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Risk Innovation Green Innovation Management of Chinese and Russian Stock Markets Based on Time-Space Kriging Model

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Abstract: *In recent years, due to the influence of economic globalization and financial integration, modern financial theory and financial innovation, the Chinese and Russian financial markets have developed rapidly, but at the same time, the financial markets have also shown unprecedented volatility. The Sino-Russian financial markets at the initial development stage will also face even more dramatic fluctuations. In particular, the stock market, which is the largest area for potential financial risk transmission, inevitably becomes the focus of green innovation management for financial risk transmission. This paper uses the modern risk management technology Kriging theory, through the introduction of GARCH Kriging model calculation, analyzes the comprehensive risk transmission of different markets in the Chinese and Russian stock markets, and measures several representative industry risks, indicating that Kriging risk management theory is in China and Russia. The applicability of the stock market and the risk estimation of different industries. At the same time, this paper analyzes the risk composition of the portfolio through Kriging risk analysis of the four heavyweight stocks of Sino-Russian funds, and makes relevant analysis for the selection of the portfolio and the sources of risk transmission and risk avoidance. The experimental results show that for the test sample data T = 510, at a 95% confidence level, the number of Sino-Russian real estate index, manufacturing index, financial index and IT index should not exceed the Kriging critical value nor exceed 36.*

Keywords: *Space-time Kriging Model, Sino-Russian Stock Market, Risk Transmission Measurement, Green Innovation Management*

1. Introduction

With the trend of economic globalization and investment liberalization, the economic, political, and social environments of various microeconomic entities are becoming more complex, and their operations are also facing increasingly diverse and increasing risks. This is manifested in the most active modern transactions. It is even more prominent in financial markets.

Due to the importance of research on stock market risk management, many research teams have begun to study stock market risk and achieved good results. For example, Juanjuan discussed the basic principles and application prospects of the Kriging risk management model, and introduced and evaluated the historical simulation model , Monte Carlo simulation model, variance-covariance model and other basic Kriging risk management models [1]; Diboulo discussed the mean variance investment decision-making model under the constraints of kriging risk, and Jing Wen also analyzed the application of Kriging risk in the domestic securities market The management model mainly faces the problems of limited sample data and effective model selection [2].

In the research of stock market risk conduction green management, the use of space-time kriging model calculation is a good method, which can solve many problems, so it is widely used in the research of stock market risk conduction green management, for example, Echaubard applies various kriging risk management The model empirically analyzes the volatility risk of the Hong Kong Hang Seng Index and compares the practicality of each model through the BaCk-Test test. The results show that due to the peak and fat tail characteristics of the stock market return distribution, the left tail probability is less than or equal to 1% The Kriging risk management model based on the normal distribution assumption will underestimate the risk of the portfolio. In this case, using the t distribution as an approximation is better. For the 95% or higher left tail probability, the Kriging model based on

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the normal distribution assumption is Appropriate, but from the perspective of the overall effect, the GARCH (l, 1) model has the best effect [3].

This article mainly discusses the related financial risks and stock market risk management theories, and focuses on the applicability of the Kriging risk management model and the empirical analysis of the Chinese and Russian stock markets to prove the applicability of the Kriging model in the Chinese and Russian financial markets. And analyze the risk exposure of different markets and different industries through Kriging analysis of different markets and industry indexes of the securities market. And through its Kriging analysis of the asset portfolio and the analysis of the marginal Kriging, component Kriging and incremental Kriging of the portfolio, analyze the risk exposure of the asset portfolio and the rationality of resource allocation, analyze the risk exposure of different industries and the overall risk to the portfolio The degree of impact, improve market risk.

2. Proposed Method

2.1 Empirical Analysis of the Risk Transmission of Chinese and Russian Stock Markets by Kriging Model

As an emerging market, the stock market of China and Russia has developed rapidly. The Sino-Russian stock market took ten years to complete the course of the foreign stock market in the past one or two hundred years. The stock market has changed from the embarrassment that everyone waits and sees, and the stocks are unneeded to become the "eye-barometer" of the economies of the two countries, and the "gathering place" of the rich people of the two countries, which has become a small and important part of the national economy. The total number of listed companies in China and Russia has increased by more than 180% annually [4]. The ability of finance to penetrate the economy is constantly strengthening, and the status of the Chinese and Russian securities markets in the national economy has been increasing. The basic structure of this article is shown in Figure 1 below.

