Risk measurement and management of coal futures based on VaR model

Shaohui Zou [1, 2], Tingyan Ma [1]

[1]School of Management, Xi'an University of Science and Technology, Xi'an 710054, China;

[2]Energy Economy and Management Research Center, Xi'an University of Science and Technology, Xi'an 710054，China

Abstract

Based on the price data of steal coal futures from September 2013 to the end of July 2008, the VaR value of coal futures price yields is measured by VaR-GARCH variance covariance method, historical simulation method and Monte Carlo simulation method, and the risk is compared under different confidence levels. The empirical results show that VaR estimation is too conservative at 95% and 99% confidence levels based on VaR-GARCH, which overestimate the risk to some extent, mainly because of the non-linear and "rough tail problem" of coal futures fluctuations; the result of historical simulation method is more reliable without hypothetical distribution; Under the hypothetical distribution, the changes of the estimated future risk factors have a counterforce to the real market changes, which can reduce the estimation error. Combined with the specific empirical results, we use VaR model to put forward measures to further prevent the risk of coal futures in China.

Keywords

Coal futures; VaR model; risk management.

1. Introduction

As a product of the development and maturity of modern market economy, coal futures market has become a research hotspot in the field of economics. Coal futures is a standardized contract based on coal resources and related interests, which has the function of price discovery and arbitrage. Under the comprehensive influence of various factors at home and abroad, the coal futures market, as a supplement to the spot market, has a risk spillover effect on the spot market under the linkage effect, so it is particularly important to measure the risk of the coal futures market. In this paper, under the three methods of VaR model, the risk of China's coal futures market is measured reasonably in order to quantify China's coal market and avoid the price risk of coal futures.

VaR risk measurement method was first proposed by J.P.M. organ bank for the shortage of market risk measurement technology. The model has been improved by many scholars at home and abroad. In order to solve the dimension problems caused by multiple risks and high dimensions, we choose Copula. For example, Zhao Lutao et al. [1], based on Copula-VaR model, we build the energy price risk model. The results show that the model can better reduce the risk of energy portfolio investment. Tail extreme risk is also the focus of attention of many institutions, such as Yang Chao et al. [2] Introducing Markov volatility transfer in VaR calculation, combining extreme value theory to measure the systemic risk of international carbon trading market; Manel Youssef et al. [3] Using three GARCH-type long memory models and extreme value theory, evaluated the value at risk (VaR) and expected shortage (ES) of crude oil and gasoline markets. Because extreme value theory can not solve the problem of heteroscedasticity of volatility, there are some methods to combine VaR with ARCH family models, such as Boqiang Lin, etc. [4] using VAR-GARCH, VAR-AGARCH and DCC-GARCH frameworks to study the dynamic volatility and volatility transmission between oil prices and returns of Ghana stock market; Alessandro G. Laporta and others [5]using GARCH, EGARCH, GJR-GARCH, GAS-GARCH. The VaR model and CAViaR model have different predictions for the yield of energy commodities in Japan. For comparison of VaR values of GARCH family models under different distributions, such as Liu Guirong and Zhou Weijie [6], four GARCH models are used to model VaR risk measurement under different distributions. The results show that more characteristics of financial assets can be captured under t distribution. In terms of the improvement of VaR method, Xu et al. [7] proposed to simulate the non-linear structure of financial system by using quantile regression of neural network (QRNN). Combining with POT method of extreme value theory, QRNN+POT method was applied to extreme VaR risk measure. Mawuli Segnon and Mark Trede [8] found copula-MSM under the combination of Copula function and Markov switch multifractal (MSM) process. The model provides the best fitting for prediction accuracy and VaR prediction. Modified models for VaR, such as Emmanouil N. Karimalis and Nikos K. Nomikos [9], propose a new method for estimating CoVaR based on Copula function, and extend this method to estimate other "common risks", such as conditional expectation shortage (COES). Empirical research on the test effect of various VaR methods, such as Ren Jiqin, etc. [10] Use GARCH model and VaR method to evaluate the risk of China's main board and GEM market, and use Mann-Whitney U test method to compare them. The results show that the risk of the GEM market is significantly greater than that of the main board market.

