Optimal Asset Allocation Model during the Economic Recession

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Abstract. Due to the impact of the COVID-19 pandemic, the economic situation of various industries around the world has been affected to varying degrees. Different asset types are affected in different ways. As most non-institutional investors lack sufficient professional skills, investors tend to invest in low-risk assets. Some investors only invest in a single asset without a reasonable portfolio allocation of multiple assets, resulting in the risk of one asset being equal to or higher than the portfolio investment of multiple assets. This report mainly uses the CAPM model, based on financial data from China and America from 2020 to 2022, to analyze the correlation coefficients, alpha, beta, and excess returns between different time series and different variables to get a Sharpe ratio, aiming to find the optimal model in various asset allocation combinations (stock indexes, bonds, commodity futures, and cryptocurrency). This paper mainly analyzes the forecasting ability of future returns of different asset types through a time series model and risk premium scatter diagram.

Keywords: Optimal asset allocation model; economic recession; COVID-19 pandemic.

1. Introduction

In the context of the COVID-19 pandemic, managing portfolio risk is a considerable challenge for investors. The sudden twists and turns of the COVID-19 public health trajectory have had a broad impact on the global economy, individual asset classes, industries, and companies, as well as investment portfolios. The outbreak not only affected human activities but actually paralyzed the economy. The global economic losses in 2020 accounted for 0.1% to 0.4% of the global GDP, pushing the economy into a recession [1]. The epidemic has spillover effects on almost all other economic sectors worldwide [2]. The Chinese government's epidemic prevention policies have increased the likelihood of business closures and income uncertainty, which in turn affects people's behavioral choices [3]. A long period of uncertainty is not beneficial for investors, as the basic goal of investment is to generate sustained returns over a period of time and to safely preserve capital [4]. Investors' decisions in crisis environments are influenced by emotional factors. Investors' emotions, such as bad moods and anxiety, can make them averse to risk, thereby affecting asset returns [5]. Research has shown that using the Sharpe ratio and correlation analysis of various asset classes, a reasonable asset allocation through long-term, medium-term, and short-term perspectives will bring stable long-term investment returns to investors, but portfolios with a low return target perform better in the medium and short term [6]. Due to the cyclical characteristics of stock indexes, bonds, commodity futures, and cryptocurrencies' returns, and their close relationship with the stage of the economic cycle, we can use this to carry out asset allocation [7]. Among them, commodity futures will affect the performance of traditional investment portfolios by affecting correlations and variances in terms of increasing returns and reducing risks [8]. The target of asset allocation in broad categories is no longer to minimize risks under existing expectations but to find assets with risk premiums and realize returns through reasonable allocation [9]. Diversified investments can effectively reduce risks. Under different risk levels, the risk of a portfolio can be lower than that of a single asset, and the return rate will rise or stay the same [10].

This article aims to use the CAPM model and the Sharpe ratio to analyze the impact of COVID-19 on different financial product markets and find the optimal model for asset allocation. The research will mainly focus on the historical data of different financial targets during COVID-19. In order to help investors find a better asset allocation model, this article will analyze the stock indexes and cryptocurrencies in the US market and other targets in the Chinese market. To ensure the consistency of factors in the Chinese and US markets, the study will use historical data from the same time period in China and the US market. This article will use Sharpe ratio maximization to construct the optimal model for asset allocation, while seeking the correlation between targets and whether short selling will bring greater returns to the asset allocation portfolio. Part one of this article will mainly introduce the historical data of US stock indexes, cryptocurrencies, and Chinese commodity futures and bonds and analyze relevant factors. Part two will focus on the construction of investment portfolio strategies through the CAPM model and Sharpe ratio maximization. Part three analyzes how the Sharpe ratio affects the asset allocation portfolio model and brings benefits to decision-makers. The final part summarizes the entire article.

2. Investment Portfolio Strategy and Performance Model Selection and Analysis

To ensure finding the optimal model for asset allocation, this article will discuss the most commonly used CAPM model and Sharpe ratio in theory and practice and provide a reasonable performance evaluation model.

2.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) provides a model for measuring the size of asset risk, helping investors determine whether the additional return obtained matches the risk. The mathematical expression of the Capital Asset Pricing Model is:

$$E(r_i) = r_f + \beta_i(E(r_m) + r_f) \tag{1}$$

where E(r_i) is the expected return of the portfolio, r_f is the risk-free rate, β_i (E(r_m) + r_f) is the ratio of the covariance between the return rate of asset i and the return rate of the asset portfolio to the variance of the return rate of the asset portfolio, reflecting the change in the return rate of asset i caused by the change in the return rate of the asset portfolio, and measuring the systematic risk of the market.

2.2 Sharpe Ratio

For the evaluation of investment portfolios with different effects, the Sharpe ratio can provide a comprehensive measure of risk and investment return. The Sharpe Ratio Index represents that excess returns over a period of time may mean more volatility and risk, and the historical record of relative risk-adjusted returns at least has some predictive value. Therefore, this article chooses the Sharpe ratio as the evaluation index of the investment portfolio, which is sufficient to achieve the purpose. The formula for this ratio index is:

$$\text{Sharpe Ratio} = \frac{E(r_p) - r_f}{\sigma_p} \tag{2}$$

where E(r_p) is the return rate of the investment portfolio, r_f is the risk-free return rate, and σ_p is the standard deviation of the return rate of the investment portfolio.

