an extension of [22]. Zhou Quan and Chen Zhenlong used the Cteng Copula model to study the characteristics of asset portfolios owned by financial institutions under mixed operation, and used Monte Carlo simulation to conduct reverse simulations. accuracy [23]. Yang Kun, Yu Wenhua and others conducted a scientific analysis of the actual situation of financial risks in the oil price market by combining the extreme value theory with the R-Ren Copula model, which confirmed the practicability of the R-Ren-Copula model in the field of financial risk analysis [24].

Synthesizing domestic and foreign literature on Copula theory research, this paper finds that the application of R-vine Copula model in the field of financial risk analysis can not only accurately analyze the correlation between various risks, but also reduce the error of empirical research. At the same time, when studying the correlation of various risks of insurance companies in our country, most scholars only analyze the relationship between these risks in pairs, and rarely analyze the overall analysis of three or more types. Therefore, this paper establishes the R-vine Copula model to conduct an overall analysis of insurance risk, credit risk and market risk in order to better study their intrinsic correlation.

3. Model Introduction

3.1 Basic Knowledge of Copula Theory

Copula translated into Chinese means connection and exchange. According to Copula theory, the joint distribution function of multiple random variables can be decomposed into a combination of marginal distribution and Copula function. The marginal distribution can describe the distribution of a single random variable, while the Copula function is used to describe the dependencies between random variables. This theory provides a simple and efficient method for analyzing events in which multiple risks act together and the interrelationships among various risks.

3.1.1 Definition Introduction

The Copula function is essentially a multivariate distribution function, which is different from the general joint distribution function in that each marginal distribution of it needs to be a uniform distribution defined in the [0.1] interval. The n-dimensional Copula function can be written as C (u1... un), namely:

$$C(u_1,\cdots,u_n)= P(U_1 \leqslant u_1,\cdots, U_n \leqslant u_n) \quad (1)$$

Where $U_i(i=1,2,\cdots,n)$ is a uniform distribution defined on the interval [0,1].

It can be seen from the definition of the Copula function that all joint distribution functions imply a Copula function, and the application of the Copula function can connect the univariate marginal distribution function into a multivariate distribution function. This is also the main conclusion of Sklar's theorem.

Theorem: Let F(x1... xn) denote the joint distribution function, and its marginal distribution function is F1, F2... Fn, then there is a Copula function C, such that:

$$F(x1,\cdots,xn) = C[F1(x1),\cdots,Fn(xn)] \quad (2)$$

Conversely, if C is a Copula function and F1, F2,...,Fn are unary distribution functions, then the function defined by equation (1) is a joint distribution function, and the marginal distribution functions are F1, F2,...,Fn.

3.1.2 Dependency Metrics

(1) Linear correlation coefficient

The linear correlation coefficient, or Pearson's correlation coefficient, is one of the most common correlation measures. The linear correlation coefficient between two random variables X and Y with both standard deviations greater than 0 can be expressed as

$$\rho_{XY} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (3)$$

Where cov(X, Y) =E (XY)-E(X) E(Y).

The value range of the linear correlation coefficient ρ XY is [-1, 1]. The upper and lower bounds represent a complete positive correlation and a complete negative correlation, respectively. A value of 0 means that there is no linear correlation between the two random variables.

(2) Kendall rank correlation coefficient

Assuming that (X1, Y1) and (X2, Y2) are two pairs of independent random variables from (X, Y), the Kendall rank correlation coefficient can be expressed as:

$$\rho_\tau(X, Y) = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0]$$

$$= 4 \int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1$$

$$= 4E[C(U_1, U_2)] - 1 \quad (4)$$

The Kendall rank correlation coefficient is only related to Copula and has nothing to do with marginal distribution. Compared with the linear correlation coefficient, it can better measure the dependence between two random variables.

