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Exploration of Profitability in Rotational Trading Strategy Based on Monte Carlo Simulation

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Abstract: Rotational trading strategy is an active trading strategy that adjusts positions to manage risk based on Value at Risk (VaR) in quantitative investment. Unpredictable and unusual Black Swan events make it difficult to predict and effectively mitigate the risks associated with such events. The importance of rational and efficient risk management has been highlighted by events such as the US-China trade war starting in 2018, the global spread of the COVID-19 pandemic from 2019 to 2022, stock market circuit breakers, and the oil crash in the Oil Fund. In this paper, we start from the perspective of VaR backtesting, count the occurrences of abnormal losses within a statistical interval, and establish a risk avoidance model for rotational trading to identify potential market risks and reallocate assets at suitable times. The aim of this paper is to explore whether this rotational trading strategy based on Monte Carlo simulation can effectively manage risks and achieve robust profitability in the US market under a volatile financial environment.

Keywords: VaR, stochastic process, Monte Carlo simulation

1. Introduction

The US capital market is the most mature and largest capital market in the world. While the stock market brings high returns, it also carries high risks. Black Swan events are unpredictable and unusual, and it is difficult for human judgment to timely and effectively avoid the risks associated with such events. Many scholars have used event study methods to empirically analyze the impact of different events on different markets. Niederhoffer [1] analyzed the correlation between major world events from 1950 to 1966 and stock returns. Agmon and Findlay [2] and Tzachi Zach [3] found that political risk events bring investment risks.

Events such as the US-China trade war that started in 2018, the global outbreak of the COVID-19 pandemic from 2019 to 2022, stock market circuit breakers, and the crude oil collapse of the oil fund have made people realize the importance of reasonable and efficient risk management. With the expansion of the stock market, the increase in trading types, and changes in investor preferences, the stock market has become a complex dynamic system combining nonlinearity, non-stationarity, and other attributes. In 1952, Markowitz published "Portfolio Selection" in the Journal of Finance, using mean and variance as basic measures of return and risk.

The birth of the Basel Accord in 1988 introduced a relatively generic analysis method for measuring risk in banks by assigning different weights to different types of assets. This sparked

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research on risk management in banks, including Asset Liability Management, interest rate sensitivity analysis, gap management, and duration management. However, these traditional methods have difficulty in clearly defining and measuring the financial risks that financial institutions face. Previous risk measurement techniques were only applicable to specific financial instruments or within specific ranges, making it difficult to comprehensively reflect the risks being borne. Risk regulators increasingly need a technical approach that is easy to grasp and understand, while also providing a comprehensive reflection of the market risks undertaken by financial institutions. The Value at Risk (VaR) method emerged in this context. In 1993, the G30 Group published a report titled "Practices and Principles for Derivatives" based on their research on derivative products, which first proposed the VaR model for measuring market risk.

2. Theoretical Foundation

2.1. Fundamental Concepts of Value at Risk

The concept of VaR (Value at Risk) can be traced back to the mean-variance investment portfolio theory proposed by Markowitz (1952) [4]. Markowitz suggested using variance as a measure of risk instead of relying on subjective judgments. The idea that directly inspired VaR came from Roy (1952), who proposed the "safety-first" model [5] for portfolio selection. This model suggests that investment portfolios should be selected based on the minimization of the probability of losses exceeding a certain "disaster level" at a given confidence level. Baumol (1963) also introduced a risk measure based on lower confidence intervals at certain probability levels [6]. The authoritative explanation given by Philippe Jorion defines VaR as the "maximum possible loss of a financial asset or portfolio within a specific period of time with a certain probability level (confidence)" [7].
Mathematically, VaR is defined as:

$$P(Lost \leq VaR(a)) = 1 - a \tag{1}$$

Among them, Lost is the value of losses of assets held during the holding period. VaR is used to measure risks that occur under general stock market volatility conditions. Therefore, the calculation method of VaR (Model 1)is based on the risk exposure faced by the asset portfolio. It is simple, cost-effective, and has a certain comparability. This financial risk quantification method does not need to separately consider the impact of multiple factors such as interest rates and exchange rates on the fluctuation of asset prices on losses. Instead, it comprehensively considers the impact of various risk factors on losses and quantifies them uniformly. Therefore, the VaR risk measurement method can adapt to complex and volatile financial markets and is in line with the development trend of increasing global integration. It has become the mainstream tool for financial risk measurement methods. In 1994, JP Morgan introduced the Risk Metrics risk control model for calculating VaR, and based on this, they also introduced the Credit Metrics TM risk control model for calculating VaR. The Credit metrics TM technology publicly released by JP Morgan has successfully expanded the application scope of the standard VaR model to credit risk evaluation and developed into the "Credit Value at Risk" (Credit VaR) model [8,9].

