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# Research on Value at Risk of Lombarda China Medical Health Fund Based on Monte Carlo Simulation

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***Abstract:*** *Since its official launch on August 17, 2016, Lombarda China Medical Health Fund has mainly focused on the potential leaders of medical services. It has performed very well in the medical-theme funds. Thus, it has become a signature product in the field. However, with the acceleration of the process of centralized pharmaceutical purchase in the second half of 2021, the relevant top holdings of the fund continued to slump, resulting in the continuous decline of its revenue. This paper selects the top ten holdings of Lombarda China Medical Health Fund as the representative portfolio, estimating its VaR (Value at Risk) using Monte Carlo Simulation method to provide investors with quantifiable fund risk information so that they can choose a more appropriate investment scheme.*

***Keywords:*** *Monte Carlo Simulation; Value at Risk; Financial Risk Management; Fund*

## 1. Introduction

In recent years, with the continuous advancement of economic globalization and the emergence of a variety of economic innovations, financial risk management issues have caused discussions in the industry and academia, and the corresponding research has been carried out. For the financial industry, financial risk is well-known for its significant concentration, potential destruction and far-reaching dissemination. Nowadays, with the increasingly complex asset structure, the defects of the traditional financial risk management methods are becoming much more obvious [1]. Compared with the commonly used risk quantification indicators in the past, such as the standard deviation of return, σ, β, Sharpe ratio, maximum retracement rate and so on, VaR is more concise and effective. Therefore, it has become a common indicator of the risk of funds [2].

The calculation of Value at Risk (VaR) has become the mainstream method of risk management and financial regulation in the international financial market [3], and has been widely used in the measurement of financial market risks. Its basic idea is to calculate the maximum potential loss of a financial asset or portfolio on the premise of a certain period and a certain confidence level [4]. Compared with other risk quantification indicators, the greatest advantage of VaR is that it can accurately estimate the risk using algorithm before the event happens. There are numerous methods to calculate VaR, and three of them are commonly used: Extreme Value Theory, Historical Simulation Method and Monte Carlo Method.

In the financial market, Monte Carlo Simulation Method is used to simulate the asset portfolio in different situations in certain periods, and it is the most effective method to calculate VaR. For different distributions of portfolio and various nonlinear situations, satisfactory results can be obtained by Monte Carlo Simulation Method. It has the following advantages: it can produce a large number of scenarios and is more accurate and reliable; it is a full-value estimation method, which can deal with nonlinear, large fluctuation problems, namely thick tail problems; different behaviors (such as white noise, auto regression and bilinear, etc.) and different distributions of returns can be simulated [5].

## 2. Data Sources and Processing

### *2.1. Data Sources*

In this paper, the top ten holdings in the fourth quarter of 2021 in Lombarda China Medical Health Hybrid Fund A (003095) are chosen to be the representatives of the fund to measure the value at risk of

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the fund, WuXi App Tec (603259), Aier Eye Hospital (300015), Asymchem (002821), Tigermed Consulting (300347), Pharmaron (300759), Mindray Medical (300760), Pien Tze Huang (600463), Topchoice Medical (600763), Porton Pharma Solutions (300363) and Jiuzhou Pharmaceutical (603456). They make up 56.68% of the total, and the positions are 65716080, 140833948, 11987613, 36283674, 32347682, 11871360, 7869304, 15711313, 26660397, and 40737316, respectively.

Since these ten had ex-dividend date in 2021, the closing quotations of the stock jumped on the second day of the ex-dividend date, so the value of portfolio is discontinuous. To solve this problem, this paper selects the split-adjusted share prices of 243 trading days from January 4, 2021 to December 31, 2021 of 10 stocks as the daily stock prices.

Respectively, Set the selected ten shares as variables $X_1$、$X_2$、$X_3$、$X_4$、$X_5$、$X_6$、$X_7$、$X_8$、$X_9$、$X_{10}$.

