Draft version June 7, 2025
Typeset using LaTeX twocolumn style in AASTeX7.0.1

Index Event Trading Strategy

Michael Girma,[1] Pranit Gunjal,[1] Otis Otieno,[1] and Andrew Sinclair[1]

[1] *California Institute of Technology*

ABSTRACT

This project studies the impact of index reconstitution events, in which equity is added and removed from the main equity indices, specifically Standard & Poor's. We aim to analyse the profitability of such index driven strategies during index reconstitution events. We aim to exploit forced buying on index addition and selling for deletions on passive index funds. Using scrapped data from press releases from 2012 to 2023 and CRSP daily data from 1986 to 2023 in combination with Yfinance, we test a trading strategy that takes long positions in added stocks and short positions in deleted stocks, holding from announcements to trade dates. Markets have long been observed to experience temporary surges during index additions due to increased demand and downward pressures during deletion due to index fund outflows. Our analysis studies these asymmetric effects across different time periods in light of the growth of passive investing since the 1990's, amplifying both returns from additions and deletions.

1. INTRODUCTION

Passive index funds such as the S&P500 have experienced explosive growth since their inception due to a variety of factors such as technological advancements and lower costs associated with such funds. One key reason also lies in the diversification of such funds, primarily driven by index reconstitution events such as index addition and deletion. As of 2024, \$ 7 trillion has been invested in the S&P500 indexed products, creating a mechanical demand for added stocks and forced selling for deletions. This phenomenon is popularly known as *Index Effect* in the finance world. The Index Effect distorts short-term price movements in ways that hedge funds can exploit. In *The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation*(H. Chen et al. 2003), it is observed that index additions average 5-10% between announcements and effective dates. For deletions, Harris and Gruel observe that index deletions underperform by 3-8% due to indiscriminate selling. Forced buying from ETFs and index funds during S&P 500 changes ranges from $\mathbf{\$50 - 100B+}$ per event (A. Petajisto 2011), with megacap additions such as Tesla at the upper bound (E. Dey & D. Hull 2020). For companies to be added, they must meet certain criteria. These criteria include market capitalization usually above \$15.5 billion, profitability through at least four consecutive quarters of GAAP earnings, and diversification which emphasizes no overconcentration of certain sectors like technology. Deletion conditions are usually centered around events like mergers & acquisitions, financial distresses such as bankruptcy risk, market cap shrinkage, and sector rotations.

Let us consider a case study of Tesla to expand more on addition. This will help us understand the magnitude of such a strategy during index reconstitution events.

In November 2020, the S&P Dow Jones Indices announced that TESLA(TSLA) will join the S&P500 later in December. Tesla had met all addition requirements beforehand. However, there was a delayed inclusion due to the S&P500's investigations into its GAAP earnings on sustainability. Hedge funds had pre-announcement positioning due to fundamental analysis on Tesla as a company. The analysis argued that Tesla was a long anticipated position since it was the largest US stock not included in the S&P500 with a market cap greater than \$500 Billion and it has experienced periods of consistent profitability. Therefore, quant funds started building long positions starting from October, betting on Tesla's inclusion. These long positions rallied Tesla stocks $\mathbf{+43\%}$. In the weeks after the announcement, the stock jumped a further $\mathbf{+24\%}$ as passive index funds and ETF began accumulating shares to match the S&P500's market composition. Every hedge fund that had a pre-announcement positioning profited from this demand surge.

Although the trade was profitable for some time, there were many risk factors involved. Tesla's sheer size meant that index funds had to purchase billions of dollars worth of shares, leading to liquidity constraints and slippage. Additionally, the crowded nature of the trade, with numerous hedge funds and algorithmic traders front-running the inclusion, meant that late entrants faced

Figure 1. Tesla stock in the pre-announcement phase leading up to the announcement of its inclusion in the S&P500. Fundamental analysis pointed out to its inclusion and hedge fund investors were willing to bet on its inclusion.

diminishing returns. By the time Tesla formally joined the index on December 21, much of the upward pressure had already been priced in, and the stock rose only **5%** in the following weeks before consolidating.

This project does not give insights into pre-announcement fundamental analysis and positioning nor does it study post-announcement positioning. Our study will emphasize positioning from the time of announcement at the close of the market to the trade date. Also, the significant risk factors we will assess are slippage costs and timing of positions. Depending on the when the position is executed in the market from the announcement to effective date, we will observe that the strategy will have different return levels compared to the market.

