COMP4971C Independent Work (Spring, 2018/2019)

# Momentum Trading in Hong Kong Stock Market

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# Content

# Introduction

In this study, momentum trading strategies is used in Hong Kong stock market. Hong Kong stock market has total number 13,869 of listed securities. Listed companies are from all over the world, which included Hong Kong, mainland China, Taiwan, United States, etc. Upward momentum trading strategy is mainly used in this study, with additional indicators as auxiliary. Our target is to have a higher return comparing with the Hang Seng Index and beat the inflation, with a simple rule indicated by the momentum.

# Software Framework and Data

Hong Kong historical data is download from Yahoo finance. In this report, *Jupyter notebook* with *Python 3.6.3* is used in this project. The program is developed based on libraries:

- *pandas,* for data management.
- *matplotlib,* for data visualization.
- *numpy*, for mathematics computation.

# Overview

Momentum trading is aimed to capture the trend, either upward or downward, example of momentum is shown in figure 1. In this study, we believe that if the stock price is moving in one direction (either going up, or down), it would be likely to continuously move in the same direction. In this study, we only focus on the upward trend, which is the increasing trend. Since the downward trend requires us to sell the stock. If the stock in increasing while we are selling it, then there is a chance that we will lose all the money. So, we believe that the selling process required more work on stopping the loss. Therefore, in the preliminary state, we only focus on the upward trend. To determine the trend, we use long-term (in unit of day) percent change and short-term (in unit of day) percent change. After buying the stock, we will hold it for a fixed period. Then, we will optimize these three parameters, which are the days of the long-term percent change, days of the short-term percent change and the days for holding the stock, by using the around 75% of the past historical data, which is from 1/1/2005 to 1/1/2015.

After that, we implement different additional indicators to improve the strategy, such as the moving average convergence divergence. Finally, we use the tuned parameters to test the remaining 25% of the data in the period 1/1/2015 to 1/1/2018.

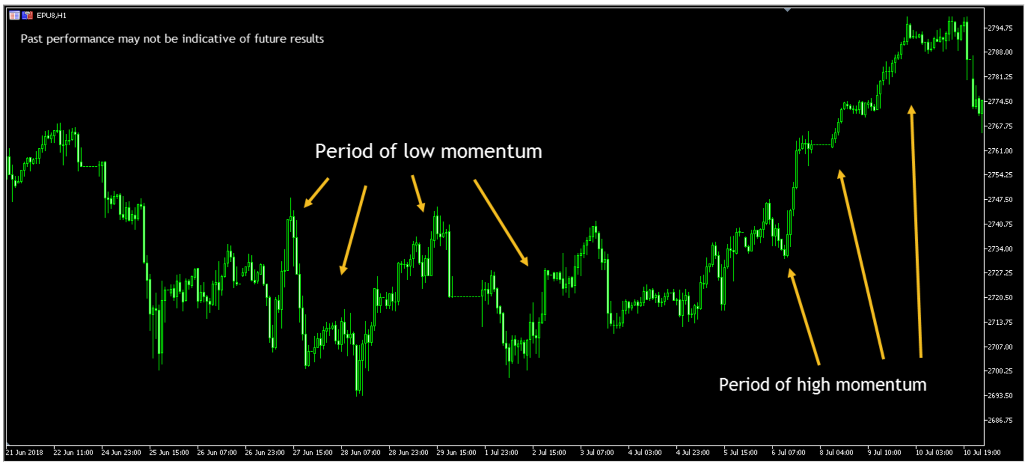


Figure 1: Example of “momentum” of the price. The right-hand side shows the high upward momentum trend, while we believe that it will continuously go up.

# 1. Methodology

We split the data into training and testing sets by the ratio around 75/25. To test our strategy, the period 1/1/2005 to 1/1/2015 (around 75%) is selected to optimize the parameters. Then, we will use the period 1/1/2015 to 1/1/2018 (around 25%) to quantify the performance of our strategy.

## 1.1. Selection of stock

There are 75 valid stocks are selected by the following rules:

1. Setting the average daily volume limit to be 1,000,000: The stocks with average daily volume larger than the limit will be selected.
2. Stock is listed within the period: Since there are some stocks that was closed during the period, and some had not yet in the list during the period. We will drop all those stocks for simplicity.

## 1.2. Stock Data used in the study

Daily stock data is collected from Yahoo Finance. For each date, there are "Open", "High", "Low", "Close", "Adj Close" and "Volume", sample data is shown in Table 1. In this study, we only focus on "Adj Close" column, for programming simplicity.

Table 1

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 4/1/2000 | 71.4718 | 72.1865 | 70.0424 | 70.0424 | 35.22998 | 3194413 |
| 5/1/2000 | 66.8261 | 67.8982 | 64.8607 | 65.218 | 32.80341 | 6058531 |
| 6/1/2000 | 65.7541 | 66.1114 | 60.751 | 62.0018 | 31.18572 | 10440480 |
| 7/1/2000 | 62.8952 | 63.6099 | 61.8231 | 63.2525 | 31.81479 | 6049796 |
| 10/1/2000 | 65.3967 | 66.4688 | 63.7886 | 63.7886 | 32.08444 | 5195405 |
| 11/1/2000 | 65.3967 | 66.1114 | 63.9673 | 65.3967 | 32.89328 | 6175861 |
| 12/1/2000 | 64.3246 | 65.9327 | 63.4312 | 64.3246 | 32.35403 | 5453898 |
| 13/1/2000 | 64.682 | 64.8607 | 63.0739 | 63.4312 | 31.90468 | 3499841 |
| 14/1/2000 | 63.6099 | 64.146 | 61.6444 | 62.5378 | 31.45531 | 3903580 |

Stock data of "0001.HK" (CK Hutchison Holdings Limited), from 4/1/2000 to 14/1/2000

# 1.3. Trading Strategy

In order to find out the momentum of the stock price, we assign two parameters to determine the trend. They are the $t_1$ days Percent Change $PC(t_1)$ and $t_2$ days Percent Change $PC(t_2)$. $PC(t_1)$ indicates the relatively long-term trend, while $PC(t_2)$ indicates the relatively short-term trend ($t_1 > t_2$). Buy signal will be generated if it is determined as upward momentum, which means the increasing trend. Sign of the momentum at time $T$ is defined by:

$$p(T) = \begin{cases} > 0, & PC(t_1) > 0 \text{ and } PC(t_2) > 0 \\ < 0, & PC(t_1) < 0 \text{ and } PC(t_2) < 0 \\ = 0, & otherwise \end{cases},$$

where $PC(\tau) = \frac{q_T - q_{T-\tau}}{q_T} \times 100\%$, $q_T$ is the price at time T, $q_{T-\tau}$ is the price at time $T - \tau$, which means $\tau$ days ago.