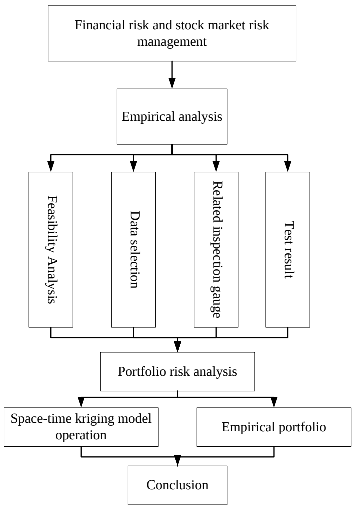

Figure 1: The basic structure of this article

(1) Measurable basis for risk in Chinese and Russian stock markets

To use the Kriging risk management system to predict the risks of Chinese and Russian stock markets, we must first analyze whether the risk characteristics of the Chinese and Russian stock markets provide a basis for the technical analysis of risks, and whether the Chinese and Russian stock markets are feasible for technical analysis.

The first is the premise. At present, the current forecast analysis of the stock market usually includes two levels, namely, fundamental and technical aspects. Fundamental analysis is to study various factors that affect the supply and demand of the stock market. Technical analysis is an analysis method to study the influence of the past and present behavior of the market on the future trend of the market, and to use various mathematical models to predict the future changes of the market according to the past and present behavior of the market. Due to the special risk characteristics of the Sino-Russian stock market, there are many uncertain factors in the investment environment, and fundamental analysis is difficult to comprehensively, and many scholars have conducted empirical research on the technical analysis and predictive power of the Chinese and Russian stock markets. It is said that technical analysis has a certain predictive power, which is mainly due to the weak effectiveness of the Chinese and Russian stock markets, so we can continue to use the technical analysis of the Chinese and Russian stock markets [5-6].

Secondly, the uncertainty in the Chinese and Russian stock markets makes Kriging a more effective method. Throughout the history of world stock development, volatility is an inevitable phenomenon that accompanies the operation of the stock market. The stock market of China and Russia was gradually bred and developed after opening to a certain stage. The operation of the stock market relies on the special environment given during the transition from the planned economy to the market economy, and thus shows the particularity of its fluctuations. The unique risks of China and Russia make the systemic risk factors in the Chinese and Russian stock markets the main source of stock market risk. The increase in the proportion of systemic risk factors increases the uncertainty of the Chinese and Russian stock markets [7]. This article believes that the Kriging method is suitable for the Sino-Russian situation, mainly because Kriging can cover various market factors that affect financial assets, including certainty and uncertainty risk factors, and the model can also measure price risk issues, so its It can measure the overall market risk of a complex portfolio of securities composed of different market factors and different financial instruments.

Thirdly, the weak validity of the Chinese and Russian stock markets enhances the predictability of the stock index. Because the Chinese and Russian stock markets are weak and effective, in the weak and effective market, the current price of securities fully reflects all information about past prices and past returns Therefore, we can use historical data as a sample to analyze the future market trends, which is also one of the reasons why the technical analysis has a certain predictive power and the Kriging system can be used in the Chinese and Russian stock markets.

(2) Green innovation management of stock market

Because many strategies of an enterprise serve the future development of the enterprise, the development strategy is actually their overall strategy, which indirectly highlights the overall characteristics of the development strategy. In other words, compared to other strategies, the problems faced by development strategies are more comprehensive. The development strategy can also be regarded as an upper-level concept and a general outline to guide other strategies [8-9]. The development strategy is closely related to other types of strategies and has an influence. The former can guide the latter strategy, and the latter needs to implement the former strategy. An in-depth understanding of the above concepts is the first step for a company to succeed. From this we can see that it is quite wise for listed companies to adopt green innovation development strategies.

1) Construct a government-enterprise cooperation promotion system

The green innovation strategy must adhere to the principles of government-led, enterprise-led, market-oriented, industry-university-research linkage, and the participation of the whole society, implementing independent innovation strategies, cultivating innovation entities, perfecting innovation systems, cultivating innovative talents, and optimizing the innovation environment .

