Broad Asset Portfolio Designed Based on the Mean-Variance Model

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Abstract. Contemporarily, broad asset class allocation has gradually become an ideal investment strategy for investors and institutions. This paper constructs the optimal asset class allocation and portfolio design with python based on the mean-variance model, using stocks, gold, crude oil, bonds, futures, foreign exchange, funds, commodities, digital currencies and treasury bonds as the main underlying assets. To compare the asset allocation portfolios constructed by different approaches (the equally weighted investment model, the minimum variance model and the maximum Sharpe ratio model), the comparative analysis is implemented in terms of five indicators, including the annualised return, annualised volatility, Sharpe ratio, maximum drawdown and return-to-drawdown ratio. After the comparison, the advantages of the maximum Sharpe ratio model are demonstrated. According to the results, the mean-variance model, as a risk management model from the investor's perspective, is consistent with the investment logic of investors and financial institutions that it outperforms the traditional minimum variance model and equally weighted model in terms of profitability and risk control. Therefore, the mean-variance model has certain theoretical guidance for broad asset class allocation. Overall, these results shed light on portfolio designed for investments.

Keywords: Broad Asset; Portfolio; Mean-Variance Model; Equally Weighted Model.

1. Introduction

Broad asset class allocation refers to the process of allocating a portfolio of broad asset classes with different expected returns and risks with the aims of hedging risks while fulfilling expected returns. Numerous quantitative models based on the mean-variance model are widely applied in the broad asset class allocation process. Two of the dominant models are Markowitz's mean-variance model and the Black-Litterman model, the latter improving the former. This paper focuses on broad asset class allocation in the context of the mean-variance model, which is a valuable reference for financial investment. For investment institutions, the quantitative approach makes it possible to measure the results of all investment practices against a uniform standard, facilitating the testing of model validity and making investment practices more efficient. With regard to investors, it provides an investment strategy for high-net-worth investors seeking sound returns and helps to increase the degree of rationality of investors. Therefore, the model is valid in the short term and provides some advantages and guidance for investment in the short time.

In retrospect, the development of broad asset allocation models has a long history according to the summary by Zhang [1]. At the very beginning, a constantly mixed-asset allocation strategy was used that fixes the proportion of each underlying assets in a portfolio. The typical constantly mixed-asset allocation strategies include the equally weighted portfolio and the classic 60/40 portfolio strategy. Then, the broad asset class allocation is constructed based on return and risk. The return of an asset is proportional to its risk when the market is assumed to be neutral, a premise born in Markowitz's mean-variance theory [2]. Many scholars and institutions have based their broad asset class models on this assumption. The most classic is the Black-Litterman model, which combines Markowitz's mean-variance theory and Bayesian mixed estimation to introduce investor views into the allocation model [3]. This has given rise to broad asset class allocations based on returns solely. Some academics and institutions tend to judge macroeconomic conditions to control risk and focus on the returns of assets to construct allocation models and seek profit opportunities. The GEYR model by Mills and the FED model by Yardeni are both methods of stock selection by examining the correlation between stocks

and bonds. The GEYR model is used to predict the future performance of the UK stock market by comparing long-term government bond returns with stock returns and setting a new confidence factor for stock ownership [4]. The FED is widely used to predict the future direction of equity indices by directly comparing the returns of equities with those of government bonds [5]. In addition, momentum theory, which is derived from behavioral economics, has shown good performance and has been used by many US financial institutions in their equity fund management activities [6]. This is followed by a broad asset class allocation approach based on risk alone, as the mean-variance model is too sensitive to small input changes. Although Bayesian resampling and shrinkage methods to eliminate estimation errors have played a role, the improved mean-variance model is still inferior to the equally weighted portfolio in terms of Sharpe ratio and returns. It has therefore been suggested that this sensitivity would result in the mean-variance model delivering unattractive returns relative to the forecast error; the error loss could be reduced by simplifying the objective. As a result, broad asset allocation strategies based solely on risk, such as minimizing risk portfolios, maximizing risk diversification ratio portfolios and risk parity portfolios, have emerged in recent years and received market attention. Gradually, a broad asset class allocation based on investor utility emerged. Most of the values used in asset allocation models are subject to many assumptions and restrictions. They are set based on statistical concepts, e.g., the returns to have a normal distribution. To break this limitation, Adler & Kritzman developed the Full-Scale model, which eliminates the setting of a normal distribution of returns and the measure of risk, and allows for the maximum presentation of investor utility by setting up four types of utility functions instead of four kinds of investor views with different characteristics, and ultimately returns determine the magnitude of utility values [7]. In the same year, Sharpe proposed a new method for improving the inverse investment allocation similar to the expected utility of investors [8]. This strategy changes the expected value of asset returns according to investors' wishes. It outputs the same allocation results as the mean-variance model when the assumptions are the same. One of the last large asset class allocations that have been studied to incorporate economic cycles and subjective judgments is the University Endowment Model constructed by Swensen, which is a typical large asset class allocation that contains economic cycles and subjective assessments and is named after several university endowments [9]. Another well-known broad asset allocation tool is the Merrill Lynch Investment Clock model, which is based on almost 20 years of US economic data and links macroeconomic cycles, broad asset class returns and sector rotation to guide investors in identifying essential inflection points in the economy and in making asset [10].