2. DATA COLLECTION

2.1. *Pipeline Construction*

To properly test this strategy, data points on index addition and deletion events needed to be gathered, as well as the returns for the stocks over the event intervals. `Selenium`, `requests` and `BeautifulSoup` were used to gather the index addition and deletion events from Standard & Poor's Press Releases. The Selenium Driver visited the page and search for all titles that contained the sequence "set to join" and collected the announcement date and the URL to each press release page. Once the URLs were collected, the python library `requests` was used to gather the content of each page. From there, `BeautifulSoup` was used to extract and parse the table, <tr>, tag. The contents of these pages were of mainly two types. The most recent type contained a table where each row contained either the trade date, the action, the index and the company with its ticker (as can be seen here: Pegasystems Set to Join S&P MidCap 400; while the older format contained a table where the title contained the index and the trade date and each row only contained the company and the action (as can be seen here: Essent Group Set to Join S&P MidCap 400; Coherus BioSciences, Patterson-UTI Energy to Join S&P SmallCap 600). Therefore, it was necessary to have two different parsers for the two different types of contents. The first one was straightforward as it was as easy as getting the table and using `pandas` built-in function `read_html()`, which is similar in functionality as the most commonly built-in `pandas` function `read_csv()`. For the latter one, the challenge came in when extracting the ticker from the page as it was not contained in the table but rather in the article. Therefore, the `re` library was needed to use regex and find the ticker in the article. More precisely, the regex expression was used to look for the sequence of letters that come right after `NYSE` or `NASDAQ`, as these companies are often traded on the two major exchanges, and articles tend to write it in the following form: `(NYSE: XYZ)`. Therefore, the regex approach was useful to gather the ticker to most companies. The rest were left empty and manually filled in by hand as it was significantly smaller as compared to the original dataset.

The stock daily return data came from a database maintained by the Center for Research in Security Prices (CRSP). The dataset used was the daily stock return from January 07, 1986 to December 29, 2023 in 79,784,443 rows. In addition to the daily stock return, a dataset mapping each ticker to its corresponding PERMNO was necessary, as the returns dataset mapped the daily returns to the stocks PERMNO. PERMNO is a permanent and unique identifier assigned by CRSP to each security in its database, which remains unchanged regardless of name or ticker change. In addition, the Center for Research in Security Prices (CRSP) data was 'point-in-time', which allowed to test in a real-life scenario, rather than data pricing in other factors such as dividends and stock splits.

The only limitation in the Center for Research in Security Prices (CRSP) data was that it only contained the closing price and returns. However, the index strategy depends on the press releases that are published after the market closes. Thus, the investor must act immediately in after hours or the following day when the market opens as the stock of the company being added tends to rise throughout the day, diminishing the potential alpha for the investor. The open price, close price, volume, along with other information were freely available on yahoo finance, which could be gathered using the python library `yfinance`. `yfinance` was necessary to build the dataframe which contained the necessary information for a given security.

2.2. *LLM Parsing*

In order procure the useful information from the press releases, there was an attempt made at utilizing a Large Language Model (LLM) to parse the raw HTML and extract the relevant details from it. To do this, a pipeline was setup that would send the html to the LLM and ask the LLM to parse the data by retrieving the following items: the announced date of the trade, the actual date of the index event, the name of the company, the sector that it belongs to, the action (i.e addition or deletion), the index, and the ticker. Unfortunately, there was a roadblock in connecting the `Selenium` data to the LLM. Most advanced models, such as Chat GPT, Claude, etc., require a premium subscription to access their resources and the open source models that are available to use (such as Meta Llama 3.2 Instruction Model for instance) took too long to process the data for one singular event and even then was poor at performing the task at hand. As a proof-of-concept, the Chat GPT GUI interface was utilized to explore the validity of using an LLM to parse the HTML. Upon providing the model with the HTML content found in the div of class wd_body wd_news_body from the website, the model was able to generate the required data. Utilizing LLM resources, it can be seen that constructing a pipeline by using Chat GPT can definitely provide speed in collecting and storing the data. Also, the LLM is not susceptible to future changes in the HTML syntax, as the reasoning model can piece together the request information regardless of how the page looks.

