2021 Applied Finance Project

Factor Research for U.S. Equity markets

Final Report

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Introduction (Background & Objectives)

The ability to predict movement of stock prices, especially relative to the market as a whole has long been of interest to investors seeing an edge in returns performance. Over time different models such as CAPM, Fama French factor models, and characteristic models have been applied to equities in order to identify signals which would provide such insights. These signals serve to simplify the process of picking winners and losers by providing objective flags by which automated algorithmic trading can be implemented.

For this project, we want to specifically examine event based signals which are repeatable with relatively short investment horizons. The events to be used are generated from a dataset provided by O'Neil Global Advisors containing dated information for stocks covering a wide gamut of metrics. Events can be defined as some change in the metrics or when ratios between different metrics exceed certain thresholds. Furthermore, as these signals are intended to be used for predictive purposes, equity performance should primarily be evaluated post signal date.

While returns tend to be the primary way of evaluating equity performance. It is important to be able to consider returns within the context of market movements as a whole, therefore alphas also become a measure of interest when evaluating our signals.

Keeping these points in mind we can define the objectives of this project as follows:

1. Exploratory testing of various event based signals in order to locate indicators of excess returns and alpha.
2. Tracking the occurrences of said events throughout the historical data in the data set in order to ensure robustness of our observations as well as practicality of the signal (a signal which occurs once a decade would not be useful for investment).
3. Confirm the reliability of signals by examining risk-adjusted performance via Sharpe and information ratios.
4. Create actionable recommendations based on the result for our signals

Additionally, we would ideally keep aways from previously established metrics such as mean reversion or price momentum as such signals would do little to add to existing understanding of performance signals.

Literature Review

For our literature review we decided to go over whitepapers as well as some textbooks. We chose textbooks that we thought would help us with the fundamental techniques of factor research. Our list of textbooks included books such as Elements of Statistical Learning: Data Mining, Inference, and Prediction by Trevor Hastie and Robert Tibshirani, Analysis of Financial Time Series by Ruey S. Tsay, and Time Series for Macroeconomics and Finance by John J. Cochrane. Our literature review also included going over multiple whitepapers that document different investment factors. Those white papers exposed us to different investment factors that have been researched as well as different methodologies that were used to research those investment factors. Below we have included some of the examples of whitepapers that we covered for our literature review:

1. Rank EPS Study by Ronald P. Ognar, Chris Graczyk, and Stephen Westwood:

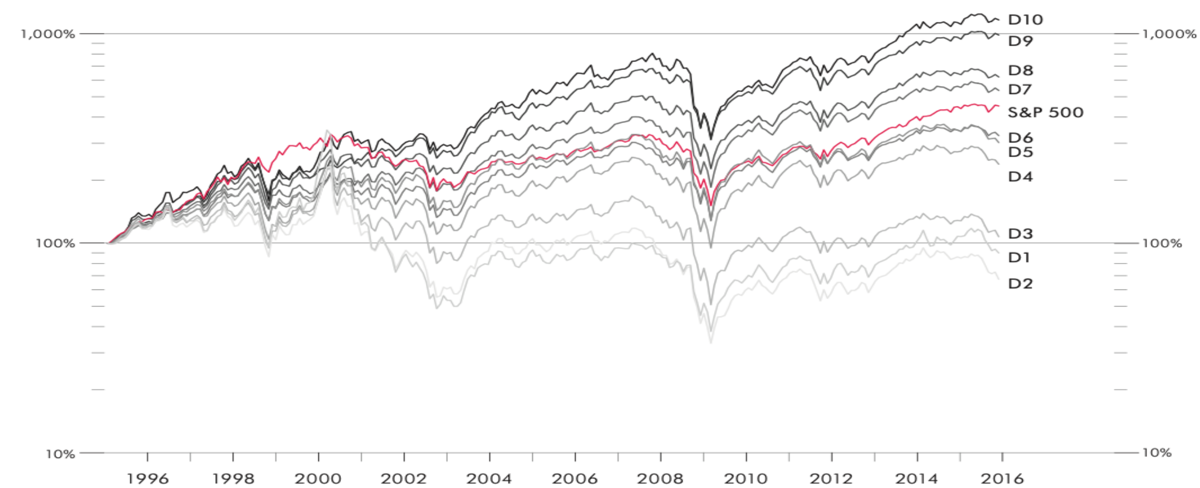
In this paper, the authors tested O'Neil's proprietary EPS rank as a factor to manage U.S. equities portfolio. They covered a 20-year time horizon from Jan. 1995 - Dec. 2015 while including 10,000+ U.S. equities. The authors decided to analyze portfolios built on EPS Rank by deciles and sectors. Their results showed that measuring earnings growth using the EPS Rank system was a good predictor of future equity performance. We can see the performance of the strategy in the chart below:

EPS Rank Study

O'NEIL GLOBAL ADVISORS INC.

Analysis of Backtest Results

Figure 1: EPS Rank Return by Decile

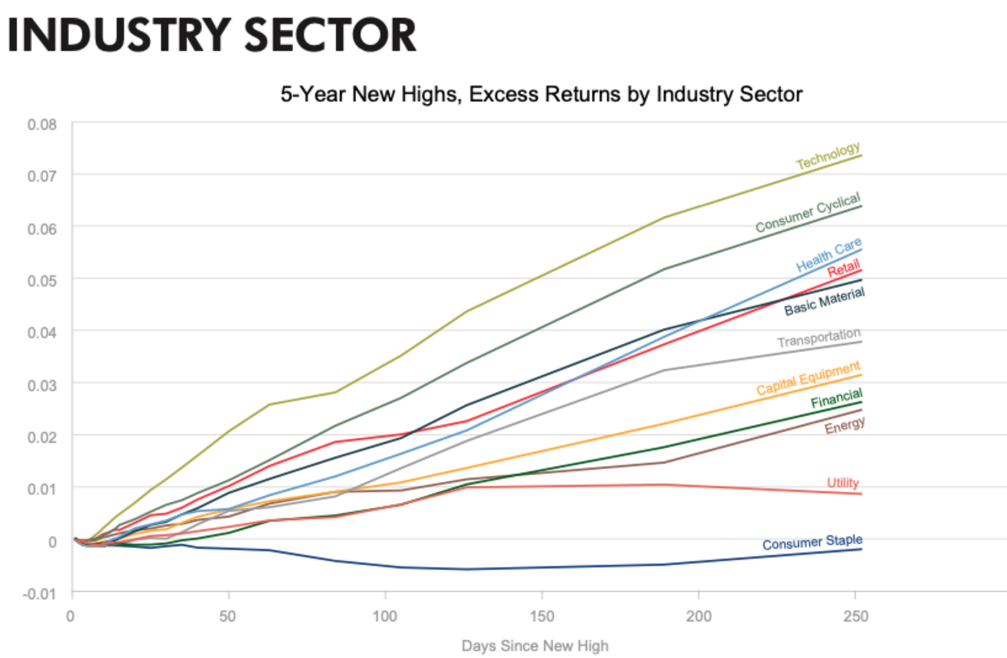


This figure shows EPS Rank performance over a 21-year period from 1995 to 2015. Each line represents a single EPS Rank decile. The red line is the performance of the S&P 500 benchmark. EPS Rank performance includes transaction costs of 20 basis points and monthly rebalancing.

2. New Highs: Segmentation **by Timothy Marble and Ronald P. Ognar**:

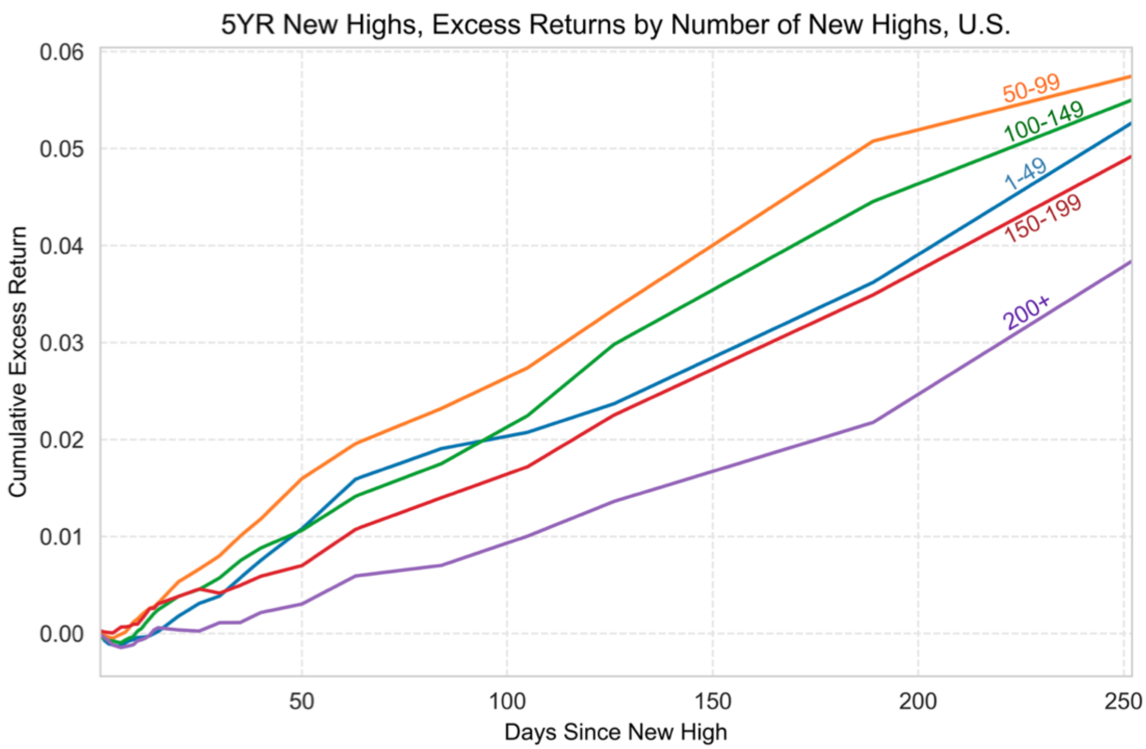
In this paper, Timothy Marble and Ronald Ognar compared one year performance following a five-year new high event. Additionally they segmented the outcomes by country, sector, style, and size. There were several insights as a result of this research:

- Historically, small -cap stocks' new highs performed better than large-cap stocks' new highs
- Historically, value stocks' new highs underperformed growth stocks' new highs However, when they controlled for volatility, the effects were not significant.
- Geographical insights:
  - In China's A-share market, a mean reversion effect seemed to be present for new highs
  - U.S. market underperformed India's market regarding new highs
- Technology sector outperformed all the sectors following new highs while Consumer Staples underperformed all the sectors



3. New Highs: Best Served Rare **by Timothy Marble and Ronald P. Ognar:**

Similar to the previous whitepaper, the authors continued their research in momentum within the markets. This time the authors segmented each event by the total number of new highs that occurred during that day. Their research discovered that during the days when there are fewer new highs, those new highs outperform the new highs that occur during the days with many of them. That effect was most prevalent within large-cap growth stocks in the U.S., especially during the days where there were 50-99 new highs. That bucket earned on average an alpha of 7% compared to the 200+ bucket that have an average alpha of only 3.5%. We can see those results visualized below:

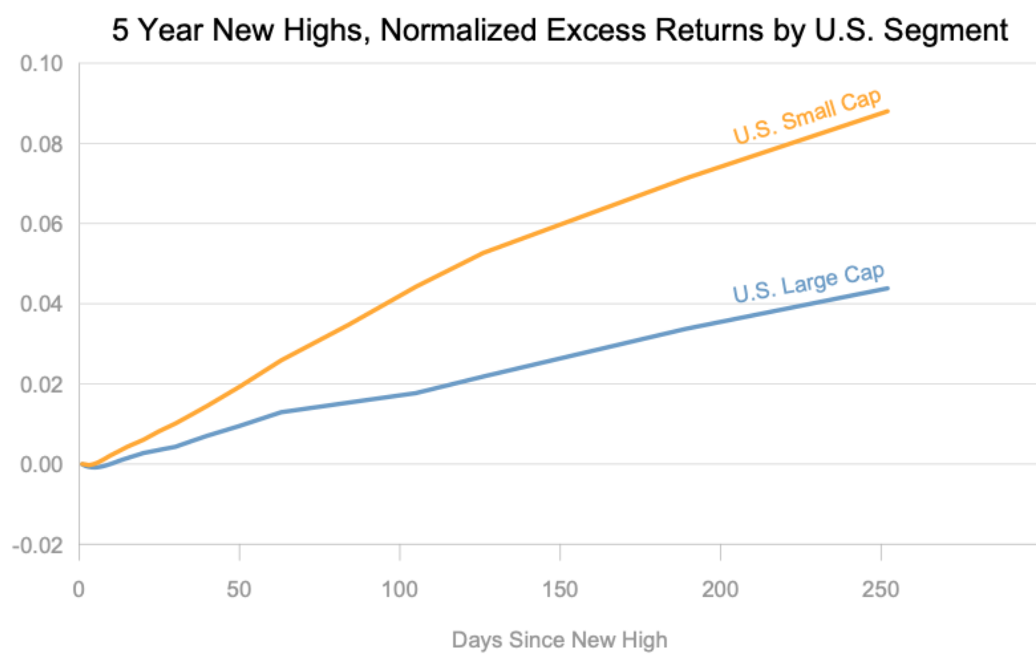


4. "New Highs: Across the Board and Around the World" - Marble & Ognar (2020): Mapping the ATH Anomaly across Style, Size, and Geography:

The findings of Marble & Ognar build off their previous findings of the All-Time-High anomaly and build upon their findings that an equity reaching its ATH is a bullish signal. They segment equity portfolios into four bins in order to determine the efficacy of microeconomic ATH effects; Size, Style, Industry, and Geography.