The reason why there are two parameters, $PC(t_1)$ and $PC(t_2)$, is to avoid the "noise". Figure 2 shows the "noise", which is not out target. The blue solid line indicates the past data, black vertical line indicates 'today", red dotted line indicates the possible price in the future. Considering the situation shown in figure 2a, if we only calculate $PC(4)$ (percent change between point R and point Q), there is a downward trend. But the pattern of stock price may be just a fluctuation only. Similarly, for figure 2b, if we only consider $PC(10)$ (percent change between point P and point Q), there is a buy signal generated. But actually, there may also be a fluctuation. There may be a wrong diagnosis.

To tackle this problem, the strategy described above is applied, to maximum the probability of capturing the real upward trend shown in Figure 3a. We define the upward trend when both long-term and short-term percent changes $PC(10)$ and $PC(4)$ are positive. Similarly, Figure 3b shows the downward trend, with both $PC(10)$ and $PC(4)$ are negative.

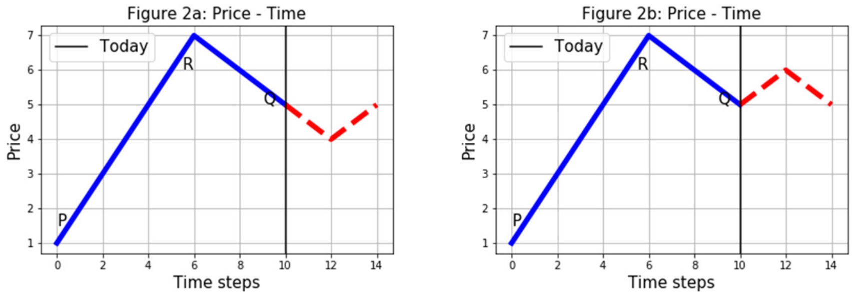


Figure 2a, b: Examples of the "noise", the blue solid line indicates the past data, black vertical line indicates 'today", red dotted line indicates the possible price in the future

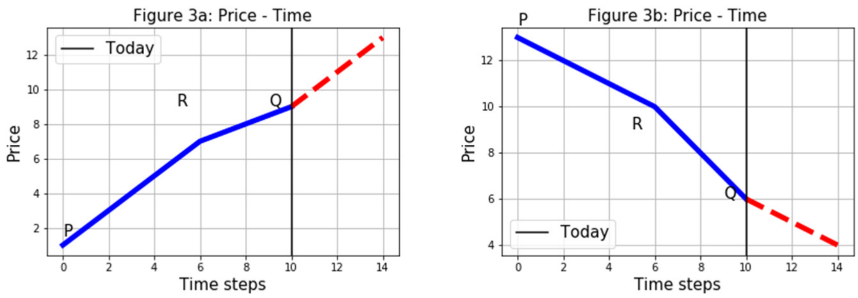


Figure 3a, b: Examples of the real trend, the blue solid line indicates the past data, black vertical line indicates 'today", red dotted line indicates the possible price in the future

Denote $t_H$ as the number of days for **H**olding the stock. For our strategy, we will hold the stock for $t_H$ days no matter how the price goes within the period. When the time reaches the holding days $t_H$, we will calculate the momentum again. If there is still an upward trend, then we will hold for one more day, until the momentum changes to downward trend. In other words, we will repeatedly calculate the momentum if it reaches $t_H$. We sell the stock if it is in downward trend.

$$Sell\ \ Signal = \begin{cases} True, & t \geq t_H\ \ and\ \ p_t \leq 0 \\ False, & otherwise \end{cases}.$$

To calculate the profit, denote $W(0) = W_0$ as the net worth at the beginning. Since there are $n$ (=75 in this study) stocks are chosen, and we assign the money to each stock equally, each individual stock's net worth will not affect each other. So, initial net worth for each individual stock $w_i(0) = W_0/n$. As we trade, net worth for an individual stock will change over time, net worth at time $t$ is denoted as $w_i(t)$. If buy signal for stock $i$ is generated at time $t$ with price $q_{i,t}$, number of shares we will buy can be calculated by $s_i = \lfloor w_i(t)/q_{i,t} \rfloor$. Including the transaction fee ε (in this study, we fix the fee for each transaction to be HKD 180), the equity for stock *i* when we close the trade, would be $w_i(t) = s_i \times q_{i,t} - \varepsilon$. Equity of the basket of all stocks at time $t$ can be calculated by $W(t) = \sum_i w_{i,t} = \sum_i (s_i \times q_{i,t} + c_{i,t})$, where $\sum_i c_{i,t}$ is the cash remained at time $t$.

### 1.3.1. Steps to calculate the equity

1 Select the stocks according to the section "Selection of stock".

2 Equally assign the money to each stock and treat each of them as an individual system. In other words, they will not affect each other.

3 Buy as many as shares if a buy signal is generated for an individual stock.

4 Sum the net worth and the remaining cash of each stock to calculate the whole net worth of our portfolio.

# 2. Optimization

## 2.1. Measurements

### 2.1.1. Compound Annual Growth Rate (CAGR)

"The rate of return that would be required for an investment to grow from its beginning balance to its ending balance, assuming the profits were reinvested at the end of each year of the investment's lifespan" (Investopedia, 2019).

$$CAGR = (\frac{EB}{BB})^{\frac{1}{n}} - 1,$$

where $EB$ is the ending balance, $BB$ is the beginning balance, $n$ is the number of years.

### 2.1.2. Maximum Draw Down (MDD)

"The Maximum loss from a peak to a trough of a portfolio, before a new peak is attained" (Investopedia, 2019).

$$MDD = \frac{(Trough - Peak)}{Peak}.$$

### 2.1.3. Sharpe Ratio

"The average return earned in excess of the risk-free rate per unit of volatility or total risk" (Investopedia, 2019).

$$Sharpe\ \ Ratio = \frac{R_p - R_f}{\sigma_p},$$

where $R_p$ is return of portfolio, $R_f$ risk-free return (return of Hang Seng Index) $\sigma_p$ is standard deviation of the portfolio's excess return.

## 2.2. Result

We try different combinations of $t_1$, $t_2$, $t_H$, which are the days for long-term and short-term trend and the days for holding, to select the highest return. Figure 4 shows all the combinations in the 3D plot (axes are $t_1$, $t_2$, $t_H$). $t_H$ is in the range from 10 days to 100 days, in the steps of 10 days. $t_2$ is from 20 days to 150 days. $t_1$ is from 20 days to 150 days. With the constraint that $t_1 > t_2 > t_H$. Table 2 shows the best five combinations according to the *CAGR*.