(3) Tail Dependency Index

The tail dependence index is a measure of the dependence of two random variables at the tail, including the left tail dependence index and the right tail dependence index. Let the distribution functions of random variables X1 and X2 be F1 and F2, respectively. Left-tailed dependency index:

$$\lambda_L = \lim_{u \to 0^+} P[X_1 \le F_1^{-1}(u) | X_2 \le F_2^{-1}(u)] \quad (5)$$

Right-tailed dependency index:

$$\lambda_U = \lim_{u \to 1^-} P[X_1 > F_1^{-1}(u) | X_2 > F_2^{-1}(u)] \quad (6)$$

3.2 Introduction to GARCH Model

As a modern financial event sequence model, the GARCH model is modeled based on the characteristic of volatility aggregation. The volatility aggregation tells us that the current volatility has a certain relationship with the past volatility, and the concept of variance is also extended to the conditional variance. The so-called conditional contrast refers to the variance of the known information at the past time. The GARCH model believes that the conditional variance of the current period is the linear combination of the conditional variance of the past N periods and the square of the sequence, and the sequence is the product of the conditional variance of the current period and white noise.

This paper selects the GARCH (1, 1)-t model and the GARCH (1, 1)-GED model to construct the marginal distribution in the empirical research. The details are as follows:

GARCH (1, 1)-t model:

$$y_t = \mu + \varepsilon_t \quad (7)$$

$$\sqrt{\frac{v}{h_t(v-2)}} \cdot \varepsilon_t | I_{t-1} \frown t(v) \quad (8)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (9)$$

In the formula, μ represents the mean value of the substituted data, v represents the degrees of freedom, h_t represents the conditional variance ε_t, and $t(v)$ represents the t distribution with 0 and variance 1. When $v < 4$, there is no kurtosis; when $v \to \infty$, it means Normal distribution; when $4 < v < \infty$, the peak value of $t(v)$ is larger than 3. $\alpha_1 \ge 0$, $\beta_1 \ge 0$.

GARCH (1, 1)-GED model:

$$y_t = \mu + \varepsilon_t \quad (10)$$

$$\varepsilon_t | I_{t-1} \frown GED(0, h_t, v) \quad (11)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (12)$$

Where μ represents the mean of the substituted data, v represents the shape parameter, and h_t

represents the conditional variance. When $v>2$, the tail of $GED(0, h_t, v)$ is thinner than the Normal distribution, when $v<2$, $GED(0, h_t, v)$ is a thick-tailed distribution, and when $v=2$, $GED(0, h_t, v)$ is a Normal distribution.

3.3 Introduction to the Vine Copula Model

According to the pair-Copula theory proposed by Aas, ... the multivariate joint density function can be decomposed into the product of several pair-Copula density functions and marginal distribution functions according to a certain structure. Let X be a multivariate random variable, then the pair-Copula theory can be expressed as:

$$f(x_1, x_2, \ldots, x_n) = f_n(x_n) \cdot f(x_{n-1}|x_n) \cdot f(x_{n-2}|x_{n-1}, x_n) \ldots f(x_1|x_2, \ldots, x_n) \quad (13)$$

From Sklar's theorem, we know that:

$$f(x_1, x_2, \ldots, x_n) = c\big(F_1(x_1)\big), \ldots, F_n(x_n)\big) \cdot f_1(x_1) \ldots f_n(x_n) \quad (14)$$

Bring the binary and ternary cases into the discussion and deduce the decomposition formula of the conditional density function:

$$f(x|v) = c_{xv_j|v_{-j}}(F(x|v_{-j}), F(v_j|v_{-j})) \cdot f(x|v_{-j}) \quad (15)$$

Among them, v_j is a component of the n-dimensional vector v, v_{-j} refers to the remaining n-1-dimensional components in the vector v_j.

$c_{xv_j|v_{-j}}(\cdot, \cdot)$ is the pair-Copula density function. Then its conditional distribution function is:

$$F(x|v) = \frac{\partial c_{xv_j|v_{-j}}(F(x|v_{-j}), F(v_j|v_{-j}))}{\partial F(v_j|v_{-j})} \quad (16)$$

4. Empirical Research

4.1 Data Sources and Data Processing

4.1.1 Data Sources

The main business of my country's insurance companies is divided into two categories, one is underwriting business, and the other is investment business. In terms of investment business, due to the uncertainty of risks and the consideration of capital security, for a long time, the funds of insurance companies have been mainly used to purchase government bonds and bank deposits, and stocks do not account for a large proportion of the investment business of insurance companies. In 1988, insurance companies were allowed to conduct bond activities in the national interbank market. In 2004, insurance companies were allowed to invest in the stock market, but the investment ratio was limited to 5%. In recent years, the scale of funds invested by insurance companies in the stock market has been expanding, and they are increasingly affected by market risks. Based on the research of other scholars in the academic field, insurance companies have three main risks in the operation process, namely insurance risk, credit risk and market risk. The following three risks will be introduced and quantified with data.