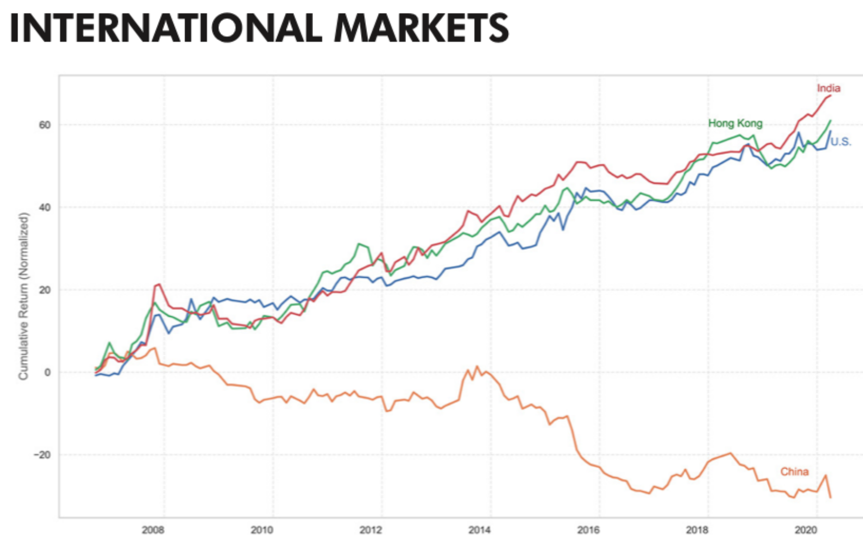
The results from segmenting the ATH portfolios by Style, Industry, and Geography were initially hopeful, but turned out not to be robust to controls for volatility, and therefore were not determined to be a source of alpha. Interestingly the Size portfolio segmentation was robust to controls for volatility - in particular Small-cap ATH signals were found to be a better indicator of potential outperformance (relative to risk) compared to Large-cap ATH signals.

The researchers mention that this can be potentially explained by low coverage of Small-cap equities in markets which leads to market inefficiencies from gaps in information. It is also possible, however, that the aforementioned signal is not algorithmically tradable - transaction costs present in Small-cap equities, such as low-volume movers and bid-ask spread, make realistically trading this factor difficult and were not considered in the original research.

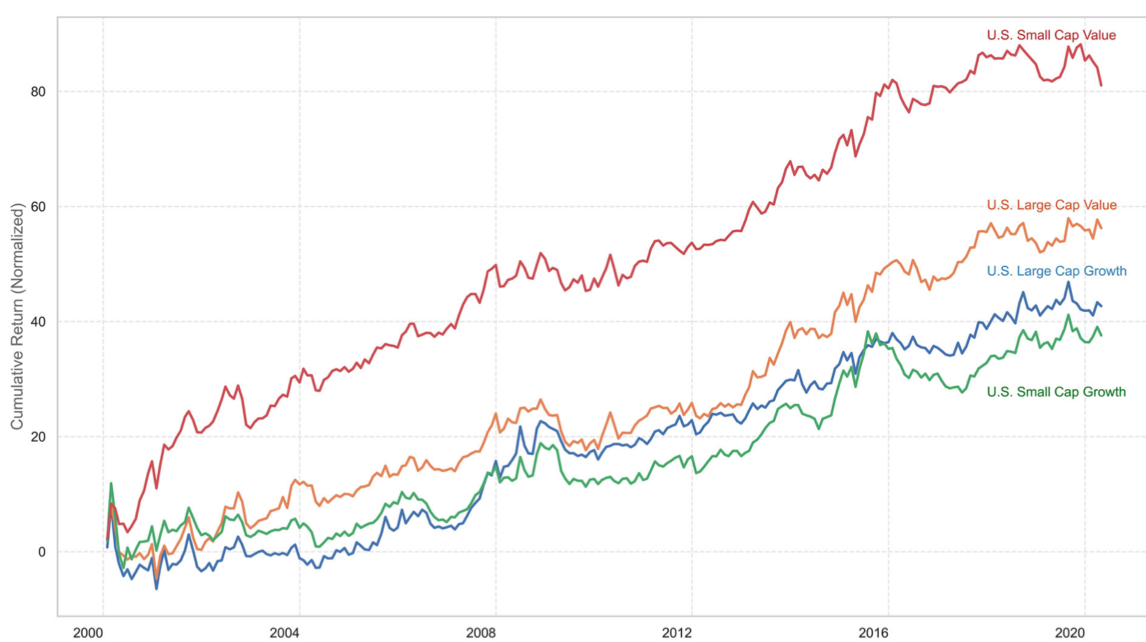


***5. RS Rating: Pharma Flameouts and Small-Cal Values* by Timothy Marble and Ronald Ognar:**

In the paper authors tested O'Neil's proprietary Relative Strengths (RS) Rating as a factor to identify stocks that overperform and underperform. To measure performance, Timothy Marble and Ronald Ognar constructed long/short portfolios based on quintiles. More specifically, they comprised the quintiles based on country, sector, size, and style. RS Ratings quintile-based portfolios showed great performance in all markets except China as we can see below:



Additionally, they noticed that long/short portfolios based on RS ratings of small cap stocks performed better than of large cap stocks. Additionally, they found that, generally speaking, value stocks outperform growth stocks within the 20-year timeframe.



Data

Project data from O’Neil was provided as a single large CSV file with close to 3 million rows of data. The data covers metrics for US equities during a period from 1995 to 2021, excluding very small stocks. Every row of data represents information for one company at a trading date. In other words, each row within the dataset represents a unique OSID (O’Neil Security Identifier) and date pairs.

The data set also contains 150 columns representing the various features of each entry. The features of note include:

- Tradedate - trade date of observation
- OSID - O’Neil Security Identifier
- Symbol - Stock ticker symbol
- Coname - Company name
- Sector_group – 4 (Technology), 7 (Consumer Cyclical)
- Max_dt - Max date
- Previoustradedate – Previous trade date
- Tickssinceipo – Number of trading ticks since the IPO
- Alpha - Outperformance indicator measured using daily CAPM
- Stdev_alpha - Standard deviation of alpha
- Pricehigh – Highest price of the stock on one day
- Pricelow – Lowest price of the day
- Priceclose – Closing price of the day
- Priceopen – Opening price of the day
- Splitfactor – Split factor (for example, for 7/1, the split factor is 7)
- Cumsplitfactor – Cumulative split factor (used to adjust prices after the splits)
- Volume – Volume of the stock on a specific trade date
- Unadjustedpriceclose – Unadjusted price close (price close without splits and stock dividends)
- Pricepctchgd – percent change in unadjusted price close from previous trade date
- Avgvol50d – 50 day volume average
- Avgdollarvol50d – 50 day dollar volume average (dollar volume = price * volume)
- Growthscore - O’Neil score for growth
- Growthrank - Cross sectional rank according to Growthscore
- Epsq1,, … , Epsq8 - Quarterly earnings per share for 1-8 quarters ago
- Epshighq1, … , Epshighq8 - Max quarterly earnings per share analyst estimate for 1-8 quarters ago
- Epslowq1, … , Epslowq8 - Min quarterly earnings per share analyst estimate for 1-8 quarters ago
- Salesq1, …, Salesq8 - Quarterly sales for 1-8 quarters ago
- Saleshighq1, …,Saleshighq8 - Max quarterly sales analyst estimate for 1-8 quarters ago
- Saleslowq1, …,Saleslowq8 - Min quarterly sales analyst estimate for 1-8 quarters ago
- Cfpsq1, …,Cfpsq8 - Quarterly cash flow per share for 1-8 quarters ago
- Cfpshighq1, …,Cfpshighq8 - Max quarterly cash flow per share analyst estimate for 1-8 quarters ago

- Cfpslowq1, …,Cfpslowq1 - Min quarterly cash flow per share analyst estimate for 1-8 quarters ago
- Epsa1, … , Epsa4 - Annual earnings per share for 1-4 years ago
- Epshigha1, … , Epshigha4 - Max annual earnings per share analyst estimate for 1-4 years ago
- Epslowa1, … , Epslowa4 - Min quarterly earnings per share analyst estimate for 1-4 years ago
- Salesa1, …,Salesa4 - Annual sales for 1-4 years ago
- Saleshigha1, …,Saleshigha4 - Max annual sales analyst estimate for 1-4 years ago
- Saleslowa1, …,Saleslowa4 - Max annual sales analyst estimate for 1-4 years ago
- Cfpsa1, …,Cfpsa4 - Annual cash flow per share for 1-4 years ago
- Cfpshigha1, …,Cfpshigha4 - Max annual cash flow per share analyst estimate for 1-4 years ago
- Cfpslowa1, …,Cfpslowa4 - Max annual cash flow per share analyst estimate for 1-4 years ago
- Pricetarget - Price target
- Pricetargethigh - Max analyst price target
- Pricetargetlow - Min analyst price target
- Numberofpricetargets - Number of price targets
- Numpricetargetsraised - Number of price targets raised
- Numpricetargetslowered - Number of price targets lowered
- Pricetargetsmean - Average price target
- Pricetargetsmedian - Median price target
- Pricetargetsstandarddeviation - Volatility in price target
- Reportdate - Date of company financial statement reporting
- Duedate - Due date for company financial statements
- Sp100f - Indicator of whether a stock is in the S&P100 index
- Sp500f - Indicator of whether a stock is in the S&P500 index
- Nasdaq100f - Indicator of whether a stock is in the NASDAQ100 index
- Shortpctfloat - Percentage of float that is short
- Captl – representative of shares outstanding
- Inuniverse - O'Neil identifier for whether a stock is in their tradable universe

With this dataset, we begin our analysis by computing rolling 1 week, 2 week, 3 week, and 4 week cumulative return and cumulative alpha. That is, we group stocks by OSID and compute the cumulative returns and cumulative alpha of holding that security for 5, 10, 15, and 20 trading days, respectively. We do this by considering valid lags only (that is, we avoid calculating cumulative returns/alpha using lags that are longer than 1 trading day and only keep those observations for which the lags are valid). Finally, we create a new file to contain our results, which includes all of the data described above in addition to the following variables:

- week - a unique number assigned to each trading week in the data

- ret5d - rolling 5 day cumulative returns computed using “Pricepctchgd” from the original dataset
- ret10d - rolling 10 day cumulative returns computed using “Pricepctchgd” from the original dataset
- ret15d - rolling 15 day cumulative returns computed using “Pricepctchgd” from the original dataset
- ret20d - rolling 20 day cumulative returns computed using “Pricepctchgd” from the original dataset
- alpha5d - rolling 5 day cumulative alpha computed using “Alpha” from the original dataset
- alpha10d - rolling 10 day cumulative alpha computed using “Alpha” from the original dataset
- alpha15d - rolling 15 day cumulative alpha computed using “Alpha” from the original dataset
- alpha20d - rolling 20 day cumulative alpha computed using “Alpha” from the original dataset

Defining the returns in this way allows us to follow in line with our sponsor company’s request to have an average holding period of 10 days, although we may define different horizons to compute cumulative returns and cumulative alpha in the future.

Of particular interest to our implementation of this project are the features relating to indicators, such as whether the company is included in an index, whether the company beat or fell short of analyst estimates, and flips in the security’s cross sectional rank when sorted with respect to many variables (including short interest, size, value, or momentum). That is, we will buy when a company is included on a major index like the S&P and sell when it is removed from the index, we will buy when a company beats analyst estimates and sell when it falls short of analyst estimates, and we will trade when the security’s cross sectional decile rank falls(rises) from a high(low) decile to a low(high) decile.

Although trading on the discrete event that we define as flips in a security’s decile (especially when sorted with respect to short interest, size, value, or momentum) will mirror the performance of a similar strategy that is implemented with continuous based factors, these events will help us later in the project to specify an event as being a composite of many events. For example, we can sell a stock that both recently underperformed relative to analyst estimates and whose decile rank (sorted with respect to short interest) recently rose from a low decile to a high decile.

Our intention is to form an equal weighted portfolio tomorrow by using information about the occurrence of events available today. We will then hold this portfolio for 5, 10, 15, and 20 trading days before rebalancing.

For measuring performance, we will create a performance plot of the strategy and we will also create summary statistics. Our summary statistics will include annualized average alpha, annualized tracking error, annualized information ratio, skewness of alpha, and turnover of the trading strategy.

Methodology

Our methodology begins by defining an event. As described above, this event can come from an indicator variable (for example, an indicator for whether a stock is included on the S&P 500 index) or from flips in the cross sectional rank of a stock when sorted according to any financial variable that can predict future returns. We will convert this event into an equal weighted portfolio for each day, and we will hold this portfolio for a pre-specified time period. Then, we will assess the ability of this strategy to predict outperformance/underperformance in returns visually via performance plots and analytically via summary statistics.

<u>We follow the following steps for all the events that we test:</u>

1) Set columns ‘buy_tomorrow’/‘sell_tomorrow’ to be dummy indicators. This way, we can define discrete event based strategies such that the signal will either be a 1 if we want to buy/sell, or a 0 if we don’t want to include that stock in the buy/sell portfolios the next day

2) Then, we erase all ‘buy_tomorrow’ and ‘sell_tomorrow’ signals for which the change in date from ‘today’ to ‘tomorrow’ is more than 20 days. This allows us to disregard the ‘buy_tomorrow’ signal in these cases when the change in date from ‘today’ to ‘tomorrow’ is more than 20 days.

3) In order to simulate holding periods of 1, 5, 10, 15, and 20 days, we create five dataframes with ‘buy_tomorrow’ and ‘sell_tomorrow’ signals that are pulled forward for 0, 4, 9, 14, and 19 days ahead within the same security. This way, our signal that arises will stay “live” for the number of days in the holding period.

4) Make sure that step #2 is satisfied in all five dataframes from step #3

<u>Next, we compute the following for the buy/sell signals separately in all five dataframes (1, 5, 10, 15, and 20 day holding periods):</u>

1) Group stocks by date and create an equal weighted portfolio with all stocks whose signal=1 on the given day; that is, we count the number of buys/sells in each date (set this number equal to N) and then set the weight of any single security on that date to be 1/N
2) Generate time series of returns/alphas for the equal weighted portfolios
3) Compute the following annualized statistics: mean return, standard deviation, SR, mean alpha, tracking error, information ratio, and skewness in return/alpha; these statistics are computed not net of transaction costs
4) Compute the time series of portfolio turnover (manually set turnover=100% when the change in date is less than 6 days)

5) Compute a dollar metric for transaction costs by accumulating 5bp of cost each time there is turnover in the portfolio by keeping track of starting and ending capital each period (start the portfolio with $1 of capital and 100% turnover)
6) Regress our excess returns on FF5 + Momentum factors to get our portfolio's factor exposures
7) Plot the cumulative return of our strategy net of T-cost; the backtest is intended to be realistic due to the inclusion of transaction costs.

Executive Summary

The following table is a condensed compilation of results from our signal study. Detailed descriptions and analysis of each signal and its results will be provided in the following Results section.