3. Variable Selection and Data Source

This section will explain in detail the selection of data and indicators and give a statistical and characteristic analysis of the data based on the S&P 500 return rate as the market return rate and the 10-year US Treasury yield as the risk-free rate.

3.1 Stock Index Fund

The data for this article was selected from VIMAX and SWPPX for the stock index fund targets from 2020 to 2022 on the English financial website. The stock index fund has low volatility and low risk, making it more su0table for investors. Stock index funds often have a high positive correlation with the overall market, so when the market falls, the stock index fund will also fall.

3.2 Cryptocurrency

The data for this article was selected from Dogecoin and Cardano for the cryptocurrency targets from 2020 to 2022 on the English financial website. Cryptocurrencies have high volatility and high returns, and increasing their allocation in the asset portfolio can help increase the desired returns. Through data screening, the data targets were unified with the time of other asset portfolios.

3.3 Bond

The data for this article were selected from the China Treasury Futures, which are the five-year main continuous contracts, and the US Treasury Futures, which are the two-year main continuous contracts, from the Choice Financial Terminal. Since the holidays in China and abroad are different, this article cleans the data and unifies the background with the time of the two targets. The yield of the Treasury Futures is small, so this article multiplies the yields of the two targets by a leverage of 10.

3.4 Commodity Futures

The data for this article was selected from the Shanghai Futures Exchange's precious metal gold and the Zhengzhou Futures Exchange's soft commodity cotton for the commodity futures targets on the English financial website. Since short-term stock market volatility may deviate significantly from equilibrium value, based on the availability of data, 2020 to 2022 were selected as the sample period and back-testing interval. Gold plays an important role in asset allocation. The price of gold is often highly negatively correlated with assets such as stocks. China's cotton industry has the characteristics of high output and active market participation, so cotton prices are highly volatile.

4. Investment Portfolio Strategy

4.1 Stock Index Fund

Table 1. Basic Statistics of the Stock Index Fund (2020-2022)

VIMAX	r_{Mkt}-rf	$r_{VIMAX}-r_f$
Average	0.03%	0.03%
Variance	0.02634%	0.03086%
SWPPX	r_{Mkt}-rf	$r_{SWPPX}-r_f$
Average	0.03%	0.03%
Variance	0.02634%	0.02647%

As shown in Table 1, with the same mean value as VIMAX, SWPPX has a smaller variance than VIMAX, indicating that the stock index fund market of SWPPX was less volatile and more stable from 2020 to 2022.

Table 2. Basic Data Description of Stock Index Fund (2020-2022)

	Covariance	Correlation	α	β	R^2	Sharpe Ratio
VIMAX	0.02751%	0.96632	0.00%	1.04	0.9338	0.0000%
SWPPX	0.02632%	0.99798	0.00%	1.00	0.996	0.0000%

The beta values of the two stock index funds tend to be 1 (see Table 2), indicating that the magnitude of their yield changes is the same as the magnitude of the market yield changes. Both of their alpha values are close to zero, and their excess returns are almost zero. From the table, it can be seen that R2 is close to 1, and both have a very good fit with the market. The regression effect is significant, and the model obtained is more accurate. The Sharpe ratio is 0, indicating that the average net asset value growth rate of the stock index fund is equal to the risk-free rate during the measurement period. In the case of using the 10-year US Treasury yield as the risk-free rate, the stock index fund is almost no different from the 10-year US Treasury.

