# Portfolio Investment Based on Gene Expression Programming*

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## Abstract

A novel method of stock portfolio management by using technical indicators is proposed in this paper. The method hybridizes the consensus trading signals generated by the gene expression programming (GEP) proposed by Lee *et al.*, and the portfolio redemption scheme proposed by Tsai *et al.* with our stock ranking functions. The indicators were used not only for trading, but also for selecting promising stocks into our portfolio. In order to search effective indicators for ranking stocks, the Pearson's product moment correlation coefficient between the technical indicators with various parameters and one-day-ahead returns of the portfolio index (PI) are calculated. Then, seven significant indicators are found. Four weight functions $W^{(k)}$, $k = 1, 2, 3, 4$ are considered to aggregate these indicators. To get adaptive weights, the data of every three years are divided into the weighting interval (first year), aggregating interval (second year) and testing interval (third year).

The experiment data set consists of 100 Taiwan stocks, from 2002/1/4 to 2015/12/31, containing a total of 3473 trading days. The highest average annualized return of our portfolio management method is 17.17% with the weight function combination $(W^{(1)}, WA^{(2)})$. Furthermore, if the portfolio size and the redemption threshold are confined to $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$, respectively, the highest average annualized return is 17.26% with the weight function combination $(W^{(3)}, WA^{(2)})$, which is better than the annualized returns of the buy-and-hold (BAH) rule (9.26%) and Lee's method (11.05%).

*Keywords*-gene expression programming; portfolio redemption scheme; stock investment; majority vote; technical indicator;

## I. Introduction

An aggressive investor desires the best trading strategy for earning profit in the stock market. However, searching a profitable strategy is very difficult. Many machine learning and data mining approaches are applied to the design of profitable strategies, such as *support vector machine* (SVM) [5, 9], *genetic algorithm* (GA) [6, 11], *genetic programming* (GP) [4, 7], *gene expression programming* (GEP) [8] and *artificial neural network* (ANN)[1, 4], among others. These previous studies mainly focused on predicting prices or trend

of financial assets. Much effort can still be made in portfolio investment.

This paper proposes a novel portfolio management method by ranking the stocks in a predefined candidate set. Our portfolio management method hybridizes the survival-of-the-fittest trading strategies proposed by Lee *et al.* [8], and the portfolio redemption scheme proposed by Tsai *et al.* [11] with our stock ranking functions.

Lee *et al.* [8] used 27 technical indicators as the features of the GEP to search profitable strategies in the template intervals. On the current trading day, the *dynamic time warping* (DTW) is utilized to find the template intervals similar to the leading interval, which is an interval just before the current day. Then the suitable strategies of the found template intervals are combined to generate the final consensus trading signal. The trading target is the *portfolio index* (PI), which is the average value obtained by 100 stocks selected from the Taiwan stock market. Although Lee's method can track the trend of PI, to analyze which stock in PI drives the trend up or down is still difficult.

To select promising funds in the mutual fund market, Tsai *et al.* [11] proposed a scoring function for evaluating the funds. The score comes from the ranks of a fund's *return on investment* (ROI) in the historical intervals with various lengths. The funds with the highest scores will be selected into the portfolio. After several trading periods (days), if the rank of a fund's score falls outside a given redemption threshold, the capital invested in the fund is redeemed, and the capital is reinvested in another fund with the highest score. Although Tsai's scoring function performs well in the fund market, the function may not be suitable for the stock market, because the stock market is more volatile and more complex than the fund market.

We propose new scoring functions for ranking the stocks. First, we calculate the Pearson's product moment correlation coefficient between one-day-ahead returns of PI and some technical indicators with various parameters. We find out seven significant indicators, RSI, CMO, MOM, BIAS, OSC, TAPI, and MACD. Next, four weight functions are utilized to aggregate these indicators. To get adaptive weights, every three years are divided into the weighting interval (first year), aggregating interval (second year) and testing interval (third year). The weighting interval is used for calculating the weights of one indicator with various parameters; the aggregating interval is used for calculating the aggregating weights of different indicators; the testing interval is used for

evaluating the investment return of the portfolio.

