Enhanced Value/Growth Factor Strategy: Case Study Report

Goal

This case study aims to revisit and enhance the traditional Value/Growth factor.

Traditional Value/Growth Factor

The conventional approach uses valuation ratios (e.g., P/E, P/B, EV/EBITDA) to build a long-short portfolio—longing undervalued stocks and shorting overvalued or growth stocks.

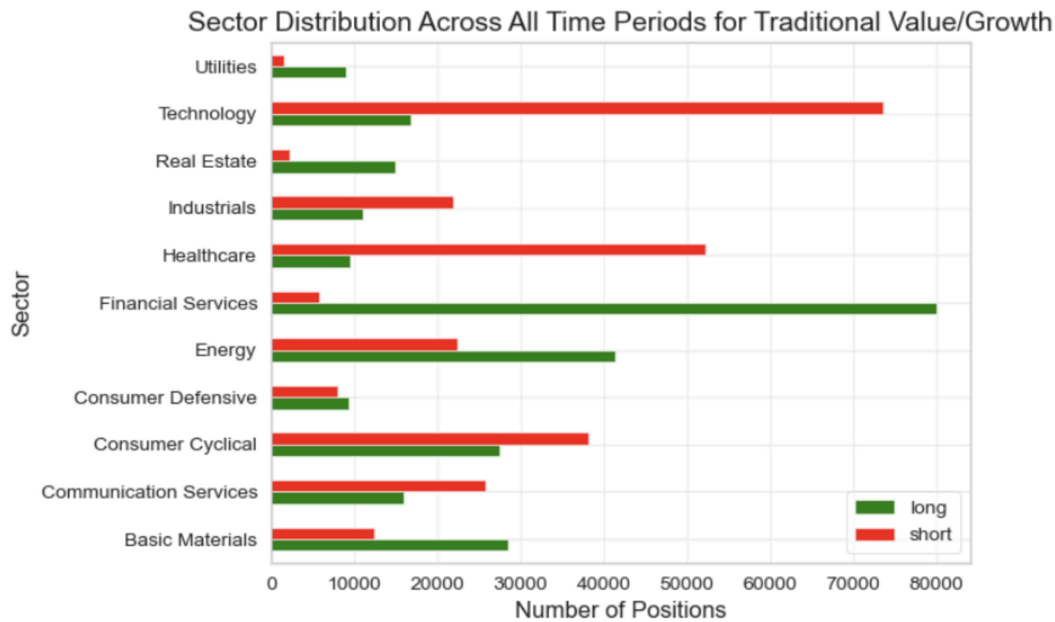
For my implementation, I used the following value metrics:

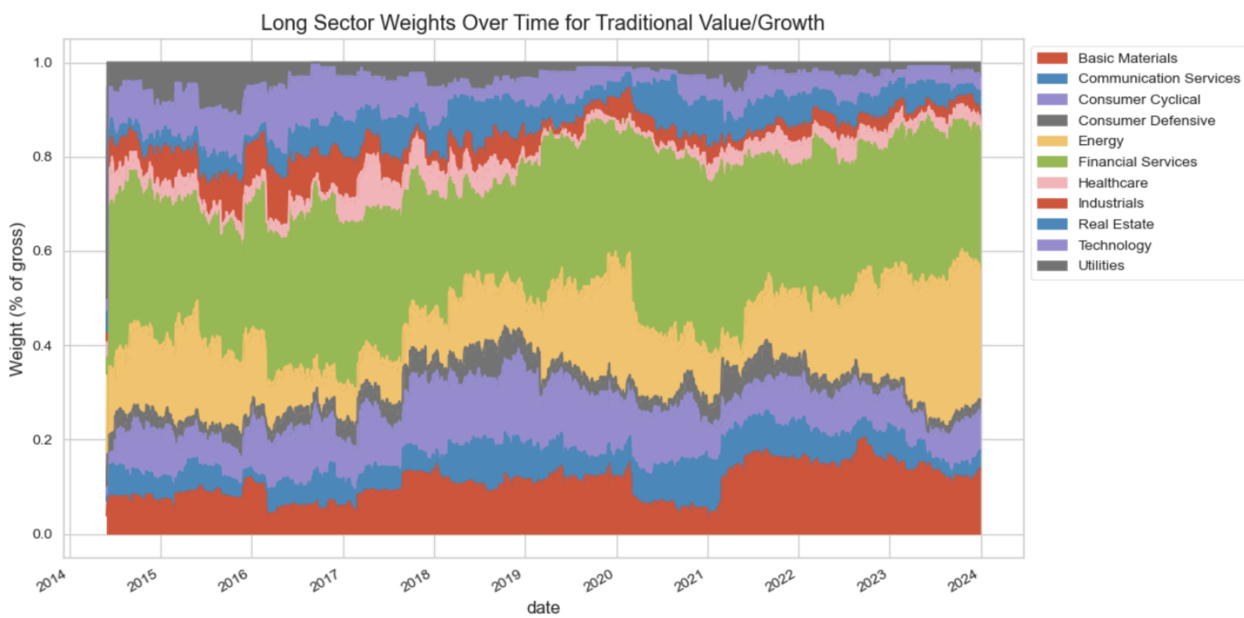
- Earnings/Price (E/P)
- Book/Price (B/P)
- EBITDA/EV
- Dividend Yield
- Free Cash Flow Yield

