ANDERSON
STUDENT ASSET MANAGEMENT

ANDERSON STUDENT ASSET MANAGEMENT
2022 ANNUAL REPORT

UCLA Anderson
School of Management

TABLE OF CONTENTS

PREFACE

The Anderson Student Asset Management (ASAM) Fellowship is designed to provide UCLA Anderson students the opportunity to apply their academic studies in finance to the practical world. Founded in 2006 by the Laurence and Lori Fink Center for Finance, the ASAM fund gives its Fellows the chance to gain invaluable experience by using quantitative investment strategies to manage real money.

Every year, after a rigorous selection process, the existing group of ASAM Fellows hand-picks a new group of students to manage the ASAM fund and act as portfolio managers during the five-quarter period starting that spring. The new class overlaps with the departing class during the spring quarter to effectively learn the investment processes, to maintain continuity, and to ensure the smooth transition of the fund's management. Once accepted into the ASAM Fellowship, student portfolio managers are organized into strategy teams that work to build a portfolio, subject to certain constraints, based on multiple quantitative strategies. The student managers execute a demanding agenda as they tackle asset allocation, investment strategies, security and risk analysis, portfolio management, proper benchmark selection, and organizational and group dynamic issues. Each strategy team finds, prepares, backtests, and presents investment ideas that are based on academic papers to all other fellows and the faculty advisor. Only after they have backtested the strategy with historical data and the team gets concurrence from the faculty advisor will the student portfolio managers execute their trades.

Over the 15-month period, the student-managers work closely with the previous class and the faculty advisor in fulfilling all the responsibilities of managing the portfolio, including the development of investment guidelines, analysis of capital market conditions, rebalancing of existing asset positions, performance analysis, and performance attribution. The students are aided in their research and deliberations by their faculty advisor, as well as outside "investment advisors" and practitioners. As distinguished members of the investment industry and/or academic community, these investment advisors and practitioners offer resources and feedback in the investment process. Additionally, they are important supporters of the UCLA Anderson School of Management.

This is the formal annual report prepared by the 2022 Fellows that summarizes our year and describes in detail the current strategies of the ASAM portfolio.

ANNUAL SHAREHOLDER LETTER

To the Stakeholders of the ASAM Fund:

Now in its 17th year, the ASAM program continues to provide an exceptional capstone experience for the selected Fellows at Anderson. Fellows learn the fundamentals of quantitative investment strategies, learn basic programming skills and apply academic research methods to develop and implement investment strategies to manage what is now over $1.2 million in assets. The 20 members of the 2021-2022 cohort inherited and managed the ASAM Fund from June 2021 to June 2022, incepting our own High Dividend Yield, Neglected Beta, Low Beta, and Low Leverage & High Dividend strategies in January 2022. Additionally, the Fellows welcomed the new 20-person 2022-2023 cohort after a rigorous selection and interview process, which saw the ASAM program receive nearly double the applications from the previous year.

The 2021-2022 Fellows would like to acknowledge and thank the individuals and organizations who made our ASAM experience possible. Particularly, we thank UCLA Anderson and the Laurence and Lori Fink Center for Finance & Investments for its sponsorship of the ASAM Fellowship and the attendance of two Fellows to the 2022 Alternative Investments Conference in London; our faculty advisor and mentor, Professor Ivo Welch, for his wisdom and guidance; and our six guest speakers for taking time out of their busy schedules to educate us on careers in asset management and the real-world application of quantitative strategies.

With UCLA's return to in-person instruction in fall 2021, ASAM held classes on campus for the first time since the start of the pandemic. This was a welcomed change, as we got to attend on-campus group dinners with our faculty advisor and host cohort happy hours again to build camaraderie among the Fellows. We also took advantage of remote flexibility to host some speakers virtually when their schedules did not permit on-campus visits. Despite global geopolitical instability and large market volatility during the holding period, the overall fund outperformed its benchmark with a return of –0.54%. After controlling for risk-adjusted factor exposures, however, the fund did not achieve any positive alpha. The details of our performance are discussed more in-depth in the "Fund Performance" section of the report.

Finally, participating in the ASAM program and serving the cohort as president has been an incredibly rewarding and memorable experience for me. I cannot thank the cohort enough for allowing me and the ASAM board to grow both personally and professionally with it over the last 12 months. My hope is subsequent cohorts continue to drive change within the program to make it an even better experience for those Fellows who will come after them. I look forward to staying connected to and involved with the Fellowship after my time at Anderson.

Best Regards,

Jonathan Andritsch
2022 ASAM President

FUND MANAGEMENT OVERVIEW

Purpose of Fund

The Anderson Student Asset Management (ASAM) Fund is a student-run, quantitatively driven investment fund that aims to:

1. Enhance the educational and professional development of the ASAM Fellows through experiential learning in strategy development and portfolio management

2. Preserve capital for future ASAM Fellows while providing favorable risk-adjusted returns

The ASAM Fund is designed to donate a portion of the fund's assets under management (AUM) and long-term profits to UCLA Anderson for student scholarships and research in finance.

Investment Philosophy

Investments are constrained to long only, liquid, domestic equities. Additionally, the Fellows adhere to stated investment policies established by the UCLA Anderson School of Management and the ASAM faculty advisor, Professor Ivo Welch.

The Fund seeks to achieve its objectives through a diversified portfolio of equity securities that fall within its constraints and meet the fundamental and technical specifications adopted and developed by student portfolio managers. The Fellows study academic and professional papers to decide on their strategy. Thus, the student portfolio managers leverage research and analytical capabilities within the ASAM class, the world-renowned Anderson finance faculty, other academic resources, and outside investment management professionals.

The student portfolio managers backtest the strategies to determine promising investments. When a strategy requires a position in other asset classes besides equities, student portfolio managers can also test and combine exchange-traded funds (ETFs) that track selected asset classes.

The ASAM Fund may hold stock or ETFs traded on U.S. exchanges subject to minimum liquidity thresholds. To minimize the idiosyncratic risk from holding large positions in individual securities, strategies hypothetically establish maximum position limits. Furthermore, the fund is highly diversified to mitigate risks associated with sector or industry concentration. Once a strategy has been vetted, backtested, approved, and executed, the Fellows study and attempt to create appropriate benchmarks by constructing factor portfolios that reflect the asset allocation decision of each individual strategy. This makes it possible to attribute alphas to the stock selection process.

FUND PERFORMANCE

The 2022 ASAM Fellows inherited four funds from the previous cohort: **Dual Momentum**, **Low Beta**, **Value, Momentum, Profitability (VMP)**, and **Pure Momentum**. These funds were held unchanged until December 2021. In the previous Annual Report, the Fund reported a total return of –8.6% during the holding period of January 15, 2021, to May 7, 2021.

In January 2022, the 2022 ASAM Fellows switched to three new trading strategies and one revised strategy. The four strategies inherited from the previous class — **Dual Momentum**, **Low Beta**, **VMP**, and **Pure Momentum** — were replaced by **High Dividend Yield**, **Neglected Beta**, **Low Beta**, and **Low Leverage & High Dividend**, respectively.

The combined ASAM Fund performance from portfolio inception from January 10 to May 6, 2022, was –0.54%. At the end of our tenure on May 6, 2022, the ASAM Fund outperformed its unadjusted benchmark by 1561 basis points and outperformed its beta-adjusted benchmark by 689 basis points. The Fund excess return of 6.89% is the difference between the portfolio return net of the risk-free rate and the Russell 2000's risk-adjusted return net of the risk-free rate from January 10, 2022, to May 6, 2022. The overall portfolio has an ex-post beta of 0.48, and the risk-free rate was calculated using the 1-year T-bill return of 0.62%, adjusted for the holding period. The Fund has an annualized Sharpe ratio of –0.2 (–1.1 for the holding period) compared to the annualized market Sharpe ratio of –1.6 (–9.7 for the holding period). The negative portfolio Sharpe ratios indicate the risk-free rate was greater than the portfolio's return and the portfolio's return is expected to remain negative.

ASAM PERFORMANCE SUMMARY

Date: 5/7/2022

ASAM Returns Summary	Inception Date: 1/10/2022			As of 5/7/2022		
Portfolio	**Security Value**	**Cash Value**	**Total Portfolio**	**Security Value**	**Cash Value**	**Total Portfolio**
ASAM	$ 1,264,260	$ 1,467	$ 1,265,728	$ 1,240,026	$ 16,179	$ 1,278,387
High Dividend Yield	$ 233,404	$ 1	$ 233,405	$ 241,479	$ 4,423	$ 259,053
Neglected Beta	$ 329,567	$ 102	$ 329,669	$ 275,632	$ 1,622	$ 288,611
Low Beta	$ 387,306	$ 1,361	$ 388,667	$ 378,057	$ 4,974	$ 376,517
Low Leverage & High Dividend	$ 313,983	$ 3	$ 313,986	$ 344,859	$ 5,160	$ 354,205

ASAM PERFORMANCE SUMMARY

Holding Period: 1/10/2022 to 5/6/2022

ASAM Returns Summary

Portfolio *Benchmark*	Return ex-cash	Return since Inception	Performance Compared to Benchmark	Beta (β)	$R_p - R_f$ vs $\beta(R_m - R_f)$	Risk Adjusted Excess Return $(R_p - R_f) - \beta(R_m - R_f)$
ASAM *Russell 2000*	−0.55%	−0.54% −16.15%	15.61%	0.48	−1.17% −8.05%	6.89%
High Dividend Yield *Russell 2000*	5.24%	5.12% −16.15%	21.27%	0.55	4.50% −9.23%	13.73%
Neglected Beta *Russell 2000*	−15.78%	−15.67% −16.15%	0.48%	0.95	−16.30% −15.93%	−0.36%
Low Beta *S&P 500*	−1.07%	−1.05% −11.71%	10.66%	0.19	−1.68% −2.34%	0.67%
Low Leverage & High Dividend *S&P 500*	11.99%	11.76% −11.71%	23.47%	0.33	11.13% −4.07%	15.2%

T-bill Return (1 year)	1.94%
T-bill Return (holding period)	0.62%

R_f	1-year T-bill, compounded by days
R_p	Portfolio Return
R_m	Benchmark Return (Russell 2000/S&P 500)
$R_m - R_f$	Market net of risk-free rate return
$(R_m - R_f)*\beta$	Market risk adjusted net of risk-free frate return
Portfolio Beta	0.48

Sharpe Ratio	ASAM	Russell 2000
Holding Period	−1.1	−9.7
Annualized	−0.2	−1.6

ASAM Performance Analysis and Attribution

A Fama-French five-factor regression analysis over the holding period from January 10, 2022, to April 29, 2022, quantified ASAM returns against factor exposures. Controlled for risk-adjusted exposures, the four combined strategies underperformed the Fama-French five-factor performance attribution benchmark by 130 basis points; however, the Fund outperformed against value and investment stocks.

ASAM PERFORMANCE ANALYSIS AND ATTRIBUTION

R	$Mkt - R_f$	SMB	HML	RMW	CMA	Net
Regression Output (β)	0.80	0.14	0.16	−0.09	0.51	
Factor Returns (f)	−12.3%	−2.3%	9.6%	0.3%	17.3%	
Return Contribution ($\beta*f$)	−9.9%	−0.3%	1.5%	−0.02%	8.8%	0.1%
$R_p - R_f$	−1.2%					
Alpha (α) [$(R_p - R_f) - $ Net]	−1.3%					

ASAM Top & Bottom Performers

The table below lists the top five and bottom five performers in the overall ASAM portfolio over the holding period. Excess return of individual equity was calculated as the difference between the equity return net of risk-free rate and the market risk adjusted return net of risk-free rate. Holding period betas were used as a measurement for equity risk and adjustment to the market benchmark. The market return is the return on the Russell 2000 index over the holding period.

Company	Ex-Post Beta (β)	Market Return (R_m)	$R_m - R_f$	β*($R_m - R_f$)	R_i	$R_i - R_f$	Excess Return ($R_i - R_f$) − β*($R_m - R_f$) (α)
LANTHEUS HOLDINGS INC.	1.42	−16.15%	−16.77%	−23.82%	143.27%	142.65%	166.47%
GRAN TIERRA ENERGY INC.	0.3	−16.15%	−16.77%	−5.03%	105.06%	104.44%	109.47%
TALOS ENERGY INC.	0.73	−16.15%	−16.77%	−12.24%	91.97%	91.35%	103.59%
EAGLE BULK SHIPPING INC.	0.38	−16.15%	−16.77%	−6.37%	52.59%	51.96%	58.34%
DEVON ENERGY CORPORATION	0.68	−16.15%	−16.77%	−11.41%	43.69%	43.07%	54.47%
…							
LIVEPERSON INC.	1.76	−16.15%	−16.77%	−29.52%	−43.20%	−43.83%	−14.30%
INVACARE CORPORATION	0.96	−16.15%	−16.77%	−16.10%	−44.81%	−45.44%	−29.34%
ALIGN TECHNOLOGY INC.	1.45	−16.15%	−16.77%	−24.32%	−48.92%	−49.54%	−25.22%
AMPLITUDE INC.	2.2	−16.15%	−16.77%	−36.90%	−62.13%	−62.76%	−25.86%
NEKTAR THERAPEUTICS	1.77	−16.15%	−16.77%	−29.69%	−65.31%	−65.93%	−36.25%

2022 ASAM INVESTMENT STRATEGIES

LOW LEVERAGE & HIGH DIVIDEND

Henry Ma, Sarah Russell, Lawrence Ham, Fame Sritrairatana, Alexa Kolodny

EXECUTIVE SUMMARY

Market Opening

Our strategy, Low Leverage & High Dividend, opened positions on January 10, 2022, with a beginning cash balance of $315,253. The performance of our portfolio from January 10, 2022, to April 29, 2022, was 9.3%, while our benchmark index (the S&P 500) returned –13.8% (over the same time period). The ending balance of our portfolio on April 29, 2022, was $332,176.

Team Goal

Low Leverage & High Dividend was based on the research paper "Leverage- and Cash-Based Tests of Risk and Reward with Improved Identification" by Ivo Welch (2018). This paper suggests that increased leverage lowers average rates of return, possibly because it increases risk without increasing average return. Combined with an increased cash dividend, returns can be improved.

IMPLEMENTATION

Our portfolio consists of the top 10 stocks for each year ranked by the weighted leverage ratio and dividend yield score.

In implementing our portfolio, we began by pulling CRSP and Compustat data and organizing market information to get an initial filter for the universe of securities in consideration. This was followed by ranking the data based on leverage ratios and dividend yield into quartiles. After weighting our ranked signals, we ran a time-series regression against various benchmarks to determine the alpha of our strategy.

Data Gathering

We began by pulling CRSP monthly data from 1980 to 2020 for holding period return, number of shares outstanding, and price. We used the following constraints to shape the data:

- Share code 10, 11, 12 for ordinary common shares
- Exchange code 1, 2, 3 to screen for the NYSE, NYSE MKT, and NASDAQ exchanges
- Dates: January 1, 1980, to December 31, 2020

In compiling the Compustat Annual Data, we used the following parameters:

- Dates: 1980 to 2020
- Total Assets
- Total Liabilities

- Cash
- Dividends per Share – Ex-Date Fiscal Year
- Annual Price Close Fiscal Year

Portfolio Construction

After gathering the data, we made several calculations to begin sorting the data. We calculated the market capitalization to create the lagged market cap variable by multiplying the absolute value of share price by the number of shares outstanding. Next, we calculated the compounded annual return from the CRSP monthly returns data by adding 1 to all monthly returns and multiplying them together for each year and subtracting 1 from the product. To filter the top 1,000 companies, we lagged the market capitalization by one year.