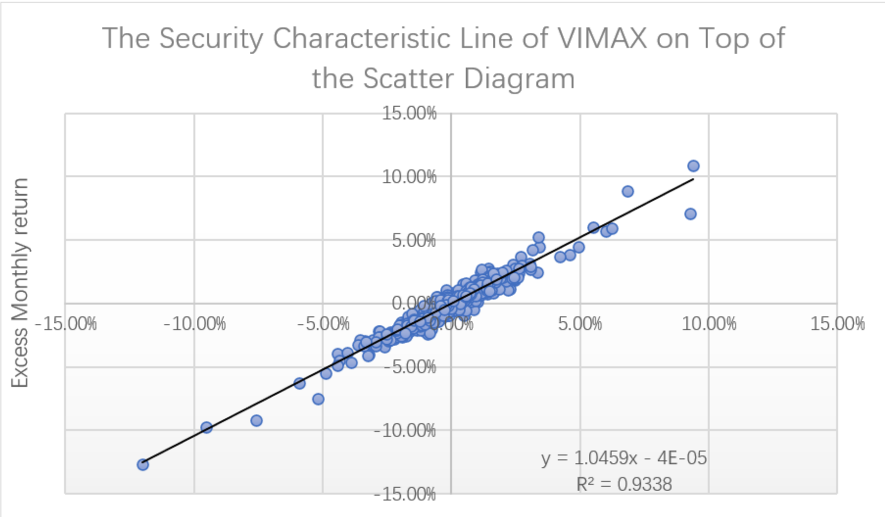

Figure 1. VIMAX Risk Premium Scatter Plot

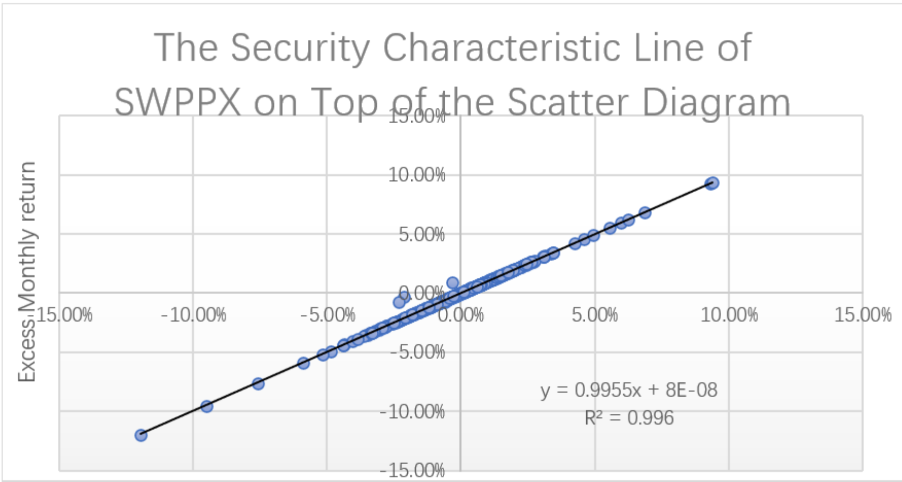

Figure 2. SWPPX Risk Premium Scatter Plot

As shown in the Figure 1 and Figure 2, the X of both graphs increases with the increase of Y, and the changes of both are in the same direction, showing a positive correlation between the two. From the graph, it can be seen that the fit between the points and the line on SWPPX is better, and the R2 of SWPPX is higher than that of VIMAX, indicating that VIMAX has a greater deviation from the overall market. The beta of the two stock index funds is greater than or equal to 1, indicating that the volatility of the individual stocks is equal to or greater than that of the overall market.

4.2 Cryptocurrency

Table 3. Basic Statistics of Cryptocurrency (2020-2022)

Dogecoin	r_{Mkt}-rf	$r_{Dogecoin}$-rf
Average	0.03%	9.96%
Variance	0.02634%	549.256%
Cardano	r_{Mkt}-rf	$r_{Cardano}$-rf
Average	0.03%	0.55%
Variance	0.02634%	0.55033%

As shown in Table 3, the means and variances of Dogecoin in the 2020–2022 market differ greatly from those of Cardano, indicating that Dogecoin is much riskier and more unstable than Cardano in terms of returns and risks.

Table 4. Basic Data Description of Cryptocurrency (2020–2022)

	Covariance	Correlation	α	β	R^2	Sharpe Ratio
Dogecoin	0.04782%	0.01259	9.91%	1.82	0.0002	0.0101%
Cardano	0.03991%	0.33196	0.51%	1.52	0.1102	0.0310%

The beta and alpha values of cryptocurrencies are both high and positive (see Table 4), not only positively correlated with the market, but also capable of obtaining excess returns. Dogecoin has a higher alpha than Cardano, so its excess return rate will also be higher. Both of their beta values are greater than one, indicating that their fluctuations are relatively larger than those of the market. Dogecoin's R2 is almost zero, which is related to its rapid and unpredictable growth relative to other times during the period of 2020–2022. Cardano's Sharpe ratio is higher than Dogecoin's, as the market's volatility is higher.