2.2. Measurement of VaR

In VaR measurement, the following methods are representative:

1. Historical simulation method: The idea behind this analytical method is to consider future asset return changes as a reproduction of history. The historical simulation method is empirically based, using historical return sequences to simulate the distribution of returns and losses for this type of asset. It replaces the historical distribution of returns with its true distribution and calculates the value of

VaR through the quantile at a given confidence level. This method has the following advantages: it does not require assuming the distribution of asset returns or considering the correlation between each financial asset in the portfolio. The disadvantage of this method is that it assumes the changes in market factors are consistent with historical patterns, resulting in the "ghost effect" in the model. Additionally, this method requires high data requirements and accurate predictions can only be obtained through extensive simulations of historical data.

2. Monte Carlo simulation method: This method does not assume the distribution of asset returns but uses Geometric Brownian Motion (GBM) model to describe asset price changes. The advantage of Monte Carlo simulation method is that it can compensate for the lack of sample size by artificially setting hypothetical data for different scenarios. It can also fit multiple times with different assumed distributions of returns, which is more consistent with the actual distribution of returns in the financial market. In finance, geometric Brownian motion is commonly used to qualitatively describe stock prices in the Black-Scholes pricing model [10].

2.3. Basics of Monte Carlo Simulation Method

Geometric Brownian Motion (GBM) is a random process in continuous time, where the logarithm of the random variable follows a Brownian motion. [11] According to the theory of stochastic processes, if the price of the underlying asset follows a geometric Brownian motion, it can be described by the following stochastic differential equation (SDE):

$$dS = \mu S dt + \sigma S dw \tag{2}$$

In the above equation (Model 2), S represents the stock price, μ stands for the percentage drift of the stock price, σ represents the volatility of the stock, and dw represents the Wiener process. In practical applications, lnS is more accurate than S, so lnS is used here. The logarithmic form of the stock price, LnS=LnS(S,t), is a twice continuously differentiable function of S,while:

$$\frac{\partial LnS}{\partial t} = 0 \qquad \frac{\partial LnS}{\partial S} = \frac{1}{S} \qquad \frac{\partial^2 LnS}{\partial S^2} = -\frac{1}{S^2}$$

The stochastic differential of LnS(S,t) can be expressed as follows:

$$dLnS = \left(0 + \frac{1}{S}\mu S - \frac{1}{2}\frac{1}{S^2}\sigma^2 S^2\right)dt + \frac{1}{S}\sigma S dW = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dW$$

The above equation can be directly integrated, yielding:

$$LnS_T - LnS_0 = \left(\mu - \frac{1}{2}\sigma^2\right)(T - 0) + \sigma(W_T - W_0) = \left(\mu - \frac{1}{2}\sigma^2\right)T + \sigma W_T$$

The logarithmic form of stock prices follows a normal distribution:

$$LnS_T = LnS_0 + \left(\mu - \frac{1}{2}\sigma^2\right)T + \sigma W_T \sim N\left(LnS_0 + \left(\mu - \frac{1}{2}\sigma^2\right)T, \sigma^2 T\right)$$

By exponentiating both sides of the equation, the final expression for stock prices can be obtained:

$$S_T = S_0 e^{\left(\mu - \frac{1}{2}\sigma^2\right)T + \sigma W_T} \tag{3}$$

In Model 3, S_T represents the stock price at time T, S_0 represents the initial stock price, μ represents the expected return rate of the stock, σ represents the volatility of the stock's return rate, and W_T represents the standard Brownian motion.

