2021 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)

Big Data Analysis with Momentum Strategy on Data-driven Trading

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***Abstract*—Data-driven trading approaches have become more widespread in quantitative hedge funds due to the availability of large amount of financial data and the popularization of quantitative trading strategies. One of the most popular trading strategy is called momentum strategy which seeks the opportunity of market volatility by buying the stock when the price goes up and selling them as soon as there is a sign showing they would go down. Although this concept is clear to the majority, building one concrete momentum strategy remains a problem to every investor. In response to this concern, in this paper, we propose a the detailed algorithm to build a concrete momentum strategy. First, we compare the performance of four basic momentum strategies with respect to their return in S&P 500 index and its option investment. Then we optimize the momentum trading strategy by adding one extra accelerating factor and then enhance with decision tree investment method so as to capture more market trading opportunities and become more profitable. From the experiment, we find that straddle hedging strategy is proved to effectively lower the draw-down risk. In addition, although using options rather than stocks would largely raise the portfolio variance, it will significantly avoid the bad performance of momentum strategy during the bear market.**

***Index Terms*—Big data analysis, data-driven trading, momentum strategy, Black-Scholes formula, decision tree**

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I. Introduction

Thanks to the improvement of data storage techniques [1] and the popularity of big data analysis tools [2], data-driven decision making has become more and more popular in a lot of fields such as agriculture [3], healthcare [4], logistics [5] and business [6]. To be specific, data-driven decision making involves making decisions that are backed up by hard data rather than making decisions that are intuitive or based on observation or experience alone. Fields such as medicine, transportation and pricing in e-commerce stores have already relied heavily on data-driven decision making to a certain degree.

In addition to these fields, a lot of financial traders and companies are in the process of developing data-driven decision makers to help optimize their trading strategy . The reason for its usage in financial area is very obvious. Large amount of available financial data provides financial analysts with opportunities to find useful and safe information from the data [7]. In addition, compared with machine analysis, manual analysis sometimes is less efficient and impossible to scale quickly.

Among most of the data-driven trading strategies, momentum trading strategy [8] is one of the most important candidates. The word momentum originates from physics to measure the object's ability to continue moving in one direction, with a formula mass multiplied by velocity of an object. Similarly, the momentum investment strategy is a strategy that aims to capture the continuance of existing trends in a market. The basic idea behind this trading strategy is that it assumes that a trend is more likely to continue for some time before it switch to move into the opposite direction.

Another reasonable data-driven trading strategy is called mean reversion [9], which agrees with the assumption that the price of an asset would fluctuate between its actual value. Therefore, although its price might be overestimated or underestimated within a short period of time, in the long run its price would go back to its actual value level. These two seemingly contradicted trading strategies converge if we split the investment range into small pieces. In other words, mean reversion strategy [9] is more suitable in the long run while in each small period of time, we prefer momentum trading strategy [8], which means value investing is a long-term game whereas momentum is usually seen in the short-to-intermediate term.

Multiple academic studies have shown that a momentum investing strategy can be lucrative for investors. Kahneman and Tversky(1982) [10], De Bondt and Thaler(1985) [11] and Shiller(1981) [12] conclude that investors tend to overreact to information. Fuertes, Ana-Maria, Jeolle Miffre and Tan, Wooi-Hou(2009) [13] proves the presence of short-term continuation and long-term reversal in commodity futures prices. Chan, Jegadeesh and Lakonishok(1995) [14] show that market responds only gradually to the new information. Jegardeesh and Titman (1993) [15] documents that the strategies to buy past winners and sell past losers can generate significantly positive return, outperforming to the S&P 500's average annual return by 10%.

