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MSDS 451: Financial Engineering

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Programming Assignment 3

Technical Report 11/2/2025

Problem Definition

This report aims to build on what has been done in Assignments 1 and 2. However, the goal is to focus on automated trading strategies and to backtest the chosen strategy. There were no machine-learning requirements for this particular assignment. The chosen method of trading was a simple momentum strategy. In short, a momentum strategy is the principle that assets that have seen positive performance in the recent past are more likely to perform at a higher level (generate better returns) than other assets in the future. This method simply tracks trends and as an investor you'd like to buy assets that have momentum, and sell ones that do not.

Data Preparation

The data used for this assignment was Yahoo! Finance historical data, similar to that which was used in assignments 1 and 2. The data was collected for each ticker of the above assets using Python's built-in "yfinance" library. For the data retrieval, the time period was specified as the 20 year period between 2005-01-01 and 2025-01-01. This is important so that we can account for large market movements and real-world events. This time period includes the 2008 financial crisis, as well as the resulting market crash due to COVID-19. The data was unable to include the Dot-Com Bubble due to limited data availability in regard to the TLT ETF, and the earliest data for that fund was 2005.

Simple pandas manipulation was performed after the data was retrieved from Yahoo! Finance. The historical data for each asset was combined into one single dataframe to be used going forward in the program.

Research Design / Programming

As mentioned above, the chosen strategy for this assignment was a simple momentum strategy. Structurally, the outline used in Clenow's *Trading Evolved: Anyone Can Build Killer Trading Strategies in Python* served as the basis of my experiments. In Clenow's words, "Momentum is a market phenomenon that has been working well for decades. It has been confirmed both by academics and practitioners and is universally known as a valid approach to the financial markets" (2019).

Clenow's model tries to capture long-term stable performance, which is pertinent to my personal term project given my fund's philosophy. The following bullet points serve as the summary to my momentum trading model, extracted from Clenow's textbook. However, due to my unique ETF historical data, certain constraints needed to be altered to run with my program:

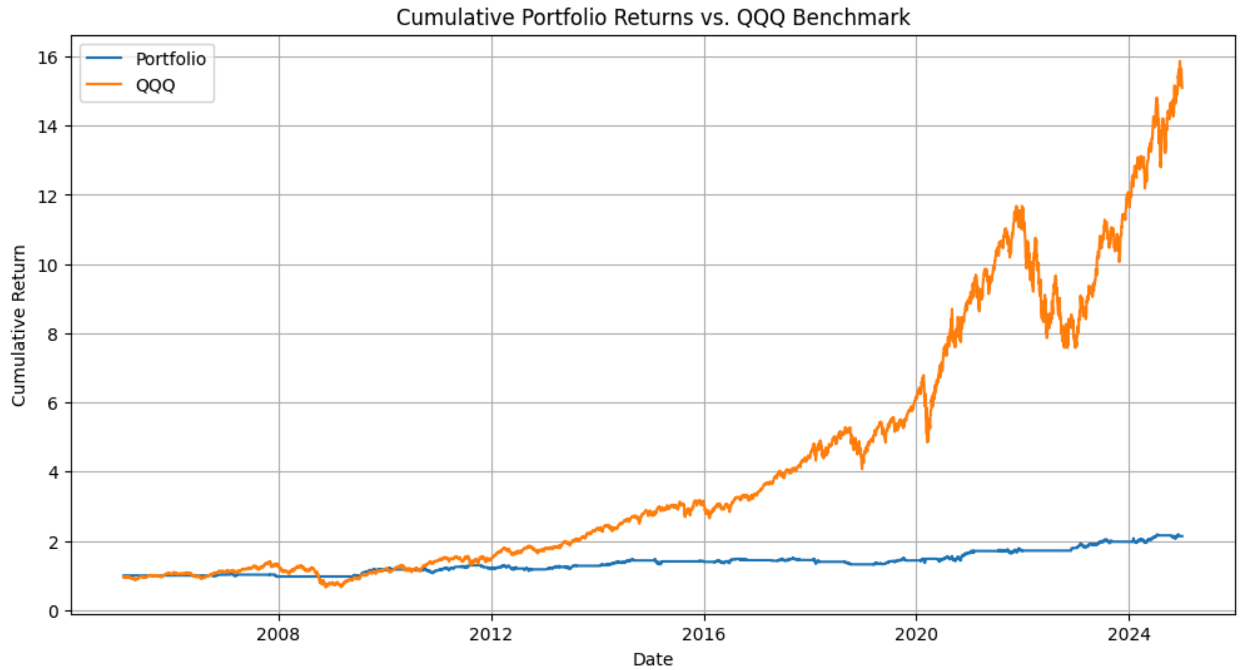
- Trading is only done monthly, with the investor rebalancing and repeating the process after each month
- Momentum slope is calculated using a 125-day window
- Weights will be calculated for my assets using inverse volatility
- Volatility itself is derived from 20-day standard deviation
- The trend filter is calculated based on a 200-day average of the S&P index
- If the trend filter is positive, investor is allowed to buy
- Minimum required momentum value is set to 0.0005. If the assets have a value higher than 0.0005 then the investor buys. If an asset in the portfolio falls below the minimum value, or it leaves the index during the time period, the investor sells