3. Empirical Analysis

3.1. Data Acquisition

This paper utilized the Choice Financial Data Terminal to obtain data for 30 well-known US stocks listed on the NASDAQ. The data includes daily closing prices from January 2017 to December 2022, as well as adjusted closing prices for the S&P 500 index and NASDAQ index for the same period. The fixed asset return rate is defined as the yield on 10-year US Treasury bonds, with a daily average return rate of approximately 0.015%. To demonstrate the performance of different strategies under different levels of significance, we selected significance levels of 1%, 3%, 5%, and 10% for abnormal loss.

3.2. Strategy Logic

This paper constructed a rotational trading strategy (Fig. 1) between stocks and fixed-income products starting from 2018. The constituent stocks were monitored daily, and Monte Carlo simulations were conducted using historical one-year stock price data to estimate parameters such as average returns and volatility. This simulation generated 100,000 future stock prices for the next day and calculated the corresponding Value at Risk (VaR) value. At the same time, the actual daily returns were calculated. If the actual return exceeded the VaR value, it was considered an outlier. If there were more than three outliers in the past 30 days, the strategy adjusted to holding fixed-income products.

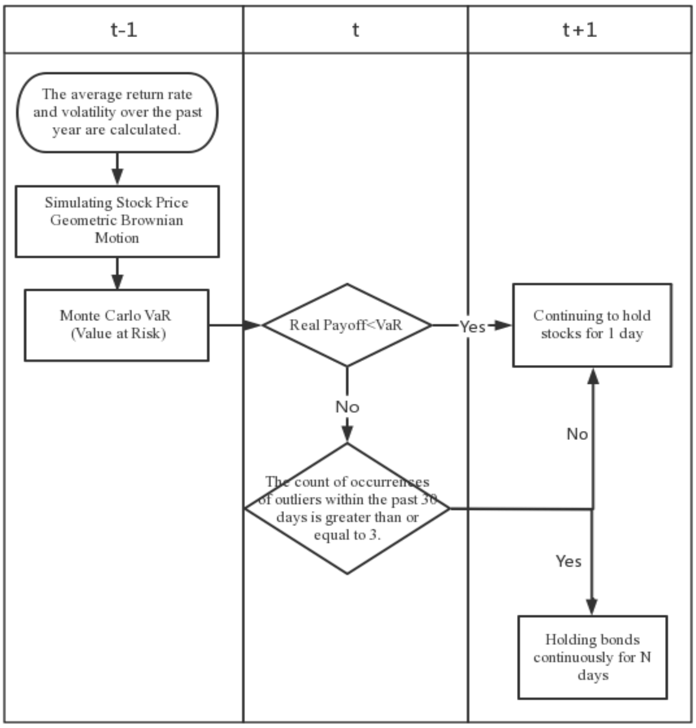

Figure 1: Strategy Logic Diagram

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3.3. Performance of Returns

The returns of the four stocks from 2017 to 2022 were calculated and plotted to observe their performance (Fig. 2). It can be observed that all four stocks experienced significant declines in returns during a series of black swan events from 2018 to 2020. This indicates that individual stocks have difficulty in effectively managing risks in the face of unpredictable black swan events.