Insurance risk, for insurance companies, refers to the probability that the insured event deviates from expectations (such as death, disability, or property damage), thereby adversely affecting the company's operations. This paper selects the overall monthly compensation amount and premium income of the insurance industry announced by the China Banking and Insurance Regulatory Commission on the official website from May 2003 to May 2021 to calculate the monthly compensation rate. The calculation formula is: $l_t = x_t/y_t$, Among them, xt represents the insurance industry compensation amount in the current month, and yt represents the insurance industry premium income in the current month.

Credit risk refers to the risk of economic losses to the insurance company due to the failure of the party involved in the transaction with the insurance company to perform the obligations stipulated in the contract. In recent years, with the expansion of insurance companies' investment in treasury bonds, the purchase of treasury bonds has become the main source of credit risk for insurance companies. This

paper selects the monthly yield calculated by the Shanghai Stock Exchange Treasury Bond Index from May 2003 to May 2021 and takes the inverse number to measure the credit risk of insurance companies. The monthly rate of return is the logarithm, and the calculation formula is: $r_t = -(\ln p_t - \ln p_{t-1})$, Among p_t is the SSE Treasury Bond Index of the current month and p_{t-1} is the SSE Treasury Bond Index of the previous month.

Market risk refers to the potential losses caused by the uncertainty of changes in the market environment to the business activities of insurance companies. With the increase in the scale of insurance companies' investment in stocks, the proportion of stock risks in the market risks faced by insurance companies is increasing. Therefore, this paper selects the monthly rate of return calculated by the Shanghai Composite Index from May 2003 to May 2021 and takes the inverse number to measure the market risk of insurance companies. The monthly rate of return is the logarithm, and the calculation formula is: $r_t = -(\ln p_t - \ln p_{t-1})$, among them, p_t is the Shanghai Composite Index of the current month, and p_{t-1} is the Shanghai Composite Index of the previous month.
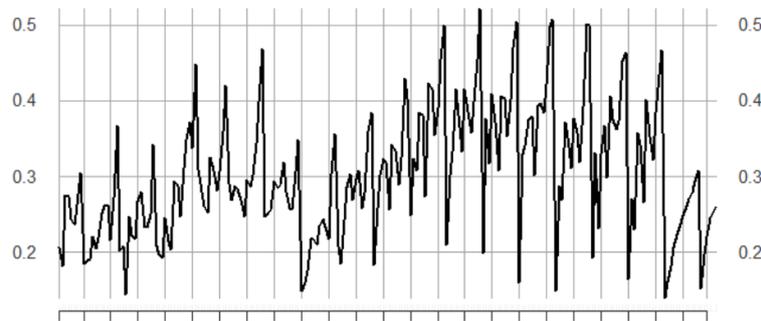
4.1.2 Data Descriptive Statistics

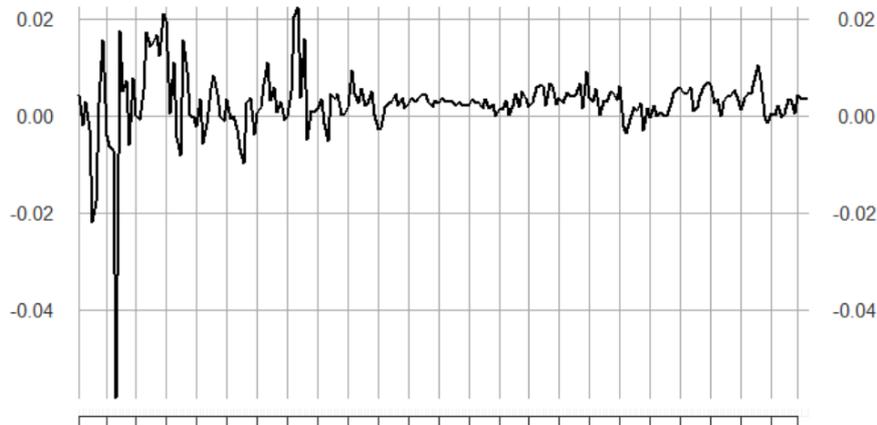*Figure 1: Time series plot of the logarithmic rate of return on the raw data of insurance risk*