In this paper, we study the performance, especially the return, of momentum strategies in S&P 500 index investment. From traders' perspective, return is at least ten times as important as other indexes such as Sharpe ratio [16], Treynor

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DOI 10.1109/ISPA-BDCloud-SocialCom-SustainCom52081.2021.00182

ratio and volatility [17]. Therefore, our goal is to find a trading strategy which put return maximization into priority and also consider other indexes at the same time. No matter how good performance of our strategy in simulation is, one big problem in analyzing financial data is that it can often cause overfitting issues because people may come up with strategies especially for improving the goodness of fitting of financial data, even though these strategies may have poor performance in prediction. In addition, the time series data make cross-validation testing very difficult to implement. To avoid this, this paper will not only use the return-performances as the measurements of trading strategies but also try to explain the strategies in aspects of finance, psychology and investor behavior in order to rationalize the specific momentum strategies.

The Main contributions and innovations of this paper are presented in twofold:

1) We examined the different usages of momentum strategy and proposed a new strategy to construct portfolios with index and options with various indicators. After analyzing the results quantitatively, we found that our option strategies have a remarkable improvement of cumulative return in comparison to a momentum strategy purely based on stocks,
2) The simulation results demonstrated that the cumulative return of most investment strategies are significantly better than the benchmark, i.e., S&P500 cumulative return.

The remainder of this paper is organized as follows. The research background of momentum trading strategies [8] and data-driven trading approaches is presented in Section II. Section III shows the model we use to analyze the financial market, followed by Section IV presenting algorithms to execute the momentum trading strategies. Several related works are listed in Section V. Section VI shows a brief description of our data used for experiments, presents four basic strategies that we examine their performance, and specifies a better strategy to optimize the performance based on the four basic strategies, and also presents more comparisons of the investment performance among five strategies. Section VII draws a conclusion.

II. BACKGROUND

A. Big data analysis

With the significant advance of computing power [18] [19], algorithm design [20] [21], and machine learning techniques [22] [23], the performance and outcomes had been increased sharply in many aspects of our daily life. Data analysis is to gain useful information and then learn from the given data set [24]. This involves digging through information to identify predictable patterns, interpret results and make decisions based on the analysis. The popularity of electronic devices and the development of data storage technologies help leverage the widespread of big data analysis application, such as healthcare [25] [26], cloud computing [27], smartphone [28], etc. As we know, more data is generated and more data is available for people to analyze.

As for companies, they prefer to use big data analysis to make business decision in terms of sales and employees management rather than use manpower to do so since analysis from data would be more objective than analysis from human beings. In response to the growing need of human to do data analysis, several data analysis techniques and algorithms have also been proposed by experts in this fields so that the data analysis tools could be more convincing and the results could be generated as soon as possible from developed speeding up algorithms.

Here are some of the fields where big data analysis has been implemented for a long time. For e-commerce platform such as Amazon and Alibaba, customers' historical ordering will be recorded and taken as the input for their inner consumers' behavior analysis system. By using these precious record, this system can precisely recommend specific products to the customers when they come back to this platform again, which not only help the users find the product they want but also earn more profits for this platform.

In addition to e-commerce platform, daily navigation system could be another place where big data analysis plays an important role. When a person provides his/her destination address, the navigation system would take into consideration the current transportation [29] situation together with which transportation methods the person prefer, before offering the suggested choice. Even most experienced drivers would rely on such navigation system to some extent since they cannot have an omniscient overview of the traffic situation all they time.

Compared with all fields mentioned above, the financial area is more likely to become an area where people want to prefer to finalize their decision by leveraging big data analysis methods due to several reasons. First of all, collecting large amount of financial data is relatively easy and cheap compared with other fields. Currently a lot of platforms (e.g. Bloomberg, Yahoo Finance, Wind) have already stored large amount of trading data together with each company's financial data. However, if we want to collect the consumers' preference data, we need to take a survey and motivate people to provide their feedback which is both time-consuming and money-consuming.

In addition, financial data is prone to be unpolluted since it reflects the actual financial market accurately, but if we consider the collected data from surveys or other path, the data might have some problems such as missing values due to sensitivity reasons or unconvincing data due to people's unwillingness to present their actual opinions [30] [31]. Hence, we do not need to worry about how to clean the financial data but just take it as a given and continue our analysis. Last but not the least, financial area is a fields which is highly possible to be subjective since the traders' personal idea would largely affect their instant action. If more data analysis tools can be combined in this process, the final decision would be moderated to be objective to some extend, which is of great importance to avoid sharp fluctuation of the balance of the trading account [32].