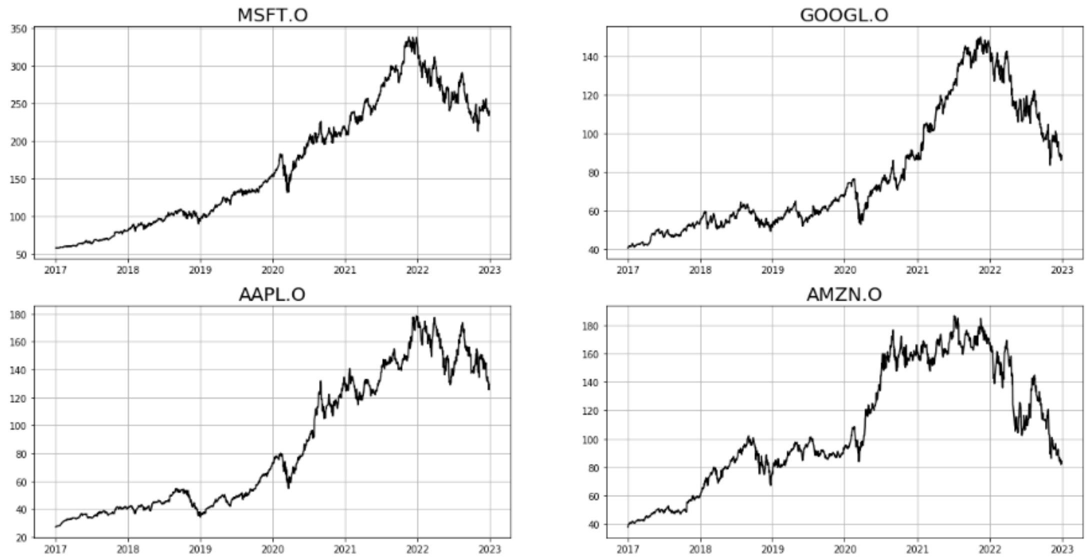

Figure 2: The Returns of the Four US. Stocks from 2017 to 2020

Fig. 3 illustrates the daily and cumulative returns of an equally weighted portfolio consisting of 30 US stocks. The overall trend of the returns exhibits noticeable upward volatility. However, significant fluctuations and substantial drawdowns were observed during the early months of 2020 and the period spanning 2022 to 2023.

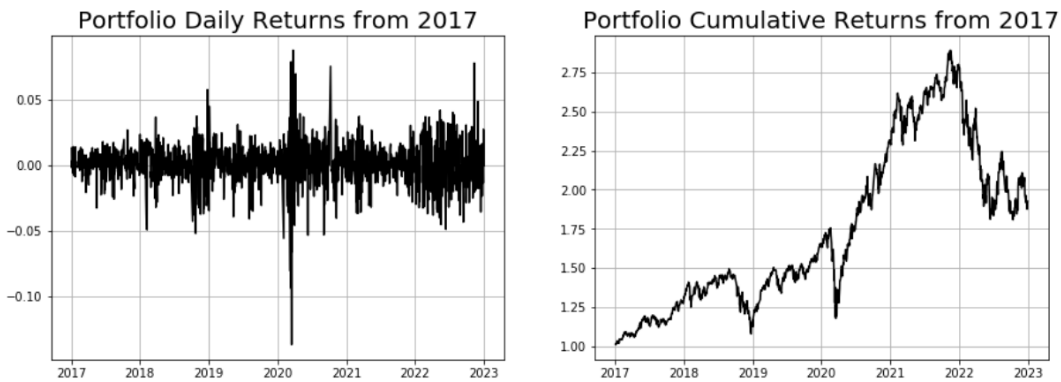

Figure 3: The Daily and Cumulative Returns of the Portfolio

3.4. Value at Risk (VaR) analysis

Fig. 4 presents the value-at-risk (VaR) analysis of Amazon (AMZN.O) returns data at a 95% confidence level. Starting from January 2018, a Monte Carlo simulation method was employed to generate 100,000 future stock prices for one day based on historical stock prices over the past year, from which parameters such as the mean return and volatility were calculated. The VaR value was then computed, along with the actual daily return. From the graph, it can be observed that on certain trading days, the portfolio's return fell below the VaR value at the 95% confidence level, indicating abnormal trading occurrences on those days.

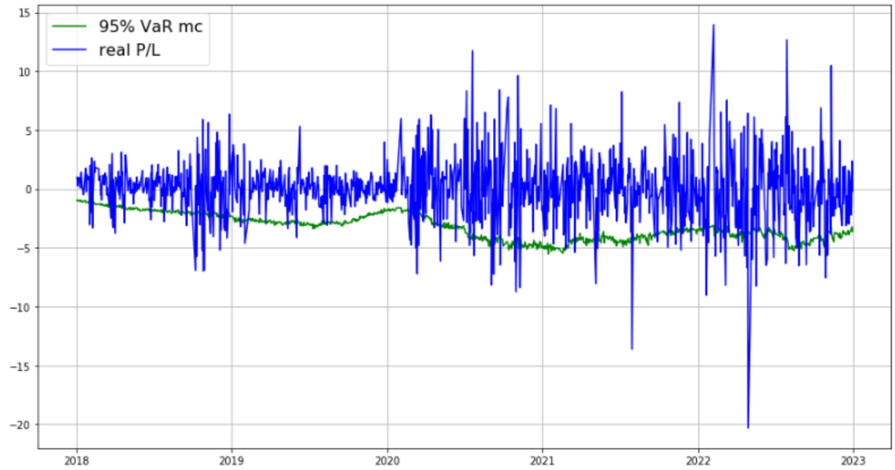

Figure 4: The VaR Analysis of Amazon (AMZN.O) Returns Data at a 95% Confidence Level.

