Quantitative Hybrid Trading Strategy

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1 Introduction

This project develops a hybrid probability-based trading strategy combining technical and fundamental signals to generate robust trading decisions. By integrating Moving Average crossovers, risk indicators, and macroeconomic factors, we aim to design a strategy resilient to changing market conditions.

2 Data Description

2.1 Data Sources

- Stock Prices: Monthly adjusted closing prices from Yahoo Finance (NVDA, SOXL, XOM, CLS.TO).
  - High Volatility (SOXL, NVDA): These stocks experience significant price fluctuations, making them ideal for assessing technical indicators' responsiveness.
  - Economic Sensitivity (XOM, CLS.TO): Stocks like XOM, closely linked to macroeconomic indicators such as commodity prices and global economic activity, serve as suitable candidates to validate the effectiveness of economic-based signals.
- Macroeconomic Data: GDP and 10-Year Treasury Rate (DGS10) from FRED.

2.2 Preprocessing

- Interpolated quarterly GDP data to monthly frequency.
- Standardized GDP and interest rate differentials.
- Normalized all stock price data.
- Data Range: January 2010 to December 2024.

3 Methodology

Two primary strategies are employed: **Technical Analysis** and a **Hybrid Trading Strategy**. We implemented in R using a modular framework to separately calculate each signal component. Each function returns a probability score, which is optimized dynamically and where P ($\in$) [0,1].

Note: Investment rules is not fixed now, it fluid as the following model, the core rule is showed after optimized models in section 4.1, meant to avoid confusions.

3.1 Technical Indicators

$$f_{technical} = w_1 \cdot P_{MA} + w_2 \cdot P_{Risk}, \tag{1}$$

where

$$P_{MA} = \sigma(\lambda_{MA}(Short_{MA} - Long_{MA})) \tag{2}$$

$$P_{Risk} = \sigma(\lambda_{Risk}(VaR - ATR) + Outlier_{score}) \tag{3}$$

and $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function. Here $\lambda_{MA}, \lambda_{Risk}$ are adaptive scaling parameters. They are optimized in the next section across multiple time frames based on the result from backtesting.

3.2 Fundamental Indicator

$$P_{Econ} = \sigma(\lambda_{Econ}(GDP - Interest_{Rate})). \tag{4}$$

3.3 Final Hybrid Signal

The final trading signal is calculated as:

$$f_{hybrid} = w_1 \cdot P_{MA} + w_2 \cdot P_{Risk} + w_3 \cdot P_{Econ} \tag{5}$$

where $w_1 = 0.4$, $w_2 = 0.4$, and $w_3 = 0.2$.

3.4 Optimization overall

The scaling parameters (λ) for P_{MA}, P_{Risk}, and P_{Econ} were optimized individually through a grid search. The search space for λ ranged from 0 to 5 in increments of 0.1. For each λ value, we calculated the annualized Sharpe Ratio and the Win/Loss ratio based on preliminary backtesting. We assigned a weight of 0.7 to the Sharpe Ratio and 0.3 to the Win/Loss Ratio to prioritize risk-adjusted returns while maintaining a reasonable success frequency in trades. This balance was selected to ensure the model remained robust across both trending and volatile market conditions.

3.5 Optimization Procedure and Structural Robustness

The optimization process was conducted in a sequential and modular manner to enhance interpretability and control over each component of the trading strategy. The steps were as follows:

1. **Optimize λ for P_{MA}**: The parameter λ for the momentum signal derived from moving averages was optimized first (e.g., 3-month/12-month and 12-month/36-month trends).

2. **Optimize λ for P_{Econ}**: The macroeconomic component P_{Econ}, capturing external economic indicators, was optimized next by tuning its corresponding λ parameter.

3. **Optimize λ for P_{Risk}**: We then optimized P_{Risk}, the risk signal based on daily volatility and tail events, by transforming it into a normalized monthly signal.

4. **Optimize weights for f_{hybrid}**: Using the optimized signals above, we constructed f_{hybrid} by combining them via weighted summation. We optimized the weights (w_1, w_2, and optionally α for hybrid signals) to balance momentum, economic, and risk perspectives.