The paper is divided into four parts in total, which successively describe the research background, the relevant literature and the theoretical model, and conclude with a practical analysis to obtain the conclusions on the broad asset class allocation. The framework of this paper is as follows. The first part will introduce the background of the study and explain the significance of the survey. Afterwards, it will provide a literature review of past scholars on broad asset class allocation to understand the history of broad asset class allocation theory and possible future directions. Eventually, it will describe the research framework to make the structure of the article clear. The second part will explain which data are used and state the frequency and sources of the data, followed by combining the concepts and theoretical models involved in the mean-variance model in the study. The third part will analyse and establish the optimal portfolio allocation based on the mean-variance model and derive the annualized return, annualized volatility, Sharpe ratio and maximum drawback subsequently for each asset allocation portfolio and compare them. The fourth section will draw conclusions based on the theoretical research and empirical analysis conducted in this paper and further elaborates on this paper's research limitations and outlook.

2. Methodology

2.1 Data

The empirical part of this paper is based on the mean-variance model, which selects representative assets in different markets for allocation. It constructs a broad asset class allocation by diversifying

assets with low correlation. Taking into account the risk, return, liquidity and correlation of the assets, as well as concerning the industry's choice of broad asset classes, this paper identifies the broad asset classes for study as stocks, gold, crude oil, commodities, foreign exchange, bonds, treasury bonds, futures, digital currencies and funds, and the data selected covers the period from 5 January 2015 to 31 December 2021, the frequency of data is daily. The chosen data is from the Wind database, except for Bitcoin data from cryptodatadownload.com.

Among the many indices that reflect the movement of asset prices in various markets with consideration of the representativeness of the index and whether there is duplication of samples among assets in the compilation of the index, the subjects of this paper are CSI 800 Index (000906.SH) to represent the stock market; SHFE Gold (AU.SHF) to mean the gold market; NYMEX Crude Oil (CL.NYM) to define the crude oil market; China Bond Aggregate Wealth (Total) Index (CBA00101.CS) to represent the bond market; 7 Wind Commodity Index Futures to represent the futures market, namely Wind Agricultural Products (APFI.WI), Wind Non-Ferrous (NFFI.WI), Wind Non-Metallic Building Materials (NMBM.WI), Wind Coal, Coke, Steel and Mining (JJRI.WI), Wind Oil and Oilseeds (OOFI.WI), Wind Chemicals (CIFI.WI) and Wind Soft Commodities (SOFI.WI); the US Dollar Index (USDX.FX) to represent the foreign exchange market situation; the South China Commodity Index (NH0100.NHF) to describe the commodity market situation; the mainstream currency Bitcoin (BTC) to represent the digital currency market; CFFEX 5-Year Treasury Futures (TF.CFE) to represent the Treasury market; and 5 major fund categories to describe the fund market, namely, Total Mixed Fund Index (885013.WI), Total Bond Fund Index (885005.WI), Total Equity Fund Index (885012.WI), EFT Fund WI), the EFT Fund Price Index (885173.WI) and the LOF Fund Price Index (885172.WI), which are selected to be classified mainly according to the different investment objects.

2.2 Model

This section focuses on three broad asset allocation models involved in the study, namely the equally weighted model, the mean-variance model and the minimum variance model. This section attempts to introduce these models from their theoretical underpinnings and summarise their advantages and disadvantages. It is a unique form of a constant ratio investment model that allocates equal weights to each asset in an asset allocation portfolio, with changes in asset prices leading to changes in asset weights, with rising assets becoming more heavily weighted and falling assets becoming less heavily weighted. Therefore, it is necessary to periodically sell investments that have increased in price and buy assets that have fallen in price, thus ensuring that the weights remain constant. The equally weighted model relies on selling high and buying low to hedge risk and ensure returns. The asset weighting in the equally weighted model does not involve return or risk, and different assets are assigned the same weight, with the initial weight of each asset being

$$w = \frac{1}{n} \tag{1}$$

Here, *w* is the weight, and *n* is the number of assets. The equally weighted model sells assets that have grown more and buys assets that have fallen more when rebalancing asset weights, exhibiting the characteristics of a reversal strategy under certain circumstances.