Next, we calculated the ratios for the signals used in our portfolio strategy. We calculated the leverage ratio by taking total assets / total liabilities and the dividend yield by taking fiscal year dividends per share / fiscal year closing price. We then lagged the data by one year for both the leverage ratio and dividend yield.

We then took the top 1000 companies lagged by market capitalization to use as the universe for our portfolio. We then normalized the lagged leverage ratio and lagged dividend yield by taking the signal for each company in time period *t* (mean of the signal for each time period *t* / standard deviation of the signal for time period *t*).

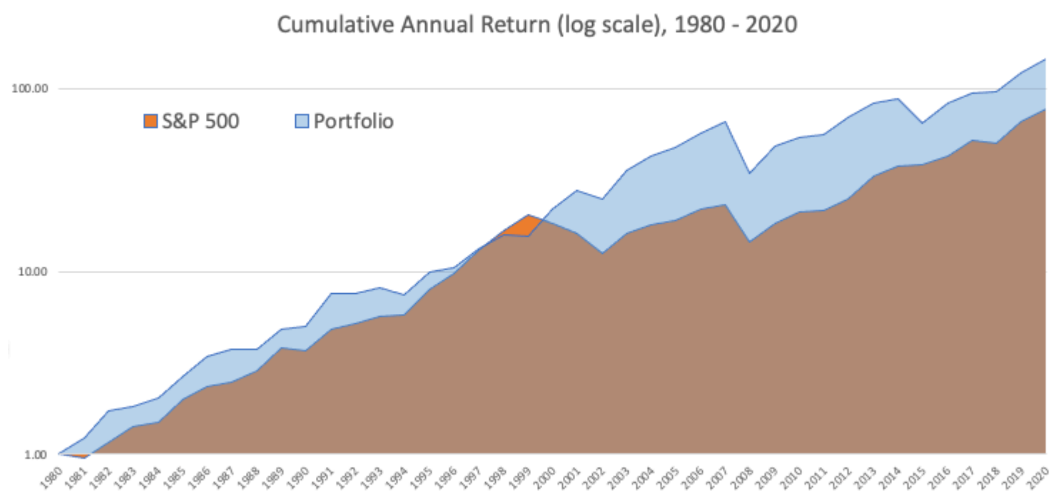
Finally, we created the weighted signal of the 50% normalized lagged leverage ratio * –1 (as we wanted low leverage stocks) + 50% normalized lagged dividend yield. We ranked by the weighted signal for each year, 1 being the security with the highest weighted signal (high dividend, low leverage). We equal weighted the top 10 stocks from each year to form the portfolio and ran the Fama-French regression.

BACKTEST PERFORMANCE

We backtested our portfolio against the S&P 500, CAPM, Fama-French three-factor model, and Fama-French five-factor model from January 1, 1980, to December 31, 2020.

Cumulative Return vs. S&P 500

The following graph shows our backtested portfolio's cumulative return for the past 40 years, from 1980 to 2020, against the S&P 500's. Our cumulative returns are consistently higher than the S&P 500, except for the period between 1997 and 2000, which coincides with the dot-com bubble.



CAPM (One-Factor Model) Analysis

When benchmarked against the CAPM factor model, our portfolio had an alpha of 4% per annum and a beta of 0.71. We suspect that our portfolio has a lower-than-average market beta, as our holdings are comprised of dividend-paying low-leverage firms, which are more established and less sensitive to market changes.

CAPM Regression – Annual Returns, 1980-2020		
	Coefficient	**T-stat**
Alpha	4% per annum	1.87
Mkt-R_F	0.71	

Fama-French Three-Factor Model Analysis

When benchmarked against the Fama-French three-factor model, our portfolio generated a slightly lower alpha of 3%. Our excess return was captured by the additional value factor with a coefficient of 0.43. This aligns with our portfolio selection, which focuses on value stocks rather than growth stocks.

Fama-French Three-Factor Model Regression – Annual Returns, 1980-2020		
	Coefficient	**T-stat**
Alpha	3% per annum	1.29
Mkt-R_F	0.82	
SMB	0.08	0.31
HML	0.43	2.59

Fama-French Five-Factor Model Analysis

The five-factor model adds two additional variables: RMW (robust minus weak profits) and CMA (conservative minus aggressive investments). In the Fama-French five-factor model analysis, we generated a –1% alpha, as our exposures shift toward the RMW and CMA factor risk premiums. Since profitable companies with healthy cash flows are more likely to pay out dividends, our portfolio has some exposure to RMW. Our second-highest coefficient is attributed to the CMA factor (0.67). While the CMA factor does not directly measure a company's leverage, low-leverage stocks could have a higher sensitivity to this risk premium due to conservative financial investment decisions.

Fama-French Five-Factor Model Regression – Annual Returns, 1980-2020		
	Coefficient	**T-stat**
Alpha	–1% per annum	–0.32
Mkt-R_F	0.97	5.58
SMB	0.18	0.71
HML	0.05	0.18
RMW	0.31	0.99
CMA	0.67	1.70

PORTFOLIO CONSTRUCTION

In constructing our portfolio, we created the weighted signal of the 50% normalized lagged leverage ratio * –1 (as we wanted low-leverage stocks) + 50% normalized lagged dividend yield. We sorted our universe of stocks for each year by the following:

1. We assigned a weighted leverage ratio and dividend yield score.

2. We ranked stocks into four separate quartiles, with 1 as the security with the highest-weighted signal (high dividend, low leverage).

Based on these rankings, we selected the top 11 stocks to form our portfolio. Our portfolio's holdings and values for all positions are listed from the inception date of January 10, 2022, until May 6, 2022. Performance metrics are reported for the same holding period.

Portfolio					
	Ticker	**Name**	**Inception Value***	**Current Value****	**Percentage Change**
1	PBA	Pembina Pipeline Corporation	$28,842	$35,238	22.2%
2	XOM	Exxon Mobil Corporation	$28,261	$35,187	24.5%
3	OKE	ONEOK Inc.	$29,832	$31,084	4.2%
4	LUMN	Lumen Technologies Inc.	$28,236	$20,810	–26.3%
5	KMI	Kinder Morgan Inc.	$28,286	$29,454	4.1%
6	ENB	Enbridge Inc.	$29,232	$31,313	7.1%
7	WMB	The Williams Companies Inc.	$28,930	$35,492	22.7%
8	CNA	CNA Financial Corporation	$28,231	$28,709	1.7%
9	CVX	Chevron Corporation	$28,270	$35,401	25.2%
10	COTY	Coty Inc.	$28,844	$24,676	–14.5%
11	KHC	The Kraft Heinz Company	$28,290	$32,281	14.1%
Total			**$315,254**	**$344,859**	**7.7%**

* As of January 10, 2022
** As of April 29, 2022

Our portfolio consists of 10 large cap securities with market capitalizations over $10 billion and one security with a market capitalization between $2 billion and $10 billion.

Equity Capitalization	
Category	**Weight**
Large cap	90.9%
Mid-cap	9.1%

Sector Allocation

Our largest sector allocation was energy, followed by consumer goods, communication services, and financial services.

ACTUAL PERFORMANCE

For the 16-week holding period, we benchmarked our portfolio against the S&P 500 given the large cap exposure of our portfolio. Our portfolio outperformed the index with a total holding period return of 9.3% (7.7% + 1.6% dividend yield) compared to the S&P loss during the same period of –13.8%.

The energy sector represents 64% of our holdings and accounts for 89.1% of our overall positive returns. Energy had the highest year-to-date sector return, at 53.9%,[1] while our energy equities generated a holding period return of 15.6%. Dividends accounted for 17.2% of our returns, and, specifically, our energy sector dividends accounted for 78.9% of our dividend yield.

The sectors that underperformed in our portfolio were communication services and consumer goods, which generated holding period losses of –26.3% and –0.3%, respectively.

PERFORMANCE ATTRIBUTION

We ran a regression against our daily returns for this holding period against the Fama-French five-factor model, indicating a significant exposure to the investment factor, suggesting that our portfolio companies resemble those with conservative investment approaches, which mirrors low-leverage companies. While a Fama-French four-factor regression without the investment factor yielded an alpha of 7.3%, our large exposure to the investment factor eroded our alpha to –0.2% in a five-factor regression. The five-factor regression also attributes moderate exposure to the value factor.

	Regression Output	Factor Returns	Return Contribution
Alpha*			–0.2%
Mkt – R_F	0.83	–12.5%	–10.4%
HML	0.01	–2.6%	0%
CMA	0.37	9.3%	3.4%
SMB	–0.47	0.2%	–0.1%
CMA	0.90	16.8%	15.1%

* Holding period: January 10, 2022, to April 29, 2022

In adjusting for our risk — or return standard deviation — of 18.1%, our portfolio produced an annualized Sharpe ratio of 1.28 on a risk-free rate of 0.35%.

---

[1] Fidelity. (2022, May 25). *Sectors & Industries – Performance*. https://eresearch.fidelity.com/eresearch/markets_sectors/sectors/si_performance.jhtml?tab=siperformance

SUGGESTIONS

Additional research and backtesting should be explored to determine if other signals or variables could improve our results. Some suggestions for improvements are as follows:

1. *Refinements to the Leverage and Dividend Signals*

Further research could be implemented to test whether *different* (not additional) leverage and dividend signals are better predictors of higher returns. For example, Welch 2018 studies the impact that changes in leverage have on U.S. stock returns rather than the leverage ratios themselves. Other leverage signals include, but are not limited to, operating financial leverage, cash flow leverage, debt-to-equity ratios, and total-debt-to-enterprise-value ratios. Other dividend signals include dividend payout ratios, dividend per share, and dividend growth rate. It is important to note that testing overcomplicated signals, or signals that are not widely available to the public, can hinder the identification process and devalue the strategy's findings.

2. *Testing Other Factor Signals*

An additional screen of signals from the profitability (RMW) or investment (CMA) factors can be implemented to determine if other variables explain stock return performance. A low-leverage, high-dividend strategy could suggest that companies with high stable cash flows yield a higher premium. Signals that indicate robust earnings include gross profitability and cash flow margin ratio. As discussed in earlier sections, signals from the investment factor align with the philosophy of our low-leverage, high-dividend strategy. Conservative investment signals to be tested include the reinvestment rate of a company, asset growth rate (such as current and fixed assets), and CAPEX ratios.

Our strategy generates a positive alpha when backtested against the Fama-French three-factor model but fails when backtested against the Fama-French five-factor model. While this is expected based on our investment strategy, it would be valuable to explore other signals that can outperform the five-factor model. However, additional signals may overcomplicate the strategy and be unable to generate any meaningful excess returns.

3. *Sector Allocation*

We did not place constraints on sector exposure. This led to a heavily weighted portfolio of oil and gas stocks. We recommend performing additional backtests to determine if this strategy would be successful with equally weighted sectors. This includes backtesting individual sectors to determine if the strategy results are ubiquitous or just limited to certain industries. While portfolio diversification could result in slightly lower returns, it can be a more prudent investment choice if it yields a higher Sharpe ratio.

2022 ASAM INVESTMENT STRATEGIES

NEGLECTED BETA

Blake Anderson, Nathan Jensen, Greg Steinbrecher, Amy Tran, Ceecee Wang

EXECUTIVE SUMMARY

Our Neglected Beta strategy opened positions on January 10, 2022, with a beginning cash balance of $337,000. For comparative purposes with the remaining Anderson Student Asset Management (ASAM) group strategies, we measure performance of the Neglected Beta strategy from January 10, 2022, through May 6, 2022. During this four-month period, our strategy produced a total return of –15.7% versus –16.2% for the Russell 2000 and –11.7% for the S&P 500. The ending balance of our portfolio on May 6, 2022, was $277,894.73.

Our team's goal was to implement a neglected beta strategy based on two academic literatures. We took a position by limiting the returns based on both the minimum and maximum coefficient slopes, which eliminated the outliers and confined the returns. The actual performance of our portfolio was negatively impacted by and significantly underperformed due to the current economic and political environment.

ACADEMIC INSPIRATION

We reviewed one research papers and used a textbook.

Ang's "Asset Management: A Systematic Approach to Factor Investing" provided a high-level introduction to beta and low-volatility anomalies. He explained certain ways of measuring beta are better than others, such as estimating betas from options or with valuation information. While Professor Welch suggested that some of Ang's conclusions about the difficulty of predicting betas were outdated, Ang did at least pique our curiosity about the importance of quality beta measurements.

Welch's "Simpler Better Market Betas" offered a robust measurement of beta that predicts future betas better than other such estimators. It is based on a "slope winsorized" beta, which deems stock returns outside of certain bounds to be "uninformative outliers." Using one to three years' worth of daily stock returns, he winsorizes each return and then runs a standard OLS regression on those winsorized returns. His sample period was 1926 to 2019 and included the biggest 1,000 and 3,000 stocks that had at least 126 returns in the calendar year from the early 2020 CRSP database. The slope-winsorized betas were 30% better at forecasting actual future OLS betas than the Bloomberg beta, 8-10% better than the OLS beta, and 4-5% better than the Vascike beta.

IMPLEMENTATION

The steps in forming our neglected beta formation are below.