B. Momentum vs mean reversion strategies

Among all data-driven trading strategies, we can divide them into two main types: momentum strategy and mean reversion strategy [9]. As for momentum strategy, it predicts the prices will continue moving in the same direction as what it was before, and then propose that the corresponding trading strategy should be follow the current trend of this underlying asset price. As for mean reversing strategy, it assumes that the prices will finally go back to a level which matches it real value, and therefore it bets that the prices will revert back towards the mean or average if it stays in one trend for some time. Although it seems to us that the two strategies conflicts to each other, they are both correct under different circumstances. In the long run, mean reversion [9] should be more accurate since the stock price must match its real value by the reasonable assumption that all investors should be rational. However, in the short run, momentum strategy dominates the market because even if the investors overestimate or underestimate one asset's price, this trend cannot stop immediately and it might take some time to reverse such trend.

Actually, markets are forever moving in and out of phases of momentum and mean reversion. Therefore, it is possible to develop strategies for both phases. One simple example would be we develop an indicator to detect which phase the current market belongs to at that moment. If the market is in the phase of momentum, then we implement momentum trading strategy [8]. Otherwise, we switch to the mean reversion strategy [9]. However, if the market quickly switch between momentum phase and mean reversion phase, the lag of such indicator might mislead the traders' action and therefore we come up with the pure momentum strategy with some special handling for the situation where we strongly believe that the market is in the phase of mean reversion.

III. Models and Concepts

In this section, we express the model we use in designing the momentum trading strategy. One important steps in developing the trading strategy is to build one model to convert the financial market to digits which can be recognizable by programs. Especially in the situation where we want to capture the momentum of price trend and the starting and ending signal of that particular momentum, we consider the moving average as the representative of the stock price level during a period. The basic concept behind is that the moving average of stock prices would represent the relative market reaction to one particular underlying assert and if the moving average goes upward, this shows one upward trend, which might resume for another period of time. The goal of our investment strategy is to capture the trend of stock price in the beginning and capture the turning point when the trend switches to the opposite direction.

Depending on each traders' preference, they may choose short period average if they are sensitive to price fluctuation or choose long period average if they like low frequency trading and want to capture a more deterministic trend. We have the following setting. Let P_t be the price of the underlying asset at time t, which is guaranteed to be positive. Then, $Avg_n = \frac{1}{n}\sum_{i=1}^{n} P_{t+i}$ would represent the average price over a time period of n. For any value n_1 and n_2, where $n_1 < n_2$, we set $trend = Avg_{n_1} - Avg_{n_2}$. If $trend > 0$, this means the moving average within the previous n_1 days is greater than the average within the previous n_2 days, and we can say that it is highly possible for the future price to continue increasing and vice versa. More advanced strategy would consider different time period length or consider more elements in addition to pure trend itself to make the final decision more optimal. The asset balance at day t is represented by $Asset_t$. The asset value consists of the value of equity, the value of cash and the value of options.

IV. The Algorithms

Based on the model setting, we develop one corresponding algorithm as a benchmark to present our momentum trading strategy that tries to capture the trend of price. The final version of trading strategy can be some mutation of this proposed algorithm. The general difference is about the concrete action implemented when the signal clearly shows the trend.

Algorithm 1 *Momentum trading* Algorithm

Require: Input data of size M that represents the stock price for previous M days.

Ensure: A trading strategy to simulate on these data and test its performance with respect to final investment return. We can trade both naive underlying assert and options.

