Momentum-Based Algorithmic Trading Strategy

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1 Introduction

This project develops a momentum-based trading strategy in QuantConnect using technical indicators discussed in class, including simple moving averages (SMA), the relative strength index (RSI), and Bollinger Bands (BB). The goal is to construct a fully systematic strategy that uses historical price-based signals to identify attractive long opportunities while controlling downside risk.

The final strategy is implemented over a fixed candidate universe of three S&P 500 stocks: PLTR, GEV, and TSLA. Rather than holding all three simultaneously, the strategy rotates into at most two names that satisfy a set of technical filters. The overall objective is to achieve strong risk-adjusted performance on the training set while satisfying the assignment constraints on Sharpe ratio and drawdown.

2 Security Selection and Exploratory Research

2.1 Universe Selection Logic

To choose candidate stocks, we first conducted universe research within the SPY universe over the training period. The selection procedure was updated once per month rather than daily, which allowed us to focus on medium-term persistence rather than short-term noise. Starting from the SPY universe, we applied basic investability filters by requiring each stock to have an adjusted price above $20 and daily dollar volume above $20 million. We also excluded several more defensive sectors (Utilities, Real Estate, and Consumer Defensive), because the goal was to search for stocks with stronger momentum and trend-following characteristics rather than lower-volatility defensive behavior.

After this initial screen, stocks were grouped by sector, and within each sector we kept only the top 10 names ranked by dollar volume. This sector-level liquidity filter reduced noise from less actively traded names while preserving a diverse cross-section of sectors. We then retrieved recent daily price history for the remaining candidates and computed a medium-term momentum score for each stock using the most recent 60 trading days. The score rewarded strong 60-day returns but penalized instability through two terms: short-term realized volatility, measured as the standard deviation of recent log returns, and maximum drawdown over the lookback window. Specifically, the score took the form of medium-term return minus weighted penalties for volatility and drawdown, so that stocks with strong but smoother trends ranked higher than names whose gains came from highly erratic price paths.

Within each sector, only the single highest-scoring stock was retained. These sector winners were then ranked across sectors, and the top five names for each month were recorded. At the end of the training period, we aggregated these monthly selections and ranked stocks by how frequently they appeared. To avoid ending up with a final universe concentrated in a single industry, the final step imposed sector diversification by selecting the most frequently appearing names subject to no repeated sector exposure. This process produced a final candidate universe of three stocks: PLTR, GEV, and TSLA.

This design was intended to identify stocks with relatively strong momentum characteristics while avoiding names whose recent gains were driven entirely by unstable price paths or concentrated sector-specific noise.

2.2 Exploratory Research and Indicator Analysis

We then conducted exploratory research on the final candidate stocks using statistical summaries and visualizations. At the stock level, we compared cumulative returns (Figure 1), drawdown curves (Figure 2), and summary statistics (Figure 3) including total return, annualized volatility, a Sharpe-like return-to-risk ratio, and maximum drawdown. These results showed that PLTR had the strongest overall momentum and the best risk-adjusted performance, while GEV also exhibited strong positive momentum with relatively attractive return-risk tradeoffs. TSLA was more volatile and less consistent on a risk-adjusted basis, although it still displayed occasional tradable momentum phases. Overall, this analysis suggested that the three stocks were suitable as a fixed candidate universe, but not as a buy-and-hold equal-weight portfolio. Instead, they were better suited to a rotation-style strategy that selectively held only the strongest names.

We next studied how technical indicator states related to short-horizon forward returns in order to refine the final trading rules. First, we grouped observations by RSI bins and compared subsequent 5-day forward returns (Figure 4). The relationship was not monotonic: very low RSI values sometimes generated strong short-term rebounds, while highly overbought states above 70 were generally less attractive. Since the goal of the project was to design a momentum continuation strategy rather than a contrarian reversal strategy, we used an intermediate RSI band in the final strategy rather than directly trading low-RSI rebounds.

Second, we examined SMA trend alignment, defined by whether price and moving averages formed a strong upward structure. The evidence was mixed across stocks. For some names, especially PLTR (Figure 5) and GEV (Figure 6), short-horizon returns were sometimes stronger outside the fully aligned state, suggesting rebound effects within broader uptrends. However, when incorporated into the complete systematic strategy, stricter trend filters improved overall risk-adjusted performance, so trend alignment was retained as a structural filter rather than treated as a stand-alone alpha signal.

