Algorithmic Trading with Cross-Asset Momentum Signals

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Introduction

The purpose of this study is to investigate whether a simple, rule-based momentum strategy can generate superior returns compared to a passive benchmark such as the S&P 500 index. While equity markets are difficult to outperform over long horizons, commodity markets—especially crude oil—are highly volatile and may contain exploitable patterns. This project focuses on the United States Oil Fund (USO), an exchange-traded fund that tracks West Texas Intermediate (WTI) crude oil. The strategy draws signals from multiple asset classes, including equities, bonds, and gold, under the hypothesis that cross-asset momentum information can help identify major trend regimes in oil. The broader motivation aligns with the adaptive markets hypothesis, which suggests that investors are not always rational and that systematic, data-driven methods can occasionally capture excess returns (Lo 2017).

Literature Review

Momentum-based investing has a long history in both academic research and practice. Jegadeesh and Titman (1993) demonstrated that stocks that performed well in the past three to twelve months tended to continue performing well in the future, introducing the concept of time-series momentum. Antonacci (2014) extended this insight to "dual momentum," combining relative momentum across assets with absolute momentum rules. Carver (2015) and Clenow (2019) emphasized that simple trend-following systems using moving averages remain effective across asset classes, though they carry substantial risk of drawdown.

From a theoretical standpoint, momentum strategies contradict the strong form of the efficient market hypothesis (Malkiel 2023), which asserts that prices fully reflect all available information. Instead, behavioral and adaptive models argue that investor biases, herding, and structural frictions allow trends to persist (Lo and Zhang 2024). Recent literature in financial machine learning has further emphasized that technical rules like moving averages should be evaluated with robust methods, such as cross-validation or Monte Carlo simulation, to avoid false discoveries (López de Prado 2018).

The specific focus on crude oil is motivated by its role as both a financial and real asset. Bouchouev (2023) highlights how oil’s price dynamics often diverge from fundamentals due to financial flows, while Covel (2017) notes that commodity trend-following has historically provided crisis alpha. Together, these works suggest that a systematic cross-asset momentum strategy targeting USO could potentially capture oil’s extreme moves, albeit with significant risks.

Methods

This project employs a rule-based momentum strategy, designed to evaluate whether cross-asset information can generate profitable trading signals for crude oil. The dataset spans ten years, from January 2015 through December 2024, and was obtained through the Yahoo Finance API using the Python yfinance library. The primary tradable instrument is the United States Oil Fund (USO), which serves as a liquid proxy for West Texas Intermediate (WTI) crude oil. To construct trading signals, I selected four additional exchange-traded funds (ETFs) that represent major asset classes with potential influence on oil markets: SPY, representing broad U.S. equity performance; GLD, reflecting gold as a risk-off asset; TLT, capturing long-term U.S. Treasury bonds as a measure of interest rate regimes; and VGT, reflecting the performance of technology stocks as a proxy for risk-sensitive growth. These four ETFs were chosen because they provide diversified perspectives on market conditions that may affect oil demand and pricing.

For each of the signal-generating ETFs, I computed two exponential moving averages (EMA) with window lengths of forty and eighty days. The signal rule is straightforward: when the forty-day EMA exceeded the eighty-day EMA, the asset was coded as being in an uptrend and contributed a vote of one; otherwise, it contributed a zero. At each decision point, these binary signals were aggregated into a consensus score, defined as the proportion of uptrend votes across the four ETFs. Trading decisions were then based on this consensus score relative to a predefined threshold. Three thresholds were examined, representing different investor risk preferences: an Aggressive configuration at 0.50, where the strategy entered a long position in USO if at least half of the signals were positive; a Moderate configuration at 0.60, which required stronger cross-asset confirmation; and a Conservative configuration at 0.70, which required near-unanimous agreement before entering a trade. When the consensus score failed to exceed the threshold, the portfolio remained in cash. Transaction costs were modeled as five basis points per trade to reflect realistic ETF trading costs.

