IEOR 4733 - Project 4

Beta Based Portfolio Construction:

Stock Selection Based on Upside- and Downside Market Risk

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MEET THE TEAM

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Motivation

Motivation

CAPM

The traditional Capital Asset Pricing Model (CAPM) assumes that an asset's beta represents an average of its upside and downside market risk (Johansson & Petersson, 2017).

Correlation Between Stocks

However, the correlation between stocks tends to increase during market turmoil. This suggests that an asset's downside beta may be different from its upside beta.

Portfolio Construction

By separating upside and downside beta, investors can potentially construct more efficient portfolios.

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Market Microstructure

Market Microstructure

S&P 500

The U.S. stock market, including the S&P 500, operates as a continuous double auction market

Liquidity

We assume unlimited liquidity and instant order fills at the adjusted close

Transaction Costs

We assume no transaction costs for portfolio rebalancing

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Data and EDA

Data

Data sources:

- CRSP (Center for Research in Security Prices) database accessed through WRDS (Wharton Research Data Services)

Tables used:

- crsp.dsp500list: S&P 500 constituent information
- crsp.dsf: Daily stock file containing stock returns
- crsp.dsenames: Company attributes and identifiers
- crsp.dsp500: S&P 500 index returns

Data retrieval:

- Retrieved daily returns for S&P 500 constituents and their membership dates using SQL queries
- Merged constituent data with company attributes and identifiers
- Limited returns data to US ordinary common shares listed on one or more of NYSE, ARCA, NASDAQ, NYSE MKT

Data Preprocessing:

- Data between 2003-01-05 and 2023-07-01 and dropping NA values
- Considering only returns in period of company's SP500 membership
- Converting daily returns to expected weekly returns

EDA

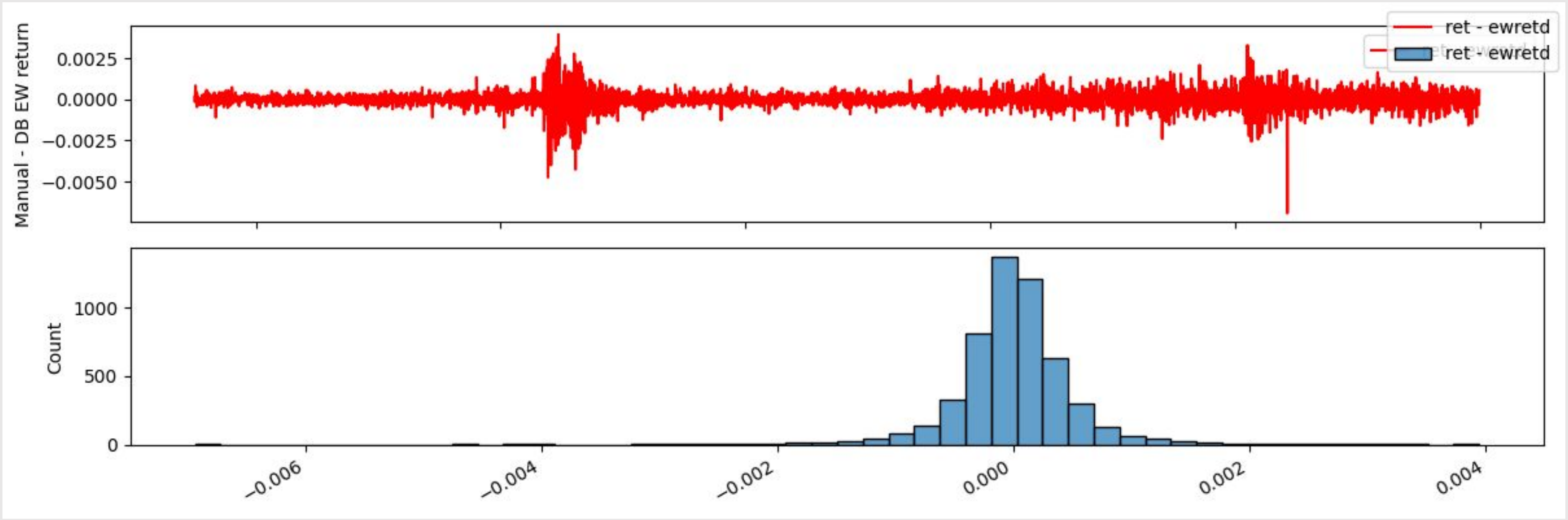


Fig: shows the difference between manually calculated equal weighted S&P 500 returns and EWRET provided by database