The closing price data of each stock is shown in Table 1:

*Table 1: Ten heavy warehouse stocks before the right to close*

| data | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | $X_9$ | $X_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021.01.04 | 114.02 | 52.52 | 297.44 | 166.53 | 120.83 | 431.69 | 279.39 | 268.00 | 37.04 | 34.84 |
| 2021.01.05 | 118.08 | 53.17 | 303.11 | 170.90 | 125.31 | 433.82 | 295.76 | 283.69 | 36.62 | 35.55 |
| 2021.01.06 | 119.54 | 55.04 | 302.59 | 165.52 | 124.86 | 447.53 | 293.83 | 296.5 | 34.77 | 35.06 |
| 2021.01.07 | 121.37 | 59.59 | 307.86 | 170.21 | 125.21 | 453.69 | 299.28 | 303.44 | 35.29 | 34.96 |
| 2021.01.08 | 121.59 | 58.46 | 294.78 | 164.72 | 116.34 | 447.63 | 295.97 | 304.84 | 32.84 | 33.05 |
| … | … | … | … | … | … | … | … | … | … | … |
| 2021.12.27 | 114.19 | 43.99 | 448.7 | 120.6 | 143 | 371.21 | 472.3 | 200.36 | 84.72 | 56.5 |
| 2021.12.28 | 119.1 | 43.6 | 455 | 124.88 | 146.41 | 379 | 476.15 | 199.21 | 90 | 56.68 |
| 2021.12.29 | 119.19 | 43.49 | 443 | 124.79 | 145 | 376.14 | 428.54 | 203.02 | 92.33 | 57.87 |
| 2021.12.30 | 120.01 | 43.65 | 456.08 | 127.31 | 143 | 383 | 423.03 | 205.73 | 93 | 58.11 |
| 2021.12.31 | 118.58 | 42.28 | 435 | 127.8 | 141.27 | 380.8 | 437.15 | 199 | 89.45 | 56.26 |

Data source: Wind

### *2.2. Data Processing*

For the individual stocks can vary from each other vastly, the differences in closing prices of each stock can be relatively obvious. Therefore, to make the data more stable and eliminate the influence brought by dimensional, logarithmic return rate will be used in this paper to represent the changes of stock prices. The logarithmic return of the stock is calculated from the previous and closing prices: $R = \ln\frac{P_t}{P_{t-1}}$。 The mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$ of changes in price are calculated by logarithmic return rate R:

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} R_i \quad (1)$$

$$\hat{\sigma} = \sqrt[2]{\frac{1}{n-1}\sum_{i=1}^{n}(R_i - \hat{\mu})^2} \quad (2)$$

Since the stocks of this portfolio belong to Chinese Stock Market and the pharmaceutical sector, there is a significant correlation among them. The correlation coefficient matrix $\rho$ of the price changes of ten stocks is calculated by logarithmic return rate. The calculation results are shown in Table 2 and Table 3:

*Table 2: Parameters results*

| Variable | $\hat{\mu}$ | $\hat{\sigma}$ |
|---|---|---|
| $X_1$ | 0.0002336739 | 0.03264120 |
| $X_2$ | -0.0012765615 | 0.03381816 |
| $X_3$ | 0.0015474796 | 0.03361441 |
| $X_4$ | -0.0009588617 | 0.03619305 |
| $X_5$ | 0.0006635860 | 0.03915683 |
| $X_6$ | -0.0004407461 | 0.03189977 |
| $X_7$ | 0.0020297207 | 0.03226022 |
| $X_8$ | -0.0013538203 | 0.03905935 |
| $X_9$ | 0.0036958306 | 0.04130748 |
| $X_{10}$ | 0.0018789867 | 0.03513666 |

