

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.

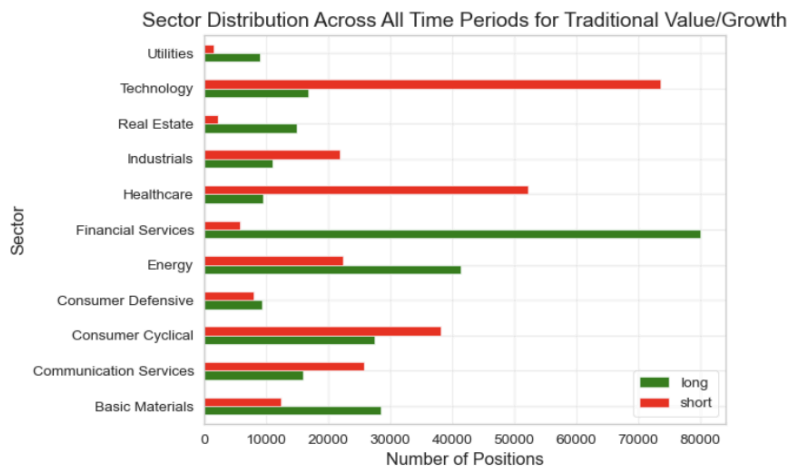
For my implementation, I used the following value metrics:

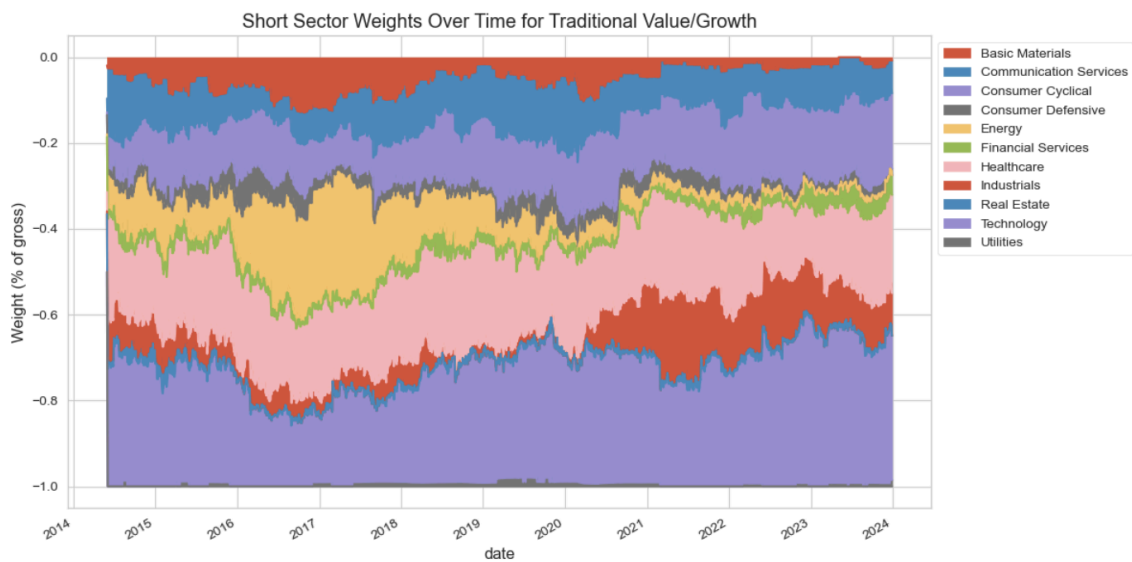
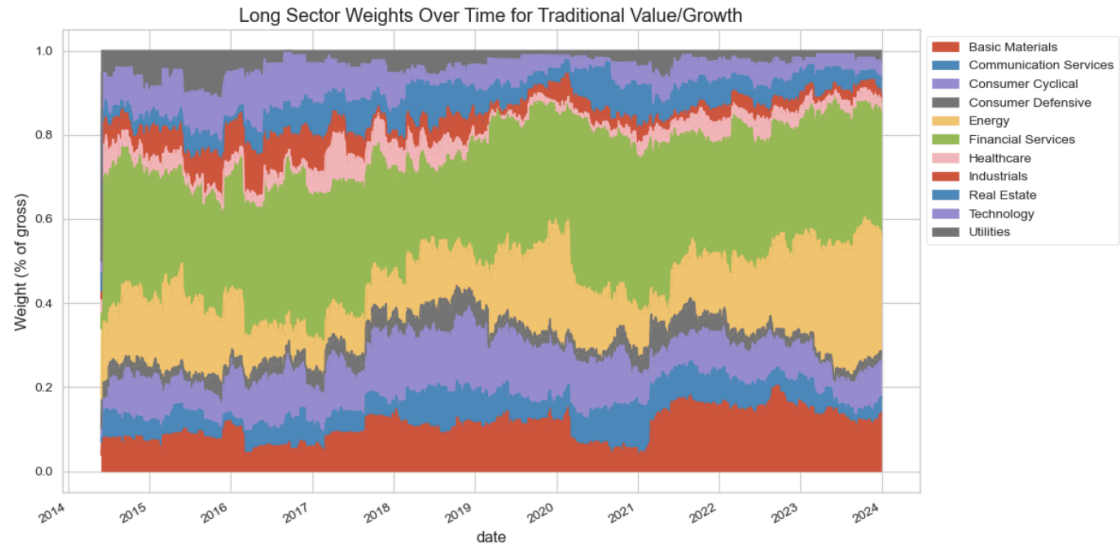
- Earnings/Price (E/P)
- Book/Price (B/P)
- EBITDA/EV
- Dividend Yield
- Free Cash Flow Yield