3. PORTFOLIO CONSTRUCTION

The position was opened on the day the announcement was made or the following morning and closed on the trade date, which is when the index acts on the announcement: buys or sells. One type of portfolio was equal-valued, meaning that each security in the portfolio had the same weight (including the short positions for the companies getting removed from the stock). In a period where there is only a single event happening, 50% of the portfolio contained a long position in the stock getting added and the other 50% of the portfolio was a short position in the stock getting removed. Similarly, in the event there are multiple events, say n, the portfolio would have n long positions, each of weight $\frac{1}{2n}$, and another n short positions, each of weight $\frac{1}{2n}$. If two different events overlap, meaning that another announcement is made when the portfolio was already at its capacity of 100%, the portfolio is rebalanced so that it also incorporates the new information (which may require selling some of the long position and covering some of the short position).

Similar to the Equal Portfolio, Risk Parity and Mean Variance portfolio were also constructed, in order to study how the different portfolio construct plays a role in the performance of the strategy. Risk Parity was chosen specifically because this strategy is of high volatility, therefore it was necessary to understand how volatility could play a factor and generate addition alpha. Following the papers (V. Bhansali 2015) and (A. ANG et al. 2006), each stock's daily return over the previous 20-trading-day rolling window was estimated everyday–for the stocks that are being traded. For each stock, the inverse of its volatility is then computed and those values were normalized so their sum equals 1. These normalized values are used as the portfolio weights, so that less volatile stocks are given higher weight. The Mean Variance portfolio was constructed by first getting the previous 20-trading-day returns of the stocks being traded in the given window. Then, the covariance matrix and the mean return were computed for the stocks over the 20-trading-day period. After that, the weights were determined by minimizing the mean variance optimization problem (M. B. Haugh 2016):

$$\frac{1}{2}\mathbf{w}'\Sigma\mathbf{w}$$

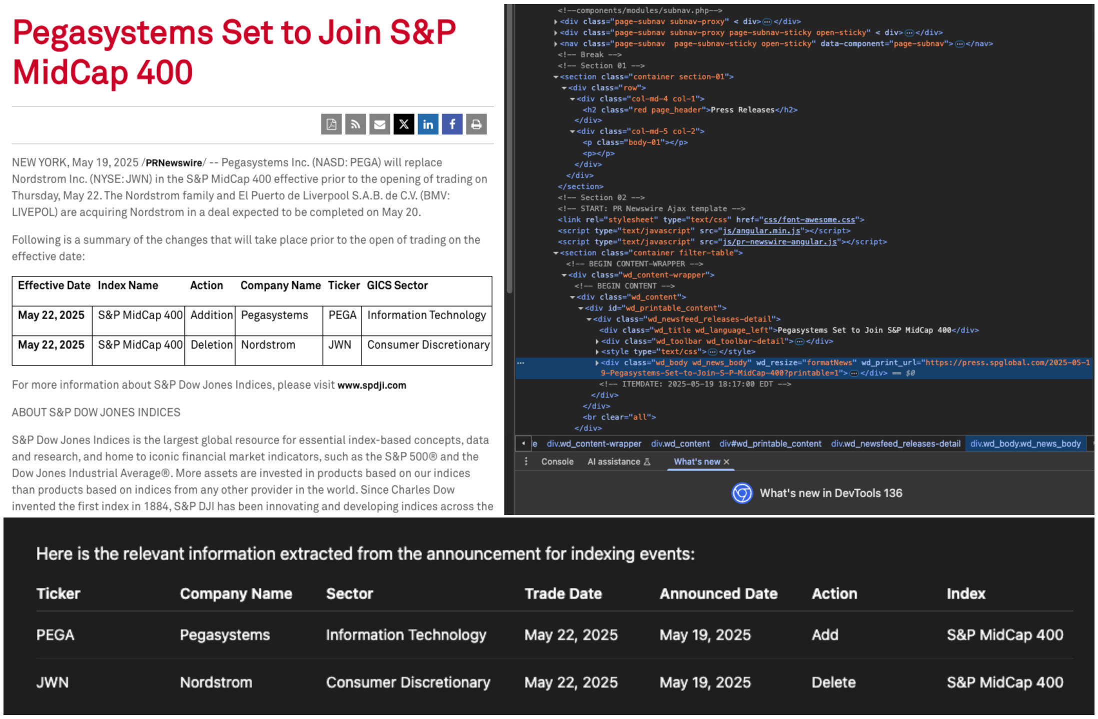

Figure 2. Sample output from passing in the content from the wd_body wd_news_body class. The LLM was successful at this task and provided with the proper API access, the parsing of the raw HTML can probably be done by using the LLM. Thorough testing needs to be done however, and proper RAG search methods need to be considered.

$$\text{subject to } w'\mu = p \text{ and } w'\mathbf{1} = 1.$$

This would result in a portfolio were stocks of higher expected Sharpe ratio, estimated over the previous 20-trading-days, are given higher weights.