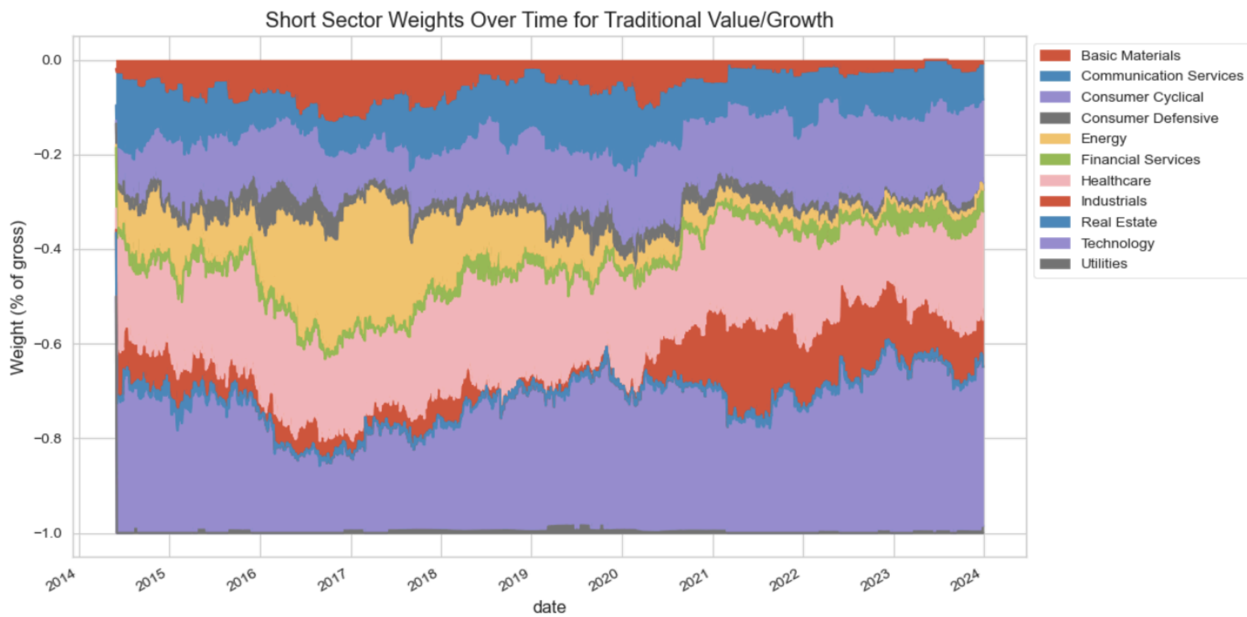
Each stock is ranked across these five metrics, and an average rank is calculated. The strategy takes equal-weighted long positions in the top quantile and short positions in the bottom quantile. Since I didn't have universe constituent information I defined my universe by filtering on liquidity and market cap: min $1B market cap and min $2M daily volume.