In addition to the study of VaR risk method, in terms of its applicability, Chinese scholars generally believe that VaR is suitable for China's securities market. For example, Li Yunliang [11] first analyzed the current situation of risk control of securities companies'self-operating business, pointed out the existing problems, and introduced VaR model to quantify the self-operating business of securities companies. Foreign scholars have studied this applicability, such as Kostas Andriosopoulos and Nikos Nomikos [12] quantifying energy price risk by calculating VaR and anticipated shortage measures; Cyprian O. Omari [13] using GARCH-EVT Copula model to estimate the risk portfolio value of currency exchange rate, and found that semi-parametric method provides accurate estimation of VaR value; Wenhua Yu [14] using GARCH model, extremum theory, etc. On the basis of EVT and Fujimoto portfolio theory, the risk value (VaR) and expected shortage (ES) of four crude oil portfolios are measured; Daywes Pinheiro Neto and others [15] analyze the investment risk of power plants based on the value at risk (VaR) and conditional risk value (CVaR); Alessandra La Notte and others [16] apply VaR to the risk degree brought by greenhouse gases (GHG). The results show that the measurement method improves the design of appropriate strategies for reducing greenhouse gas emissions.

At present, the research on VaR risk measurement mainly focuses on the financial field, and the research on energy is very few, especially in the coal field. Therefore, this paper will analyze the risk measurement of coal futures based on the above related research results. This paper chooses the coal futures price from September 2013 to the end of July 2018, calculates the VaR value of the coal futures price return rate by VaR-GARCH normal parameter method, historical simulation method and Monte Carlo simulation method, and conducts empirical research comparison and test under 95% and 99% confidence.

2. Theoretical model

VaR (Value at Risk) refers to the worst expected loss in a certain confidence level and holding period. The model is based on the hypothesis of market efficiency and stochastic volatility without autocorrelation. Formulas are used to express that:

$$\Pr ob(\triangle p \le -VaR) = \alpha \tag{1}$$

Among them, $\triangle p$ is for the expected loss during the holding period $\triangle t$, VaR represents the value at risk under the confidence level $1-\alpha$. VaR has many calculation methods. This paper mainly uses VAR-GARCH (1,2) variance covariance analysis method, historical simulation method and Monte Carlo simulation method to analyze and compare the risk measurement of coal futures market.

2.1 VaR-GARCH variance covariance analysis

Based on the GARCH risk measurement method, the time-varying variance is taken into account, which can well describe the time-varying of the peak, thick tail, aggregation and volatility of the return series. The basic principle of the model is to predict the standard deviation and calculate the VaR value on the basis of establishing a GARCH model with the best fitting degree. Finally, the failure frequency test method is used to test the model. The expression of GARCH (m, s) model is as follows:

$$r_t = \beta_0 + \beta_1 r_t + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_i \sum_{i=1}^{m} \varepsilon_{t-i}^2 + \beta_j \sum_{j=1}^{s} \sigma_{t-j}^2 \tag{3}$$

Among them, α_i, β_j are the estimated parameters, $\alpha_i \geq 0$, $\beta_j \geq 0$,m is the order of ARCH term and s is the order of GARCH term. On the basis of variance covariance, this paper presents a VaR metric under GARCH.

$$VaR_{t+i} = P_0 Z_\alpha \sigma_{t+i} \tag{4}$$

Among them, Z_α is the quantile corresponding to the error distribution at the confidence level $1-\alpha$, σ_{t+i} is the square root of conditional variance.

2.2 VaR measurement based on historical simulation

The historical simulation method calculates the frequency distribution of portfolio risk and return in the past period through financial commodity risk factors. The steps are as follows:

1) Firstly, the profit and loss of the assets are obtained by using historical data.

2) Secondly, the income and loss data are arranged in ascending order.

3) Finally, according to the confidence level α, the corresponding quantile is found and VaR is obtained.