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





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

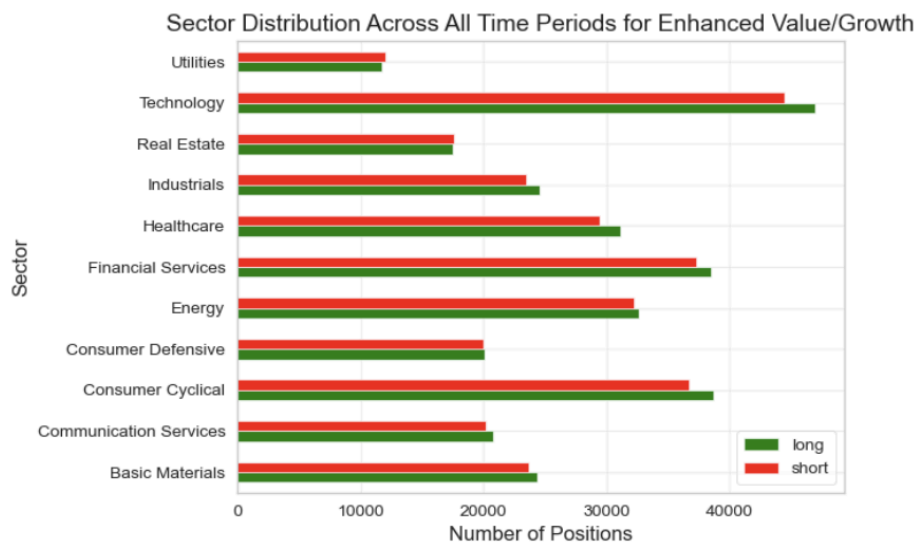
Position sizing and rebalancing respect turnover, exposure, and constraint limits.

