RISK MEASUREMENT OF CHINA'S FOREIGN ENERGY INVESTMENT PORTFOLIO BASED ON COPULA-VAR

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ABSTRACT

Energy is an important resource for the development of the country, and investment in energy can promote the development of the national economy. Many scholars are currently using Copula models to predict the risk of energy investments to improve investment efficiency. However, most studies are not systematic enough and focus on countries outside of China. We use the Copula-VaR method with the Archimedean Copula function and the Copula-VaR method with the introduction of tail correlation to calculate the energy futures risk. The risk of six different percentages of China's foreign energy portfolio for three futures on natural gas, oil, and coal between January 3, 2015 and December 30, 2021 is calculated and compared to the traditional method. The results show that the risk values calculated using the improved Copula-VaR model are 0.00836, 0.00922, 0.00217, 0.00635, 0.00612 and 0.00827 higher under the 0.98 confidence level than under the 0.96 confidence level. It has a high accuracy compared with the traditional method. The research in this paper provides an idea for the design of energy investment programs in China

KEYWORDS

Copula- VaR method; energy investment; degree of confidence; portfolio risk; confidence level.

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1. INTRODUCTION

Energy is an important resource for national development. The development of industry and manufacturing industries cannot be separated from the supply of energy. With the development of economic globalization, each country cannot stay away from the development of energy [1-3]. At present, the world energy market is also suffering from an unprecedented impact with the spread of the economic globalization crisis. The world energy structure is currently undergoing a transformation, which brings a certain degree of impact on the economic trade and energy import and export of each country [4-6]. During World War II in the 19th century, the main conflicts in the world at that time were focused on the competition for resources and territories. Countries vigorously developed their industries. The Western countries successfully entered industrialized societies thanks in part to low energy prices [7-8]. But in the 21st century, there was a conflict over oil resources in the Middle East, which at once broke the world energy pattern. The increasing price of oil has led to an energy crisis in many countries and a gradual widening of the gap between countries' economic development [9-12]. Each country has its own energy advantages, for example, Russia has rich oil resources and China has rich coal resources. Figure 1 shows China's coal energy and crude oil energy production from 2011-2022. It can be seen that China's coal and crude oil resources have been increasing in the last decade, so it is important to be well-positioned for strategic energy investment.

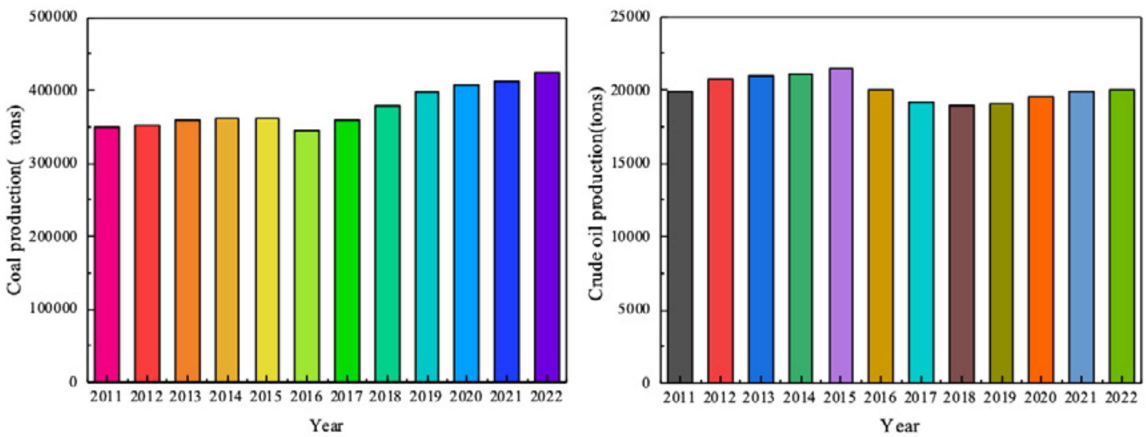

Figure 1. Coal and crude oil production 2011 - 2022

With the increasingly complex international situation, the price of energy is also changing. The recent conflict between Russia and Ukraine has caused an increase in the price of oil. Changes in energy prices can have a relatively large impact on a country's political economy. China is rich in energy, so it is necessary to make a good risk assessment of energy investments [13-16]. The Copula model, proposed in the 20th century, is well suited for the pricing of financial investments and the comprehensive measurement of investment risk, in which the investment risk is assessed by the magnitude of the VaR (Value at Risk) value [17-20]. Subsequently, some scholars used the Copula model to measure energy portfolio risk [21-24].