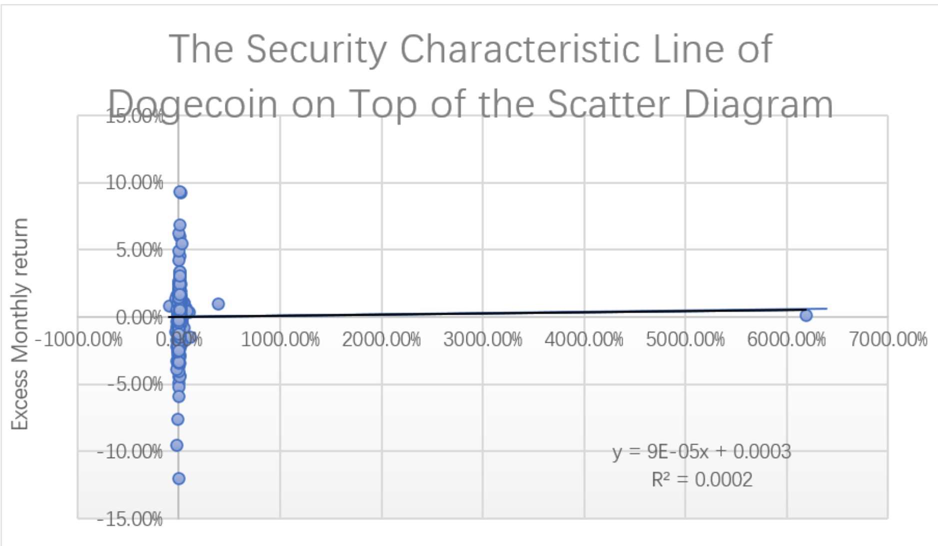

Figure 3. Dogecoin Risk Premium Scatter Plot

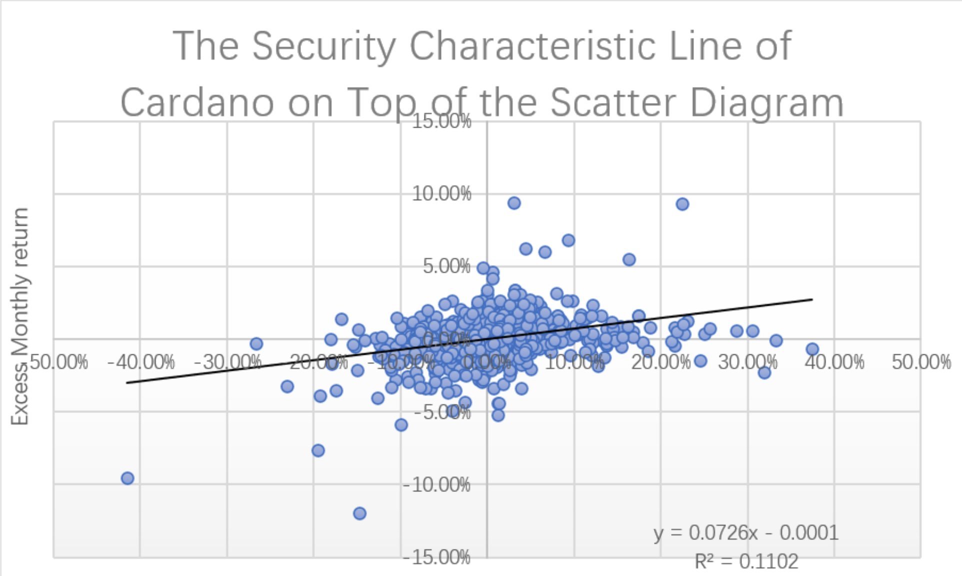

Figure 4. Cardano Risk Premium Scatter Plot

From the Figure 3 and Figure 4, it can be seen that Dogecoin's concentration point deviates greatly from the overall market, which has a lot to do with its small R2. When X changes, the change in Y is very small. When X increases in both charts, Y also increases, and Y is positively correlated with X. VIMAX's alpha is large, showing that the point on the chart changes vertically very quickly. Both of their betas are greater than 1, indicating that the volatility of individual stocks is greater than that of the overall market and positively correlated with it.

4.3 Bonds

Table 5. Basic Statistics of Bonds (2020-2022)

TFM.CEF	r_{Mkt}-rf	$r_{TFM.CEF}$-rf
Average	-0.18%	0.01%
Variance	0.02635%	0.0283%
TU00.CBT	r_{Mkt}-rf	$r_{TU00.CBT}$-rf
Average	0.03%	-0.08%
Variance	0.02635%	0.01023%

The Table 5 shows that from 2020 to 2022, the Chinese five-year treasury bond futures have a similar risk-free rate of return to the market, but a higher one compared to it. However, the two-year treasury bond futures in the United States have a smaller risk-free rate of return than the market, and it is lower, indicating that the rate of return on these two treasury bond futures is very low. The small variance of these two treasury bond futures makes them more stable and suitable for risk-averse investors.

Table 6. Basic Data Description of Treasury Bonds (2020-2022)

	Covariance	Correlation	α	β	R^2	Sharpe Ratio
TFM.CEF	-0.00118%	-0.04322	0.00%	-0.045	0.0019	0.0002%
TU00.CBT	-0.00067%	-0.04114	-0.08%	-0.026	0.0017	0.0000%

The stability of the national debt is strong and the yield is low (see Table 6), so we leveraged its yield by 10 times. The covariance and beta value of the bond are both negative, and their absolute values are less than 1, indicating that they move in the opposite direction to the overall market and their rate of return changes are smaller than the average rate of return of the market portfolio. The systematic risk they contain is smaller than the risk of the market portfolio. The Sharpe ratio of the

5-year Chinese government bond futures is greater than that of the 2-year US government bond futures, indicating that the former has greater market volatility than the latter. However, the Sharpe ratio of the 5-year Chinese government bond futures is very small, almost zero, and in the case of using the 10-year US government bond interest rate as the risk-free interest rate, there is almost no difference between the national debt and the 10-year US government bond.

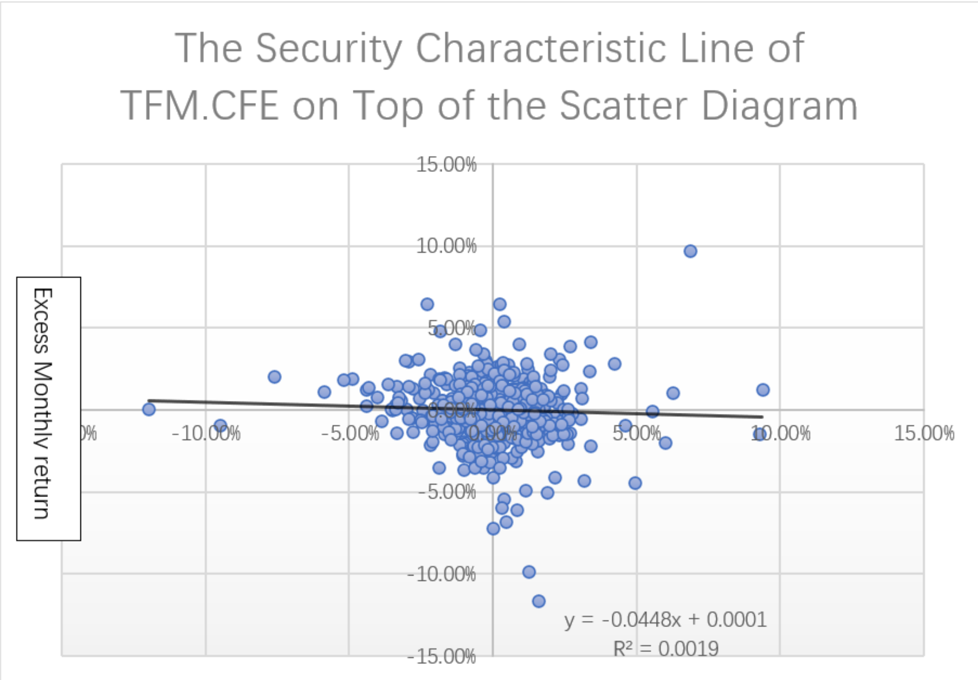

Figure 5 Scatter plot of risk premium of 5-year Chinese government bond futures.