The candidate stock set consists of the 100 listed companies in the Taiwan stock market which have the largest market capitalization on 1995/1/5 and have not been delisted before 2015/12/31, proposed by Lee *et al.* [8]. When the portfolio size and redemption threshold are confined to $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$, respectively, the average annualized return reaches 17.26 %, which is better than 9.26% of the buy-and-hold rule and 11.05% of Lee's method.

The rest of this paper is organized as follows. Section II presents Lee's trading strategy training method, and Tsai's portfolio redemption scheme. Section III gives our stock portfolio management method and scoring functions. Section IV presents the experimental results. Section V provides the conclusion of this paper.

## II. Preliminaries

### A. Lee's Trading Strategy Training Method

Lee *et al.* utilized the GEP for training profitable strategies on the *portfolio index* (PI), which is calculated from the 100 listed companies with the largest capitalization in the Taiwan stock market, defined as follows [8].

$$
\begin{array}{rcl}
R_i(t) & = & \frac{C_i(t)}{C_i(t-1)} - 1, \\
PI(t) & = & PI(t-1) \times \left(1 + \frac{\sum_{i=1}^{N_c} R_i(t)}{N_c}\right), \\
PI(0) & = & 100,
\end{array} \qquad (1)
$$

where $C_i(t)$, $R_i(t)$, and $PI(t)$ are the close price, return of the $i$th stock , and portfolio index on day $t$, respectively, and $N_c = 100$.

Each strategy trained from GEP produces a buying, a selling or a waiting signal. And then majority vote is used to decide the final trading consensus signal. The steps of their method are described as follows.

- **Step 1: Strategy training**
  Every $L$ days of the historical data forms a *template interval*, where every two consecutive intervals have a gap of 10 days and an overlap of $t - 10$ days. Some profitable strategies are obtained from the GEP training for each template interval.
- **Step 2: Template Searching**
  The *leading interval* with length $L$ is from day $t - L + 1$ to current trading day $t$ . The DTW is applied to search historical template intervals similar to the leading interval.
- **Step 3: Validation Checking**
  The *validation interval* with length $L_v$ is from day $t - L_v + 1$ to day $t$. The trading strategies of template intervals obtained from Step 2 are verified in the validation interval to check if they are suitable for the validation interval. If a strategy is suitable, it becomes a member for the majority vote in the next step.
- **Step 4: Final trading consensus signal**
  Suitable strategies are collected to decide the final trading consensus signal with the majority vote. The result of the
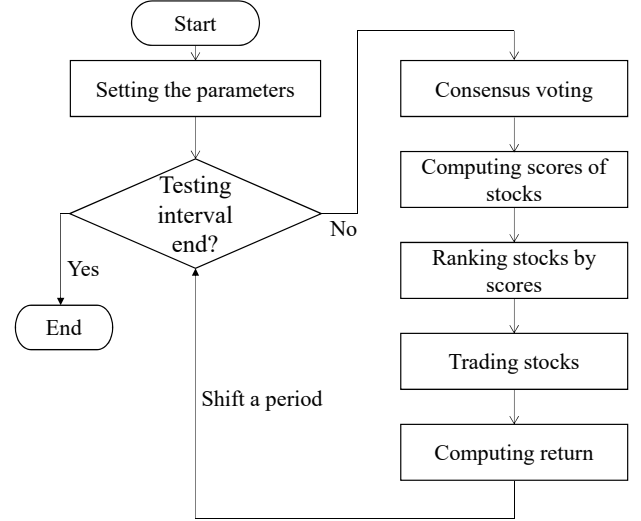


Figure 1: The flowchart of our stock portfolio management method.

vote may be a buying signal, selling signal, or waiting signal.

Steps 2 to 4 are repeated on each trading day in the testing period to compute the overall return.

### B. Tsai's Portfolio Redemption Scheme

Tsai *et al.* proposed the portfolio redemption scheme for the fund market [11], and the scheme is applied to the stock market with redesigned scoring functions in this paper.

Assume that the portfolio size is $P$, there are $N_c$ stocks in the candidate set, and the redemption threshold is $T\%$. A stock can be kept in the portfolio only if its score is still in the top $N_c \times T\%$ among the candidate set. The procedure of replacing inferior stocks by superior ones is given as follows.