Taking listed companies as an example, the government needs to cooperate deeply with listed companies to jointly promote cooperation in data resources, data technology, and data applications to improve the efficiency and effectiveness of data development and use. Centering on the data link of city company products, fully applying market means to rationally use innovative elements, to achieve strategic cooperation between enterprises, universities and research institutions, and to form data value and core competitiveness through win-win, collaborative development, resource sharing, and integrated innovation [10]. Use market methods to drive big data innovation, allocate resources for big data innovation through the market, and exchange value-added for big data innovation through market openness and fairness principles to form a benign ecosystem. Establish a big data management system for independent innovation of listed companies, strengthen cooperation between industry, universities and research institutes, and use the capital advantages of listed companies to cooperate with the scientific research strength of scientific research institutions to achieve resource sharing and win-win results for both parties.

2) Establish and improve an innovative public service platformThe country also attaches great importance to big data. Big data is an innovative method that can affect all aspects of society, and the role of the country's strategy and economy cannot be underestimated. Therefore, from the national perspective, the integration of resources can provide a better environment for the research and development of related institutions. From a legal point of view, the provision of opinions and policy

protection through legislation. Through the creation of an authorized sharing mechanism, relevant institutions can communicate better. Both the government and relevant institutions can participate, and at the same time, it is also conducive to the cultivation of relevant professionals [11]. Through these series of measures, the cost in the field of big data usage can be effectively reduced. By creating a big data alliance, creating laboratories and R & D centers in provinces and cities as a unit, so that the use of big data can be more extensive and sufficient; starting from the application of big data innovation and industrialization, companies related to it will be jointly created Joint entity; through the form of contracts and contracts, the use of all aspects of resources can be effectively regulated; pay more attention to technological innovation, combine with market needs, and from the actual situation, research and development are more in line with the needs of green products with progress. When HS companies use big data, they need to coordinate production, education, and research to work out a strategy that is more suitable for the enterprise to promote the continuous development of the enterprise [12].

2.2 Application of Kriging Model in Chinese and Russian Stock Markets

(1) Data selection

The purpose of our analysis is to find an effective method that can quantify the risk of the stock market, so the analysis index that can express the risk in a timely, accurate and dynamic manner is the key to the analysis. In the stock market, the stock index is a technical tool to measure the stock price level. It is widely used in stock price analysis and is an important indicator to measure stock price fluctuations and trends. And in a certain sense, the stock market index is equivalent to the investment portfolio of a certain market, which can reflect the comprehensive risk of the market [13]. Generally, a single-day stock market index has the opening index, closing index, highest index and lowest index. In finance, the closing index is usually used as a statistical indicator. Here, we will also use the closing index of the stock market as an analysis object to start a measurement analysis of the comprehensive risk of the stock market.

According to the definition of the stock index, the index is relative to the price. Due to the imbalance of the price series, in financial research, more attention is paid to price changes and rates of return rather than price[14]. There are two types of rate of return: general rate of return and geometric rate of return. The general rate of return R_t can be calculated using formula (1):

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

In the above formula, R_t refers to the daily rate of return of the stock index on day t; R_t refers to the closing index of the stock index on day t; R_{t-1} refers to the closing index of the stock index on day t-1. The geometric rate of return can be calculated using formula (2):

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

In the above formula, R_t refers to the daily geometric rate of return of the stock index on day t; P_t refers to the closing index of the stock index on day t; P_{t-1} refers to the closing index of the stock index on day t-1.

When the general rate of return is small, the general rate of return is approximately equal to the geometric rate of return, and the geometric rate of return has better statistical characteristics than the general rate of return. This is because: the logarithmic function can extend the range of returns to the entire real number domain, which is more suitable for modeling the behavior of financial assets; through logarithmic transformation, multiplication operations are converted into addition operations, making the calculation easier [15-16].