Drawbacks Identified:

- **Sector Bias**: Overweights financials and energy; underweights tech (see the chart below)
- **Equal Weighting**: Doesn't account for relative informativeness of each metric
- **No Quality Filter**: Increases exposure to value traps
- **Borrow Costs**: High short interest can erode returns


Sector Distribution Across All Time Periods for Traditional Value/Growth
Sector
Utilities
Technology
Real Estate
Industrials
Healthcare
Financial Services
Energy
Consumer Defensive
Consumer Cyclical
Communication Services
Basic Materials
long
short
0
10000
20000
30000
40000
50000
60000
70000
80000
Number of Positions


Long Sector Weights Over Time for Traditional Value/Growth
Weight (% of gross)
0.0
0.2
0.4
0.6
0.8
1.0
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
date
Basic Materials
Communication Services
Consumer Cyclical
Consumer Defensive
Energy
Financial Services
Healthcare
Industrials
Real Estate
Technology
Utilities



Enhanced Factor Strategy

To address these issues, I developed a multi-factor model integrating the following signals:

- **Value**: E/P, B/P, EBITDA/EV, Dividend Yield, FCF Yield
- **Quality**: ROE, ROA, , ROIC, Debt-to-Equity, Gross Margins
- A machine learning model (ridge regression) was trained to determine optimal weights across these features based on historical return prediction. Factor scores are computed using rank-based transformations.

Risk Controls:

- Sector-neutral selection using within-sector rankings
- Market neutrality (dollar-neutral portfolio)
- Borrow cost penalization for expensive shorts
- Minimum 5-day holding period
- Limit of 400 total positions

Each day, stocks are ranked within their sectors using the machine learning-weighted composite score. The strategy takes:

- Long positions in the top quantile
- Short positions in the bottom quantile

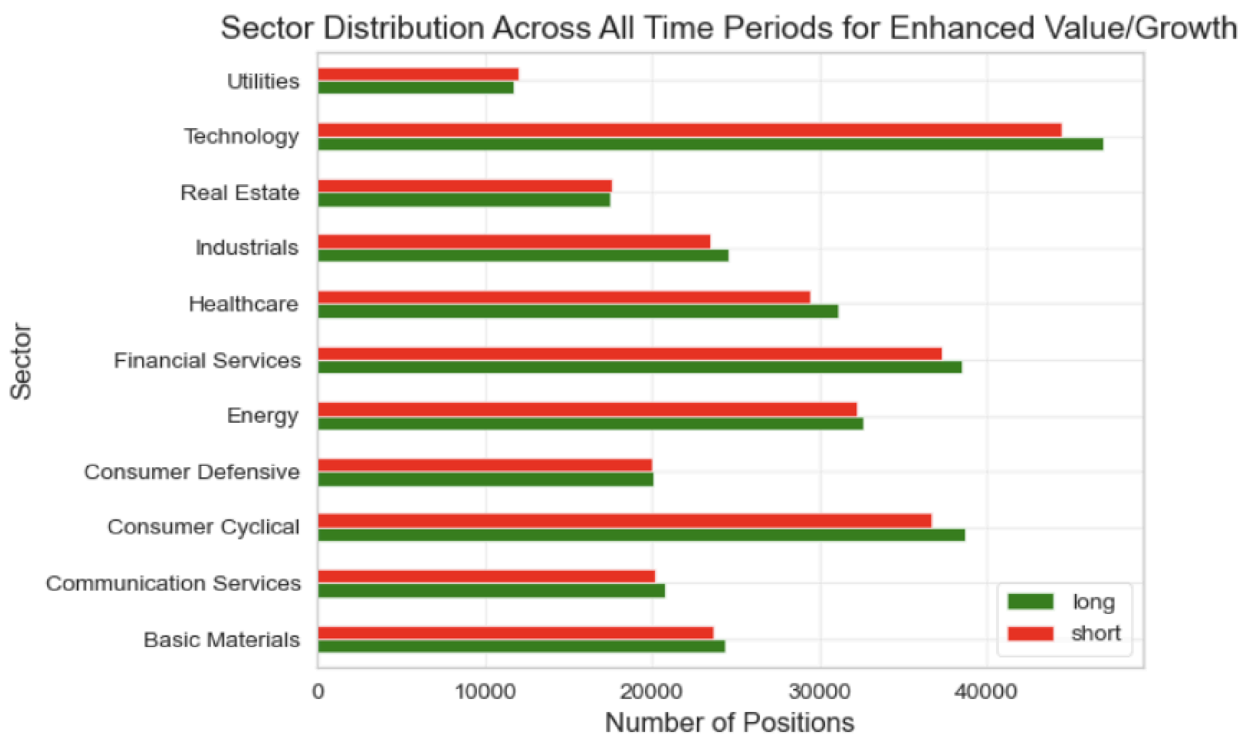
Position sizing and rebalancing respect turnover, exposure, and constraint limits.