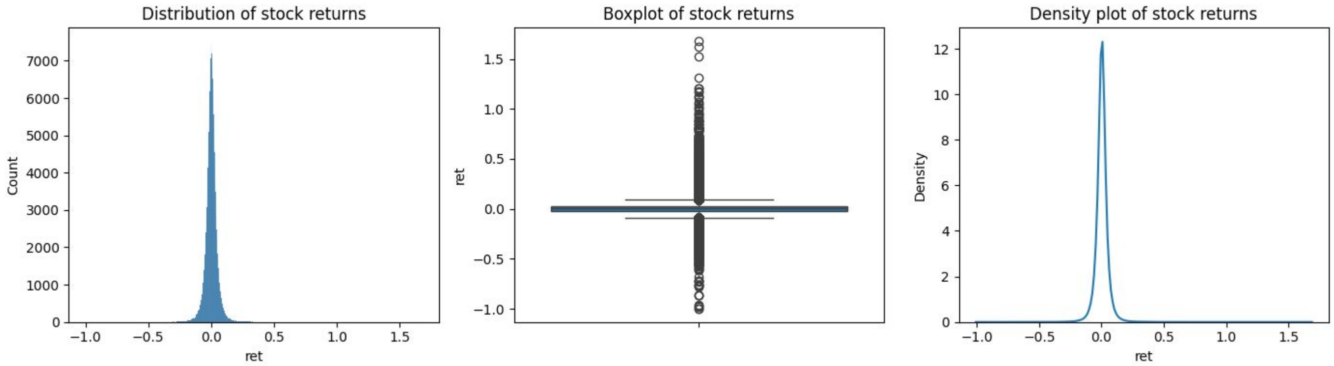
EDA

Calculated descriptive statistics for weekly returns of listed, delisted, and all stocks, as well as the S&P 500 index

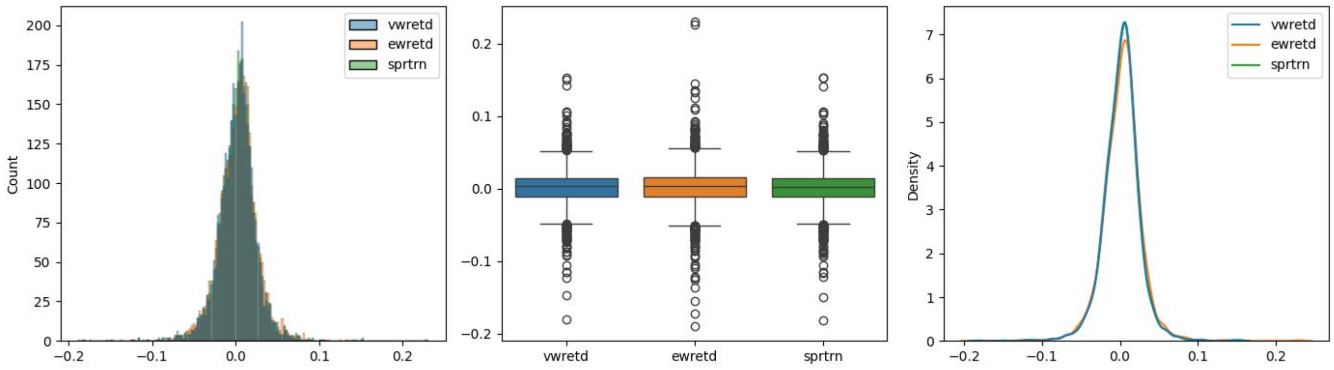
Category	Number of Indices	Avg. Return % (Max/Min)	Avg. SD %	Avg. Skewness	Avg. Kurtosis
Listed Stocks	505	0.317 (167.8 / -96.2)	4.723	1.09	31.96
Delisted Stocks	454	0.229 (161.7 / -99.8)	5.759	0.83	454
All Stocks	930	0.289 (167.8 / -99.8)	5.076	1.01	32.57
Market	1	0.203 (15.3 / -18.2)	2.52	-0.32	7.3