3.5. Rotational trading strategy

Based on the above analysis, it is evident that investment portfolios are difficult to predict and anticipate risks when facing unpredictable black swan events, making it challenging to maintain stable returns. On the other hand, fixed income products primarily invest in debt-based assets such as deposits and bonds. These products can effectively avoid interest rate and exchange rate risks during black swan events, enabling investors to navigate economic instability and control risks to achieve fixed returns. Therefore, we propose a rotational trading strategy between stock portfolios and fixed income products. Starting from the second month of 2018, we simulated trading and monitored the occurrence of outliers in 30 US stocks on a daily basis. If the frequency of abnormal losses in a particular stock exceeds the predetermined threshold within the past 30 days, we immediately switch to holding bond products for continuous N days. If the abnormal frequency is below the significance level, we continue to hold the stock.

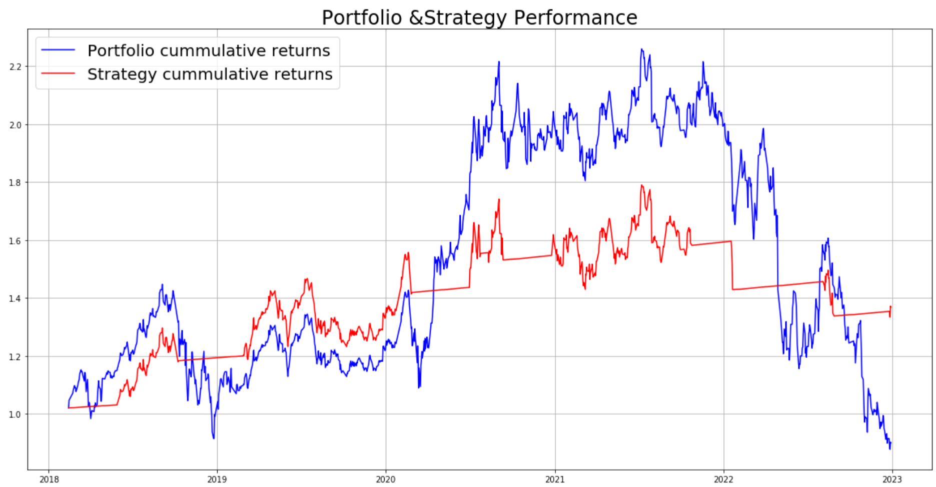

Figure 5: Comparison between the Strategy and Stock (AMZN.O) Net Value Trend

Fig. 5 presents the net value trend of the rotation strategy on Amazon stock compared to the stock's own performance. It can be observed that, after incorporating the risk management strategy, the strategy's return rate avoids potential downturns caused by black swan events, resulting in a more stable trend and ultimately surpassing the stock itself in terms of net value. Therefore, we continue to conduct risk testing on the stock pool for the rotation trading strategy, setting a significance level of 5% for abnormal losses. If the outliers exceed the threshold, fixed income products are held continuously for 10 days.

Fig. 6 compares the trends of the strategy, investment portfolio, S&P 500 index, and NASDAQ index. In the long term, the rotation trading strategy yields significantly higher cumulative returns compared to an equally weighted stock investment portfolio. The annualized return rate reaches 10.73%(Table 1), with a maximum drawdown of 18.46%, significantly lower than the portfolio itself (37.45%). The cumulative returns of the stock investment portfolio experienced a sharp decline. In contrast, the rotation trading strategy, with its allocation to fixed income products, continues to maintain steady profits. This demonstrates that the rotation trading strategy is effective in helping investors efficiently manage risks and capture potential market crises in the face of highly unpredictable black swan events.