The following is an introduction to the Mean-Variance model, which measures return based on mean and risk in terms of variance. The M-V model theory is based on the following premises: (1) participants in the market are perfectly rational; (2) there is complete information; (3) assets are perfectly divisible, and there are no trading time and volume restrictions; (4) the market does not incur costs in the trading process; and (5) investors can sell short. Based on the above premises, Markowitz established a method for calculating a portfolio's expected return and risk and an efficient frontier theory and built a mean-variance model for asset allocation. By defining risk as to the volatility of the expected return μ, i.e., the variance σ^2, the innovatively applied mathematical and statistical methods to the field of finance, greatly enriching the research tools for optimal portfolio selection.

The idea of the Markowitz portfolio is to take all securities traded in the secondary market (assumed to be S_1, S_2, S_3..., here, the securities include not just stocks but also bonds and volatile marketable assets) based on the returns and risks of these securities, plotting the information on a two-dimensional chart with the expected return as the vertical axis and the standard deviation of the return as the horizontal axis. Markowitz assigned the weights w_1, w_2, w_3... to each of them and the expected returns of these securities are y_1, y_2, y_3... by simply multiplying the return on assets by the weights one gets

$$E(y) = w_1 y_1 + w_2 y_2 + w_3 y_3 + \cdots \tag{2}$$

Meanwhile, the risk should be the sum of the covariances between the different assets as

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_1 \, w_2 \, Cov(y_i \, , y_j) \tag{3}$$

Where $Cov(y_i, y_j)$ represents the covariance of y_i and y_j, which is an indicator of the correlation of the two variables. Subsequently, the model can be described as:

$$min\sigma_p^2 = \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i \, w_j \, Cov(R_i, R_j) \tag{4}$$

With the constrains:

$$\begin{cases} \sum_{i=1}^{N} w_i E(R_i) = E(R_p) = \mu \\ \sum_{i=1}^{N} w_i \ = 1 \\ w_i \geq 0, i = 1,2, \ldots, N \end{cases} \tag{5}$$

Where i means a particular asset class i, w_i is the weight of the i asset allocations, R_i is the return on i asset class, σ_i is the volatility of i asset class, R_p is the whole return of the portfolio and μ is the expected return. This optimization problem can be summarized simply by finding the asset portfolio allocation that minimizes the variance given a given rate of return.

The minimum variance model is a particular form of the mean-variance model. As shown in Fig. 1, the minimum variance model takes the point marked by the leftmost triangle in the effective frontier of the mean-variance model, where the portfolio variance is the smallest, i.e., the portfolio is the least risky. When investors use the mean-variance model for asset allocation, they tend to choose the point of tangency between their undifferentiated curve and the efficient frontier for asset allocation. Thus, the minimum variance determined by the minimum variance model will not be chosen. In practice, however, the minimum variance model is of broad interest to investors, since it achieves the smallest portfolio variance and provides a hedge in extreme situations of severe market volatility.

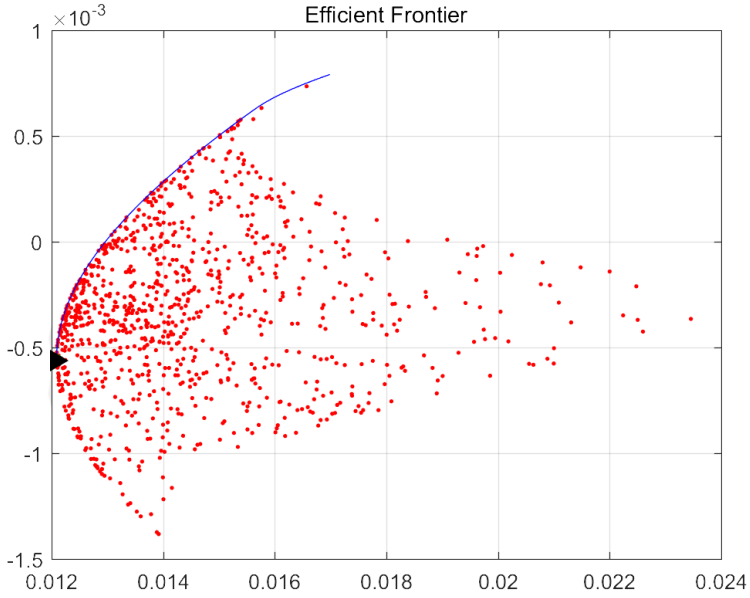


Figure 1. Effective Frontier and Minimum Variance Point.