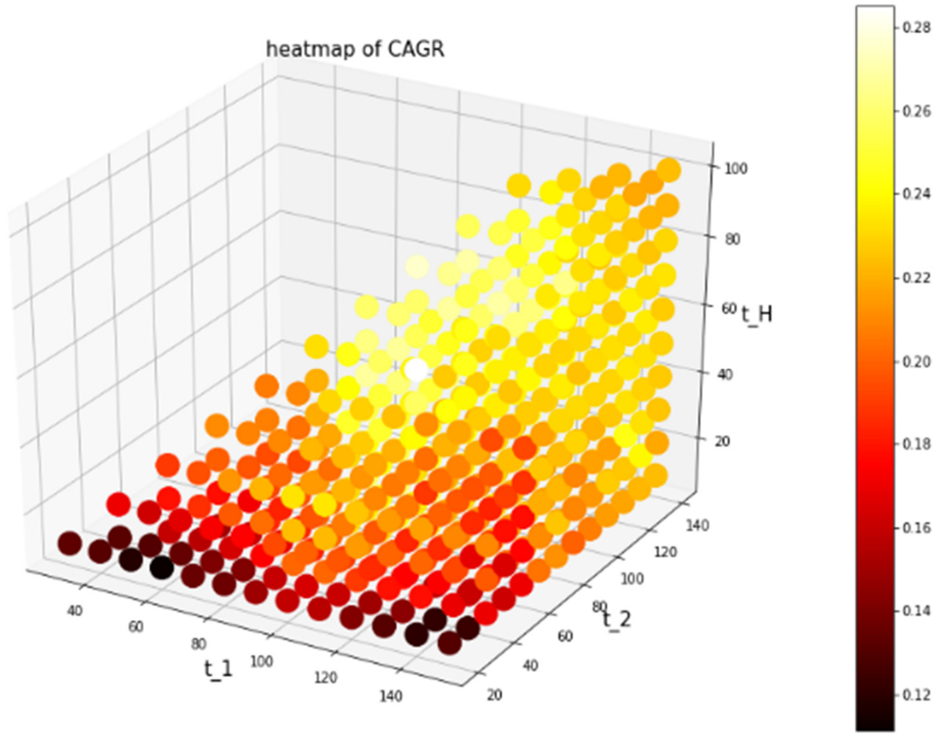


Figure 4a: CAGR 3D plot of $t_1$, $t_2$, $t_H$

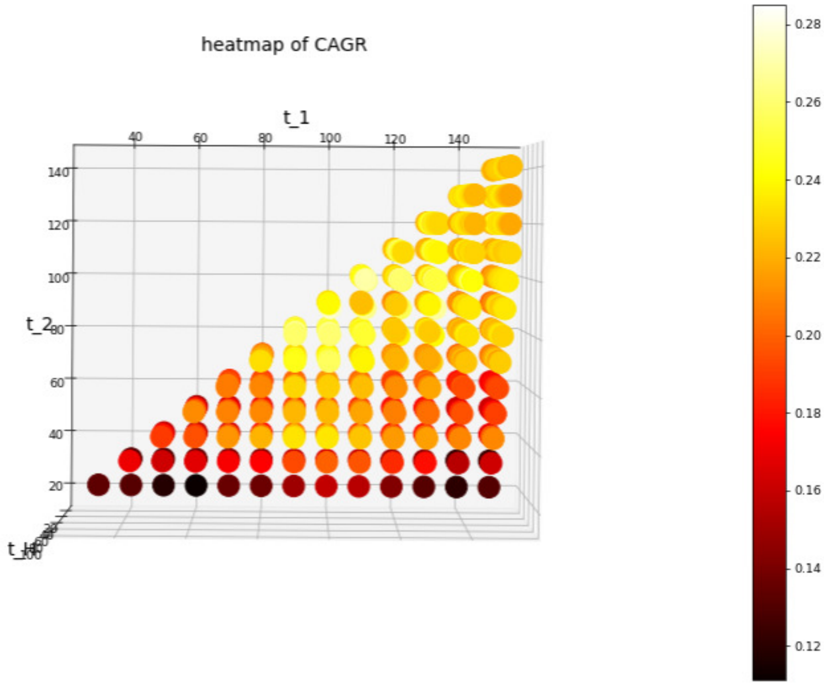


Figure 4b: CAGR 2D plot of $t_1$, $t_2$

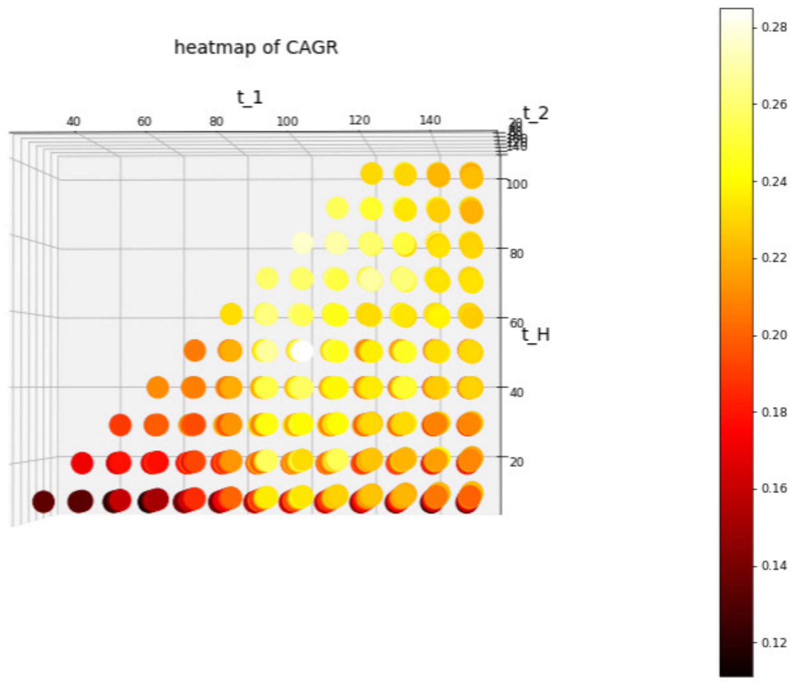


Figure 4c: CAGR 2D plot of $t_1$, $t_H$

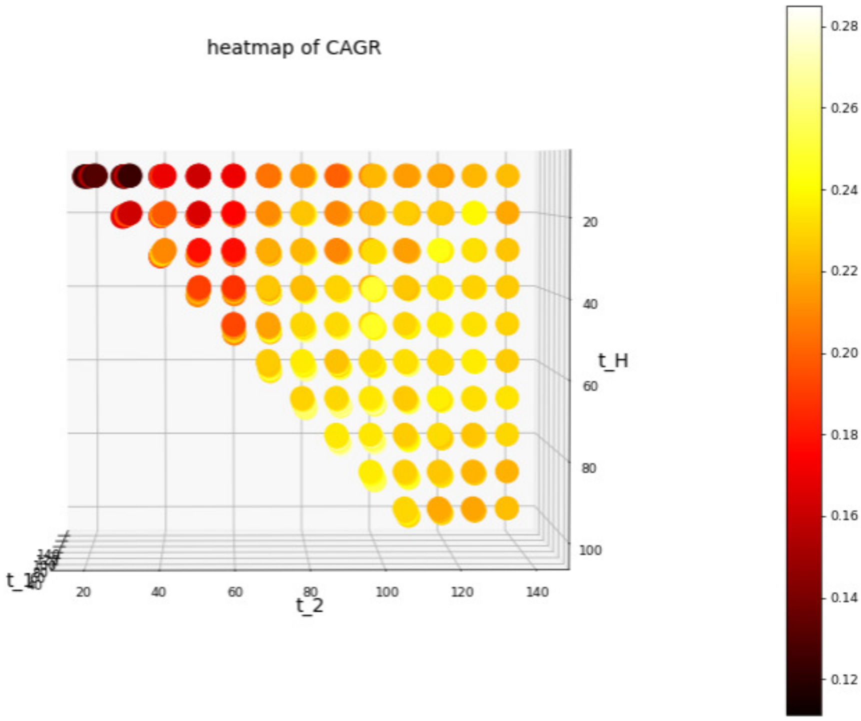


Figure 4d: CAGR 2D plot of $t_2$, $t_H$

Table 2: Best five combinations based on CAGR
(The best result of each column is bolded)

| | $t_1$ | $t_2$ | $t_H$ | CAGR | MDD | Sharpe Ratio |
|---|---|---|---|---|---|---|
| **1** | 100.0 | 90.0 | 50.0 | **0.285020** | -0.419225 | **19.122591** |
| **2** | 100.0 | 90.0 | 80.0 | 0.275732 | -0.452795 | 18.105107 |
| **3** | 110.0 | 100.0 | 80.0 | 0.269722 | -0.462103 | 17.258386 |
| **4** | 120.0 | 100.0 | 70.0 | 0.269038 | -0.422275 | 18.200563 |
| **5** | 90.0 | 80.0 | 50.0 | 0.267857 | **-0.393082** | 18.567482 |

To avoid overfitting, we set the threshold to be the highest 5% combinations of *CAGR*, which is around 26%, in this study. We keep the combinations which the *CAGR* is greater or equals to 26%. Then, we calculate the average $t_1$, $t_2$, $t_H$ of this subset of data, as follow

$$\overline{t_1} = \frac{\sum_i^S t_{1_i}}{N}, \qquad \overline{t_2} = \frac{\sum_i^S t_{2_i}}{N}, \qquad \overline{t_H} = \frac{\sum_i^S t_{H_i}}{N},$$

where $S = \{(t_1, t_2, t_H), CAGR(t_1, t_2, t_H) > 26\%\}$.

The results are $\overline{t_1} \approx 111\ \ (days), \overline{t_2} \approx 91(days), \overline{t_H} \approx 76\ \ (days)$ in this study. The performance is shown in figure 5.


Figure 5: The equity curve of the strategy from 2005 to 2015. Black curve indicates the equity of HSI, for comparison. Green curve indicates the equity of our strategy. Red curve indicates the drawdown of our strategy. The bar below are the annual returns of our strategy.

From the above equity curve, we can see that our strategy (green line) had a better performance comparing to the HSI (black line). Because the CAGR of our strategy is around 25.41%, while HIS's CAGR is only 5.7%. But we can also see that the drawdown of our strategy is also very high, with the maximum value 43.37%, in the financial crisis period, from the end of 2007.Besides, from 2011 to 2012, our strategy is also losing money. In order to reduce the loss, some additional constraints are introduced to help.

# 3. Additional constraints

## 3.1. SMA of the HSI

We first calculate the $n$ days Simple Moving Average is calculated by the equation:

$$\mathrm{SMA}(n) = \frac{q_{t-n}+q_{t-n-1}+\cdots+q_{t-1}}{n},$$