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*Table 3: Correlation coefficient matrix*

| Variable | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | $X_9$ | $X_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $X_1$ | 1 | 0.62211 | 0.68210 | 0.77992 | 0.77892 | 0.69029 | 0.47891 | 0.64099 | 0.57083 | 0.60239 |
| $X_2$ | 0.62211 | 1 | 0.48616 | 0.61543 | 0.54613 | 0.65036 | 0.49305 | 0.77994 | 0.37651 | 0.46592 |
| $X_3$ | 0.68210 | 0.48616 | 1 | 0.64976 | 0.69272 | 0.49963 | 0.42002 | 0.49042 | 0.62733 | 0.6175 |
| $X_4$ | 0.77992 | 0.61543 | 0.64976 | 1 | 0.74423 | 0.60216 | 0.48587 | 0.61911 | 0.56439 | 0.605074 |
| $X_5$ | 0.77892 | 0.54613 | 0.69272 | 0.74423 | 1 | 0.59977 | 0.46690 | 0.57727 | 0.65205 | 0.595733 |
| $X_6$ | 0.69029 | 0.65036 | 0.49963 | 0.60216 | 0.59977 | 1 | 0.51296 | 0.62670 | 0.36807 | 0.463517 |
| $X_7$ | 0.47891 | 0.49305 | 0.42002 | 0.48588 | 0.46690 | 0.51296 | 1 | 0.53070 | 0.30359 | 0.29977 |
| $X_8$ | 0.64099 | 0.77994 | 0.49042 | 0.61911 | 0.57727 | 0.62670 | 0.53070 | 1 | 0.39857 | 0.478429 |
| $X_9$ | 0.57083 | 0.37651 | 0.62733 | 0.56439 | 0.65205 | 0.36807 | 0.30359 | 0.39857 | 1 | 0.593063 |
| $X_{10}$ | 0.60239 | 0.46592 | 0.61749 | 0.60507 | 0.59573 | 0.46352 | 0.29977 | 0.47843 | 0.59306 | 1 |

## 3. Calculation of VaR Based on Monte Carlo Simulation

### *3.1. Model Specification*

As is assumed that stock price changes follow Geometric Brownian Motion, GBM model is selected as a stochastic model to reflect asset price changes.

Because the logarithmic distribution of geometric Brownian Motion obeys the normal distribution, that is, the log-return obeys the normal distribution, the model should generate random numbers obeying the normal distribution.

The continuous geometric Brownian Motion model is discretized and can be expressed as:

$$\begin{cases} S_{1,t+i\Delta t}=S_{1,t+(i-1)\Delta t}(1+\mu_1\Delta t+\sigma_1\varepsilon_{1,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{2,t+i\Delta t}=S_{2,t+(i-1)\Delta t}(1+\mu_2\Delta t+\sigma_2\varepsilon_{2,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{3,t+i\Delta t}=S_{3,t+(i-1)\Delta t}(1+\mu_3\Delta t+\sigma_3\varepsilon_{3,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{4,t+i\Delta t}=S_{4,t+(i-1)\Delta t}(1+\mu_4\Delta t+\sigma_4\varepsilon_{4,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{5,t+i\Delta t}=S_{5,t+(i-1)\Delta t}(1+\mu_5\Delta t+\sigma_5\varepsilon_{5,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{6,t+i\Delta t}=S_{6,t+(i-1)\Delta t}(1+\mu_6\Delta t+\sigma_6\varepsilon_{6,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{7,t+i\Delta t}=S_{7,t+(i-1)\Delta t}(1+\mu_7\Delta t+\sigma_7\varepsilon_{7,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{8,t+i\Delta t}=S_{8,t+(i-1)\Delta t}(1+\mu_1\Delta t+\sigma_8\varepsilon_{8,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{9,t+i\Delta t}=S_{9,t+(i-1)\Delta t}(1+\mu_9\Delta t+\sigma_9\varepsilon_{9,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \\ S_{10,t+i\Delta t}=S_{10,t+(i-1)\Delta t}(1+\mu_{10}\Delta t+\sigma_{10}\varepsilon_{10,i}\sqrt{\Delta t}), i=1,2,\ldots,\mathrm{n} \end{cases} \tag{3}$$

$S_{1,t+i\Delta t}\sim S_{10,t+i\Delta t}$ represent the share prices at time t, $S_{1,t+(i-1)\Delta t}\sim S_{10,t+(i-1)\Delta t}$ represent the share prices at time t-1, $\mu_1\sim\mu_{10}$ represent the mean of log-return, $\sigma_1\sim\sigma_2$ represent the standard deviation of log-return, $\varepsilon_{1,i}\sim\varepsilon_{10,i}$ respectively are random numbers obeying the standard normal distribution, calculated by $\varepsilon_1\sim\varepsilon_{10}$, random variables generated by randomness.