- **Step 1: Redeem inferior stocks**
  If the portfolio is not empty, find out $N_i$ stocks in the portfolio whose ranks fall outside the threshold $N_c \times T\%$.
- **Step 2: Invest superior stocks**
  If the portfolio is empty, the first $P$ highest-rank stocks are selected and invested equally. Otherwise, $N_i$ highest-rank stocks in the candidate set are selected into the portfolio and these new selected stocks are invested equally with the redeemed capital.

## III. Our Portfolio Management Method

### A. Overview

Our portfolio management method hybridizes Lee's trading strategy training method [8] for generating trading signals, and the concept of Tsai's portfolio redemption [11] for investing promising stocks. Also, four weight functions for aggregating technical indicators are proposed. These weight functions are inspired from the odds ratio [2, 3]. Figure 1 illustrates the flowchart of our portfolio management method, and the procedure is described as follows.

- **Step 1: Consensus voting**
  The consensus trading signal of each trading day is generated with Lee's method.
- **Step 2: Computing the scores of stocks**
  The score of each stock in the candidate set is calculated by the scoring function (2) with some significant technical indicators.
- **Step 3: Ranking stocks by the weighted scores**
  With respect to the return obtained from one technical indicator with some specific parameter, we assign a weighted score to each stock. Here, four weight functions are used. Then the rank of each stock is determined according to its weighted score.
- **Step 4: Trading stocks**
  The stocks in the portfolio, formed by the high-ranking stocks, are traded according to the consensus signal generated in Step 1.
- **Step 5: Computing return**
  If the end of investment is not reached, go to Step 1. Otherwise, calculate the return and related statistics of the portfolio. Then, stop.

## B. The Scoring Functions with Technical Indicators

The goal of a scoring function is to find out the stocks whose prices will rise up in the future. For searching useful features for ranking stocks, the Pearson's product moment correlation coefficient of the technical indicators with various parameters and one-day ahead returns of PI are calculated. The interval for correlation calculation is from 1995/1/5 to 1999/12/31, and the statistics are illustrated in Table I.

There are seven indicators significant with respect to the returns of PI, which are the RSI, CMO, MOM, BIAS, OSC, TAPI, and MACD. The *augmented Dickey-Fuller* (ADF) test is a statistical test for a unit root in a time series. The ADF test in Table I shows that these significant technical indicators are stationary series.

Let $N_D$ denote the number of technical indicators, and $N_{d,G}$ denote the number of distinct parameters of the $d$th indicator. Our scoring functions for combining these significant indicators are given as follows.

$$S^{(k)}(x,t) = \sum_{d=1}^{N_D} \sum_{g=1}^{N_{d,G}} (-W_{d,g}^{(k)} \times V_{d,g}(x,t)), \qquad (2)$$

where $S^{(k)}(x,t)$ denotes the score of stock $x$ on day $t$ with the $k$th weight function, $W_{d,g}^{(k)}$ is the weight of the $d$th indicator with the $g$th parameter in the $k$th weight function, and $V_{d,g}(x,t)$ is the value of the $d$th indicator with the $g$th parameter of stock $x$ on day $t$. Note that $V_{d,g}(x,t)$ has been normalized in the range $[-1,1]$.

When the weighted value $-W_{d,g}^{(k)} \times V_{d,g}(x,t)$ in (2) is high, it represents that the stock's price may arise; on the other hand, if the value is low, it means that the stock's price is too high, and the probability of price reversion in the future is also high.

Table I: Pearson's product moment correlation coefficient between technical indicators with various parameters and the one-day-ahead returns of PI, and the ADF test of the technical indicator. Here $\gamma$ is correlation coefficient, $P_\gamma$ is the P value of correlation statistical test, $ADF$ is the statistics of the ADF test and $P_{ADF}$ is the P value of the ADF test. The symbols $*$, $**$, and $***$ before the P value indicate that the results are of significance levels $10\%$, $5\%$, and $1\%$, respectively.