EDA

S&P 500 Constituents returns

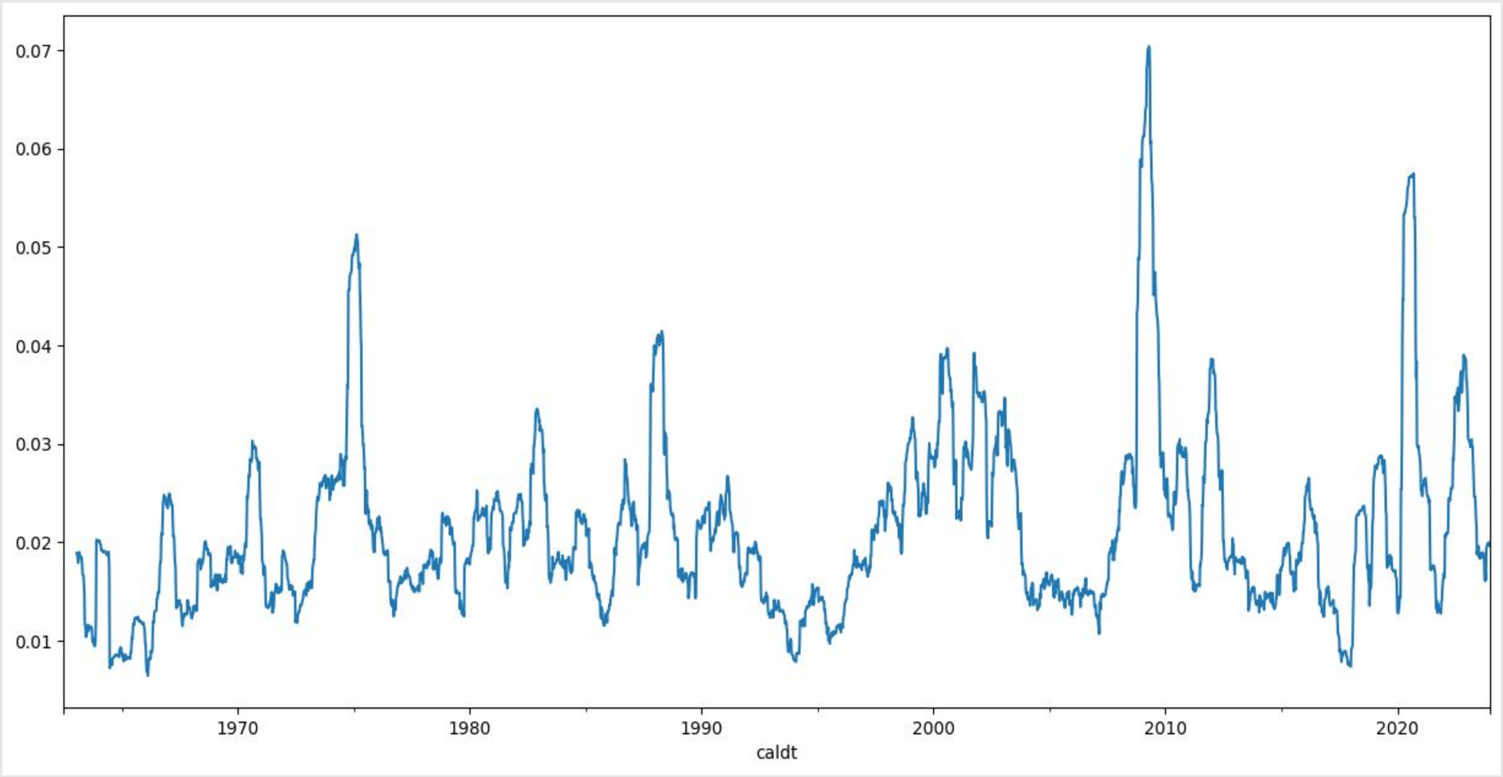


S&P 500 Index returns



EDA

SP500 index weekly returns volatility



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Methodology

Empirical Model

1. Two year rolling window for parameter estimation and portfolio construction. Holding portfolio for the next six months to compute realized returns and rebalancing thereafter.
2. Excluding stocks not listed for entire two-year window period and those delisted within the next six months
3. Using OLS to compute regular, upside, and downside market betas for stocks in train set. Separating stocks by their beta value into 5 portfolios, looking at 20, 40, 60, 80, and 100%iles.
4. Computing annualized, realized return on the test set using equal-weight portfolio scheme to generate 15 time-series of returns.
5. Additionally, computing a benchmark equal-weight portfolio using all estimated regular market betas to have a fair comparison for return (weighting and rebalancing scheme)

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Backtesting

Backtesting

- Generated time-series of annualized portfolio returns, divided by beta type (3 choices) and quantile (5 choices)
- Generated time-series of two-year rolling betas
- Compared portfolio returns to benchmark market portfolio as well as the SP500 index directly

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Performance and Optimization

Motivation

Portfolio performance was tracked for each equal-weight beta-quantile portfolio

The paper author's choice for training set and test set (rebalancing) window as well as quintile cutoffs could be points to optimize in a real world application