### *3.2. The Empirical Analysis*

Assume that 1000 trades are spaced over the next trading day, so the mean and standard deviation of each time period $\Delta t=\frac{1}{1000}$ are respectively $\frac{\mu}{1000}$ and $\frac{\sigma}{\sqrt{1000}}$, and GBM model can be expressed as:

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$$\begin{cases} S_{1,t+\frac{i}{1000}} = S_{1,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_1}{1000}+\frac{\sigma_1\varepsilon_{1,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{2,t+\frac{i}{1000}} = S_{2,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_2}{1000}+\frac{\sigma_2\varepsilon_{2,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{3,t+\frac{i}{1000}} = S_{3,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_3}{1000}+\frac{\sigma_3\varepsilon_{3,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{4,t+\frac{i}{1000}} = S_{4,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_4}{1000}+\frac{\sigma_4\varepsilon_{4,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{5,t+\frac{i}{1000}} = S_{5,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_5}{1000}+\frac{\sigma_5\varepsilon_{5,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{6,t+\frac{i}{1000}} = S_{6,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_6}{1000}+\frac{\sigma_6\varepsilon_{6,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{7,t+\frac{i}{1000}} = S_{7,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_7}{1000}+\frac{\sigma_7\varepsilon_{7,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{8,t+\frac{i}{1000}} = S_{8,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_8}{1000}+\frac{\sigma_8\varepsilon_{8,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{9,t+\frac{i}{1000}} = S_{9,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_9}{1000}+\frac{\sigma_9\varepsilon_{9,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \\ S_{10,t+\frac{i}{1000}} = S_{10,t+\frac{(i-1)}{1000}}\left(1+\frac{\mu_{10}}{1000}+\frac{\sigma_{10}\varepsilon_{10,i}}{\sqrt{1000}}\right), i=1,2,\dots,\mathrm{n} \end{cases} \quad (4)$$

Due to the correlation among the price changes of ten stocks, the random variable $\varepsilon_{1,i}\sim\varepsilon_{10,i}$ cannot simply be directly generated by the random number generator, but is determined jointly by the computer-generated random number and the correlation coefficient.

The correlation coefficient matrix in Table 3 is decomposed into lower triangular matrix T by Cholesky factor decomposition method, as shown in Table 4:

*Table 4: Cholesky decomposed the lower triangular matrix T*

| variable | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | | $X_9$ | $X_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $X_1$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 | 0 |
| $X_2$ | 0.62211 | 0.78293 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 | 0 |
| $X_3$ | 0.68210 | 0.07897 | 0.72699 | 0 | 0 | 0 | 0 | 0 | | 0 | 0 |
| $X_4$ | 0.77992 | 0.16635 | 0.14394 | 0.58595 | 0 | 0 | 0 | 0 | | 0 | 0 |
| $X_5$ | 0.77892 | 0.07862 | 0.21351 | 0.15859 | 0.56246 | 0 | 0 | 0 | | 0 | 0 |
| $X_6$ | 0.69029 | 0.28219 | 0.00895 | 0.02656 | 0.06007 | 0.66294 | 0 | 0 | | 0 | 0 |
| $X_7$ | 0.47891 | 0.24921 | 0.10135 | 0.09613 | 0.06648 | 0.15777 | 0.81223 | 0 | | 0 | 0 |
| $X_8$ | 0.64099 | 0.48686 | 0.02031 | 0.06021 | 0.04593 | 0.06382 | 0.10025 | 0.57605 | | 0 | 0 |
| $X_9$ | 0.57083 | 0.02733 | 0.32436 | 0.11596 | 0.20913 | -0.07877 | -0.02719 | 0.00686 | | 0.70994 | 0 |
| $X_{10}$ | 0.60234 | 0.11644 | 0.27154 | 0.13107 | 0.06863 | 0.00725 | -0.07826 | 0.04590 | | 0.17821 | 0.69850 |