Another method of portfolio construction that was experimented with was Volume Weighted Portfolios. The weights for each day were determined by taking the companies being invested in each day and normalizing their 20-day rolling volume in comparison to the rest of the stocks that were being invested for that day. This weighting scheme hopes to capture market insight from larger investments that might have better information in regards to what companies that might see a larger spike due to these index events.

One thing that was noticed was that when companies tended to drop, it was mostly due to mergers occurring, where the company to be dropped was being purchased by a larger company and in turn their stock would be dropped. This presented an interesting situation as oftentimes, even though the index would sell the company to be removed, there wasn't always negative returns correlated with this which could be explained by circumstances around the index event.

4. RESULTS

When analyzing the performance of this strategy, a few metrics stood out. Namely, the variability in its performance. When compared to the common market performance models, this model produced pretty significant alpha ranging from about 9-10%, and going all the way up to 20%. On paper, this looked to be pretty profitable, however further testing revealed some issues. Namely, the Sharpe ratios for the various portfolios for this strategy were pretty low, indicating that this strategy is volatile. Another thing to note is that this strategy has started to perform exceptionally well more recently when compared to the past. Specifically, after 2023 there seems to be a large spike in returns for each of the constructed portfolios. Overall, this volatility might not be appealing for a hedge fund to take on, in comparison to other strategies.

5. RISK ANALYSIS

The two main risk with this strategy are the slippage costs that could arise from the way the portfolio is constructed and the race against high frequency traders. The first risk applies to investors with a large amount of assets under management where allocating even 1% of their portfolio into one security could significantly move the market making it go against them. The best advice for large investors is to calculate the previous 20-day

Table 1. Results: S&P 500 Long Only

Portfolio	Purchase Time	Parameter	CAPM	FF3	FF5	FF5 + MOM
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Equal Weighted	After Hours	α	13.87%	14.09%	14.34%	14.35%
		β	32.92%	29.04%	27.12%	26.98%%
	Next Day	α	6.02%	6.24%	6.20%	6.20%
		β	28.88%	25.10%	25.49%	25.62%
Volume Weighted	After Hours	α	19.60%	19.88%	20.77%	20.71%
		β	43.25%	39.06%	36.68%	36.80%
	Next Day	α	15.75%	16.03%	16.26%	16.27%
		β	33.90%	31.04%	29.35%	29.34%
Risk Parity	After Hours	α	13.84%	14.05%	14.32%	14.32%
		β	31.76%	28.10%	25.96%	25.83%
	Next Day	α	6.42%	6.62%	6.60%	6.59%
		β	27.71%	24.12%	24.30%	24.43%
Mean Variance	After Hours	α	13.65%	13.85%	14.09%	14.10%
		β	37.44%	33.98%	31.58%	31.46%
	Next Day	α	5.94%	6.15%	6.10%	6.09%
		β	33.13%	29.39%	29.43%	29.57%

NOTE—These are the alpha and beta calculations for the Long only portfolio in comparison to various market performance indexes. One thing to note is that these are the yearly adjusted values calculated by multiply the original daily values were multiplied by 252 trading days. Across the board, trading on After Hours prices produced more alpha indicating the importance of speed in this trade.