2.3 VaR measurement based on Monte Carlo simulation

Monte Carlo simulation is a method to solve some financial calculations by using random numbers. Its basic foundation is a stochastic process. The calculation steps are as follows:

1) Choose geometric Brownian motion to establish a dynamic model describing price changes. Among them, dS_i is price fluctuation, μ_t is return on assets (drift term of the model), σ_t is standard deviation of return, $d\omega$ is Brownian motion obeying normal distribution, ε_t is random variable and obeying.

$$S_{t+1} = S_t + S_t(\mu_t \Delta t + \sigma_t \varepsilon_t \sqrt{\Delta t}) \tag{5}$$

2) In the standard normal distribution, the random sequence is extracted and substituted into formula (5) to obtain the simulated price as S_1, $S_2 \ldots S_T$。

3) Repeat the second step k times to get a series of asset prices S_T^1, $S_T^2 \ldots S_T^k$ at the target time T.Prices are arranged in ascending order, At a given confidence level $1-\alpha$,we will find the quantile and then estimate the corresponding VaR value.

$$VaR = S_t - S_T^* \tag{6}$$

3. Empirical Analysis

3.1 Data Selection

The data are all from the windows database and collated. Because China's coal futures market is dominated by power coal futures, we choose the settlement price (active contract) date data of power coal futures as the coal futures price. From September 2013 to the end of July 2018, 1761 valid samples were obtained. For convenience, the coal futures price is recorded as F. Because of the discontinuity of the futures price of power coal, in order to solve this problem, a continuous futures price series is composed of data by linear method. At the same time, the empirical research is carried out under 95% and 99% confidence.

3.2 Risk Analysis Based on VaR-GARCH

Because GARCH model is suitable for analyzing stationary series and eliminating possible heteroscedasticity, it is necessary to process the sequence F to make it a relatively stationary profit sequence, namely LF:

$$LF_t = \ln F_t - \ln F_{t-1} \tag{7}$$

3.2.1 Basic descriptive statistics of coal futures yield and its test are as follows,see table 1:

Table 1 Basic description of statistics

Sample	Max	Min	St.d	kurtosis	skewness	ADF	LF(-1)	P value
LF	0.112	-0.15	0.001	69.064	-2.948	-37.093	27.276	0

Table 1 shows that the skewness of power coal futures series is -2.9484 less than 0, showing left skewness; the kurtosis is 69.0644 greater than 3, showing the characteristics of peak and thick tail; after correlation test, the absolute value of ADF is 37.0932 obviously greater than 2, and the p value is 0, indicating that the coal futures earnings series test is stable, rejecting the unit root hypothesis at 1% significance level, so the LF series is a stable series. In the correlation analysis of sequence autocorrelation and partial autocorrelation graph, we find that the lag first-order autocorrelation coefficient is larger than other orders, so we use LF sequence to construct a lag first-order mean equation. Under this equation, we obtain the residual wave diagram as shown in Fig. 1.

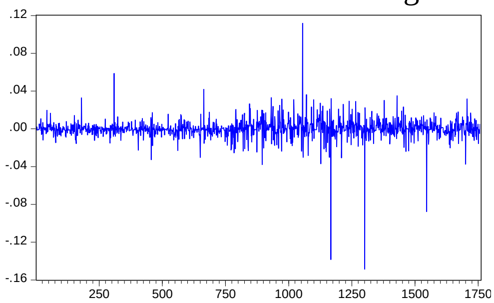

Fig. 1 Residual fluctuation chart

As can be seen from the figure above, the residual sequence has obvious volatility aggregation, and the volatility range is very large between 750 and 1164 trading days, indicating the existence of ARCH effect, so we can build GARCH model accordingly. The Q-Q chart of coal futures return series under normal distribution and t distribution is as follows:

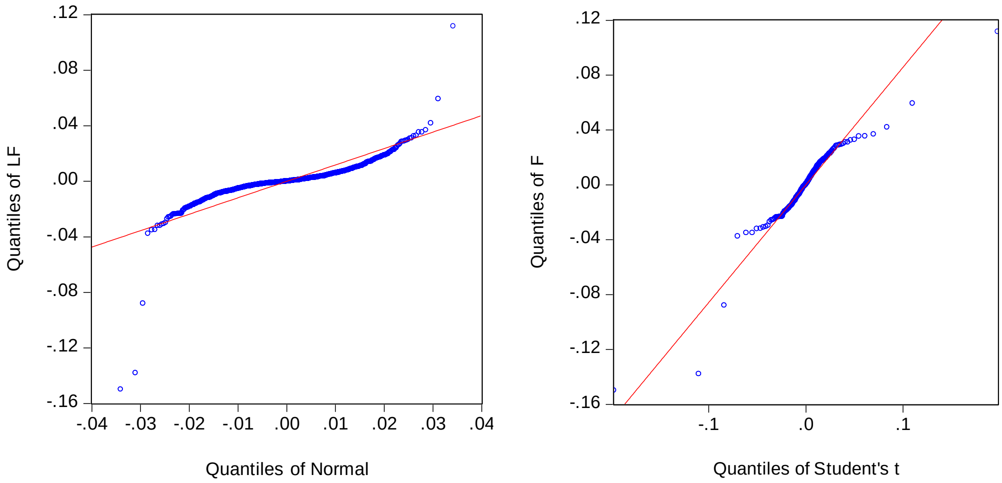

Fig. 2 Q-Q Diagram under Normal Distribution and t Distribution

From Figure 2, we can clearly see that LF sequence has a higher degree of fitting under t distribution. Under the criteria of AIC and SC, the values of AIC (-7.312065) and SC (-7.290297) under t distribution are significantly smaller than those under normal distribution (-6.505673) and SC (-6.487015). In the selection of GARCH (p, q), we finally choose to establish a lag 1-order GARCH (1, 2) equation under t distribution:

$$r_t = \text{-4.83E-05} + 0.304766 r_{t-1} + \varepsilon_t \tag{8}$$

$$\sigma_t^2 = \text{6.47E-05} + 3.139333\varepsilon_{t-1}^2 + 0.070747\sigma_{t-1} + \text{-}0.016276\sigma_{t-2} \tag{9}$$

By ARCH-LM test on the above models, we find that F statistic is 0.027735 (0.8678), LM statistic is 0.027766 (0.8677), and its probability is greater than 0.05, indicating that the original hypothesis can not be made, and GARCH (1, 2) has eliminated conditional heteroscedasticity. Therefore, based on GARCH (1,2), this paper carries out parameter analysis.

3.2.2 VaR Computation

VaR value can be calculated by variance covariance model, so VaR value can be calculated every day. Among them, the conditional variance equation can be used to calculate the estimated value, and then the estimated value of standard deviation can be obtained. At that time,; when,. The formula used in this paper is: the product of current yield and current price. VaR values and actual gains and losses at the left deviation probability levels of 0.01 and 0.05 are shown as follows:

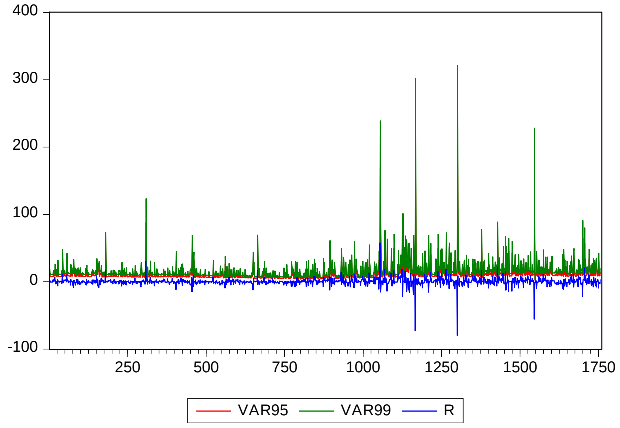

Fig. 3 VaR and actual profit and loss chart

From Figure 2, we can see that the estimated value of VaR at the level of 0.01 and 0.05 respectively is larger than the rise or fall level of logarithmic yield. At the same time, we know that the mean and standard deviation under the confidence level of 95% (11.8768, 12.26638) and 99% (16.74268, 17.29188) are greater than the mean and standard deviation of actual profit and loss (0.063431, 5.119595). Therefore, we preliminarily believe that the VaR value under GARCH (1, 2) is volatile and the risk under the confidence level of 95% is smaller.