Including transaction costs would make backtesting more realistic

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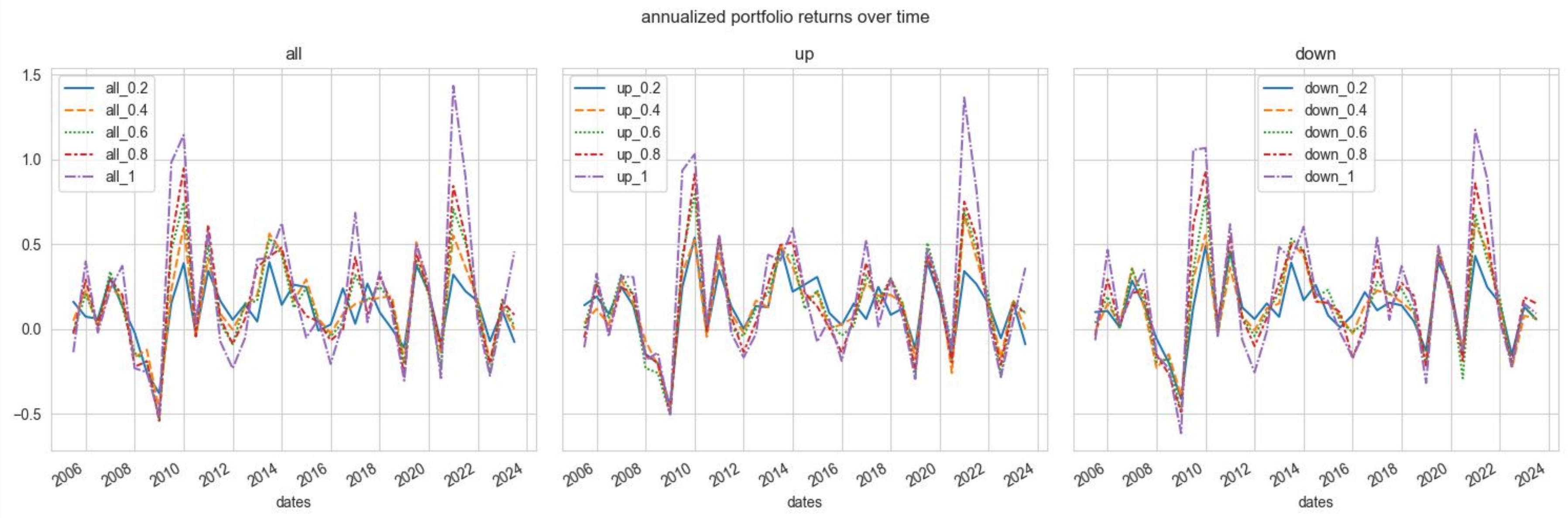
Results and Evaluation

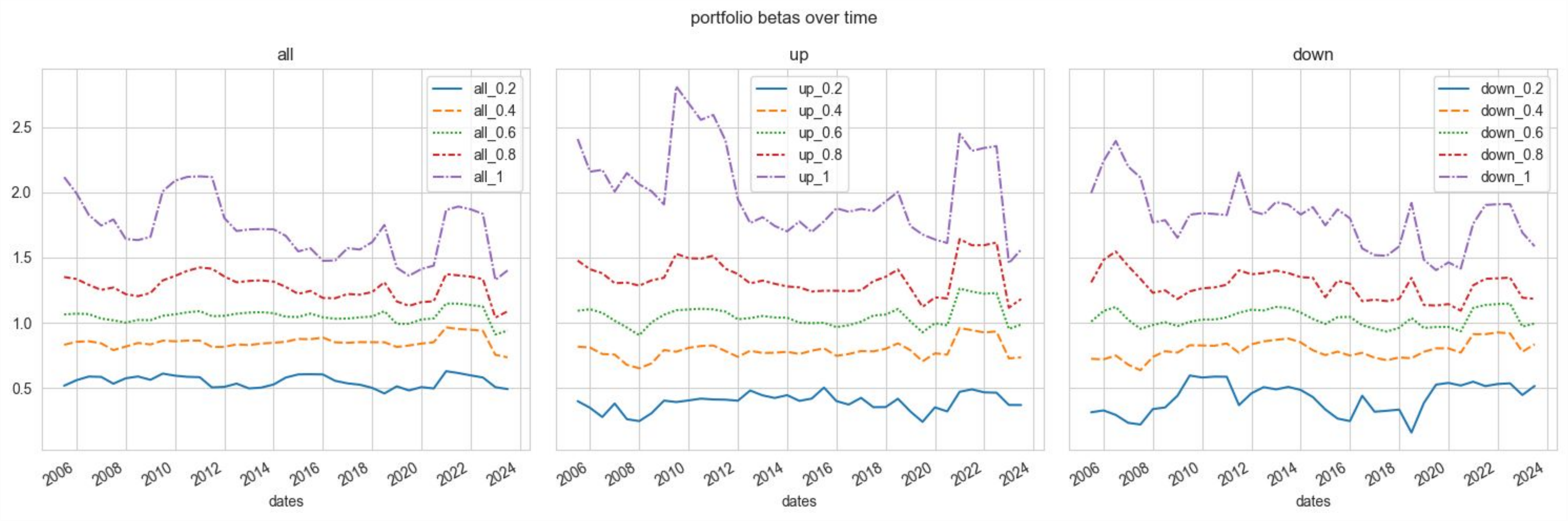
Portfolio Return Statistics

Portfolio	Ending Value of $1	Geometric Average %	Arithmetic Average %	Standard Deviation %	Tracking Error %
all_bench	71.63	12.24	15.39	26.72	0.00
all_0.2	29.81	9.61	11.08	17.49	16.06
all_0.4	61.22	11.76	14.31	23.48	8.16
all_0.6	56.29	11.51	14.98	27.47	4.20
all_0.8	80.39	12.59	16.72	30.92	6.31
all_1	115.63	13.70	20.90	43.76	20.93
up_0.2	41.64	10.60	12.51	19.79	13.00
up_0.4	53.62	11.36	13.94	23.57	6.96
up_0.6	70.86	12.20	15.78	27.96	4.46
up_0.8	57.62	11.58	15.33	29.48	4.90
up_1	127.73	14.01	19.98	39.85	17.44
down_0.2	37.22	10.27	11.91	18.64	12.92
down_0.4	50.01	11.15	13.60	23.34	7.01
down_0.6	60.11	11.71	14.96	26.71	4.87
down_0.8	93.29	13.04	17.01	30.62	5.92
down_1	112.93	13.63	20.27	40.75	17.33