Performance evaluation employed several standard financial metrics, including compound annual growth rate (CAGR), the Sharpe ratio, maximum drawdown, and trade-level win rate. CAGR measures the annualized return, while the Sharpe ratio evaluates risk-adjusted efficiency. Maximum drawdown is particularly important for commodity strategies, as it captures the extent of potential capital loss during adverse market conditions. The win rate helps to identify whether performance comes from frequent small gains or from rare but large profits. To ensure robustness, I conducted one thousand Monte Carlo simulations using block bootstrap resampling of daily returns. This approach preserves time-series properties such as autocorrelation and volatility clustering, offering a realistic test of how the strategy might perform under alternative market histories. Finally, I evaluated commercial viability by applying a hedge fund fee model of two percent annual management fees and twenty percent performance fees, following the standard “2 and 20” structure.

Results

The results of the backtest show important contrasts across the three threshold settings. The Aggressive strategy, with a threshold of 0.50, delivered the strongest raw returns, with a compound annual growth rate of 7.2 percent and a Sharpe ratio of 0.38. However, these gains came with significant downside risk, as the strategy experienced a maximum drawdown of –60.7 percent. Over the ten-year period, the Aggressive strategy generated only fifteen trades, with a win rate of 43 percent. This suggests that profitability depended heavily on capturing a small number of major oil trends rather than producing consistent gains across many trades.

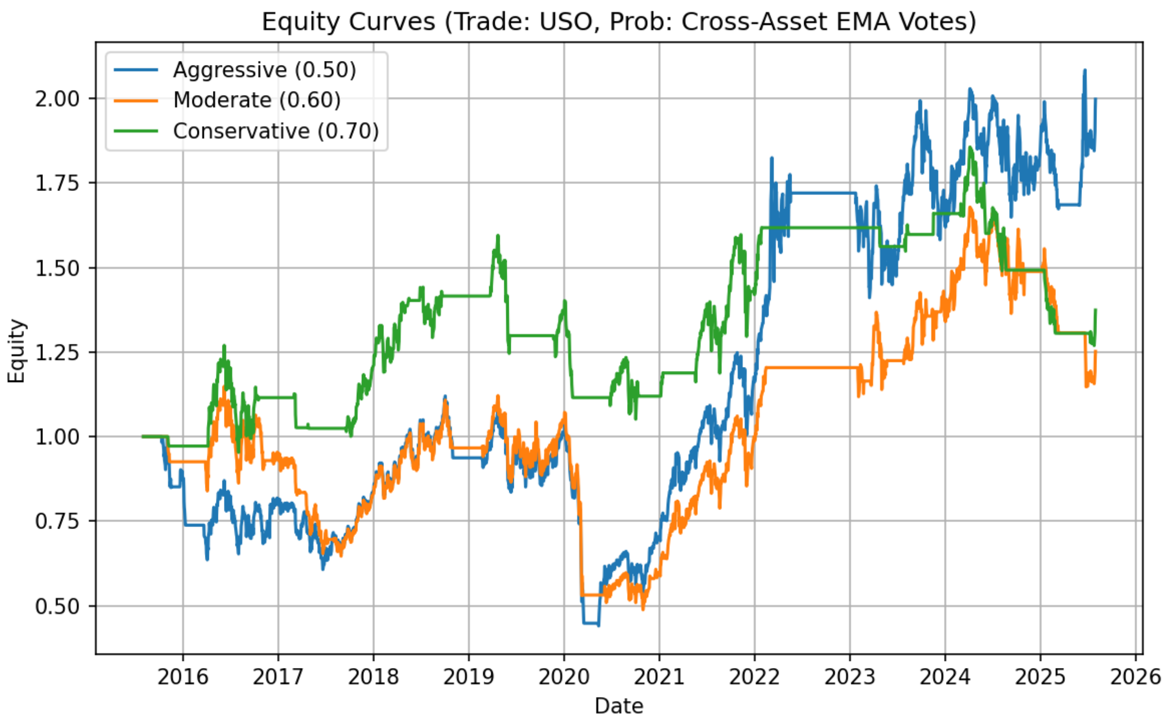

Figure 1: Equity Curves of Momentum Strategies (Aggressive, Moderate, Conservative)