After the momentum strategy was implemented, giving us our portfolio's expected return, Sharpe Ratio, and expected max drawdown, the results were run against a benchmark to evaluate performance. The benchmark used in this assignment was the QQQ ETF, which is a market-cap-weighted index of non-financial NASDAQ-listed stocks.

Results and Conclusions

In the plot above, we can see a fairly steady up-and-right growth trajectory for our portfolio over time, albeit for a few rough spots which will be addressed later. The momentum strategy gives us a 1.14% total return, and a 4% annualized return with a roughly 9% annual volatility. The portfolio's Sharpe Ratio given the strategy is 0.4503. As we know, the closer to 1 the ratio is, then the "better off" we are considered to be. However, a Sharpe Ratio that significantly exceeds 1 can be considered high-risk. For a conservative investor, the Sharpe Ratio produced by the momentum strategy is a good place to be, with room for improvement to possibly generate higher returns.

Below is the result of the benchmark test which compares our hypothetical portfolio against the QQQ.



As you can see there is quite a large gap between the performance of the QQQ vs our portfolio's returns. The QQQ's Sharpe Ratio over the period was 0.6918. The plot shows that the QQQ had a significantly higher annualized return. However, there are nuances. Our portfolio had much lower annualized volatility, this is also supported by the lower Sharpe Ratio. The max drawdown for the QQQ benchmark was 0.2585, and our portfolio's was 0.0892. This leads me to believe that given the specific 20-year time period, our portfolio ultimately proved to be a better investment given the risk-adjusted return and lower max drawdown.

This all needs to be put into historical context and applied to real-world events. If you examine the volatility in both the COVID-19 and post-COVID era of 2020-present, you can see our portfolio – while still not generating the same returns - was relatively stable compared to the QQQ index. The QQQ suffered a pretty dramatic decline over the course of that specific time period while our portfolio remained flat and did not see significant losses even during the COVID-19 pandemic.

In conclusion, even though our portfolio cannot generate the excess returns that the QQQ benchmark did, the lower max drawdown and strong Sharpe Ratio seem worth the investment. A low max drawdown is considered favorable for investors because it indicates less exposure to huge losses if the market were to decline. Over the specified historical time period, our momentum strategy seemed to demonstrate limiting downside risk during economic downturns compared to a buy-and-hold strategy in QQQ. However, it may be concluded that perhaps the buy-and-hold strategy was ultimately the better route for a higher cumulative return.

References

Clenow, Andreas F. 2019. *Trading Evolved: Anyone Can Build Killer Trading Strategies in Python.* Independently Published. [ISBN-13: 978-1091983786] Author's website: Trading Evolved – Following the Trend