Portfolio Return Time-Series

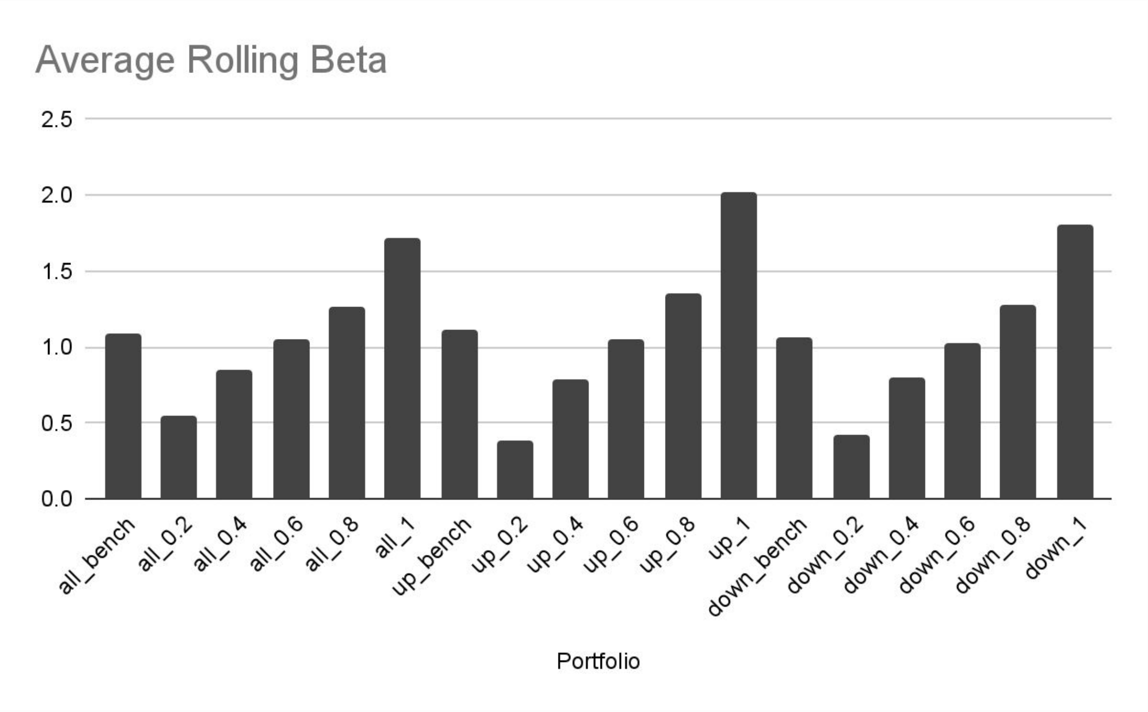


Portfolio Rolling Beta Time-Series



Portfolio Beta Statistics

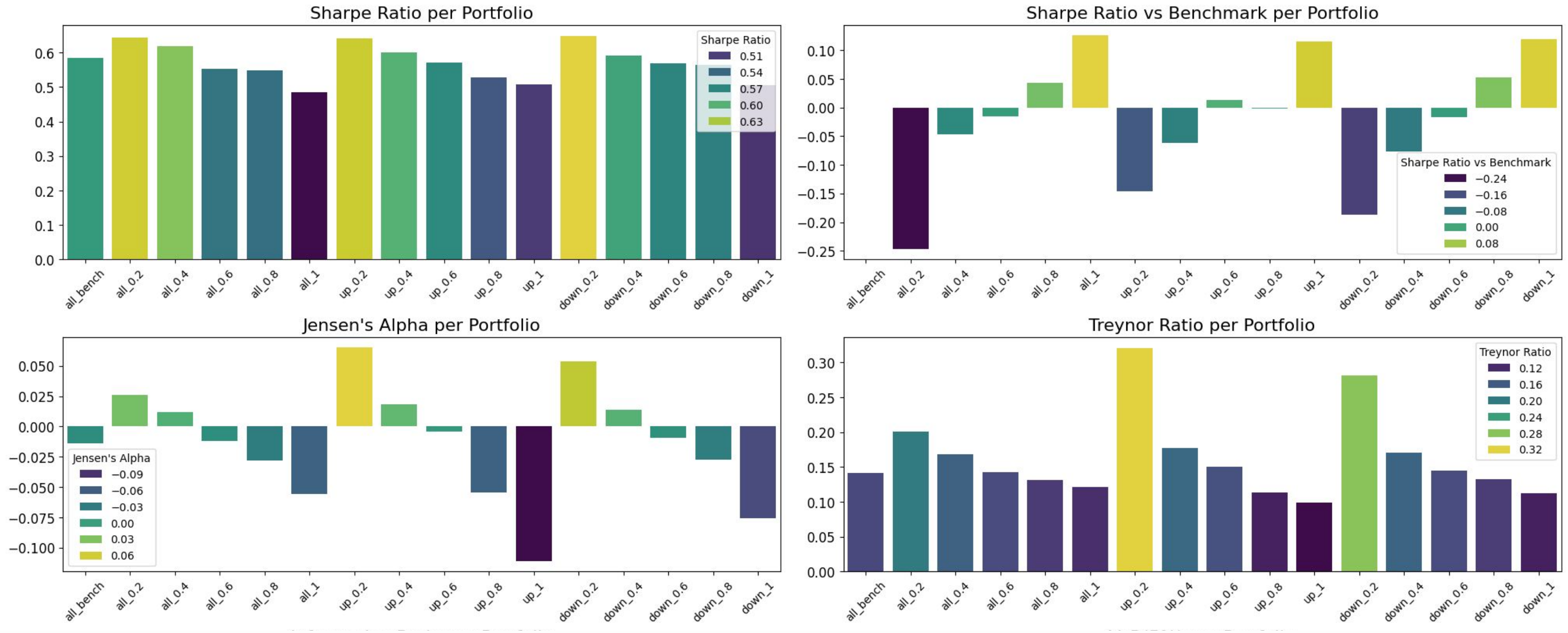
Portfolio	Average Rolling Beta
all_bench	1.089066
all_0.2	0.551438
all_0.4	0.851718
all_0.6	1.051767
all_0.8	1.270117
all_1	1.718531
up_bench	1.120306
up_0.2	0.390177
up_0.4	0.788204
up_0.6	1.052224
up_0.8	1.350407
up_1	2.017734
down_bench	1.069188
down_0.2	0.423506
down_0.4	0.794968
down_0.6	1.032294
down_0.8	1.284826
down_1	1.80837



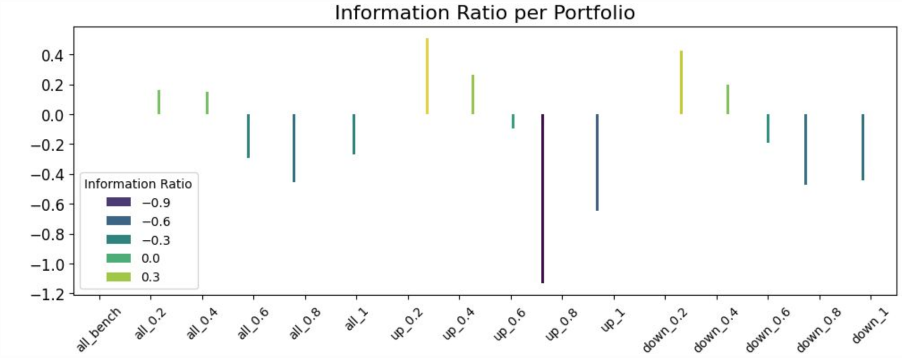
Portfolio Performance (Risk and Return)

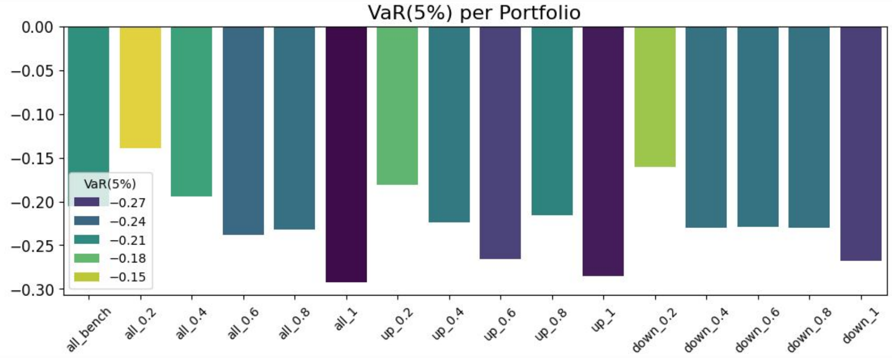
Portfolio	Sharpe Ratio	Sharpe Ratio vs Benchmark	Treynor Ratio	Jensen's Alpha	Information Ratio	VaR(5%)	ES(5%)