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HB Ameur et al. analyze the risk spillover benefits between oil and gas markets by measuring their risk dependence [25]. Combining market price data for oil and natural gas from 2014-2017 reveals that the risk premium from oil to natural gas markets is higher than the risk premium from natural gas markets to oil markets. It is also found that risk upward and downward spillovers are asymmetric, due to the stronger spillover effects from risk negative spillovers. Ji explores the impact of uncertainty on energy prices by measuring four types of Delta conditional value-at-risk (CoVaR) through six time-varying copula, considering uncertainty measures among economic policies, financial markets, and energy markets. The results show a negative correlation between energy returns and changes in uncertainty, with energy being more sensitive to the response of financial and energy markets, while economic policies have a relatively weak impact. The study provides informative recommendations for energy portfolios [26]. Qiang et al. used six time-varying copula models to analyze the dynamic dependence of WTI crude oil on China and the U.S., while taking into account the structural changes in their dependence [27]. The results show that there are breakpoints in the dependence on crude oil and the dollar index on a daily or monthly basis. There is a relatively large risk spillover from crude oil to the exchange rate markets in China and the United States. It is also found that the exchange rate markets in China and the United States are not as sensitive to the spillover effects of oil price turmoil. AK Tiwari et al. analyzed the dependence relationship between the Indian stock market and crude oil prices using the dependence transformation copula model [28]. Dependence and tail dependence are investigated for four states: oil price-rising-stock-rising, oil price-falling-stock-rising, oil price-falling-stock-rising, and oil price-falling-stock-falling. The results show that the gap between CoVaR and VaR for each domain is not significant. That is, the oil market does not add additional risk to the stock market when both the oil market and stock prices are in a downward spiral. Meanwhile, oil prices are falling and entering the carbon sector is the ideal hedge investment. Ren et al. studied the investment risk of U.S. crude oil, natural gas energy and heating oil futures using energy investment risk management as an entry point [29]. An energy futures portfolio risk measurement model based on BEKK-VaR and DCC-VaR methods was developed to calculate the value-at-risk of energy investments. The results show that the DCC-VaR has more accurate calculation results compared with the BEKK-VaR method, but the BEKK-VaR method works better in terms of the generalized error distribution. In general., the DCC-VaR method is better for measuring investment risk portfolios. Lv et al. proposed a copula-based stochastic multilevel planning (CSMP) method as a way to ensure a coordinated relationship between the energy economy and the ecosystem in China [30]. The results show that by the middle of the 21st century, China's tertiary and high-tech industries will account for 62.4% and 14.9% of the market, respectively. Energy and carbon dioxide consumption decreased by 45.1% and 56.9% respectively, which shows that the ecological relationship is developing towards economic energy saving and environmental friendly. Zhang et al. proposed a copula-based multivariate model aimed at analyzing the impact of oil price fluctuations on fuel and shipping prices [31]. Data is derived from the index relationship between oil prices and shipping in West Texas, the Baltic Sea region from 2008 to 2015. The results show that high oil prices

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are not significantly dependent on each country, and copula modeling can better identify the time-varying effects of the dependence between the two and help policymakers analyze energy investment markets effectively. Cai et al. proposed an integrated approach of system dynamics, orthogonal design, and copula analysis (IA-SOC) to assess the risk of coupling water and energy resources in cities in the Jinjiang region [32]. The results show that the system dynamics model constructed in the established paper is applicable to the prediction of water and energy resources. The water and energy scarcity risks are 0.938, 0.981 and 0.835, 0.936 for the government's planning period for the city of Jinjiang with water demand of 25.206, 29.07 billion cubic meters and 433.67, 477.02 million tons of standard coal equivalent (SCE), respectively. Jiang et al. narrow the risk gap between different countries by identifying the impact of specific political risk factors on foreign energy investments and exploring the significant political risk factors for foreign energy investments in 74 developing countries [33]. In addition, practical advice is given to foreign investors based on the national conditions of different countries and the differences between them. JC A et al. systematically review the literature of the last decade to summarize the interplay between stranded risk and capital allocation decisions of others in energy technologies [34]. Coal., oil and gas companies were found to be at risk of stranding asset owners due to misjudged energy price forecasts. Investors with illiquid assets are also found to be less exposed to risk and can hedge risk and manage assets through diversification strategies. In summary, the current prediction results of energy investment risk using the Copula model are satisfactory, but there is a lack of systematic research and shortcomings for quantitative analysis of risk assessment. Most studies have been conducted on countries outside of China, and there is still a lack of work on risk assessment of China's outbound energy investments.