| Indicators | $\gamma$ | $P_\gamma$ | $ADF$ | $P_{ADF}$ |
|---|---|---|---|---|
| $ROI$ | N/A | N/A | -14.91 | ***0.01 |
| $RSI^{14}$ | 0.0857 | ***0.0000 | -10.25 | ***0.01 |
| $CMO^{14}$ | 0.0857 | ***0.0000 | -10.25 | ***0.01 |
| $MOM^5$ | 0.0337 | **0.0220 | -13.23 | ***0.01 |
| $MOM^{10}$ | 0.0411 | ***0.0051 | -13.1 | ***0.01 |
| $MOM^{20}$ | 0.0454 | ***0.0020 | -13.96 | ***0.01 |
| $BIAS^5$ | 0.0847 | ***0.0000 | -14.16 | ***0.01 |
| $BIAS^{10}$ | 0.0624 | ***0.0000 | -13.27 | ***0.01 |
| $BIAS^{20}$ | 0.0674 | ***0.0000 | -12.32 | ***0.01 |
| $OSC^5$ | 0.0501 | ***0.0006 | -13.25 | ***0.01 |
| $OSC^{10}$ | 0.0536 | ***0.0002 | -13.07 | ***0.01 |
| $OSC^{20}$ | 0.0581 | ***0.0000 | -13.76 | ***0.01 |
| $TAPI$ | 0.0697 | ***0.0000 | -5.62 | ***0.01 |
| $MACD$ | 0.0317 | **0.0310 | -9.3 | ***0.01 |
| $OBV$ | 0.0113 | 0.4405 | -2.21 | 0.49 |
| $MA^5$ | -0.0067 | 0.6453 | -1.87 | 0.64 |
| $MA^{10}$ | -0.007 | 0.6334 | -1.53 | 0.78 |
| $MA^{20}$ | -0.0085 | 0.5615 | -1.26 | 0.89 |
| $EMA^5$ | -0.0064 | 0.6604 | -1.57 | 0.76 |
| $EMA^{10}$ | -0.0071 | 0.6274 | -1.56 | 0.76 |
| $EMA^{20}$ | -0.0081 | 0.5797 | -1.55 | 0.77 |

## C. The Weight functions of the Indicators

Four weight functions used in (2) are provided as follows.

$$W_{d,g}^{(0)} = 1. \qquad (3)$$

This weight function means that all indicators with various parameters have the same weight.

$$W_{d,g}^{(1)} = \frac{P_{d,g}}{\sum_{j=1}^{N_{d,G}} P_{d,j}}, \qquad (4)$$

where $P_{d,g}$ is the normalized return of the $d$th indicator with the $g$th parameter. $P_{d,g} = N(R_{d,g})$, where $N(\cdot)$ is the min-max normalization function with respect to $g$, and $R_{d,g}$ is the one-year portfolio return produced by the indicator with the consensus signals generated by Lee's method. This weight function expresses the weight of a distinct parameter of the same technical indicator.

$$W_{d,g}^{(2)} = \frac{\frac{P_{d,g}}{1-P_{d,g}}}{\sum_{j=1}^{N_{d,G}} \frac{P_{d,j}}{1-P_{d,j}}}. \qquad (5)$$

This weight function is similar to (4), but considering normalized odd performance of the same technical indicator.

$$W_{d,g}^{(3)} = \frac{\log N\left(\frac{P_{d,g}}{1-P_{d,g}}\right)}{\sum_{j=1}^{N_{d,G}} \log N\left(\frac{P_{d,j}}{1-P_{d,j}}\right)}. \qquad (6)$$

This weight function is similar to (4), but considering normalized logarithmic odd performance of the same technical indicator.

The data of every three years are divided into three intervals for getting adaptive weights, and the sliding window scheme is adopted. The first, second, and third years are used for the weighting, aggregating, and testing intervals, respectively.

The weighting interval is used for calculating the weight of the $g$th parameter in the same $d$th indicator. Lee's method is utilized for getting the trading consensus signals of the PI. After a series of replacing stocks in the portfolio with the indicator, $R_{d,g}$ is reported at the end of the weighting interval. The returns of the same indicator are normalized, thus $P_{d,g}$ is got.

Next, the aggregative weights of distinct indicators are calculated in the aggregating intervals as follows.

$$WA_d^{(k)}(x,t) = -\sum_{g=1}^{N_{d,G}} W_{d,g}^{(k)} \times V_{d,g}(x,t), \qquad (7)$$

where $WA_d^{(k)}(x,t)$ is the $k$th aggregative weight function of the $d$th indicator of stock $x$ on day $t$ in the aggregating interval.