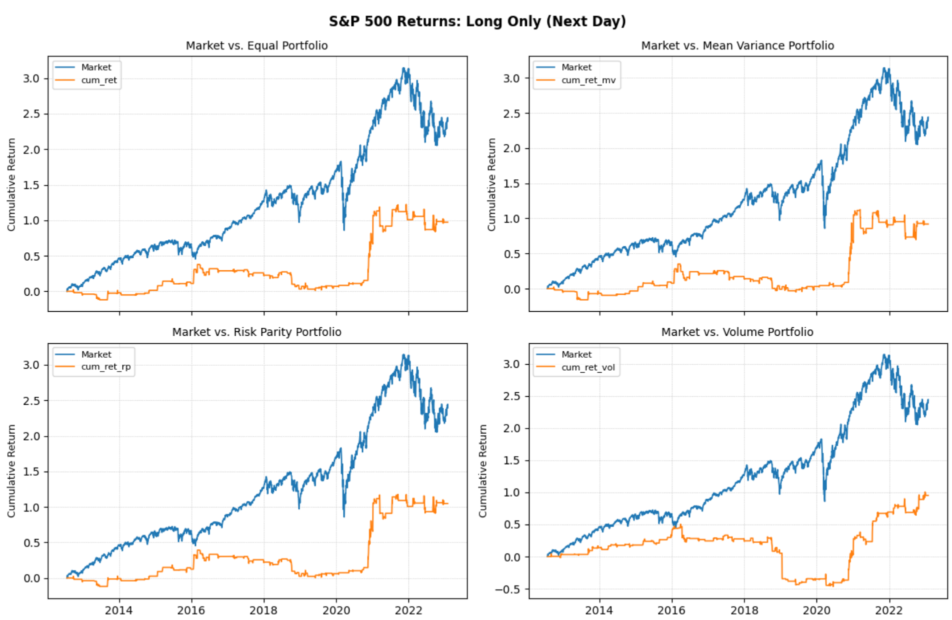

Figure 3. These are plots related to the various portfolio returns trading the Long Only Strategy on the next day prices.

Table 2. Results: S&P 500 Long-Short

Portfolio	Purchase Time	Parameter	CAPM	FF3	FF5	FF5 + MOM
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Equal Weighted	After Hours	α	9.78%	9.85%	10.16%	10.16%
		β	−1.92%	−3.38%	−5.09%	−5.01%
	Next Day	α	3.12%	3.20%	3.33%	3.33%
		β	−2.52%	−3.88%	−4.18%	−3.98%‘
Volume Weighted	After Hours	α	16.45%	16.72%	17.18%	17.02%
		β	−2.00%	−5.71%	−8.78%	−8.40%
	Next Day	α	−0.78%	−0.84%	−0.22%	−0.34%
		β	−3.74%	−4.61%	−8.22%	−7.95%
Risk Parity	After Hours	α	6.92%	7.08%	7.09%	7.09%
		β	41.97%	39.13%	38.28%	38.30%
	Next Day	α	1.29%	1.44%	1.23%	1.23%
		β	37.12%	34.35%	35.13%	35.31%
Mean Variance	After Hours	α	5.97%	6.27%	6.43%	6.45%
		β	51.58%	46.39%	43.65%	43.47%
	Next Day	α	−0.35%	−0.05%	−0.25%	−0.27%
		β	44.40%	39.16%	38.98%	39.16%

Note—These are the alpha and beta calculations for the Long-Short portfolios in comparion to various market performance indexes. One thing to note with the Long-Short portfolios are that they produce significantly less alpha in comparison to the Long only portfolios, likely due to the poor performance across the Merger events.