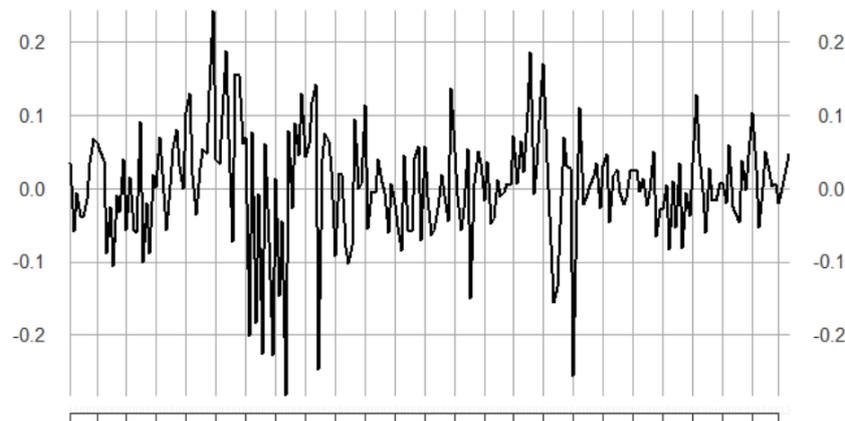*Figure 2: Time series plot of logarithmic rate of return on credit risk raw data*

Figure 3: Logarithmic return time series chart of raw market risk data

As can be seen intuitively from Figure 1-3, the monthly insurance claim ratio fluctuates greatly, and in the long run, it tends to increase first and then decrease. Except for the extremely low value in April 2004, the monthly yield of the Shanghai bond index fluctuates around 0 at other times. The Shanghai Composite Index is relatively stable as a whole, and the fluctuation range is smaller than that of the insurance monthly loss ratio and basically fluctuates around 0. To get a better understanding of the data and to build the Garch-Copula model later, I calculated basic statistics (calculated in R) for these three types of data.

Table 1: Three risk descriptive statistics

index	Mean	Standard Deviation	Max	Min	Skewness	Kurtosis
Insurance industry monthly loss ratio	0.3033	0.0845	0.5214	0.1394	0.3701	-0.4139
SSE Treasury Bond Index Monthly Yield	-0.0028	0.0068	0.0581	-0.0224	3.1780	30.2966
Shanghai Composite Index Monthly Yield	-0.0039	0.0765	0.2828	-0.2426	0.5836	2.0969

The following conclusions can be drawn from Table 1:

(1) The average monthly loss ratio of the insurance industry is 30.33%, and the maximum can reach 52.14%, with a large fluctuation range. From the perspective of skewness and kurtosis, the insurance monthly loss ratio is skewed to the right and flat compared to the normal distribution, with a flat peak.

(2) The average monthly yield of the Shanghai Stock Exchange Treasury Bond Index is -0.28%, which is close to 0, and the maximum is only 5.81%, which is in line with the characteristics of low yield and low risk of treasury bonds. From the perspective of skewness and kurtosis, the monthly yield of the Shanghai bond index is skewed to the right and has serious peaks.

(3) The average monthly rate of return of the Shanghai Composite Index is -0.39%, the maximum value is 28.28%, and the minimum value is -24.26%, with a relatively even distribution. From the perspective of skewness and kurtosis, the monthly yield of the Shanghai Composite Index is skewed to the right with a slight peak.