3. Results & Discussion

3.1 Correlation analysis

This paper transforms the equivalently substituted price data for each market transaction into return yield data. This is necessary for conducting a quantitative analysis of broad asset class allocation. Given the actual situation that the digital currency market does not coincide with the trading days of the stock and commodity markets, digital currencies have redundant values on individual trading days, the redundant dates are censored, and the trading price data is transformed afterwards to ensure that the price transformation does not affect the subsequent correlation analysis results due to data overlap. The correlation coefficients for each asset class were calculated based on the collated daily frequency return data for bonds, stocks, commodities and digital currencies, as illustrated in Fig. 2. According to the results, following statements can be given

- The correlation coefficient between bond assets and stock assets was relatively low at -0.1, confirming the significant divergence between bond market movements and stock market movements during the period of empirical analysis. Economic fundamentals did not improve significantly during the period, with equity market prices exhibiting a downward swing, while policy hedging triggered an upward move in bond market prices.
- The correlation between fund assets is high, with correlation coefficients above 0.7, exceeding the threshold of 0.5.
- Commodity assets show a strong correlation with commodity index futures assets, with correlation coefficients of 0.71, 0.52, 0.76, 0.51, 0.76 and 0.5 with Wind non-ferrous, Wind non-metallic building materials, Wind coal, coke, steel and ore, Wind oil and oilseeds, Wind chemicals and Wind soft commodities respectively, indicating that their correlation coefficients have exceeded the 0.5 thresholds. As for the correlation with other assets, commodity index futures assets show better stability.
- Treasury assets exhibit a strong correlation with bond assets, with a correlation coefficient of 0.61, exceeding the threshold of 0.5.

As a whole, the current strong correlation characteristics between commodity assets and commodity index futures assets and fund assets do not meet the broad asset class allocation selection requirements, so the assets need to be deleted. Based on the above analysis, the fund, commodity and treasury assets were chosen to be deleted to ensure the weak correlations between the broad asset classes.