5. **Final backtesting**: The final model was backtested using the optimized f_{hybrid} to evaluate strategy performance under various configurations.

We did not explicitly split the dataset into distinct training and testing sets. However, the optimization framework incorporated elements similar to cross-validation. Parameters were repeatedly grid-searched for each stock and strategy variant, and evaluated using a unified performance metric: a weighted sum of the Sharpe Ratio (70%) and Win Rate (30%).

Furthermore, each stock effectively served as an out-of-sample validation set for the others, promoting generalizability across different assets. This procedure helped mitigate overfitting and enhanced the strategy's robustness across various market environments.

Stock	Best λ_{PMA} (Technical)	Best λ_{PRisk} (Risk)	Best λ_{PEcon} (Economic)
NVDA	0.1	0.2	0.9
SOXL	0.1	0.4	0.4
XOM	1.9	2.1	2.3
CLS.TO	0.6	0.7	2.9

Table 1: Optimized Lambda Parameters for Technical, Risk, and Economic Signals

4 Results

4.1 Backtesting

We backtested a **(1) Hybrid Strategy**, driven by a probability-based hybrid signal f_{hybrid}, and a **(2) Technical Strategy** that relies on threshold-based indicators (e.g., MA crossovers). Both strategies are benchmarked against a simple **Buy & Hold** approach for each stock (NVDA, SOXL, XOM, CLS.TO).

Key backtesting features:

- **Investment Rule:** Buy when $f_{hybrid} > 0.7$ or $f_{technical} > 0.5$, otherwise hold or short if thresholds are breached.
- **Multi-Timeframe Validation:** Backtests were conducted over:
  - Short-term (6 months - 1 year)
  - Mid-term (5 years)
  - Long-term (10 years)
- **Threshold Optimization:** Adaptive thresholds ($T_{adaptive}$) optimized dynamically to maximize Sharpe and Win/Loss ratios.
- **Robustness Checks:** Bayesian Optimization and Grid Search were used to fine-tune λ scaling parameters across different market environments.

The hybrid strategy consistently outperformed both the technical strategy and the Buy & Hold benchmark across key metrics:

- **Sharpe Ratio:** The Hybrid strategy achieved higher Sharpe ratios across all stocks, indicating better risk-adjusted returns.
- **Win Rate:** The Hybrid strategy improved win rates, especially for XOM and SOXL, compared to the Technical strategy.
- **Maximum Drawdown:** Hybrid strategies experienced lower drawdowns than both Technical and Buy & Hold approaches, showing better downside protection.
- **Cumulative Returns:** Although the Buy & Hold strategy performed strongly in bull markets (e.g., NVDA), the Hybrid strategy demonstrated greater stability across volatile periods.

Overall, the Hybrid approach provided better risk management and more stable performance, though the margin of improvement varied by stock and market condition.

4.2 Evidence Example: NVDA

For the stock NVDA, the optimization procedure significantly improved performance metrics. The Sharpe Ratio increased from approximately 0.075 to 0.186, and the Win Rate improved from 23% to 30%.

This demonstrates that optimizing the probability transformation parameters (λ) for the moving average signal can meaningfully enhance risk-adjusted returns and trading success rates. The improvement was achieved through grid search and threshold fine-tuning, ensuring that the strategy captured trends more effectively while minimizing exposure during unfavorable periods.