Signal Name	Average N-Period Return	Standard Deviation	Sharpe Ratio	Information Ratio
High EPS relative to current EPS (Long/Short) - 5 Day	29.02% 23.39%	27.64% 29.91%	1.05 0.78	0.36 -0.01
Strong Alpha Deviation (Long/Short) - 5 Day	39.52% 27.98%	27.87% 25.86%	1.42 1.08	0.84 0.21
Price Target Moves (Long/Short) - 5 Day	38.31% -3.30%	25.30% 27.35%	1.51 -0.12	2.01 -1.60
Unusual Volume (Long/Short) - 1 Day	78.13% 16.86%	150.9% 25.54%	0.52 0.66	1.39 -0.35
Momentum + Earnings Surprise (Long/Short) - 10 Day	35.11% 18.52%	40.85% 46.39%	0.86 0.40	0.53 -0.01
Index Inclusion/Removal (Long/Short) - 20 Day	75.03% 4.38%	69.76% 47.59%	1.08 0.09	0.69 -0.50
EPS High Moves (Long/Short) - 5 Day	45.68% 14.17%	27.03% 26.67%	1.69 0.53	1.51 -0.43
2F CAPM - 10 Day	5.36%	4.88%	1.05	1.68
Stock split - 20 Day	38.95%	44%	0.27	0.89
Change in sector group - 20 Day	43.25%	38.66%	1.17	0.9

Long/Short Signal: High EPS estimate vs current EPS

Hypothesis: EPS has long been used by financial analysts as a means of setting the price targets which help drive investor sentiment. However due to differing methodology, research, analyst bias/optimism, and weighting schemes, EPS estimates for a future period usually exist as a range. As the current EPS nears the high end of the estimate range, the performance of the stock would appear to confirm the more optimistic views held by the analysts with high price targets. Therefore, it would reason the market would also adopt an optimistic view of the equity, driving up returns.

Additionally, we may consider expectations and rumors that as EPS approaches the high end estimates, the general range of EPS estimates from analysts will be revised upwards. In these cases, optimism and overreaction to positive private information (regardless of credibility, thus including rumors) combined with underreaction to available public information (existing EPS estimates) may result in higher performance in the short run.

Buy Signal Definition:

$$\begin{cases} signal = 1 \quad when \ \dfrac{high\ EPS\ estimate}{EPS} < 1.02 \\ signal = 0 \quad when \ \dfrac{high\ EPS\ estimate}{EPS} \geq 1.02 \end{cases}$$

The buy signal as defined occurs 285,935 times across 6,546 trading days within the historical data.

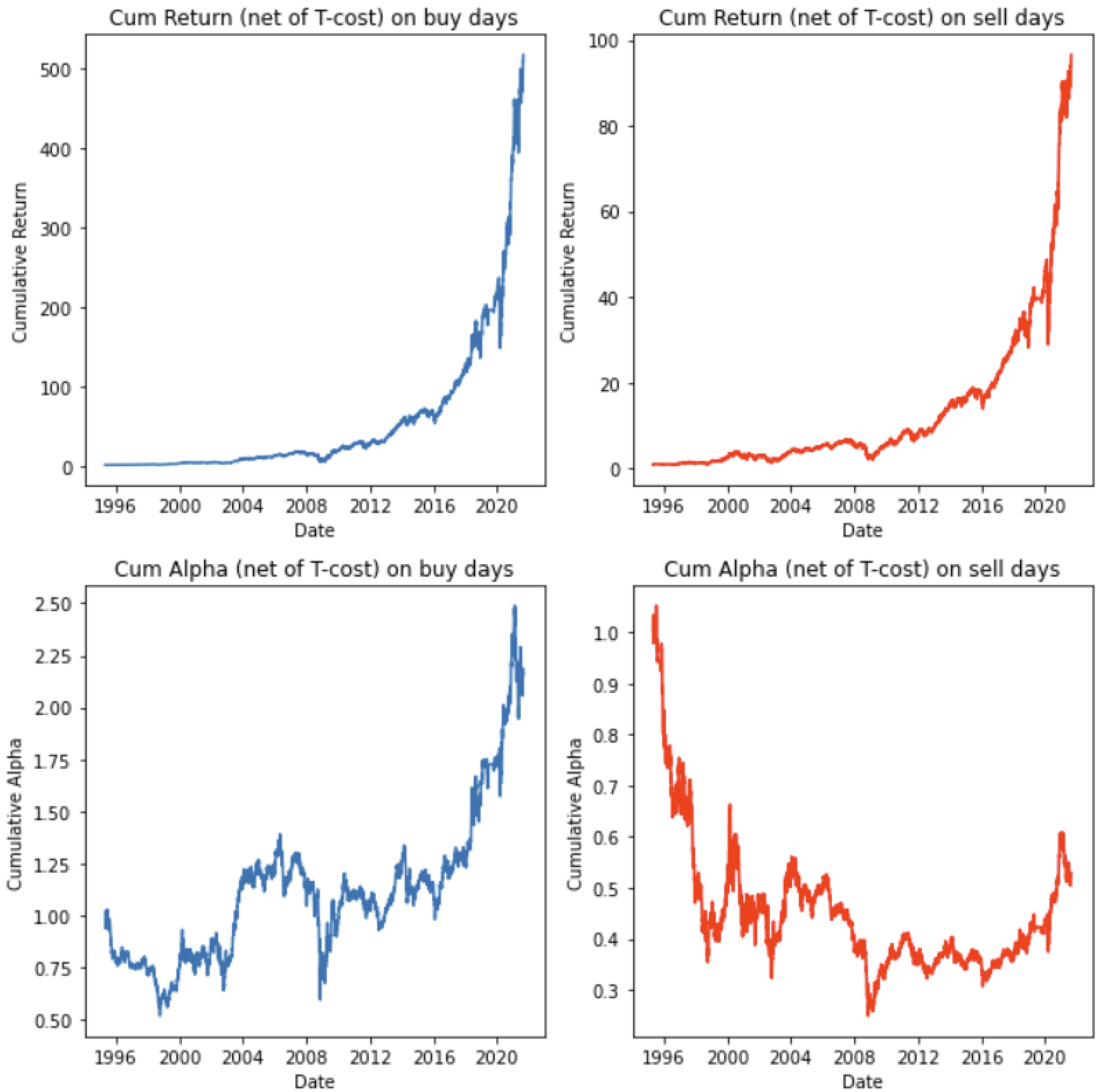
Sell Signal Definition:

$$\begin{cases} signal = 1 \quad when \ \dfrac{high\ EPS\ estimate}{EPS} > 1.2 \\ signal = 0 \quad when \ \dfrac{high\ EPS\ estimate}{EPS} \leq 1.2 \end{cases}$$

The sell signal as defined occurs 308,410 times across 6,440 trading days within the historical data.

Signal Results:

The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	29.02%	23.39%
Volatility	27.64%	29.91%
Sharpe Ratio	1.05	0.78

Skewness of Returns	-0.13	0.09
Mean Alpha	5.19%	-0.14%
Tracking Error	14.49%	16.26%
Info. Ratio	0.36	-0.01
Average Turnover	0.04	0.04

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
SMB	0.1175 (3.242)	0.0800 (2.031)
CMA	-0.1660 (-2.698)	-0.1571 (-2.346)
MOM	0.1572 (1.965)	0.1407 (1.615)

Analysis and Interpretation:

While a huge cumulative performance differential is present between the buy and sell portfolios, it should be recognized that the cumulative sell portfolio would have still performed exceedingly well over the historical period. This indicates that both extremes of the high EPS estimate to current EPS ratio can be used as a long signal. However, only the buy side portfolio, as defined, contains a high enough Sharpe and information ratios to warrant consideration for investment.

The impressive performance at both extremes helps support our hypothesis on the buy signal, but implies further forces at work which drives optimism even at the opposite extreme of the ratio. One possible explanation is the stubborn tenacity by which investors cling to good news, especially that of great magnitude. The buy being focused on the most positive of EPS estimates, investors assume a increase in value of the equity of over 20% in the near future, too attractive of a gain not to bet on.

Long/Short Signal: Daily Alpha more than 2 standard deviations away from 0

Hypothesis: While similar to a common mean reversion signal, an alpha based signal measures performance relative to the market rather than pure price performance. However, the basic concept is similar. We expect that any equity with an extreme alpha on a given trading day will undergo a correction in the opposite direction.

Instead of using percentage of price change as a signal, we count the standard deviations of the alpha. By doing so, we aim to make the signal more robust as it captures not only the performance of the equity, but also its performance relative to the market, as well as any aberrant behavior of the stock itself. That is to say, it can help us ignore huge swings from equities which are naturally highly volatile, and hone in on equities experiencing more unexpected fluctuations.

Buy Signal Definition:

$$\begin{cases} signal \ = \ 1 \quad when \ \dfrac{Alpha}{St\ Dev\ Alpha} < -2 \\ signal \ = \ 0 \quad when \ \dfrac{Alpha}{St\ Dev\ Alpha} \geq -2 \end{cases}$$

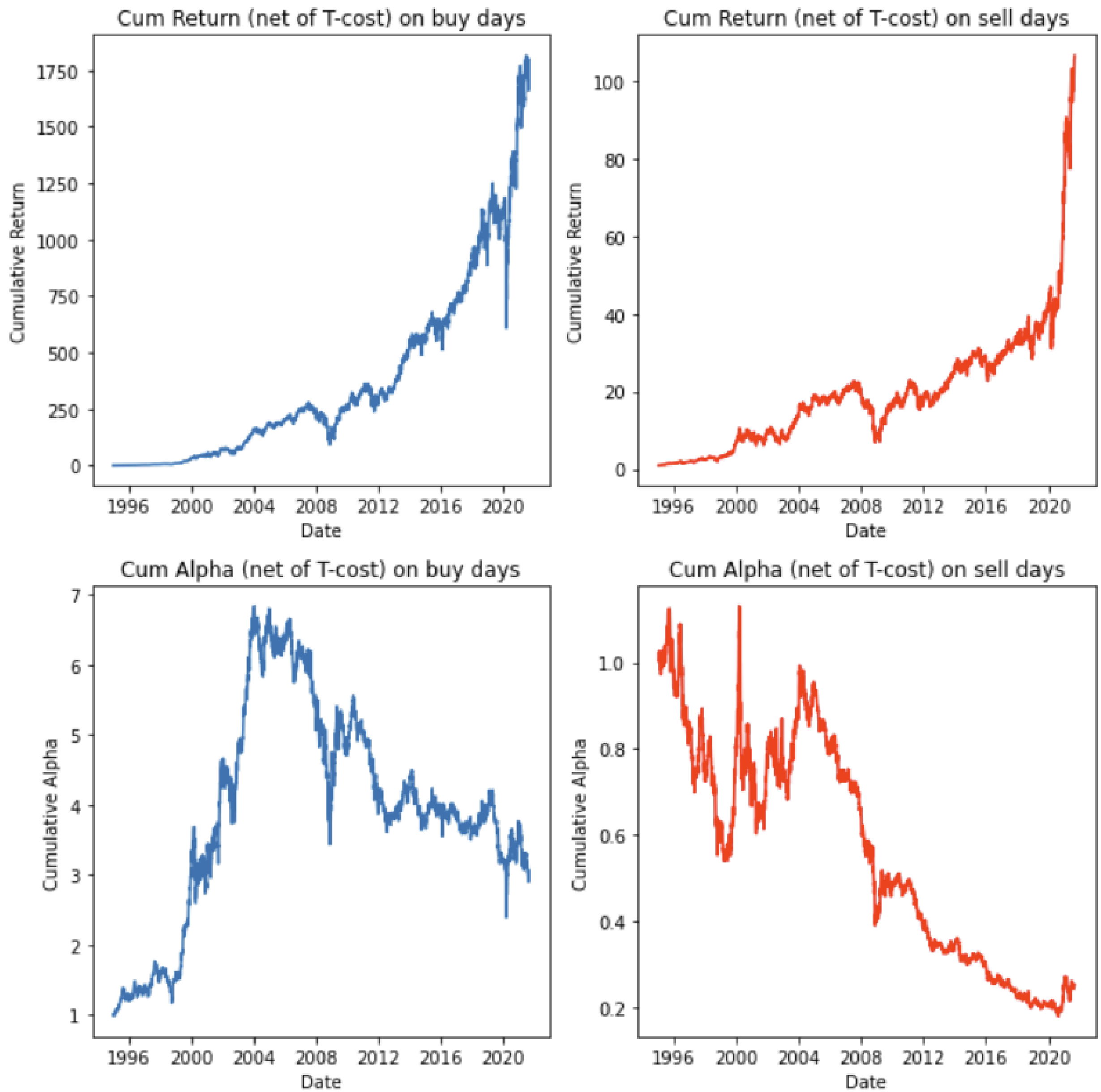
The buy signal as defined occurs 120,396 times across 6,712 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal \ = \ 1 \quad when \ \dfrac{Alpha}{St\ Dev\ Alpha} > 2 \\ signal \ = \ 0 \quad when \ \dfrac{Alpha}{St\ Dev\ Alpha} \leq 2 \end{cases}$$

The sell signal as defined occurs 137,208 times across 6,715 trading days within the historical data.

Signal Results:
The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	39.52%	27.98%
Volatility	27.87%	25.86%
Sharpe Ratio	1.42	1.08

Skewness of Returns	0.15	0.01
Mean Alpha	12.78%	2.85%
Tracking Error	15.16%	13.65%
Info. Ratio	0.84	0.21
Average Turnover	0.30	0.28

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
Beta	-0.0465 (-2.345)	-0.0435 (-2.366)
SMB	0.0948 (2.615)	0.0849 (2.524)
CMA	-0.1942 (-3.147)	-0.1607 (-2.807)

Analysis and Interpretation:

As was with the previous signal, we once again witness a sizable performance differential between the buy portfolio and the sell portfolio. And again we see that the sell portfolio actually performed remarkably well. This would indicate that extreme alphas in either positive or negative directions would generate returns. However, the higher returns, accompanied by the stronger Sharpe and information ratios, exhibited by the buy portfolio indicates that corrections from a particularly negative alpha on a given day are a surer bet to invest on.

Having the positive returns from both extremes of alpha deviation can be a sign that we are actually capturing two phenomena at once: short-term mean reversion as well as short-term momentum. Investors simultaneously believe in recovery after a sharp fall and continued growth after a sudden performance spike. In behavioral finance this kind of reaction is attributed to investors’ tendency to overreact to positive news and underreact to negative news.