1. ***Calculate OLS Beta.*** We initially calculate the betas for all stocks.

$$\beta_p = \frac{Cov(r_p, r_b)}{Var(r_b)}$$

2. ***Calculate Winsorized Beta.*** We limit returns based on minimal and maximum coefficient slopes. This eliminates the outliers and confines the returns based on the winsorization parameter, which was set to 3.0.

$$\mathrm{rsw}_{i,d} \in \left(1.0 + [-\Delta, +\Delta]\right) \cdot \mathrm{r}_{m,d} ,$$

We calculate the winsorized beta for each stock.

$$\mathrm{bsw}_{i,y} \equiv \frac{\mathrm{cov}[\ \mathrm{rbsw}_{i,d}(\Delta)\ ,\ \mathrm{r}_{m,d}\ ]}{\mathrm{var}(\ \mathrm{r}_{m,d}\ )}$$

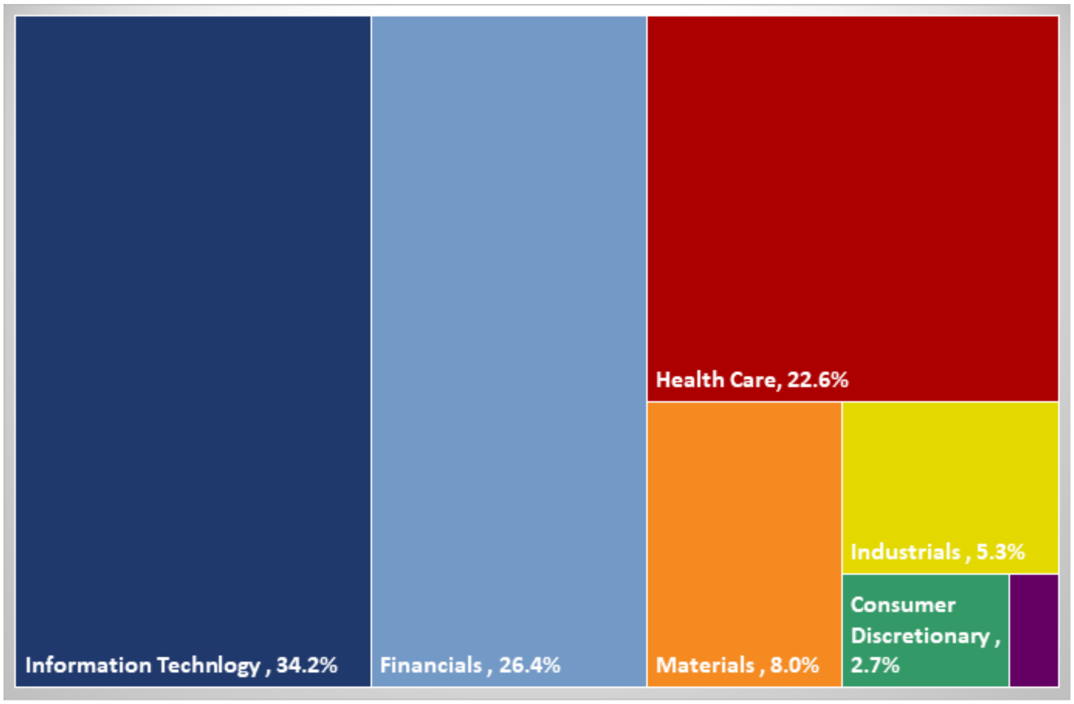
3. ***Create a "Neglected Beta" Flag.*** We pare down the stocks to those only with OLS Beta – Winsorized Beta <1. The goal is to identify stocks that were over time historical outliers of high betas. We also create a new flag for stocks that met that "Neglected Beta" criteria over 50% of the years.

	permno	jdate	month	year	mktSD	covmktstock	win_beta	normal_beta	beta_delta	better_beta_flag
0	10001	2011-12-31	12	2011	0.015311	0.000047	0.198816	0.191367	-0.007449	0
1	10001	2012-12-31	12	2012	0.008042	0.000011	0.168342	0.177603	0.009261	1
2	10001	2014-12-31	12	2014	0.007163	0.000010	0.195414	0.214663	0.019250	1
3	10001	2016-12-31	12	2016	0.008193	0.000009	0.130659	0.233114	0.102455	1
4	10002	2002-12-31	12	2002	0.019160	0.000068	0.185383	0.150805	-0.034578	0

In this example permno 10001 would be flagged since it had over 50% of the years that met the criteria

4. ***Sort the "Neglected Beta" by largest signed difference between OLS Beta and Winsorized Beta.*** We use the top 20% of stocks that show the greatest signed difference.

WEIGHTING



Our portfolio was heavily weighted in information technology, financials, and health care at 34.2%, 25.4%, and 22.6%, respectively. The above chart represents the sector weighting; however, when looking at the top companies in our portfolio, the table below shows that majority of our portfolio holdings are in two stocks: Citigroup and ServiceNow.

Company Name	Ticker	Industry	$ Value	% Weight
Citigroup	C	Financials	72,565	21.5%
Service Now	NOW	Information Technlogy	61,380	18.2%
Align Technology	ALGN	Health Care	25,200	7.5%
Cadence Design Systems	CDNS	Information Technlogy	24,246	7.2%
Dow	DOW	Materials	23,386	6.9%

We decided to use a value-weighted method as it performed slightly better than the equal weighted portfolio.

BACKTEST PERFORMANCE

Below are the backtested results of our Neglected Beta strategy. We looked at data going back to 1990. We felt that 30 years was adequate. For the Fama-Macbeth regression, we had an average annual slope coefficient of 0.04, which came with a T-stat of 2.23. This result showed some promise with the signal and led us to build a strategy around the top quintile of companies that fit our neglected beta criteria.

<u>Fama-Macbeth Results (Annual: 12/1990 – 12/2020)</u>

Description	Results
Mean (%/yr)	0.04
Std. Error	0.04
T-Stat	2.23
N	30

We then ran our portfolio through the CAPM, Fama-French three-factor, and Fama-French five-factor models. Our alphas were directionally encouraging for all benchmark models. The abnormal performance not explained by these models was about 0.04% per year. As for factor exposures, the strategy had greater exposure to the market premium with betas above 1 and a negative coefficient to the HML factor indicating a growth tilt. The SMB exposure was positive in the three-factor model and turned negative when run through the five-factor model. The portfolio had negative exposure to the RMW factor, indicating more exposure to less profitable companies and positive exposure to the CMA factor, indicating more exposure to companies that invest conservatively.

<u>CAPM and Fama-French Results (Annual: 12/1990 – 12/2020)</u>

Description	CAPM	FF3	FF5
Annual Alpha (%/yr)	0.02	0.04	0.05
T-Stat	1.03	2.04	2.40
Mkt – R_F	1.31	1.39	1.05
SMB		0.25	-0.23
HML		-1.60	-1.33
RMW			-2.47
CMA			0.15

ACTUAL PERFORMANCE

Our Neglected Beta portfolio launched on January 10 with $337,000 of initial capital. Below is a summary of our top 10 holdings at inception. The strategy was quite concentrated, with Citigroup and ServiceNow totaling 39.5% of the portfolio. The top 10 names in our strategy represent roughly 80% of the portfolio's assets. Going forward, we would recommend implementing caps on individual weights and sectors.

Inception Weights as of January 10

	Name	Ticker	GICS Sector	Inception Weights	OLS Beta	Win. Beta
1)	Citigroup Inc.	C	Financials	21.5%	1.56	1.54
2)	ServiceNow Inc.	NOW	Information Technology	18.0%	1.61	1.49
3)	Align Technology Inc.	ALGN	Health Care	7.1%	1.64	1.48
4)	Dow Inc	DOW	Materials	6.9%	1.52	1.48
5)	Cadence Design Systems Inc.	CDNS	Information Technology	6.4%	1.54	1.50
6)	Veeva Systems Inc.	VEEV	Health Care	6.2%	1.56	1.49
7)	AstraZeneca PLC	AZN	Health Care	5.8%	1.53	1.47
8)	Zendesk Inc.	ZEN	Information Technology	2.8%	1.57	1.47
9)	VMware Inc.	VMW	Information Technology	2.6%	1.53	1.47
10)	Five9 Inc.	FIVN	Information Technology	1.9%	1.49	1.47

The OLS and Win. Beta columns show the effects of our strategy. For example, the delta for ServiceNow was (1.61 – 1.49 = 1.01) almost 500x the average. Due to the historical flag, the deltas are a mix of the average (e.g., Citigroup) and the extreme (e.g., ServiceNow). If we had only used the prior year, then stocks like ServiceNow and Align (aka the extreme) would have stayed in the portfolio, and the weaker deltas would've been replaced.

As for performance, our strategy produced a return of –15.70% through May 6. Although this is disappointing, we are still pleased to have outperformed the Russell 2000 Index by 45 bps.

Actual Return (January 10 – May 6)

	Total Return
Neglected Beta	–15.7%
Russell 2000	–16.2%
S&P 500	–11.7%

To help explain why our strategy performed the way it did, we looked back at the performance of the top five companies in our portfolio. The key takeaway is that, apart from Dow Inc., we've been overweight on stocks that have performed poorly. That said, Citigroup bounced back since May 6 and posted a positive 7% return for the month of May (through May 28).

Performance of Top Five Weighted Holdings (January 10 – May 6)

Name	Ticker	Weight	Performance
Citigroup Inc.	C	21.5%	–21.8%
ServiceNow Inc.	NOW	18.0%	–20.2%
Align Technology Inc.	ALGN	7.1%	–48.9%
Dow Inc.	DOW	6.9%	16.3%
Cadence Design System Inc.	CDNS	6.4%	–11.8%

To get a better picture of why our strategy produced a negative return, we've included a breakdown below showing the GICS sector exposure in our portfolio sorted from largest weight to the smallest weight. Our largest sectors posted negative returns, and our smallest sector exposure (energy) produced a significantly positive return.

Sector Performance (January 1 – April 30)

Sector	Sector Performance	Portfolio Weight
Information Technology	–18.9%	31.2%
Financials	–11.7%	27.8%
Health Care	–7.6%	19.5%
Materials	–6.3%	11.6%
Industrials	–10.1%	5.6%
Consumer Discretionary	–21.0%	3.6%
Media	–26.0%	0.5%
Energy	35.4%	0.3%

Next, we regressed the excess daily returns of our portfolio across some Vanguard factors to create an attribution.

Performance Attribution (January 10 – May 7)

r	Mkt-Rf	VV-VBR	VTV-VUG	VIG-VOO	Net
b	0.89	–0.47	–0.36	0.20	
f	-10.1%	-0.1%	19.4%	3.5%	
b*f	-9.0%	0.0%	-7.0%	0.7%	-15.2%

Rp - Rf	-15.7%
Alpha	-0.5%

Our Neglected Beta portfolio followed the market closely because the largest deltas occurred for the highest OLS betas. This is due to our criterion that the winsorized beta is less than beta more than 50% of the time, after which we select the portfolio of the highest signed difference quantile. The portfolio was moderately tilted toward size and value factors and weakly tilted towards the dividend yield factor. Unfortunately, the market performed poorly, and that drove over half of the poor performance. Also, the portfolio was on the wrong side of the value factor, contributing the other half of poor performance.

We also did an industry attribution of our portfolio using Vanguard industry ETFs. VGT, VFH, and VHT represents the tech, financial, and health sectors. We chose these ETFs since they correspond with our portfolio's biggest sector weights.

Industry Performance Attribution (January 10 – May 7)

r	Mkt-Rf	VGT-Rf	VFH-Rf	VHT-Rf	Net
b	–0.52	0.80	0.46	0.11	
f	–10.1%	–17.1%	–15.8%	–4.5%	
b*f	5.3%	–13.7%	–7.3%	–0.5%	–16.1%

In this attribution, the market was a positive, and our exposure to tech and financials outweighed any positive returns. This attribution gave our portfolio an alpha of 0.4%, indicating that our "alpha" is more likely to be due to noise, since the previous attribution was –0.5%.

SUGGESTIONS

We have three thoughts on future changes after reviewing the last few months of our portfolio performance:

1. *Placing an emphasis on more recent year's neglected beta:* Our current portfolio methodology promoted a red flag whenever more than half of the portfolio contained neglected data. We believe that by including more recent years' neglected beta, our portfolio would be better balanced, and recent years' economic landscape would also be better captured in our portfolio

2. *Constricting portfolio weights:* As stated previously, our portfolio was heavily weighted with two stocks: Citigroup (21.5%) and ServiceNow (18.0%). The cumulation of these two stocks made up ~40% of our portfolio, and as both these sectors did not perform well since inception, our portfolio was greatly impacted negatively. We would like to limit per-stock weight in our portfolio so that instances like this would not occur

3. *Using age decay:* As stated in "Simpler Better Market Betas" (Welch, 2020), slope-winsorized betas can be better improved by decaying the weight of each observation with age, and each day receives a weight higher than its preceding day. We believe that this would help our portfolio become more balanced and economically sound.

APPENDIX

Alternatives Considered

We initially considered whether replace or supplement our low-beta strategy with a low-volatility strategy. According to Ang's book, the cumulative returns of the VOL factor are larger than BAB, the Sharpe ratio is higher, and the alpha is more statistically significant. We decided to focus purely on the performance of a Neglected Beta portfolio without any added signals, but adding the VOL factor could be an interesting topic for future inquiry.

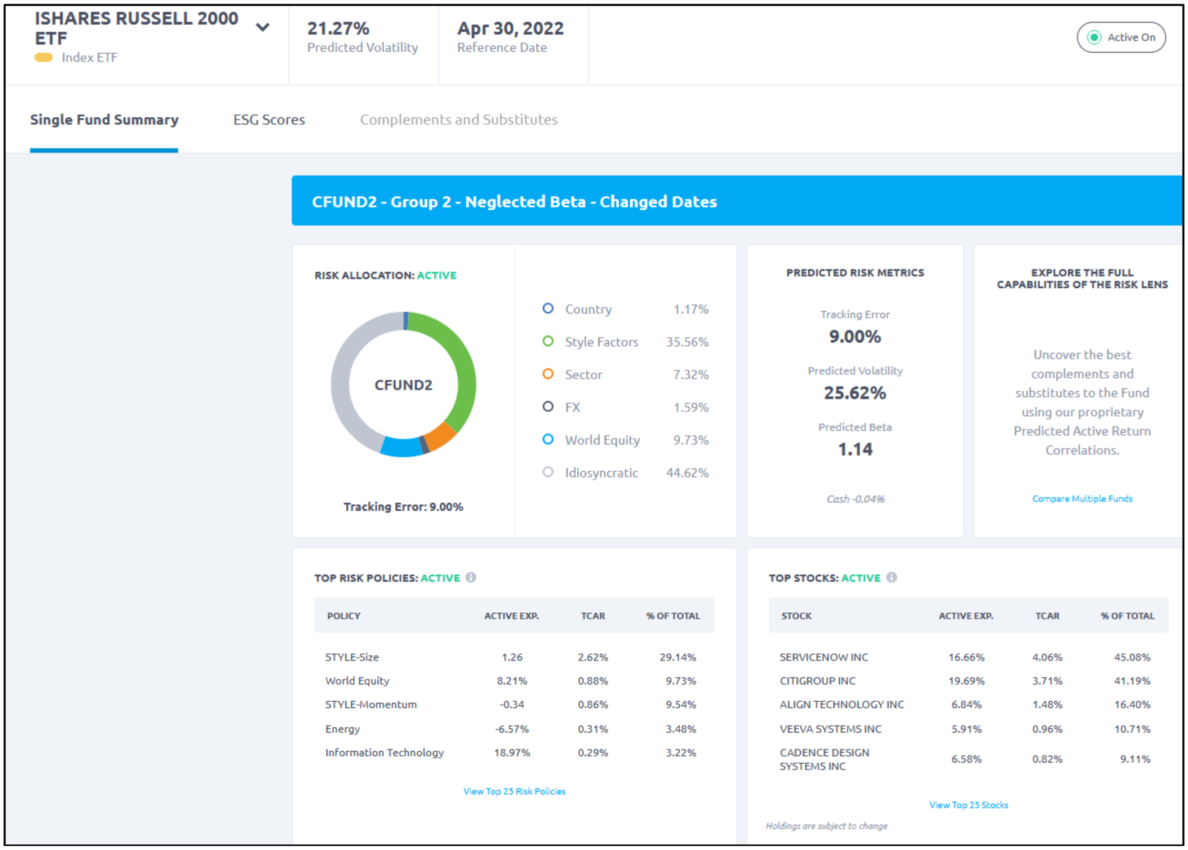
Another idea we considered was whether to pursue a high-beta strategy using the slope-winsorized betas. With better beta data, perhaps some of the attendant problems that lead to the success of a low-beta strategy would be mitigated, and the reward/risk payoff would be higher. But a line in the appendix of Welch's paper dissuaded us: "The relationship between estimates and all beta estimators and future average rates of return was generally negative but insignificant and unreliable."

Lastly, we considered a BAB strategy using sector caps. We decided not to institute such caps for similar reasons as introducing the VOL factor (we were more interested in the performance of Neglected Beta on its own), but sector caps might also be an avenue worth exploring for future groups.