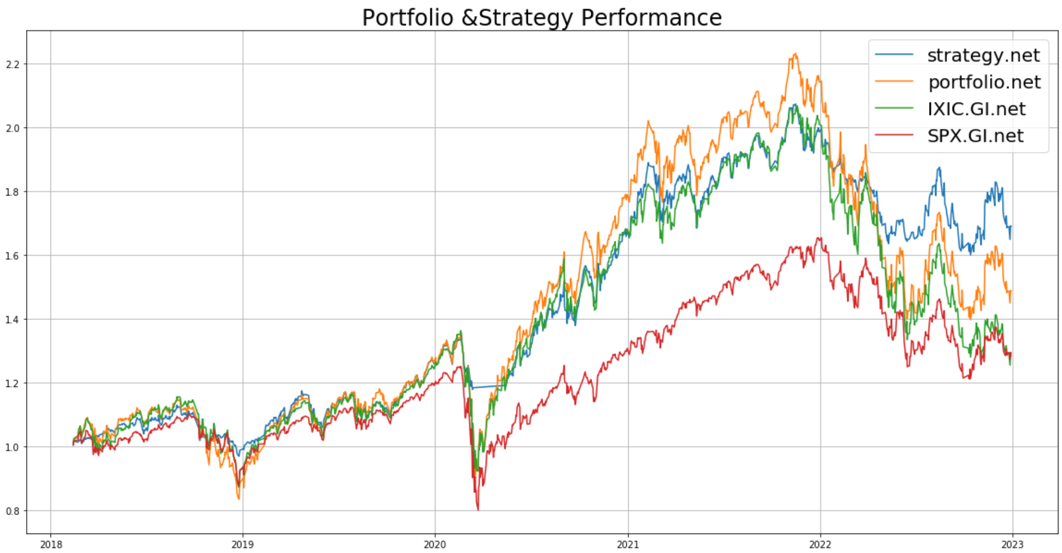

Figure 6: Comparison between the Strategy and Portfolios Net Value Trends

Table 1: Important Evaluation Indicators for the Strategy and Portfolios

Asset	Annualized return	Maximum draw-down rate	Annualized volatility	Sharpe ratio	Annualized Sharpe ratio.
Strategy	11.80%	22.84%	16.87%	0.04	0.57
Portfolio	8.80%	37.45%	27.19%	0.02	0.34
IXIC.GI	5.46%	39.36%	25.59%	0.01	0.22
SPX.GI	5.58%	36.10%	21.90%	0.01	0.22

3.6. Extension of Research

Fig. 7 illustrates the strategy returns at different levels of significance for abnormal losses, as well as the returns of the stock portfolio without the application of the strategy. The lower the significance level, the higher the threshold for the occurrence of outliers and the threshold for switching to fixed-income products. When setting the significance level for abnormal losses at 3% or below, the threshold for the strategy's abnormal value becomes extremely small, resulting in a slow response to downturns (Table 2). Following the market, the strategy may experience multiple downturns, which can lead to a larger maximum drawdown and an unfavorable risk management effect. Furthermore, the performance of the returns is not as good as that at the significance levels of 5% and 10%.