Based on the good statistical characteristics of geometric returns, so in the following research, we mainly use the geometric returns of stock indexes as analysis indicators.

l) Index selection

At present, when analyzing the risks of the Shanghai Stock Exchange, most of them use the Shanghai Composite Index to measure the risk of the Shanghai Stock Market. The Shanghai Composite Index has the longest history and the most available data points. It reflects the information of the entire Shanghai Stock Market to a certain extent. It is more convenient to conduct research on the comprehensive index. However, due to the compilation rules of the Shanghai Composite Index, the Shanghai Composite Index has been distorted in recent years, especially since the end of 2016, the

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degree of distortion has been more serious [17]. Therefore, this article uses the Shanghai 180, which officially appeared on the Chinese and Russian stock markets on July 9, 2016, to analyze the Shanghai stock market risk. While expanding the scope and scale of the sample stocks, the SSE 180 Index 6 adjusted the index weighting method from the original weighting of tradable shares to the internationally-used free float weighting method, which more objectively comprehensively reflected the economic scale and circulation scale of listed companies The impact of the listing of non-tradable shares such as state-owned shares on the index. And the selection criteria for sample stocks are stocks that are representative in the industry, have sufficient size, and have good liquidity. At the same time, due to the high proportion of blue-chip stocks in the sample stocks of the Shanghai 180 Index, this will also help guide investors to value investment. Therefore, choosing the Shanghai 180 Index has better practical value [18].

(2) Calculation of Kriging value

The following conditions should be met when building a model with GARCH. First, the financial return series does not obey the normal distribution and has the characteristics of sharp peaks and thick tails; second, the volatility of the return series is clustering and time-varying, that is the error term has heteroscedasticity. The distribution characteristics and volatility characteristics of each index return have been analyzed above, so we can establish a calculation method based on these characteristics based on these characteristics to measure the time-varying conditional variance, and then calculate its Kriging value [19].

It is assumed in the GARCH model that it follows a conditional normal distribution and its conditional variance is. Since the changed conditional variance allows for more outliers or very large observations in the reward sequence, the unconditional distribution of the reward sequence is sharp and has a thicker tail than the normal distribution. Therefore, the GARCH model is particularly suitable for modeling the volatility of financial time series data.

According to the calculation formula of the variance-covariance method, the formula for obtaining the Kriging-GARCH model is as follows:

$$\mathrm{kriging}_t = -\alpha\sigma W_{t-1} \tag{3}$$

Where W_{t-1} is the asset value of the previous period, a is the quantile of the standard normal distribution (other conditional distributions) under confidence c, and σ is the conditional variance of the yield series kriging_t, so as long as it is calculated The kriging value can be calculated by the conditional variance of the return rate series. Then the conditional variance of kriging_t can be calculated using the GARCH model. As long as the basic conditions of the model are met, we can get the value of Kriging [20].

(3) Test of the common index return rate in the stock market

Financial time series usually have some obvious characteristics. Compared with the normal distribution, the actual distribution of the return time series is significantly thicker in the tail, and the middle waist is thinner and more pointed, which is commonly referred to as "spike thick tail"; the fluctuations in returns sometimes have large periods, and there are The period of time is very small, that is to say, it shows volatility aggregation and explosiveness [21-22]; the return sequence shows obvious autocorrelation. Sometimes, although the return sequence itself is not related, its square sequence is autocorrelated, And the autocorrelation of the squared returns is much more significant than the return sequence; the volatility of returns shows persistence, that is, the impact on volatility will last for a period of time. Next, we take the selected index data as an example to examine the characteristics of the return series [23]. Due to the good statistical characteristics of the stock logarithmic return series, the geometric return, which is the logarithmic return, is used in the process of our modeling above. Below we make a relevant test on the selected data.

First, the skewness, kurtosis, Jarque-Bera statistics graph are used to test the normality of the logarithmic returns of each index. The method of Jarque-Bera test is as follows:

Let $\mathrm{Y}_1, \mathrm{Y}_2, \ldots\ldots, \mathrm{Y}_\mathrm{N}$ be a set of samples of random variable Y, the sample mean $\overline{\mathrm{Y}}$, sample standard deviation S, sample skewness Sk, and sample kurtosis ku are:

$$\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i \tag{4}$$

$$S = [\frac{1}{N-1}\sum_{i=1}^{N}\left(Y_t - \overline{Y}\right)^2]^{\frac{1}{2}} \tag{5}$$

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$$Sk = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \bar{Y}\right)^3}{S^3} \tag{6}$$

$$ku = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \bar{Y}\right)^4}{S^4} \tag{7}$$

Under the null hypothesis that the random variable Y is normally distributed, the Jarque-Bera statistic $\frac{N}{6}[Sk^2 + \frac{1}{4}ku^2]$ is subject to χ^2 with 2 degrees of freedom. Therefore, we can use Jarque-Bera statistics to test whether random variables follow a normal distribution [24].