Risk Lens

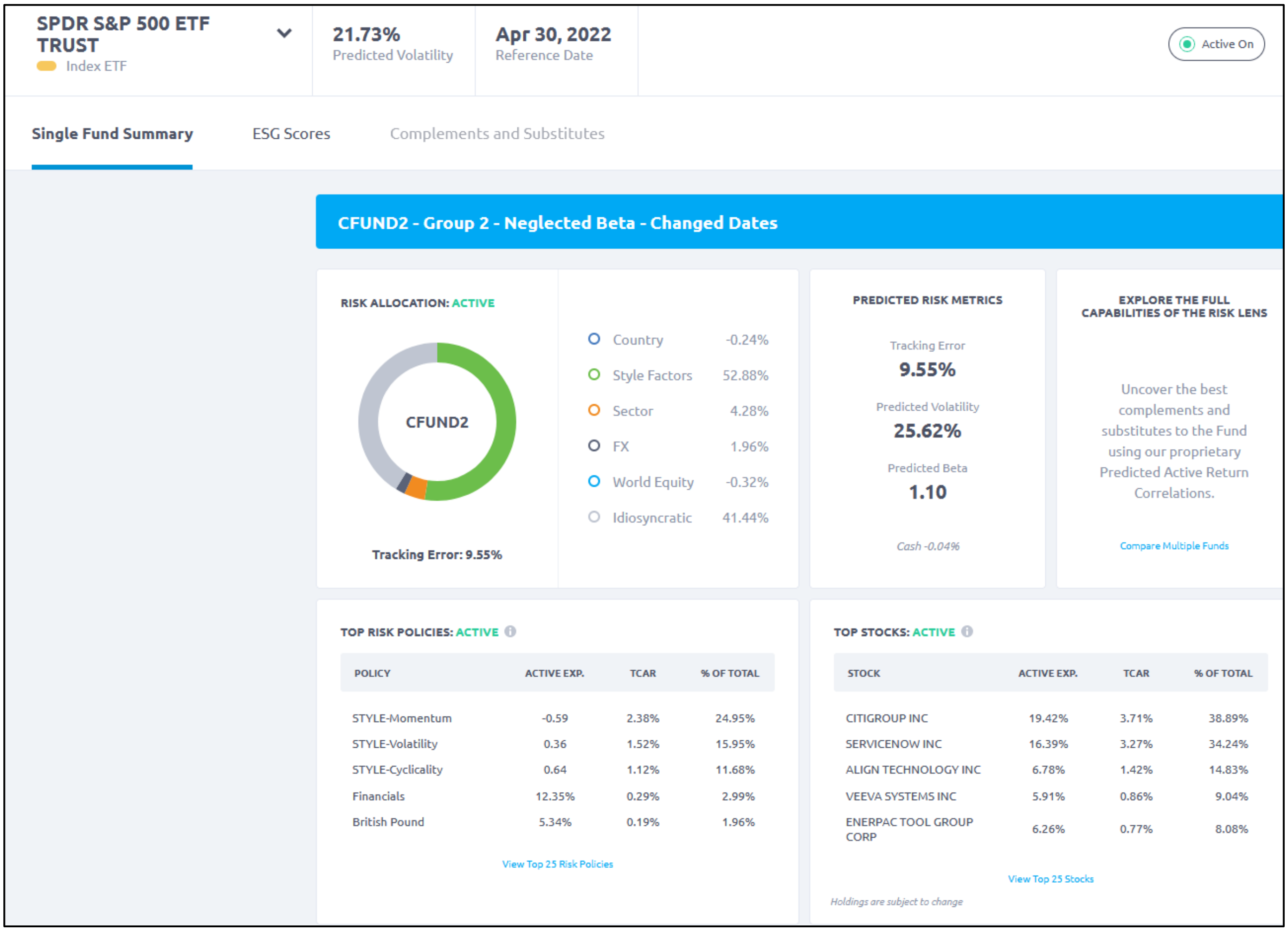
We utilized Causeway Capital's Risk Lens, a tool they claim allows the user to "make a variety of risk predictions and disaggregate portfolio risks across idiosyncratic and systematic factor groups." The output helped explain some of fund's performance. We utilized two benchmarks: the Russell 2000 and the S&P 500.

Russell 2000



With the Russell 2000 as our benchmark and a reference date of April 30, 2022, our fund's tracking error is 9% and its volatility is 25.62%, for an information ratio of 0.35. Our fund has a beta of 1.14, higher than that obtained from the five-factor Fama-French model, but lower than the CAPM and three-factor Fama-French model from our attribution. According to this measure, most of our risk allocation comes from the size factor, with a significant portion coming from world equities, a negative loading of MOM, as well as the energy and information technology sectors. The beta results reinforces that our portfolio did not produce a low-beta strategy. Instead, it is slightly more volatile than the market. Furthermore, according to this Risk Lens, we are heavily loaded on the size factor, and small stocks are getting punished this year. It is worth noting that this result is incongruous with our performance attribution, which suggests a loading of the size factor in the other direction. This is likely due to the proprietary assumptions of Causeway's Risk Lens.

S&P 500



Using the S&P 500 as our benchmark gives us results that are similar in some ways but strikingly different in others. The tracking error is slightly elevated, so our information ratio increases to 0.37. Our fund’s beta decreases very slightly to 1.10. The SMB factor does not show up in our risk policies; instead, a negative loading of momentum and positive loadings of volatility and cyclicality make up the bulk of our risk allocation. The latter two would be more surprising if we had not already seen that our fund acted less like a low-beta portfolio than we would have expected. Instead, our fund closely matches the market.

REFERENCES

Ang, Andrew. Asset Management: A Systematic Approach to Factor Investing. New York, NY: Oxford University Press, 2014.

Welch, I. 2020. Simpler Better Market Betas. https://ssrn.com/abstract=3371240

2022 ASAM INVESTMENT STRATEGIES

LOW BETA

Jonathan Andritsch, Brady Huang, Ahmed Khan, Rebecca Phuong, Sandy Wu

EXECUTIVE SUMMARY

Our low-beta strategy incepted on Monday, January 10, 2022, with an initial value of $385,874.56. For benchmarking purposes with the remaining other Anderson Student Asset Management (ASAM) strategies, we measured our performance from January 10, 2022, through May 6, 2022. During this four-month holding period, our strategy produced a total return of –1.06% and an ending value of $381,797.28, compared to a –11.71% return for the S&P 500.

The low-beta strategy is based on academic literature about the anomalous performance of low-beta equities. Backtesting suggested that a long-only portfolio of low-beta stocks could achieve comparable (or higher) returns as a portfolio of higher-beta equities. This goes against the traditional theory that high-beta stocks should have higher average rates of return, as suggested by models such as the Capital Asset Pricing Model (CAPM).

ACADEMIC INSPIRATION

Korn and Kuntz's "Low-Beta Strategies" (2016) and Welch's "Simply Better Market Betas" (2021) formed the basis for our strategy.

Korn and Kuntz analyze various low-beta trading strategies. The paper explores risk-return characteristics of the portfolios and their sensitivities to risk factors.

Korn and Kuntz define low-beta strategies as zero-cost strategies with zero ex-ante market exposure that are long in low-beta stocks and short in high-beta stocks. They achieve these zero ex-ante market exposures by using the following conditions to define a low-beta strategy:

$$Condition\ (i){:}\ \ X_L \geq 0\ \&\ X_H \leq 0, with\ at\ least\ one\ of\ these\ being\ a\ strict\ inequality$$

$$Condition\ (ii){:}\ \ X_L\beta_L + X_H\beta_H + X_M = 0$$

$$Condition\ (iii){:}\ \ X_L + X_H + X_M + X_R = 0$$

$$Condition\ (iv){:}\ \left|X_{L,i}\right| + \left|X_{H,i}\right| = \left|X_{L,j}\right| + \left|X_{H,j}\right| = 0;\ i\ \&\ j\ indicate\ different\ low\ beta\ strategies$$

$$\begin{aligned} X_L &= amount\ invested\ in\ low\ beta\ portfolio \\ \beta_L &= beta\ of\ low\ beta\ portfolio \\ X_H &= amount\ invested\ in\ high\ beta\ portfolio \\ \beta_H &= beta\ of\ high\ beta\ portfolio \\ X_M &= amount\ invested\ in\ the\ market\ portfolio \\ X_R &= amount\ invested\ in\ the\ risk\ free\ asset \end{aligned}$$

Focused on the U.S. market, the authors test four different strategies, and they examine equal weighting, value weighting, and beta weighting the portfolios of those four strategies. They use S&P 1500 stocks and the S&P 500 stocks as the investment universes and daily equity data from December 1991 to April 2016, and they calculate factor returns to match the monthly and annual holding periods.

Their empirical results show that the low-beta strategy is productive only in a larger stock universe, such as the S&P 1500 Index. The equity weightings within the long and short legs have the greatest impact on a portfolio generating above-average returns. Korn and Kuntz also find using a shorter period to estimate an equity's beta (one month versus 12 months) results in higher average returns, with annual portfolio rebalancing being sufficient to generate those returns.

In the smaller S&P 500 Index stock universe, the authors observe no significant alphas but emphasize that portfolio return characteristics strongly depend on the design elements. Strategies that over-weight the long investment position (low-beta stocks) deliver higher average returns, and they are sensitive to the value factor. Comparatively, strategies that over-weight the short investment position (high-beta stocks) have no value exposure but maintain a higher size exposure.

Welch's "Simply Better Market Betas" (2021) introduces a different, and arguably more accurate, beta estimator. This new estimator uses daily stock returns, but it winsorizes their variance with respect to the market's daily return. Winsorization entails limiting the range of daily stock returns to within suggested multiples of −2 to +4 the market's return. This range limitation attenuates the impact of daily return outliers, thereby increasing the predictive accuracy of the beta estimator calculated. Using Welch's example beta calculation for any stock with daily return rd, its slope-winsorized r_{SW} is defined as:

$$r_{sw} = r \quad \text{for } -2 \cdot r_m \leq r_d \leq 4 \cdot r_m$$

and

$$r_{sw} = (1.0 + [-3, 3]) \cdot r_m \text{ otherwise.}$$

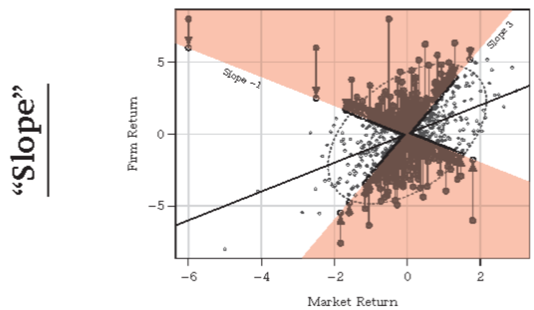
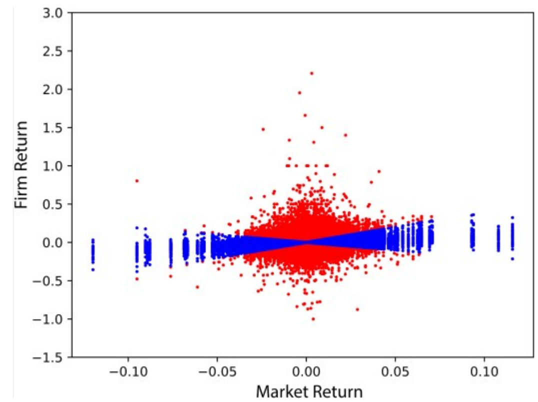
For example:

$$r_{sw}: E(1 + [-3, +3]) \times 5\%$$

$$r_{sw}: E(-2, +4) \times 5\%$$

$$r_{sw}: -10\% \;\&\; 20\% \; return \; boundaries$$

The resultant calculation re-maps relative returns, which appears as follows when plotted for a given security (Welch, 2021):

	
Slope winsorization of market returns, remapping the outlying relative multiples of stock return vs. market return to a preset limit (Welch, 2021).	Sub-sample of slope winsorized returns (r_{sw}, in blue) as a function of market returns (x-axis). Original returns plotted in red.

The slope-winsorized returns (r_{SW}) of each security are then used as an input to a traditional Ordinary Least Squares β calculation to determine β_{sw}:

$$\beta_{sw} = \frac{\mathrm{cov}[\mathrm{r}_{sw}, \mathrm{r}_m]}{\mathrm{var}(\mathrm{r}_m)}$$

The slope-winsorized beta estimator outperformed other beta estimators for the top 1,000 and 3,000 stocks and full CRSP universe (Welch, 2021). Because of its improved performance over the traditional beta estimator, we used winsorized betas when implementing our strategy.

IMPLEMENTATION

We used daily CRSP data from 2000 to 2021 to obtain each security’s daily returns, slope winsorized beta, market capitalization, and subsequent returns. For backtesting, we ranked securities annually from highest to lowest trailing 12-month winsorized betas. We used only the bottom 10% of securities, as ranked by their winsorized beta estimators. We then normalized the rank order of the beta estimators by subtracting them from one and subsequently multiplied these normalized estimators by a given security’s market capitalization. This gave us our market-capitalization-weighted low-beta signal. For our risk-free rate in backtesting, we used the 12-month Treasury Bill.

To verify calculation accuracy to replicate our portfolio, the following table illustrates example calculations using sample data from our portfolio in 2020:

Example Fama-Macbeth Signal Calculation
(Sample Year: 2020)

COMPANY NAME	TICKER	12-MONTH TRAILING WINSORIZED BETA (β_{sw})	12-MONTH TRAILING MCAP WGHT	SIGNAL ([$1-\beta_{sw}$] x MCAP WGHT)	ANNUAL RETURN (*R*)
VERIZON COMMUNICATIONS INC.	VZ	0.38	14.69%	9.11%	—0.12%
MCDONALD'S CORP.	MCD	0.42	8.61%	4.99%	11.32%
NEXTERA ENERGY INC.	NEE	0.18	6.84%	5.61%	30.08%
CME GROUP INC.	CME	0.41	4.15%	2.45%	—6.33%
DOMINION ENERGY INC.	D	0.31	3.94%	2.72%	—5.28%

BACKTEST PERFORMANCE

We backtested both the bottom 2% and bottom 10% of equities as ranked by their trailing 12-month winsorized beta estimators. We compared equal, β_{sw}, and market capitalization weightings of our trailing 12-month beta estimators. We backtested a β_{sw} weighting because of a suggestion from the 2021 ASAM Low Beta strategy group's paper. The market capitalization weightings for the bottom 2% and bottom 10% ranked beta securities indicated potential predictive power of subsequent returns in the time series of 2000 to 2021, while the β_{sw} weighting did not.

Signal: *Bottom 2% MCAP WGHT* β_{sw}
Time Period: 2000 to 2021
N: 22

Fama-Macbeth	Results
Mean	—2.01
Standard Deviation	4.68
T-Stat	—2.77

Signal: *Bottom 10% MCAP WGHT* β_{sw}
Time Period: 2000 to 2021
N: 22

Fama-Macbeth	Results
Mean	—3.11
Standard Deviation	8.93
T-Stat	—2.25

We thus ran Fama-French regressions on the returns for both the bottom 2% and bottom 10% of market-capitalization-weighted beta securities to evaluate each portfolio's long-only annual performance from 2000 to 2021. The Fama-French regressions were benchmarked against the zero-factor, one-factor, three-factor, and five-factor models, which included the style factors of the market premium, size (SMB), value (HML), profitability (RMW), and investment (CMA).
The Fama-French results indicated that the bottom 2% of beta estimators signal was not a statistically significant predictor of abnormal returns. However, the alpha of 7.6% for the bottom 10% of beta estimators signal was statistically significant.