all_bench	0.58	0.00	0.14	-0.01		-0.21	-0.35
all_0.2	0.64	-0.25	0.20	0.03	0.16	-0.14	-0.32
all_0.4	0.62	-0.05	0.17	0.01	0.15	-0.19	-0.34
all_0.6	0.55	-0.02	0.14	-0.01	-0.29	-0.24	-0.40
all_0.8	0.55	0.04	0.13	-0.03	-0.46	-0.23	-0.41
all_1	0.48	0.13	0.12	-0.06	-0.27	-0.29	-0.41
up_0.2	0.64	-0.15	0.32	0.07	0.51	-0.18	-0.33
up_0.4	0.60	-0.06	0.18	0.02	0.26	-0.22	-0.36
up_0.6	0.57	0.01	0.15	0.00	-0.10	-0.27	-0.39
up_0.8	0.53	0.00	0.11	-0.05	-1.13	-0.22	-0.37
up_1	0.51	0.12	0.10	-0.11	-0.64	-0.29	-0.40
down_0.2	0.65	-0.19	0.28	0.05	0.42	-0.16	-0.30
down_0.4	0.59	-0.08	0.17	0.01	0.20	-0.23	-0.31
down_0.6	0.57	-0.02	0.14	-0.01	-0.19	-0.23	-0.39
down_0.8	0.56	0.05	0.13	-0.03	-0.47	-0.23	-0.38
down_1	0.50	0.12	0.11	-0.08	-0.44	-0.27	-0.47