1: Determine two time period n_1 and n_2.
2: Set one value for initial asset balance $Asset_0$
3: Decide the strategy when we find the price trend by analyzing price data.
4: while (time $< M$)
5: Get average price for previous n_1 and n_2 days, represented by Avg_{n_1} and Avg_{n_2}.
6: Compare the value of Avg_{n_1} with the value of Avg_{n_2}.
7: If $Avg_{n_1} > Avg_{n_2}$, then it is more likely for the price to increase in the future, and we long the assert. Otherwise, it seems like the trend starts to go down, and therefore we short the asset.
8: Calculate the total asset balance at the end of that trading day and calculate the return by the formula $\frac{Asset_t - Asset_{t-1}}{Asset_{t-1}}$.
9: time++;
10: Output results: The final asset balance and we measure the daily return figure together with the total return figure to calculate more features such as sharp ratio [16].
11: All the calculation is based on the assumption that there is no transaction fee and all trading requests can be executed immediately.

To be specific, we will measure the trading strategy over M days. At any day i, this algorithm compares the average price over the previous n_1 and n_2 days. If the average of the previous n_1 days is larger, some action to long particular assets would be implemented since we hold the belief that the price is likely to be within an increasing trend. Otherwise, this algorithm chooses action to short assets so that it can earn profit from decreasing price. Then, based on the actual price level at day i, corresponding investment return is calculated and we continue to record the cumulative return for a time period.

At a really high level, this algorithm is to compare the average price over the recent short period with the average price over the recent long period. If the former value is larger, it means the current stock price has a trend to go up and such momentum will keep for a while until the former value becomes smaller when the trend starts to reverse. Some mutations of this algorithm, shown in the experiments section, would presents different long/short strategy when we have already been able to predict the future price trend.

Finally, we not only care about the return performance, even though it is the most important one, but also consider other features such as sharp ratio and maximum drawdown, since sometimes people might use economic leverage in trading and also might be sensitive to abruptly large loss. The more features we show to the traders, the less likely that they would meet unexpected situations from such strategy.

V. Related work

In spite of the good performance of momentum strategy, that is not convincing enough to extend this strategy to everywhere. Several related works have presented the usefulness of momentum trading strategy and also motivate us to do more experiments within this paper.

Momentum trading strategy in exchange rate: RDF Harris and F Yilmaz [33] developed a momentum trading strategy based on the low frequency trend component of the spot exchange rate, that offers better performance especially greater directional accuracy. However, that restricts the signal of momentum to be achieved from low frequency trend component and also from the price data of exchange rate. Since exchange market is a zero-sum market while the S&P500 market is not the case because of dividend creation, the results shown in this paper could be complementary to the strategy mentioned in that paper.

Test the performance of mean reversion trading strategy: B Li, SCH Hoi, P Zhao, V Gopalkrishnan [34] proposed a novel strategy named Confidence Weighted Mean Reversion (CWMR) to do online portfolio selection. Given the good performance of their proposed mean reversion trading strategy, it is natural to present the performance of our momentum trading strategy and compare against several other strategies. This provides the base for us to design a new mechanism to switch between these two strategies by further exploring the market information and spot the convincing switching signal.

VI. Experiments

A. Data Description

Our dataset comes from Bloomberg and Investing.com. We took S&P 500 index from 1/1/1996 to 12/31/2017 since a longer time period will be more stable in matching the trend. We used 30-day historical volatility of the SPX as our volatility and 3-month bond yield as risk free rate since all of the options in our research will be expired in 90 days. We use these data

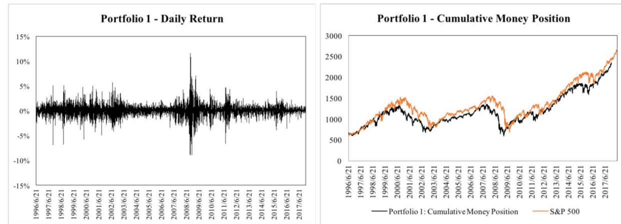

Fig. 1. The first strategy.

to calculate call option, put option and corresponding straddle prices by following the Black-Scholes formula [35].

To make the calculation simple, we assume that all trading is without any transaction fee. In addition, we believe that the market is liquid enough that we can long or short the financial instrument with the at market price. Another assumption is that we can trade options with any strike price and any maturity date. These assumptions are not that strong and if people decide to put this momentum trading strategy into practice, they can add more assumptions to make the simulation closer to the reality.