Third, we analyzed Bollinger Band position (Figure 7). This provided the strongest direct support for the final trading rule. In particular, GEV showed the strongest 5-day forward returns when price was above the Bollinger middle band but not excessively above the upper band (Figure 8). More generally, overextended states above the upper band were weaker than more moderate middle-to-upper conditions, which supported using Bollinger Bands to avoid chasing overheated momentum.

3 Strategy Design

3.1 Overall Strategy Framework

The final strategy is a filtered momentum rotation strategy over the fixed universe {PLTR, GEV, TSLA}. It uses weekly rebalancing to select eligible stocks and daily monitoring for exits and risk management.

The strategy first applies a broad market regime filter: long positions are only allowed when SPY is above its 200-day moving average. This is intended to reduce exposure during weak market environments.

Conditional on the market filter passing, a stock becomes eligible if it satisfies the following entry conditions:

- strong trend structure based on moving averages,
- RSI within a continuation-style range,
- price above the Bollinger middle band but not excessively overextended,
- positive recent momentum as measured by 20-day rate of change.

Eligible stocks are ranked by a momentum score, and the strategy holds at most two names. Capital is allocated equally across the selected positions, with total portfolio exposure capped below full investment.

3.2 Exit and Risk Management Rules

The strategy includes multiple exit rules:

- a fixed stop-loss,
- a trailing stop,
- exit upon trend deterioration,
- exit upon RSI weakening,
- liquidation of names no longer selected at rebalance.

These controls were motivated by the exploratory research, which showed that the raw drawdowns of the candidate stocks were far too large for a naive buy-and-hold implementation.

4 Backtest Setup and Bias Control

The assignment specified an in-sample period from July 1, 2024 to June 30, 2025. I split this period into:

- **Training set:** 2024/07/01 - 2025/03/31
- **Validation/in-sample test set:** 2025/04/01 - 2025/06/03
- **Out-of-sample test set:** 2025/07/01 - 2025/10/17

Strategy parameters were tuned only on the training set. After selecting the final rule set, we evaluated the strategy on the validation period without re-optimizing based on the validation performance. This was done to reduce look-ahead bias and to ensure that the final strategy logic was not chosen using information from the testing segment.

All backtests were implemented in QuantConnect using an initial capital of $10 million, as required.

5 Results

Table 1 summarizes the main backtest statistics.

Table 1: Backtest Summary

Period	Net Profit	Sharpe Ratio	Max Drawdown
Training	$3,639,843.78	1.062	13.2%
Validation	$439,009.36	0.442	9.4%
Out-of-sample	$2,772,142.27	2.538	15%

Therefore, the training-period results satisfied the assignment requirements, with a Sharpe ratio above 1.0 and a maximum drawdown below 15%. This suggests that the strategy was capable of delivering acceptable risk-adjusted performance under the calibration sample. However, performance weakened materially in the validation period. Net profit declined, the Sharpe ratio fell from 1.062 to 0.442, and risk-adjusted performance became much less convincing, although the drawdown remained controlled at 9.4%. This indicates that while the risk controls continued to function reasonably well, the return-generating component of the strategy was less stable outside the training segment.

One interpretation is that the strategy may have been partially overfit to the training sample, especially since the final rule set was refined using exploratory analysis on a relatively small universe of momentum-oriented stocks. At the same time, the validation window was short and may have reflected a different market environment, so some deterioration should not be interpreted as definitive failure. In particular, a concentrated strategy holding at most two names can be highly sensitive to short-term regime changes, which makes validation performance inherently noisier.

The out-of-sample results were stronger, with a Sharpe ratio of 2.538 and net profit of $2,772,142.27, suggesting that the strategy may still have practical value when market conditions are supportive. However, these results should be interpreted cautiously. A single favorable out-of-sample window does not eliminate the evidence of instability observed in validation, and the mixed results across subperiods suggest that performance is likely regime-dependent rather than uniformly robust. Although the stronger out-of-sample results are encouraging, the evidence overall is more consistent with a strategy that can work well in favorable momentum environments than with one that is uniformly robust across all conditions. This pattern is broadly consistent with the earlier exploratory analysis. The selected stocks exhibited strong momentum potential but also substantial drawdown risk and heterogeneous behavior across indicators. As a result, the strategy appears to benefit from active filtering and disciplined exits, but it remains vulnerable to shifts in trend persistence and cross-sectional leadership.