Therefore, this paper calculates the risk of six different percentages of China's foreign energy portfolio for three futures of natural gas, oil, and coal for the period from January 3, 2015 to December 30, 2021 by using the Copula-VaR method. The values at risk of different proportional investment approaches were compared at confidence levels of 0.96 and 0.98, and the results calculated by the improved Copula-VaR method were compared with the traditional calculations. The research in this paper provides a reference for the formulation of China's outbound energy investment strategy.

2. COPULA-VAR MODELING

2.1. COPULA FUNCTION DEFINITION

The analysis of a single variable in financial risk analysis cannot correctly reflect the deep relationship between financial risk and investment behavior. Therefore, multiple variables need to be analyzed, and the analysis of multiple variables requires an in-depth analysis of the correlation of these variables. In this paper, we use the Cupula

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function to measure financial risk and time series and optimize the distribution function, and the Copula function is defined as follows:

Suppose there is a p element distribution function: $f(x_1, \cdots, x_p)$, where $x_i \in R,\ i = 1,\cdots,p$ with marginal distribution $F_i,\ i = 1,\cdots,p$. For $Copula\ C : [0,1]^p \to [0,1]$ such any $x_i \in R,\ i = 1,\cdots,p$ satisfies the following equation.

$$F\left(x_1, \ldots, x_p\right) = C\left(F_1\left(x_1\right), \ldots, F_p\left(x_p\right)\right) \tag{1}$$

The above theorem shows that for n marginal distributions and n elements of the Copula function, a distribution function consisting of n variables can be formed. The marginal distribution in this distribution function represents the distribution of each variable that has a correlation with financial risk. Copula function refers to the composite function composed of these variables fitted into a distribution function. The above theorem can confirm the existence of the Copula function, and through this theorem can show that the Copula function can describe the correlation of financial risk variables without considering the preconditions of the multivariate normal distribution function, which is more concise and convenient for us to study the existence of multivariate variables in the risk measurement of foreign energy portfolios.

With the above existence theorem of the Copula function, we can further introduce the definition of Copula, namely Sklar's theorem.

If the n element function $C : I^2 = [0,1]^n \to [0,1] = I$, if for all $t \in I^n$ the following four conditions are satisfied: $C(u) = 0$ if either component of t is 0; for $k \in \{1,2,\cdots,n\},\ u_k \in [0,1]$, both have $C\left(1,\cdots,1,u_k,1,\cdots,1\right) = u_k$; The function $C\left(u_1, u_2, \cdots, u_k\right)$ is increasing; For any $0 \le a_i \le b_i \le 1$, we have $\Delta_{a_n}^{b_n}\Delta_{a_{n-1}}^{b_{n-1}}\cdots\Delta_{a_1}^{b_1}C\left(u_1, u_2, \cdots, u_n \ge 0\right)$, then the function represented by C can be called a Copula function.

2.2. COPULA DISTRIBUTION FAMILY

Copula function has many distribution families, of which several are more important function families, including: the normal Copula distribution family, Archimedean Copula distribution family, t-Copula distribution family and elliptic distribution family, etc.. Several common families of Copula distributions are described below.