B. Strategy one

The first portfolio is constructed with a simple momentum strategy by purely using equity: when the 60-day moving average is greater than 120-day moving average, we long one unit of S&P 500 index. Otherwise, we would short one unit. This strategy is to capture the upward trend of the index. The daily return steam and the cumulative return are shown in figure 1.

Over the period of our investment, the first portfolio generates a cumulative return of 250% and annual return of 4.34%, with annual standard deviation of 19.06%. As the cumulative position illustrates, the first strategy under-performed the index over the investment periods. The strategy could perfectly capture the long-term trend of the S&P 500 index. Moreover, the momentum strategy could even present the trend in advance the equity, indicating momentum as a leading indicator.

Since the essence of momentum strategy is trend-following, it's unsurprisingly to find that the strategy is prone to the bear market, e.g. the Dot-Com Bubble during 2000 to 2002 and the 2008 financial crisis. Our result is in consistent with the fact that momentum strategy would perform badly after the peak of bull market.

The result of the first portfolio suggests that the importance of the timing of using momentum strategy. To improve the strategy to avoid suffering from the market draw-down, we might add additional indicator to monitor the forthcoming bull market and stop exercising the momentum strategy by learning from the added indicator.

C. Strategy two

For comparison, we assume if we have $100 capital to invest at the very beginning of time. We invest only one unit of option, and the spare amount of $100 would be held in pocket. By adding on our daily profit and loss, we compute our cumulative return. It ends up with approximately $1200. As

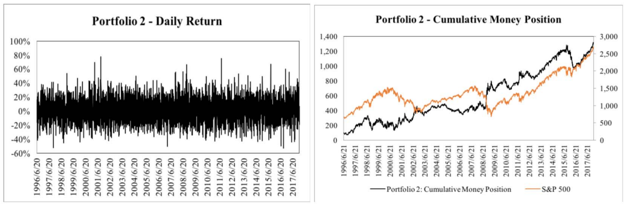

Fig. 2. The second strategy.

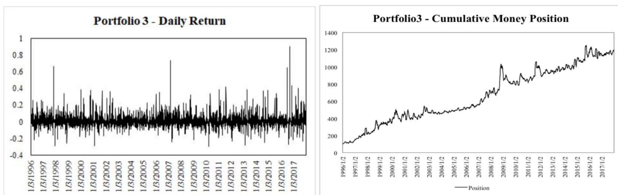

Fig. 3. The third strategy.

what is shown from the figure 2, though the strategy remains the same, the cumulative performance is quite different from that of first portfolio. It still captures the main trends, but perform much better in the bear market. Since we buy a put when the momentum is decrease, indicating the market should start going down, the put position indeed offers a strong protection of our portfolio. The downside protection effect achieved remarkable success especially during the Dot-Com Bubble and the financial crisis.

D. Strategy three

In portfolio 2, given a put or call, we match the moving average by longing one of them each day, depending on the value of 60-day and 120-day moving-average time series; however, in portfolio 3, we plan to to match the same time series given a straddle. Since longing a straddle has the same effect as longing a put or a call, we construct a daily time series of the returns of the at-the-money straddles, with maturities of 90 days, to match the time series of the moving average. Each day, we buy a straddle and sell it next day with the maturity left to be 89 days. Thus, by longing a straddle the first day and shorting this straddle the second day, we can replicate the moving average of S&P 500.

The everyday return is calculated as the formula: $Return_{day_{n-1}} = (Call_{day_n} + Put_{day_n} - Call_{day_{n-1}} - Put_{day_{n-1}})/(Call_{day_{n-1}} + Put_{day_{n-1}})$.

As we can see from figure 3, most daily returns range from -20$\%$ to 20$\%$, and they are distributed around 0 with seemingly equal probability, except there exist 3 positive outliers which are over 60$\%$. We calculate money position by adding each day's profit and loss to it, still starting from \$100 at the first day. It turns out that the cumulative return becomes a steadily increasing trend with tiny fluctuations, and the small peaks in the cumulative returns correspond to intensive positive returns. The money position ends up with approximately \$1200.