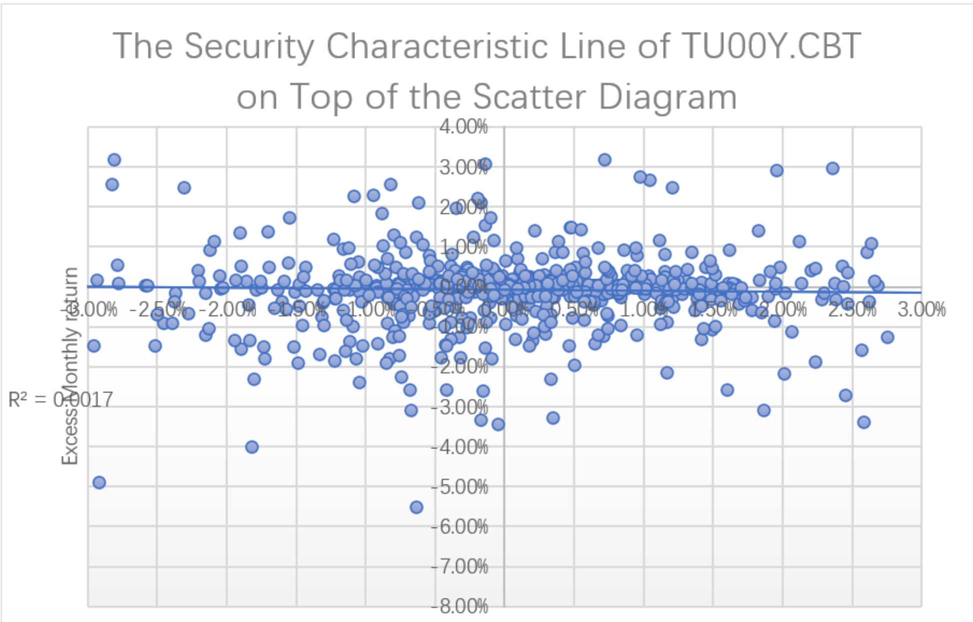

Figure 6. Scatterplot of Risk Premiums for Two-Year US Treasury Futures

From the Figure 5 and Figure 6, it can be seen that as X increases, Y gradually decreases. The defense range of Y is smaller than the change range of X. The changes of Y and X are in the opposite direction, and Y and X are negatively correlated. The values of β for both are less than 0, and |β|<1 can explain the above phenomenon well. The small R2 value indicates that the fit of bonds to the market is not high, and the points in the figure are more scattered.

4.4 Commodity Futures

Table 7. Basic statistics of commodity futures (2020-2022)

Gold	r_{Mkt}-rf	r_{Gold}-rf
Average	0.01%	0.02%
Variance	0.0360%	0.0099%
Cotton	r_{Mkt}-rf	r_{Cotton}-rf
Average	0.03%	0.01%
Variance	0.0264%	0.0187%

After calculation (see Table 7), the basic statistics of commodity futures are shown in the table. The mean of gold is similar to that of cotton, but the variance of cotton is smaller than that of gold, indicating that the Chinese cotton commodity futures market has smaller fluctuations and is relatively stable.

Table 8. Basic Data Description of Commodity Futures (2020-2022)

	Covariance	Correlation	α	β	R^2	Sharpe Ratio
GOLD	-0.0097%	-0.5173	0.02%	-0.2706	0.2676	0.0027%
Cotton	0.0016%	0.0704	0.01%	0.06	0.0049	0.0005%

The basic data shows that the covariance of gold is less than 0, and it is negatively correlated with β (see Table 8). The situation with cotton is the opposite. The β values of gold and cotton are both less than 1. The magnitude of the changes in their returns is smaller than the magnitude of the changes in the average return of the market portfolio, and the system risk contained is smaller than the risk of the market portfolio. However, the value of gold is less than 0, indicating that the direction of gold's changes in average market returns is the opposite. The larger the value of the market, the smaller the return. Cotton is the opposite. From the Sharpe ratio, gold is higher than cotton, and the market fluctuates more. To illustrate the investment effect of the portfolio strategy more comprehensively and clearly, it is shown in Figure 7 and Figure 8.