The Moderate strategy, which required a threshold of 0.60, demonstrated weaker performance. Its CAGR was only 2.3 percent, with a Sharpe ratio of 0.22 and a drawdown of –57.5 percent. While the strategy made thirty-three trades during the period, its win rate was 36 percent. Tightening the threshold reduced participation in profitable rallies without meaningfully lowering downside risk, thereby resulting in a less attractive risk-return tradeoff.

The Conservative strategy, with a threshold of 0.70, produced the lowest risk exposure but also the weakest consistency in returns. Its CAGR was 3.3 percent, with a Sharpe ratio of 0.28 and a maximum drawdown of –34.1 percent. It generated forty-three trades, yet its win rate was just 18 percent. This version of the strategy avoided some of the most severe losses but spent long stretches out of the market, missing opportunities to participate in favorable trends.

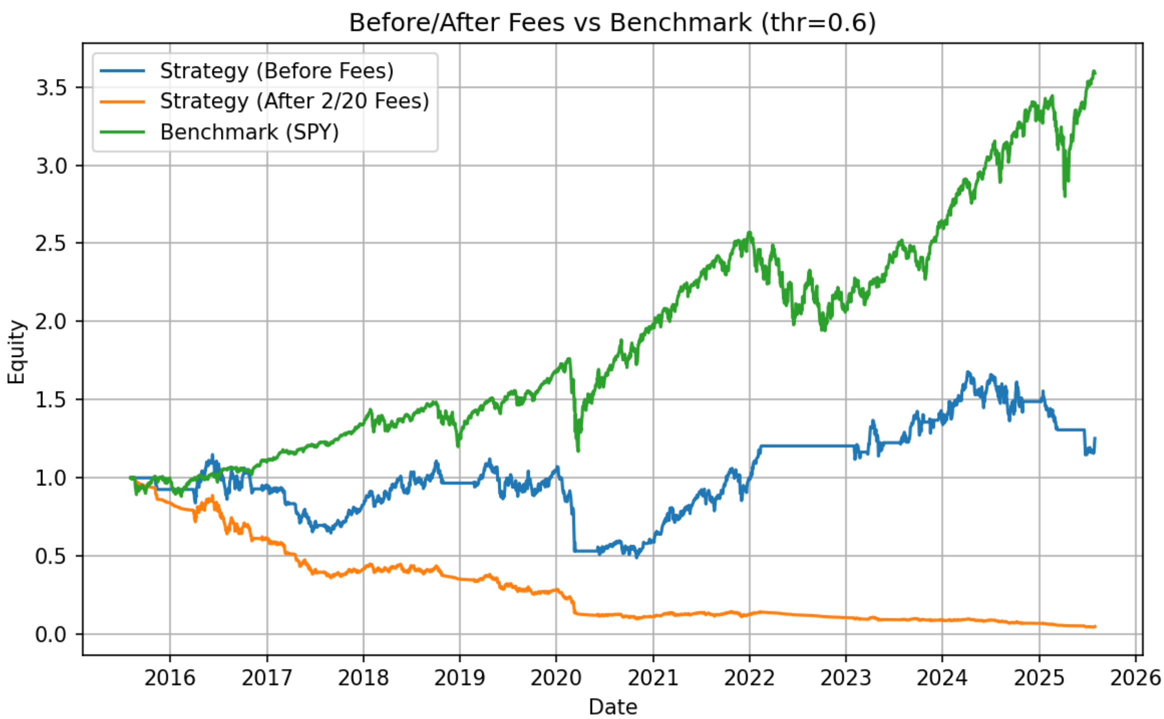

Figure 2: After-Fee Equity Performance under 2/20 Hedge Fund Structure

Across all configurations, win rates remained below fifty percent, indicating that the strategy depended on rare but powerful oil price movements. This reliance on infrequent large gains is consistent with the broader literature on trend-following strategies in commodities, which typically show positive skewness but long periods of flat or negative performance.