Fama-French Results

Signal: *Bottom 10% MCAP WGHT β_{sw}*
Time Period: 2000 to 2021
N: 22

		Coefficients	T-Stat
Zero-Factor	*Alpha (annual)*	14.0%	3.00
	R_F	—3.10	–
One-Factor (CAPM)	Alpha	3.4%	1.41
	Mkt — R_F	0.74	–
Three-Factor	*Alpha (annual)*	2.7%	1.00
	Mkt — R_F	0.76	–
	SMB	0.14	0.42
	HML	0.05	0.30
Five-Factor	*Alpha (annual)*	7.7%	1.82
	Mkt — R_F	0.50	–
	SMB	0.14	0.42
	HML	0.19	0.73
	RMW	—0.63	—1.51
	CMA	—0.11	—0.28

PORTFOLIO CONSTRUCTION

HOLDINGS

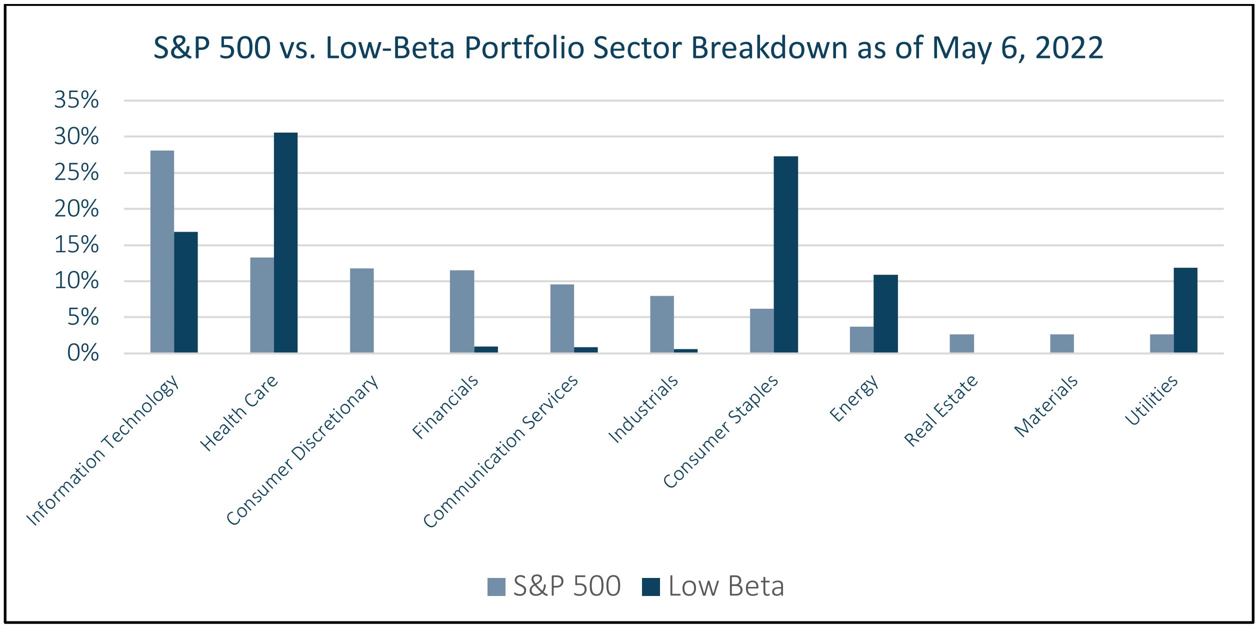
We incepted our portfolio on January 10, 2022. Using annualized CRSP data from 2021, we calculated our investment signal as outlined in our implementation section. Our initial portfolio of the bottom 10% market-capitalization-weighted β_{sw} stocks contained over 200 securities, which was too many for the purposes of ASAM. We thus trimmed our portfolio to 54 securities that accounted for 94% of the original portfolio's weight.

SECTOR ALLOCATION

Low-beta portfolios have narrower positive and negative swings in performance. Therefore, industries typically associated with high speculation and growth are underrepresented. Low-beta stocks also tilt away from consumer demand, economic cycles, and seasonality.

Low-beta securities in our portfolio tilt toward health care, consumer staples, information technology, and utilities. The economic fallout from the pandemic and business and service lockdowns may have influenced less consumer discretionary, real estate, and materials trading.

We did not limit sector exposure. However, we reduced exposure to financials by eliminating SPACs from our portfolio. We also removed stocks that were de-listed from the S&P 500.



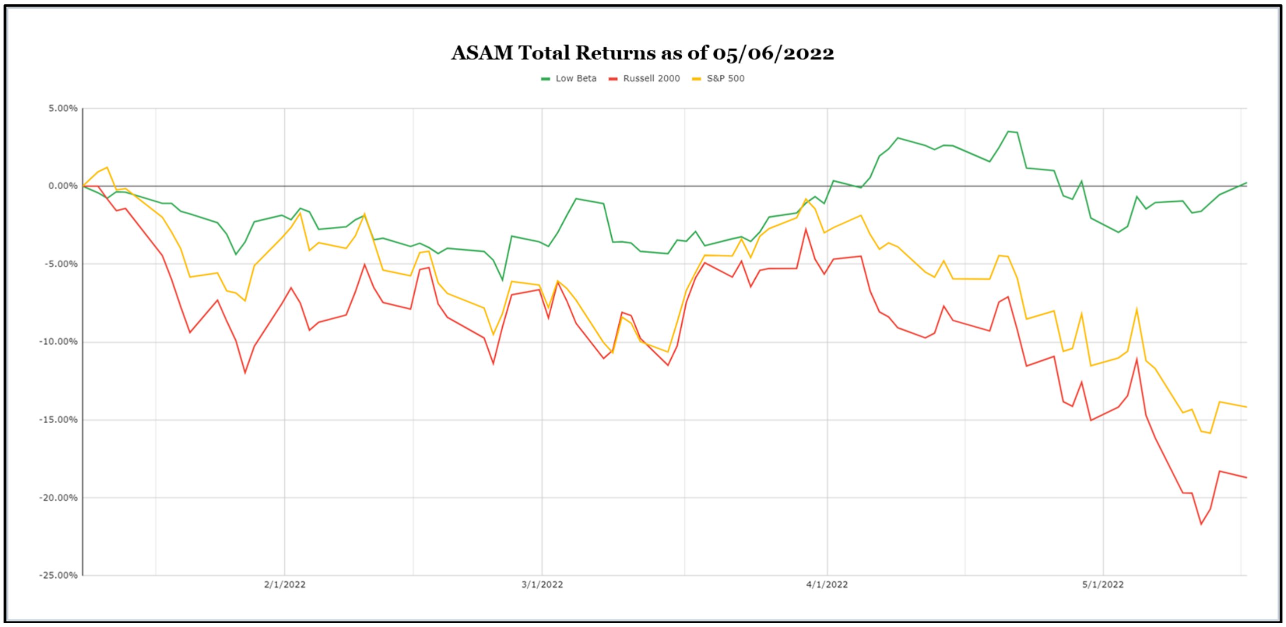
ACTUAL PERFORMANCE

PERFORMANCE TO DATE

From January 10, 2022, to May 6, 2022, our portfolio had a rate of return of −1.06%, which is a −2.2% annualized rate of return. This is a 10.7-percentage-point holding period outperformance of our S&P 500 benchmark. The benchmark rate of return was –11.71% during our portfolio's holding period, which is a –30.2% annualized rate of return.

The following table and graph show our portfolio Sharpe ratios along with our holding period portfolio performance versus our strategy's benchmark and the ASAM portfolio's benchmark (Russell 2000) performance:

Sharpe Ratio	
Portfolio Holding Period Return (R_P)	–1.1%
Risk-Free Holding Period Return (R_F, 1-Year T-Bill)	2.1%
Holding Period Standard Deviation (σ_P)	2.2%
Daily Sharpe Ratio	–1.4
Annualized Sharpe Ratio	–0.29



PERFORMANCE ATTRIBUTION

We used the iShares 1-3 Year Treasury Bond ETF (SHY) for our risk-free rate in our attribution analysis. We also used various Vanguard funds as style-factor proxies to examine one-, three-, four-, and industry-factor models because sufficient Fama-French factor data was not available for our entire holding period.

The performance attribution tables in this section illustrate that our low-beta strategy somewhat mirrored the exposure results of the Korn and Kuntz paper. When Korn and Kuntz tested their low-beta strategies within the smaller stock universe (S&P 500), the four strategies exhibited higher value tilts and statistically significant size tilts when compared to the same strategies tested within the larger stock universe (S&P 1500). However, none of their alphas was significant.

Our portfolio's market exposure is higher than the market exposure in comparable portfolios from Korn and Kuntz (2016). This illustrates that much of our portfolio performance can be attributed to market exposure. The large value tilt in our portfolio matched the results of Korn and Kuntz's analysis, which found that heavier weights to low-beta stocks tended to increase value exposure. To explain this value factor tilt, Korn and Kuntz reference Blitz (2016), who purports that the apparent value factor in low-beta portfolios is more reverse causality because low beta is the more robust anomaly.

Our low-beta strategy generated no excess return, as indicated by the zero-value exposures for alpha and their insignificant t-statistics for each of our attribution analysis regressions. Each of the factor exposures in our three-, four-, and industry-factor models were statistically significant, indicating most of our portfolio performance can be explained by them and less so by unexplained risk. The four-factor model indicates the market, value, and dividend exposures drove portfolio performance, while the statistical significance of our industry factor suggests our portfolio's IT and health care industry exposures account for some of the unexplained returns in our four-factor model.

All tables in this section reflect the portfolio's holding period of January 10, 2022, to May 6, 2022.

Zero-Factor Performance Attribution

Vanguard Fund Factor Proxies (*f*)	Exposure (β)	T-Stat (*N = 81*)	Risk Premium (Net Return, R_N)	Return Attribution in % (β x R_N)
Alpha	0.0	0.27	–	0%
R_F (SHY)	0.85	1.13	2.1%	1.8%

Market-Factor Performance Attribution

Vanguard Fund Factor Proxies (*f*)	Exposure (β)	T-Stat (*N = 81*)	Risk Premium (Net Return, R_N)	Return Attribution in % (β x R_N)
Alpha	0.0	0.27	–	0%
Mkt – R_F (VOO – SHY)	0.31	5.21	–8.5%	–2.6%

Three-Factor Performance Attribution

Vanguard Fund Factor Proxies (*f*)	Exposure (*β*)	T-Stat (*N = 81*)	Risk Premium (Net Return, R_N)	Return Attribution in % (*β* x R_N)
Alpha	0.0	−0.64	–	0%
Mkt – R_F (VOO – SHY)	0.75	–	−8.5%	−6.3%
VV – VBR (Large Cap – Small Cap)	0.34	3.16	−5.3%	−1.8%
VTV – VUG (Value – Growth)	0.67	9.70	15.6%	10.5%

Four-Factor Performance Attribution

Vanguard Fund Factor Proxies (*f*)	Exposure (*β*)	T-Stat (*N = 81*)	Risk Premium (Net Return, R_N)	Return Attribution in % (*β* x R_N)
Alpha	0.0	−0.45	–	0%
Mkt – R_F (VOO – SHY)	0.76	–	−8.5%	−6.4%
VV – VBR (Large Cap – Small Cap)	0.31	3.12	−5.3%	−1.7%
VTV – VUG (Value – Growth)	0.45	5.23	15.6%	7.0%
VIG – VOO (Dividends – Mkt)	0.85	3.89	2.8%	2.4%

Health Care & IT Industry Factor Performance Attribution

Vanguard Fund Factor Proxies (*f*)	Exposure (*β*)	T-Stat (*N = 81*)	Risk Premium (Net Return, R_N)	Return Attribution in % (*β* x R_N)
Alpha	0.0	0.15	–	0%
VHCOX – R_F (SHY)	0.18	3.21	−10.8%	−1.9%

PORTFOLIO'S TOP INDIVIDUAL GAINS AND LOSSES

Three of the five worst performers in our portfolio came from the information technology (IT) sector. The best performers were mixed in between pharmaceuticals, utilities, and the energy sector. Merck & Co. Inc (MRK), a pharmaceuticals company, led the pack with the highest gains in value over the period, with American Electric Power Company Inc. (AEP) and Consolidated Edison Inc. (ED) performing second and third best, respectively. The AEP and ED performances are unsurprising given the long-term stability of utilities and the recent volatility in the energy sector largely attributed to global geopolitical instability.

Company Name	Industry	% of Portfolio on JAN 10, 2022	% of Portfolio on MAY 6, 2022	β_{sw}	Total % Gain or Loss
MERCK & CO. INC.	Pharmaceuticals	12.67%	15.38%	0.30	20.20%
AMERICAN ELECTRIC POWER COMPANY INC.	Energy	2.95%	3.34%	0.38	11.90%
CONSOLIDATED EDISON INC.	Utilities	1.98%	2.22%	0.17	11.04%
NISOURCE INC.	Utilities	0.72%	0.79%	0.39	9.14%
KELLOGG COMPANY	Consumer Staples	1.44%	1.56%	0.10	7.24%
AMPLITUDE INC.	IT	0.38%	0.13%	−0.29	−66.40%
ROCKET LAB USA INC.	Industrials	0.36%	0.14%	0.09	−62.13%
CLEARWATER ANALYTICS HOLDINGS INC.	IT	0.45%	0.24%	−0.83	−46.28%
THOUGHTWORKS HOLDING INC.	IT	0.58%	0.32%	0.09	−46.22%
THE HAIN CELESTIAL GROUP INC.	Consumer Staples	0.27%	0.16%	0.33	−41.31%

SUGGESTIONS

Our portfolio outperformed both our benchmark and other ASAM portfolios. Given the time constraints on the research, backtesting, and performance evaluation timelines, we have several suggestions for how we could improve or refine our low beta strategy:

1. *Improved data preparation*:

   We did not remove all SPACs, over the counter, or non-U.S. listed equities in our initial database build. This proved cumbersome to fix at the tail end of our portfolio implementation. A simple line of code removing relevant sharecoded PERMNOs could save time that can be used more effectively elsewhere in the research process.

2. *Explore different security weighting techniques other than beta-weighting*:

   We backtested several portfolio weighting techniques for our bottom 2% and bottom 10% of β_{sw} ranked securities. Neither equal weighted nor β_{sw} weighted signals came out as statistically significant in our Fama-Macbeth regressions. Only market capitalization weightings indicated some predictive power. We recommend trying other security weighting techniques, such as a momentum-type weighting. Over-weighting securities that exhibited the lowest β_{sw} over the preceding 3-, 6-, 18-, or 24-month time periods could be interesting. This would require more flexible backtesting code to easily change the β_{sw} calculations.

3. *<u>Refine backtesting calculations</u>*:

   We suggest comparing Fama-Macbeth and Fama-French backtests with β_{sw} signals derived from both monthly return data and daily return data to see if there is a significant and demonstrable difference between the two. Additionally, we recommend testing a shorter period for the chosen stock universe. For example, testing only the previous 10, 12, or 15 years, which now include multiple significant economic downturns and a period of high inflation, could yield insights on the relative effect of older and arguably less relevant data points.