Finally, in the testing interval, the aggregative weights of distinct indicators are combined as the weight of a stock, as follows.

$$WT^{(k)}(x,t) = \sum_{d=1}^{N_d} WA_d^{(k)}(x,t) \times VA_d(x,t), \qquad (8)$$

where $WT^{(k)}(x,t)$ and $VA_d(x,t)$ are the $k$th weight function and aggregative value of the $d$th indicator for stock $x$ on day $t$ in the testing interval, respectively.

Note that the weights of the aggregating interval and testing interval are updated annually.

## IV. Experimental Results

The candidate stock set consists of the 100 listed companies which are with the largest market capitalization on 1995/1/5, and these companies have not been delisted before 2015/12/31 in the Taiwan stock market. The 100 selected stocks are listed in Table II. The data was extracted from the Taiwan economic journal database, and the adjusted stock close price is used to avoid the effect of dividend and right.

### A. Experimental Environment

In this paper, we assume that the stocks always can be bought and redeemed on the after-hour-trading in the Taiwan stock market, and the transaction tax for buying and redeeming stocks takes 0.1425% and 0.3%, respectively. The training interval for GEP to generate profitable strategies is from 1996/1/6 to 2015/12/31, and the testing interval is from 2002/1/2 to 2015/12/31. The parameters of the technical indicators for calculating the stock scores are listed in Table III.

The GEP is implemented by using PyGEP [10] and the parameters of PyGEP are the same as Lee' method. [8].

Table II: The 100 stocks in the candidate stock set.

| Symbol | Symbol | Symbol | Symbol | Symbol | Symbol |
|---|---|---|---|---|---|
| 1101 | 1312 | 1503 | 1904 | 2303 | 2609 |
| 1102 | 1313 | 1504 | 1905 | 2308 | 2610 |
| 1103 | 1314 | 1507 | 1907 | 2311 | 2704 |
| 1104 | 1326 | 1513 | 1909 | 2315 | 2801 |
| 1108 | 1402 | 1603 | 2002 | 2330 | 2809 |
| 1109 | 1409 | 1604 | 2006 | 2371 | 2812 |
| 1110 | 1414 | 1605 | 2007 | 2501 | 2820 |
| 1201 | 1416 | 1608 | 2008 | 2504 | 2903 |
| 1210 | 1417 | 1609 | 2009 | 2505 | 2905 |
| 1216 | 1418 | 1704 | 2010 | 2506 | 2913 |
| 1218 | 1419 | 1710 | 2014 | 2511 | 2915 |
| 1229 | 1434 | 1712 | 2015 | 2515 | 9906 |
| 1301 | 1440 | 1718 | 2103 | 2601 | 9907 |
| 1303 | 1444 | 1802 | 2105 | 2603 | 9908 |
| 1304 | 1446 | 1810 | 2107 | 2605 | 9945 |
| 1305 | 1449 | 1902 | 2201 | 2606 | |
| 1310 | 1456 | 1903 | 2204 | 2608 | |

Table III: The parameters of the technical indicators and of 1% significant level with respect to the return of PI.

| Indicators | All parameters | Significant parameters |
|---|---|---|
| $BIAS^h$ | $2 \leq h \leq 120$ | $5 \leq h \leq 50$ |
| $MOM^h$ | $2 \leq h \leq 120$ | $10 \leq h \leq 30$ |
| $OSC^h$ | $2 \leq h \leq 120$ | $5 \leq h \leq 40$ |
| $CMO^h$ | $2 \leq h \leq 120$ | $5 \leq h \leq 30$ |
| $RSI^h$ | $2 \leq h \leq 120$ | $10 \leq h \leq 30$ |
| $MACD^{n,m}$ | n=13, m=26 | n=13, m=26 |
| $TAPI$ | N/A | N/A |

The parameters of our portfolio management method are the length of template interval $L = 90$, the length of validation interval $L_v = 20$, the portfolio size $P \in \{1, 2, \cdots, 10\}$, the redemption threshold $T \in \{10\%, 20\%, \cdots, 100\%\}$, and the initial capital $F = 100$. Thus there are $|P| \times |T| = 100$ parameter combinations.

The cumulative return processes of PI obtained from the BAH rule and by Lee's method in the testing interval are shown in Figure 2, and the corresponding annualized returns are 9.26% and 11.05%, respectively.



Figure 2: The cumulative return processes of PI in the testing interval. The green curve (the lower one on the right part) is obtained by the BAH rule and the red curve is obtained by Lee's method.