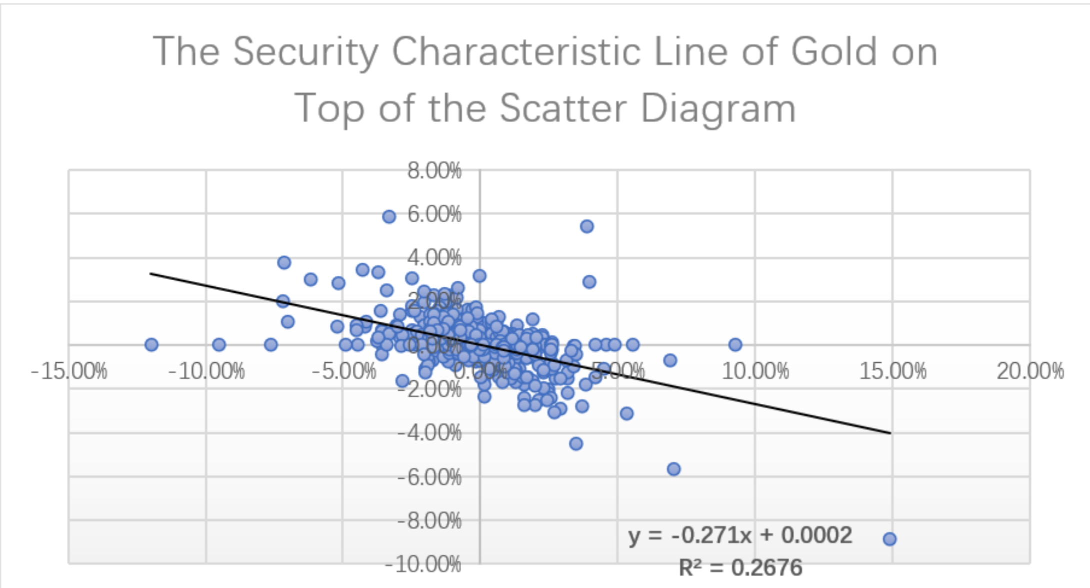

Figure 7. Scatter Plot of Gold Risk Premium

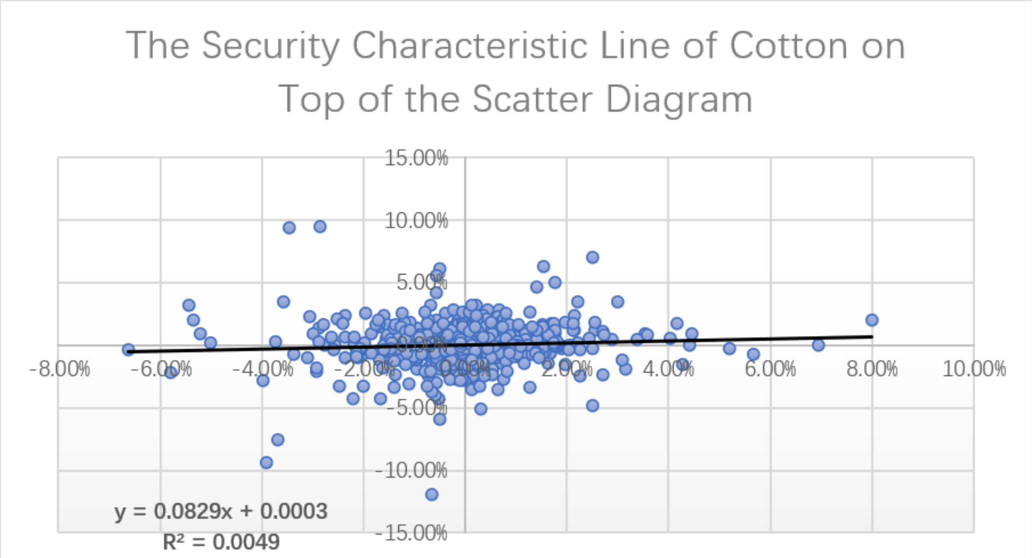

Figure 8. Cotton Risk Premium Scatter Plot.

As shown in Figure 7, Y decreases as X increases as a whole trend, i.e. the change of Y and X is inverse. Therefore, X and Y are negatively correlated. However, figure 8 indicates that Y increases as X increases as a whole trend, and the change of Y and X is in the same direction. The relationship between cotton and β is positively correlated. The α of gold and cotton in the formula are both close to 0, and there is no significant difference. |β|<1 indicates that the volatility of the individual stock is smaller than that of the market.

5. Empirical Analysis of the Impact on Investment Portfolio

Using the above data and various models for estimation, we conducted data preprocessing in Table 9 and analyzed the results using methods such as correlation analysis and time series model regression analysis and summarized the empirical results.

Table 9. Impact of Correlation on Investment Portfolio

	VIMAX	SWPPX	Dogecoin	Cardano	Gold	Cotton	TFM	TU00Y
VIMAX	1.000							
SWPPX	0.965	1.000						
Dogecoin	0.014	0.013	1.000					
Cardano	0.331	0.332	0.035	1.000				
Gold	0.024	0.006	-0.002	-0.010	1.000			
Cotton	0.083	0.068	-0.104	0.022	0.074	1.000		
TFM	-0.034	-0.042	0.004	0.015	0.062	-0.048	1.000	
TU00Y	-0.026	-0.041	0.013	-0.019	-0.009	-0.075	0.093	1.000

5.1 Stock index fund

The beta coefficients of the two selected targets are both equal to 1, indicating that the risks of the two stock indexes are greater than or equal to the market risk, and the excess returns obtained will also be higher. However, since the alpha tends to 0, it indicates that the returns from non-market premium that investors can obtain are very small, making it difficult to obtain higher excess returns.