3.2.3 LR Test Based on Failure Rate

We use "Failure Frequency Test" to test. The principle of this method is to compare the estimated value of VaR with the actual value of profit and loss. When the value of VaR is less than the absolute value of the actual value of profit and loss, it is regarded as failure, and vice versa, success. Then the actual probability of failure is compared with the expected probability of failure at a certain confidence level. Kupiec assumes that the VaR estimator is time independent, and the probability of failure is $p = N/T$ (T is the number of samples, N is the number of failures), and the expected probability of failure $p^* = 1-\alpha$ at the confidence level α . Then the likelihood ratio test is proposed under the zero hypothesis $p = p^*$.

$$LR = \text{-}2\ln\left[\left(1-p^*\right)T - N\left(p^*\right)^N\right] + 2\ln\left[\left(1-N/T\right)T - N(N/T)^N\right] \tag{10}$$

Statistical LR obeys the distribution of degree of freedom 1. According to this method, the acceptance domain under 95% confidence level is LR_3.84, and the acceptance domain under 99% confidence level is LR_6.63. At 95% confidence level, LR is 5.9915, 99% confidence level and LR is 9.2103. Therefore, the original hypothesis is rejected, indicating that GARCH (1,2) does not pass the test under normal distribution. It can be concluded that at 95% and 99% confidence levels, the VaR estimation based on GARCH (1,2) is too conservative and overestimates the risk to some extent, which may be affected by the left-sided characteristics of historical data.

3.3 VaR measurement based on historical simulation

Under the operation steps of the historical simulation method, we can obtain the following results, in which only part of the data is intercepted due to the limitation of space:

Seventeen hundred and sixty-one yield data are arranged in ascending order:

Table 2 Coal Futures Revenue Sequence

Sequence	Return Rate
1	-0.14995915
2	-0.13811368
3	-0.08800857
4	-0.03769041
5	-0.03521379
6	-0.03518933
7	-0.03217714
8	-0.03213535
9	-0.0311293
10	-0.03077166
11	-0.02994349
12	-0.02724128
…	…
1761	0.111566897

At 95% confidence level, the corresponding quantile is 1761* (1-95%)= the corresponding value of 5 and 88 numbers, i.e. the average value of 5 and 88 numbers, i.e. VaR value is -0.0237. Similarly, at 99% confidence level, the corresponding quantile is the average of 17 and 61, that is, the VaR value is -0.01951. It is found that the higher the confidence level, the greater the risk, but the VaR value calculated by historical simulation method is much smaller than the VaR mean calculated by variance covariance method, which shows that compared with variance covariance method, when the sequence does not obey normal distribution, the estimated results obtained by historical simulation method are more reliable.

3.4 VaR Measurement Based on Monte Carlo Simulation

Firstly, EVIEWS is used to test the stability and correlation of coal futures price series, as shown in the table.

Table 3 ADF and D-W Test

	ADF	ADF(P)	5% Test	D-W value
F	-1.0337	0.7431	-2.862979	1.995149

As can be seen from the above table, ADF (-1.0337) is significantly greater than the critical value of 5% of the significant level - 2.862979, which can be concluded that the coal futures price series is non-stationary. The D-W value (1.995149) is obviously around 2, so there is no autocorrelation in the sequence. We should accept the zero hypothesis that the sequence is white noise, that is, its distribution is independent. In conclusion, it can be concluded that the daily settlement price of coal futures price in China obeys the geometric Brownian motion. Using this data, MC is used to calculate the VaR value of the next trading day. Among them, we divide the holding period of a day into 20 periods (in units of hours). The mean and standard deviation of futures prices is $\mu / 20$ and $\sigma / \sqrt{20}$ in each period are respectively sum.

According to descriptive statistics of daily return series of coal futures prices, the average sample value is 8.29E-05, and the standard deviation of sample is 0.0099. Starting from the settlement price 612.6 on July 23, 2018, the settlement price on the next trading day is generated by using geometric Brownian motion, and the process is repeated 1000 times. The possible price trend of 1000 July 24 is simulated by using MATLAB software. The histogram is drawn as follows:

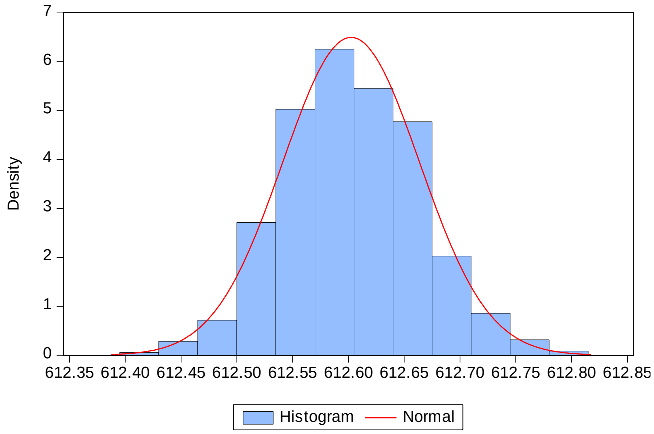

Fig. 4 Density histogram under Monte Carlo simulation

From Figure 4, we know that the coal futures prices on July 24, 2018 simulated by Monte Carlo basically show normal distribution, and the values fluctuate around 612.6. The settlement price data of 1000 Chinese coal futures generated above are arranged in ascending order, and the settlement price of 1000*5%=50 representative is found to be 612.508298. Therefore, on July 24, 2018, the VaR value of coal futures at the confidence level of 95% is 0.091702, and it is also known that the VaR value at the confidence level of 99% is 0.072804. The simulated VaR values of the two methods are similar in shape, but larger than that of the historical simulation method and much smaller than that of the variance covariance method.

3.5 Result Analysis

This paper calculates the VaR value of coal futures price return by VaR-GARCH parameter method, historical simulation method and Monte Carlo simulation method, and establishes VaR risk assessment model. The following conclusions can be drawn:

1) The distribution of China's coal futures market yield does not fully conform to the normal distribution, and can be better fitted under the t distribution. Based on the risk measurement of VaR-GARCH, we find that the VaR estimates calculated at 95% and 99% confidence levels are too conservative and overestimate the risk to some extent. This is because the change of coal futures is non-linear, and this method reflects the risk in a linear way, and often encounters the "coarse tail problem" (that is, the possibility of deviating from the mean is greater than predicted), plus the influence of left-biased distribution. Therefore, with the change of holding period, the gap between the actual change of VaR and the linear change will become larger and larger.

2) The VaR value calculated by historical simulation method is much smaller than that calculated by normal parameter method, which shows that the historical simulation method is more reliable when the sequence does not obey the assumption of normal distribution. This is mainly because the historical simulation method has no hypothetical distribution and directly depends on historical data. When selected for a representative period, the VaR value estimated by this method can better measure market risk.

3) Monte Carlo simulation directly evaluates the market risk of coal futures contracts and obtains the potential maximum loss on the next trading day. From the test results, the VaR value under historical simulation method is larger than that under variance covariance method, which shows that although Monte Carlo simulation method also depends on the historical data of the survey period, under the

hypothesis distribution, the estimated future market factors have a counterforce to the actual changes, which reduces the estimation error. However, when the actual distribution is different from the hypothetical distribution, the reliability of the measured VaR value will be reduced.

4. Conclusions and Suggestions

4.1 Conclusion

Through GARCH normal parameter method, historical simulation method and VaR measurement method under Monte Carlo simulation method, risk managers can make quantitative analysis of risk size, and make more accurate risk management decisions. At the same time, they can play an important role in controlling risk of exchanges and investors and preventing risks. With the development of information age, information transmission will be more rapid and effective, and the Risk Spillover Effect of coal futures market will become more obvious, which must be paid enough attention. China's coal futures market started relatively late, so the application of VaR method to the market still has some limitations, but the use of VaR method to quantify risk analysis, risk management of domestic coal futures market is still of great significance.

4.2 Recommendations

1) Setting up dynamic margin. Risk managers should actively apply VaR technology to the risk management of coal futures, especially to set the dynamic margin level according to the VaR value under a certain confidence level, so as to manage the risk of coal futures market more effectively and in real time. The implementation of this mechanism can improve the stability of coal futures, give full play to the function of hedging and speculation, and make investment more rational and risk more controllable.

2) Improving the risk management system. Firstly, the government should decentralize power, strengthen cooperation with mature securities market, form a vertical management system, and establish effective management mechanism for risk events; secondly, in view of the problems before, during and after risks, the exchange should improve the prevention and control measures and systems, and solve the problems in time to cope with risks.

3) Strengthen investor risk education. As a direct participant in the market and a risk bearer, the education of investors themselves is particularly important. Coal futures companies should strengthen the propaganda and depth of risk control in order to cultivate mature and rational investors. Institutional investors, as the main participants in the financial derivatives market, can stabilize the market and disperse risks to a certain extent, so the government should Increase the cultivation of institutional investors.