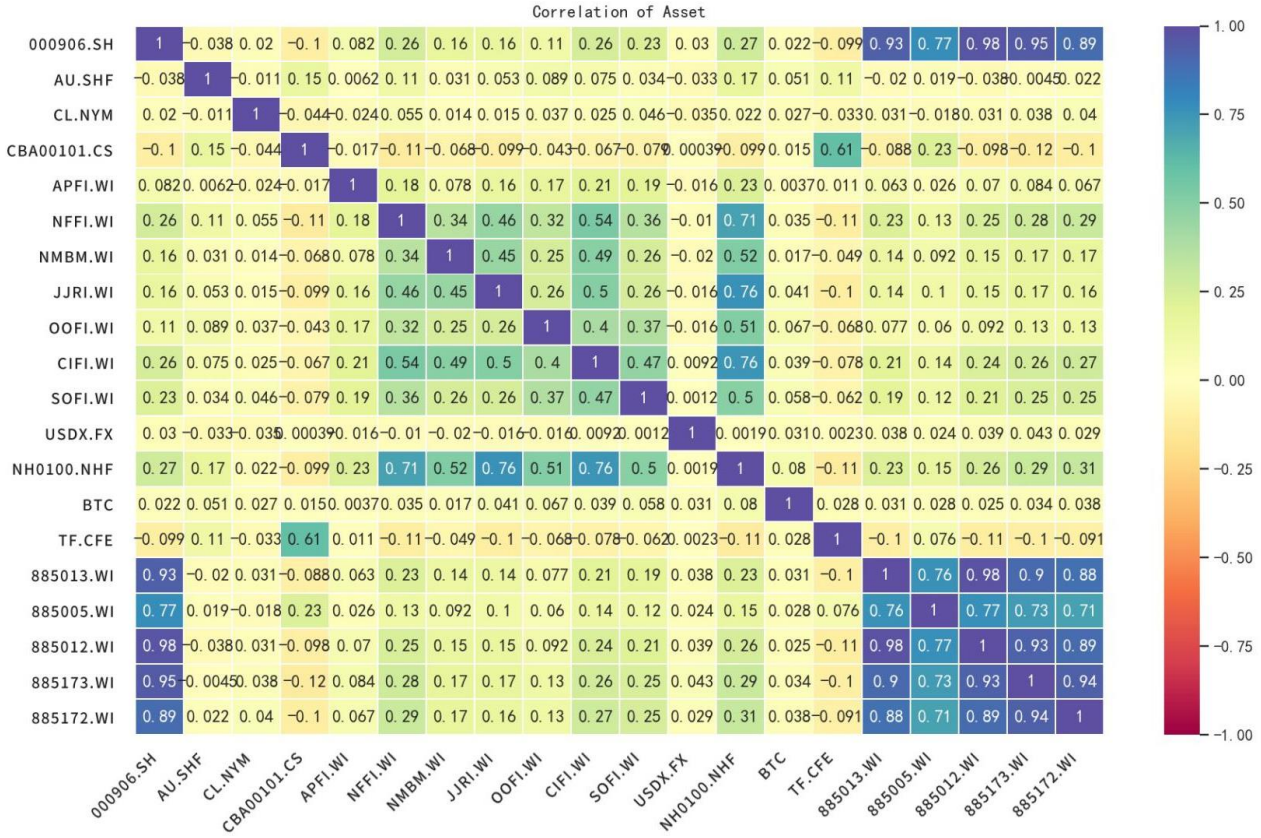


Figure 2. Correlation coefficients of Asset. The y and x ticks give the name of the underlying assets.

Afterwards, the adjusted asset price trends were plotted based on the collated daily frequency price data for bonds, stocks, gold, crude oil and other assets as illustrated in Fig. 3. One notices that the trends for the other assets are not obvious, except for the high growth and high volatility of Bitcoin, hence the variance is further calculated and ranked to more clearly characterise the assets.

Based on the daily frequency return data collated for bonds, stocks, gold, crude oil and other assets, the returns were calculated and ranked. As depicted in Fig. 4, BTC had the highest ultra-high growth rate relative to the other assets, while agricultural futures and foreign exchange had the slowest growth during the study period.

According to the daily frequency return data collated for assets such as bonds, stocks, gold, crude oil and other assets, the variance of returns was calculated and ranked. Seen from Fig. 5, BTC had the highest variance during the study period, which confirms the claim that high returns are high risk, followed by crude oil and equities and bonds had the lowest variance, i.e., the least risk.

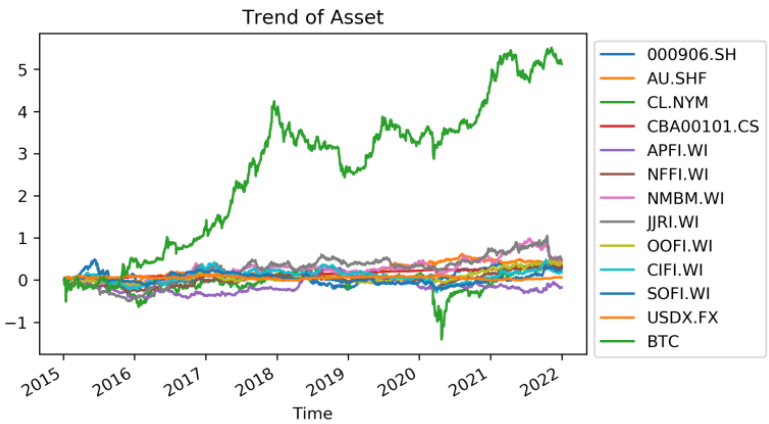


Figure 3. Log return of different assets for different time.