$q_{t-n}$ is the price at $n$ days ago. The constraint requires today's HSI to be greater that its simple moving average. In this study, we set the $n$ to be $t_2$, which is day for determining the short-term trend mentioned above. In other words,

$$Buy\ \ Signal = \begin{cases} True, & p_i(t) > 0\ \ and\ \ HSI_t > SMA_{HSI}(91) \\ False, & otherwise \end{cases}.$$

The result of the training period is shown in figure 6. After introducing this constraint, the CAGR decreases a lot, from 25.41% to 14.92%. However, we can see that this constraint can effectively stop loss during the period of financial crisis (from around June 2008). Overall, the maximum drawdown decreases from 43.37% to 37.92%.


Figure 6: The equity curve of adding the constraint "SMA of the HSI", from 2005 to 2015

# 3.2. SMA of individual stock

The rule is similar to the above constraint, but we are now only considering each individual stock. In other words, the buy signal would be

$$Buy\ \ Signal = \begin{cases} True, & p_i(t) > 0\ \ and\ \ q_{i,t} > SMA_{q_i}(91) \\ False, & otherwise \end{cases} .$$

$q_{i,t}$ is the price of an individual stock at time *t*. $SMA_{q_i}(n)$ is the *n* days simple moving average of that individual stock. The result is shown in figure 7. This constraint also helps to reduce the loss, maximum drawdown decreases from 43.37% to 40.18%, while it can keep the high CAGR which is around 23.92%. It is better than the SMA of HSI constraint.


Figure 7: The equity curve of adding the constraint “SMA of the individual stock”, from 2005 to 2015

# 3.3. Z-score of individual stock

The z-score will be used to measure the uncertainty. The *n* days moving standard deviation of each individual stock will be first calculated by:

$$\sigma_i(n) = \sqrt{\frac{\sum |q_i - \overline{q_i}|^2}{n}}$$

$\overline{q_i}$ is the average price from time *t-n* to *t*. The z-score is calculated by:

$$z_i(n) = \frac{q_{i,t} - SMA_i(n)}{\sigma_i(n)}$$

The reason we add the z-score is to diagnosis the real upward trend. When the price has a larger upward momentum, which means that the price is increasing and would be higher than the average price of previous period. We believe that this increasing trend is reflected by the z-score, in this study, we set the threshold to be 2, and the range of the previous period *n* to be $t_1$. Therefore, by adding this constraint the buy signal will be

$$Buy\ Signal = \begin{cases} True, & p_i(t) > 0\ \ and\ \ |z_i(91)| > 2 \\ False, & otherwise \end{cases} .$$

The result is shown in figure 8. From figure 8, we can see that this constraint can also reduce the loss. The equity curve does not decrease a lot in the financial crisis period (from 2008). And the CAGR also does not decrease a lot, only from 25.41% to 22.55%.