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2.2.1. NORMAL COPULA FAMILY OF DISTRIBUTIONS

The probability density function of the family of normal Copula distributions is shown below.

$$C\left(u_1,u_2,\ldots,u_p\right)=\phi_R\left(\phi^{-1}\left(u_1\right),\phi^{-1}\left(u_2\right),\ldots,\phi^{-1}\left(u_k\right)\right) \quad (2)$$

R in the above function equation represents a symmetric positive definite matrix, and the right-hand side of the equation represents the standard multivariate normal distribution function. $\Phi^{-1}(\cdot)$ is the inverse function of the standard normal distribution function. For the vast majority of cases, the data related to energy investment risks and returns show an asymmetric distribution, which is clearly different from the normal distribution. Therefore, the normal Copula family of distributions does not provide a valid analysis of the Chinese outbound energy portfolio risk measures we study.

2.2.2. T-COPULA DISTRIBUTION FAMILY

The probability density function for the family of t-Copula distributions is shown below:

$$C\left(u_1,u_2,\ldots,\quad u_k;R,v\right)=T_{R,v}\left(T_v^{-1}\left(u_1\right),T_v^{-1}\left(u_2\right),\ldots,T_v^{-1}\left(u_k\right)\right) \quad (3)$$

As with the probability density function of the family of normal Copula distributions, *R* is a symmetric positive definite matrix. The function $T_{R,v}()$ is a standard multivariate t distribution function, which R denotes the correlation matrix and v represents the degrees of freedom. $T_v^{-1}(\cdot)$ is the inverse function of $T(\cdot)$. Compared to the normal Copula family of distributions, the t-Copula family of distributions has a better fit in the tails of the financial risk and return distributions, but like the normal Copula family of distributions, it is less effective in characterizing asymmetry.

2.2.3. ARCHIMEDES COPULA DISTRIBUTION FAMILY

There are three types of probability density functions for the Archimedean Copula family of distributions, namely Gumbel Copula, Frank Copula and Clayton Copula, and their functional formulas are shown below.

$$C(u,v,\alpha)=\exp\left(-\left((-\log u)^{\alpha}+(-\log u)^{\frac{1}{\alpha}}\right),\alpha\in[1,+\infty)\right) \quad (4)$$

$$C(u,v,\alpha)=-1/\alpha\log\left(1+\frac{\left(e^{-\alpha u}-1\right)\left(e^{-\alpha v}-1\right)}{e^{-a}-1}\right),\alpha\in[-\infty,0)\cup(0,+\infty) \quad (5)$$

$$C(u,v,\alpha)=\max\left(\left(u^{-\alpha}+v^{-\alpha}-1,0\right),\alpha\in[-\infty,0)\cup(0,+\infty)\right) \quad (6)$$

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2.3. DEFINITION OF THE VAR METRIC

The traditional methods are ALM (Asset-Liability Management) and CAPM (Capital Asset Pricing Model), but each of these methods is overly dependent on the analysis of the data in the statements. As a result, the analysis results are not real-time and the risk measurement is too abstract to reflect the analysis results visually. These two traditional methods are unable to accurately analyze and measure investment risk because they can only show the volatility of assets and cannot incorporate other financial derivatives.

VaR (Value at Risk) is a method of measuring market risk proposed by the G30 Group in a report published in 1993, and the method has been widely promoted in the financial community. VaR means the maximum possible loss of a portfolio of financial assets under normal market volatility. It is the maximum possible loss of a portfolio of financial assets over the period from the present to a specific time in the future at a certain confidence level. The method is represented mathematically as follows.

$$\text{prob}\left(\Delta P_{\Delta t} \leq VaR\right) = \alpha \tag{7}$$

The definition of each variable in the above equation: P is the probability, representing the probability that the amount of loss of a financial asset is less than the maximum possible loss; $\Delta P_{\Delta t}$ is the loss amount, representing the loss amount of this financial asset during the holding time indicated by Δt. ; VaR represents the upper limit of possible loss at a certain confidence level α, which can also be the value at risk at that confidence level; α then represents the given confidence level.

2.4. CORRELATION METRIC

Correlation is a measure of the relevance of data attributes, and similarity is a measure of the similarity of data objects. Data objects are described by multiple data attributes, and the relevance of data attributes is described by the correlation coefficient. The similarity of data objects is measured by some distance measure. Because the correlation between different financial assets in a portfolio has a strong link to the overall portfolio investment risk, the analysis of correlation measures is a key part of the study of foreign energy portfolio risk.