Monte Carlo simulations further highlighted the fragility of the strategy. The distribution of Sharpe ratios clustered between 0.2 and 0.5, suggesting that the observed backtest was typical rather than exceptional. Maximum drawdowns in the simulations frequently fell between –50 and –70 percent, underscoring the risk of large capital losses under realistic return dynamics.

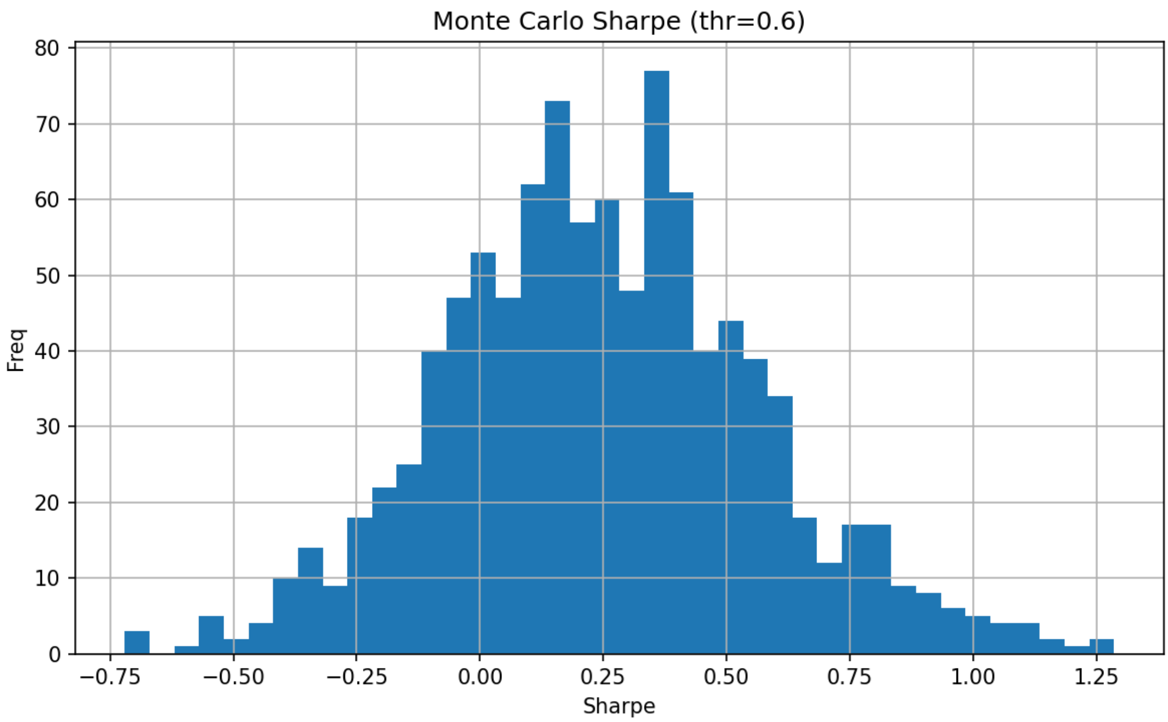

Figure 3: Monte Carlo Distribution of Sharpe Ratios

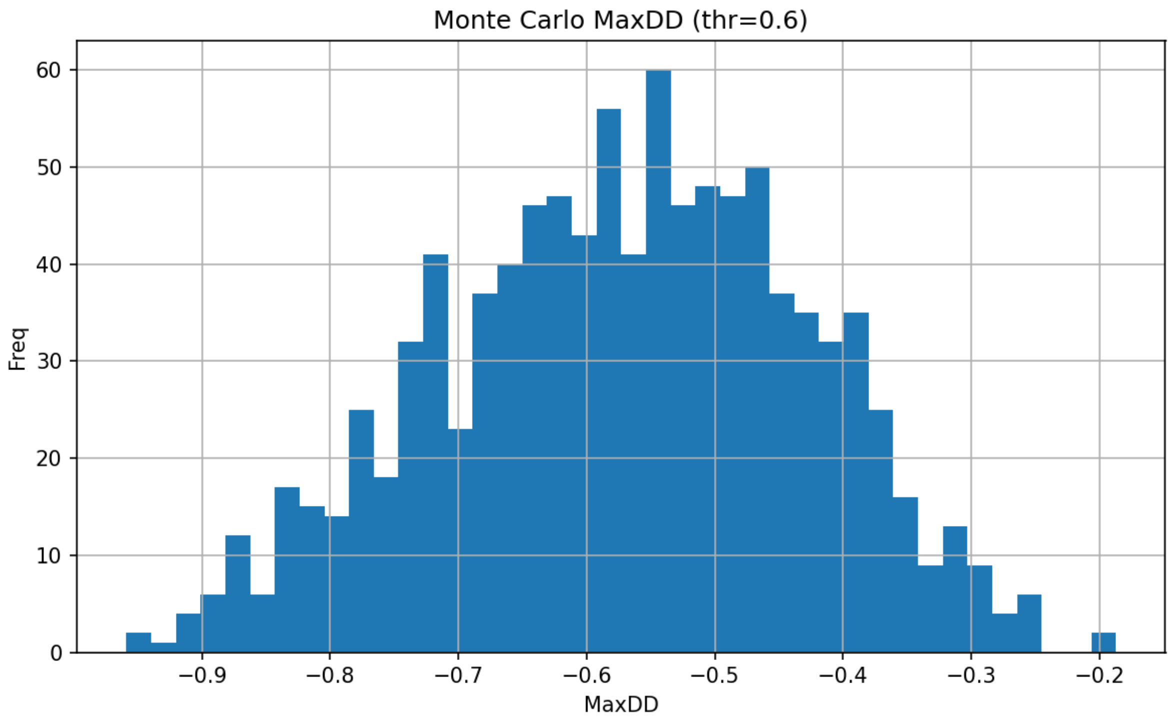

Figure 4: Monte Carlo Distribution of Maximum Drawdowns

The analysis of fees provided the clearest evidence of commercial infeasibility. When the 2 percent management fee and 20 percent performance fee were applied, the annualized return collapsed to –26 percent. The Sharpe ratio turned negative, and the maximum drawdown deepened to –95 percent. This implies that the modest pre-fee profitability was entirely eroded by typical hedge fund fee structures, leaving the strategy unattractive for institutional capital.

Management Recommendation

From the perspective of a fund manager, the evidence does not support launching this strategy as a hedge fund. Although the strategy sometimes captures oil's large trends, its overall performance is fragile, and its risk-adjusted returns are weak. More importantly, after accounting for realistic fees, the product is not investable. From the perspective of a client, the strategy also fails to provide an attractive alternative to a passive SPY investment.

That said, the strategy could still serve as a research prototype or a low-cost rules-based ETF. With low or no management fees, the modest gross alpha may remain attractive to niche investors seeking commodity diversification. Moreover, the strategy offers value as a teaching tool in quantitative finance, demonstrating the gap between appealing backtests and robust, fee-adjusted investment products. My personal inclination is to continue developing the strategy as a quantitative researcher, focusing on signal enrichment, volatility targeting, and regime-based filters to reduce drawdowns.

Conclusion

This project illustrates both the potential and the limits of cross-asset momentum strategies. A simple EMA-based voting model applied to USO can sometimes capture large oil price trends, but it also suffers from large drawdowns, low Sharpe ratios, and low win rates. Robustness checks confirm the fragility of the performance, and fee adjustments render the strategy uninvestable as a hedge fund product. The findings reinforce lessons from the literature: trend-following is powerful but risky, and strategies must be judged not just by raw backtests but also by robustness, business viability, and investor suitability. Future work may focus on improving risk controls, expanding the signal set, and testing more sophisticated machine learning approaches.

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