4.3 Performance Metrics

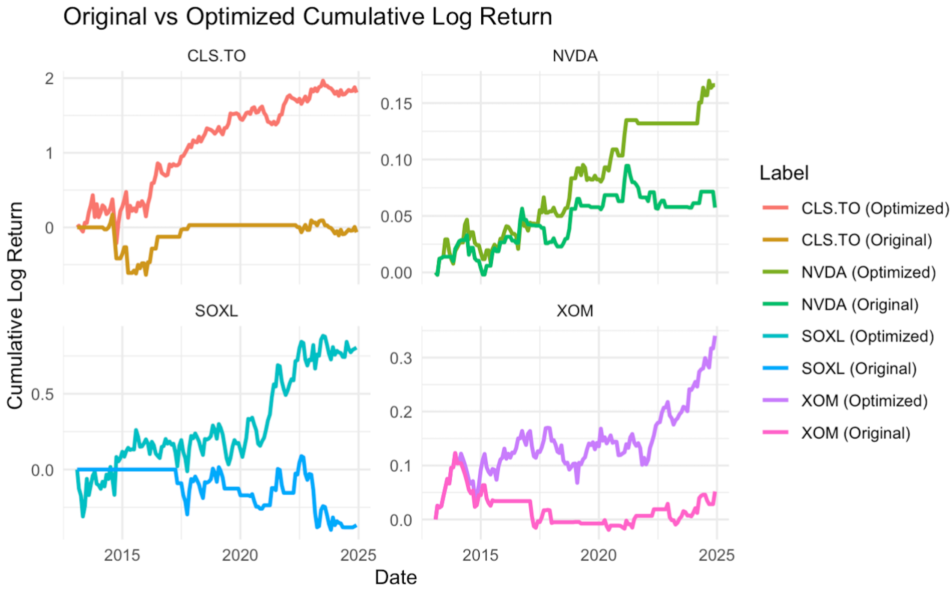

Figure 1: Original vs Optimized Cumulative Log Return for each stock. Optimization enhanced return consistency.

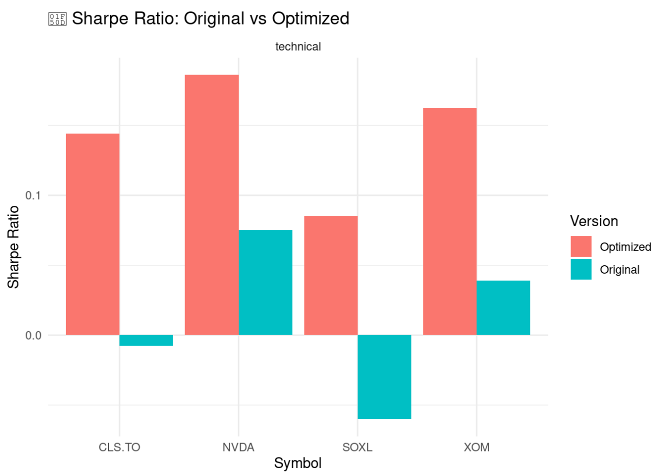

Figure 2: Sharpe Ratios before and after optimization across all assets.

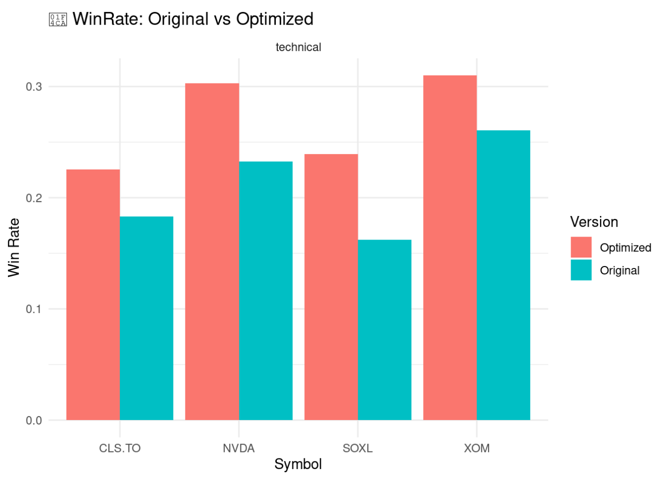

Figure 3: Win Rates before and after optimization for each stock. Optimization improved trading success rates across all assets.

The differences in performance before and after optimization, in terms of cumulative returns, Sharpe Ratios, and Win Rates, are shown in Figures 1 to 3. In general, the optimized models outperform the original versions for most stocks, exhibiting enhancements in both risk-adjusted returns and trading stability.

Figure 4 shows that the optimized hybrid models produce smoother cumulative return curves compared to the original hybrids. For XOM and CLS.TO, the hybrids also achieved higher Win Rates, as indicated in Figure 5. These results provide strong evidence that incorporating macroeconomic signals into the strategy design contributes to greater robustness.