APPENDIX

The following table shows our holdings as of the end of the final tracked trading day, May 6, 2022:

Company Name	Ticker	Value as of 5/6/22	wBeta	Gain (%) As of 5/6/22	Weight of Portfolio as of 5/6/22
AMEREN CORPORATION	AEE	$5,929.60	0.31	1.51%	1.57%
AMERICAN ELECTRIC POWER COMPANY, INC.	AEP	$12,555.90	0.38	11.90%	3.34%
AEROJET ROCKETDYNE HOLDINGS, INC.	AJRD	$817.80	0.21	0.25%	0.21%
AMPLITUDE, INC.	AMPL	$454.14	-0.29	-66.40%	0.13%
ATMOS ENERGY CORPORATION	ATO	$3,791.70	0.26	0.92%	0.98%
AVISTA CORPORATION	AVA	$750.78	0.37	0.20%	0.21%
BAXTER INTERNATIONAL INC.	BAX	$9,098.75	0.36	2.86%	2.39%
BECTON, DICKINSON AND COMPANY	BDX	$18,315.87	0.30	4.76%	4.73%
BIOGEN INC.	BIIB	$7,163.57	0.35	2.33%	1.92%
CONAGRA BRANDS, INC.	CAG	$4,270.80	0.19	1.07%	1.03%
CERNER CORPORATION	CERN	$6,862.00	0.38	1.81%	1.82%
CHURCH & DWIGHT CO., INC.	CHD	$5,839.53	0.15	1.64%	1.46%
CHANGE HEALTHCARE INC.	CHNG	$1,830.66	0.27	0.44%	0.48%
COLGATE-PALMOLIVE COMPANY	CL	$16,136.40	0.30	4.72%	4.22%
THE CLOROX COMPANY	CLX	$4,772.14	-0.08	1.40%	1.20%
CMS ENERGY CORPORATION	CMS	$4,878.00	0.31	1.25%	1.32%
CENTENE CORPORATION	CNC	$12,268.38	0.36	3.24%	3.17%
CAMPBELL SOUP COMPANY	CPB	$3,725.25	0.11	0.86%	0.92%
CLEARWATER ANALYTICS HOLDINGS, INC.	CWAN	$1,029.55	-0.83	-46.28%	0.24%
Dominion Energy, Inc.	D	$16,972.04	0.36	4.20%	4.43%
QUEST DIAGNOSTICS INCORPORATED	DGX	$4,089.00	0.20	1.38%	1.11%
DUKE ENERGY CORPORATION	DUK	$21,373.44	0.29	5.33%	5.54%
CONSOLIDATED EDISON, INC.	ED	$8,270.24	0.17	11.04%	2.22%
Embecta Corp	EMBC	$420.84	N/A	N/A	N/A
Evergy, Inc.	EVRG	$3,881.70	0.35	1.04%	1.01%
FTI CONSULTING, INC.	FCN	$1,492.11	0.40	0.35%	0.39%
FLOWERS FOODS, INC.	FLO	$1,406.62	0.10	0.38%	0.36%
GENERAL MILLS, INC.	GIS	$10,781.40	0.17	2.69%	2.71%
THE HAIN CELESTIAL GROUP, INC.	HAIN	$605.28	0.33	-41.31%	0.16%
HAWAIIAN ELECTRIC INDUSTRIES, INC.	HE	$1,126.98	0.31	0.30%	0.30%
HORMEL FOODS CORPORATION	HRL	$7,021.35	0.05	1.74%	1.73%
KELLOGG COMPANY	K	$6,182.05	0.10	7.24%	1.56%
KIMBERLY-CLARK CORPORATION	KMB	$11,558.40	0.13	3.15%	2.95%
THE KROGER CO.	KR	$10,016.10	0.17	2.22%	2.36%
ALLIANT ENERGY CORPORATION	LNT	$3,641.88	0.37	1.02%	0.97%
LUMEN TECHNOLOGIES, INC.	LUMN	$2,782.05	0.31	0.86%	0.77%
MCCORMICK & COMPANY, INCORPORATED	MKC	$6,535.18	0.31	1.69%	1.63%
MERCK & CO., INC.	MRK	$55,685.70	0.30	20.20%	15.38%
NISOURCE INC.	NI	$2,890.02	0.39	9.14%	0.79%
PREMIER, INC.	PINC	$1,104.60	0.24	0.33%	0.29%
PNM RESOURCES, INC.	PNM	$966.00	0.12	0.26%	0.26%
QUIDEL CORPORATION	QDEL	$982.90	0.39	0.37%	0.27%
REYNOLDS CONSUMER PRODUCTS INC.	REYN	$1,507.48	0.19	0.43%	0.38%
ROCKET LAB USA, INC.	RKLB	$730.24	0.09	-62.13%	0.14%
Sprouts Farmers Market, Inc.	SFM	$670.60	0.28	0.22%	0.17%
THE J. M. SMUCKER COMPANY	SJM	$3,802.68	0.06	0.97%	0.92%
TREEHOUSE FOODS, INC.	THS	$427.56	-0.02	0.15%	0.14%
TOOTSIE ROLL INDUSTRIES, INC.	TR	$544.17	-0.06	0.16%	0.15%
TYSON FOODS, INC.	TSN	$8,264.62	0.35	2.08%	2.04%
THOUGHTWORKS HOLDING, INC	TWKS	$1,329.24	0.09	-46.22%	0.32%
UWM HOLDINGS CORPORATION	UWMC	$1,448.00	0.38	0.64%	0.43%
VIRTU FINANCIAL, INC.	VIRT	$1,240.20	0.26	0.35%	0.31%
VERIZON COMMUNICATIONS INC.	VZ	$49,862.91	0.29	14.31%	13.39%
WEC ENERGY GROUP, INC.	WEC	$7,952.14	0.19	2.03%	2.14%
MAGELLAN HEALTH, INC.	MGLN	**DELISTED on January 6, 2021**			
Low Beta		$ 378,056.54			
Cumulative Dividends		$ 3,740.74			
Total Value		**$ 381,797.28**			

REFERENCES

1. Korn, Olaf and Kuntz, Laura-Chloé, Low-Beta Strategies (June 1, 2016). 28th Australasian Finance and Banking Conference, Available at SSRN: https://ssrn.com/abstract=2647474 or http://dx.doi.org/10.2139/ssrn.2647474.

2. Welch, Ivo, Simply Better Market Betas (June 13, 2021). Available at SSRN: https://ssrn.com/abstract=3371240 or http://dx.doi.org/10.2139/ssrn.3371240.

HIGH DIVIDEND YIELD

Steve Karson, Brandon Priest, Bob Yan, Jeanie Ye, Katherine Zhao

EXECUTIVE SUMMARY

Our strategy of holding the 30 highest-dividend-yielding stocks across the U.S. exchanges from January 10, 2022, to May 6, 2022, resulted in returns of 5.12%, 2127 basis points over the performance of the S&P 500 during the same holding period. This report will detail how we picked and backtested the High Dividend Yield strategy using the Fama-Macbeth cross-section and Fama-French time-series methodology. We discuss how we picked our 2022 portfolio and share analysis of our results. We end the report by discussing learnings and improvements to our process.

ACADEMIC INSPIRATION

We based our strategy on Ratul Kapur BBS and Saurabh Suryavanshi BBS's 2006 paper "Dividend Yield Strategies: Dogs of the Dow and Hounds of the Bay." The authors posit the Dogs of the Dow (DoD) strategy was losing its effect in the U.S. and in Canada, but we were interested if the strategy is making a comeback. A basic description of DoD is included in the appendix.

Dividend yield strategies hypothesize high-dividend stocks are often overlooked in favor of the much flashier growth stocks. The lack of attention on these stocks causes them to be undervalued, which make them an attractive value investment. In addition to being lower cost, high-dividend stocks also have a fallback way to return value to investors in case of underperformance.

Using the previous year's dividend yield as our key signal, we tested if we could improve the DoD's returns by (1) expanding the number of companies to all U.S. firms and (2) increasing the number of stocks in the portfolio.

IMPLEMENTATION

The primary signal, dividend yield, made the implementation straightforward. Below are the steps to construct our historical testing universe portfolios:

1. For any given year, select the top 2,000 securities by market cap. For our analysis, we started in 1963 and went to 2020. We extend the strategy to a larger stock universe than the original paper because we felt that the fundamentals behind the underlying strategy may not be limited to stocks included in the Dow Jones (DJI).

2. Select the top 30 stocks with the highest dividend yield at the end of the calendar year, which also differs from the original strategy. We felt we should extend the portfolio because we extended our universe beyond the stocks in the DJI. We selected 30 stocks for ease of implementation.
3. Create an equal weighted portfolio of those 30 stocks.
4. Hold the portfolio for one year.
5. Repeat the process at the end of the year.

BACKTEST PERFORMANCE

FAMA-MACBETH

To confirm that our chosen signal of the previous year's dividend yield is effective at predicting higher performance the following year, we performed the following analysis. An important note: We did not include any taxes or transaction costs that would be incurred from dividends.

1. We chose a backtest period of 57 years that ran from 1963 to 2020 to ensure our analysis included many different economic cycles.
2. Our signal was the previous year's dividend yield, which was calculated as the total annual cash dividend amount at the end of the previous calendar divided by previous year-end stock price.
    a. Example dividend yield calculation for AT&T

2021	11-01-21	10-11-21	$0.52
	08-02-21	07-09-21	$0.52
	05-03-21	04-09-21	$0.52
	02-01-21	01-11-21	$0.52

    AT&T paid $2.08 in dividends in the year 2021. The stock price on Dec. 31, 2021, was $18.58. AT&T's previous year dividend yield is $2.08/$18.58 = 11.2%
3. We calculated our signal for all U.S. stocks, filtering for the top 2,000 market cap. The dividend yield for all these stocks was our independent variable.
    a. For 2020, AT&T had a dividend yield of 7.5%, and IBM had a dividend yield of 5.2%
4. The dependent variable is the current-year returns for all stocks in U.S. stock exchanges, filtered to the top 2,000 firms by market cap and only those trading in ordinary shares without any further definition.
5. For each year in our test range of 1963 to 2020, we regressed each stock's annual return against the stock's dividend yield in the previous year and stored the resulting coefficient. We collected a time series of 57 coefficients.

A T-test was run on this time series with the output below:

Fama-Macbeth Results (1963-2020, n = 57)	
Mean (annual)	0.38%
T-Stat	4.93

We interpret these results to mean that every 1% higher dividend yield predicts 0.38% of return the following year. While the amount of positive return is small, the T-stat of 4.93 shows that that 0.38% return is significantly different from zero.

FAMA FRENCH

We then ran time-series regressions on the CAPM, Fama-French three-factor, and Fama-French five-factor models over the period 1963-2020.

CAPM Model

Dependent Variable: Annual excess portfolio returns

Independent Variable: Market returns less risk-free rate

CAPM (1963-2020, n = 57)	
Alpha	0.047 (T-stat = 1.92)
Mkt – R_f	0.893

Interpretation: For every 1% the market moves, the backtested portfolio moves 0.89% annually. Alpha suggests that the annual return of the portfolio is 4.7% over the market. The coefficient is significant at 1.92.

Fama-French Three-Factor Model

Dependent Variable: Annual excess portfolio returns

Independent Variable: Fama-French Three-Factor Returns

Three-Factor (1963-2020, n = 57)	
Alpha	–0.002 (T-stat = –0.08)
Mkt – R_f	1.02
SMB	0.40
HML	0.75

Interpretation: For every 1% the market moves, the backtested portfolio moves 1.02% annually. For every 1% small stocks gain, the backtested portfolio gains 0.4%. For every 1% HML stocks gain, the backtested portfolio moves 0.75%. Alpha is not significant.

Fama-French Five-Factor Model

Dependent Variable: Annual excess portfolio returns

Independent Variable: Fama-French Five-Factor Returns

Five-Factor (1963-2020, n = 57)	
Alpha	–0.02 (T-stat = –0.99)
Mkt – R_f	1.11
SMB	0.42
HML	0.61
RMW	0.32
CMA	0.27

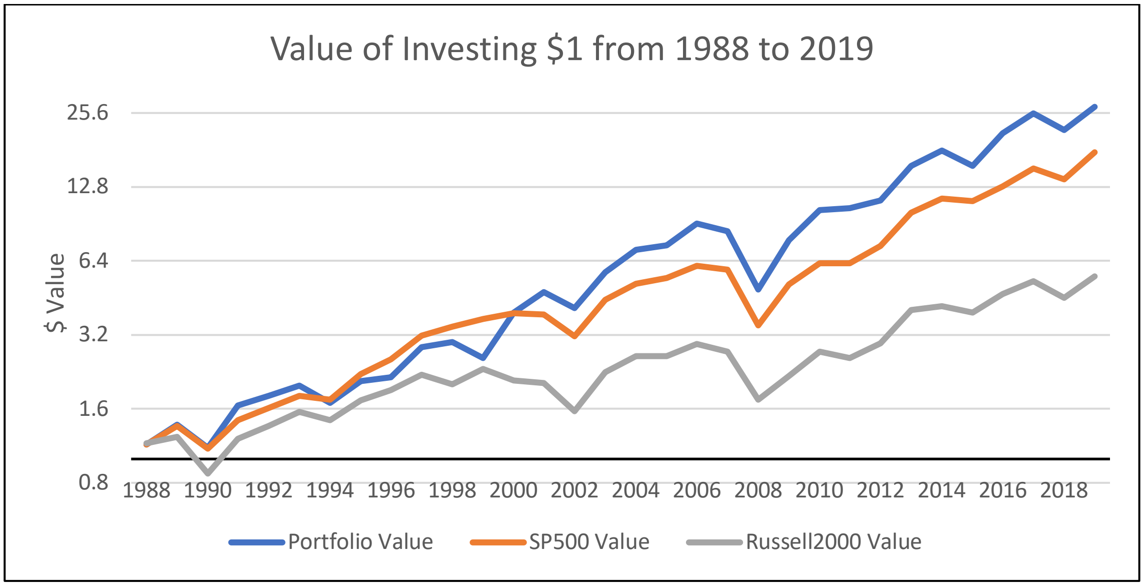
Interpretation: For every 1% the market moves, the backtested portfolio moves 1.11% annually. For every 1% small stocks gain, the backtested portfolio gains 0.42%. For every 1% HML stocks gain, the backtested portfolio moves 0.61%. For every 1% RMW stocks gain, the backtested portfolio moves 0.32%. For every 1% CMA stocks gain, the backtested portfolio moves 0.27%. Alpha is not significant.

Unsurprisingly, our portfolio had a large exposure to the value factor (HML). Over time, this has become commonly associated with high-dividend yield strategies.[2] This strategy also gives some exposure to firms with robust profitability. Companies that pay dividends may be more established companies with stronger margins that do not reinvest profits.

Perhaps more surprisingly is the positive exposure to the small cap factor (SML), as high-dividend companies are typically larger companies. However, when we extended this strategy to the larger stock universe, it included companies that issued "special dividends." We found that companies that leverage special dividends are usually smaller companies — often smaller energy or chemical companies like Future Fuel (Chemicals) or Dorian LPG (natural gas transport) — that may have had stronger earnings in a particular period. Furthermore, if a company pays out a larger one-time dividend to right-size the balance sheet and/or return money to shareholders, the relative size of that dividend has a larger impact on the dividend yield of the company than it would for a large company.