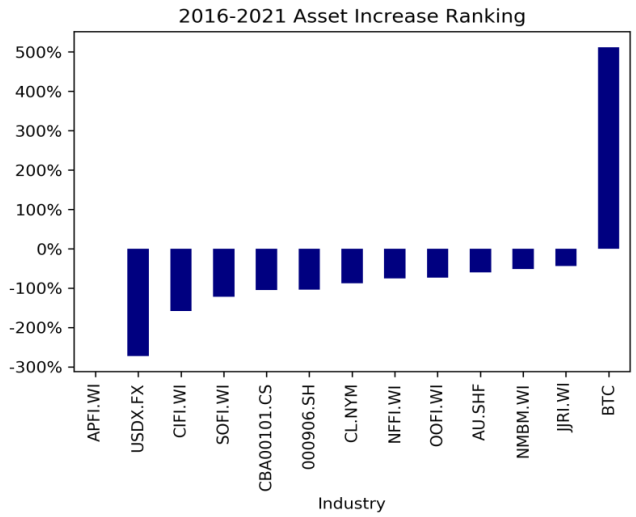


Figure 4. Yield Ranking of Assets

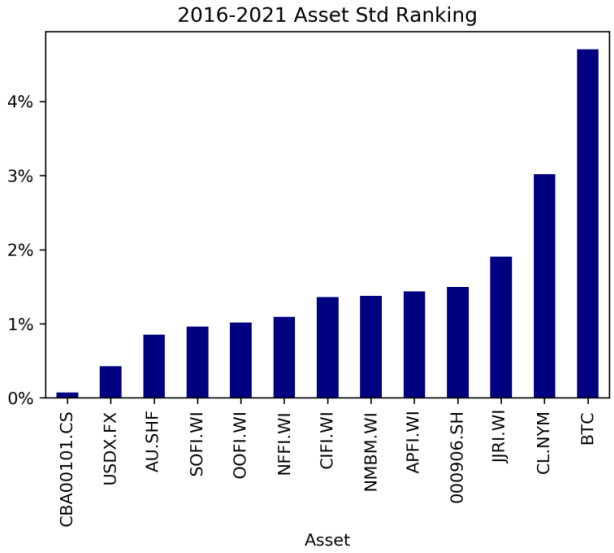


Figure 5. Variance ranking of assets

3.2 Empirical analysis

This section will plot the efficient frontier based on Markowitz's mean-variance theoretical model using historic data from 2015-2021 to derive the asset allocation for each year from 2016-2021 under the minimum variance model and the maximum Sharpe ratio model, respectively. In addition, the asset allocation portfolio based on the equally weighted model is not explicitly shown on paper as each asset is equally weighted.

Table 1. Broad Asset Class Allocation Based on the Minimum Variance Model

	000906.SH	AU.SHF	CL.NYM	CBA00101.CS	APFI.WI	NFFI.WI	NMBM.WI	JJRI.WI	OOFI.WI	CIFI.WI	SOFI.WI	USDX.FX	BTC
2016	0.39	0.0	0.13	94.61	0.00	0.65	0.27	0.14	0.34	0.0	0.60	2.88	0.00
2017	0.24	0.0	0.23	95.35	0.11	0.58	0.01	0.14	0.05	0.0	0.42	2.86	0.03
2018	0.15	0.0	0.23	93.52	0.03	0.44	0.00	0.16	0.13	0.0	0.49	2.81	0.05
2019	0.00	0.0	0.31	95.53	0.00	0.26	0.00	0.14	0.37	0.0	0.50	2.84	0.06
2020	0.01	0.0	0.29	95.31	0.03	0.27	0.00	0.40	0.33	0.0	0.12	3.23	0.02
2021	0.00	0.0	0.18	95.06	0.00	0.00	0.96	0.37	0.00	0.0	1.15	2.26	0.02

Table 2. Broad Asset Class Allocation Based on the Maximum Sharpe Ratio Model

	000906.SH	AU.SHF	CL.NYM	CBA00101.CS	APFI.WI	NFFI.WI	NMBM.WI	JJRI.WI	OOFI.WI	CIFI.WI	SOFI.WI	USDX.FX	BTC
2016	0.74	0.39	0.22	96.06	0.0	0.0	0.68	0.96	0.04	0.00	0.00	0.00	0.91
2017	0.28	0.38	0.31	96.29	0.0	0.0	0.88	0.41	0.00	0.00	0.00	0.74	0.71
2018	0.00	0.00	0.12	97.16	0.3	0.0	0.02	0.75	0.00	0.00	0.00	0.81	0.85
2019	0.32	0.02	0.52	93.26	0.0	0.0	1.67	0.71	0.00	0.00	0.00	1.12	2.38
2020	0.00	0.00	0.39	91.29	0.0	0.0	0.76	0.47	0.00	0.27	0.82	4.92	1.08
2021	0.35	0.00	0.00	97.03	0.0	0.0	0.00	0.00	0.00	0.00	0.00	2.28	0.35

The asset allocation portfolio weights based on the minimum variance model are summarized in Table I. As can be seen from the table, bonds have the highest allocation over the years, reaching over 95%, while gold, chemical commodity futures, agricultural and sideline futures and Bitcoin are almost chosen not to be purchased.