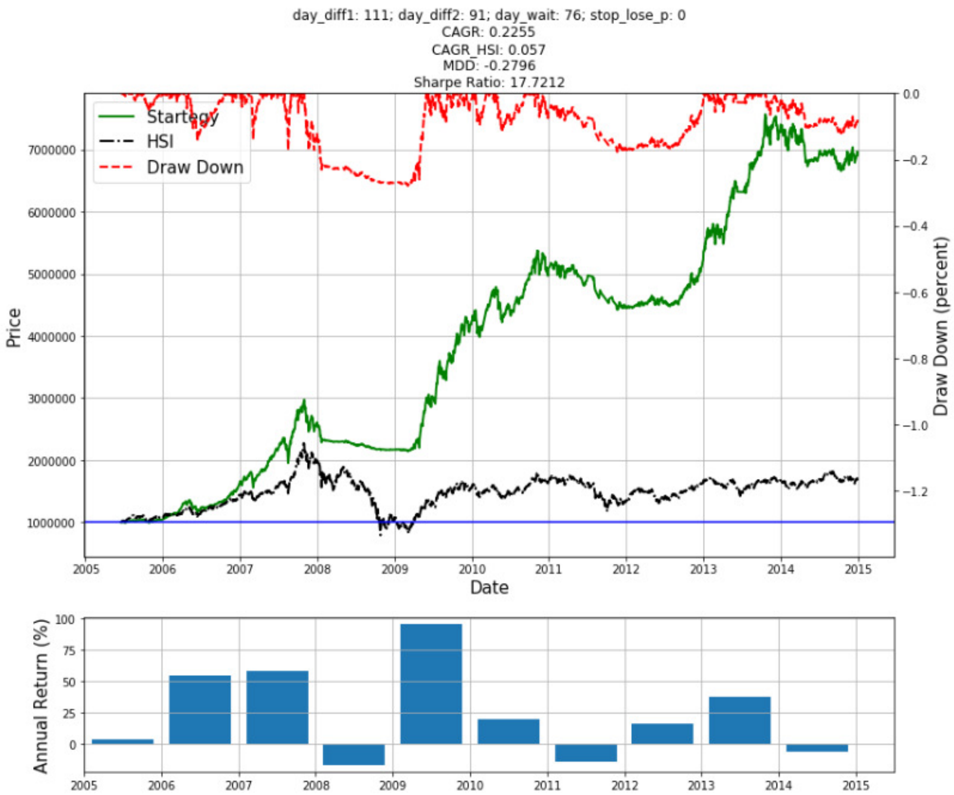


Figure 8: The equity curve of adding the constraint “Z-score” , from 2005 to 2015

# 3.4. MACD of HSI

There are two simple moving averages used to calculate the MACD. First, the difference value between them is calculated by:

$$DIF_{HSI}(n_1, n_2) = SMA_{HSI}(n_1) - SMA_{HSI}(n_2)$$

Then, the MACD is calculated by take the moving average of DIF:

$$MACD_{HSI}(n_3) = SMA_{DIF_{HSI}}(n_3)$$

In this study, we set $n_1 = 12,\ n_2 = \ 26,\ \mathrm{n}_3 = 9$. It means that the buy signal in this study is determined by

$$Buy\ \ Signal = \begin{cases} True, & p_i(t) > 0\ \ and\ \ DIF_{HSI}(12, 26) \geq MACD_{HSI}(9) \\ False, & otherwise \end{cases}.$$

The result is shown in figure 9. It also deceases the drawdown, from 43.37% to 38.19%, while the CAGR also decrease from 25.41% to 24.7%.

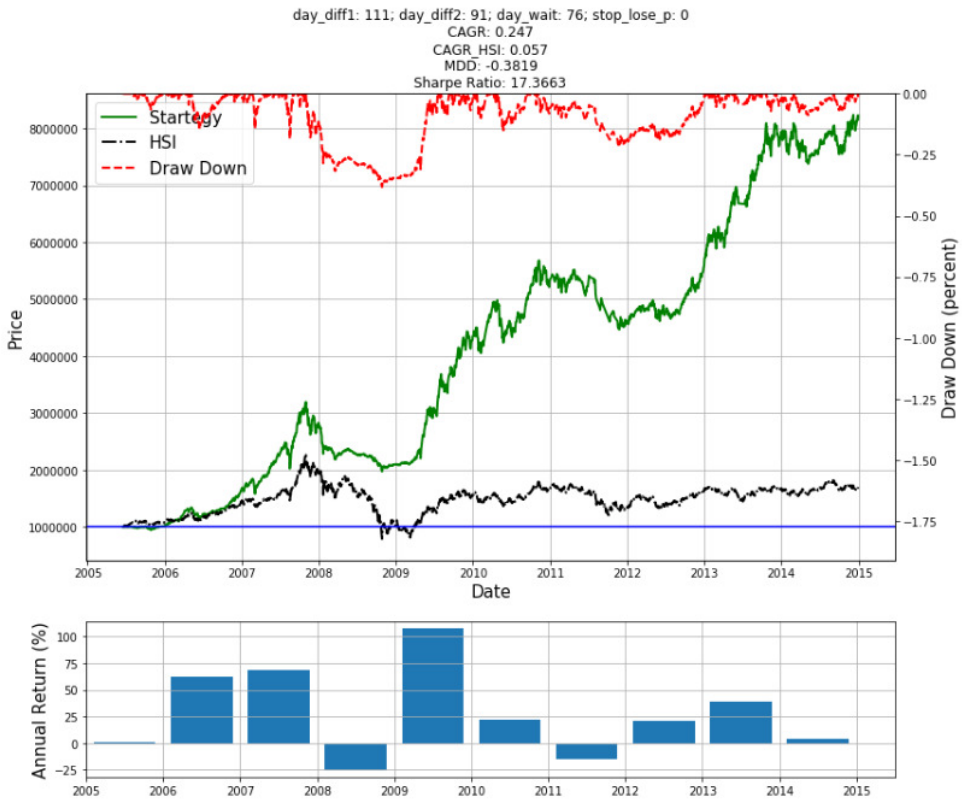


Figure 9: The equity curve of adding the constraint “MACD of HSI” , from 2005 to 2015

# 3.5. MACD of individual stock

This constraint is similar to the previous one, but the DIF and MACD are calculated based on each individual stock:

$$DIF_i = SMA_i(n_1) - SMA_i(n_2)$$
$$MACD_i = SMA_{DIF_i}(n_3)$$

The parameters $n_1, n_2, n_3$ are the same as the previous constraint. Therefore, the buy signal is generated by:

$$Buy\ \ Signal = \begin{cases} True, & p_i(t) > 0\ \ and\ \ DIF_i(12,26) \geq MACD_i(9) \\ False, & otherwise \end{cases}$$

The result is shown in figure 10. The drawdown is also decreased, from 25.41% to 24.97%, but not significant. While the CAGR decreases from 25.41% to 24,97%.