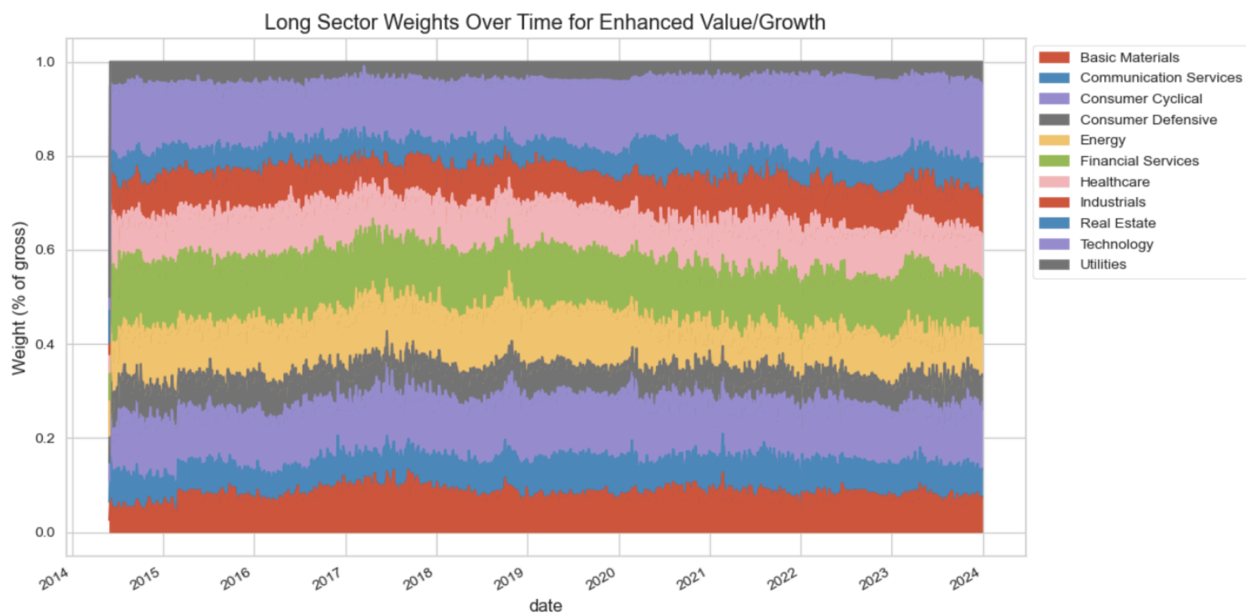
Results and Performance

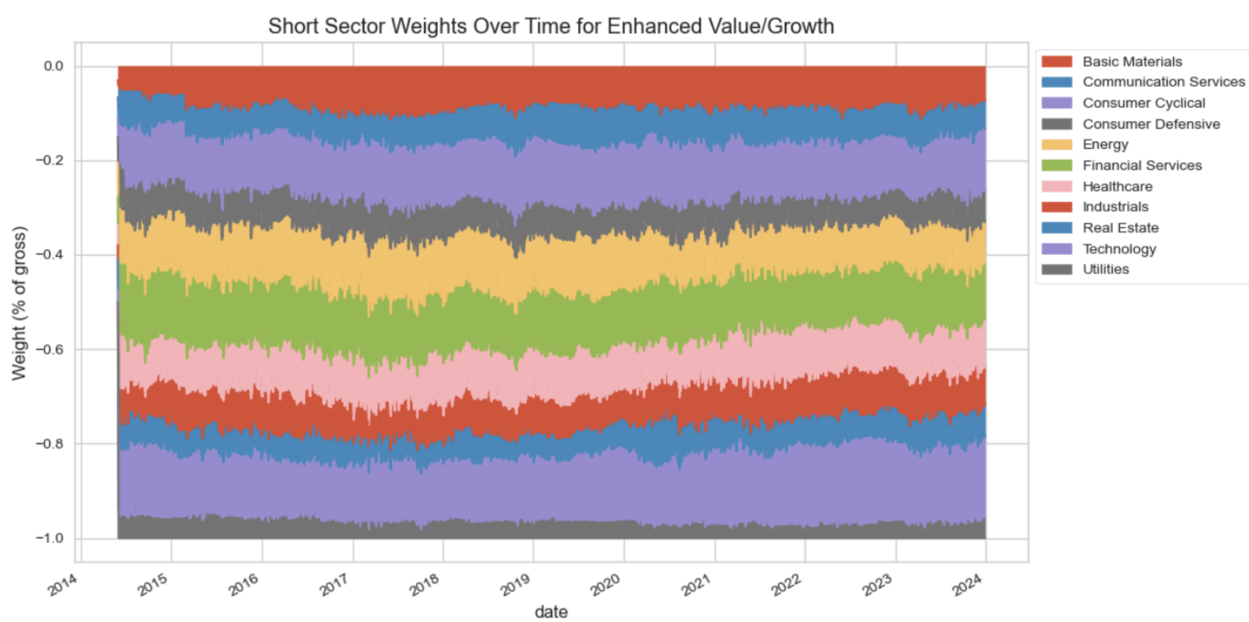
Backtesting over a multi-year period showed (2014-2023):

Metric	Traditional	Enhanced
Annualized Return	-7.4%	8.7%
