FINM33150 Quantitative Trading Project

Tactical Stock Selection Strategy

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Tactical Stock Selection Strategy

The tactical stock selection strategy employs a long-short multi-factor portfolio to generate positive returns. Using an automated factor switching model informed by macroeconomic indicators, the strategy harnesses the predictive power of macroeconomic data to construct an optimal multi-factor portfolio

Investment Universe

- Over 900+ US Equities
- Long/Short Exposure
- 5x Leverage

Portfolio Results

- Average Annual Net Returns of 31%
- Sharp Ratio of 0.64

Competitive Edge

- Addresses Time-Varying Factor Performance
- Rules-Based Stock Selection
- Beta-neutral

Investment Universe

Investment Universe

Constructed from the ***Quandl's*** end-of-day (EOD) historical prices database and ***Zacks Investment Research***, with the latter comprising more than 200 fundamental indicators, including income statement, balance sheet, cash flow line items and precalculated ratios.

From the combined dataset, we select US companies that:

- report key financial information required for our factor constructions, and
- Reports the data on a quarterly basis minimally.

The selection criteria yields a total of **900+** unique US equity stocks.

Competitive Edge & Motivation

- Research has shown that securities offering higher expected returns share certain important characteristics. One of these important characteristic is that it must be **persistent** over time.

- Factor performance is known to be highly time-varying. To address this, most strategies use fixed allocation multi-factor models to reap the benefits of diversification.

- Our Tactical Stock Selection Strategy seeks to improve on these fixed-weighted strategies by employing factor switching to dynamically allocate across the factors for better results. In addition, our overall portfolio minimizes market exposure by holding beta-neutral positions.

- We use a range of macroeconomic indicators (11 in total) as predictors to inform our automated feature and factor selection methodology.

Empirical Exploration (Time-Varying Factor Performance)

Relative performance of factors varies over time

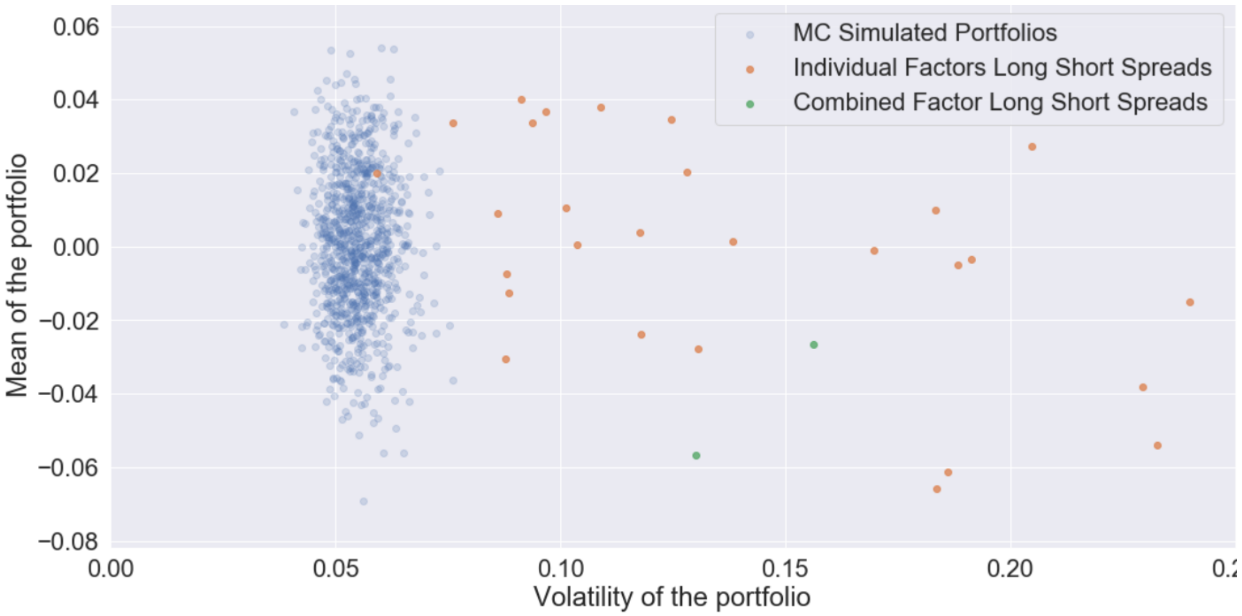
- The historical performance of 5 of the selected factors is shown in the heatmap. From the changes in the relative rankings over time, it is evident that factor performance is time-varying.
- For instance, the Return on Investment factor went from being the best performer in this mix in 2011 to being the worst in 2012.
- The implications of our findings are clear – there is scope to improve upon the performance of holding a fixed-weighted basket of the factors if we can build a strong predictive model of future factor performance. With a good model, we will have a discriminatory ability to pursue dynamic allocation across the basket of factors to capture higher expected returns.