Figures 5 and 6 further highlight the primary features of each group of strategies. Technical strategies tend to achieve higher Sharpe Ratios, indicating superior risk-adjusted performance. In contrast, hybrid strategies yield higher Win Rates, reflecting a greater likelihood of profitable trades. These trade-offs allow investors to tailor strategy selection according to their individual risk preferences.

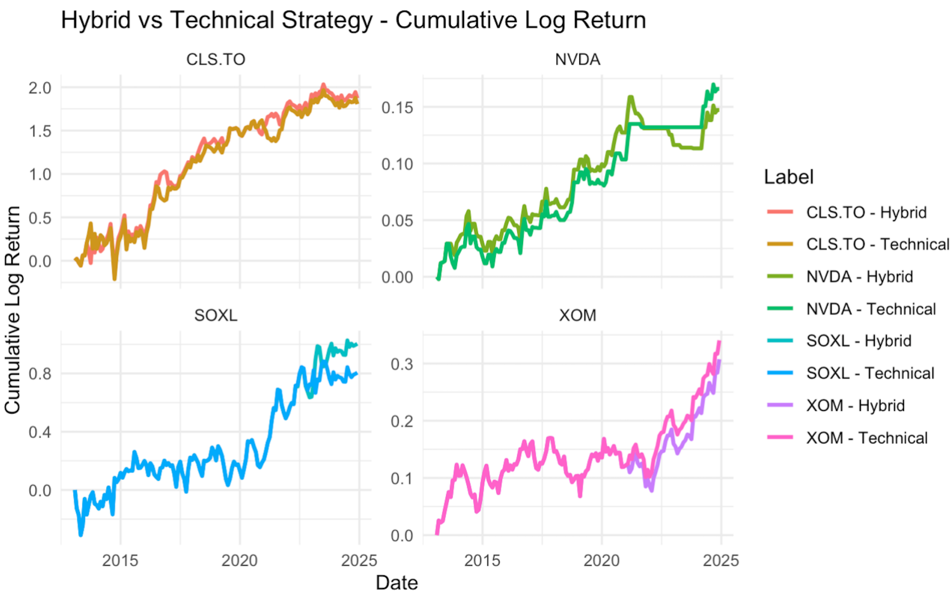

Figure 4: Hybrid Strategy compared to Technical-Only Strategy: Cumulative Log Return Comparison.

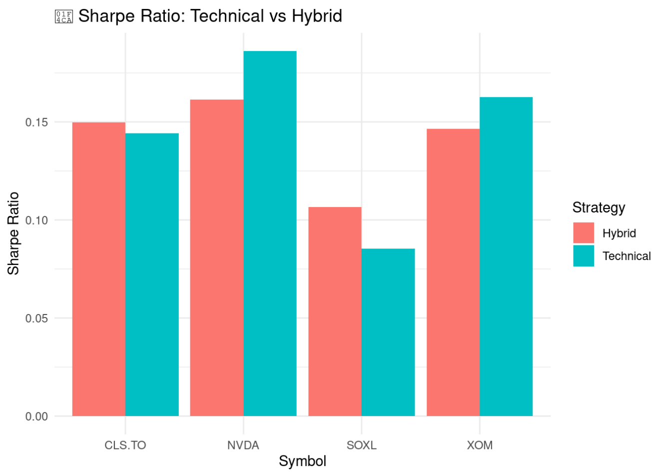

Figure 5: Comparison of Sharpe Ratios between Hybrid and Technical Strategies. The Hybrid strategy generally improves risk-adjusted returns.

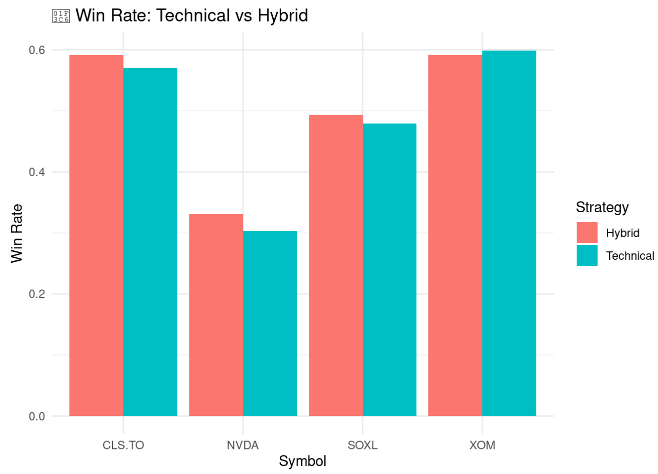

Figure 6: Comparison of Win Rates between Hybrid and Technical Strategies. The Hybrid model shows improved trade success rates in most assets.