Long/Short Signal: Price Target Moves

Hypothesis: Changes in price target may signal changes in underlying fundamentals or come from analysts' job security concerns. Investors may underreact to this information, and thus the stock may drift in one way for some time.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ Price\ Target_t - Price\ Target_{t-1} > 0 \\ signal = 0 & else \end{cases}$$

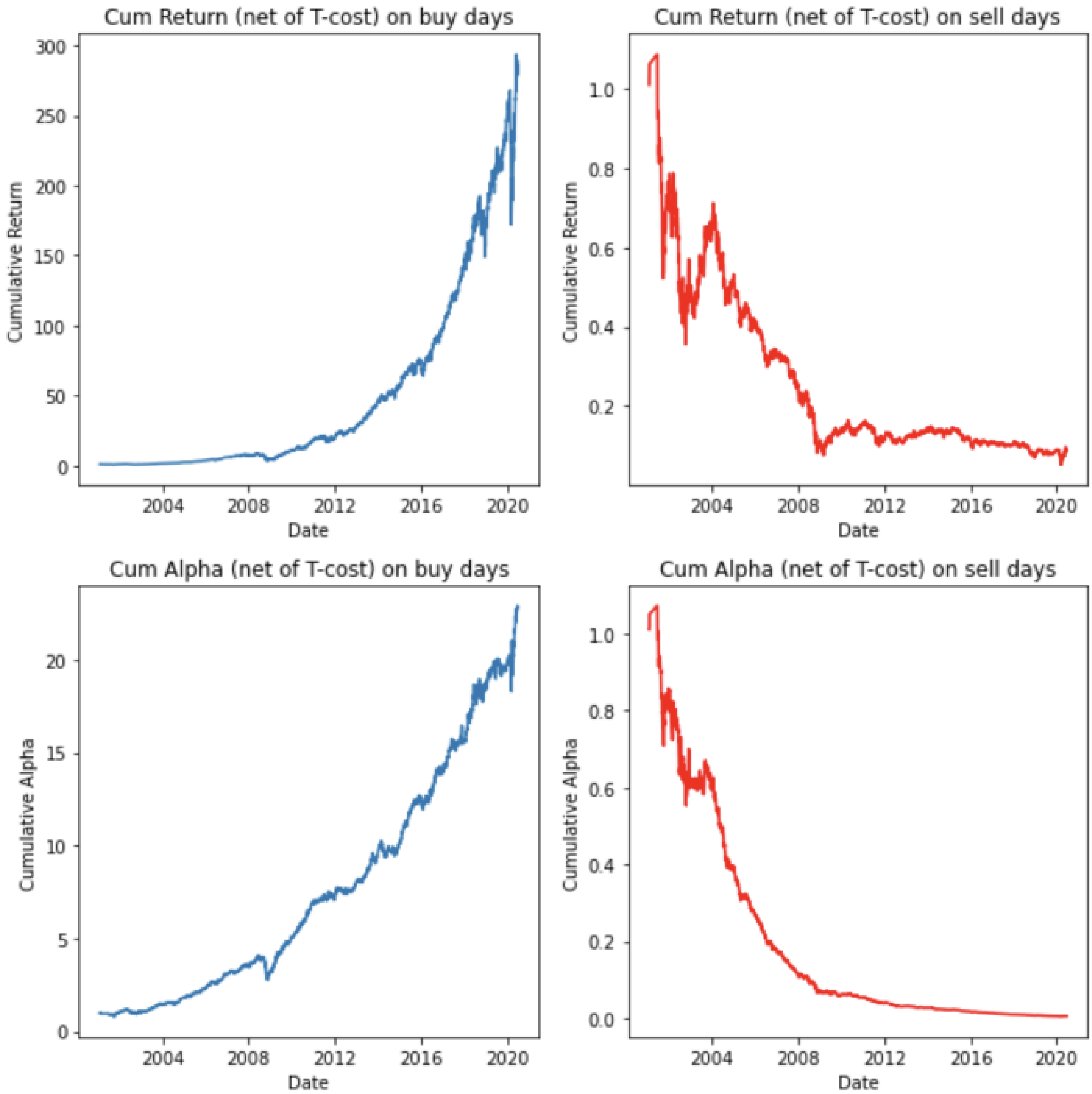
The buy signal as defined occurs 78,791 times across 4,732 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ Price\ Target_t - Price\ Target_{t-1} < 0 \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 53,551 times across 4,715 trading days within the historical data.

Signal Results:
The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	38.31%	-3.30%
Volatility	25.30%	27.35%

Sharpe Ratio	1.51	-0.12
Skewness of Returns	-0.24	-0.05
Mean Alpha	22.45%	-20.42%
Tracking Error	11.19%	12.78%
Info. Ratio	2.01	-1.60
Average Turnover	0.21	0.23

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
Beta	-0.07 (-3.4)	-0.084 (-3.74)
SMB	0.15 (3.75)	0.18 (4.03)
MOM	0.22 (2.58)	0.21 (2.30)
Intercept	0.0007 (1.66)	-0.001 (-2.23)

Analysis and Interpretation:

While defining the trade event by using the mean, median, high, and low Price Target all lead to good performing strategies, we found that the best performing one to be the price target (variable name “Pricetarget” in the dataset). Here a huge cumulative performance differential is present between the buy and sell portfolios, it should be recognized that the cumulative sell portfolio performed exceedingly poorly over the historical period (t-stat of sell portfolio’s intercept is slightly negative and significant).

For this signal, Returns, alphas, Sharpe Ratio’s and Information Ratio’s fall monotonically as you hold for longer than 5 days (10, 15, and 20 days). The sell portfolio starts to make a little money (the cumulative return net of T-cost on $1 invested was around $2.5-3.5, but the sell portfolio still had no alpha) if hold for 15-20 days. Thus, our hypothesis is that Investors underreact, thus creating profitable strategies when holding for 1-10 days.

Long/Short Signal: Price Target Moves +-1SD

Hypothesis: Changes in price target may come from changes in underlying fundamentals or from analysts' job security concerns. Investors may underreact to this information, and thus the stock may drift in one way for some time.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ (Price\ Target_t - Price\ Target_{t-1})\ /\ Price\ Target\ SD_t > 1 \\ signal = 0 & else \end{cases}$$

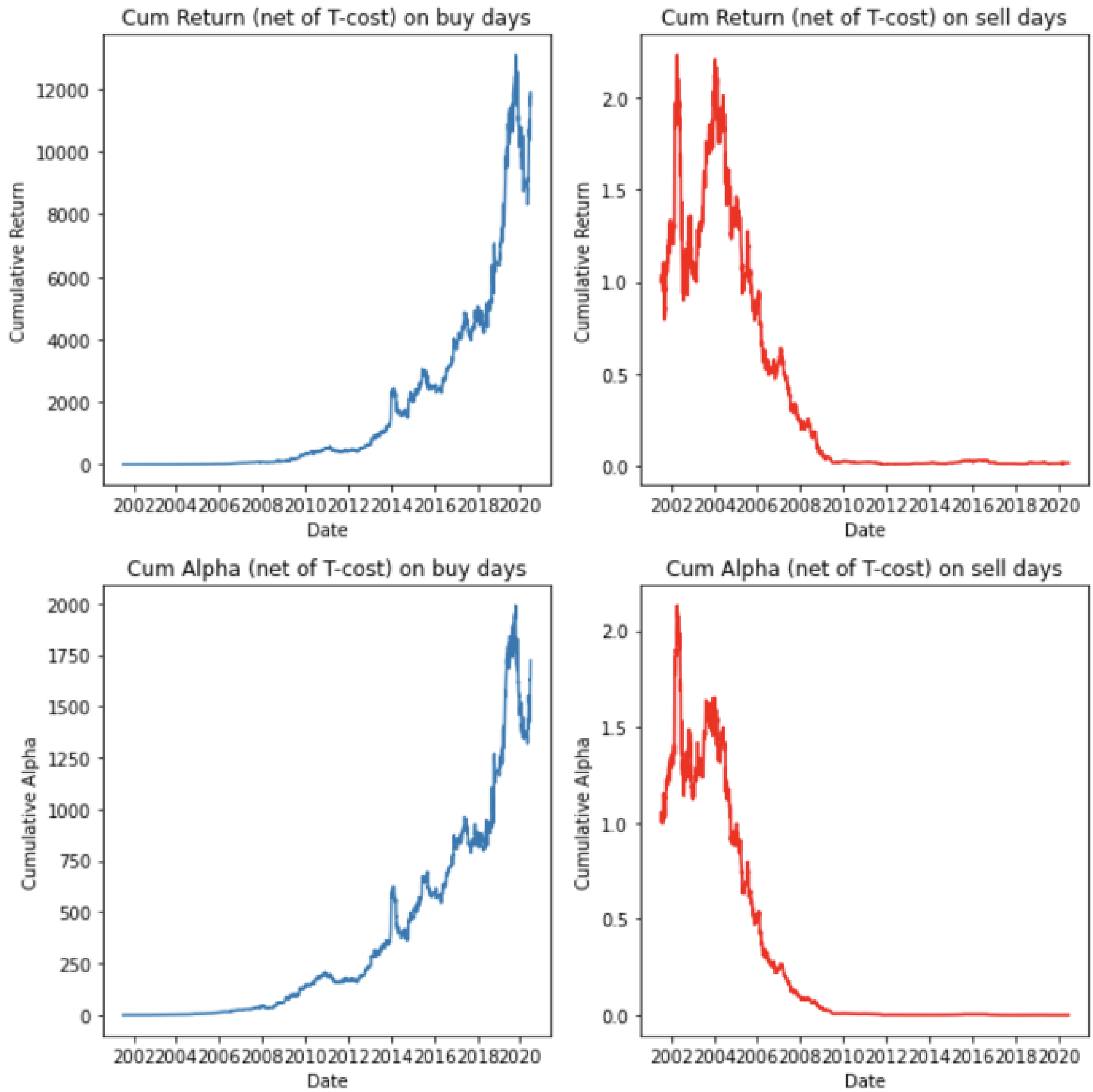
The buy signal as defined occurs 3,891 times across 2,161 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ (Price\ Target_t - Price\ Target_{t-1})\ /\ Price\ Target\ SD_t < -1 \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 2,207 times across 1,444 trading days within the historical data.

Signal Results:
The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	74.34%	-8.87%
Volatility	35.48%	47.93%

Sharpe Ratio	2.09	-0.19
Skewness of Returns	2.05	-1.34
Mean Alpha	59.85%	-28.88%
Tracking Error	28.22%	41.12%
Info. Ratio	2.12	-0.70
Average Turnover	0.35	0.35

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
Beta	-0.04 (-1.15)	-0.10 (-2.32)
SMB	0.04 (0.53)	0.32 (3.63)
HML	-0.18 (-2.71)	-0.02 (-0.27)
Intercept	0.0024 (4.01)	-0.0007 (-0.83)

Analysis and Interpretation:

While defining the trade event by using the mean, median, high, and low Price Target all lead to good performing strategies, we found that the best performing one to be the price target (variable name “Pricetarget” in the dataset). Here a huge cumulative performance differential is present between the buy and sell portfolios, it should be recognized that the cumulative buy portfolio performed exceedingly well over the historical period(t-stat of buy portfolio’s intercept is slightly positive and significant).

For this signal, Returns, alphas, Sharpe Ratio’s and Information Ratio’s fall monotonically as you hold for longer than 5 days (10, 15, and 20 days). The sell portfolio starts to make a little money (the cumulative return net of T-cost on $1 invested was around $2.5-8.0, but the sell portfolio still had no alpha) if hold for 15-20 days. Thus, our hypothesis is that Investors underreact, thus creating profitable strategies when holding for 1-10 days.

Long/Short Signal: Unusual Volume

Hypothesis: When shorting is costly or not allowed, high trading volume means optimism and overvaluation, leading to high returns in the short run and low returns in the long run.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if \ \dfrac{Volume}{Avg.50\ day\ Volume} > 1.25 \\ signal = 0 & else \end{cases}$$

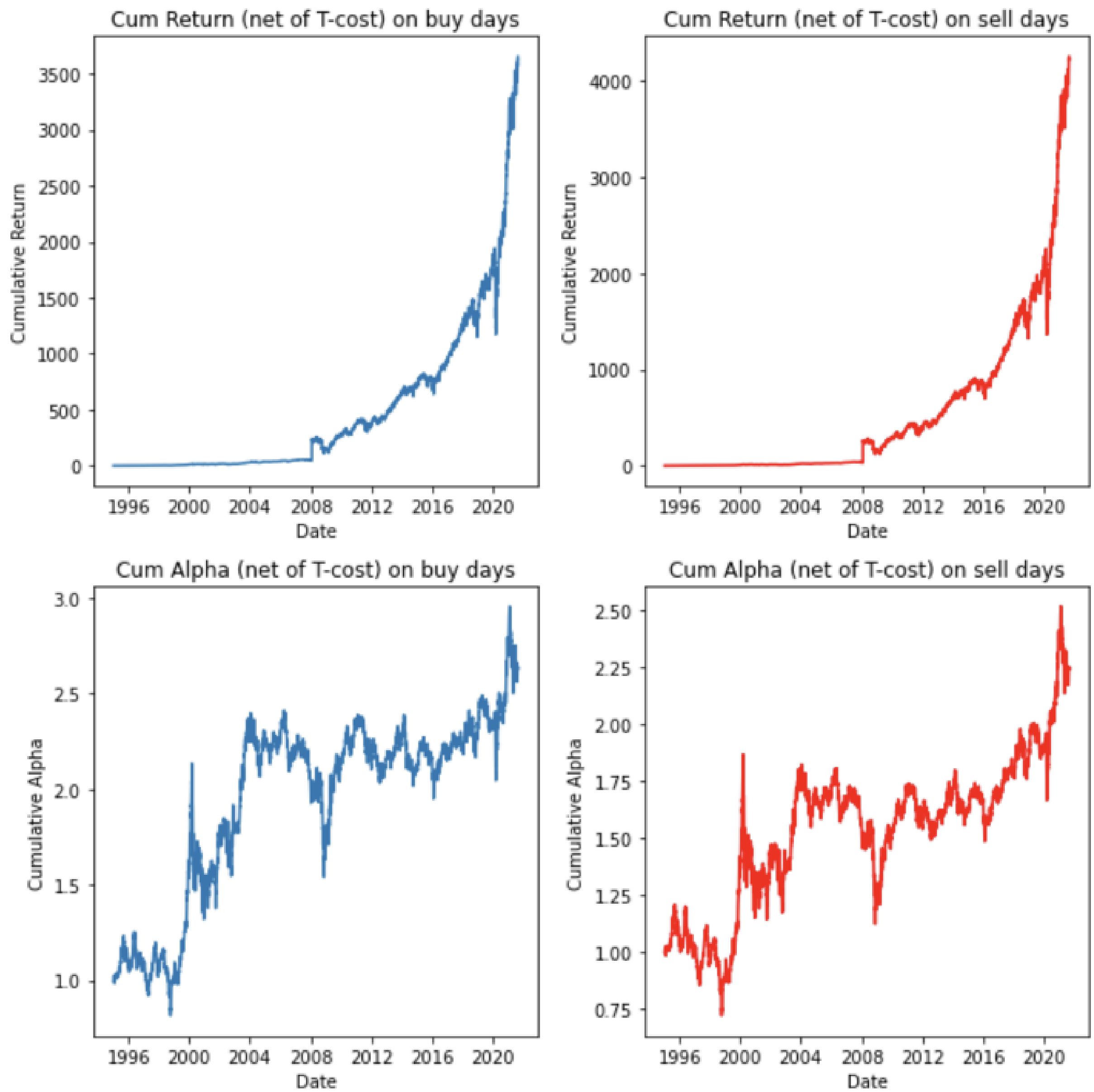
The buy signal as defined occurs 652,294 times across 6,712 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if \ \dfrac{Volume}{Avg.50\ day\ Volume} < 0.75 \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 1,206,341 times across 6,715 trading days within the historical data.