Empirical Exploration (Beta-Neutrality)

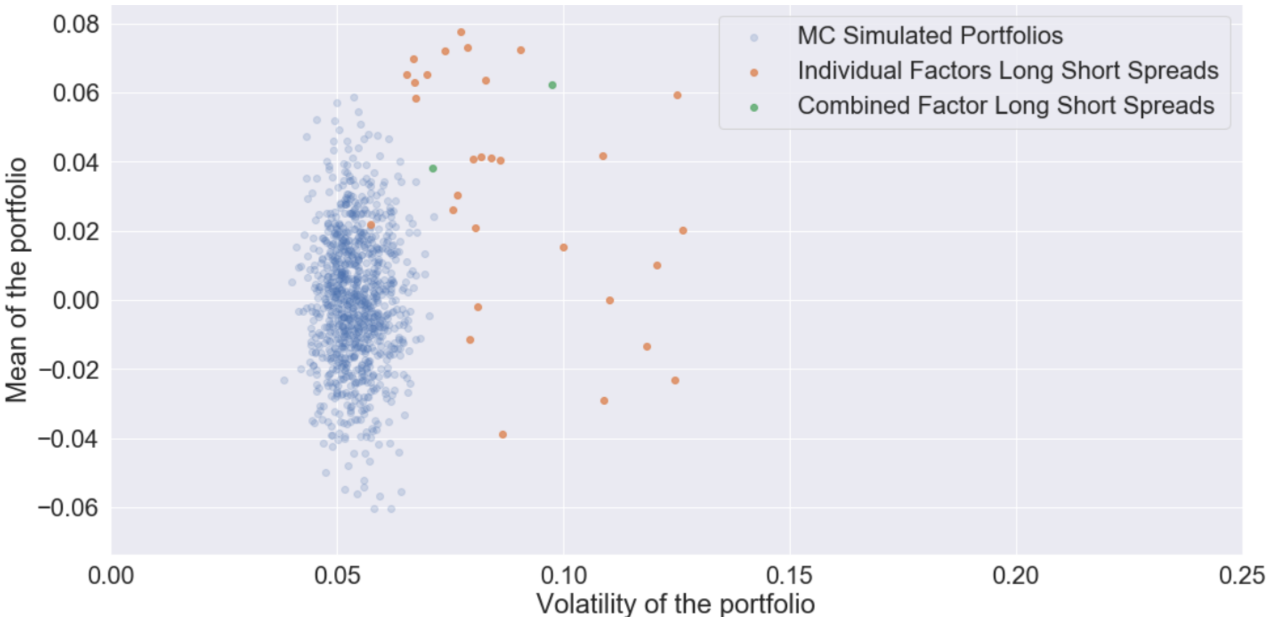
- The potential gains from using a beta-neutral construct is illustrated in the scatter plots below. Specifically, we used Monte Carlo simulations to generate 1000 portfolios which take long and short positions on a random one-tenth of stocks from our investment universe and compared our long-short strategy and beta-neutral long-short strategy against the mean-volatility frontier.

The Beta-Neutral Strategies had significantly less risk as seen in the leftward shift of the data points along the volatility axis

Mean-Variance Frontier of Non-Beta-Neutral Framework



Mean-Variance Frontier of Beta-Neutral Framework



Factor Construction

- For our trading strategy, we constructed 15 factors and their respective sector-neutral equivalents.[1] This provides us with a total of 30 factors that are available for each stock over all dates.