Then the vector formed by random variable $\varepsilon_{1,i}\sim\varepsilon_{10,i}$ is:

$$\begin{pmatrix} \varepsilon_{1,i} \\ \varepsilon_{2,i} \\ \varepsilon_{3,i} \\ \varepsilon_{4,i} \\ \varepsilon_{5,i} \\ \varepsilon_{6,i} \\ \varepsilon_{7,i} \\ \varepsilon_{8,i} \\ \varepsilon_{9,i} \\ \varepsilon_{10,i} \end{pmatrix} = \mathrm{T} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \\ \varepsilon_{10} \end{pmatrix} \quad (5)$$

Firstly, 1000 independent random variable values $\varepsilon_1\sim\varepsilon_{10}$ subject to standard normal distribution are generated by R. Through the calculation of the correlation coefficient relation described in Formula (3-3), 1000 random variables $\varepsilon_{1,i}\sim\varepsilon_{10,i}$ affecting the price changes of ten stocks can be obtained. Further, the known parameters$\mu_1\sim\mu_{10}$, $\sigma_1\sim\sigma_2$ and $\varepsilon_{1,i}\sim\varepsilon_{10,i}$, are substituted into the GBM stochastic model respectively, and 1000 possible values of ten stock price changes in the next day can be calculated, so as to obtain a sample trajectory of stock price changes in the next day. When t is 1000, we can get a set of ten stock prices in the next day that might be $P_{T,1}^1\sim P_{T,10}^1$.

Repeat the above steps 1000 times, then 1000 groups of similar possible values can be obtained, as shown in Table 5:

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*Table 5: Possible value of each share price (YUAN/share)*

| NO. | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | $X_9$ | $X_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 118.34 | 41.43 | 412.13 | 126.70 | 137.43 | 378.74 | 435.59 | 194.13 | 90.60 | 53.61 |
| 2 | 120.02 | 41.74 | 446.33 | 133.58 | 147.45 | 399.04 | 444.49 | 200.03 | 91.17 | 56.93 |
| 3 | 115.34 | 40.66 | 420.82 | 125.60 | 130.32 | 364.62 | 445.56 | 191.81 | 83.90 | 55.83 |
| 4 | 117.11 | 43.04 | 442.81 | 127.30 | 144.46 | 379.51 | 440.51 | 198.28 | 92.10 | 58.02 |
| 5 | 125.31 | 43.93 | 475.19 | 137.64 | 150.64 | 392.80 | 454.18 | 196.346 | 96.43 | 60.03 |
| 6 | 117.49 | 40.48 | 423.87 | 121.95 | 136.52 | 364.11 | 435.40 | 188.02 | 89.08 | 54.54 |
| 7 | 116.86 | 43.25 | 439.03 | 129.60 | 137.85 | 377.95 | 451.06 | 202.14 | 90.45 | 57.63 |
| 8 | 117.95 | 42.64 | 440.56 | 131.59 | 142.60 | 374.63 | 430.16 | 204.97 | 86.18 | 55.55 |
| 9 | 115.55 | 41.64 | 431.24 | 126.97 | 137.45 | 365.31 | 446.03 | 196.20 | 86.50 | 56.08 |
| 10 | 115.44 | 42.71 | 447.51 | 122.14 | 136.87 | 370.69 | 435.45 | 196.48 | 87.87 | 54.3 |
| … | … | … | … | … | … | … | … | … | … | … |
| 584 | 112.58 | 41.14 | 426.79 | 122.01 | 132.95 | 352.84 | 428.48 | 182.88 | 89.14 | 55.66 |
| … | … | … | … | … | … | … | … | … | … | … |
| 991 | 120.03 | 41.37 | 447.82 | 127.71 | 139.42 | 374.67 | 433.00 | 193.99 | 90.66 | 57.95 |
| 992 | 123.61 | 42.78 | 456.73 | 131.52 | 139.41 | 395.08 | 452.51 | 201.67 | 87.15 | 56.70 |
| 993 | 119.98 | 41.88 | 436.44 | 130.74 | 147.27 | 394.61 | 451.91 | 208.43 | 91.02 | 56.71 |
| 994 | 114.68 | 41.68 | 422.12 | 122.06 | 135.04 | 375.93 | 442.31 | 195.272611 | 91.81 | 54.88 |
| 995 | 109.88 | 40.29 | 392.93 | 118.05 | 121.17 | 366.53 | 406.01 | 182.05 | 79.06 | 52.24 |
| 996 | 112.60 | 40.04 | 424.56 | 122.33 | 137.32 | 345.23 | 430.92 | 192.71 | 89.17 | 56.55 |
| 997 | 115.75 | 40.31 | 422.98 | 122.24 | 134.19 | 373.44 | 410.47 | 191.13 | 88.66 | 56.09 |
| 998 | 123.77 | 43.56 | 440.79 | 130.14 | 147.62 | 402.72 | 441.01 | 203.51 | 91.47 | 54.07 |
| 999 | 118.30 | 42.37 | 450.16 | 133.40 | 146.82 | 383.89 | 419.667 | 195.44 | 88.39 | 57.31 |
| 1000 | 116.72 | 42.30 | 434.93 | 128.61 | 140.75 | 383.71 | 443.20 | 195.67 | 87.28 | 52.81 |