Signal Results:
The following results were calculated with a 10 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	44.39%	53.70%
Volatility	79.81%	135.74%

Sharpe Ratio	0.56	0.40
Skewness of Returns	69.79	77.69
Mean Alpha	6.01%	4.77%
Tracking Error	11.88%	11.81%
Info. Ratio	0.51	0.40
Average Turnover	0.07	0.04

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
SMB	0.25 (2.35)	0.37 (2.07)

Analysis and Interpretation:

Here, there is not a huge cumulative performance differential, however there is a slight Sharpe Ratio and Information Ratio differential is present between the buy and sell portfolios.

When holding for 1 day, profits are large and spread between the 2 portfolios is large (IR is larger although the SR is slightly lower for the buy portfolio)

Our hypothesis is that shorting is costly or not allowed, so when there is high trading volume, it implies that there is a lot of optimism and overvaluation leading to high returns in the short run (which is evident in the profits we make from 1 day holding period, but not any longer holding periods)

When holding for any period longer than 10 days, the outperformance begins to disappear (and when holding for 5 days, there is some outperformance although the spread is much smaller)

The sell portfolio starts to do well at longer horizons up to 20 days. This may lead to another interesting strategy that may work: Going long stocks that have had lowest volume 10 days ago, and going short stocks that have had the highest volume 10 days ago (that is, *buying*/selling the "*Sell*/Buy" portfolios as I defined here after 10 days passes and then holding for some time). My hypothesis for this is that investors will overreact to stocks that have had extreme volume in the first 10 days after the event occurs, at which point the two sides of this trade will become overvalued and may potentially mean revert.

Also, another improvement that can be made is to incorporate other moving average volumes at different horizons other than the 50 day moving average. Also, there is no reason why the arbitrary number I chose for for the volume event should be +25% and -25%; one could have defined the event using any other set of numbers; one suggestion for future revisions of this work may be to rank stocks according to how extreme this volume event occurs cross-sectionally and buy the highest volume event stocks and sell the lowest volume event stocks. This way, we can safeguard against potentially data mining when choosing a set of numbers to trigger the event (I use +25% and -25% volume activity for the event here).

Long/Short Signal: Momentum on report date

Hypothesis: Sophisticated investors anticipate a company's report date surprises in advance. The trend will continue in the future after earnings are reported because investors underreact to the news.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ (ret10d > 0.025)\ AND\ (date - report\ date = 1\ day) \\ signal = 0 & else \end{cases}$$

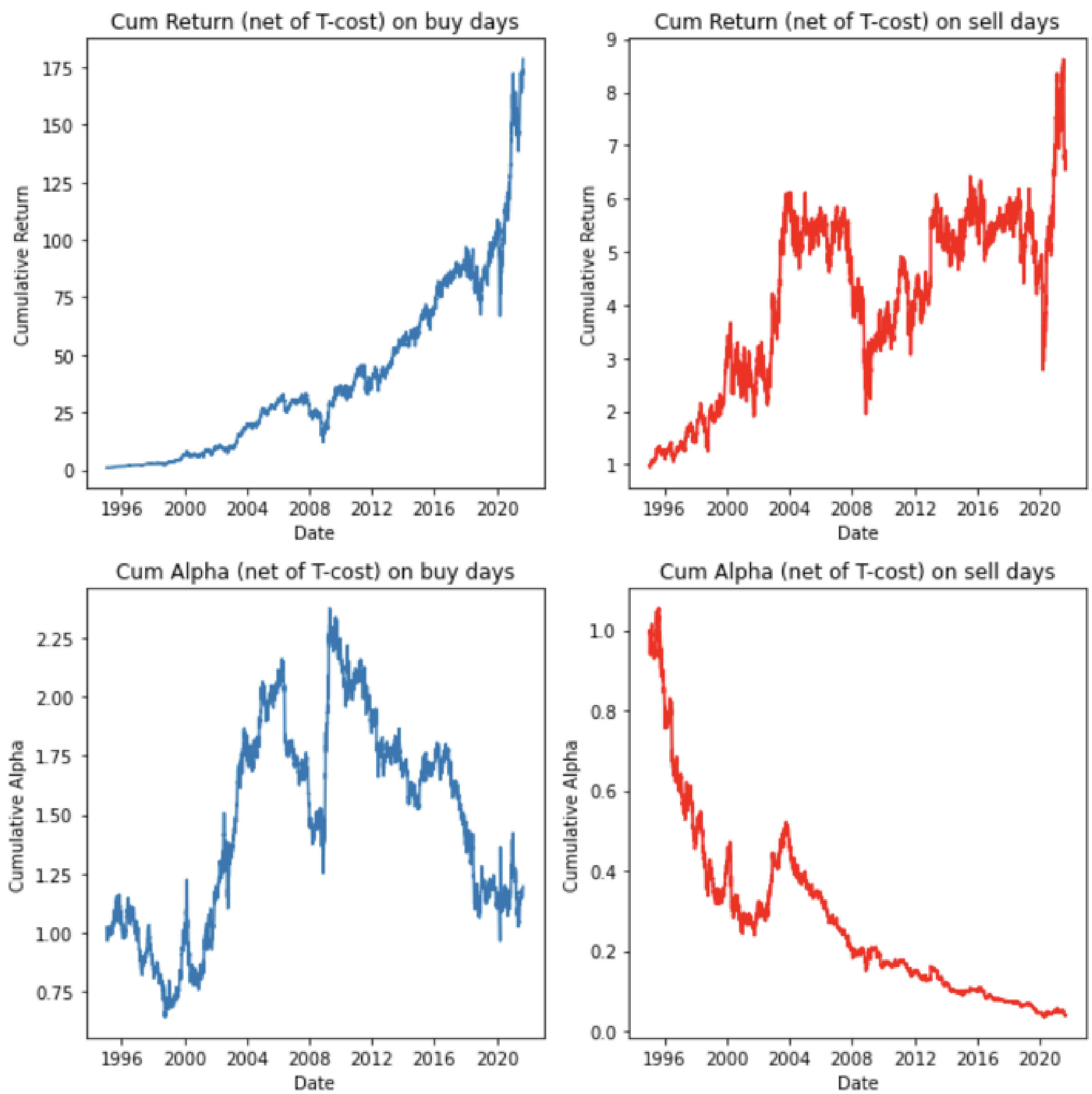
The buy signal as defined occurs 19,466 times across 3,494 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ (ret10d < -0.025)\ AND\ (date - report\ date = 1\ day) \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 13,471 times across 3,048 trading days within the historical data.

Signal Results:
The following results were calculated with a 15 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	28.34%	16.89%
Volatility	26.93%	29.78%

Sharpe Ratio	1.05	0.57
Skewness of Returns	0.22	0.26
Mean Alpha	6.90%	-5.60%
Tracking Error	16.36%	19.06%
Info. Ratio	0.42	-0.29
Average Turnover	0.19	0.20

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
SMB	0.04 (1.10)	0.12 (2.92)
CMA	-0.23 (-3.75)	-0.23 (-3.39)
MOM	0.26 (3.39)	0.20 (2.32)

Analysis and Interpretation:

While we also defined the trade event by using “duedate”, we found that the best performing strategy is to use the “reportdate” for the event. Here a large cumulative performance differential is present between the buy and sell portfolios in terms of risk adjusted performance. For this signal, 20 day holding period also performs well, but the spread between the buy and sell portfolios gets smaller because the short portfolio performs well in 2020 and rapidly spikes up, which would have led to even higher returns on the sell portfolio if you hold for 20 days. The optimal holding period was about 10-15 days here. When holding for 1-5 days, there were no profits.

Also, both portfolios do well in terms of returns net of T-costs (both the buy and sell); this may be because volume increases during earnings announcements and thus stock prices also increase around that time.

Also, instead of choosing 2.5% and -2.5% as arbitrary cutoffs for the past 10 day return (which could lead to data mining issues), one could have defined the event using any other set of numbers; one suggestion for future revisions of this work may be to rank stocks according to how extreme this 10 day momentum is leading up to the earnings report event cross-sectionally and buy the highest momentum event stocks and sell the lowest momentum event stocks. This way, we can safeguard against potentially data mining when choosing a set of numbers to trigger the event (I use +2.5% and -2.5% 10 day return cutoffs for the event here).

Long/Short Signal: Momentum + Earnings Surprise on report date

Hypothesis: Sophisticated investors anticipate a company's report date surprises in advance. If this anticipation is met with a "same side surprise", then the trend will continue in the future as investors underreact to earnings.

Buy Signal Definition:

$$\begin{cases} signal\ =\ 1 \quad if\ (ret10d > 0.025)\ AND\ [\dfrac{epsa1}{\left(\dfrac{epshigha1 + epslowa1}{2}\right)} > 1.05]\ AND\ (date - report\ date = 1\ day) \\ signal\ =\ 0 \qquad\qquad\qquad\qquad\qquad\qquad else \end{cases}$$

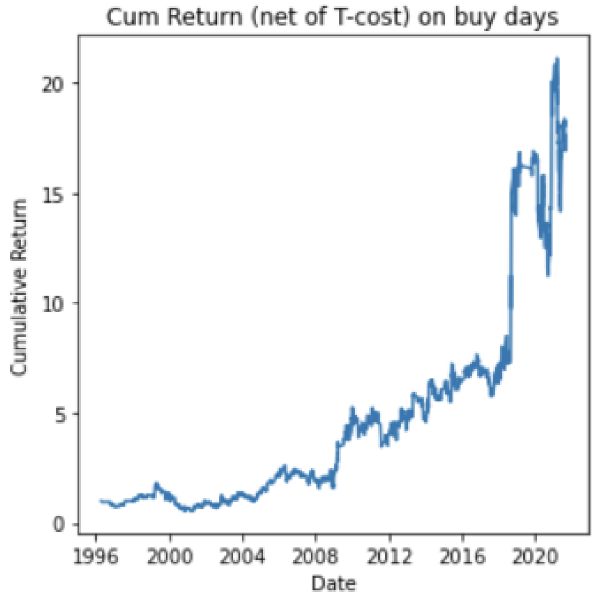
The buy signal as defined occurs 1,100 times across 771 trading days within the historical data.

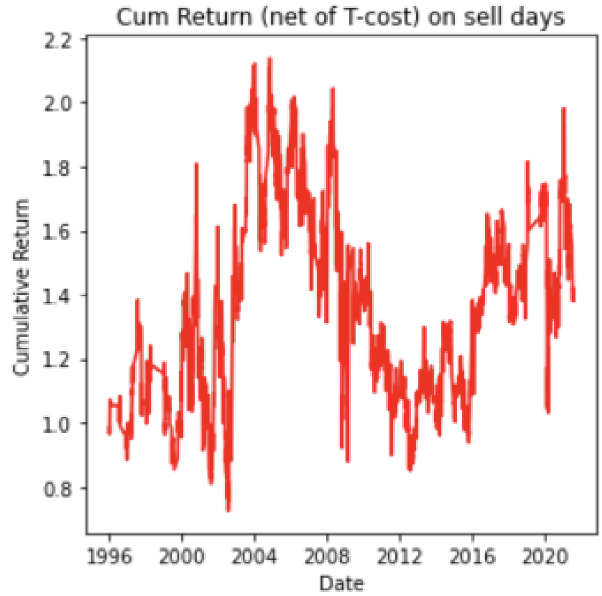
Sell Signal Definition:

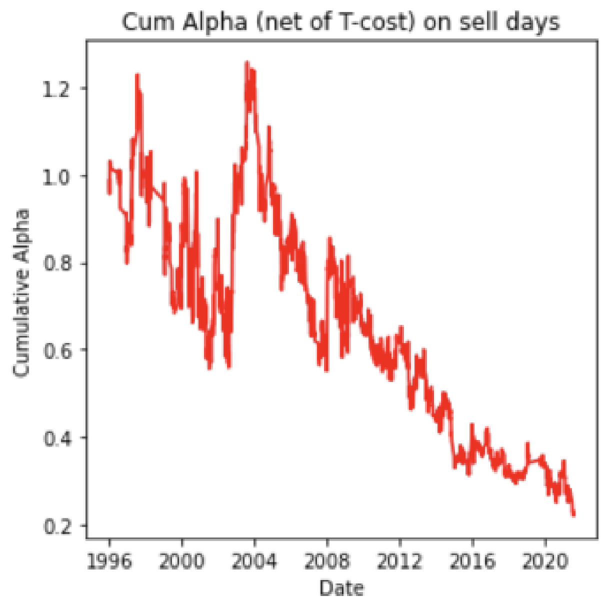
$$\begin{cases} signal\ =\ 1 \quad if\ (ret10d < -0.025)\ AND\ [\dfrac{epsa1}{\left(\dfrac{epshigha1 + epslowa1}{2}\right)} < 0.95]\ AND\ (date - report\ date = 1\ day) \\ signal\ =\ 0 \qquad\qquad\qquad\qquad\qquad\qquad else \end{cases}$$

The sell signal as defined occurs 975 times across 694 trading days within the historical data.

Signal Results:
The following results were calculated with a 10 day holding period, starting the day after the signal is observed.







Annualized Metrics	Buy	Sell
Mean Return	35.11%	18.52%
Volatility	40.85%	46.39%

Sharpe Ratio	0.86	0.40
Skewness of Returns	0.75	0.87
Mean Alpha	17.81%	-0.25%
Tracking Error	33.29%	36.36%
Info. Ratio	0.53	-0.01
Average Turnover	0.21	0.21

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
SMB	0.04 (0.49)	0.20 (2.36)
MOM	0.41 (2.53)	-0.02 (-0.08)

Analysis and Interpretation:

While we also defined the trade event by using “duedate”, we found that the best performing strategy is to use the “reportdate” for the event. Here a large cumulative performance differential is present between the buy and sell portfolios in terms of risk adjusted performance. For this signal, 10-20 day holding period performs well. When holding for 1-5 days, there were no profits.

Also, both portfolios do well in terms of returns net of T-costs (both the buy and sell); this may be because volume increases during earnings announcements and thus stock prices also increase around that time.