[2] https://www.nl.vanguard/professional/insights/portfolio-construction/high-dividend-exposures-value-factor

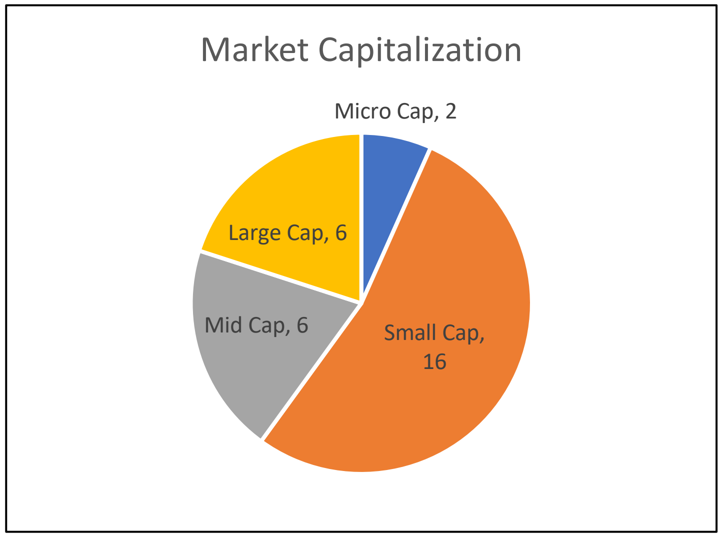
We compared the performance of our historical portfolio against the Russell 2000 and S&P 500. We did not include any taxes or transaction costs that would be incurred from dividends.



Over the stated periods, our strategy's performance over the Russell 2000 minus the risk-free rate return is as follows:

Period Return: Russell 2000	
10-year	9.1%
5-year	3.8%
3-year	3.4%
1-year	2.5%

PORTFOLIO CONSTRUCTION



We chose to pursue an equal-weighted portfolio across 30 stocks with the highest dividend yield. Our portfolio was more heavily weighted in the utilities, financial services, insurance, and oil industries, with holdings in other industries such as real estate and textiles. Our portfolio market capitalization is shown by the adjacent chart.

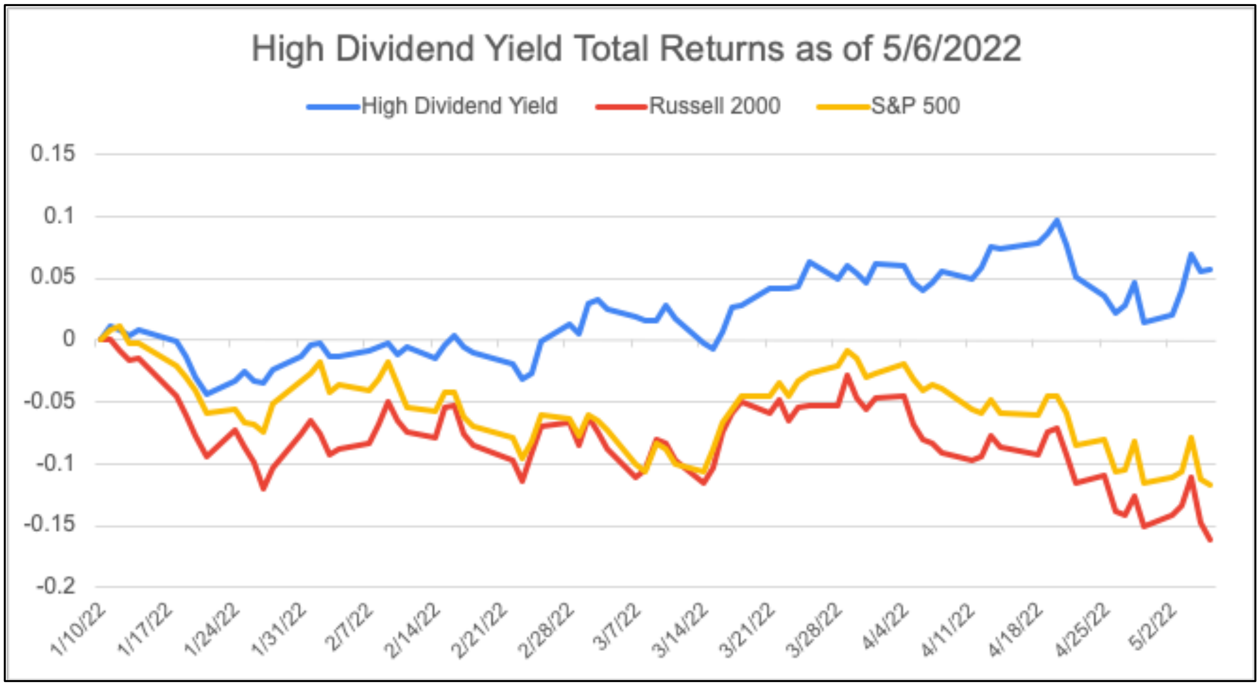
As noted above in our backtesting, our current portfolio had a large exposure to small cap stocks due to the inclusion of special dividends.

Portfolio Details

Ticker	Company Name	Dividend Yield (%)	Industry	Market Capitalization (in $millions)	Value as of Inception 1/10/22 (in $)	Value as of 5/6/22 (in $)
FF	FutureFuel Corp.	35.90%	Chems	348.4	7,699.1	9,460.5
LPG	Dorian LPG Ltd.	31.50%	Trans	540.3	7,612.0	9,595.3
ECVT	Ecovyst Inc.	31.30%	Chems	1,359.6	7,514.1	7,347.1
OMF	OneMain Holdings, Inc.	19.60%	Banks	6,795.4	7,774.6	6,448.3
EGLE	Eagle Bulk Shipping Inc.	17.60%	Trans	609.1	7,587.1	11,577.0
BKE	The Buckle Inc.	16.70%	Rtail	2,009.2	7,359.1	6,104.6
IEP	Icahn Enterprises L.P.	16.10%	RlEst	14,763.3	7,565.8	7,756.0
FLMN	Falcon Minerals Corporation	12.70%	Oil	247.2	7,518.0	10,582.5
DHIL	Diamond Hill Investment Group Inc.	11.80%	Fin	598.7	7,759.7	7,084.4
MC	Moelis & Company	11.00%	Fin	3,764.7	7,626.0	5,249.6
ITIC	Investors Title Company	10.10%	Insur	395.7	7,762.6	6,640.8
ORI	Old Republic International Corporation	9.68%	Insur	7,485.6	7,660.5	6,823.7
AMSF	AMERISAFE Inc.	9.59%	Insur	1,047.7	7,803.5	6,705.4
AM	Antero Midstream Corporation	9.30%	Util	4,870.5	7,625.3	7,993.8
CFFN	Capitol Federal Financial Inc.	8.47%	Banks	1,582.2	7,680.3	6,280.9
T	AT&T Inc.	8.46%	Telcm	186,451.5	5,831.2	5,848.8
LUMN	Lumen Technologies Inc.	7.97%	Telcm	13,341.3	7,616.7	6,087.8
AROC	Archrock Inc.	7.75%	BusSv	1,257.0	7,662.2	8,375.9
SBR	Sabine Royalty Trust	7.72%	Oil	625.5	7,886.2	10,700.1
BCC	Boise Cascade Company	7.70%	Paper	2,777.1	7,695.6	8,439.3
DVN	Devon Energy Corporation	7.63%	Oil	32,734.9	7,614.5	10,941.3
ISSC	Innovative Solutions and Support Inc.	7.62%	Chips	113.1	7,413.2	8,453.4
NPK	National Presto Industries Inc.	7.62%	Txtls	587.1	7,659.0	6,706.8
MO	Altria Group Inc.	7.60%	Smoke	90,398.2	7,783.2	8,711.8
HESM	Hess Midstream LP	7.39%	Oil	954.7	7,828.3	8,345.5
ETD	Ethan Allen Interiors Inc.	7.27%	Rtail	673.9	7,685.0	7,348.6
RTLR	Rattler Midstream LP	7.03%	Util	482.9	7,601.7	8,628.7
VGR	Vector Group Ltd.	6.97%	RlEst	1,707.4	7,994.6	8,824.0
ENB	Enbridge Inc.	6.96%	Util	80,990.6	7,699.9	8,586.3
KMI	Kinder Morgan Inc.	6.81%	Util	38,591.6	7,756.4	8,588.5
WBD	Warner Brother Discovery				**Stock Split 4/11/22**	1,242.5
	High Dividend Yield				228,275.0	241,479.2
	Cumulative Dividends					4,421.3
	Total Value					**245,900.5**

ACTUAL PERFORMANCE

Our portfolio has consistently outperformed both the Russell 2000 and the larger S&P 500 throughout our 17-week holding period.



Likewise, our year-to-date returns as of May 6, 2022, yielded positive returns, while both the Russell 2000 and the S&P 500 yielded negative returns.

Portfolio	Year-to-Date Returns
ASAM Group 4	**5.12%**
Russell 2000	–16.15%
S&P 500	–11.71%

Sharpe Ratio Summary	High Div. Yield	Russell 2000	S&P 500
Sharpe Ratio (Holding Period)	0.06	–0.12	–0.10
Sharpe Ratio (Annualized)	0.94	–1.89	–1.57

Our Sharpe ratio was calculated using the formula: [Expected Return – Risk-Free Rate]/Standard Deviation of Portfolio's Excess Return. The annualized Sharpe ratio multiplies the holding period

Sharpe ratio by the square root of 252. Average returns and standard deviation are based on daily returns for both our portfolio and the index. The risk-free rate is the mean of daily three-month Treasury Bill divided by 91 days to compound it to the daily rate. Our portfolio yielded higher the average returns compared to the risk-free asset.

Below are the top five and bottom five stocks in the portfolio based on return:

Ticker	Company Name	Return	Industry
EGLE	Eagle Bulk Shipping Inc.	53%	Transportation
DVN	Devon Energy Corporation	44%	Oil
FLMN	Falcon Minerals Corporation	41%	Oil
SBR	Sabine Royalty Trust	36%	Oil
LPG	Dorian LPG Ltd.	26%	Transportation
MC	Moelis & Company	–31%	Financial
LUMN	Lumen Technologies Inc.	–20%	Telecom
CFFN	Capitol Federal Financial Inc.	–18%	Banks
OMF	OneMain Holdings Inc.	–17%	Banks
BKE	The Buckle Inc.	–17%	Retail

PERFORMANCE ATTRIBUTION AGAINST VANGUARD ETFs

To identify the characteristics that really impacted our return over our January 10, 2022, to May 6, 2022, holding, we regress our portfolio's daily percentage change against the daily percentage change of for Vanguard ETFs. The rationale for ETFs is as follows[3]: We did not include weights in our analysis because we were an equally weighted portfolio.

- VOO – SHY: Vanguard ETF VOO's daily percentage change minus iShares 1-3 ETF's daily percentage. The latter is our proxy for the risk-free rate.
- VTV – VUG: Vanguard ETF VTV's daily percentage change minus Vanguard ETF VUG's daily percentage change. This shows the difference in return between value companies and growth companies.
- VIG – VOO: Vanguard ETF VIG's daily percentage change minus Vanguard ETF VOO's daily percentage change. This shows the difference in return between dividend companies and the returns of the S&P 500-tracking ETF.
- VV – VBR: Vanguard ETF VV's daily percentage change minus Vanguard ETF VBR's daily percentage change. This shows the difference between smaller-cap companies and larger-cap companies

	Betas	Factor Return	Attribution
ALPHA	0.02		2.02%
VOO – R_f	0.61	–8.90%	–5.45%
VTV – VUG	0.52	14.62%	7.59%
VIG – VOO	0.14	2.71%	0.38%
VV – VBR	–0.20	–4.84%	0.96%
		Portfolio Return	5.50%

The largest driver of our return was the performance of the value companies over growth companies. Because our strategy is choosing stocks based on high dividends, it is highly correlated to value. This tilt toward value is also supported by the risk analysis tool created by Causeway Capital; a full Risk Lens assessment is included in the appendix.

The largest negative driver of our return is the decline of the market over our holding period. Due to our tilt toward value, our portfolio had no exposure to the growth stocks that drove much of the market decline.

[2] VOO–SHY regressed against FF's Mkt–RF / VTV–VUG regressed against FF's HML/ VIG–VOO regressed against FF's CMA/VV–VBR regressed against FF's SMB showed no meaningful R^2. The Vanguard ETFs are not a good proxy for FF-factor portfolios.

	Betas	Factor Return	Attribution
ALPHA	0.02		1.97%
VDE – SHY	0.19	18.88%	3.62%
VPU – SHY	0.40	–0.17%	–0.07%
		Portfolio Return	5.52%

Lastly, we wanted to examine industry tilt attribution to our returns and approximated this by running our portfolio's daily returns against Vanguard's Energy ETF VDE and Utility ETF VPU. As shown in the table above, the overperformance of energy contributed to the majority of our returns.

SUGGESTIONS

STRATEGY

We neglected to remove the issuance of special dividends, which skewed our calculated returns on stocks. Special dividends are one-time payments made in addition to quarterly dividends. These payments are usually not recurring, and they cause the company to appear to have much higher dividend yields. By removing these companies from our analysis, we will be able to select a portfolio that is likely to pay dividends consistent with our selection year.

If we were not constrained by time, we would have liked to backtest different portfolio sizes instead of defaulting to a portfolio of 30. There is a chance that a different portfolio size would have increased our alpha.

PROCESS

In addition to strategy changes, our group would benefit from changes in our process. One major change would be utilizing code-sharing platforms (e.g., GitHub) from day one. By streamlining our collaboration, we would have reduced double work and miscommunication. Furthermore, we would also outline the steps and required segments of code so that we could better divide the work between group mates and avoid bottlenecks in our development process.

ADVICE TO FUTURE COHORTS

While strategy and process improvements are important, we encourage future cohorts to continuously iterate and improve their code. Trial and error was the key to our success in developing our coding skills and understanding of portfolio construction, so ensuring ample time for this process is critical.

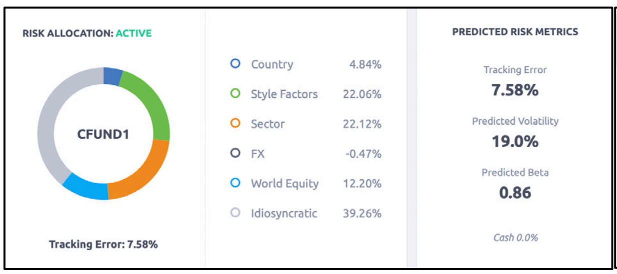
APPENDIX

Dogs of the Dow Strategy

1. Select any starting day and construct an equally weighted portfolio consisting of the 10 stocks in the DJIA30 with the highest current dividend yield.
2. Hold the portfolio for one year. After one year, determine the total value of the portfolio, including all dividends and other cash distributions. Stocks that drop off the top 10 should be sold and replaced with new additions to the portfolio.
3. Repeat every year.

Causeway Capital Risk Lens

In doing our risk-attribution analysis, we submitted our portfolio to Causeway Capital to check our work. According to their breakdown, the strongest style factor that drove our portfolio was energy exposure, followed by exposure to the market, and then value. All three of these tilts are shown in our backtesting and attribution analysis.