E. Strategy four

In portfolio 4, we aim to construct an at-the-money straddle at the beginning of the moving average time series and dynamically hedge that portfolio on a daily basis so it is

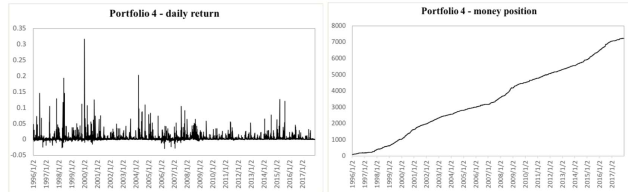

Fig. 4. The fourth strategy.

equivalent to an at-the-money straddle each day; we re-balance each time at option expiration. To dynamically hedge the portfolio, we decide to use the delta hedge.

The delta measures the sensitivity of the option price to the change in the underlying stock prices and can be defined as the first derivative of the option value with respect to the underlying stock's price. Traditional delta neutral hedging guarantees the delta of the portfolio to be zero, so people long or short different shares of stocks according to the delta of the straddle.

However, delta neutral hedging cannot link the holding straddle to an at-the-money straddle each day. So instead of delta neutral hedging, we choose to trade stocks on a daily basis to make the delta of the portfolio equal to that of at-the-money straddles. Given the Black-Scholes-Merton formula [35], we derive delta of calls and puts to be N(d_1) and -N(-d_1) respectively, so the delta of straddle equals to $2N(d_1)$ -1, where $N(.)$ represents the value of cumulative distribution of one normally distributed random variable.

We have two kinds of straddle in this situation, the straddle we have to hold until the maturity, and the at-the-money straddle each day. The daily number of shares traded to hedge our portfolio is the difference between the deltas of these two straddles.

At the beginning of the moving average time series, we short an at-the-money straddle and then dynamically hedge it by trading S&P 500 index to ensure our portfolio having the same delta with an at-the-money straddle every day, re-balancing each time at option expiration. To determine the daily return, we first calculate the daily PnL (Profit and Loss) by adding the change in holding straddle's values and profits from stock. We use Black-Scholes [35] to calculate the remaining value in holding straddle each day, and stock's profit can be derived by multiplying the index change and the number of shares held the day before. Then we measure the daily principal by adding the values of straddle and stock the day before, which is the product of index price and the number of shares we held. Finally, we get the time series of daily return by dividing principal with PnL.

From figure 4, most daily returns are positive and smaller than 5$\%$, while only a few of them are above 10$\%$. This strategy seems to work very well in terms of daily returns. Then we compute the daily position to compare the overall performances with other strategies. Suppose we have \$100 from the beginning. After using this strategy, the money position will be changed according to PnL. After 20 years, the money position goes up to over \$7000. In terms of money position, this strategy is promising as well.

F. New strategy

1) Consider 'Accelerating' Factor: Based on our understanding of the former strategies, we want to analyze the trend of S&P 500 index in more details and find more optimal ones to improve investment performance.

As for the momentum strategy we use from strategy 1 to strategy 4, we make the assumption that when the 60-day average is larger than 120-day average, it is more likely that S&P 500 index would continue to increase so we buy the index or long a call option. In spite of the good performance of these momentum strategy, it is sometimes unrealistic or unreasonable because we do not take the 'momentum of momentum' into consideration.

If we divide this formula by time interval (which is 120-60=60 days), this means the 'velocity' of the market price. If the value is positive, it means the trend will still go up and vice versa. However, this strategy only focuses on whether the velocity is positive or not, without any consideration of the absolute value of velocity. To improve this, we take other elements which measure the change of velocity value into consideration. To be specific, we think of both the difference between 60-day average and 120-day average together with the difference between value (60-day average - 120-day average) and (120-day average - 180-day average). As for the latter one, if we divide that formula by time interval (120-60), this means the 'accelerated speed' which measures the changing rate of velocity. Based on the value of 'velocity' and 'acceleration', we will take a long position when both values are positive and take the short position when both values are negative. Otherwise,we will just keep the capital without any investment. We believe that the strategy with the combination of 'velocity' and 'acceleration' will make the investment performance better.

