OAS Algorithm #2 – Reallocation Strategy

Theory:

Unlike the previous volatility algorithm, this reallocation strategy is based on riding momentum of a strongly performing equity. In theory, a strongly moving trend is likely to continue and the objective is to continuously shift capital to ride the strongest trend in any given universe of stocks (3x leverage ETFs). By nature, this strategy should be more passive in the sense that reallocation will only occur based on a set time frame. Given that the client would only like to make 2-3 trades a month, performance analysis and reallocation will be set to a bi-weekly basis.

Method:

Four equities from the 3x leverage ETF Universe will be added/set to variables in order to pull data and execute performance analysis. This analysis and any subsequent market action will occur in a reallocation function which will be called on a scheduled basis. Equity performance will be measured by a simple ratio (current price/last price). This ratio will serve as input for conditional statements/comparisons. The equity with the highest ratio will be purchased (if not already), and all other positions will be closed. For consistency, this algorithm will be back-tested 10 years to match the conditions of the first algorithm. Results will be compared to benchmarks set by a simple buy and hold strategy for the same universe of equities. (TQQ = 8466%, UDOW=1382%, UPRO=2809%, URTY=465%)

1 . First Iteration

1. Hypothesis

Switching to ride the momentum of the top performing equity, should ensure that the optimal position is always being held, thus outperforming a simple hold strategy, which suffers during rotational periods and downtrends in specific sectors.

1. Implementation

Set the reallocation function to be called in a bi-weekly basis. Divide the current price by the price from 14 days. Compare the performances and rebalance portfolio accordingly.

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1. Results

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1. Conclusion

While the rate of return was respectable, it failed to outperform UPRO and TQQ benchmarks. There were large periods of downturn that ate into capital and resulted in smaller returns. The biggest advantage of flexible strategies in comparison to buy and hold, is their ability to navigate away from downturns, so this will need to be considered. A possible remedy could be the implementation of a conditional to stay out of the market during periods of low performance, and/or to add risk management to the algo.

2. Second Iteration

a. Hypothesis

Addition of basic risk management will preserve more capital and lead to a greater return over time, playing on the weakness of buy/hold strategies.

b. Implementation (Iteration 2)

A trailing stop loss will be set to 15%, with a max drawdown of 70% using the module provided by QuantConnect. Stop loss amount was determined by insights gained from this article: https://www.quant-investing.com/blogs/general/2015/02/16/truths-about-stop-losses-that-nobody-wants-to-believe.

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c. Results

Graphical user interface, chart

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1. Conclusion

There was no difference in return, suggesting the stop losses/drawdown conditions were never met. A more restrictive risk management may protect more capital, but it could also negatively affect returns. Attention will be shifted to staying out of the market during downturns.

3. Third Iteration

a. Hypothesis

Staying out of the market during poor performance periods will protect capital and yield greater overall returns.

b. Implementation (Iteration 3)

Performance ratios will be stored in list, which will be sorted in ascending order. The last item in the list (highest performing asset) will be put through a conditional to determine whether or not a position will be taken in the market. If the ratio of the top performing stock ratio is below 0.85, all positions will be liquidated, and no new positions will be taken until the next reallocation period.

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c. Results

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d. Conclusion

Performance suffered and returns dropped by approximately 400%. Despite staying out of the market during poor performance periods, there were still large periods of downturns. Analyzing feedback from the console, it was found that there were multiple instances where market orders weren’t filled due to insufficient buying power. This suggests that there could have been instances where buying opportunities were missed. Before continuing to address the downturn issue, this will need to be fixed.

4. Fourth Iteration

a. Hypothesis

Instances where market orders where not executed could be hindering the overall return, as well as masking the true performance of the algorithm. Will aim to eliminate most situations resulting in invalid orders. After researching the issue, it was found that there could be various reasons buying power is insufficient, ranging from sell orders not executing, to a lag between selling and availability of capital for purchases.

b. Implementation (Iteration 4)

To circumvent all possible situations, a different method will be called to make purchases (based on quantity). The quantity that can be purchased with current buying power will be calculated prior to calling the function/placing the order.

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c. Results

Graphical user interface, chart

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d. Conclusion

Returns doubled by implementing a fix to the issue of invalid orders, which was proven to be a hindrance to the algorithm. Focus will shift to continue dealing with downturns. Given that reallocation occurs every two weeks, the issue could lie in the short term analysis. If performance was tracked over longer periods, this may catch periods of extended downturns, allowing us to stay out of the market.