The Kendall correlation coefficient is an important measure derived from the Copula function and is a statistical value used to measure the correlation of two random variables. the mathematical definition of the Kendall correlation coefficient τ is shown in equation (8). Suppose there are two mutually independent continuous random vectors (X_1, Y_1) and (X_2, Y_2), and these two vectors have the same joint distribution H. Then τ is defined as the difference between the positive and negative correlation probabilities, i.e.

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$$l = P\left(\left(X_1 - X_2\right)\left(Y_1 - Y_2\right) > 0\right) - P\left(\left(X_1 - X_2\right)\left(Y_1 - Y_2\right) < 0\right)$$
$$= 4\int_0^1 \int_0^1 C_2(u,v)dC_1(u,v) - 1 \tag{8}$$

It can be seen from the above equation that the calculation process of Kendall correlation coefficient τ is very tedious and requires the calculation of differentiation and double integration. However, under the calculation function of the Archimedean Copula family of distributions, it is only necessary to calculate its generating element φ first to calculate its Kendall correlation coefficient τ. Converting a two-dimensional problem to a one-dimensional direction greatly simplifies the computational process. According to the above method, we assume that there are two continuous random variables X and Y with Archimedean Copula family of distributions, and their generating elements φ are obtained by calculation, at which time the definition of Kendall correlation coefficient τ can be transferred from the above tedious formula as shown:

$$\iota = 1 + 4\int_1^0 \frac{\varphi(t)}{\varphi'(t)}dt \tag{9}$$

The Kendall correlation coefficient takes values between -1 and 1. When τ is 1, it means that the two random variables have consistent rank correlation; when τ is -1, it means that the two random variables have exactly opposite rank correlation; when τ is 0, it means that the two random variables are independent of each other.

3. ANALYSIS AND DISCUSSION

3.1. SELECTION AND DESCRIPTION OF DATA

The data selected for the empirical analysis in this paper are from Chinese industrial enterprise data for the period from January 3, 2015 to December 30, 2021, with a total of 1,498 sets of data for natural gas, oil, and coal futures as the data for the model analysis. The impact of price fluctuations between these three is studied by building a Copula-VaR foreign energy investment model. A comparative analysis of different foreign energy investment portfolio returns is conducted and the Kendall correlation coefficient is calculated to analyze the risk of the portfolio. The following variables are used in the Copula-VaR model calculation: (1) Vc is the coal futures price in USD/ton in the data of Chinese industrial enterprises; (2) Vo is the crude oil futures price in USD/barrel in the data of Chinese industrial enterprises; (3) Vg is the natural gas futures price in USD/mmBtu in the data of Chinese industrial enterprises.

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3.2. RISK METRICS FOR TRADITIONAL VAR METHODS

The analysis of single-asset risk measures is relatively simple and can be calculated using traditional methods. Table 1 shows the single-asset return VaR values calculated by traditional methods for natural gas, oil and coal futures.

Table 1. VaR values for each of the three futures

	Confidence level	Natural Gas	Oil	Coal
VaR value	0.96	0.01637	0.01357	0.03547
	0.98	0.02347	0.02367	0.03277

In a portfolio of foreign energy investments, the combination of different types of financial assets and the proportion of each financial asset in the portfolio in the overall portfolio are factors that affect the portfolio investment risk. Therefore, in this paper, three different energy futures are combined in different ratios: 0.2:0.2:0.6, 0.2:0.6:0.2, 0.6:0.2:0.2, 0.4:0.4:0.2, 0.4:0.2:0.4, 0.2:0.4:0.4, and 0.2:0.4:0.4. A total of six different combinations of ratios are used to calculate the data for in-depth analysis of the model. In this section, the VaR values of six different portfolios are calculated using the traditional VaR method at two different confidence levels, and the results are shown in Figure 2.