1. Price to Earnings
2. Return on Investment
3. Debt To Market Cap
4. Asset Turnover
5. Profit Margin
6. Free Cash Flow Yield
7. Revenue Growth
8. Dividend Yield
9. Price To Book Ratio
10. 1 Month Volatility
11. 3 Month Volatility
12. 6 Month Volatility
13. 12-1 Momentum
14. 3 Month Momentum
15. 6 Month Momentum

16. SN – Price to Earnings
17. SN – Return on Investment
18. SN – Debt To Market Cap
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21. SN – Free Cash Flow Yield
22. SN – Revenue Growth
23. SN – Dividend Yield
24. SN – Price To Book Ratio
25. SN – 1 Month Volatility
26. SN – 3 Month Volatility
27. SN – 6 Month Volatility
28. SN – 12-1 Momentum
29. SN – 3 Month Momentum
30. SN – 6 Month Momentum

[1] See Appendix 1 for detailed description of each factor.

Portfolio Construction

Data Preparation

- The selected stocks and factors are identified and constructed from data obtained from *Quandl* and *Zacks Investment Research* databases. Using daily end-of-day closing prices, we are able to calculate the historical monthly returns and in turn the factors' respective beta-neutral long-short spreads over the period of interest (2007 – February 2020).

Factor Switching

- Using machine learning models, we then analyze the beta-neutral long-short spreads together with a set of 11 macroeconomic variables[2] as predictors to obtain probabilities corresponding to the factors' ability to generate positive returns in the next month. Our model subsequently picks the top 4 factors with the highest probabilities, subject to the constraint that none of the factors' beta-neutral long-short spreads have a correlation greater than 80%.

Final Stock Selection

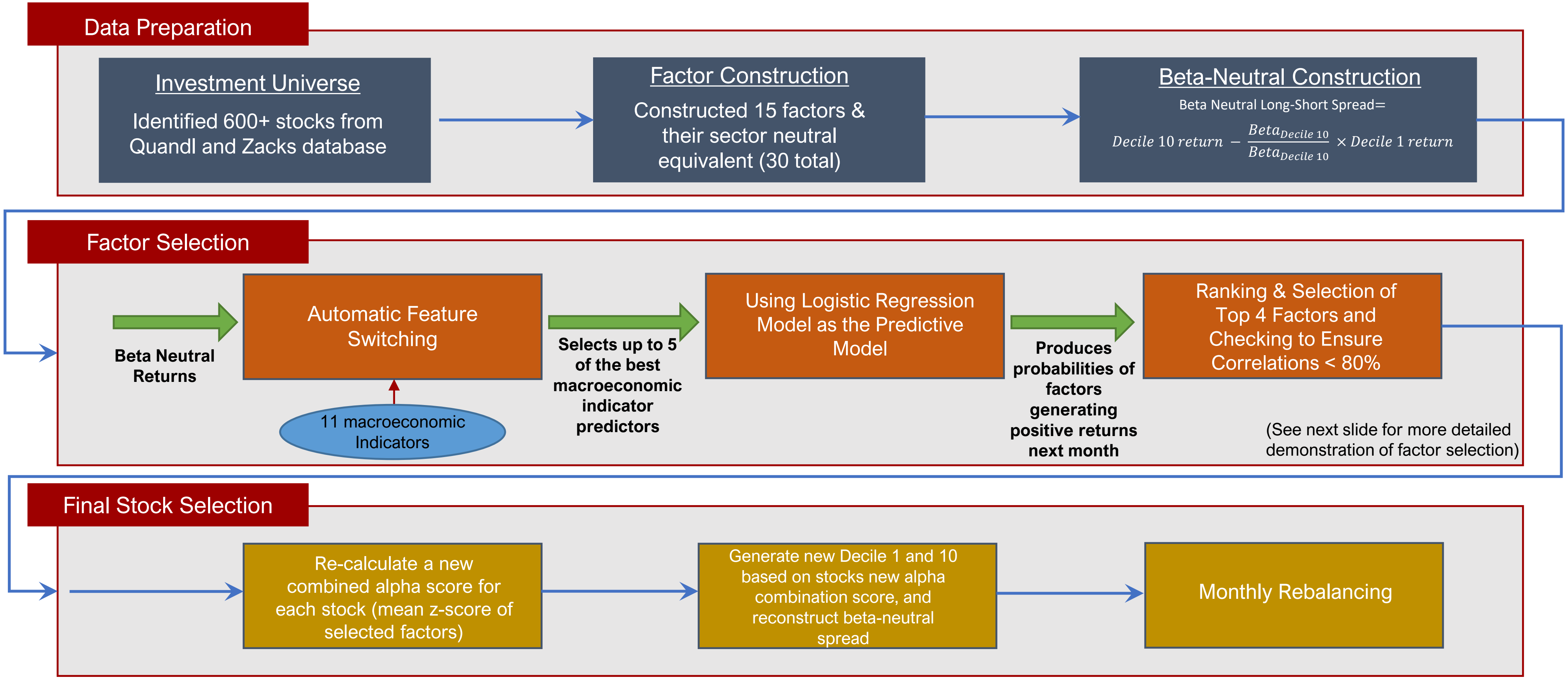
- With the top 4 factors selected, our model then recalculates a new alpha score for each stock. The alpha score of each stock is tabulated by first calculating a z-score for each of the 4 factors, and then taking an average. Our model then generates a new Decile 1 and 10 based on the new alpha score and reconstructs a beta-neutral long-short spread.