By substituting the holding position of each stock into the calculation, 1000 possible values of profit and loss in the next day of the portfolio composed of the ten can be obtained, and the 1000 possible values are sorted, that is, the distribution table of investment income of the portfolio as shown in Table 6 can be obtained:

*Table 6: Portfolio income distribution statement*

| NO. | Portfolio income (YUAN) | Rank of return |
|---|---|---|
| 1 | -763,561,919.3 | 759 |
| 2 | 927,446,284 | 211 |
| 3 | -1,449,846,707 | 897 |
| 4 | 332,061,475.7 | 372 |
| 5 | 2,390,634,012 | 31 |
| 6 | -1,288,542,955 | 865 |
| 7 | 234,085,655.6 | 405 |
| 8 | 105,645,226.9 | 458 |
| 9 | -731,914,276.8 | 745 |
| 10 | -637,224,423.8 | 713 |
| … | … | … |
| 584 | -1,819,261,553 | 950 |
| … | … | … |
| 991 | -24,562,473.29 | 504 |
| 992 | 1,024,972,267 | 191 |
| 993 | 841,711,491.5 | 230 |
| 994 | -974,305,652 | 807 |
| 995 | -3,482,565,927 | 1000 |
| 996 | -1,725,787,815 | 943 |
| 997 | -1,487,042,047 | 904 |
| 998 | 1,206,634,229 | 151 |
| 999 | 416,555,463.3 | 348 |
| 1000 | -275,944,014.6 | 593 |

At the 95% confidence level, the confidence upper limit is $1000 \times 95\% = 950$. In the results shown in Table 6, the corresponding profit and loss value at the 950th is the VaR, that is, the VaR at the 95% confidence level is the loss value of 1,819,261,553 yuan obtained from the 584th simulation result.

## 4. Conclusion

In this paper, with the top ten holdings of The Lombarda China Medical Health Hybrid A Fund constituting a portfolio as its representative, the split-adjusted closing prices of 243 trading days from January 4, 2021 to December 31, 2021 are selected as sample data to study the value at risk of the fund. The empirical results show that on January 3, 2022, the first trading day of 2022, the VaR of the portfolio at the 95% confidence level is 1,819,261,553 yuan. That is, under the 95% confidence level, the fund represented by this portfolio may suffer a maximum loss of 1,819,261,553 yuan on the first trading day

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of 2022, but in a more extreme market environment, the loss value may be higher than the estimated value at risk.

To sum up, VaR can be used as a practical risk management tool for investors, financial institutions and financial regulators. Investors and financial institutions can analyze individual stocks, portfolios and even financial markets through the estimation of VaR, and combine the estimated VaR with their own risk preferences for asset allocation. By estimating VaR in the market, financial regulatory departments detect market risks, give early warning to corresponding risks and take corresponding preventive measures, so as to promote the overall positive and healthy development of the financial market [6].

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