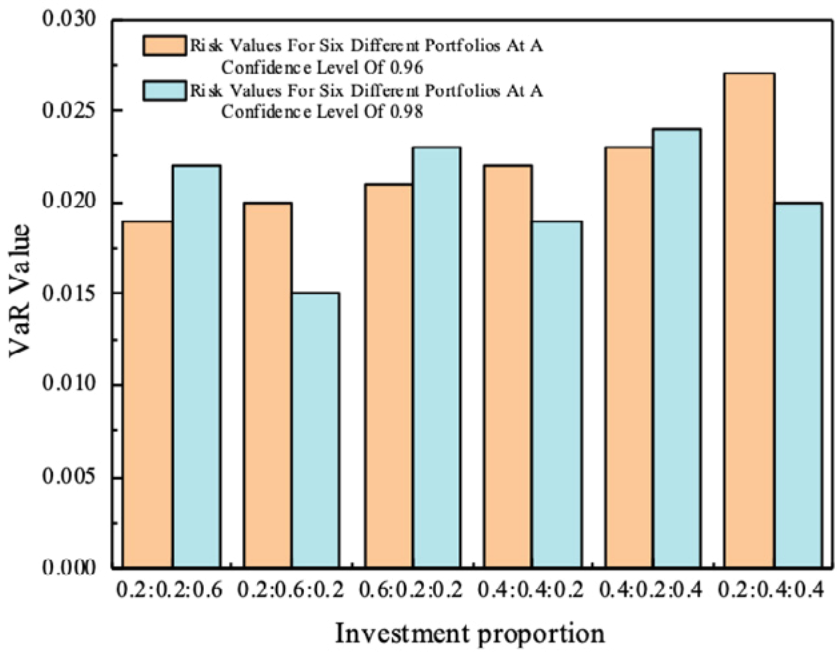

Figure 2. Coal and crude oil production 2011 - 2022

From Figure 2, it can be seen that there is a direct relationship between the investment risk value and the confidence level. When the confidence level is relatively high, it is accompanied by a greater investment risk. There is no obvious pattern of investment risk for the six portfolios with the same confidence level, and the highest risk value is when the investment allocation ratio is 0.2:0.4:0.4. At a confidence level

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of 0.98, the investment risk further increases when the 0.4:0.2:0.4 investment allocation brings a higher risk. Also, the risk values calculated using the traditional VaR method were 0.00434, 0.00462, 0.00167, 0.00870, 0.00193 and 0.00125 higher than those at the confidence level of 0.96, respectively.

Figure 3 shows the calculation of VaR for the single investment approach and portfolio investment approach, from the figure it can be seen that the VaR of the two investment approaches are different at different confidence levels. In general., the VaR values of natural gas and oil investment approaches are smaller, while the investment in coal has a greater risk, and the portfolio investment approach can reduce the risk value of coal investment to some extent.