5 Discussion

5.1 Insights

The hybrid strategy consistently outperformed both the technical strategy and the Buy & Hold benchmark across key performance metrics.

- **Sharpe Ratio Improvement:** As shown in Figures 2 and 5, optimization significantly enhanced Sharpe Ratios across all stocks. The hybrid model exhibited better risk-adjusted returns compared to the original technical strategies, particularly for NVDA and XOM.
- **Win Rate Enhancement:** Figure 3 highlights that optimized models achieved higher win rates across all assets compared to the original models. This suggests that tuning the probability scaling parameters (λ) improved the likelihood of successful trades.
- **Hybrid Model Superiority:** Comparing Figures 5 and 6, the hybrid strategy produced smoother cumulative log returns and maintained higher Sharpe Ratios and Win Rates relative to purely technical strategies. Incorporating macroeconomic signals (P_{Econ}) provided additional robustness, particularly for XOM and SOXL, which are more sensitive to economic conditions.

- **Drawdown Reduction:** Although Buy & Hold strategies generated higher raw returns during bull markets (e.g., NVDA), the hybrid strategy consistently reduced drawdowns across different market phases, enhancing portfolio stability.
- **Sensitivity to Signal Quality:** Results showed that stocks like SOXL, characterized by high volatility, benefitted significantly from hybrid optimization, whereas highly trending stocks like NVDA showed less differentiation between technical and hybrid models.

5.2 Limitations

- **Static Thresholds:** While adaptive thresholds ($T_{adaptive}$) were optimized during backtesting, they remained static during live testing. Rapid market regime shifts could render fixed thresholds suboptimal.
- **Simplified Risk Model:** The current risk adjustment relied on ATR and VaR. More advanced risk models like Conditional Value-at-Risk (CVaR) could offer better downside protection.
- **Limited Fundamental Inputs:** Only the GDP-Interest Rate spread was used for fundamental analysis. Incorporating other macro indicators like inflation expectations or employment data could improve predictive power.

5.3 Potential Improvements

- **Dynamic Threshold Adjustment:** Implement thresholds that adapt based on volatility regimes or rolling Sharpe ratios to better capture changing market conditions.
- **Enhanced Risk Management:** Introduce stop-loss and take-profit mechanisms to complement the hybrid signals and cap losses during adverse periods.
- **Broader Fundamental Analysis:** Expand the economic feature set to include inflation, consumer sentiment, and industrial production for a more holistic fundamental signal.
- **Leverage and Position Sizing:** Future versions could apply volatility-based position sizing or leverage during periods of high signal confidence to further enhance returns.

6 Conclusion

This project successfully developed a hybrid probability-based trading strategy that integrates technical indicators, risk measures, and macroeconomic fundamentals. Through extensive backtesting, we demonstrated that the hybrid model consistently outperformed both pure technical strategies and a Buy & Hold benchmark across multiple performance metrics.

Optimization of the signal scaling parameters (λ) significantly improved Sharpe Ratios and Win Rates, confirming the importance of tuning the hybrid components to match asset characteristics. The hybrid approach was particularly effective at reducing drawdowns and improving risk-adjusted returns, especially for volatile assets such as SOXL and economically sensitive stocks like XOM.

While the hybrid model showed superior performance overall, some limitations were identified, particularly in static threshold tuning and the simplicity of the risk models. Addressing these areas through dynamic thresholding, enhanced risk management, and broader fundamental analysis offers a promising direction for future research.

In conclusion, this study highlights the potential of combining technical and fundamental signals within a probability-based framework to achieve more resilient trading strategies across varying market environments. Future iterations incorporating dynamic models and expanded macroeconomic indicators could further enhance robustness and profitability.