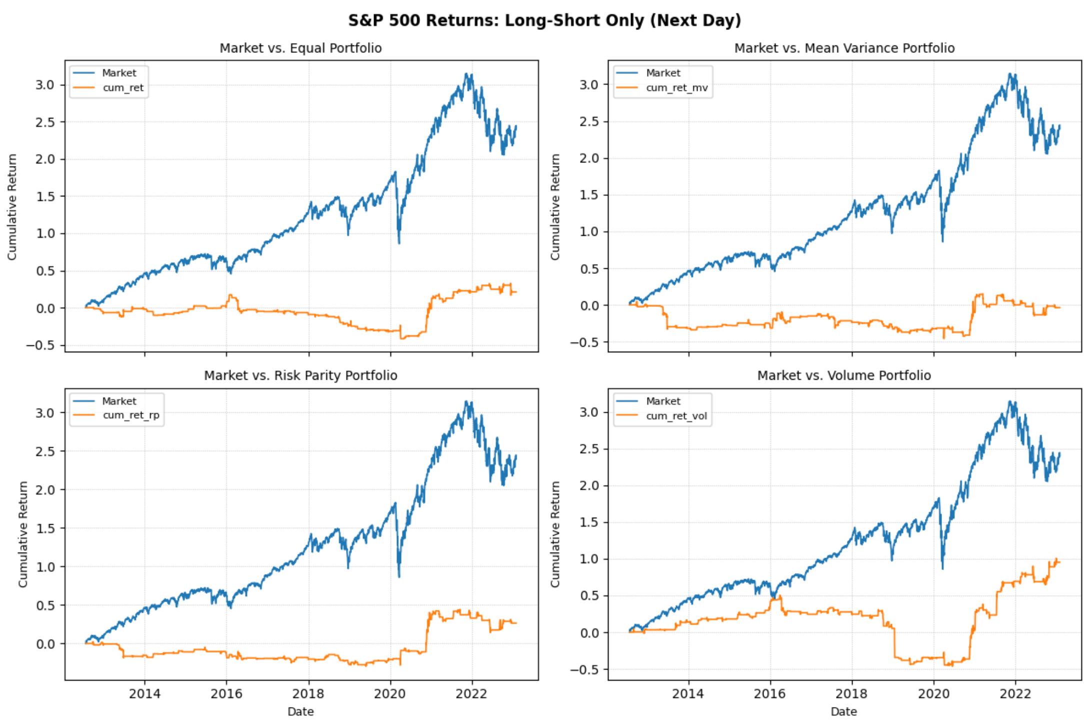

Figure 4. These are plots related to the various portfolio returns trading the Long-Short Strategy on the next day prices.

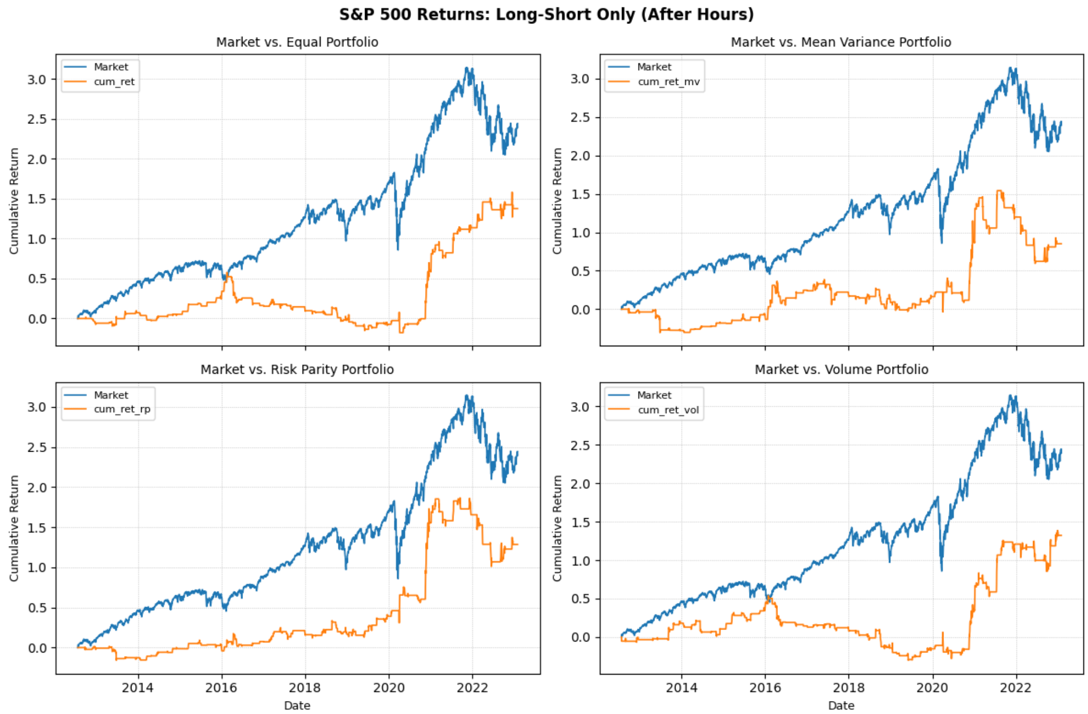

Figure 5. These are plots related to the various portfolio returns trading the Long-Short Strategy on the after hours prices.