3. Experiments

3.1 Experimental Subjects

The China-Russia Constituent Stock Index is compiled by the China-Russia Stock Exchange. Through inspections of all companies listed on the China-Russia Stock Exchange, 40 representative listed companies are selected as constituent stocks according to certain criteria7. The number of tradable shares is weighted and prepared using the weighted average method. The base day index is 1000 points, and the total transaction amount of each company over a period of time is used as a measure. After the preliminary list is determined according to the selection criteria, the company’s stock average price-to-earnings ratio over a period of time, the company’s industry representativeness and the development prospects of its industry, the company’s financial status in recent years, profit records, growth prospects and management quality 40 listed companies (including both A-shares and B-shares) were selected as constituent stocks by factors such as the region and representativeness of the sector, and the China-Russia component index was calculated. Therefore, the SSE 180 Index and the China-Russia Component Index more realistically represent the risks of the Shanghai and Shenzhen markets. This paper intends to use the SSE 180 Index and the China-Russia Component Index to conduct research to test the degree of risk in different markets. In addition, in order to understand the degree of risk estimation in different industries, this paper also selects data from several representative industries such as financial index, real estate index, IT index and manufacturing index for risk analysis, in order to study the degree of risk estimation in emerging industries and traditional industries.

3.2 Experimental Method

(1) Selection of experimental sample interval

The stock market in China and Russia was still in the initial stage of development in the 1990s. The market capacity was relatively small, price fluctuations were affected by various factors, the system was not sound, and the market was extremely irregular. The characteristics are somewhat distorted, and many scholars have studied the risks of this stage before. At the same time, in order to reflect the representativeness of the Shanghai Stock Exchange 180 Index to stock market risks, this paper selects data after 2016 as the basis for analysis.

(2) Choice of experimental confidence

According to the definition of Kriging theory, when calculating Kriging, a reasonable confidence must be selected. However, the theory does not have a strict requirement for confidence. In general, when considering effectiveness, a lower confidence level needs to be selected; while internal venture capital requirements and external regulatory requirements require a higher confidence level; For statistical and comparison purposes, you need to choose a medium or high confidence level. This article gives the confidence levels selected by some famous companies in the world when using the Kriging method for risk management, as shown in Table 1 below.

Table 1 Confidence levels selected by famous companies

Company name	Confidence level (%)
Dongfeng Motor Corporation	94.3%
China Resources Corporation	96.
SEVERSTAL	95
EVRAZGROUP	99.4

For the purpose of statistic and comparison of Sino-Russian stock market risks, Muwen research is suitable for selecting a medium confidence level. Therefore, in the empirical research of various

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specific methods of Kriging below, we select 95% as the confidence level of our research.

4. Discussion

4.1 Yield of China-Russia Component Index and Fluctuation of Stock Index

We know that the ARCH type nonlinear model is very suitable for describing the volatility characteristics of the stock market, but we must use a quantitative method to test whether there is an ARCH effect in the Shanghai 180 index number series and the China-Russia component index series. For the ARCH effect test, the most commonly used test method is the Lagrange multiplier method, or LM test. The Lagrange multiplier method was used to test the ARCH effect. The results obtained are shown in Table 2 below.

Table 2: ARCH Effect Test of SSE 180 and China-Russia Component Index

Order	Shanghai 180 Index (LM)	China Component Index (LM)	Russia is a finger (LM)	P value
1	15.3122	405.3843	81.2602	0.0003
2	16.3843	425.8432	95.9532	0.0000
3	22.5742	437.9653	101.4847	0.0001
4	32.474	458.9473	108.9130	0.0002

It can be seen from Table 2 that the P values of the LM test from the 1st to the 4th orders are all less than the significance level a = 0.05 and thus reject the null hypothesis. The results show that there are high-order ARCH effects on the residual sequence of the Shanghai 180 Index and the China-Russia component index returns. According to the same method, the residual sequence of the real estate index, financial index, manufacturing index, and IT index return rate also has a high-order ARCH effect. It can be seen that it is appropriate to use the ARCH model to fit the yield residual sequence, so you can consider using the GARCH model to calculate the Kriging value.