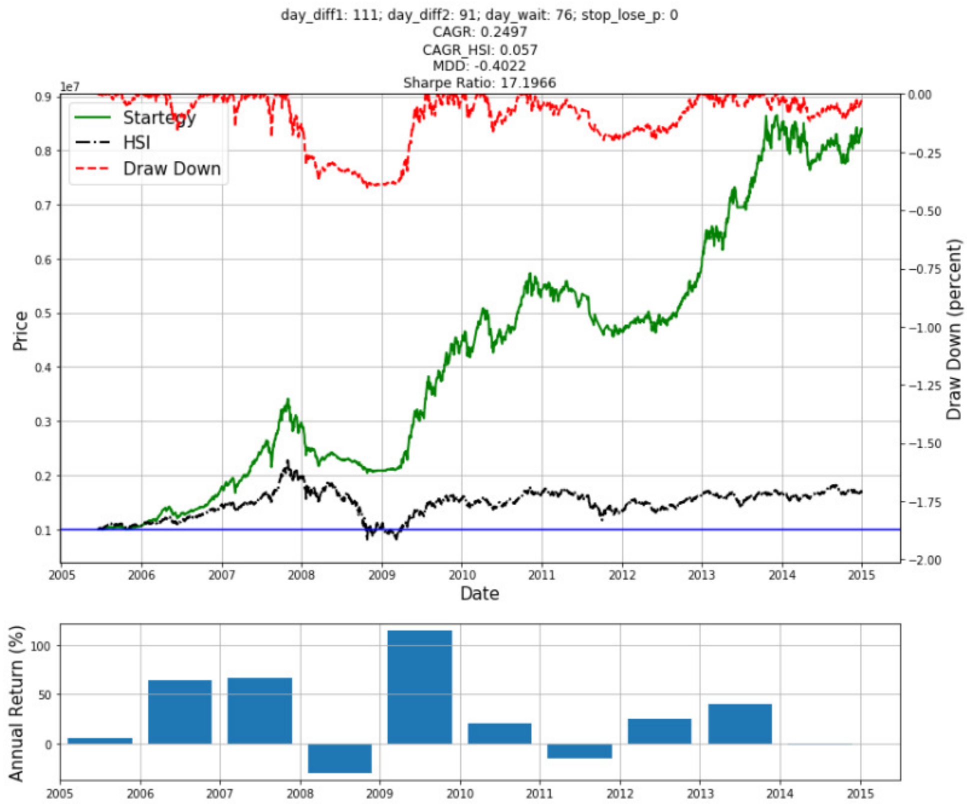


Figure 10: The equity curve of adding the constraint “MACD of individual stock” , from 2005 to 2015

# 3.6. Comparison

Table 3: Performance of the strategies, from 2005 to 2015
(The best result of each row is bolded)

| | Original | SMA of HSI | SMA of stock | Z-score | MACD of HSI | MACD of stock |
|---|---|---|---|---|---|---|
| CAGR (%) | **25.41** | 14.92 | 23.92 | 22.55 | 24.70 | 24.97 |
| MDD (%) | -43.37 | -37.92 | -40.18 | **-27.96** | -38.19 | -40.22 |
| Sharpe Ratio | 16.68 | 9.36 | 17.15 | **17.72** | 17.37 | 17.20 |

Table 3 shows the comparison of all methods which are used in this study. The best result of each row is bolded. We can see that all constraints can help decrease the drawdown. Since maximum drawdowns of all constraints are less than the original strategy. The “Z-score” constraint has the best performance in reducing the drawdown, which decrease the MDD from -43.37% to -27.96%. It also has the best performance in term of Sharpe ratio, which means it earns more than others under the same amount of risk for CAGR, the original strategy has the highest CAGR, which is 25.41%. The second high is MACD of stock, with 24.97%. Overall, ‘Z-score” performs better in the training.

# 4. Testing

Historical data from 1/1/2015 to 1/1/2018 is used to test the strategy. The process is similar to the training:

1. Select the stocks by using the criterions mentioned in section 1.1.
2. Trading according to section 1.3.
3. Trading with constraints according to section 3.1. – 3.5.

## 4.1. Testing results

## 4.1.1. Original

Original result is shown in figure 11. The equity curve of our strategy is closed to the equity of HSI, except the period during 11/2015 to 07/2016. Our strategy loss less than HSI index. CAGR is closed to the HSI's CAGR, which are 8.17% and 8.07% respectively.

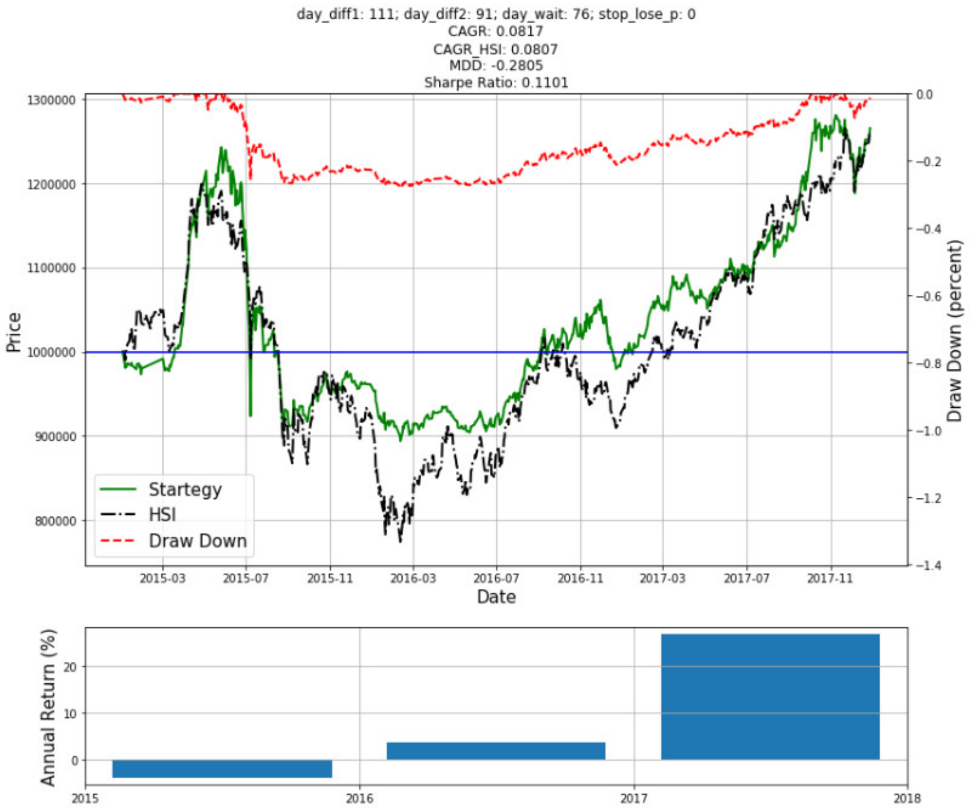


Figure 11: The original equity curve from 2015 to 2018

## 4.1.2. SMA of HSI

Figure 12 shows the result of the SMA of HSI constraint. The CAGR of this constraint is larger than the original one, which is 9.13%. And the MDD is also less, which is 25.47%. Besides, we can also see that the constraint did well to stop the drawdown in the period from 11/2015 to 07/2016. Since our equity curve fluctuate around the blue line (original capital), which means that our strategy is stopped to loss during this period, while HSI's equity curve drops below the blue line.