- The portfolio is rebalanced on a monthly basis, reflecting information from new macroeconomic data releases.

2. US unemployment rate, University of Michigan Consumer Sentiment Index, US Leading Index, US National Home Prices, US Housing Starts, TED spread, T10Y2Y, US Composite PMI, US Non-Farm Payroll, VIX Index, WTI oil prices)

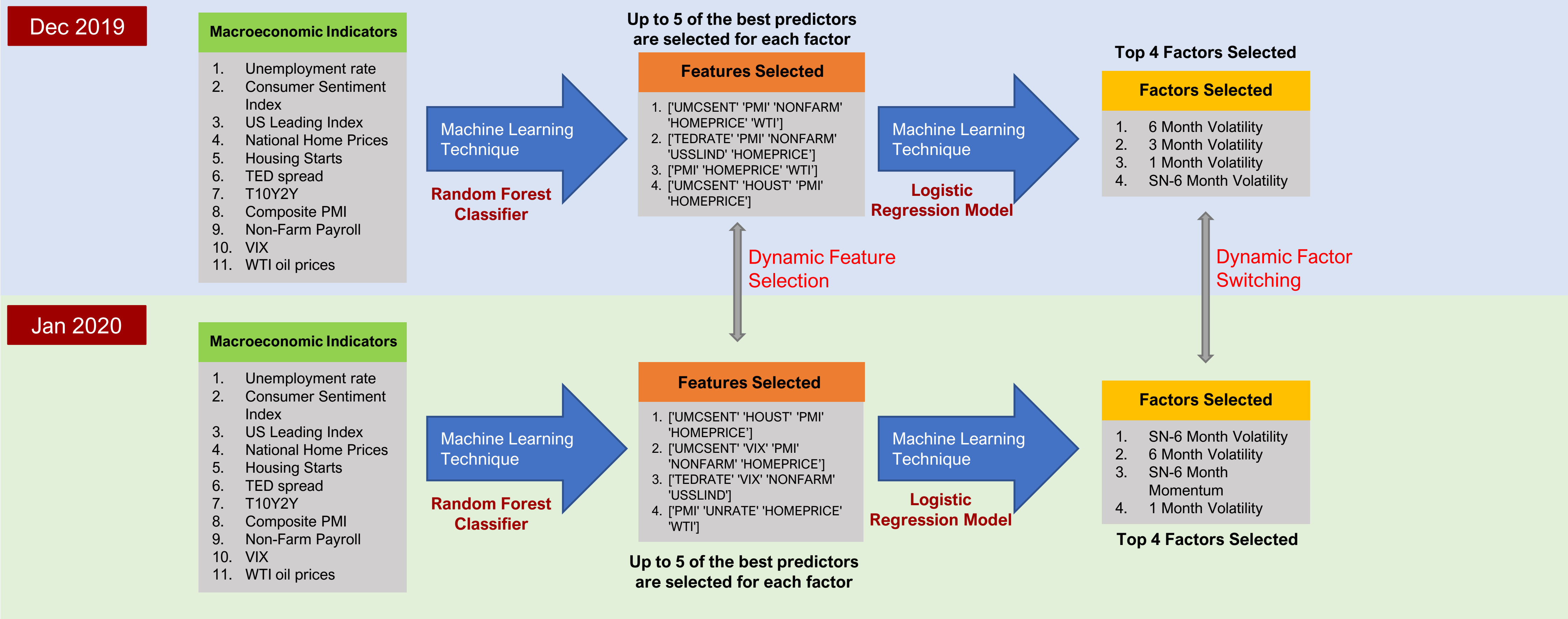
Portfolio Construction (Overview)