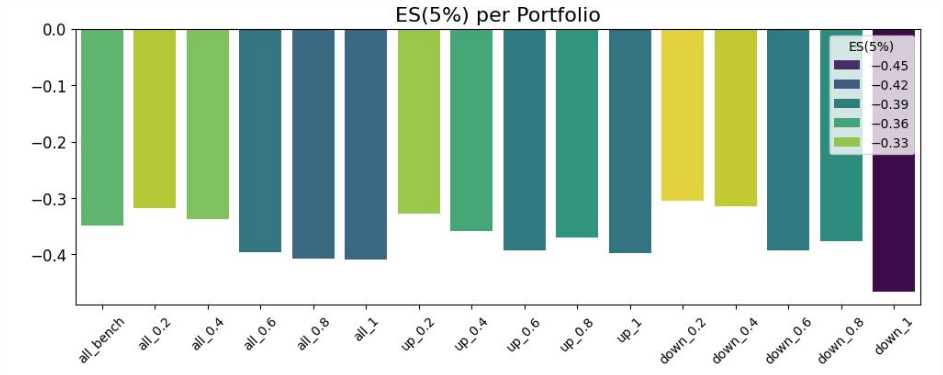
Portfolio Performance



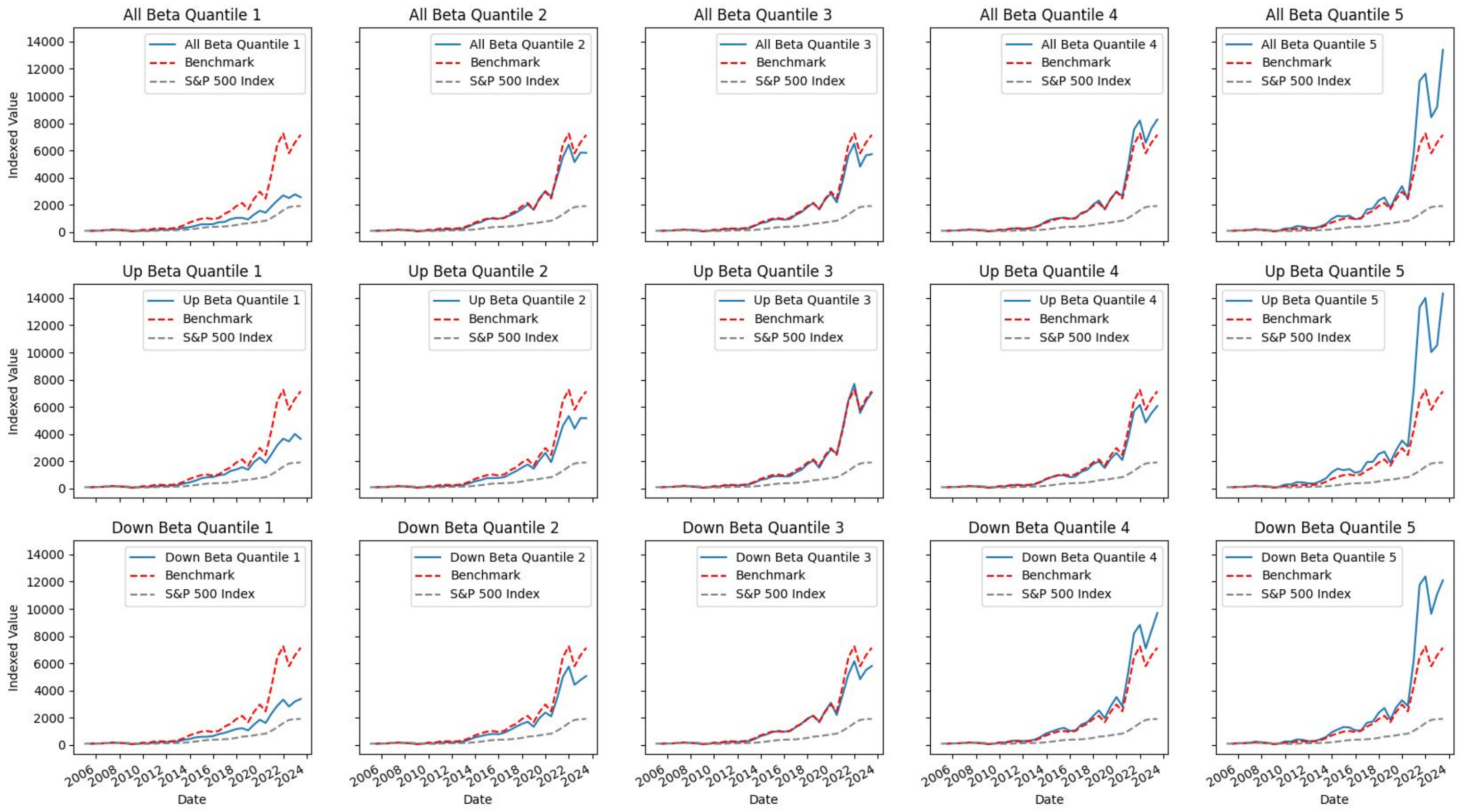
Portfolio Performance







Portfolio Growth vs Benchmark (and Index)



Portfolio Growth vs Market

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Comparison

Comparison to Other Papers

Ang, Chen, and Xing's "Downside Risk" (2006)

Investigates the relationship between downside risk and stock returns. They find that stocks with high downside risk have higher expected returns, which is similar to our findings on the importance of considering downside risk in portfolio construction.

Post and van Vliet's "Downside Risk and Asset Pricing" (2006)

Examines the relationship between downside risk and asset pricing, showing that downside risk is a key determinant of expected returns. This is similar to Johansson et al.'s findings on the importance of considering downside risk in portfolio construction.

Estrada's "Mean-Semivariance Behavior: Downside Risk and Capital Asset Pricing" (2007)

Proposes a downside risk measure called the semideviation and shows that it can be used to improve portfolio optimization. This is comparable to Johansson et al.'s approach of using downside beta to construct portfolios.

Bawa et al.'s "Capital Market Equilibrium in a Mean-Lower Partial Moment Framework" (1977)

Introduces the concept of lower partial moments as a measure of downside risk, which is similar to the downside beta used by Johansson et al.

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Limitations

Limitations

Limitation 1: Transaction Costs

The liquidity of SP500 constituents (large-cap US equities) is high and the trading-frequency is low. Thus market (price and liquidity) impact is limited and can be assumed to be negligible. However, portfolio rebalancing remains as a significant potential problem to strategy return (despite steps taken to minimize rebalancing).

Limitation 2: Paper's Look-ahead Bias

In constructing benchmarks for each equal-weight beta-quantile portfolio, the author used testing (future) data to generate training (current) portfolios. This is incorrect and leads to bias.

Limitation 3: Up- and Downside Betas as Lasting Factors

Despite the author's intuition that upside and downside betas may be different due to the asymmetry of exposure, there must be concrete economic study of the reasoning behind upside and downside betas producing lasting outsize excess return (if any).

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Conclusion

Conclusions