Also, instead of choosing 2.5%/-2.5% and 5%/-5% as arbitrary cutoffs for the past 10 day return and the earnings surprise respectively (which could lead to data mining issues), one could have defined the event using any other set of numbers; one suggestion for future revisions of this work may be to rank stocks according to how extreme this 10 day momentum is leading up to the earnings report event (and also rank stocks according to how extreme their earnings surprise is) cross-sectionally and buy the highest momentum/earnings surprise stocks while selling the lowest momentum/earnings surprise stocks. This way, we can safeguard against potentially data mining when choosing a set of numbers to trigger the event (I use 2.5%/-2.5% 10 day return and 5%/-5% earnings surprise cutoffs for the event here).

Long/Short Signal: Index Inclusion and Removal

Hypothesis: Investors overreact to a stock's index inclusion and removal ahead of the event. When the event occurs, the stock is mispriced such that future returns become lower for stocks being included and higher for stocks being removed.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ (sp100f_t - sp100f_{t-1} < 0)\ OR\ (sp500f_t - sp500f_{t-1} < 0)\ OR\ (nasdaq100f_t - nasdaq100f_{t-1} < 0) \\ signal = 0 & else \end{cases}$$

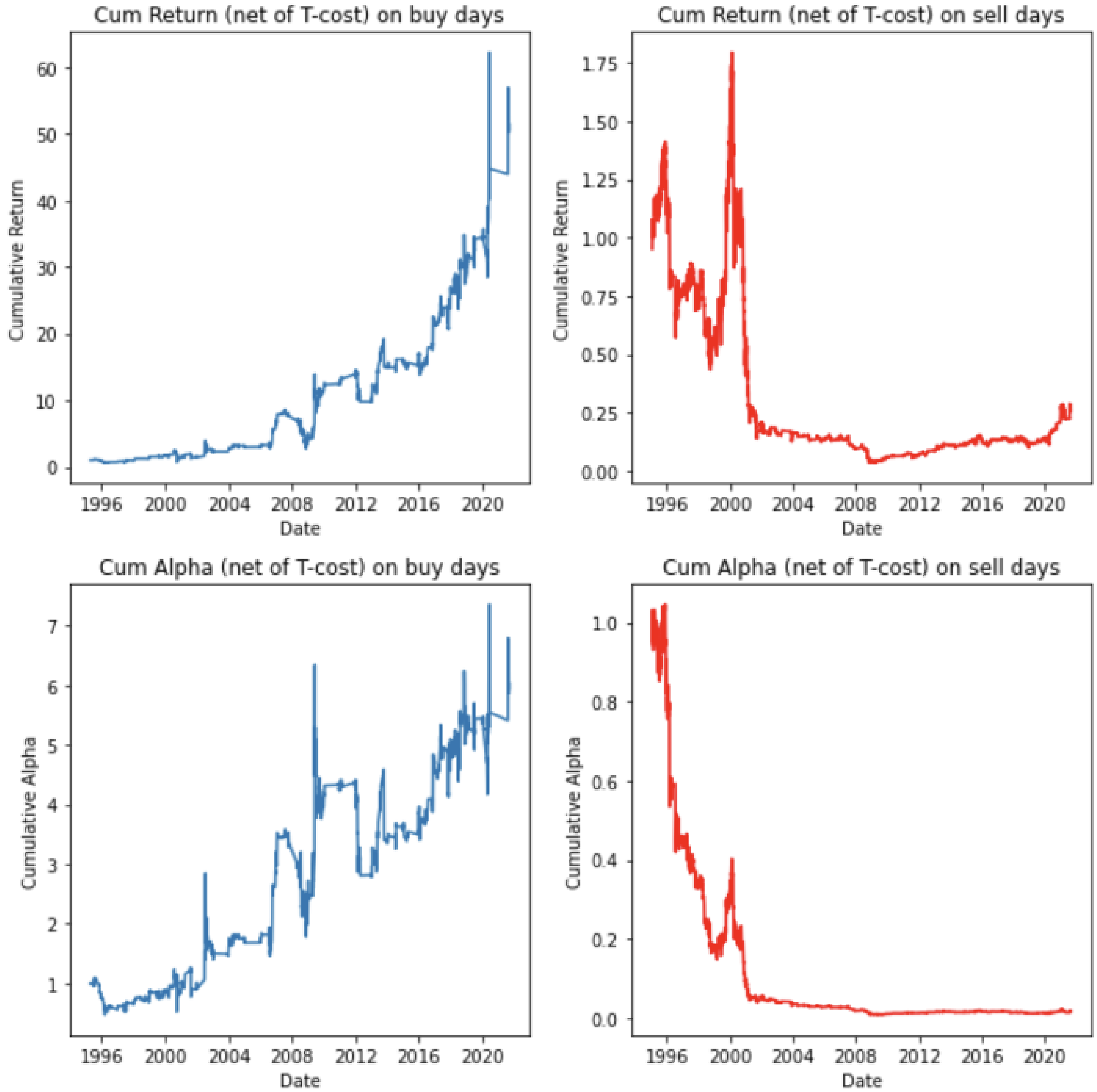
The buy signal as defined occurs 232 times across 147 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ (sp100f_t - sp100f_{t-1} > 0)\ OR\ (sp500f_t - sp500f_{t-1} > 0)\ OR\ (nasdaq100f_t - nasdaq100f_{t-1} > 0) \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 439 times across 286 trading days within the historical data.

Signal Results:
The following results were calculated with a 20 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	75.03%	4.38%
Volatility	69.76%	47.59%

Sharpe Ratio	1.08	0.09
Skewness of Returns	0.77	0.06
Mean Alpha	41.74%	-19.18%
Tracking Error	60.33%	38.03%
Info. Ratio	0.69	-0.50
Average Turnover	0.08	0.09

Analysis and Interpretation:

Here, there is a large cumulative performance differential between the buy and sell portfolios in terms of risk adjusted performance. For this signal, 20 day holding period performs best; the performance of this strategy improves monotonically as we hold for longer periods between 10-20 days. When holding for 1-5 days, there were no profits.

Also, this event did not have any statistically significant exposure to any of the FF5+Momentum factors. It is also important to note that there were few occurrences of this event in our sample, so perhaps more data is needed to build more conviction in this strategy.

Long/Short Signal: 1 Year EPS High Forecast Moves

Hypothesis: Changes in analyst forecast may come from changes in underlying fundamentals or from analysts' job security concerns. Investors may underreact to this information, and thus the stock may drift in one way for some time.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ (epshigha1_t - epshigha1_{t-1} > 0) \\ signal = 0 & else \end{cases}$$

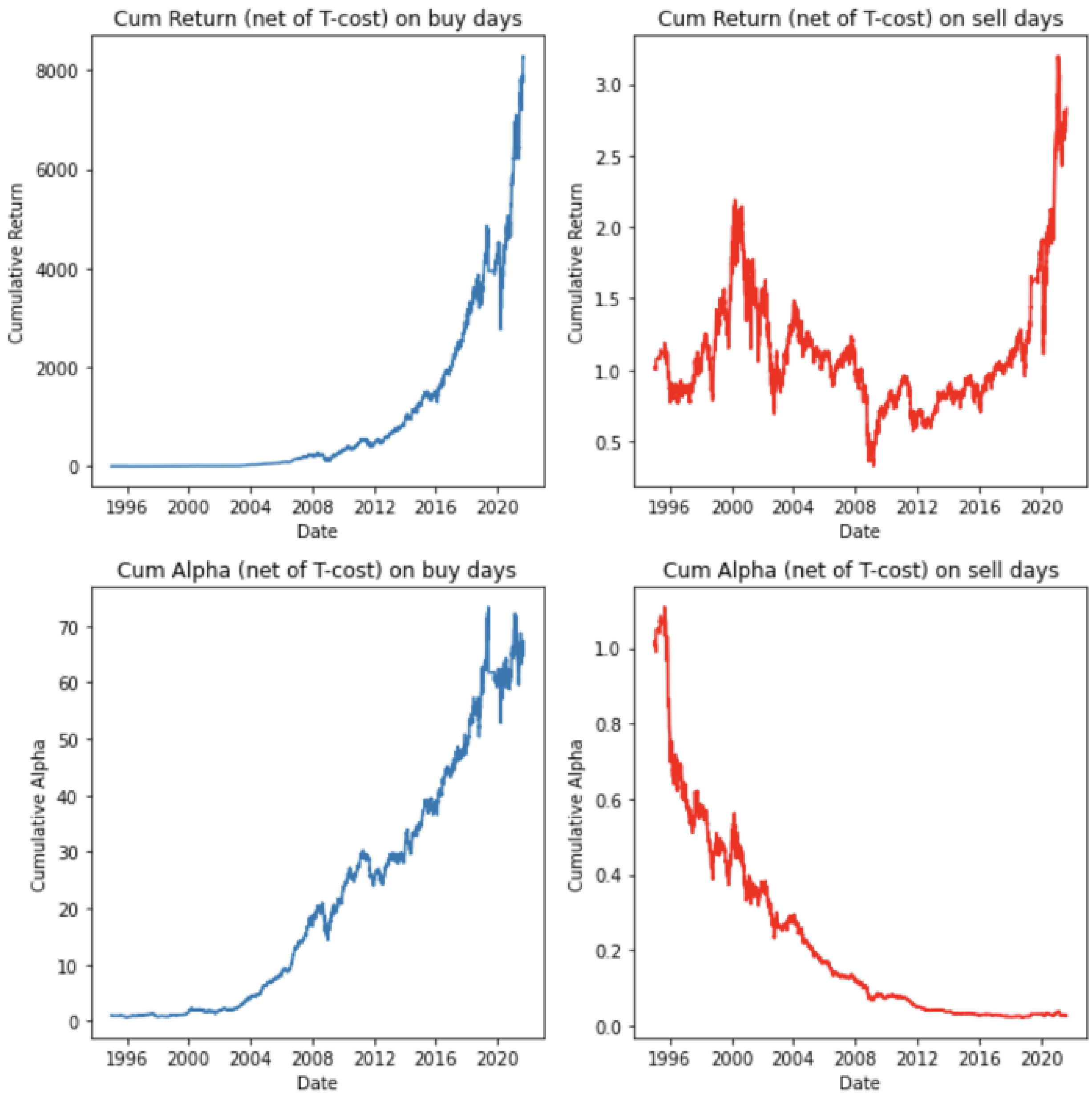
The buy signal as defined occurs 37,027 times across 5,916 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ (epshigha1_t - epshigha1_{t-1} < 0) \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 41,421 times across 6,103 trading days within the historical data.

Signal Results:
The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	45.68%	14.17%
Volatility	27.03%	26.67%

Sharpe Ratio	1.69	0.53
Skewness of Returns	0.07	0.06
Mean Alpha	24.58%	-6.58%
Tracking Error	16.24%	15.27%
Info. Ratio	1.51	-0.43
Average Turnover	0.28	0.26

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
SMB	0.03 (0.90)	0.08 (2.28)
CMA	-0.10 (-1.67)	-0.13 (-2.23)
MOM	0.19 (2.39)	0.11 (1.43)
Intercept	0.001 (2.94)	0.000 (0.24)

Analysis and Interpretation:

While defining the trade event by using the 1-2 Year High EPS Estimate worked well (1 Year was the best performing), defining the event by using the 3-4 Year High EPS Estimate did not work as well. Also, we tried this event with the Low EPS estimate, and although it was informative and profitable, it did not work as well as the High EPS Estimate

Here, there is a huge cumulative performance differential between the buy and sell portfolios in terms of risk adjusted performance, it should be recognized that the cumulative buy portfolio performed exceedingly well over the historical period (t-stat of buy portfolio's intercept is slightly positive and significant). For this signal, 1-5 day holding period performs best, but the performance of this strategy gets worse monotonically as we hold for longer periods between 5 days (10, 15, and 20 days).

Long/Short Signal: 1 Year Sales High Forecast Moves

Hypothesis: Changes in analyst forecast may come from changes in underlying fundamentals or from analysts' job security concerns. Investors may underreact to this information, and thus the stock may drift in one way for some time.

Buy Signal Definition:

$$\begin{cases} signal = 1 & if\ (saleshigha1_t - saleshigha1_{t-1} > 0) \\ signal = 0 & else \end{cases}$$

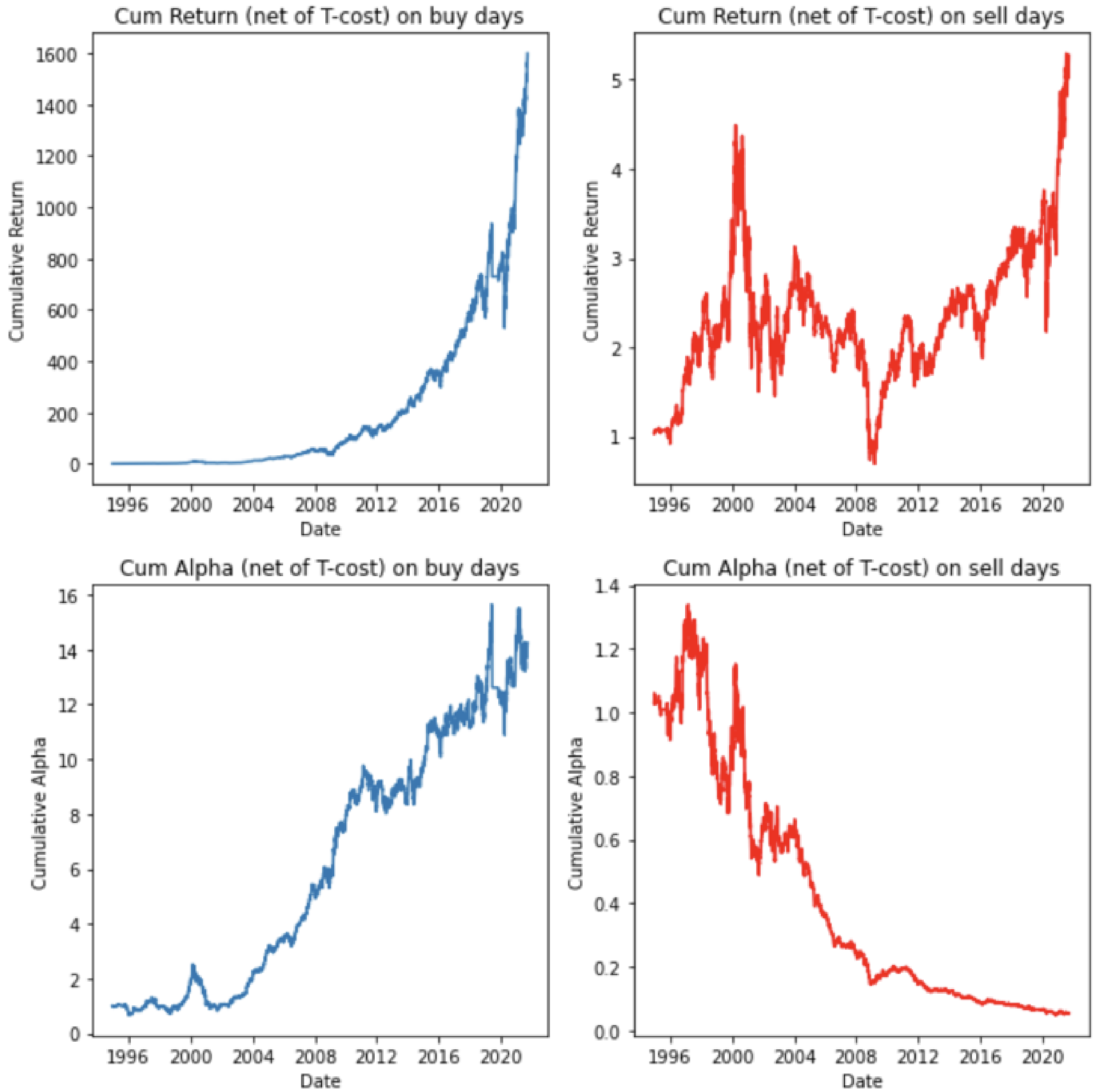
The buy signal as defined occurs 34,369 times across 5,589 trading days within the historical data.