- An overview of key stages of our portfolio construction methodology are shown below:



Portfolio Construction (Factor Switching)

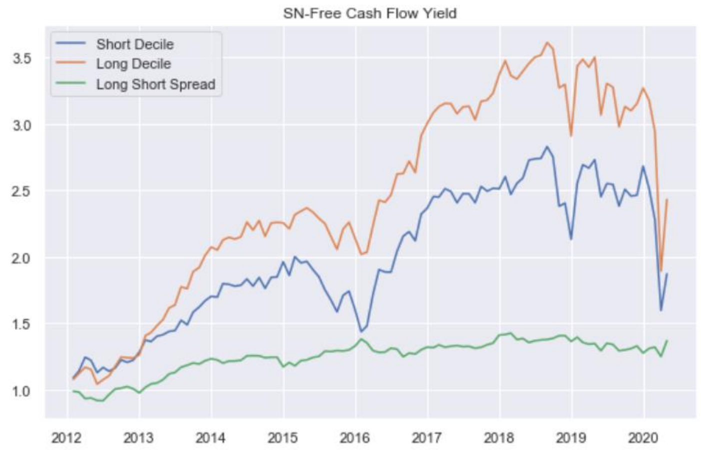
- Our model employs feature selection scores to directly rank and select features. Features and in turn factors selected vary from month to month reflecting new information gathered from latest macroeconomic data.
- A stylized representation of the selection process is outlined below:

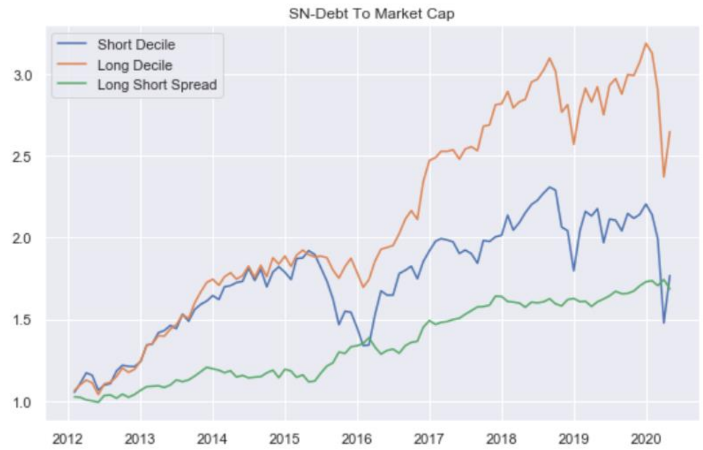


Portfolio Construction (Feature & Factor Selection)

- Of the 30 factors, the 4 most frequently selected factors are:
    1) SN Free Cash Flow Yield
    2) SN Debt to Market Cap (inverse)
    3) SN 1-Month Volatility (inverse)
    4) Price to Earnings ratio (inverse)

- As seen in the cumulative returns charts, the respective factors’ long-short strategy returns are positive and largely exhibit a consistent uptrend (barring early-2020). This is expected given our selection criteria, which chooses factors with the highest probability of generating positive returns.