Annualized Volatility	24.1%	12.4%
Sharpe Ratio	-0.31	0.7
Max Drawdown	-76.7%	-20.8%
Hit Rate	46.83%	53.5%

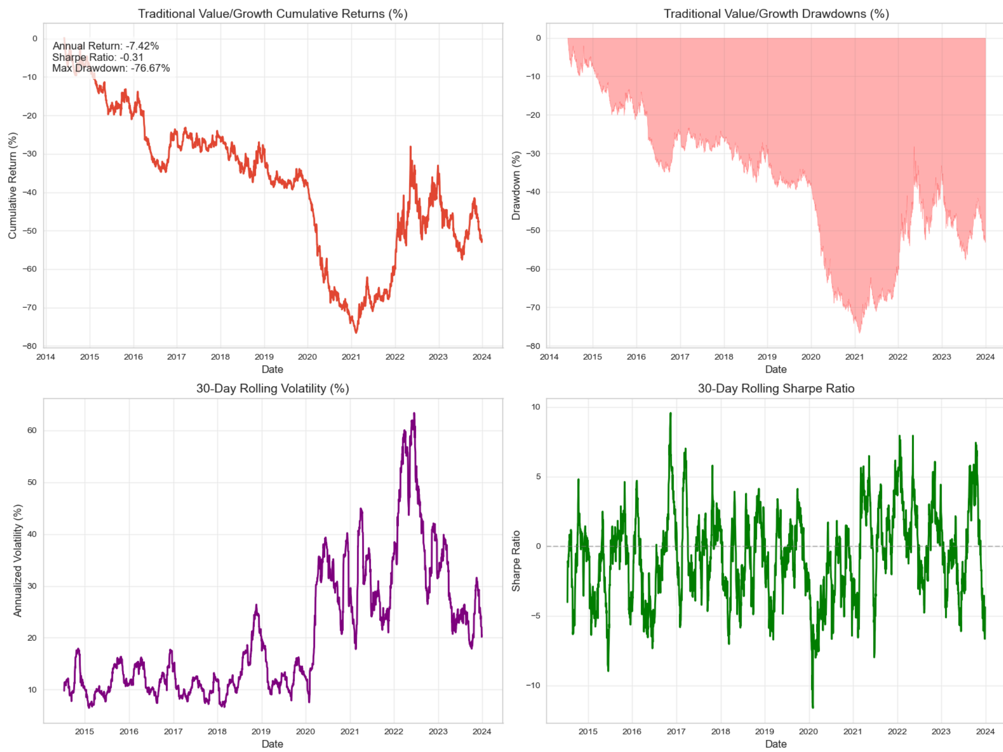
The enhanced strategy also achieves more balanced sector exposures, helping reduce concentration risks:

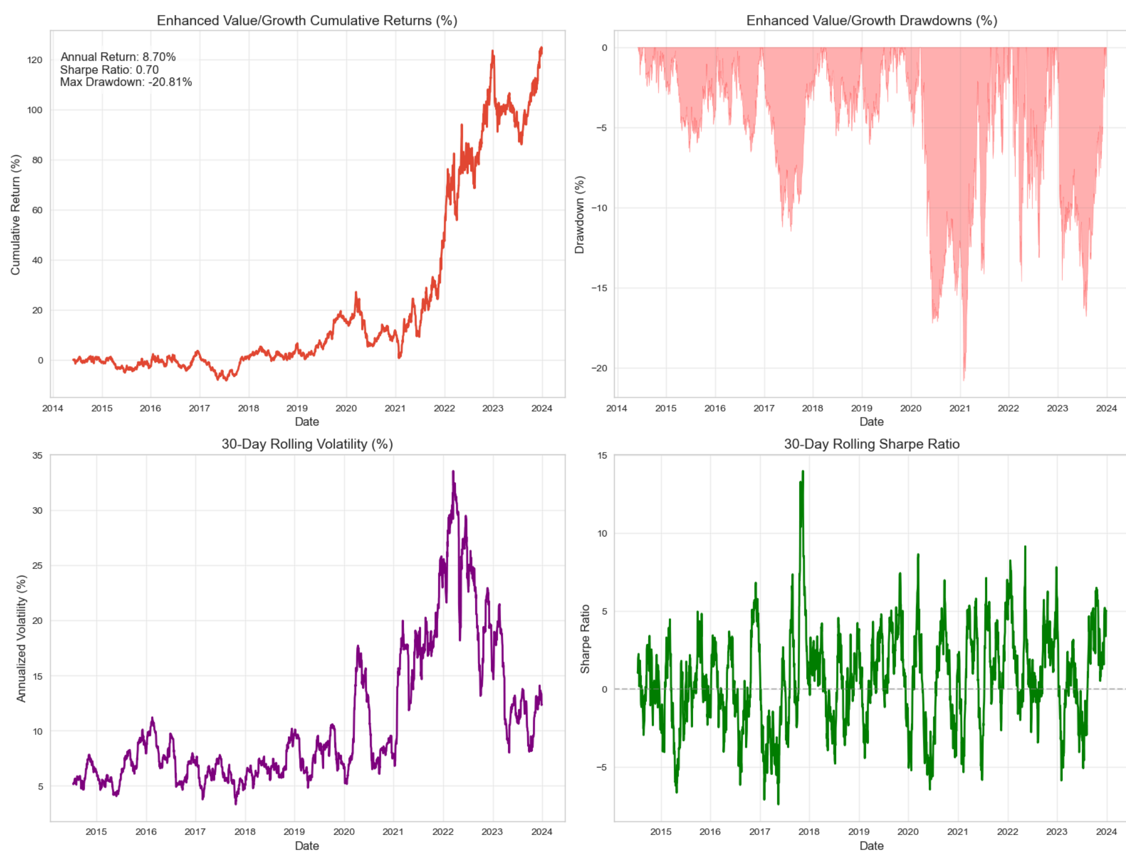






Performance Visualizations





Risk Considerations

- Risk of overfitting due to model complexity
- Crowded trades reducing alpha
- Exposure to quality/tech bubbles if not actively monitored
- Sensitivity to macroeconomic regime changes

Future Work

With more time, I would:

- Incorporate **momentum and sentiment** factors (e.g., 1M/3M/6M/12M momentum, analyst revisions, insider activity)
- Implement **market regime detection** to dynamically shift factor emphasis
- Use **alternative data** (news, social sentiment) for early signal detection
- Explore **advanced ML models** and feature importance for better signal weighting
- Add **transaction cost modeling** and **risk optimization** using tools like BARRA factors
- **Parallelize** backtesting using multiprocessing

Conclusion

This enhanced Value/Growth strategy outperforms the traditional approach by integrating machine learning for smarter signal weighting, using robust rank-based metrics, and applying rigorous risk controls. The result is a more consistent and investable factor with materially better return/risk profile and drawdown characteristics.