Sell Signal Definition:

$$\begin{cases} signal = 1 & if\ (saleshigha1_t - saleshigha1_{t-1} < 0) \\ signal = 0 & else \end{cases}$$

The sell signal as defined occurs 39,312 times across 5,918 trading days within the historical data.

Signal Results:
The following results were calculated with a 5 day holding period, starting the day after the signal is observed.



Annualized Metrics	Buy	Sell
Mean Return	40.70%	17.17%
Volatility	29.74%	27.98%

Sharpe Ratio	1.37	0.61
Skewness of Returns	-0.36	-0.-0.03
Mean Alpha	19.50%	-3.55%
Tracking Error	19.66%	16.88%
Info. Ratio	0.99	-0.21
Average Turnover	0.28	0.26

Factor Exposure	Coefficient / (T-Stat) Buy	Coefficient / (T-Stat) Sell
Beta	-0.05 (-2.26)	-0.02 (-0.98)
SMB	0.09 (2.28)	0.08 (2.15)
CMA	-0.19 (-2.86)	-0.10 (-1.51)
MOM	0.18 (2.09)	0.13 (1.55)

Analysis and Interpretation:

While defining the trade event by using the 1-2 Year High Sales Estimate worked well (1 Year was the best performing), defining the event by using the 3-4 Year High Sales Estimate did not work as well. Also, we tried this event with the Low Sales estimate, and although it was informative and profitable, it did not work as well as the High Sales Estimate

Here, there is a huge cumulative performance differential between the buy and sell portfolios in terms of risk adjusted performance, it should be recognized that the cumulative buy portfolio performed exceedingly well over the historical period. For this signal, 1-5 day holding period performs best, but the performance of this strategy gets worse monotonically as we hold for longer periods between 5 days (10, 15, and 20 days).

Long Signal: Stock Split

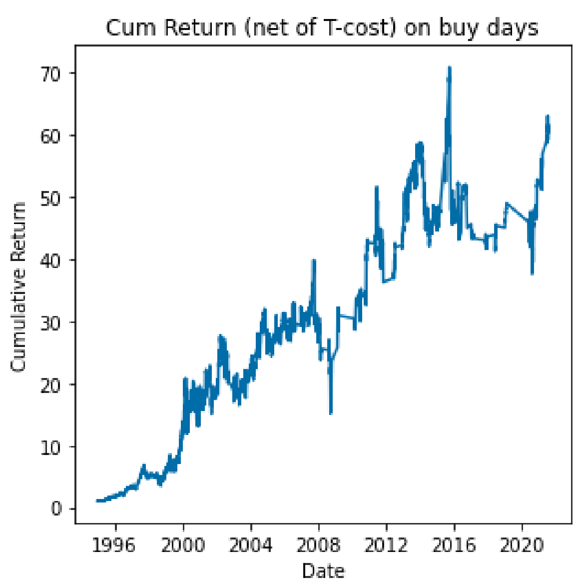
Hypothesis: Many companies announce stock splits so that the share price for a stock remains affordable for retail investors. This can be viewed as a positive sign since the stock price increased to a point where the shares need to be split for them to be affordable. Therefore, we would like to test whether a stock split would be a bullish signal. For the stocks that announce stock splits, we will buy them the next day after the announcement and see how that strategy performs.

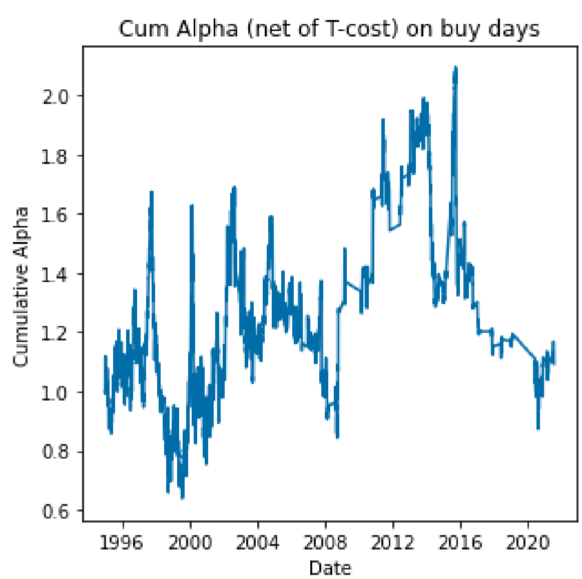
Signal Definition:

$$\begin{cases} signal = 1 & when\ Split\ Factor > 1 \\ signal = 0 & Otherwise \end{cases}$$

There were 955 occurrences of the signal within the 25-year period.

Signal Results:





Annualized Metrics	20-Day Holding Period
Mean Return	38.95%
Volatility	44%
Sharpe Ratio	0.89
Skewness of Returns	0.19
Mean Alpha	9.75%
Tracking Error	35.51%
Info. Ratio	0.27
Average Turnover	0.11

Factor Exposure	Coefficient / (T-Stat)
Beta	0.088 (1.98)
RMW	0.234 (2.34)
CMA	-0.363 (-2.88)

Result Interpretation: As we can see, the strategy's returns over the 25-year period is positive. The return progression over the time period is not as straightforward as we would like to see. Nonetheless, it achieved a sharpe ratio of 0.89, which is sizable. It also has factor exposure to market, RMW, and CMA factors.

Long Signal: Change in sector group of a company

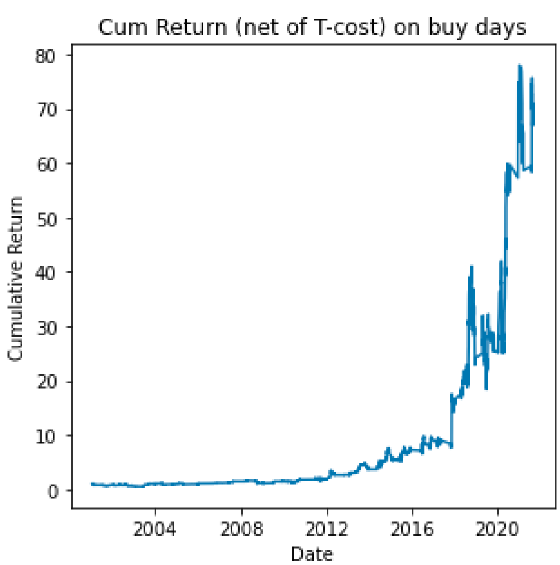
Hypothesis: Some companies that are experiencing financial hardship and are close to bankruptcy decide to pivot and change the direction where they are headed. Sometimes when they do that, they decide to pursue a different industry. This would result in the change of their sector group. Therefore, it is possible to expect the market to buy the stock since this event sparks the possibility of the company becoming profitable again. We would like to test whether this event could be used as a signal. For the companies that change their sector groups, we will purchase their stock one day after the change in the sector group and test how that strategy performs.

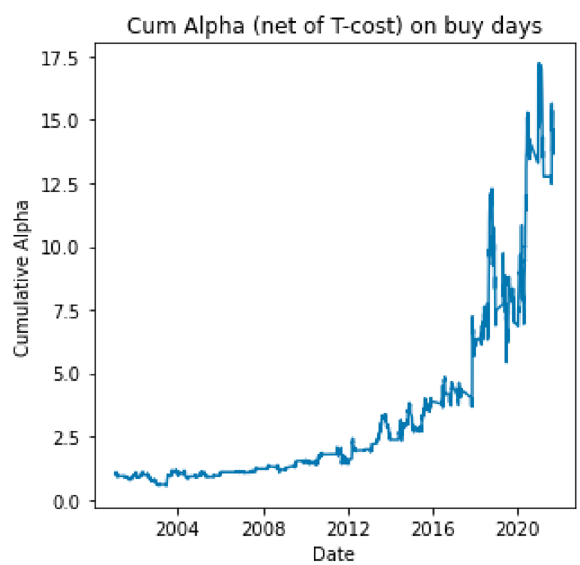
Signal Definitions:

$$\begin{cases} signal = 1 & when\ sector\ group\ at\ time\ t \neq\ sector\ group\ at\ time\ t-1 \\ signal = 0 & Otherwise \end{cases}$$

There were 406 occurrences of the signal within the 25-year period.

Signal Results:





Annualized Metrics	20-Day Holding Period
Mean Return	65.74%

Volatility	56.03%
Sharpe Ratio	1.17
Skewness of Returns	2.28
Mean Alpha	44.33%
Tracking Error	49.44%
Info. Ratio	0.90
Average Turnover	0.09

Factor Exposure	Coefficient / (T-Stat)
SMB	0.23 (1.89)

Result Interpretation: As we can see, the strategy's returns over the 25-year period is positive. The return progression over the time period is quite consistent with a sharpe and information ratios of 1.17 0.90 respectively. Additionally, the signal has a great advantage of only having a significant exposure to the SMB factor.

Long Signal: CAPM 2-Factor Trading Signal

For our final factor we sought to exploit assets where we observed returns in excess of what we would ascribe as “fair” for a given risk-sensitivity model. To achieve this we constructed a modification of the traditional Capital Asset Pricing Model (CAPM herein) which controls for both market & sector sensitivities. The model would issue a “Buy” signal on days where the compounded trailing 10-day return is greater than some multiple of what our model would ascribe as “fair" over the same period.

A possible economic explanation for this strategy’s performance can be attributable to the Lindy Effect. The Lindy Effect is a phenomenon where the survival of a non-perishable quantity is indicative of its potential to survive for an *n*-length period of time going into the future. A famous anecdote to visualize this phenomenon is given by Statistician and author Nassim Taleb, where he states:

> “*If a book has been in print for forty years, I can expect it to be in print for another forty years. [But…] if it survives another decade, then it will be expected to be in print for another fifty years.*”

We can apply this intuition in our analysis of assets returns by postulating if a stock exhibits a return in excess of what our risky-model implies is “fair,” then it will continue to do so for a similar period of time going forward into the future.

An important distinction between this strategy and Momentum strategies is that it is not simply enough for a stock to give a positive return for *n* days in the past; It must give a return for *n* days in the past in excess of what our model deems is fair. Additionally, we can actually be given “buy” signals when a stock outperforms its sector despite the sector losing money - a type of value purchasing strategy.

To construct the 2-Factor CAPM model we first analyzed the structure of the traditional CAPM factor model:

$$r_{i,t}^{r} = r_t^{f} + \beta_{i,t} \cdot (r_t^{M} - r_t^{f})$$

…Which simply states that the risky return of an asset is equal to the sum of a risk-free asset’s return plus the product of the asset’s sensitivity to the market and the market risk premium.

Our modification to the CAPM is instead formulated as:

$$r^r_{i,t} = r^{f,\omega}_t + \beta^S_i \cdot (r^S_t - r^{f,S}_t) + \beta^M_i \cdot (r^M_t - r^{f,M}_t) + \epsilon_{i,t}$$

...

where:

$r^r_{i,t} =$ the risky return of asset 'i' at time 't'

$r^{f,\omega}_t =$ the proportionally weighted r.f. return attributable to the sector r.f. rate & the market r.f. rate

$\beta^S_i =$ the asset's sensitivity to its own sector

$r^S_t =$ the value-weighted return of the asset's overall sector

$r^{f,S}_t =$ the return of the sector's appropriate r.f. asset

$\beta^M_i =$ the asset's sensitivity to the rest of the market (using our universe as a proxy)

$r^M_t =$ the value-weighted return of the market (universe)

$r^{f,M}_t$ the return of the market's appropriate r.f. asset

$\epsilon_{i,t} =$ an error term that accounts for the asset's real return's dispersion from our model

And for simplicity as further assume that the relevant sector risk-free rate is equal to the market risk-free rate, which was assumed to be equal to LIBOR (But may be more accurately supplemented by SOFRS in the future):

$$r^{f,S}_t = r^{f,M}_t := r^f_t$$

Which simplifies our final model into:

$$r^r_{i,t} = r^f_t + \beta^S_i \cdot (r^S_t - r^f_t) + \beta^M_i \cdot (r^M_t - r^f_t) + \epsilon_{i,t}$$