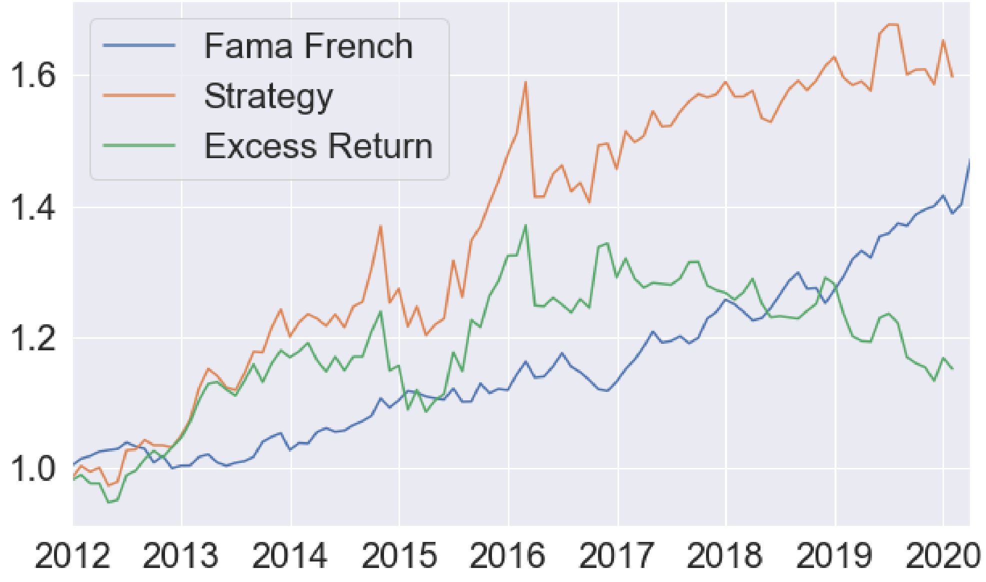
Portfolio Results

- The table below presents the summary statistics for our Tactical Stock Selection Strategy (TSSS), and the benchmark Fama-French Five Factor portfolio weighting each factor based on our strategies' risk profile. The calendar year statistics are derived from monthly returns following industry convention and covers the backtest period from end-2011 to February 2020. The cumulative returns of the strategy versus the Fama French portfolio is also shown on the right panel.

TSSS delivers higher returns >66% of the time

Date	Fama French	Strategy	Excess Return
2012	-0.000077	0.032846	0.032922
2013	0.052884	0.189382	0.136498
2014	0.037368	0.015400	-0.021968
2015	0.026569	0.146998	0.120430
2016	-0.001683	0.050390	0.052073
2017	0.103737	0.050850	-0.052887
2018	0.011628	0.028112	0.016485
2019	0.113037	-0.014559	-0.127596
2020	0.051293	0.008788	0.016560

TSSS outperforms Fama-French benchmark on a cumulative basis



- **Backtesting period:** End-2011 to February 2020
- **Training period:** End-2007 to End-2011
- **Leverage:** 5x
- **Cost:** Results incorporates transaction cost (0.2%), funding cost (risk-free rate from Fama-French database)

Portfolio Results (Risk-Return Profile)

	Annualized Mean Returns	Annualized Standard Deviation	Annualized Sharpe Ratio	Annualized Information Ratio	Hit Rate	Average Winner to Loser Ratio	Maximum Drawdown
Strategy	31.1%	48.8%	0.64	0.17	63.3%	96.8%	58.7%
Fama-French 5 Factor	23.5%	22.0%	1.08	-	67.0%	106.3%	51.0%

- As indicated by the risk-reward statistics above, our strategy's expected annualized mean returns outperform the Fama-French Five Factor reference portfolio.
- On a risk-adjusted basis, despite having a lower Sharpe ratio, our strategy has an Information Ratio of 0.17, confirming that it delivers returns in excess of the reference portfolio. The lower Sharpe ratio mainly reflects the higher volatility associated with our strategy.
- The hit rate and average winner-to-loser ratio of our strategy are slightly lower than those of the Fama-French reference portfolio, though they are broadly comparable.
- However, in terms of the drawdown profile, our strategy has a larger maximum drawdown than the Fama-French portfolio.

Risk Management

Addressing Biases

- In the construction of our model, we made a conscious effort to address several biases. Namely:

    1. we tried to eliminate survivorship bias by allowing stocks which are no longer actively traded to be a part of the analysis.

    2. we eliminated look-ahead bias by building factors by considering only financial data available as on the last available filing date.

Sensitivity Analysis

- Further, we tested multiple variants of our strategy to see its sensitivity to some of our parameters such as training period, beta estimation period and number of selected best factors to build the combined factor. We observed that results do not change drastically upon changes in any of the parameter values. Thus our strategy is fairly robust.