“The theory underlying factor investing is that there are **more dimensions to building efficient portfolios in practice than simply taking on market risk**. Certain factors deliver positive returns beyond market risk either because they **offer compensation for an additional risk exposure in efficient markets that some investors care about** or because they **exploit or take the other side of different preferences or beliefs some investors have**” (Fact, Fiction, and Factor Investing 2023).

The study aimed to investigate the potential benefit of constructing portfolios based on **upside and downside betas using the SP500 as market proxy**. We may be able to capture excess risk-adjusted return because **stocks (and betas) behave differently in normal times versus sharp upturns (and downturns)**.

The results showed that **returns had a directly proportional relationship to the beta quantile irrespective of beta type** (ordinary, upside, downside). In fact, the **only portfolios with a positive Sharpe ratio vis a vis benchmark were the top 80-100% of stocks ranked by beta**. Thus, we are getting excess return beyond the market for taking on additional risk. Moreover, we are taking advantage of conservative investor sentiment by trading against those who would like low volatility of return.

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Real World Implementation

Implementation in the Real World

- This paper and our subsequent study made good inroads in handling: overfitting (parsimonious model); look-ahead (sliding window); survivorship (including delisted)
- Some other backtest issues are likely to not be relevant: bid-ask spread, market impact, latency
- However, the major thing to include in a real world implementation of this paper is the impact of rebalancing transaction cost on portfolio performance
- Moreover, this strategy could be combined with other strategies to generate a stronger signal for expected risk-adjusted return
- Overall, the appeal of this strategy is simplicity, low-frequency trading, high liquidity, tight spread, and negligible market impact

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References

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2. Bender, et al. "Foundations of Factor Investing." *Research Insight*, Dec. 2013.
3. Ee, et al. "A Guide to Smart Beta and Systematic Factor Portfolio Construction Methods." Paragon National Group.
4. Johansson, et al. "Beta Based Portfolio Construction: Stock Selection Based on Upside- and Downside Market Risk." Oerebro University School of Business, 2017.

Thanks!

Do you have any questions?

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"Train with brain"

—Vadim Kozevnikov