2) 'Two-step' Decision Process: In philosophy, everything advances wave upon wave with spiral escalation, the stock index trend is not an exception. In other words, index trend is similar because it also gradually increases with fluctuation. Therefore, a decision tree with several layers is more reasonable to make final decision with more decision layers. With this concept as prior knowledge, we would find the defect of the original momentum strategy that it could only catch the long-term trends but ignore the short-term trends within long-term trends. To be specific, there are a lot of small fluctuations between 120-day average greater than 180-day average and 120-day average smaller than 180-day average. Therefore, if an investor wants to earn more profits, it is a good idea to find trading opportunities in these periods. In our strategy, we come up with another method to further optimize the investment performance.

Suppose after making the initial comparison between 120-day average and 180-day average, we believe that the future big trend is to go up, so we take the long position. Since there may be several small variations during these times, we then induce the comparison between 60-day average and 120-day average. If the former one is smaller, it seems that the trend should be downward in short-term and uncertain about the long-term trend therefore, we close our long position but not take the short position to wait for another clear information. When 60-day average turns to be bigger than 120-day average, we take the long position again and if the index continue to decrease until 120-day average is less than 180-day average, we take the short position.

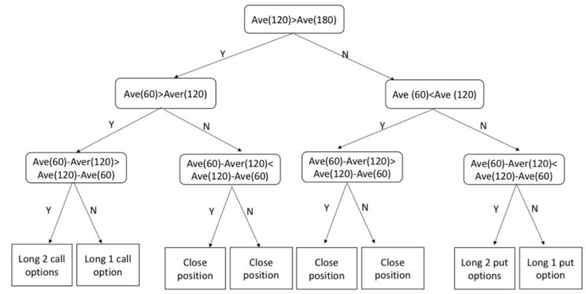

Fig. 5. The decision tree of trading strategy.

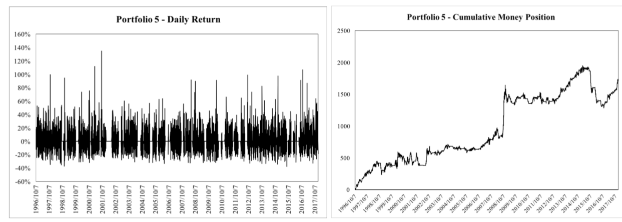

Fig. 6. Optimal strategy.

3) Decision Tree: Based on the analysis above, we test each of the strategy respectively and finally find that the combination of them shows the best performance. The trading strategy can be represented by a decision tree [36] with execution condition and concrete executions listed over all the nodes in figure 5.

From figure 6, we find that some of the daily return are zero because they fail to meet our trading requirement. It is more realistic because sometimes traders will keep position zero. As for the daily return performance, most of the returns are positive and the absolute values of positive return series on average are higher than that of negative return series, which means the strategy can 'cut losses, let profits run'. When it comes to the cumulative money position, the fluctuation is a little bit higher because the amount of position we hold varies as the market situation changes. Therefore, we can witness comparatively large profits during trend market such as during the 2008 financial crisis.

G. Strategy comparison

After comparing and analyzing the outcomes of the above five strategies, we find that the return streams produced varies from strategies to strategies. Figure 7 and figure 8 show the distributions of five daily return time serials. It is obvious that the distributions are not the same and none of the three given option strategies replicate the returns from the momentum strategy quite well.