Risk Management

Strategy Risk Decomposition

1. While we attempted to achieve beta neutrality, our strategy does have some positive exposure to the Fama-French Market Risk Factor. As we based our long-short positions on the betas obtained from the relationships in the trailing 48 months, our beta hedging is effective but imperfect.

2. Our long-short model does not have a strong exposure to the size premium, however, there is some downside exposure to the Fama-French Value Factor. There is significant (strongest) exposure to the Fama-French RMW Factor, which is unsurprising considering that profitability-based factors (Profit Margin, Earnings Yield) featured noticeably in our factor selection.

About the Team

- The investment team comprising Manoj, Umang and Ian are UChicago Financial Mathematics students from the Class of 2020. Currently based in two different time zones, 13 hours apart, the team has literally worked around the clock, 24/7, for the past week to complete this final project. They are in full agreement that without a doubt, FINM 33150 has been the most enjoyable but also the most demanding class in the Financial Mathematics program thus far.

Appendix 1

- **1-Month Volatility:** This is essentially a low risk factor. We take a long position in low volatility stocks whereas short position in high volatility stocks.
- **Price to Earnings:** This is essentially a value factor. PE factor would put stocks with negative earnings into the long decile, thus we have converted this into earnings yield, and we go long on stocks with high earnings yield and short on stocks with low earnings yield.
- **3-Month Volatility:** Much like the 1-month volatility factor, this is a low risk factor, and we take a long position in low volatility stock and vice versa.
- **3-Month Momentum:** This is essentially a price momentum factor, we have computed the past 3 months' returns for each stock and hypothesize that stocks which have done well will continue to do so and thus take long positions in them, while taking a short bet on stocks which have not performed well.
- **Profit Margin:** This is essentially a quality or a profitability factor which measure the amount of earnings a company generates per dollar of revenue it makes. We would take long position in stocks with high profit margin and vice versa.
- **Dividend Yield:** This is a value factor, and much like earnings yield, we take long positions in stocks with high dividend yield and vice versa.
- **12 - 1 Month Momentum:** Most tests on momentum show the factor is not persistent in the very short term or in periods of greater than a year. This measure takes that into consideration by looking at a stock's return over the past 12 months while at the same time excluding the most recent month. We take a long bet on stocks with high score and vice versa.
- **Debt-to-Market Cap:** This is a low risk metric, and we take an inverted position in this factor, such that we take long positions in stocks with low debt to market cap and vice versa.
- **6 Month Volatility:** This is a low risk metric, and we take a long position in stocks with low metric and vice versa.
- **6 Month Momentum:** This is a price momentum factor, and we take a long position in stocks with high score and vice versa.
- **Asset Turnover Ratio:** This is a quality factor and we take a long position for stocks which generate higher sales for every dollar of asset it possesses and vice versa.
- **Return on Investment:** This is a quality factor and we take a long position in stocks which generate a higher return on investment and vice versa.
- **Revenue Growth:** In this factor we calculate the growth of a stock’s total revenue over a year and we take a long position in stocks with higher score and vice versa.
- **Free Cash Flow Yield:** This factor is a value factor again, and might give a strong representation of company's operations, especially to investors who recognize importance of cash generations. We take a long position in stocks which have higher free cash flow to market price.
- **Price-To-Book ratio:** This factor is a value factor and assesses how much expensive a stock is trading relative to its book value. We take a long position in stocks with lower price to book ratio or cheap stocks whereas, a short position in stocks with higher price to book (expensive stocks).

Note: The sector neutral version of each of these factors are calculated by converting them into z-scores using sector means and standard deviation of these factors.

References

1. Bender, Sun , Thomas and Zdorovtsov, April 2017. “The Promises and Pitfalls of Factor Timing”, The Journal of Portfolio Management Quantitative Special Issue 2018, 44 (4) 79-92.

2. Ilmanen, Israel, Moskowitz, Thapar, and Wang, December 2019. “How Do Factor Premia Vary Over Time? A Century of Evidence”.

3. Zhang, Lin, Chen, Zhao and Yuan, June 2018. “Adaboost-SVM Multi-Factor Stock Selection Model Based on Adaboost Enhancement”, International Journal of Statistics and Probability; Vol. 7, No. 5.