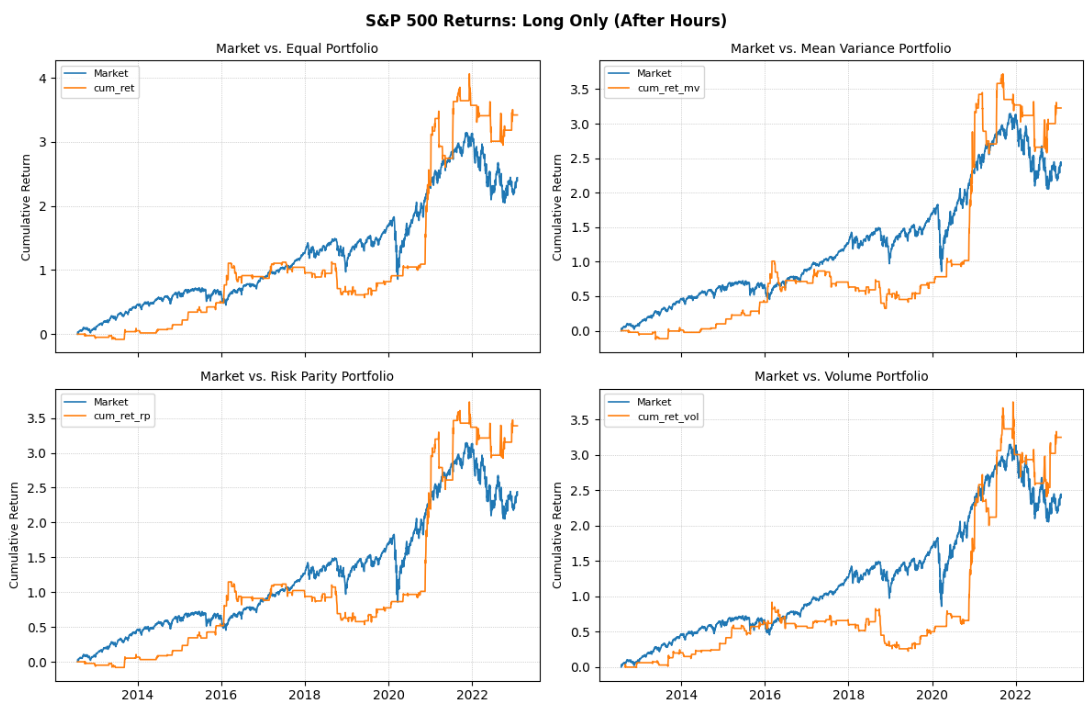

Figure 6. These are plots related to the various portfolio returns trading the Long Only Strategy on the after hours prices.

Table 3. Sharpe Ratio, Mean Return, and Volatility Analysis: S&P 500 Long-Short

Portfolio	Purchase Time	Sharpe	Mean	Volatility
(1)	(2)	(3)	(4)	(5)
Equal Weighted	After Hours	0.048	0.052	1.08
	Next Day	0.027	0.026	0.97
Volume Weighted	After Hours	0.047	0.065	1.37
	Next Day	0.041	0.056	1.34
Risk Parity	After Hours	0.034	0.035	1.02
	Next Day	0.013	0.012	0.922
Mean Variance	After Hours	0.024	0.036	1.51
	Next Day	0.01	0.01	1.38

Note—Sharpe Ratio along with Mean and Standard Deviation of Returns for the Long-Short Portfolios. One thing to note is that these Sharpe ratio's are quite low indicating large exposure to volatility.

Table 4. Sharpe Ratio, Mean Return, and Volatility Analysis: S&P 500 Long Only

Portfolio	Purchase Time	Sharpe	Mean	Volatility
(1)	(2)	(3)	(4)	(5)
Equal Weighted	After Hours	0.065	0.072	1.10
	Next Day	0.042	0.040	0.96
Volume Weighted	After Hours	0.067	0.088	1.30
	Next Day	0.059	0.069	1.18
Risk Parity	After Hours	0.065	0.071	1.08
	Next Day	0.043	0.041	0.943
Mean Variance	After Hours	0.057	0.072	1.08
	Next Day	0.037	0.041	1.11

Note—Sharpe Ratio along with Mean and Standard Deviation of Returns for the Long-Short Portfolios. These ratios seem to be better than that of the Long-Short, but they have comparable volatility highlighting the generally inconsistency in this strategy.

moving average volume and limiting their position to 1% percent of that, in order to minimize market impact.

The second risk is due to the fact that most of the alpha is embedded in the closing price. This means that it is highly important to act as fast as possible when the press releases are published. With high performance computers (i.e those that can compute results to the millisecond level) and fast data processing, it is possible to capture the closing price in the after hour markets. However, the difficulty with after hours trading is liquidity but often times the securities being added into these major indices are quite liquid.

Another risk that should be addressed is that of shorting a merging company. Oftentimes, companies that are dropping out of an Index are doing so as a result of the company being purchased by another company in a merger situation. An example of this occurred on 19 May 2025 when Capital One acquired Discover Financial Services(DFS). As a result of this, Discover Financial Services was going to be removed from the S&P 500 and when taking a short position on this, proper caution must be taken due to the merger situations. In addition to the proper caution, the market has already priced in this acquisition long before S&P 500 drops DFS shares from its holdings and S&P 500 tends to drop these shares a few days before the stock is de-listed and after the acquisition is complete. As a result, there is no alpha in trading those securities.