## B. The Experiments of All and Significant Indicators

In order to investigate the influence of distinct indicators with various parameters in our portfolio management method, we compare the results with all indicators and significant indicators, which are shown in Table III.

The weight functions used in the weighting interval $W^{(k_1)}$, and used in the aggregating interval $WA^{(k_2)}$ are denoted as a weight combination $(W^{(k_1)}, WA^{(k_2)})$, $k_1, k_2 \in \{1, 2, 3, 4\}$. There are sixteen combinations of the weighting and aggregating intervals. For each weight combination, there are 100 parameter combinations. The statistics (average, maximum, minimum, and standard deviation) of the annualized returns of each weight combination with all indicators are shown in Table IV. In addition, the results of the same experiments but with only significant indicators are shown in Table V.

If the extreme conditions are excluded, the annualized returns get higher and more stable than containing extreme conditions. That is, we confine $P$ and $T$ to the ranges $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$, then the annualized returns and their statistics are shown in Tables VI and VII, respectively.

The best average annualized returns are 17.17% and 17.26% by using weight combinations $(W^{(1)}, WA^{(2)})$ with all indicators, and $(W^{(3)}, WA^{(2)})$ with only significant indicators, respectively. The overall average annualized return with all indicators for scoring stocks is better than that with only significant indicators.

## C. The Experiments of Evenly-Combined Indicators

In these experiments, we show the results of considering all indicators with all parameters simultaneously, where the aggregating interval is removed since we do not calculate the aggregating weights of distinct indicators. The weighting and testing intervals are set to two years and one year, respectively, so that the sliding window still consists of three years. The average annualized return and the statistics are shown in Table VIII. The results show that without the aggregating interval, the average annualized return becomes worse.

## V. Conclusion

We propose the stock portfolio management method by hybridizing Lee's trading strategy-mining method, and Tsai's portfolio redemption scheme with new scoring functions. Our candidate stock set consists of the 100 listed companies with the largest market capitalization on 1995/1/5 and they were not delisted before 2015/12/31. The portfolio is traded daily with the consensus trading signal, and the stocks in the portfolio are replaced according to the scoring functions. If a buying signal comes up, the inferior stocks are replaced by the superior stocks; if a selling signal appears, all stocks in the portfolio will be redeemed; if a waiting signal shows, then the portfolio is kept the same state as the previous one.

The annualized return of the PI by the BAH rule and Lee's method are 9.26% and 11.05%, respectively. The best average annualized return of our portfolio management method is 17.17%. When $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$, the average annualized return is 17.26%, which is better than the BAH rule and Lee's method.

In the future, we may extend the portfolio management method into an online version, making the weight of the scoring function be updated more rapidly to fit the fast changes in the stock market.

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Table IV: The statistics of the annualized returns of each weight combination with all indicators in Table III.

| Avg | Aggregating | | | | Std | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 10.76% | 12.78% | 16.69% | 9.63% | 0 | 5.30% | 4.60% | 4.03% | 10.04% |
| | 1 | 10.44% | 12.77% | 17.17% | 11.44% | 1 | 5.79% | 3.87% | 3.96% | 5.01% |
| | 2 | 8.77% | 10.32% | 16.12% | 9.42% | 2 | 4.00% | 4.39% | 4.85% | 4.28% |
| | 3 | 10.13% | 13.03% | 17.00% | 11.29% | 3 | 8.01% | 3.27% | 3.80% | 4.00% |

| Max | Aggregating | | | | Min | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 16.04% | 22.52% | 27.84% | 21.07% | 0 | -20.13% | -9.06% | 3.29% | -34.76% |
| | 1 | 17.87% | 19.21% | 26.50% | 19.79% | 1 | -10.65% | -1.29% | 6.89% | -16.57% |
| | 2 | 16.42% | 21.57% | 34.69% | 20.84% | 2 | -6.87% | 1.81% | 2.86% | -2.30% |
| | 3 | 17.97% | 20.62% | 24.92% | 20.09% | 3 | -33.74% | 3.90% | 4.89% | -2.12% |

Table V: The statistics of the annualized returns of each weight combination with significant indicators.