Backtest URL for selection:
https://www.quantconnect.cloud/backtest/787f3764c6d1c224b81fa662e2e142a9/?theme=chrome

Backtest URLs for train set, in-sample test set, and out-of-sample test set:
https://www.quantconnect.cloud/backtest/8cb5d886bdbe40e97f25587602cc2633/?theme=chrome
https://www.quantconnect.cloud/backtest/c82f170774b80d32d0bcbec18eddeb09/?theme=chrome
https://www.quantconnect.cloud/backtest/7410eac1c84099fc1f75e9efed83a7f0/?theme=chrome

Appendix: Figures

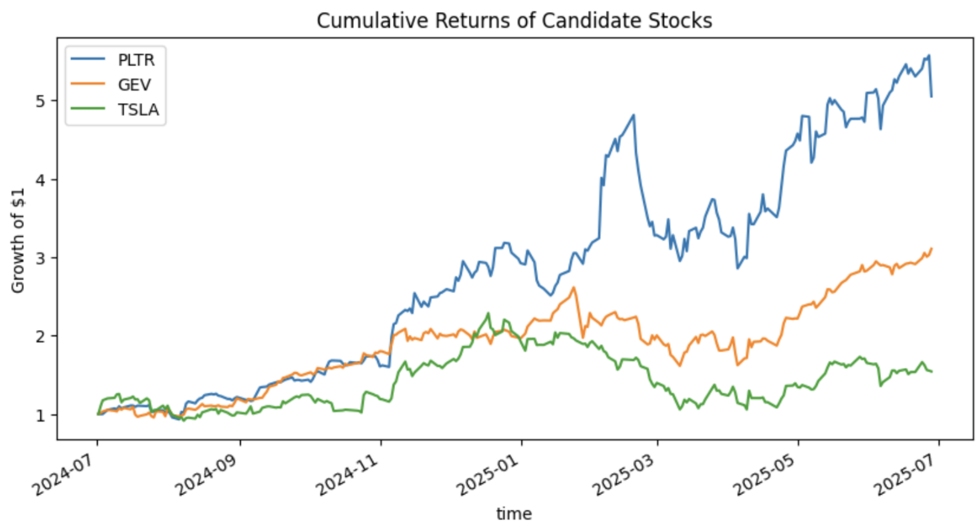

Figure 1: Cumulative Returns of Selected Stocks

