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MSDS 451 - Financial Engineering
Week 5 Programming Assignment 03

Problem Description

For this assignment, my goal was to create an automated trading strategy that utilizes commodity futures signals for common agricultural commodities such as Corn, Soybeans, Cotton, and Wheat to determine the optimal time to invest in a portfolio of agricultural heavy equipment manufacturers.

Deere & Company	Caterpillar	AGCO Corporation	CNH Industrial
DE	CAT	AGCO	CNH

I wanted to compare this strategy with buy and hold benchmarks to determine if commodity price fluctuations predict or influence agricultural equipment revenues and stock returns.This project supports my ultimate research goal which is to investigate if commodity price trends provide predictive signals for equity returns of agricultural equipment manufacturers. If this hypothesis is true, I wanted to understand the quantify this relationship relative to benchmarks and after accounting for trading frictions.

Instead of explicitly employing machine learning or complex regime detection methods, I developed a trading strategy that focuses on simple, rule based momentum signals derived from commodity futures. I automated the trading process and performed backtesting over a long historical period (2000-2025), comparing this strategy's performance to common benchmark funds:

- S&P 500 ETF (SPY)
- NASDAQ 100 ETF (QQQ)
- U.S. Aggregate Bond ETF (BND)

Also, to measure performance, I used the Sharpe ratio as a return based statistic to assess risk adjusted returns. I then compared the cumulative performance of the strategy to the benchmark indices listed above. For this project, I referenced the programming approach outlined by (Clenow, Andreas F. 2019)

Data Preparation & Pipeline:

1. Data Ingestion

I used the Yahoo Finance API (yfinance) to pull in historical price data from January 1, 2000, to October 25, 2025 (latest date of project completion).
As mentioned above, the asset I pulled include:

- Agricultural equipment manufacturers: DE, CAT, AGCO, CNH
- Commodity futures: ZC=F (Corn), ZS=F (Soybeans), CT=F (Cotton), ZW=F (Wheat)
- Benchmarks: SPY, QQQ, BND

The data I pulled is adjusted close prices, that I stored in a single pandas DataFrame.

2. Data Cleaning & Processing

- I aligned all the adjusted close prices by trading date.

- During rolling percentage change calculations, I handled the missing values by filling them with 0 as needed using the .fillna(0) command in Python.
- I calculated the returns using daily percentage changes in adjusted close prices.

3. Signal Creation Process

To generate the commodity signals, I used the following approach:

- I computed a 20 day moving average (MA) for each commodity future.
- Then, I generated a binary signal for each commodity, by incorporating a logic where signal hits 1 when the commodity's current price exceeds its 20 day moving average, or hits 0 otherwise.
- I then aggregated the four commodity signals each day and computed their sum.
- Lastly, if at least 2 out of 4 commodities are above their 20 day moving average, I set a concurrent investment signal equal to 1; otherwise, 0. This binary signal then determines if the strategy holds a position in the ag equipment stocks or remains out of the market.

4. Strategy Return Calculation Process

To calculate strategy returns,

- I calculated daily returns for the ag heavy equipment manufacturers using a simple percentage change in their adjusted close prices (See Figure 3).
- The formula I used to compute strategy return for a given day was:
  - (avg of all ag heavy equipment daily returns on a given day) x (the previous day's investment signal).
  - I used this lag approach to ensure that the signal is applied without lookahead bias
- This strategy also assumes equal weightage among all ag heavy equipment stocks when the signal is active.

5. Calculating Cumulative Value of Overall Portfolio

To create an equity curve plot of the strategy, I compounded daily returns starting from an initial portfolio value of 1 (See Figure 2). I also incorporated an additional exposure plot to track the cumulative number of days where the strategy is active or the signal is 1.

Research Design

1. Rule For Trading:

As stated in the problem description, I used a momentum based strategy using short term moving averages of the commodity futures. The logic I used was if at least 2 commodities were to trade above their 20 day moving average, then the model would take an equal weigted long position across all of the ag hevay equipment manufacturers. In contrast to that, if less that 2 commodities were to trade above their 20 day moving average, then no position is to be taken therefore stay in cash. This is a fitting strategy based on my experience in the industry because it captures broader commodity strengths as potential signals for strength in the ag heavy equipment sector.