| Avg | Aggregating | | | | Std | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 2.99% | 7.17% | 12.68% | 6.64% | 0 | 6.75% | 6.53% | 6.11% | 6.57% |
| | 1 | 4.97% | 5.84% | 13.05% | 3.05% | 1 | 5.56% | 6.40% | 5.33% | 8.14% |
| | 2 | 1.01% | 4.78% | 11.01% | 2.63% | 2 | 10.79% | 8.53% | 4.76% | 9.42% |
| | 3 | 5.27% | 5.87% | 13.10% | 3.24% | 3 | 6.80% | 7.00% | 6.03% | 10.14% |

| Max | Aggregating | | | | Min | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 12.44% | 18.60% | 24.92% | 17.40% | 0 | -16.90% | -19.11% | -11.65% | -17.29% |
| | 1 | 14.45% | 16.60% | 24.63% | 16.00% | 1 | -17.12% | -18.44% | -6.44% | -22.93% |
| | 2 | 16.35% | 17.93% | 26.87% | 16.56% | 2 | -32.13% | -34.15% | 0.39% | -29.66% |
| | 3 | 15.44% | 15.76% | 31.14% | 16.02% | 3 | -29.69% | -18.80% | -17.62% | -32.80% |

Table VI: The statistics of the annualized returns of each weight combination with $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$ using all indicators.

| Avg | Aggregating | | | | Std | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 12.76% | 14.01% | 16.69% | 9.63% | 0 | 1.76% | 1.85% | 2.27% | 1.68% |
| | 1 | 13.75% | 14.21% | 16.78% | 13.27% | 1 | 1.70% | 2.62% | 2.90% | 1.89% |
| | 2 | 10.09% | 10.95% | 15.12% | 10.92% | 2 | 3.22% | 4.21% | 2.97% | 4.29% |
| | 3 | 13.29% | 14.22% | 17.26% | 13.01% | 3 | 1.48% | 2.00% | 2.80% | 1.83% |

| Max | Aggregating | | | | Min | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 16.01% | 18.43% | 23.15% | 16.05% | 0 | 8.36% | 10.04% | 12.58% | 5.96% |
| | 1 | 17.87% | 19.21% | 23.12% | 18.92% | 1 | 9.19% | 8.78% | 9.93% | 9.75% |
| | 2 | 15.08% | 20.69% | 22.86% | 20.84% | 2 | 3.07% | 1.81% | 9.73% | 2.19% |
| | 3 | 17.32% | 18.81% | 24.26% | 16.60% | 3 | 9.68% | 10.49% | 11.65% | 8.22% |

Table VII: The statistics of the annualized returns of each weight combination with $3 \leq P \leq 10$ and $40\% \leq T \leq 80\%$ using significant indicators.

| Avg | Aggregating | | | | Std | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 6.04% | 9.51% | 14.51% | 9.24% | 0 | 4.33% | 4.43% | 3.51% | 4.41% |
| | 1 | 6.72% | 7.41% | 13.90% | 6.81% | 1 | 3.21% | 4.51% | 2.88% | 5.13% |
| | 2 | 6.86% | 7.80% | 11.08% | 6.80% | 2 | 4.70% | 3.67% | 2.66% | 3.54% |
| | 3 | 7.78% | 8.03% | 14.25% | 7.96% | 3 | 3.24% | 4.46% | 2.73% | 4.46% |

| Max | Aggregating | | | | Min | Aggregating | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 | $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
| Weighting | 0 | 12.44% | 17.35% | 21.65% | 17.40% | 0 | -15.82% | 0.02% | 9.00% | 1.52% |
| | 1 | 13.37% | 14.27% | 21.43% | 14.02% | 1 | 0.51% | -7.22% | 8.92% | -8.04% |
| | 2 | 16.35% | 13.23% | 17.15% | 13.06% | 2 | -4.75% | -3.68% | 5.56% | -1.50% |
| | 3 | 14.39% | 14.30% | 19.49% | 13.78% | 3 | -0.38% | -8.38% | 8.02% | -8.09% |

Table VIII: The statistics of the annualized returns without the aggregating interval.

| $W^{(\cdot)}$ | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| Avg | 10.88% | 11.74% | 13.09% | 11.22% |
| Std | 4.69% | 4.01% | 3.59% | 4.67% |
| Max | 16.04% | 23.50% | 21.55% | 17.21% |
| Min | -12.14% | -3.92% | 2.67% | -12.14% |