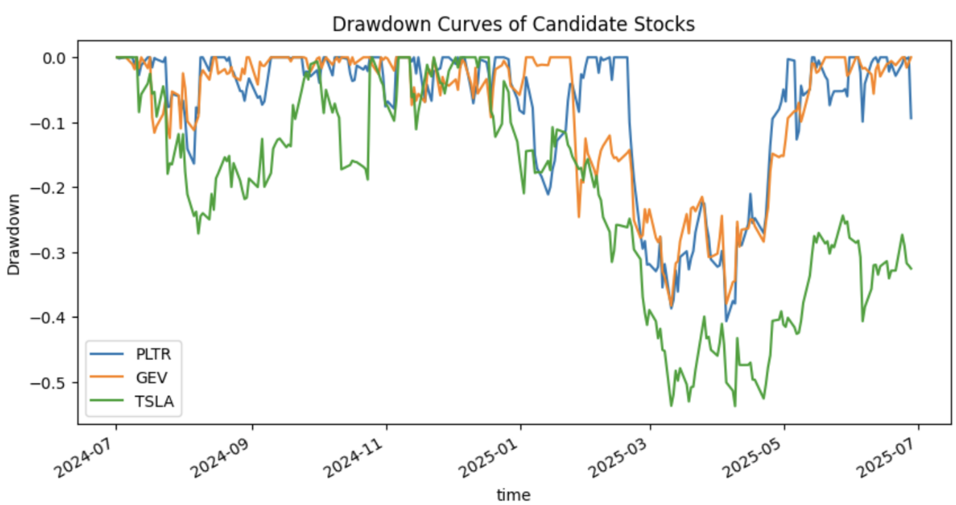

Figure 2: Drawdown Curves of Selected Stocks

	total_return	ann_vol	sharpe_proxy	max_drawdown	win_rate
PLTR	4.051777	0.734668	2.601780	-0.406709	0.572581
GEV	2.106776	0.562018	2.340805	-0.382856	0.592742
TSLA	0.542123	0.747254	0.955429	-0.537657	0.508065

Figure 3: Summary statistics

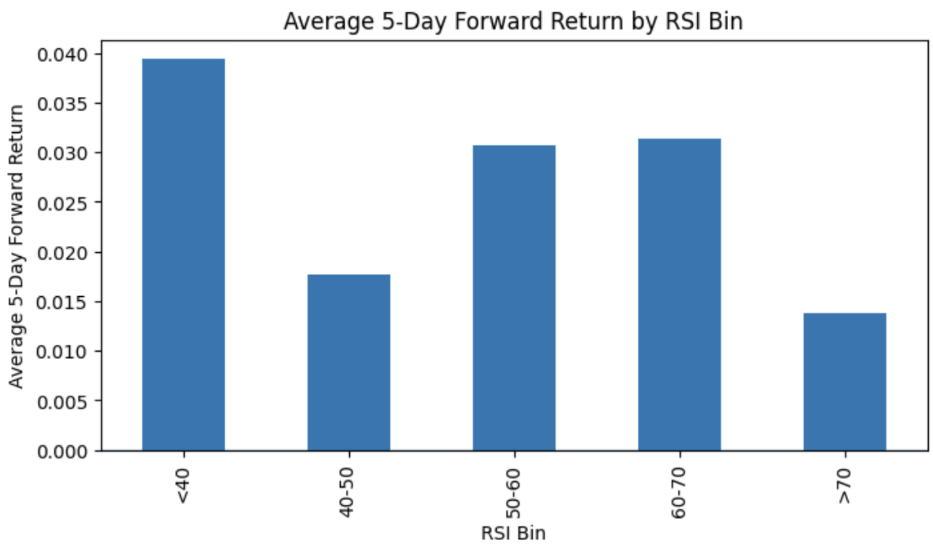

Figure 4: Average 5-day forward returns grouped by RSI bins

```
PLTR
                 mean    median  count
Not aligned  0.046925  0.036179    155
Aligned      0.027886  0.031546     89
```