Results and Performance

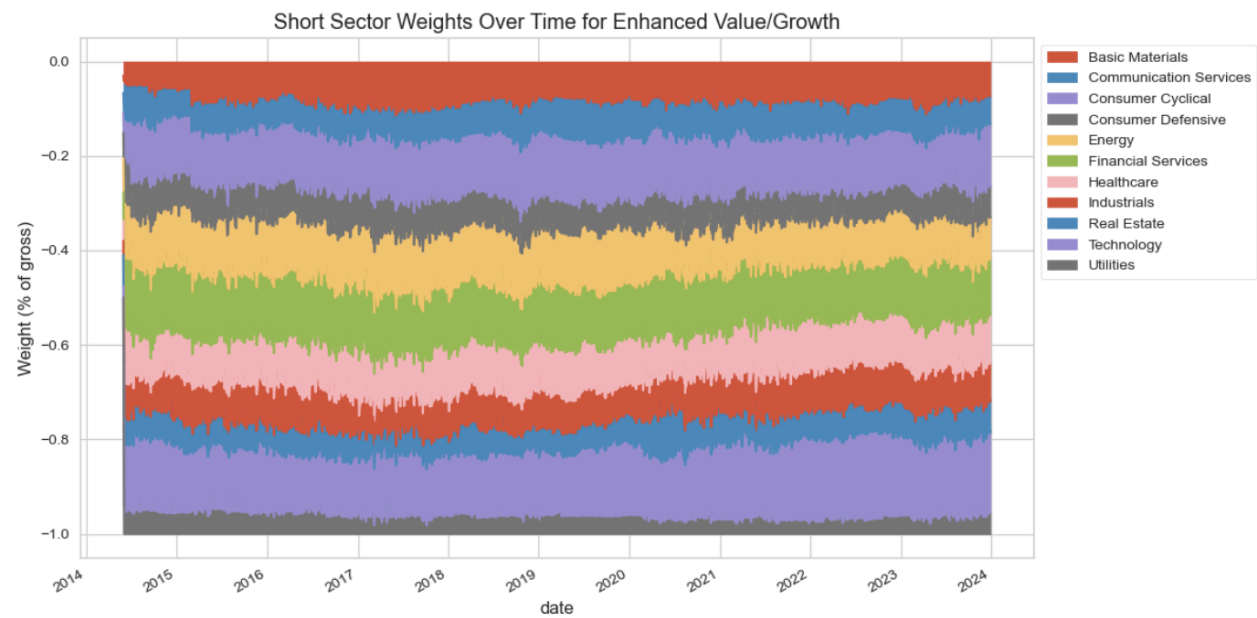
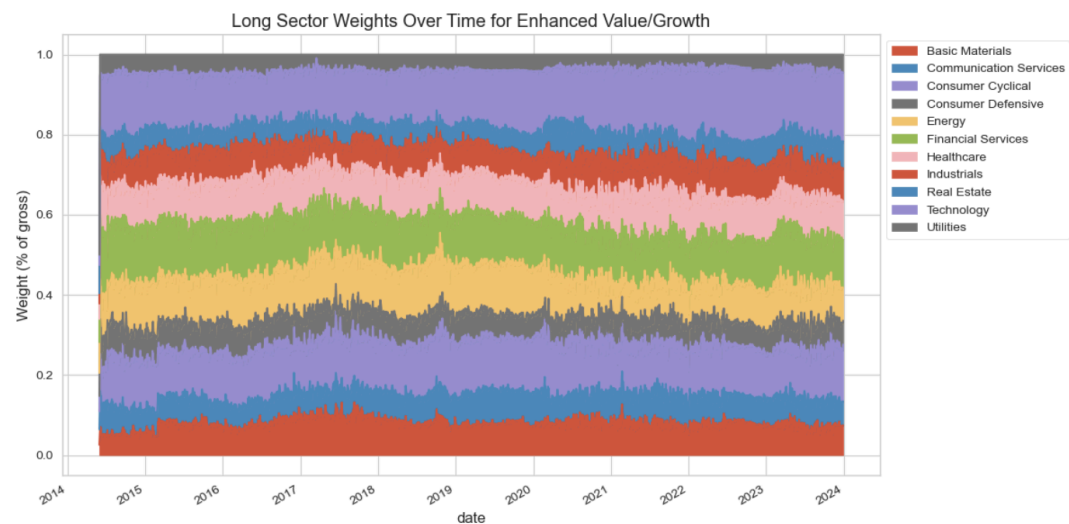
Backtesting over a multi-year period showed (2014-2023):