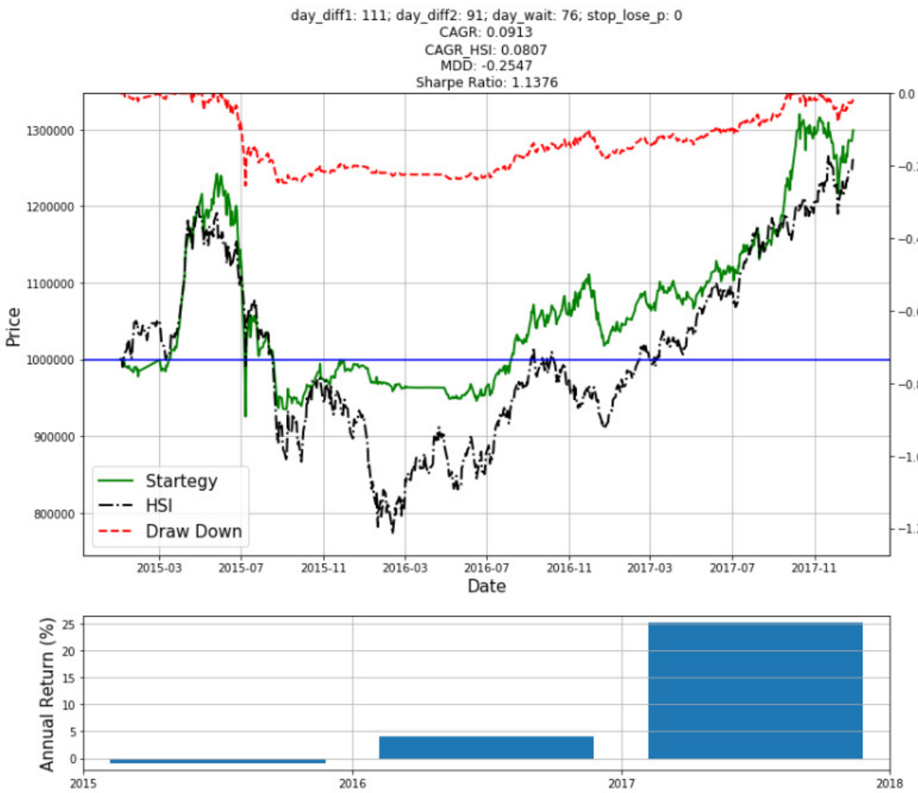


Figure 12: The equity curve of adding the constraint "SMA of the HSI" , from 2015 to 2018

### 4.1.3. SMA of stock

Figure 13 shows that the SMA of stock constraint performed similar to the original strategy, the equity curve is also closed to the HSI curve. But the CAGR is only 7.65%, slightly less than the CAGR of HSI.


Figure 13: The equity curve of adding the constraint “SMA of the individual stock” , from 2015 to 2018

## 4.1.4. Z-score

The result is shown in figure 14, the strategy does not perform well in the testing period. Although the drawdown from 11/2015 to 07/2016 in less, the growing rate is less than HSI in period, 03/2017 to 12/2017. Also, the overall performance is also worse than HSI, because the CAGR is only 4.4%, while CAGR of HSI is 8.07%.

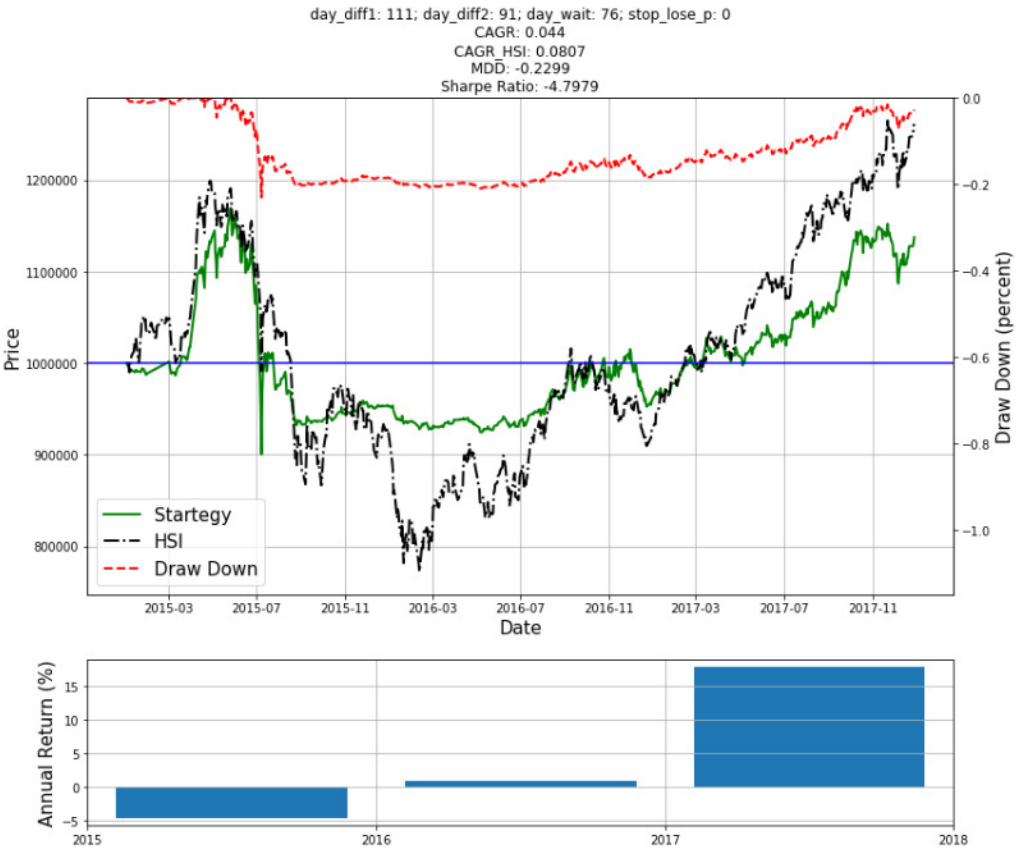


Figure 14: The equity curve of adding the constraint “Z-score” , from 2015 to 2018

## 4.1.5. MACD of HSI

We can see from figure15, this strategy also performed normally. The curve is similar to the HSI, and also the origianal strategy. The CAGR of this strategy is only 7.63% which is less than the HSI's CAGR.