The asset allocation portfolio weights based on the maximum Sharpe ratio model are shown in Table II. Similar to the minimum variance model, the highest allocation to bonds has been above 90% over the years, whereas agricultural and non-ferrous commodity futures are barely bought.

3.3 Comparison

The net portfolio values of the three models are given in Fig. 6. Apparently, after the asset allocation, the equally weighted model has the highest net portfolio value, followed by the maximum Sharpe ratio model and the minimum variance model. The main reason for this result is the high yield of the Bitcoin; when the proportion of BTC is higher, the more substantial the return brought, but its high volatility, i.e., high risk, cannot be ignored.

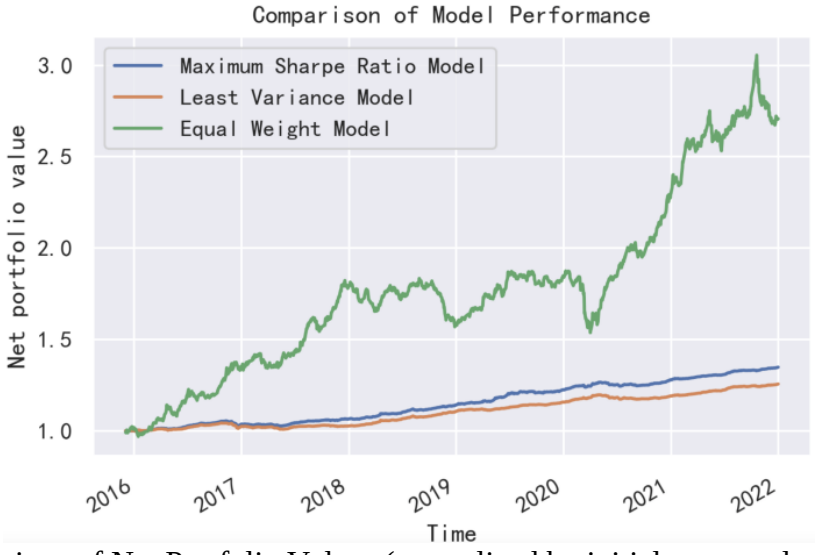


Figure 6. Comparison of Net Portfolio Values (normalized by initial assets value) under Different Models.

In order to further investigate whether the mean-variance model has advantages over traditional models in broad asset class allocation, this paper compares the constructed portfolio using the equally

weighted model and the minimum variance model based on the same data and the same back-testing rules. The three models are compared in terms of five indicators, including annualised return, annualised volatility, Sharpe ratio, maximum drawback and return-to-drawback ratio. The equally weighted model was selected for comparison with the mean-variance model for the following reasons. All three models are independent of the expected return when determining the weight of each asset for allocation. The minimum variance model is risk-dependent and the equally weighted model portfolio is always equally weighted and its weights do not change over time. Moreover, as a typical low-risk asset allocation model, the minimum variance model is a good choice as a criterion to test the risk control ability of the maximum Sharpe ratio model.

The results of the five indicators were calculated as shown in Table III. The equally weighted model has the best return performance among the three models with an annualised return of 14.34%, higher than the other two models, followed by the maximum Sharpe ratio model at 4.42% and the minimum variance model at 3.37%, respectively. In terms of volatility, the equally weighted model had a much higher annualised volatility of 174.43% than the other two models. The maximum Sharpe Ratio model and the minimum variance model have similar annualised volatilities of 21.82% and 16.54%.

When the Sharpe ratio is used as a performance indicator, the equally weighted model has the highest Sharpe ratio of 0.08589, indicating that the portfolio exceeds the risk-free assets by 0.08589 units per unit of risk, which is higher than the maximum Sharpe ratio model portfolio of 0.030492 and much higher than the minimum variance model portfolio of 0.0092. As for maximum drawback, after taking absolute values, the minimum variance model and the maximum Sharpe ratio model are close to each other with drawback values of 0.019115 and 0.019130, respectively. In contrast, the equally weighted model has a maximum of 0.135329, showing that the equally weighted model has worse downside risk control than the other two models. In addition, from the perspective of the return-to-drawback ratio, the maximum Sharpe ratio portfolio has a return-to-drawback ratio of 2.312827, the minimum variance portfolio has a return-to-drawback ratio of 1.765209, and the equally weighted portfolio has a return-to-drawback ratio of 1.059917. Therefore, a maximum Sharpe ratio with the highest return-to-drawback ratio is the best for profitability and risk control.