We find that the returns of the various indexes are not normally distributed, and many scholars have found that the stock market often shows the phenomenon of volatility clustering (volatility clustering), that is, large fluctuations are concentrated in a certain period of time, and small fluctuations are concentrated in another period of time. The statistical manifestation of the price fluctuations of financial assets is the variance of returns. The magnitude of volatility in different time periods is different. In other words, there is "heteroskedasticity" in the time series. From the earnings of SSE 180 and China-Russia Component Index, we can see that there is a significant difference in the degree of fluctuation in their earnings. The experimental results are shown in Figure 2 below.

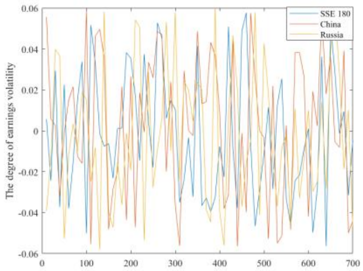

Figure 2: SSE 180, China-Russia Component Index Yield Volatility Chart

As shown in Figure 2 above, from the above graphical analysis of the heteroscedasticity of the returns of various indexes, we judge that the returns of the stock market have a clear heteroscedasticity. The ARCH model is widely used in the research of the stock market, currency market, foreign exchange market, and futures market to describe the volatility characteristics of financial time series such as stock prices, interest rates, exchange rates, and futures prices. The volatility of the stock price index itself will be affected by the previous volatility.

4.2 Analysis of the Expected and Actual Results of the GARCH Model of Chinese and Russian Stories

We use the "failure rate" to conduct an ex-post test on the model to see whether the model has better grasped the market risk. The sample size of SSE 180 and China-Russia Component Index is 727 observations. At a 95% confidence level, the number of actual losses exceeding the Kriging threshold should not exceed 727 × 0.05 = 36. The number of indexes, manufacturing indexes, financial indexes and IT indexes that exceed the Kriging threshold should also not exceed 36.

Table 3: Comparison of expected and actual results of GARCH model

	Russia is a finger	China Component Index	Real estate index	Manufacturing index	Financial index	IT index
Desired result	36	36	36	36	36	36
Actual results	23	22	17	35	24	30

As shown in Table 3 above, this article lists the test results of the model, from which we can see that the number of days when the actual profit and loss value exceeds the Kriging critical value is less than the expected number of days. Overall, the results based on the GARCH model are better in the market Risk value.

4.3 Kriging Model Test and Empirical Results Analysis

Under the null hypothesis, the statistic LR follows the χ ^ 2 distribution with a degree of freedom of 1, and gives the confidence domain at the 0.05 level in the non-rejection area. The experimental results are shown in Figure 3 below.

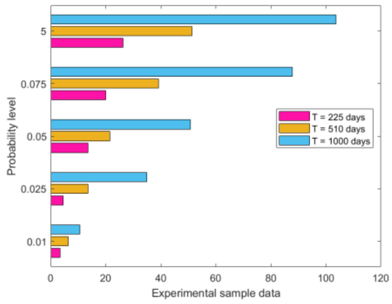

Figure 3: Failure frequency return test method: non-rejected domain at 5% level

As shown in Figure 3 above, it can be seen from the figure that for the test sample data T = 510, at a 95% confidence level, the expected number of failures observed should be E (N) 2 PT = 510 * 5% = 26 Times, but as long as N is between 17 and 35, the null hypothesis cannot be rejected; when N> 35, it indicates that the Kriging risk management model underestimates the Kriging value of the asset portfolio, and when N <17, it indicates that Kriging risk management The model overestimates the Kriging value of the asset portfolio.

The Kriging value obtained by calculating the Kriging formula according to the GARCH model is a time series. To facilitate comparison, the Kriging value sequence is averaged to obtain the average Kriging, and then the empirical results of this paper are analyzed. As shown in Figure 4 below.