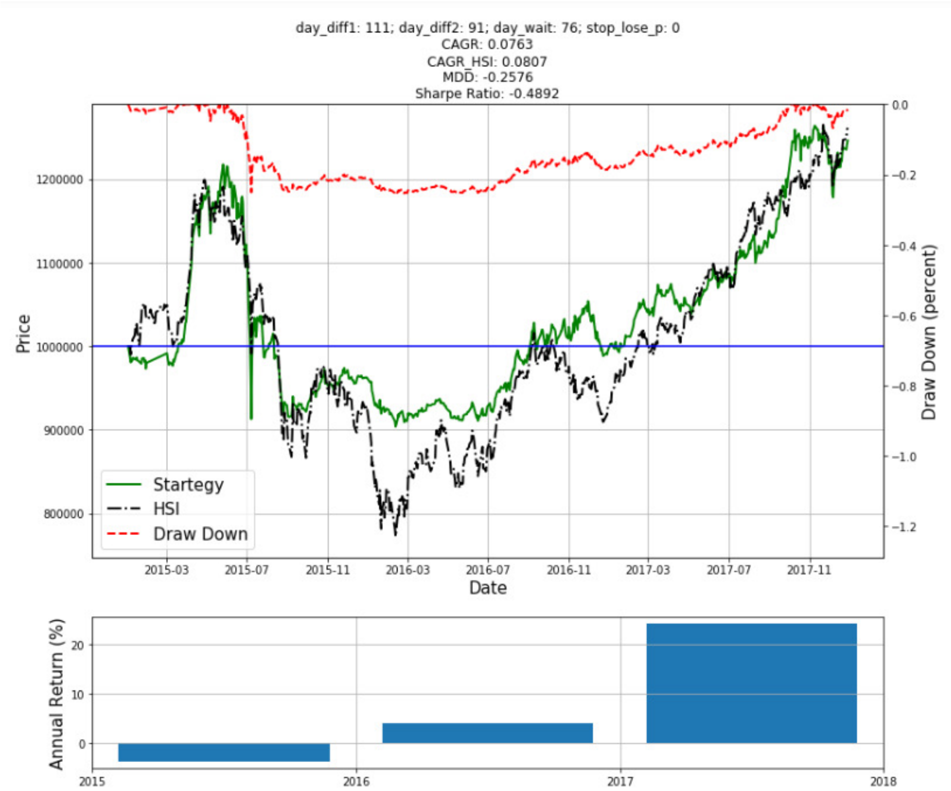


Figure 15: The equity curve of adding the constraint "MACD of the HSI" , from 2015 to 2018

## 4.1.6. MACD of stock

The result is shown in figure 16. We can see that this strategy can reduce the drawdwon, and also has a better performance in the year 2017, comparing to the other strateries. Its CAGR is 9.26%, which is the highest among all strategy mentioned above.


Figure 16: The equity curve of adding the constraint “MACD of individual stock” , from 2015 to 2018

# 4.2. Comparison

Table 4: Performance of the strategies, from 2015 to 2018
(The best result of each row is bolded)

| | Original | SMA of HSI | SMA of stock | Z-score | MACD of HSI | MACD of stock |
|---|---|---|---|---|---|---|
| CAGR (%) | 8.17 | 9.13 | 7.65 | 4.4 | 7.63 | **9.26** |
| MDD (%) | -28.05 | -25.47 | -25.75 | **-22.99** | -25.76 | -25.62 |
| Sharpe Ratio | 0.11 | 1.14 | -0.47 | -4.80 | -0.49 | **1.26** |

Table 4 shows the performance of all methods in the testing period. We can see that the "MACD of stock" has the highest CAGR and Sharpe Ratio. But all methods do not perform well in the testing. Since the CAGRs are small, comparing with the HIS, some of them are even lower that the HIS's CAGR, while others are just slightly better than HIS's CAGR. Also, the drawdowns of all methods are high, they range from 22% to 28%, while the CAGRs are only around 7% to 9% in general. It means that these strategies lose more while earn less. We can also see it from the Sharpe ratio, the positive Sharpe ratios are only in the range from 0.11 to 1.26, which means that the additional profits earned under risk are low. Even some of the strategies have negative Sharpe ratios. In other words, they are losing money under the risk.

# 5. Conclusion

Although our strategies have high CAGRs in the training, they do not perform well in the testing. There are some possibilities:

1. Our strategies do not perform well when the market is going down:
   Even in the training set, the equity curves of our strategies are also going downward, when the market is going down. The reason why we still have an overall good result in the training is because in 10 years scale, the market is generally going up. Therefore, our strategies can earn back the money. In the testing, the market is dropping 1/3 of the time. Which may yield our strategies have negative return during that period.

2. The ratio of training and testing size are not suitable in stock market:
   We used around 75% training and 25% testing, which is 10 years for training and 3 years are testing. But the market may be changing. In other words, when we are training the strategies using the past data, the strategies can really capture the properties of the market. So, they can have a positive return. But, the characteristics of the market is changing. Therefore, the strategies will not have the same performance under a market with changed features. One possibility is that trend is significant in the longer scale (e.g. "Days" or "Week") in the past. So, our strategies can capture the trend in longer scale. But, nowadays, as technology becoming more popular. The trading frequency is much higher than before, which means that the trend becomes shorter (e.g. "Minutes", "Seconds"). Since our strategies are trained with past data. The trained strategies may not work in nowadays.

3. We may overfit/underfit:
   We used the step of 10 days to try the best combinations of the parameters. But, the best cluster of the combinations may be form in between each 10 days, or maybe the best combinations are beyond the range that we are testing. Besides, the best combinations do not ensure that it is also the best combinations in the testing.

# 6. Discussion

There are some ideas to improve the strategy:

1. Include “Short selling”:
   In this report, we are only buying the stocks. In other words, the only way that our strategy can earn money is when the market is going up. Therefore, by adding the short selling signal, we wish to have more opportunity. And this may also improve the situation of losing money when the market is going down.

2. Include “Stop earn” and “Stop loss”:
   We did not consider the stopping signal in the report. It may decrease the profit of our strategy, since we may miss the best exit opportunity. For example, the ideal case would be buying the stock at the lowest price, selling it in the peak. But our strategy does not consider the exit position, which means that we may selling the stock when it passed the peak and is going downward. It will reduce the profit. Therefore, by adding the stop signals, both “Stop earn” and “Stop loss” may help to maximum our profit.

3. Focus more on the recent data while training:
   As we mentioned above, the outdated data may affect our strategy in the way that the features of the training set are different from the testing set. Therefore, the trained strategy may perform badly in the testing. So, if we focus more on the recent data, then the training and testing set will have similar features. The strategy may have a similar performance as the training.

4. Adding more constraints:
   In this study, we just added one constraint to the original strategy. It may not be enough to increase the accuracy of diagnosing the right signals (either buy or sell). Therefore, we can combine more than one constraint to the original strategy, to increase the chance of capturing the right signals. We may also test the best combinations of the constraint in the future.