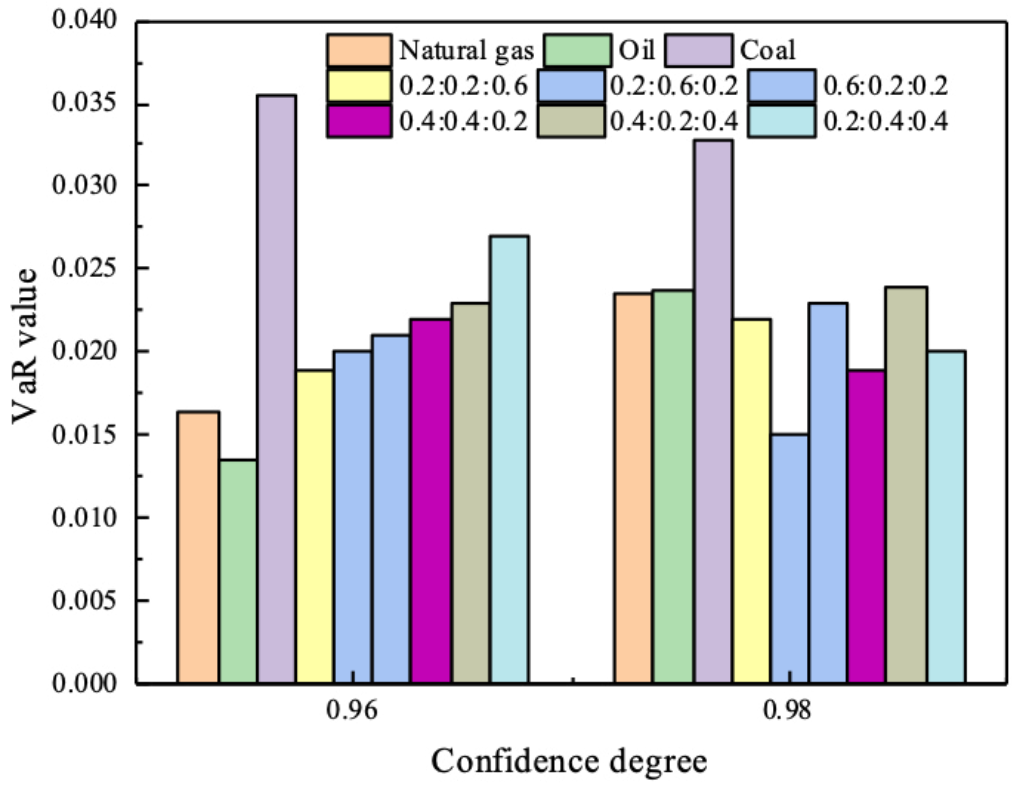

Figure 3. Risk measures for single investment approach and portfolio approach at different confidence levels

When the confidence level is 0.96, the risk of portfolio investment is greater than that of investing in natural gas and oil alone. When the confidence level is 0.98, the risk of portfolio investment is about the same as investing in natural gas and LPG alone, with a tendency to decrease in a given ratio. Therefore, when we do investment analysis, we have to divide the types of energy sources, and single and portfolio investments have different values of risk in specific conditions. There is no direct relationship between the two types of investments, which provides us with a way of thinking when doing energy investment planning.

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3.3. COPULA-VAR MODEL FOR RISK METRICS

From Section 2, we know that the introduction of Archimedean Copula function converts the two-dimensional problem into a one-dimensional direction for processing, which can make it easier to calculate the Kendall correlation coefficient τ. Using the Kendall correlation coefficient can improve the traditional VaR algorithm, and here we obtain $\tau = 0.692$ by calculating. Using the formula, the VaR values of natural gas, oil, and coal futures can be calculated for six different ratios of the portfolio, as shown in Figure 4

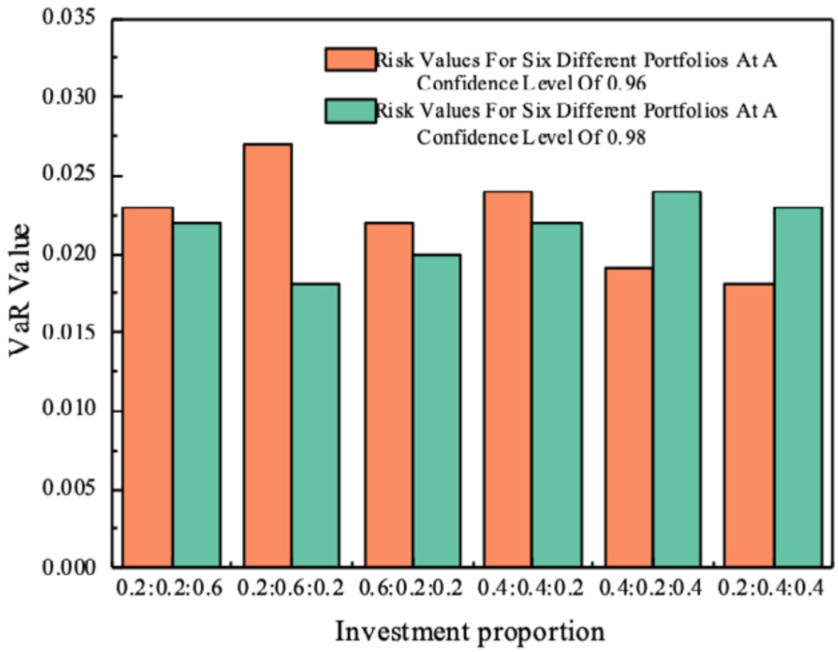

Figure 4. Risk values calculated by the Copula-VaR method at confidence levels of 0.96 and 0.98

As can be seen from figure 4, the value of investment risk is related to the confidence level, and different investment ratios have different risks at the same confidence level. This is consistent with the results calculated using the traditional method, where the 0.2:0.6:0.2 investment ratio has a higher risk when the confidence level is 0.96, while 0.4:0.2:0.4 has a higher risk when the confidence level is 0.98. The risk values under the confidence level of 0.98 are also higher than those under the confidence level of 0.96 by 0.00836, 0.00922, 0.00217, 0.00635, 0.00612 and 0.00827.