4.1.3 Statistical Tests

(1) Stationarity test

Table 2: Three indicators time series stationarity test

		Insurance industry monthly loss ratio	SSE Treasury Bond Index Monthly Yield	Shanghai Composite Index Monthly Yield
T-test critical value	ADF test value	-5.979570	-11.44242	-12.91336
	1% significance level		-3.460596	
	5% significance level		-2.874741	
	10% significance level		-2.573883	
	p-value	0.0000	0.0000	0.0000

It can be seen from Table 2 that the p-values of the test statistics of the three indicators at the 1%, 5% and 10% significance levels are all 0.0000, indicating that they are stable.
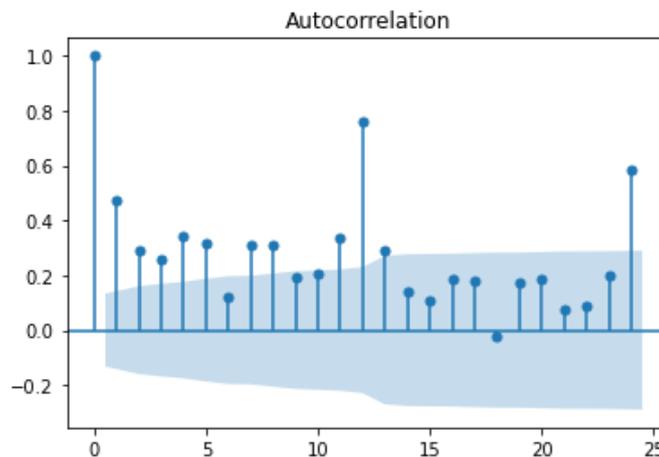
Autocorrelation test:

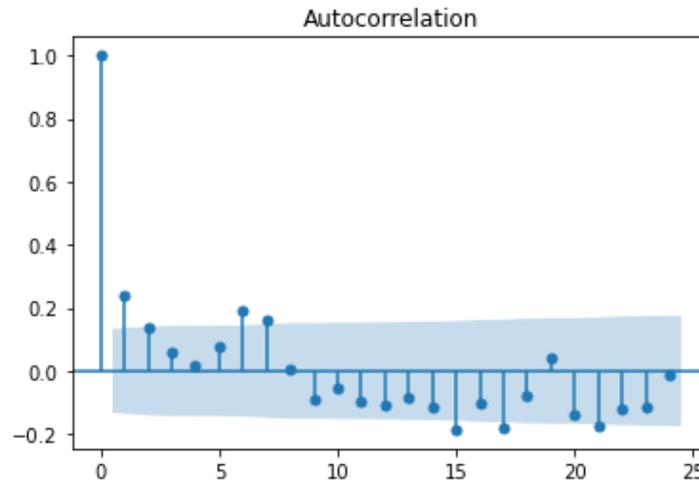*Figure 4: Autocorrelation plot of insurance monthly loss ratio*

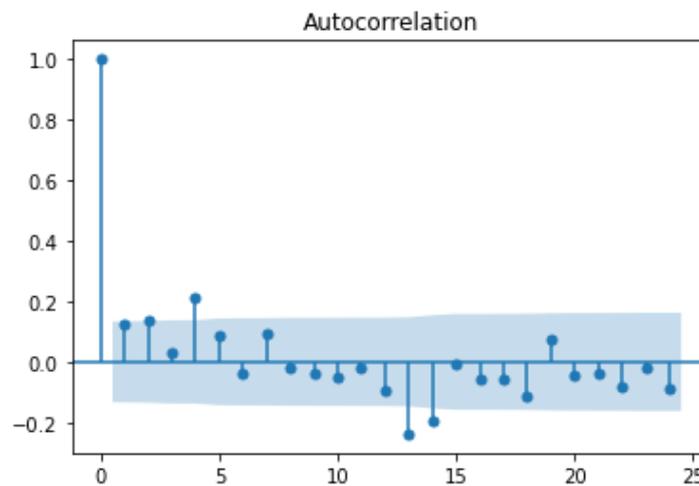*Figure 5: Autocorrelation chart of monthly yield of Shanghai bond index*

Figure 6: Autocorrelation chart of shanghai composite index monthly return

Using Jupyter Notebook (Python3 language environment) to draw the autocorrelation graph of the three indicators, we can see from the figure that most of the points of each graph fall within the blue area (confidence interval), we can see that these three indicators the autocorrelation is not strong.

(3) ARCH effect test

ARCH test is also required before marginal distribution GARCH modeling. If there is an ARCH effect, the GARCH modeling can continue. If there is no ARCH effect, the GARCH modeling cannot continue.