Acknowledgements

This paper is supported by the National Natural Science Foundation of China (No. 71273207, 71273206), the Science and Technology Research and Development Program of Shaanxi (No. 2011kjxx54), and the Scientific Research Program Funded by Shaanxi Provincial Education Commission(Program NO. 2010JK185)

References

[1] Zhao Lutao, Li Ting, Zhang Yuejun, Wei Yiming. Research on price risk measurement of energy portfolio based on Copula-VaR [J]. System Engineering Theory and Practice, 2015, 35 (03): 771-779.

[2] Yang Chao, Li Guoliang, Men Ming. Risk Measurement of International Carbon Trading Market and Its Enlightenment to China: A Comparative Study of VaR Based on State Transition and Extreme Value Theory [J]. Quantitative Economic and Technological Economic Research, 2011, 28 (04): 94-109+123.

[3] Manel Youssef, Lotfi Belkacem, Khaled Mokni. Value-at-risk estimation of energy commodities: A long-memory GARCH-EVT approach [J]. Energy Economics, 2015, 51.

[4] Boqiang Lin, Presley K. Wesseh, Michael Owusu Appiah. Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness [J]. Energy Economics, 2014, 42.
[5] Alessandro G. Laporta, Luca Merlo, Lea Petrella. Selection of Value at Risk Models for Energy Commodities [J]. Energy Economics, 2018, 74. [1] Alessandro G. Laporta, Luca Merlo, Lea Petrella. Selection of Value at Risk Models for Energy Commodities [J]. Energy Economics, 2018, 74.
[6] Liu Guirong, Zhou Weijie. Research on VaR measure of Shanghai-Shenzhen 300 index based on multi-distributed GARCH family model [J]. Dong Yue Lun Cong, 2016, 37 (12): 43-50.
[7] Xu Qiqiu, Chen Shijun, Jiang Cuixia, Liu Xi. A new method of extreme VaR risk measurement: QRNN + POT [J]. Journal of Systems Engineering, 2016, 31 (01): 33-44.
[8] Mawuli Segnon, Mark Trede. Forecasting market risk of portfolios: copula-Markov switching multifractal approach [J]. The European Journal of Finance, 2018, 24 (14).
[9] Emmanouil N. Karimalis, Nikos K. Nomikos. Measuring systemic risk in the European banking sector: a copula CoVaR approach [J]. The European Journal of Finance, 2018, 24 (11).
[10] Ren Jiqin, Shan Xiaotong, Liang Ze. A comparative analysis of market risks between China's main board and GEM based on GARCH-VAR method [J].Finance and Trade Research, 2015, 26 (03): 128-132.
[11] Li Yunliang. Self-operation risk analysis of securities companies based on VaR model [J]. Southwest Finance, 2009 (11): 47-49.
[12] Kostas Andriosopoulos, Nikos Nomikos. Risk management in the energy markets and Value-at-Risk modelling: a hybrid approach [J]. The European Journal of Finance, 2015, 21 (7).
[13] Cyprian O. Omari, Peter N. Mwita, Antony W. Gichuhi. Currency Portfolio Risk Measurement with Generalized Autoregressive Conditional Heteroscedastic-Extreme Value Theory-Copula Model [J]. Journal of Mathematical Finance, 2018, 08 (02).
[14] Wenhua Yu, Kun Yang, Yu Wei, Likun Lei. Measuring Value-at-Risk and Expected Shortfall of crude oil portfolio using extreme value theory and vine copula [J]. Physica A: Statistical Mechanics and its Applications, 2018, 490.
[15] Daywes Pinheiro Neto, Elder Geraldo Domingues, Wesley Pacheco Calixto, Aylton Jos Alves. Methodology of Investment Risk Analysis for Wind Power Plants in the Brazilian Free Market [J]. Electric Power Components and Systems, 2018, 46 (3).
[16] Alessandra La Notte, Stefania Tonin, Greti Lucaroni. Assessing direct and in direct emissions of greenhouse gases in road transportation, taking into account the role of uncertainty in the emissions inventory [J]. Environmental Impact Assessment Review, 2018, 69.