5. Fifth Iteration

a. Hypothesis

Longer gaps between reallocations could catch longer term trends in the market, preventing large downturns. Multiple reallocation periods will be tested, including: 1 week, 2 weeks (current), 3 weeks, 4 weeks, 6 weeks, and 8 weeks. Any longer than 2 months may defeat the purpose of the algorithm, as there could be significant lag, making it harder to ride momentum.

b. Implementation (Iteration 5)

The reallocation function will be scheduled to be called at all the various time periods mentioned above. Results will be compared to provide insights into the significance of time periods when performing rebalancing/riding momentum.

c. Results

|  |  |  |  |
| --- | --- | --- | --- |
| Time Between Reallocations | Percent Return (10 Years) | Total Number of Trades | Average # of Trades per Year |
| 1 Week | 220.76% | 789 | 79 |
| 2 Weeks | 1632.53% | 395 | 40 |
| 3 Weeks | 1090.27% | 249 | 25 |
| 4 Weeks | 2574.34% | 181 | 18 |
| 6 Weeks | 324.11% | 123 | 12 |
| 8 Weeks | 52.23% | 83 | 8 |

d. Conclusion

Four weeks between performance reanalysis and subsequent allocation yields the best returns, outperforming or matching the benchmarks set by three of the four equities. The average number of trades per year was 18, which was in-line with requirements from the client. A once-a-month reallocation seems ideal given consideration of all situations and constraints. While returns improved significantly, there are still small periods (3 – 12 months) of strong downward momentum that decrease overall return.

6. Sixth Iteration

a. Hypothesis

Market direction in a very simplistic sense is determined by the length of trends on either side. Long term downtrends are composed of short term downtrends that are more impactful/longer than their short term uptrend counterparts, and vice versa. Considering the market never goes straight in one direction, but rather in waves, the algorithm could be adjusted to stay out when both the short term and long term price action is in a downtrend, but participate in all other situations. In this way, not missing buying opportunities in downtrends, while avoiding larger drops associated with those same downtrends.

b. Implementation (Iteration 6)

In order to catch longer term trends, the same methods to pull data will be used, but in an adjusted time frame. Data will be pulled for the same set of equities, but going back one quarter (90 days). It will be analyzed in the same manner, calculating a ratio that is then used to determine performance. The conditional will be stricter in the sense that if the top performing stock is lower in price than it was 90 days ago (less than 1.0), it will trigger a liquidation if in conjunction with the short term ratio dropping below 0.85. The short term ratio is not as strict to allow for buying opportunities during market corrections.

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c. Results

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d. Conclusion

Overall rate of return dropped by about 1000% in comparison to the previous iteration (where optimal reallocation/reanalysis occurred in 4 week periods). Drawdowns were a bit more forgiving, but the added restrictions resulted in smaller risk and returns over time. Taking this into account, any further improvements in algo performance will most likely come from risk management models and not the alpha.

Final Metrics (Iteration 5 – Top performing):

Total Trades

181

Average Win

14.30%

Average Loss

-10.83%

Compounding Annual Return

35.629%

Drawdown

57.300%

Expectancy

0.469

Net Profit

2574.337%

Sharpe Ratio

0.955

PSR

23.790%

Loss Rate

37%

Win Rate

63%

Profit-Loss Ratio

1.32

Alpha

0.425

Beta

-0.12

Annual Standard Deviation

0.429

Annual Variance

0.184

Information Ratio

0.61

Tracking Error

0.463

Treynor Ratio

-3.408

Total Fees

$25079.18

Summary:

Due to time constraints, more hypotheses on navigating long term downtrends could not be explored. Regardless, the algorithm met the client conditions of a passive, low-to-medium trading frequency strategy. In the final metrics, the algorithm showed mostly favorable statistics including, but not limited to: 2,574.33% total return over a 10-yr period, a 63% win rate, positive profit/loss ratio of 1.32, 35.63% compounding annual return, and a 0.96 Sharpe Ratio (decent, but not great); this effectively matched or outperformed benchmarks set by the buy-and-hold strategy for three of the four equities (all but TQQQ, which managed an 8466% return over the same period).

Algorithm Continuance/Guidance:

Generating a signal that could provide faster insights into large market downtrends may help to preserve capital and provide greater returns over time (in other words, more extensive risk management). An EMA signal, used as input in the conditional statement to stay out of the market, could be a better alternative to a straight strategy that compares the prices between 90 day periods. This strategy may also be useful within sectors. For example, within big tech, not all companies share the same strength momentum, but are generally in an uptrend. Rotating between these stocks could be an appealing alternative to owning an ETF containing those stocks. While the strength of an ETF is it’s diversification, this same quality means it must endure downtrends for individual stocks, which bring down gains from stocks in large uptrends.