Table 3: LM test of three indicators

Indicator name	Insurance industry monthly loss ratio	SSE Treasury Bond Index Monthly Yield	Shanghai Composite Index Monthly Yield
Chi-square statistic	23.31178	12.87366	7.135195
p-value	1.37754e-06	0.0003332397	0.06771124

From Table 3, we can see that the p-values of the statistic corresponding to the LM test are all very close to 0, indicating that the null hypothesis of no ARCH effect is rejected, and the GARCH modeling can continue.

4.2 Design and Testing of the GARCH Model

I constructed GARCH (1, 1)-N, GARCH (1, 1)-GED and GARCH (1, 1)-t models for three indicators by using Eviews software, and used the AIC criterion to evaluate the fit of the models. Compare good and bad.

Table 4: Design and test of GARCH model

| name	Model	μ	ω	α	β	ν	AIC
Insurance industry monthly loss ratio	GARCH(1,1)-N	0.1508	0.4824	0.0030	0.6807	\	-2.4707
	GARCH(1,1)-GED	0.1211	0.5807	0.0027	0.8509	2.7767	-2.4735
	GARCH(1,1)-t	0.1447	0.5043	0.0029	0.7211	5.5012	-2.4614
SSE Treasury Bond Index Monthly Yield	GARCH(1,1)-N	-0.0016	0.4448	3.48E-08	0.3467	\	-8.3817
	GARCH(1,1)-GED	-0.0019	0.3684	8.12E-08	0.2939	2.7876	-8.4511
	GARCH(1,1)-t	-0.0018	0.3754	1.22E-07	0.2848	5.5543	-8.4453
Shanghai Composite Index Monthly Yield	GARCH(1,1)-N	-0.0013	0.0164	0.0003	0.2364	\	-2.4760
	GARCH(1,1)-GED	-0.0025	0.0016	0.0003	0.2222	2.7786	-2.4839
	GARCH(1,1)-t	-0.0019	-0.0086	0.0003	0.2174	5.4643	-2.4760

Note: ν represents degrees of freedom in GARCH (1, 1)-t, and shape parameter in GARCH (1, 1)-GED, and N is Normal distribution.

As can be seen from Table 4, the AIC value of the GED model is the smallest for each indicator. According to the AIC criterion, the smaller the AIC, the better the model fitting. Therefore, the GARCH (1, 1)-GED model is selected for marginal distribution modeling. It can also be seen from Table 4 that the degrees of freedom ν of each model are different, and it can be seen that the GARCH models constructed by these three indicators are not the same.

4.3 Rivne Copula Model Structure

Combined with the research of Wei Yanhua, Wang Yao, Zhang Xiaobing and others, this paper finds that the R R-vine model has a better effect on solving risk analysis problems than C R-vine and D R-vine [25]. Therefore, this paper focuses on establishing the R R-vine model and using the R language to draw the R R-vine structure of insurance risk, credit risk and market risk.

The maximum spanning tree method mentioned in the reference [26] of this paper is the MST algorithm to construct the R-vine structure, as shown in the following figure.
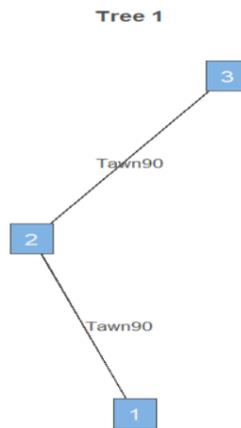
Figure 7: Tree structure of the R vine model (Tree 1 structure)

Figure 8: Tree structure of the R vine model(Tree 2 structure)

4.4 Rivne Copula Model Parameters

Table 5: Vine Copula model parameters

layers	Node	Copula function	Part1	Part2	ρ_τ	λ_U	λ_l
level one	2,1	Tawn90	-20.00	0.00	-0.00	-	-
	3,2	Tawn90	-3.60	0.03	-0.03	-	-
Second floor	3,1;2	J270	-1.05	0.00	-0.03	-	-

Note: in the table, ,ρ_τ, λ_U, $\lambda_l$respectively represent the Kendall rank correlation coefficient, upper tail correlation coefficient and lower tail correlation coefficient of each variable in the R-vine Copula model; numbers 1, 2, and 3 respectively represent the monthly insurance industry loss ratio and the monthly yield of the Shanghai Stock Exchange Treasury Bond Index. and the monthly rate of return of the Shanghai Composite Index.