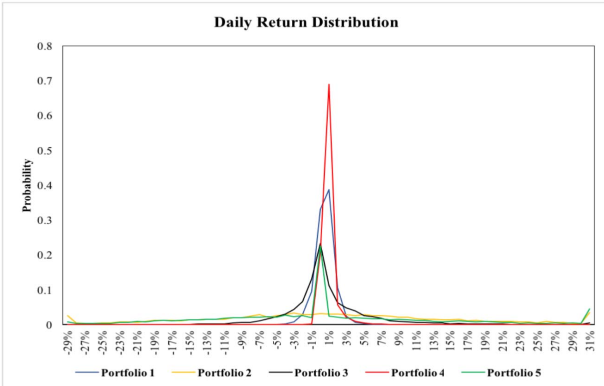

Fig. 7. Daily return figure.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean	0.03%	0.61%	0.43%	0.40%	0.77%
STDEV	1.20%	15.44%	6.10%	1.14%	15.13%
Kurtosis	8.2258	0.7556	24.7247	167.0740	5.9877
Skewness	-0.0550	0.2618	2.7278	9.6677	1.4577
Range	0.2062	1.3033	1.2018	0.3455	1.7257
Minimum	-9.03%	-53.05%	-29.95%	-2.85%	-37.57%
Maximum	11.58%	77.28%	90.23%	31.69%	135.00%

Fig. 8. Features of five strategies.

	S&P 500	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Cum Return	331%	250%	1209%	988.45%	7126%	10036%
Annual Return	5.69%	4.34%	12.24%	11.19%	21.84%	23.78%
Annual STDEV	18.93%	19.06%	245.12%	91.26%	18.07%	240.13%
Sharpe Ratio	0.1814	0.1108	0.0409	0.0982	1.085	0.0903

Fig. 9. More statistics of five strategies.

To compare performance of the five different strategies, we calculate cumulative returns based on money position for each portfolio. The way we do that is to define all the option strategies starting with a principal of $100 and each one realizes their capital accumulation in the 22-year investment period, then we can evaluate the performances of the option strategies based on the final day money position. In addition, we also calculate other features such as the annual return, annual standard deviation and Sharpe ratio [16] to help compare and evaluate different strategies overall. More detailed results have been listed in figure 9.

After preliminary analysis, portfolio 4 seems to outperform the other strategies with a largest Sharpe ratio [16]. Portfolio 5, our enhanced strategy, has the highest return, which is 24% annual rate. In a mean-variance framework, we would employ the option strategy in portfolio 4 as its return time serial has the largest mean and also a relatively small variance. To implement this option strategy, we need to short an at-the-money straddle at the beginning and then dynamically hedge it through trading the underlying stock on a daily basis so that we can keep the delta of our portfolio equal to that of an at-the-money straddle every day. Evidently, we may have some difficulty to realize this option strategy in the real market, because of the unavoidable transaction fee for our daily deals and the limit to find the exact at-the-money [37] straddle each day in the real option market.

Besides, the variance of returns of the momentum strategy, as we can see from the above table, are pretty large. It comes from the option price oscillation. If we choose to long yesterday, short today and then long the next day, we will be exposed to the risk of the price oscillation, which is actually the variance of the data that the strategy generated. If we use the straddle or options, we are also exposed to the variance of the underlying, so the same principle applies.

In terms of risk management, we also calculate value-at-risk(VaR) [38], Conditional-Value-at-Risk(CVaR) [39], maximum draw-down, duration of maximum draw-down and investment odds to evaluate the potential risk in each portfolio strategy. From the table below, we can see that among the four option strategies, portfolio 4 has the smallest value-at-risk [38], conditional-value-at-risk [39] and maximum draw-down than the other four momentum strategies. That is to say, this fourth strategy seems to reduce the risk compared to the first portfolio, and the other three option strategies have a larger potential risk.

VII. Conclusion

In this paper, we examined the different usages of momentum strategy and proposed a new strategy to construct portfolios with index and options with various indicators. The results demonstrated that the cumulative return of most investment strategies are significantly better than the benchmark, i.e., S&P500 cumulative return. After analyzing the results quantitatively, we found that our option strategies have a remarkable improvement of cumulative return in comparison to a momentum strategy purely based on stocks, although options increase the volatility sharply. The strategy we proposed can help stimulate more follow-on researches better utilize momentum trading strategy to optimize the investment return.

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