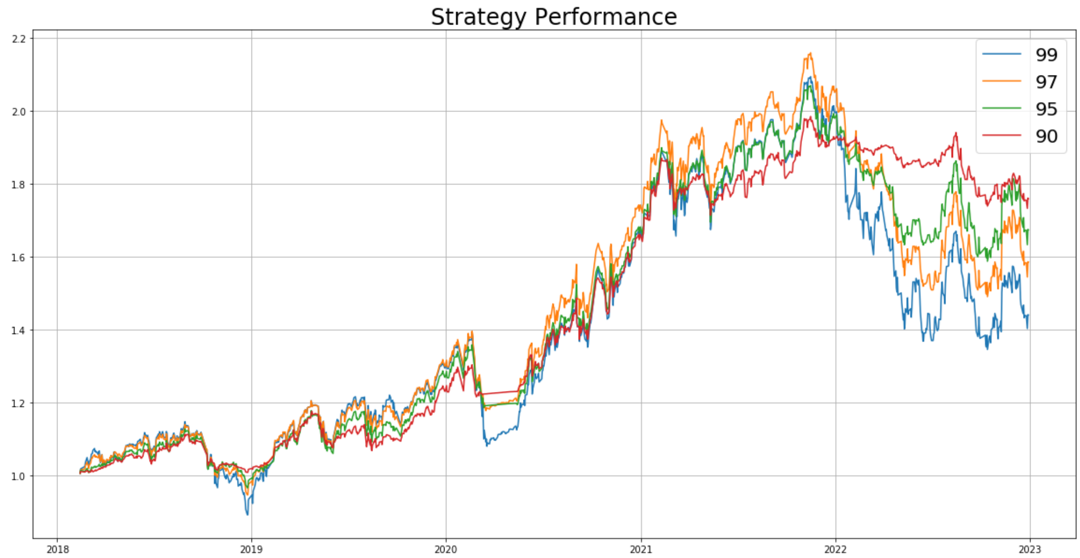

Figure 7: The Strategy Returns at Different Levels of Significance for Abnormal Losses

Table 2: Important Evaluation Indicators for Strategies at Different Levels of Significance

levels of significance	Annualized return	Maximum draw-down rate	Annualized volatility	Sharpe ratio	Annualized Sharpe ratio.
90	12.78%	12.69%	12.25%	0.05	0.80
95	11.59%	23.28%	16.88%	0.04	0.56
97	10.31%	30.97%	19.19%	0.03	0.45
99	8.08%	35.72%	22.16%	0.02	0.33

4. Conclusions

We selected 30 well-known US stocks listed on NASDAQ, including Apple, Amazon, Microsoft, and Google, as our experimental data, which is representative and reasonable. By analyzing the returns of these companies from 2017 to 2022, it can be observed that individual stocks and equally weighted stock portfolios struggle to maintain stable returns and control risks in the face of black swan events. In order to better manage risks associated with black swan events, this study utilizes historical value at risk (VaR) to forecast the risk of investment portfolios and uses the measure of abnormal losses to capture potential crises in the market, constructing a rotating trading strategy. Initially, this strategy constructs an equally weighted portfolio of the four stocks and calculates the daily VaR of the portfolio based on the previous year's return rate, identifying whether the subsequent trading days from 2018 to 2022 are abnormal trading days, thereby detecting and quantifying potential risks. Subsequently, the strategy avoids the detected potential risks and continues to generate returns by rotating positions (switching to fixed income assets). Overall, this study demonstrates that the rotating trading strategy in the US stock market can play a role in risk management, maintaining stable returns and preventing drastic declines and bankruptcies in the face of black swan events. The strategy can effectively identify market abnormalities and maintain stability during overall market downturns. However, it is possible that the strategy may result in

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lower overall returns compared to the market or insufficient sensitivity to market movements due to inadequate control over the significance level of abnormal losses.

References

[1] *Niederhoffer, V. (1971). The Analysis of World Events and Stock Prices. The Journal of Business, 44(2), 193-219.*

[2] *Agmon, T., & Findlay, C. M. (1982). Domestic Political Risk and Stock Valuation. Financial Analysts Journal, 14(4), 74-77.*

[3] *Zach, T. (2003). Political Events and the Stock Market: Evidence from Israel. International Journal of Business, 8(3), 243-266.*

[4] *Zhao, X. (2003). The Spiritual Value of Chinese Culture. Shanghai Ancient Books Publishing House.*

[5] *Xin, J. (2006). Reconstruction of Management Ethics Based on Humanistic Spirit. Enterprise Research, (10).*

[6] *Drucker, P. F. (2008). Management: Tasks, Responsibilities, Practices. Beijing Machinery Industry Press.*

[7] *Jin, C. (2003). Fierce Company. Xi'an: Shaanxi Normal University Press.*

[8] *Wang, C. et al. (2000). Financial Market Risk Measurement Model - VaR. Journal of Systems Engineering, 15(1), 67-75.*

[9] *Morgan, J. P. (1996). Risk Metrics - Technical Document (4th ed.). New York: Morgan Guaranty Trust Company.*

[10] *Ross, S. M. (2007). Introduction to Probability Models (10.3.2).*

[11] *Fan, L., & Tang, G. (1998). The Value of Investment Opportunities and Investment Decisions - Geometric Brownian Motion Model. CNKI.*