2. Performance Evaluation Metrics:

In order to get an understanding of perfromance, I calculated the equity curve that shows me the cumulative value of my portfolio (See Figure 1). I also used the unnualized Sharpe Ratio by assuming 252 trading days for each benchmark for risk-adjusted comparison. I calculated the Sharpe Ratio using the following formula:

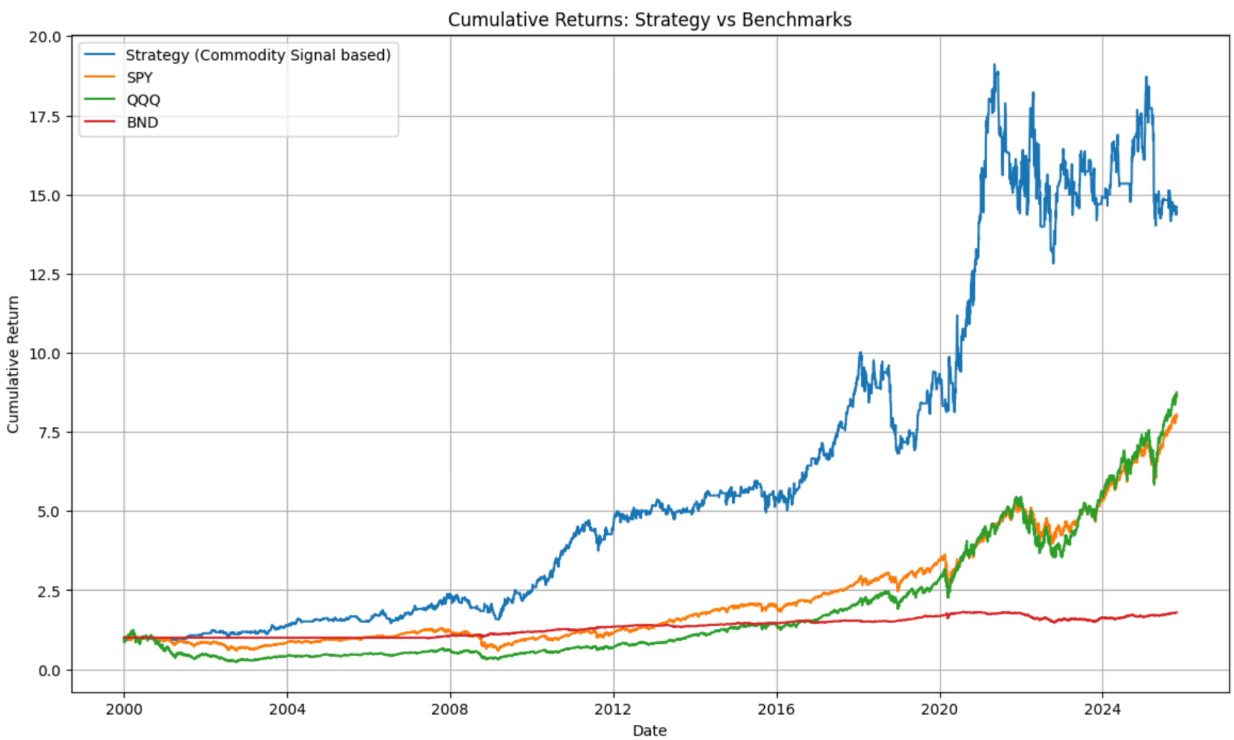
$$\text{Sharpe Ratio} = \frac{\text{Average Daily Returns}}{\text{Standard Deviation of Daily Returns}} \times \sqrt{252}$$