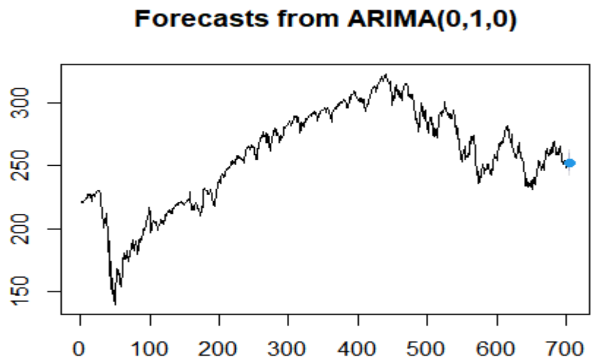

Figure 9. Time series model fitting - VIMAX

As shown in the Figure 9, it can be seen that the original data of SWPPX shows a slow fluctuating upward trend during a certain period of time, and after reaching the peak, it fluctuates downward in cycles. The model performs difference processing on non-stationary data and calculates that the p value is 0.08092, which is greater than 0.05. Therefore, we cannot reject the null hypothesis of the Ljung-Box test and believe that the residuals are independent and the model fitting effect is good.

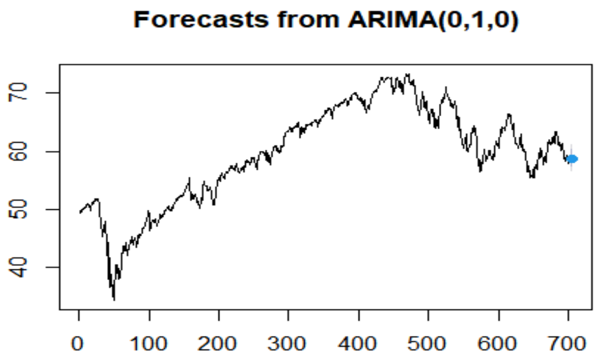

Figure 10. Time Series Model Fitting -- SWPPX

Due to the calculated p-value of 0.0003773 being less than 0.05, the null hypothesis of the Ljung-Box test is rejected (Figure 10). The probability of deviation from the null hypothesis is higher than the current data, so the null hypothesis is rejected.

5.2 Cryptocurrency

Cryptocurrency transactions are peer-to-peer transactions that do not involve third parties and are completely controlled by the network, with relatively transparent information. From the table, it can be seen that the α and β values of the two selected targets are both very high, indicating that the risk premium from the index and the non-market risk premium can significantly increase excess returns.

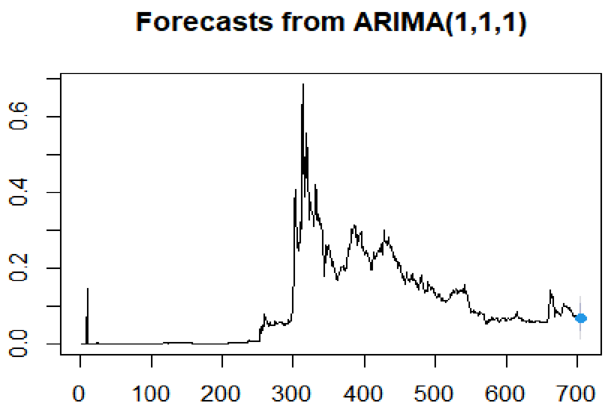

Figure 11. Time series model fitting - Dogecoin

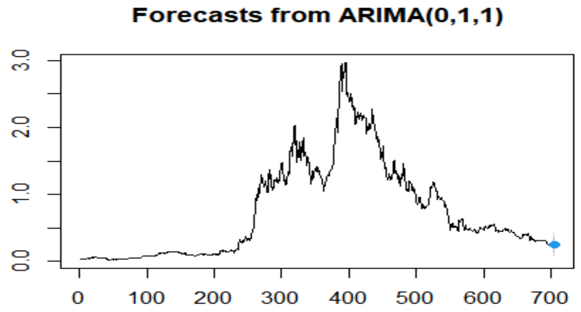

Figure 12. Time series model fitting - Cardano.

As shown in the Figure 11 and Figure 12, the original data of both remained relatively stable in the early period from 2020 to 2022 and began to rise rapidly after a certain point in time. The increase in Dogecoin was smaller than that of Cardano. In the interval after 200, after 2-3 cycles, it showed fluctuations and declines. The p-values of the two are 0.3748 and 0.8637, respectively, both larger than 0.05, and the null hypothesis of the Ljung-Box test cannot be rejected.

5.3 Bonds

The price fluctuation of national bond futures is small, and the risk is low, so the yield will be relatively low. From the table, we can see that the β values of the two selected targets are generally low, so the risk premium from the index is low and the excess returns will be less. However, due to the strong stability of bonds and their opposite correlation with market fluctuations, they can diversify investors' risks and ensure returns.

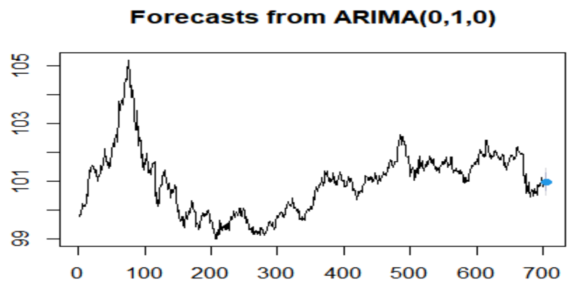

Figure 13. Time series model fitting - TFM.CFE

As shown in the Figure 13, the original data of TFM.CFE presents long-term, periodic fluctuations, but the fluctuation range is small, fluctuating back and forth between a few numbers. When zoomed in, the original data is still relatively stable. According to the calculation, the p-value is 0.6275, which is greater than 0.05. Therefore, the null hypothesis of the Ljung-Box test cannot be rejected, and the probability of appearing more deviated from the null hypothesis than the current data is relatively small.