Table 3. Comparison of Risk-return Indicators under Different Models

	Maximum Sharpe Ratio Model	Least Variance Model	Equally Weighted Model
Annualised Return	0.044245	0.033742	0.143438
Annualised Volatility	0.218240	0.165402	1.744343
Sharpe Ratio	0.030492	0.009200	0.085890
Max Drawdown	-0.019130	-0.019115	-0.135329
Return-to-Drawdown Ratio	2.312827	1.765209	1.059917

3.4 Limitation

The model studied in this paper still has some areas of consideration and design deficiencies, and there is room for future improvement. The first is the data constraints. The data used in this strategy is currently free, and some asset price data is not available, the addition of more asset classes can offer more options for the strategy. Secondly, this paper uses the cross-sectional data, while the actual price is a series of time series. Consequently, the allocation out is based on historical data derived from the optimal allocation of the current year instead of directly predicting the future. Although the broad asset class allocation results constructed based on the mean-variance model in this paper have strong return capability, the model is not very representative of the actual investment allocation in the future, and future research can take this as a direction to further explore and optimise the model.

4. Conclusion

In summary, based on a thorough study of existing theoretical approaches to broad asset class allocation and mean-variance model, this paper uses stocks, gold, crude oil, bonds, futures, foreign exchange, funds, commodities, digital currencies and treasury bonds as the main investment targets for allocation, which concludes by comparing the specific indicators of the models to demonstrate the advantages of the mean-variance model in broad asset class allocation. Specifically, the paper begins with stating the current state of research on broad asset allocation models, of which numerous quantitative models based on the mean-variance model are widely used. In this case, the mean-variance model is chosen as the theoretical basis for broad asset class allocation. Subsequently, the selected assets are analysed in terms of correlation. The results indicate that the asset allocation needs to remove the fund and commodities assets to eliminate the strong correlation and meet the broad asset class allocation selection requirements due to the strong correlation between commodity assets and commodity index futures assets as well as fund assets. Finally, in order to demonstrate the advantages of mean-variance based models in broad asset class allocation, this paper compares the equally weighted model, the minimum variance model and the maximum Sharpe ratio model. In terms of portfolio return, the maximum Sharpe ratio model allocates asset portfolios with lower annualized volatility robust annualized return performance; in terms of return-to-drawback ratio, the maximum Sharpe ratio model achieves the highest return-to-drawback ratio, representing its best profitability and ability to control risk.

Nevertheless, there are still some areas where the model studied in this paper is not sufficiently considered, firstly the constraints of the data and secondly the fact that all the data used in this paper is cross-sectional which is not reasonable to represent the future with past data. On balance, the mean-variance model as an asset allocation model outperforms the equal-weighted model in terms of risk control and profitability. Therefore, the mean-variance model has some theoretical implications for broad asset class allocation. Overall, these results shed light on portfolio design based on mean-variance model for various kinds of assets.

References

[1] Zhang, Xueyong. & Zhang, Lin. "A Review of Research on Main Asset Class Asset Allocation Theory." Economic Perspectives No.672.02(2017): 137 - 147. doi: CNKI: SUN: JJXD.0.2017 - 02 - 013.

[2] Markowitz, Harry M. Portfolio selection. Journal of Finance 7.1 (1952): 77 - 91.

[3] Black, Fischer, and Robert Litterman. "Asset allocation: combining investor views with market equilibrium." Goldman Sachs Fixed Income Research 115 (1990).

[4] Mills, Terence C. "Equity Prices, Dividends and Gilt Yields in the UK: Cointegration, Error Correction and'Confidence.'." Scottish Journal of Political Economy 38.3 (1991): 242 - 255.

[5] Yardeni, Edward. "Fed's stock market model finds overvaluation." Topical study 38 (1997).

[6] Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to buying winners and selling losers: Implications for stock market efficiency." The Journal of finance 48.1 (1993): 65 - 91.

[7] Adler, Timothy, and Mark Kritzman. "Mean–variance versus full-scale optimisation: In and out of sample." Journal of Asset Management 7.5 (2007): 302 - 311.

[8] Sharpe, William F. "Expected utility asset allocation." Financial Analysts Journal 63.5 (2007): 18 - 30.

[9] Swensen, Anders Rygh. "The asymptotic distribution of the likelihood ratio for autoregressive time series with a regression trend." Journal of Multivariate Analysis 16.1 (1985): 54 - 70.

[10] Greetham, Trevor, and Michael Hartnett. "The investment clocks." Journal of Women s Health (2004).