3. Comparing with Benchmarks

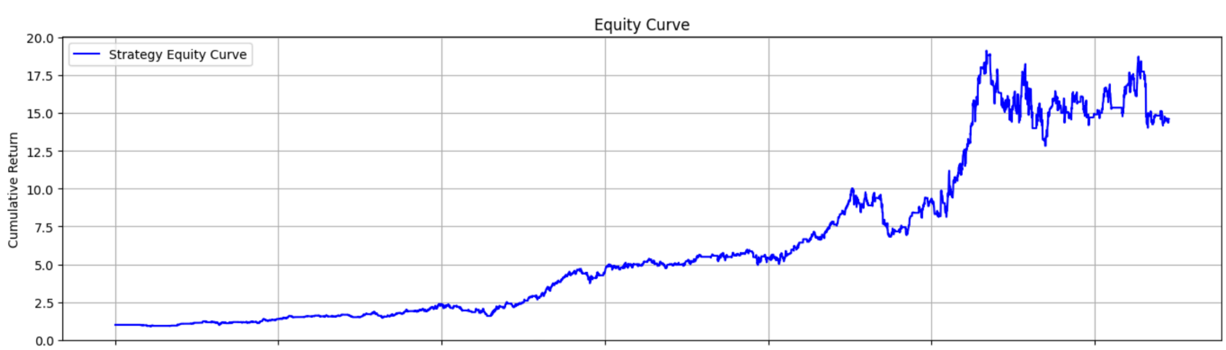
I evaluated performance by comparing my cumulative returns for each benchmark SPY, QQQ, and BND alongside the strategy's equity curve. I plotted an overlayed curve for each of these to provide a visual comparison of long term performance (See Figure 4) .

Results

Strategy Cumulative Returns Along with Benchmarks - Figure 4

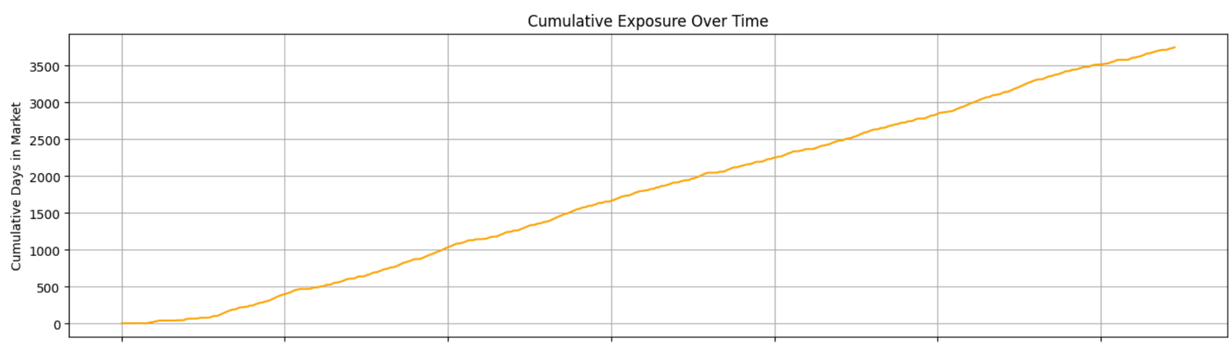


Strategy Cumulative Returns (Solo) - Figure 1



The blue line showing equity returns for my commodity signal based strategy seems to show significantly higher cumulative returns in comparison to the benchmark equity curves for SPY, QQQ, and BND over the 1999 to 2025 testing period.
I would say that my strategy sees multiple large growth phases especially around 2019–2021, where there is a sharp upward trend. However, in relation to that, there is also visible volatility and down trends in later years 2021 onwards. Even though volatility exists, the returns seem to remain well above the benchmarks. post 2009, the stratgy shows a much higher performance relative to the benchmarks
In terms of the benchmarks, the SPY and QQQ are the only ones that show steady long term upward trends. Looking closely, QQQ actually seems to slightly outperform SPY after 2020.
The BND on the other hand is only showing a flat curve throughout, Therefore BND is yielding lowest cumulative returns.

Strategy Cumulative Exposure Over Time - Figure 2



I wanted to see a cumulative exposure overtime since it was a better visual indicator of consistency of strategy showing activity over time compared to a binary time series for signal. This cumulative days in market line shows a steady and consistently increasing plot which indicated to me that the strategy has been continuously active throughout the backtesting period. The almost linear slope of the curve shows me that exposure to the market has not seen fluctuations through time or no extended periods where strategy was out of the market.

Strategy Daily Returns - Figure 3

The daily returns seem to fluctuate around zero. There are both positive and negative outliers here. and the volatility is varying over the time. We can see larger deviations around 2009 and after 2021, from my industry experience, this is consistent with events like 2008 recession, and post covid.

References:

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