In addition to the improvement of the VaR measure of risk by introducing the Archimedean Copula function, the tail correlation carve-out can also enhance the method. The tail correlation coefficient consists of two parts, the upper tail correlation coefficient and the lower tail correlation coefficient, respectively. The tail correlation reflects the probability that the return of one asset is greater (less) than a certain threshold and the return of the other asset is simultaneously greater (less) than a certain threshold, i.e., the probability that two financial assets have extreme simultaneous same-directional returns. We can calculate the upper tail correlation

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coefficient $\gamma_u = 0.901$ and the lower tail coefficient $\gamma_1 = 0.843$ for the daily log returns of natural gas, oil and coal futures from the previous data. If the relationship between two assets is positively correlated and the higher the coefficient of correlation, the higher the risk coupling and the poorer the portfolio's ability to diversify risk; conversely, if the correlation coefficient between two assets is lower, the better the ability to diversify investment risk. These two correlation coefficients allow for the calculation of VaR values for the three futures at six different ratios of the portfolio, as shown in Table 2.

Table 2. VaR values for each of the three futures

			Different proportional portfolios of three futures					
VaR value	Confidence level	Correlation coefficient	0.2:0.2:0.6	0.2:0.6:0.2	0.6:0.2:0.2	0.4:0.4:0.2	0.4:0.2:0.4	0.2:0.4:0.4
	0.96	Upper tail	0.02143	0.02216	0.02165	0.02272	0.02411	0.02314
	0.98	Upper tail	0.02165	0.03156	0.03012	0.02684	0.02742	0.02812
	0.96	Lower tail	0.02514	0.02176	0.01982	0.01871	0.02187	0.02251
	0.98	Lower tail	0.03124	0.03417	0.02981	0.02318	0.02719	0.02154

The data in the table above shows that the value of risk varies for different percentages of investments. For investors, investing different amounts of money in different assets exposes them to different risks and yields different returns. To choose what portfolio proportions to invest in, the risk can be measured by a risk metric tool. The Copula-VaR model used in this paper can effectively improve the traditional VaR method, and the results of the test can give reference to the investment choice of investors. In the specific investment, the initial investment plan can be designed before the risk assessment, which can reduce the investment risk to a certain extent.

4. CONCLUSION

In this paper, the risk of foreign energy portfolios with six different ratios of natural gas, oil, and coal futures for the period from January 3, 2015 to December 30, 2021 is calculated by the traditional method, the Copula-VaR method that introduces the Archimedean Copula function, and the Copula-VaR method that introduces the tail correlation, respectively. Comparing the risk values of the six different proportions of the foreign energy portfolios, the following conclusions can be drawn.

1. The upper tail correlation coefficient $\gamma_u = 0.901$ and the lower tail coefficient $\gamma_1 = 0.843$ for the daily log returns of natural gas, oil, and coal futures indicate that if the relationship between two assets is positively correlated, and the higher the correlation coefficient is, the higher the risk coupling is and the worse the portfolio is for risk diversification; conversely if the correlation coefficient between two assets is lower, the portfolio is able to better diversification of investment risk.

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2. The risk of a single asset investment or portfolio is different at different confidence levels. From the data, it can be seen that the confidence level and the value of risk show a positive correlation. At the confidence level of 0.98, the value of risk calculated using the traditional VaR method is 0.00434, 0.00462, 0.00167, 0.00870, 0.00193 and 0.00125 higher than the value of risk at the confidence level of 0.96, respectively.

3. The data calculated using the modified Copula-VaR model also shows that the value at risk under the 0.98 confidence level is 0.00836, 0.00922, 0.00217, 0.00635, 0.00612 and 0.00827 higher than the value at risk at the 0.96 confidence level. most of the foreign energy portfolio values at risk are in between these three single The majority of the foreign energy portfolio is between the risk values of these three single energy assets. However, this approach is a good way to avoid a special situation where all investments are placed under the same asset and an accident causes a total loss of assets in the long run. There are different values of investment risk for different percentages of natural gas, oil and coal futures.

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