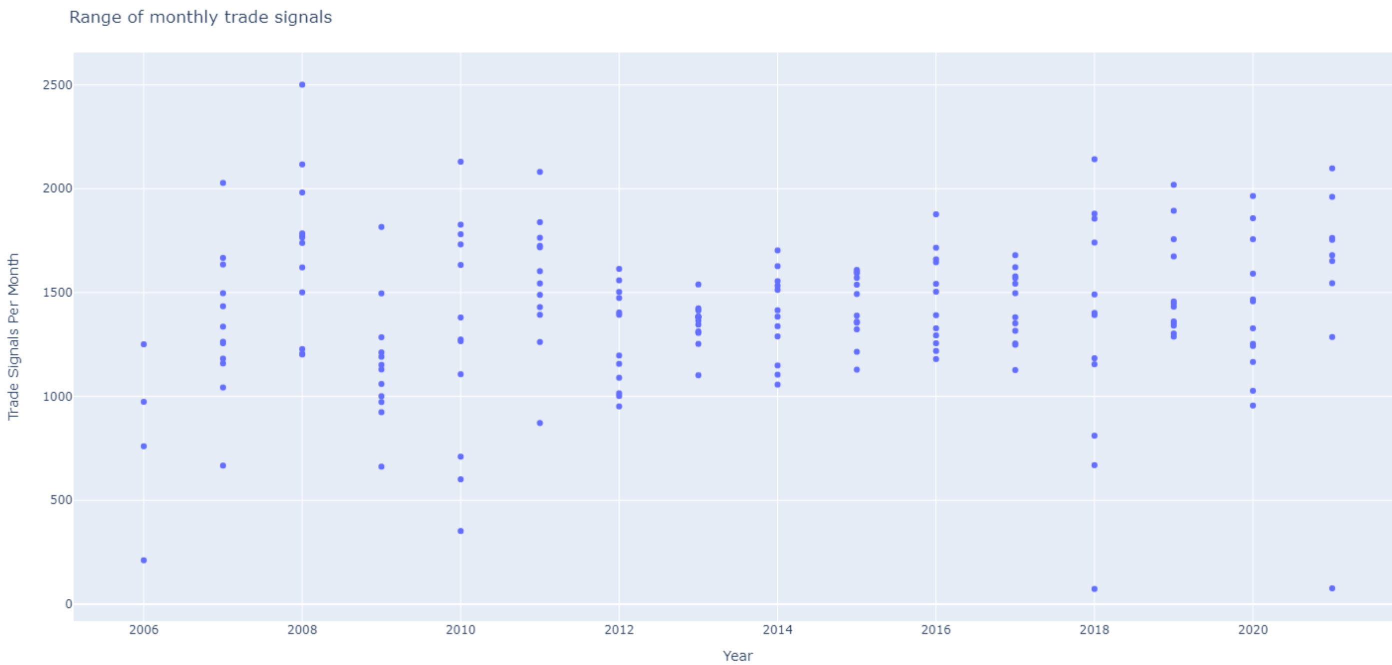
Using the model & signal criterion described above, we designate an activation term “Alpha” equal to 1.5 and then calculate our daily trading signal as an inequality operation between the 10-day compounded model return compared to the 10-day real return:

$$\begin{cases} \text{signal}_t = 1 & \text{if } \Pi_{\{t,k=10\}} r^{r,model}_t < \Pi_{\{t,k=10\}} \alpha \times r^{r,real}_t \\ \text{else signal}_t = 0 \end{cases}$$

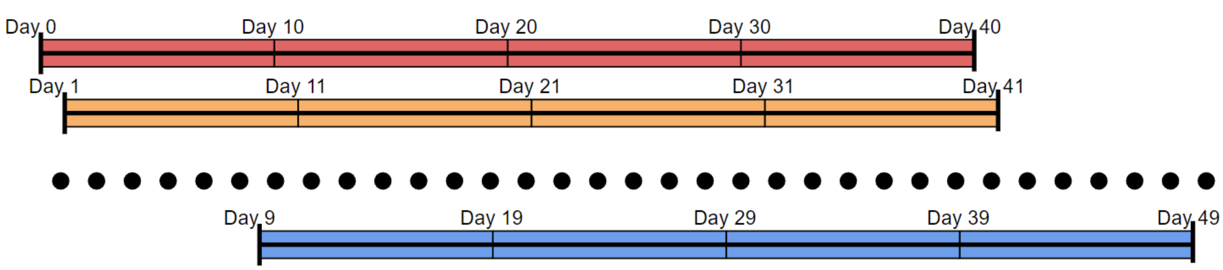
The choice of setting our activation term “Alpha” to 1.5 is not insignificant; By adjusting our Alpha value we can control the number of issued signals in our model. Increasing Alpha should, in theory, increase our expected return - this also decreases the number of signals issued & can cause concerns for overexposure to individual volatile assets (or even potentially issue no signals at all).

Conversely setting Alpha too low risks reducing performance - and we actually found that setting Alpha less than 1.0 induces consistent *underperformance* relative to our benchmark.

With an Alpha of 1.5 we are able to consistently generate a meaningful amount of signals for our entire sample, which is visualized in this plot of the monthly ranges of signal occurrences:



When constructing the 2F-CAPM factor we utilize a special portfolio structure where our nominal portfolio value is split amongst 10 sub-portfolios where the number of stocks traded on each day are equally weighted within each portfolio. Each sub-portfolio is lagged one day apart, and is rebalanced every 10 days.



There are numerous benefits to structuring our portfolio like this. Most principally it increases our backtest sample size by a multiple of 10, which helps us ascertain statistical significance. It also allows us to harvest 10-times as many signals compared to a single portfolio, as well as minimizing erroneous trade signals that are caused by quickly decaying short-run volatility.

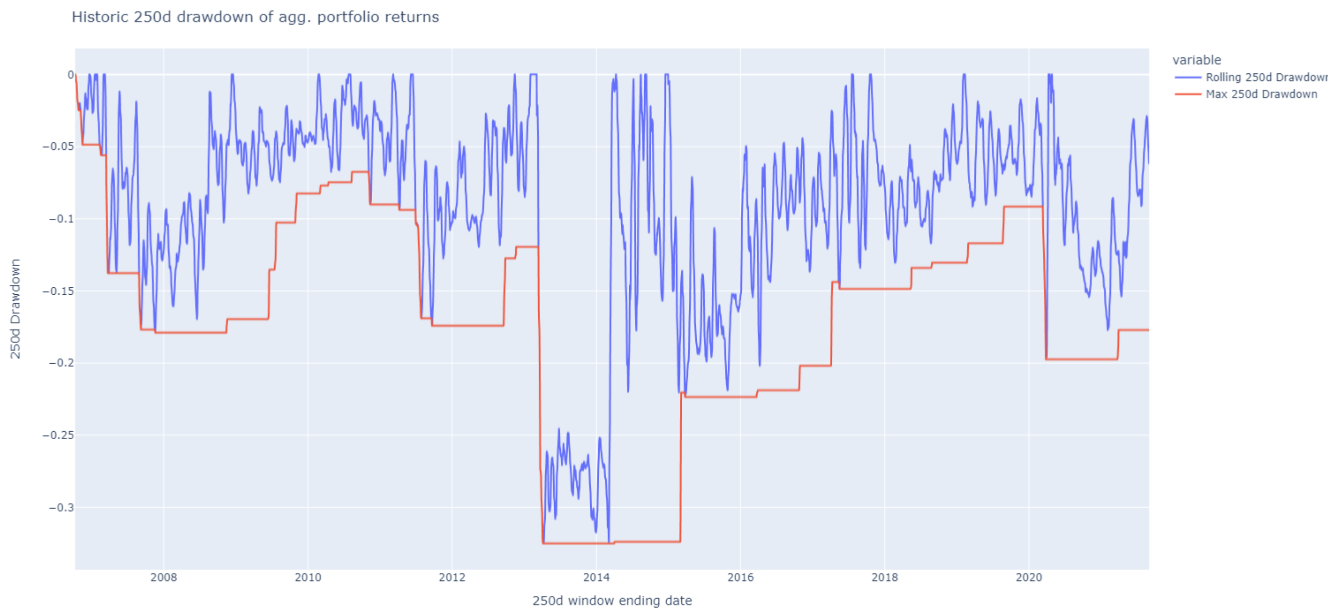
Downsides to this portfolio construction, however, is that it requires 10 days to be fully invested in the strategy and 10 days to fully divest as well. The higher portfolio turnover also means that if we were to assume fixed transaction costs, such as “each trade costs five cents” (as opposed to variable costs which our backtest implements) then we would see more of our portfolio’s returns eroded away with this method.

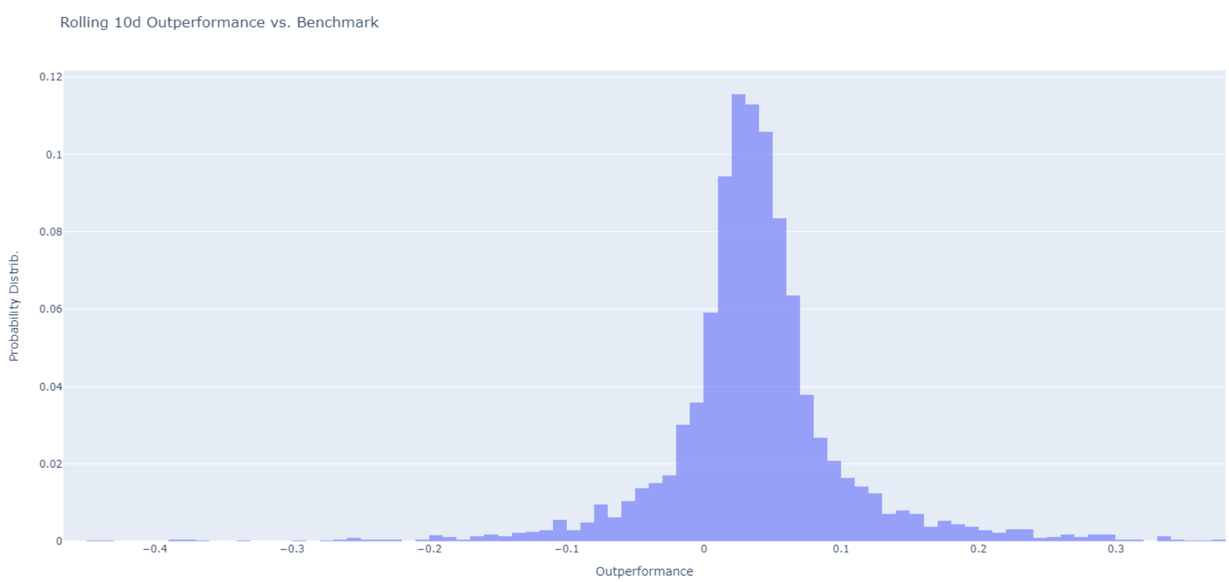
The findings for our strategy’s backtested performance was very promising. The rolling 10-day log returns of the aggregate portfolios were found to have an intercept greater than zero, and were very frequently positive throughout our entire sampled period.

We also tested the strategy’s log-performance vs. a value-weighted benchmark - this, very significantly, also yielded an intercept greater than zero. Both of these plots are visualized side-by-side in the following figure:

The strategy had an observed left tail-risk element to it; In order to visualize the magnitude of its skew we plotted its return series on a histogram in the below table as well as reported its negative skewness in our summary statistics table at the end of this report.

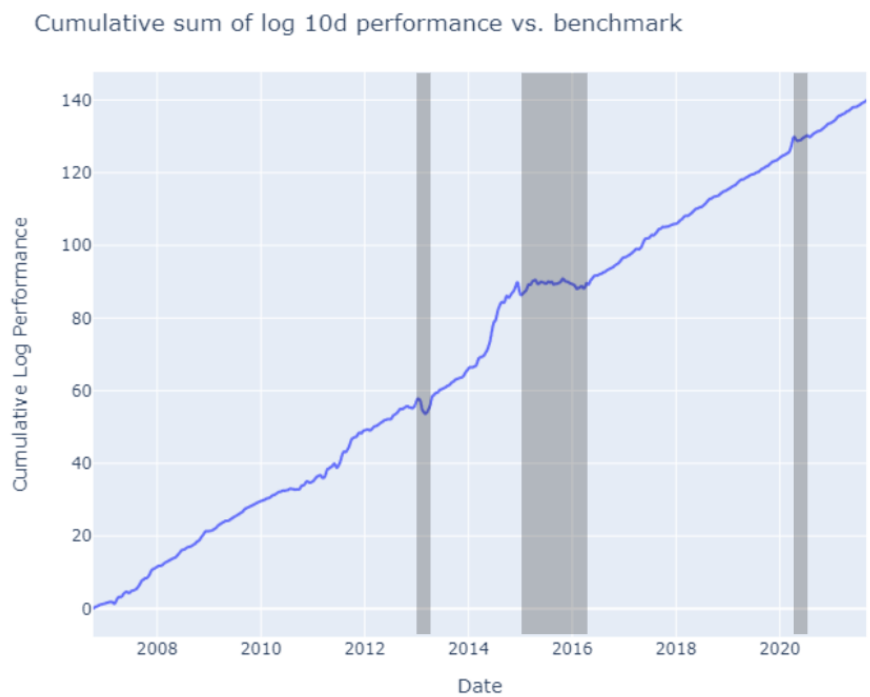
In order to provide as conservative of a backtest as possible, we began our backtest sample slightly before the largest observed drawdown so that we could see if a “hard hit” could possibly kill the portfolio’s cumulative return before it got the chance to get off the ground. We plotted the rolling 250-day drawdown, as well as the maximum 250-day drawdown in the following chart:





Mean Outperformance	3.73%
Tracking Error	5.47%
Skewness	- 5.007%

It was surprising to find that despite the large drawdowns, the portfolio's cumulative log-outperformance of the value-weighted benchmark actually remained positive throughout almost the entire sample - we only found evidence of significant underperformance / stagnation three times in this sample.



Finally we reported our (raw & benchmarked) return metrics in our summary statistics table as seen here:

Mean Rolling 10d Return	.0536
Return Standard Deviation	.0488
Sharpe Ratio	1.05
Mean Rolling 10d Outperformance	.0373
Tracking Error	.0547
Information Ratio	1.68
Outperformance Skewness	-.05007

FF Momentum R-Squared	*0.48%*

Future Extensions

Our previous portfolio assumptions all assume that we are able to invest in fractional shares. Realistically however we could run into issues where division of prices causes issues in maintaining full capital investment, or can lead to over/under exposure to certain equities in our portfolios. To remedy this, potential extensions of our research could include assumptions that remedy fractional share assumptions.

When calculating portfolio weights we also assumed universally that our portfolios were equally weighted amongst all of our issued signals. Toying with more sophisticated weighting structures could help improve risk-return metrics. It is important to note that this would further complicate our models with additional assumptions.

A popular strategy that we discussed when considering weighting extensions was developing risk-parity portfolios for our corresponding strategies. This would allow us to shrink exposures to volatile assets, which may be particularly helpful with the strategies we covered that have high measured volatility.

In equity trading a popular constraint in portfolio construction is maintaining a Beta-neutral hedged position at the end of every trading day. In many of our signals an inverse trading signal did not always correspond with an intuitively hedged position; We believe that having a simple Beta-neutral position at each EOD would help create a simple to manage hedge for many of our strategies.

Successful implementation of “alpha blending” would be a natural progression of our research findings. Finding an optimal weighting scheme based on variance-minimization before distributing capital amongst portfolios would be our first steps towards implementing our strategies into a diversified and actively traded portfolio system.

Other Alpha generating signals that are covered outside of our research, such as Momentum and Value anomalies, could be considered in a weighting scheme as well - possible implementations include weighting against relative R-Squared values measured on a rolling time interval. If the strategies are truly uncorrelated then this implementation should develop diversification benefits for our blended strategies going forward. Another route we could take is to combine signals tested in this report that have statistically significant positive Value and Momentum exposures into one signal.

Finally, our results using Income Statement and Cash Flow data warrant further research with Balance Sheet data, which could include both Balance Sheet variables as well as analyst estimates on Balance Sheet variables.

Code

Please see attached