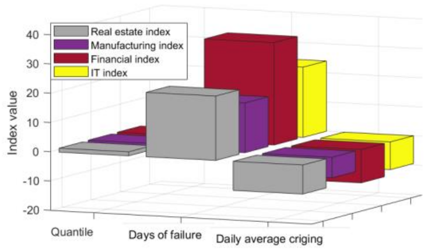

Figure 4: Comparison of criging mean under GARCH model

As shown in Figure 4 above, it is found from the test of the model that the proportion of actual losses exceeding the Kriging critical value determined by the GARCH model is less than the 50k significance level we set in advance, so it can be considered that the model fully estimates the market

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risk but in the To some extent, some indexes have a tendency to overestimate risk. The overall estimation effect of the GARCH model is better, mainly because the GARCH model fully reflects the heteroscedasticity of the returns of various indexes, so it can better grasp the risk.

4.4 Empirical Analysis of the Kriging Method in Portfolio Risk Management

Constituent Kriging, assuming that the return on assets follows a normal distribution Assuming that the return on the asset portfolio follows a normal distribution, from the marginal Kriging of individual stocks and the weighting data of individual stocks in the portfolio, you can get the component Kriging of the four heavyweight stocks at a 95% confidence level The values are shown in Figure 5 below.

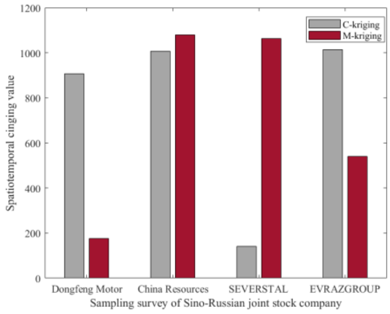

Figure 5: Marginal kriging values of the four largest Chinese and Russian heavy-weight stocks at the 95% confidence level

As can be seen in Figure 5 above, China Resources has the largest component Kriging value and Dongfeng Motor has the smallest component Kriging value, which means that the largest risk in the portfolio comes from China Resources, followed by EVRAZGROUP and Dongfeng Motor. According to the relationship between our component Kriging and the combined Kriging after risk diversification, the correctness of the results is verified. If we do not consider the errors in the calculation process, we believe that the combination of funds sought diversifies the risk, and the combined Kriging is less than the sum of the individual stock kriging, Combined Kriging, marginal Kriging and component Kriging values are all accurate.

5. Conclusions

This paper conducts an empirical statistical analysis of the comprehensive risk of the two stock markets in China and Russia represented by the Shanghai 180 Index and the China-Russia Component Index, and analyzes the basic statistical characteristics of the stock market returns in China and Russia. The index, IT index and manufacturing index conduct risk analysis to study the degree of risk estimation in emerging and traditional industries. The financial time series of the Shanghai and China-Russia stock market returns have the following characteristics: spikes and thick tails. Compared with the normal distribution, the distribution of financial time series represented by stock returns has a more fat tail, that is to say, for such financial time series, the probability of extreme values that deviate from the mean is greater than that of the normal distribution. Probability of extreme value. The kurtosis of the normal distribution is equal to 3, while the kurtosis of the financial time series is significantly greater than 3.

The analysis in this paper uses the Kriging calculation under the GARCH model to measure the Kriging values of the Shanghai Stock Index 180 and the China-Russia component index and different industry indexes at 95% confidence level. The KuPic test has been adopted and good prediction results are obtained, indicating that The Kriging model has a very effective role in the risk measurement of the Chinese and Russian stock markets. The final result shows that the Kriging value of China and Russia is higher, which is equivalent to 2.5 times the market protection. The risk of China and Russia is much greater than that of the Shanghai market, and the volatility is stronger. It is more consistent with the actual situation.

The four representative industry indexes selected in this paper also show different estimation results under the description of the GARCH model. As a traditional industry manufacturing index, the risk estimation effect is better, while the real estate industry index and financial index The risk estimates have been overestimated, and the IT index has a good degree of risk estimates. In short, the use of the

GARCH model to estimate Kriging better portrays the risk situation of the Chinese and Russian stock markets, and makes some empirical research on the analysis of the overall market and the risk of various industries.

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