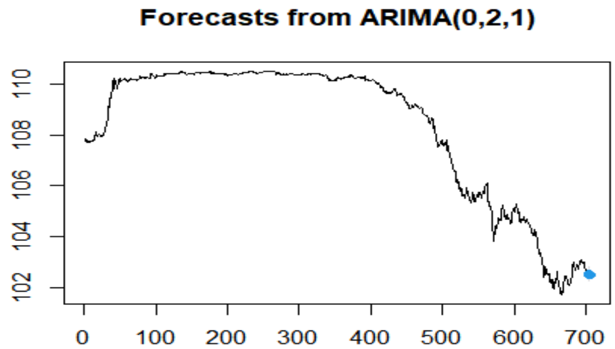

Figure 14. Time series model fitting - TU00Y.CBT

As shown in Figure 14, the original data of TU00Y.CBT first quickly rises to a peak, remains stable for a period of time, and then rapidly fluctuates downward. Observing the vertical axis indicates that the data oscillates back and forth between each data point. The calculated p-value of 0.05096 is greater than 0.05, so we cannot reject the null hypothesis of the Ljung-Box test.

5.4 Commodity Futures

Commodity futures differ greatly from traditional financial investment tools such as stock indices and bonds due to their underlying assets being physical commodities, the rights of which can only be exercised within a specified period, and the existence of delivery risks. As shown in table 9, the low correlation between commodity futures and stock indices or other commodity futures suggests that adding commodity futures to an investment portfolio can effectively diversify portfolio risk. In addition to correlation analysis, model regression can also analyse the CAPM model. According to table 8, the R-square value of gold is closer to 1 than that of cotton, indicating that the more observation values fall on the sample regression line, the higher the explanatory power of the model, and the better the model prediction results. Moreover, the time series ARIMA model predicts the future by finding the autocorrelation between historical data.

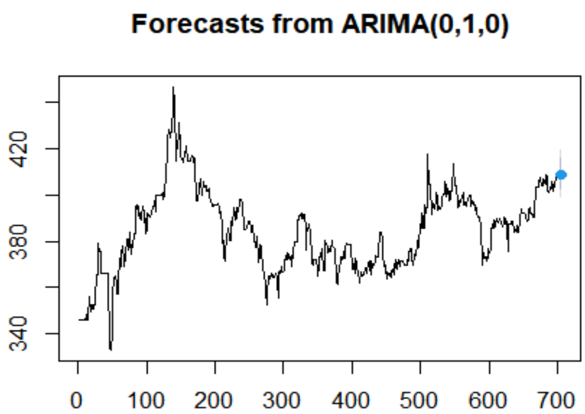

Figure 15. Time series model fitting - Gold

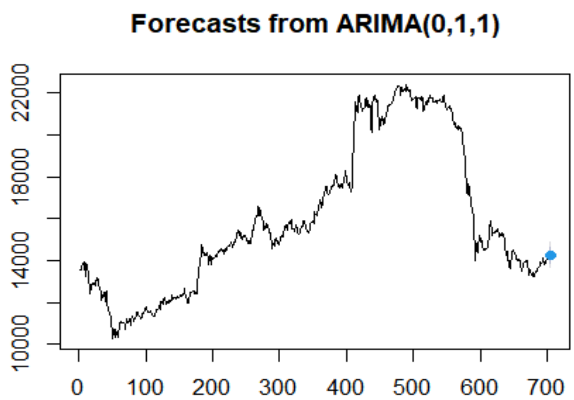

Figure 16. Cotton Time Series Model Fitting

As shown in Figure 15 and Figure 16, it can be found that the original data of gold has a periodic and long-term growth trend and does not fluctuate above or below a constant value. The model processes non-stationary data by difference, and the calculated p-value is 0.1005, which is greater than 0.05. Therefore, the null hypothesis of the Ljung-Box test cannot be rejected, and it is believed that the residuals are independent. Therefore, both tests of the model have passed, and the fitting effect of the model is good. The finally fitted graph basically conforms to the trend of the data, and the blue dots in the graph indicate the trend of future data for the next 3 years.

6. Conclusion

Studies show that after risk adjustment, when risks and yields can be considered at the same time, cryptocurrencies can achieve higher yields followed by commodity futures. The yields of bond and stock index funds are roughly the same as the 10-year Treasury yield. Allocating asset portfolios can effectively reduce the high risk of a signal asset.

According to the Sharpe maximum, the optimized asset allocation model data for all selected targets is relatively reliable. In the future, investors can diversify investment risks through investment in national bonds, observing effective frontiers, or replacing targets to improve the Sharpe ratio. Investors can use similar calculation methods to obtain the optimized asset allocation and diversify investment risks to achieve higher returns and lower risks over a longer time span. However, the data mainly adopts historical data samples during the epidemic period from 2020 to 2022. Currently, the global economy is gradually opening up, and there is a lack of reference significance for subsequent asset allocation. Since it is a historical data sample from 2020-2022, it cannot represent the whole. The analysis based on it is only a basis for investors to make decisions and cannot be copied directly. Lastly, the investment portfolio includes cryptocurrency, which is not friendly to investors who are unable to invest due to national policies.

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