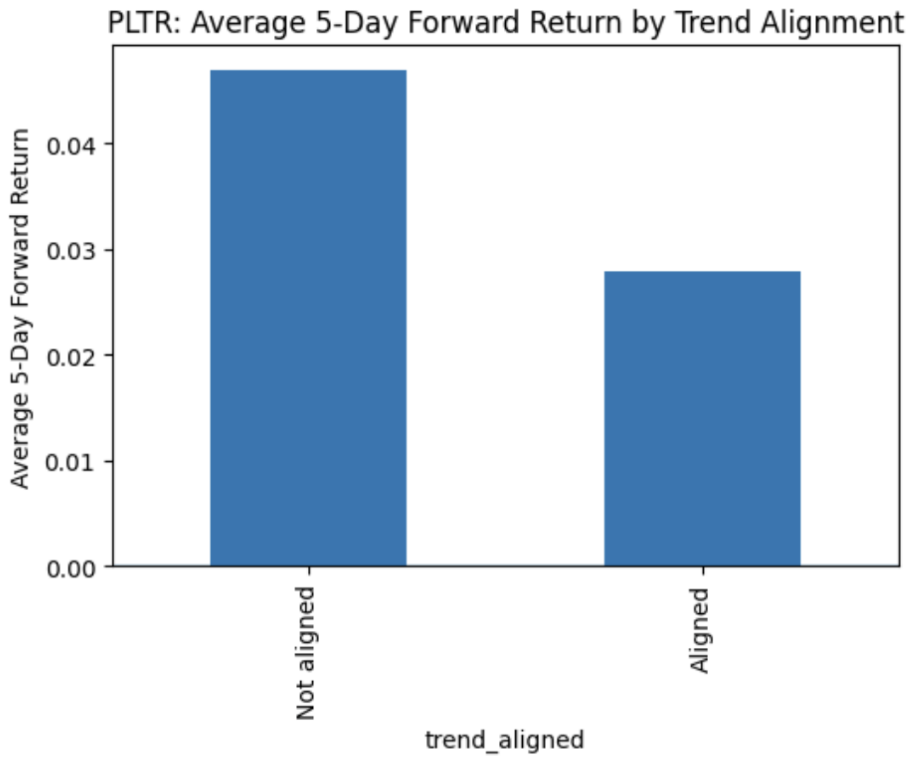

Figure 5: Short-horizon forward returns conditional on SMA trend alignment for PLTR

```
GEV
                 mean    median  count
Not aligned  0.030910  0.030645    189
Aligned      0.004016  0.013900     55
```

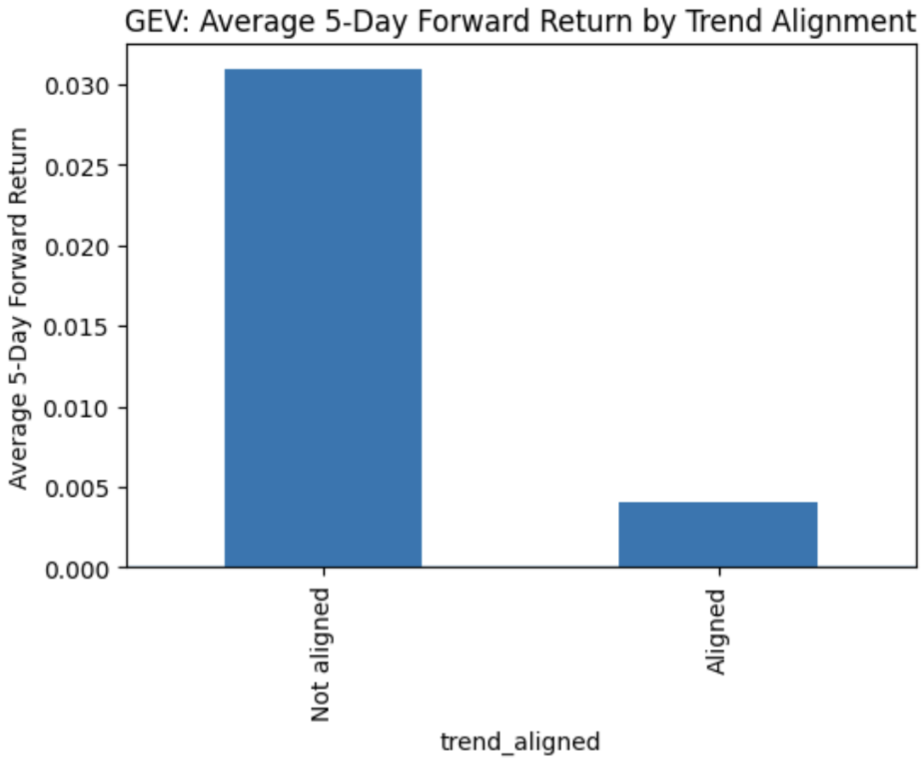

Figure 6: Short-horizon forward returns conditional on SMA trend alignment for GEV