6. CONCLUSION

From our results, we can deduce that depending on position and weightings, index reconstitution events generate varying α and β. Comparing results in table 1 and table 2, we notice that going long only generate more α than the long-short. However, analyzing β, we see that long only generates more β than long-short. Ideally from our results, it would be implied to go long only every time there is an index reconstitution event. Such motivation would probably have a convincing argument against the high β our model produces. The high α in the long only can be attributed by the fact that long only captures the full upside of market additions, creating a persistent and exploitable alpha. For deletions, the magnitude in the drops is usually smaller as selling pressure is less predictable. Also, some stocks also rebound after deletion due to overshooting. Long only avoids these flaws in deletions. However, long only has pure exposure to market risk. Long-only strategies usually have more correlation with the broader S&P 500. If the market rallies, additions benefit more. If the market drops, these strategies fail to use deletions as a hedge. Shorting deletions would introduce negative β exposure, offsetting some of the long β. In this sense, the long-short is a market neutral strategy. However, the shorting aspect of this trade can lead to difficulties in situations when there are mergers. This is due to the fact that depending on the type of merger, the stock of the company to be dropped will get purchased by the acquring company which will cancel out this Index Event. This and other volatility surrounding these merger events leads to poor performance with the Index Event Strategy and the optimal short positions to take might be to consider non Index Events. If the broader market rallies, deal premiums may be compressed lowering alpha but rising markets could also reduce deal break risks due to regulatory blocks and financing issues.

Also, while our strategies do generate +ve double-digit alphas, it is a well-known fact that the index effect in indices such as S&P 500, Russell and MSCI is decreasing. This is a working paper out of Harvard Business School by Robin Greenwood and Marco Sammons. In their paper *The Disappearing Index Effect*, Robin and Marco point to us that abnormal returns associated with index additions have dropped from 7.4% in the 1990's to less than 1% over the last decade. For deletions, it is observed that the effect has returns of 4.6% in the 1980's, which rose to 16.1% in the 1990's, dropping down to 12.4% in early 2000's before finally dropping down to 0.6% over the last decade. Robin and Marco point out four key reasons for this. The first reason is the changing compositions of additions and deletions. Simply put, for example, sizes additions and deletions have been decreasing over time relative to the S&P 500. Secondly, there is occasional inter-indice migration where a stock is removed from one index, say S&MidCap Index to S&P500. The effect of such migrations is that the forced selling in one index is cancelled out by the forced buying in the other index. As they point out, such migrations have led to the rise of Mid-Cap Focused funds investigated by Vijh, Wang 2022 (A. M. Vijh & J. B. Wang 2022). Another reason is front-running by big market participants. In front-running, market participants take advantage of returns leading up to the index addition or deletion. This is done by fundamental analysis of pre-event returns of the stocks in question. The last reason the point out is the increased liquidity of the S&P500.

While exploiting index reconstitution events can be a profitable, there is more alpha that can be generated by pre-event analysis and positioning. Studies have shown that positioning up to three months before the event leads to stronger gains. Also, with more rigorous datasets, more accurate comparison can be made on the returns of different positions, specifically long-only versus long-short.

REFERENCES

ANG, A., HODRICK, R. J., XING, Y., & ZHANG, X. 2006, The Journal of Finance, 61, 259, doi: https://doi.org/10.1111/j.1540-6261.2006.00836.x

Bhansali, V. 2015, Risk Parity and Diversification, SSRN Working Paper 2659431, SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2659431

Chen, H., Singal, V., & Noronha, G. 2003, The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation, Working Paper SSRN 427001, Social Science Research Network, doi: 10.2139/ssrn.427001

Dey, E., & Hull, D. 2020, Bloomberg. https://www.bloomberg.com/news/articles/2020-11-16/tesla-will-join-s-p-500-in-december-as-largest-ever-new-member

Haugh, M. B. 2016, Mean-Variance Optimization and the CAPM,, https://www.columbia.edu/~mh2078/FoundationsFE/MeanVariance-CAPM.pdf

Petajisto, A. 2011, Journal of Empirical Finance, 18, 271, doi: https://doi.org/10.1016/j.jempfin.2010.10.002

Vijh, A. M., & Wang, J. B. 2022, Financial Management, 51, 1127, doi: https://doi.org/10.1111/fima.12391