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%

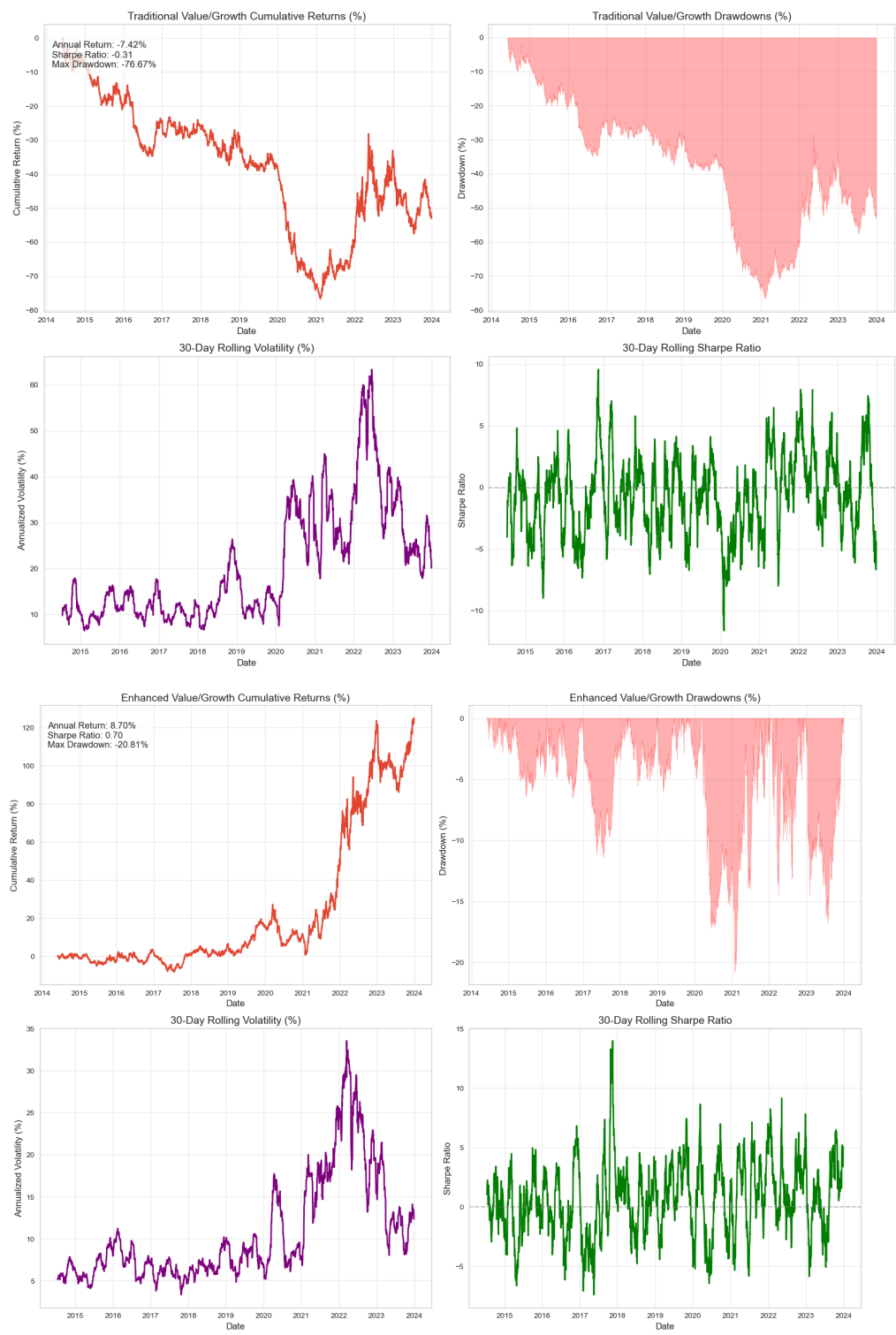
The enhanced strategy also achieves more balanced sector exposures, helping reduce concentration



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.