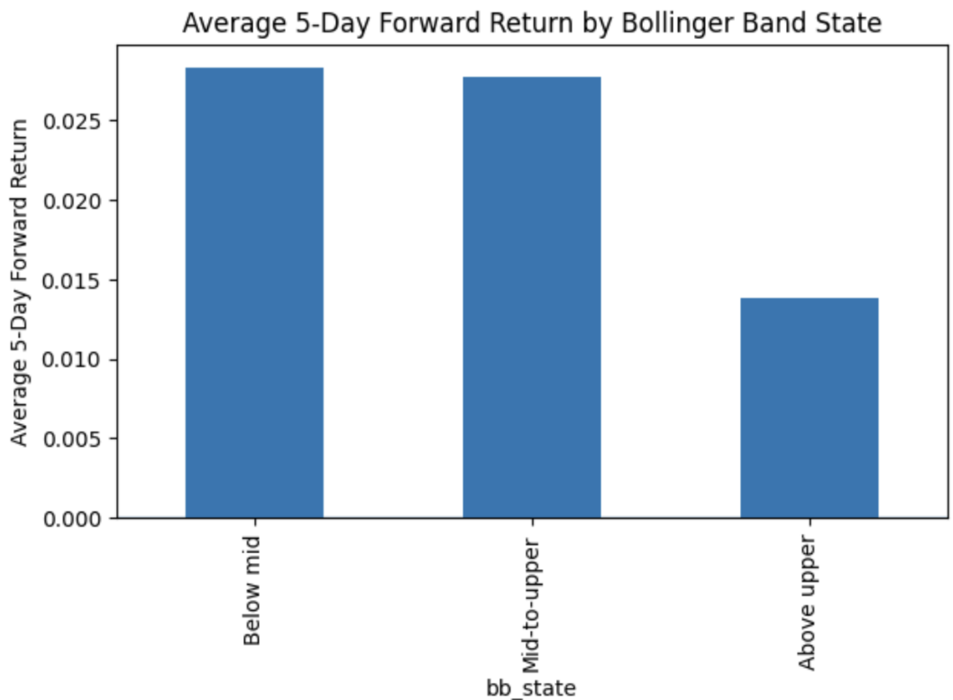

Figure 7: Average 5-day forward returns by Bollinger Band State

```
GEV
                  mean    median  count
bb_state
Below mid      0.021904  0.013651     57
Mid-to-upper   0.031572  0.030645    147
Above upper    0.004330  0.020443     40
```

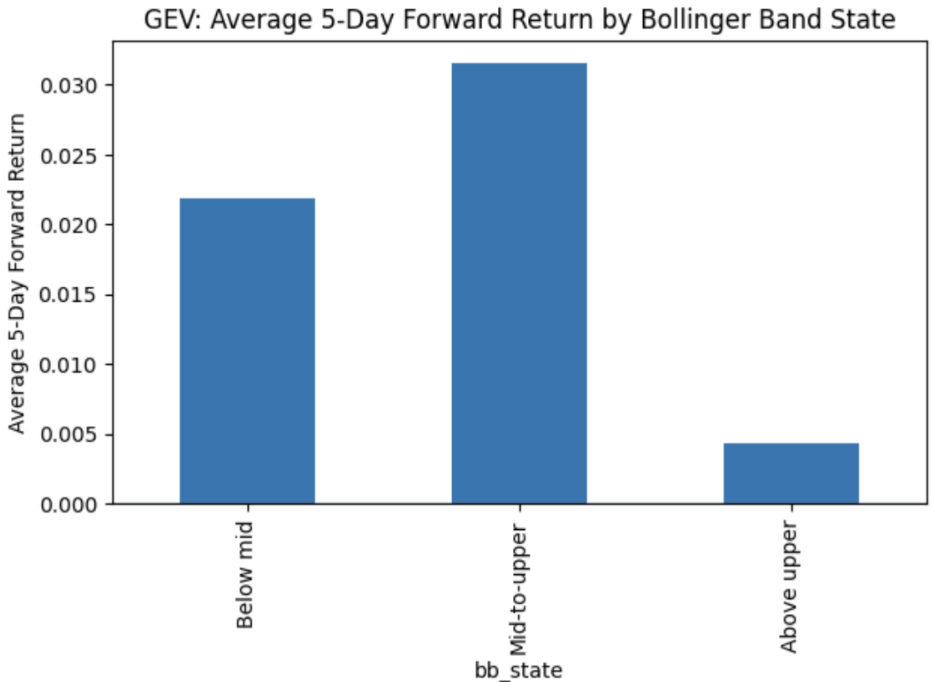

Figure 8: Average 5-day forward returns by Bollinger Band position for GEV

6 AI Declaration

ChatGPT was used in a limited and supportive capacity during this project. Specifically, they were used to assist with code debugging and refining, LaTeX formatting, and improving the clarity and structure of written explanations.

All core components of the project, including strategy design, data analysis, backtesting implementation, and interpretation of results, were developed independently by the authors.