From the rank correlation coefficient in the table, it can be seen that there is a certain negative correlation between the three indicators. The R-vine model clearly shows this relationship.

4.5 Goodness of Fit Test

Table 6 Goodness-of-fit test of the vine Copula model

Information Guidelines	R Vine
AIC	-6.26
BIC	-10.64
LogL	8.13

There are generally three criteria when judging the fitting effect of the model: AIC, BIC and LogL. When the sample size is small, the AIC criterion is more accurate, and when the sample size is large, the BIC criterion is generally referred to. As a reference value of LogL, you need to refer to the value of LogL when observing the values of AIC and BIC. If the values of AIC and BIC are both small and LogL is large, it can indicate that the fitting effect of this model is better.

It can be seen from Table 5 that the AIC and BIC of the R-vine model are both small and negative, while the value of LogL is large and close to 10. Therefore, we can draw the conclusion that using the R-vine model to fit the correlation of the three indicators is more accurate.

4.6 Calculation of VaR Value of Three Indicators

VaR (Value at Risk) literally means "value at risk", which means: the maximum possible loss of a financial asset or portfolio of securities under normal market fluctuations. More precisely, it refers to the maximum possible loss in the value of a financial asset or portfolio of securities over a specified period of time in the future under a certain probability level (confidence). The calculation formula is:$P(\Delta P_{\Delta t} \leq VaR) = \alpha$, among them, ΔP represents the value loss of a financial asset in a certain holding period Δt, VaR represents the value at risk under a given confidence level a, that is, the upper limit of possible losses, and a represents a given confidence level.

Table 7 Calculation of VaR value of three indicators

	Confidence level	Insurance industry monthly loss ratio	SSE Treasury Bond Index Monthly Yield	Shanghai Composite Index Monthly Yield
VaR	90%	0.1650	-0.0139	-0.1291
	95%	0.1380	-0.0160	-0.1535
	97.5%	0.1178	-0.0177	-0.1718
	99%	0.0857	-0.0202	-0.2008

It can be seen from Table 7 that under each confidence level, the insurance monthly loss ratio has the largest value at risk, that is, the loss suffered the most. It can be seen that the insurance risk accounts for a large proportion of the three risks. Since the monthly yield of the Shanghai Treasury Bond Index and the monthly yield of the Shanghai Composite Index are calculated by taking the opposite of the logarithmic difference of the true value, their VaR values are both negative, and their possible losses are also positive. The proportion is small compared to the insurance monthly loss ratio.

5. Conclusion

This paper conducts an empirical study on the three main risks faced by insurance companies in my country, and establishes the GARCH model and the R-vine Copula model. The relevant conclusions are

as follows:

(1) A marginal experimental design was carried out on the three indicators to quantify the three main risks. The GARCH (1, 1) model was used, and Normal distribution, GED distribution and t distribution were selected for residual distribution. The results found that the residual sequence based on GED distribution was the distribution is better than the remaining two distributions, which clarifies the direction for insurers to quantify risk and build GARCH models.

(2) From the perspective of goodness of fit, the R-vine Copula model fits the three indicators better, and the correlation of these three indicators can also be better measured. At the same time, the use of R R-vine Copula model reduces the error of pairwise analysis of risks, and improves the accuracy of simultaneous analysis of three risks.

(3) From the perspective of risk proportion, insurance risks of Chinese insurance companies account for a large proportion of the three types of risks, and appropriate strategies need to be formulated to reduce such risks.

Research limitations and prospects of this paper:

(1) In the marginal distribution model, the GARCH model used has certain problems. If the actual situation is studied, models such as SV can be selected for research.

(2) When establishing the R-vine Copula model, due to limited technology, only the R R-vine Copula model is established. If you want to conduct a more detailed comparison, you can build the C R-vine and D R-vine models.

(3) Since the problem of analysis is a problem that fluctuates with time, dynamic vine can be used for analysis, that is, the dynamic structure is combined with the vine Copula model.

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