POLICY	ACTIVE EXP.	TCAR	% OF TOTAL
Energy	13.51%	1.08%	14.23%
World Equity	-7.71%	0.92%	12.20%
STYLE-Value	0.72	0.78%	10.33%
STYLE-Volatility	-0.17	0.69%	9.16%
United States	-10.35%	0.33%	4.29%

ASAM FELLOWSHIP HIGHLIGHTS

Biographies of Graduating ASAM Fellows (2021–2022)

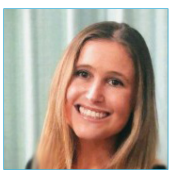
ASAM Executive Leadership

Jonathan Andritsch – President

Jonathan is a U.S. Navy veteran, having served over 10 years on active duty prior to attending UCLA. Jonathan graduated with a B.S. in economics from the United States Naval Academy, and he holds a Master of Advanced Studies in International Affairs from UC San Diego's School of Global Policy & Strategy. Jonathan will earn his MBA from UCLA Anderson in 2023, with specializations in entertainment management and marketing.

Greg Steinbrecher – VP of External

Greg initially pursued an acting career and worked in many different fields before working as an assistant to the paralegals at Steinbrecher & Span, his father's law firm. After deciding against a legal career, he will now earn his MBA from Anderson in 2023, with a specialization in finance. He graduated with distinction from the University of Virginia, where he studied philosophy and English literature. He is now pursuing a career in banking after a summer internship with Bank of America in New York.

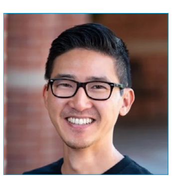


Alexa Kolodny – VP of Internal

Alexa is an investment banking and commercial finance professional with over 10 years of experience. She will join Houlihan Lokey's Los Angeles office in the Business Services Investment Banking Group, where she interned for three months in 2021. Prior to investment banking, she served as a vice president at Merchant Financial Group from 2013 to 2020, structuring senior secured debt financing and leveraged loans for startups and middle-market firms. Alexa has a B.A. in corporate communications from CUNY Baruch College and graduated from UCLA Anderson in June 2022. Alexa is originally from Great Neck, New York.

Jeanie Ye – VP of Finance

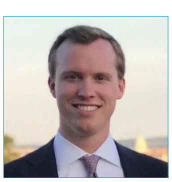
Jeanie is a business operations manager at LADWP, where she manages the budget and operations for one of the largest Power divisions. She collaborates with finance and project managers to accurately forecast spending, reconcile variances and report metrics. Jeanie is also the assistant division head of operations staff and consults with stakeholders on administrative areas such as processes, hiring, and discipline. Jeanie received her B.A. in international affairs from the George Washington University and earned her MBA from UCLA Anderson in 2022, with specializations in finance and technology management.



Lawrence Ham – VP of Technology

Lawrence is an entrepreneur, angel investor, and startup advisor. He invests in and supports underrepresented founders building game-changing companies. Lawrence earned his MBA from UCLA in June 2022, with specializations in finance and marketing. Prior to Anderson, he received a B.S. in biology from the University of California, Riverside and an M.P.H. from the University of Southern California. Lawrence is passionate about making the world a better place at the intersection of innovation, investment, and philanthropy.

ASAM Fellows



Blake Anderson

As a FEMBA student, Blake earned his MBA from Anderson in June 2022, with a specialization in finance. He previously worked for Dimensional Fund Advisors as a senior associate in its Global Client Group. Blake received his undergraduate degree in finance from the University of Minnesota and is a CFA Charterholder.

Brady Huang

Brady is an associate at a technology company, where he focuses on analytics. In his role, he uses data to help develop and support various risk management strategies. Brady earned his MBA from UCLA Anderson in 2022, with a specialization in finance. Prior to Anderson, Brady received a B.S. in business administration and management from Boston University.

Nathan Jensen

Nate is a tech lead at Hippo, where he leads financial and operational analytics for a newly public company. Nate earned his MBA from UCLA Anderson in 2022, with specializations in finance and technology management. Prior to Anderson, Nate received an M.S. in analytics from the University of Chicago and a B.S. in economics from BYU.

Steve Karson

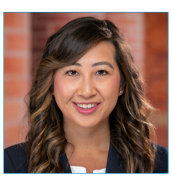
Steve worked in various finance functions at STARZ and Lionsgate Entertainment during his time at UCLA. Steve earned his MBA from UCLA Anderson in 2022. After graduating, he will work as an associate at Citi. Prior to his time at Anderson, Steve studied math and economics at The University of Texas at Austin. He has enjoyed combining theory with practice in the ASAM program.

Ahmed Khan

Ahmed is a sales strategy manager at Indeed, where he is responsible for leading sophisticated research and analysis, go-to-market strategy, and revenue acceleration and retention by working with cross-functional stakeholders to deliver high-quality and impactful results. Before joining Indeed, Ahmed was part of investor relations and sales at Kayne Anderson Capital Advisors. Ahmed earned his MBA from UCLA Anderson in 2022, with specializations in finance and real estate. Prior to UCLA Anderson, Ahmed earned his B.S. in finance and an M.S. in computational finance from DePaul University.

Henry Ma

Henry is a fixed-income portfolio analyst at Capital Group, where he monitors portfolio risk metrics, analyzes investment-grade bonds, and constructs portfolios in partnership with portfolio managers. Henry will earn his MBA from UCLA Anderson in 2023, with a specialization in finance. Prior to Anderson, Henry received his B.S. in management science from UC San Diego.

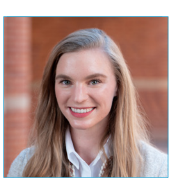


Rebecca Phuong

Rebecca began her career at Kaiser Permanente, where she was chief of staff supporting the IT CFO. She graduated from UCLA Anderson in 2022, with specializations in executive leadership and finance. Rebecca majored in public health at UC Berkeley. Post-Anderson, Rebecca will be working at a boutique health care investment banking firm in Los Angeles.

Brandon Priest

After graduating from UC Santa Barbara with a degree in biological sciences, Brandon worked in strategic finance at BioMarin Pharmaceutical. While at Anderson, he worked as a private equity intern and was awarded the 2022 Jeffrey P. Brown Fellowship in Private Equity. Brandon earned his MBA in June 2022, with a specialization in finance.



Sarah Russell

Sarah earned her MBA from Anderson in June 2022. Prior to Anderson, she worked in M&A integration at Intel and supply chain management at Masimo. She attended Penn State University and graduated in 2015 with a degree in supply chain management. After Anderson, she will be joining Bank of America as an investment banker in TMT.

Fame Sritrairatana

Fame is a senior vice president at Oaktree Capital Management. In his role, he oversees internal controls over financial reporting of all Oaktree's publicly traded entities, including business development companies covering over $150 billion in investments across the firm's various strategies. Fame earned his MBA from UCLA Anderson in 2022, with specializations in finance and real estate. Prior to Anderson, he worked as a consultant in KPMG's M&A practice.

Amy Tran

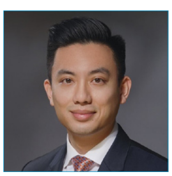
Amy is an investment banking summer associate at Goldman Sachs in Los Angeles and an investment banking fellow at UCLA Anderson's Fink Center for Finance. She previously worked at Alameda Health Systems, most recently as a strategic planning manager. Amy majored in economics and biology at Brown University, and she earned her MBA from UCLA Anderson in 2022.

Ceecee Wang

Ceecee is a director of financial planning and analysis at Hourglass Cosmetics and a Certified Public Accountant in Los Angeles. Prior to UCLA Anderson, Ceecee received her bachelor's degree from UC Berkeley. She earned her MBA in June 2022.

Sandy Wu

Sandy is a VP at Bank of America, managing agented and direct asset-backed loans for large corporate companies. She earned her MBA from UCLA in 2022, with a specialization in finance. Prior to Anderson, Sandy earned her B.S. from the University of Pittsburgh, majoring in accounting and finance, with a minor in economics.



Bob Yan

Bob is an investment banking summer associate at Bank of America in Los Angeles. In his role, Bob is involved in all aspects of due diligence and underwriting of mergers, acquisitions, equity, and debt transactions. Bob earned his MBA from UCLA Anderson in June 2022.

Katherine Zhao

Katherine is the director of international strategy for film and TV studio STX Entertainment. Katherine earned her MBA from Anderson in June 2022. For her undergraduate degree, Katherine attended Boston University, earning a degree in business administration, with a minor in anthropology.

Recruiting

Starting each fall quarter, the current ASAM class recruits the next cohort of ASAM Fellows. Through informational sessions, presentations, and active marketing efforts, we received strong interest and applications from a large pool of highly qualified candidates from both full-time MBA and FEMBA students. In the winter quarter, the current ASAM class selects the next group of ASAM Fellows through a rigorous application and interview process. After much thought and consideration, we have decided to invite 20 ASAM Fellows with diverse work experiences and educational backgrounds to form the ASAM Class of 2023.

We are pleased to announce the ASAM Class of 2023. Please join us in congratulating the new ASAM Fellows:

Andrew Cutrow	Jason Li	Malachi Nelson	Matthew Shintaku
JoJo Fallas	Iryna Lowry	Ryo Oya	Kelvin Sun
Joachim Fels	Shivam Malhotra	Rich Philip	Michael Trettin
Nicole Gebriel	Rodolfo Maya	Akshay Prakash	Amy Tyler
Catherine Hagman	Arianne Nash	Vinay Ramdev	Gary Zucker

Guest Speakers

A large part of the ASAM learning experience is engaging with local investment practitioners. This year we had speakers from several disciplines share their insights on their experiences, careers, and quantitative investment management topics. We were delighted to welcome back three Anderson alumni, including one ASAM alumnus, as guest speakers. Fellows had the opportunity to ask questions and discuss topics with senior investment professionals in the pursuit of finance knowledge beyond academia. These speakers provide an exceptional opportunity to bridge the gap between the academic world and the practitioner world. Furthermore, these interactions deepen the ASAM's relationships with key industry professionals from some of the most respected investment management firms.

We would like to extend our deepest gratitude to the following individuals, who generously volunteered their time to share their knowledge and expertise:

Dale Harvey, *Poplar Forest Capital*

Al Mordecai, *PRIMECAP Management Company*

Olivian Pitis ('04), *Avantis Advisors*

Ted Randall ('07), *Avantis Advisors*

Joe Gubler ('05), *Causeway Capital* (ASAM '05)

David Bahnsen, *The Bahnsen Group*

Trading Acknowledgement

ASAM thanks Wedbush Morgan Securities for its continued support.

APPENDIX

APPENDIX A: ASAM ALUMNI

2020–2021

Tony Huang, President
Melanie Jones, VP
Jayden Choi, VP
Troy Gilbert, VP
Joan Ramos, VP
Elizabeth Azran
Christopher Bakke
Frank Freeman
Nicholas Gentili
Victor Huang
Cody Larsen
Dennis Lee
Terri Qiao
Carson Tran
Shubhankar Tyagi
Siyu Wei
Charles Worden
Rengith Xavier
Erica Xu
Ming Yang

2019–2020

Carlos Reyes, President
Michael Silvestri, VP
Timothy Yu, VP
Adam Levi, VP
Benjamin Chernus
Eli Cole
Rochak Jain
Matthew Marine
Andy Malec
Ryan Moriarty
Steve Park
Brian Robert
David Rosen
Xavier Soto
Luis Felipe T.H. de Oliveira
Ting Wu

2018–2019

Victoria Ju, President
Vilay Khandewal, VP
Patty Nguyen, VP
Willard Phillips, VP
Andy Chiang
Tom Crecelius
Colleen Knorring
Jeff Colton
John Yoon
Kevin Vu
Maya Saraf
Nico Kutadinata
Pamela Ho
Abinaya Iyer
Rob DeMason
Zoli Jozefik

2017–2018

Naqi Jaffery, President
Frank Mihail, VP
Quang Ngu, VP
Douglas Paulus, VP
Pramol Dhawan
Brent Jospehson
Daniel Lee
Weipeng Lu
Jung Shin
Gaurav Singh
Kunjan Sobhani
Joyce Truong
Eugene Wu
Janelle Zhu
Zhenhua Gong

2016–2017

Raghudeep Bethapudi
Ole Bjoernstad
Aadit Chavda, VP
Jason Fong
Lu Hou, VP
Jeremy Mau, President
Avery Merriex
Geoff Miles
Daniel Moreira
Valerjis Nikolajevs
Alireza Safi
Rahul Sharma
Vishal Sheth
Ashkan Zarnighian, VP
Adam Lebovitz

2015–2016

David Barta
Eric Dixit, VP
Shawn Hsieh
Sam Lin
Joon Park
Douglas Stewart
Leif Brustuen
Jordan Fettman
Teddy Levitt, President
Jesse Lott, VP
Nick Rogov
Joseph Chun
Ahmed Gad
Jonathan Liang
Jennifer Niu, VP
Mark Sato

2014–2015

Stephanie Anavim, VP
Zach Conroy
Edmund Lo, VP
David Soong
Shireesh Verma
Chris Carlson
George Ku
Chris Martinez, President
Razmig Der-Tavitian
James Wooten
Man-Hong Chan
Jonathan Lea
Han Park, VP
Dan Troost

2013–2014

Nedal Alqam
Joseph Duronio, President
Thomas Gotsch, VP
Vinod Radhakrishnan, VP
Jason Stokes
Reza Banki
Nail Edikhanov, VP
Alex Jorion
Alex Revy
Tommy Taw
Matt Corbitt
Jacob Gore
James Lee, VP
Debika Seth
Kevin Zhang, VP

2012–2013
Adrian Craciun
Doug Longo, VP
Austin Myers
Julian Serafini
Andy Yin, President
Ryan Hughes
Felix Lorenzo
Farshid Poursartip
Brian Sterz
Ksenia Yudina, VP
Mahyar Kargar
Ryan Moore, VP
Carl Rodrigues
Tom Tarnacki
Bin Zhou

2011–2012
Stan Krastev
Ricky Ng, President
Sangwook Shin
Chen Wang
Stephan Chang
Aditya Kumar
Daniel Rad
Vibhu Sinha
Abhi Arunachalam
Richard Hion
Richard Magnusen
Nancy Rodriguez, VP
James Stiegler, VP
Christine Cawthon
John Hohn

2010–2011
Pankaj Chandak
Frank Jiang
Tim Lin
Steve Nguyen
Bhavik Vasha
Ben Chu
Eddie Kim
Sunan Liu
Louqman Parampath
Crhis Welton
Prabhat Dalmia
Ankur Kohli
Feng Lu
Brandon Suh
Clarence Xu

2009–2010
Anthony Arefian
Wade Hickok
Raymond Kim
Fred Myers
Harshit Patel
Ankur Desai
Arnie Huff
Vivek Laddha
Varun Nayak
Ravi Dandu
Dan Kerker
Heather Lambirth
Brian Nelson

2008–2009
John Alexander
Claire Huang
Jeff Lamarque
Payman Todorov
Huajun Xiong
Shalini Chidambaram
Jessie Huang
Uday Mathur
Brad Weekes
Julian Young
Eric Cho
Armen Karakashian
Shriram Pitchumani
Bill Wynne

2007–2008
Amit Bhatia
Brendan Hanley
Catherine Ku
Mark Perry
Ashish Shrestha
Chris Eatedali
Stephen Hughes
Carl Ludwigson
Prema Sampath
Erik Wright
Yimin Guo
Jonathan Kopitzke
Joseph Pawson
Reece Schort
Stefan Wrobel

2006–2007
Daniel Bang
Rich Colasuonno
Marc Goldberg
George Lin
Falgun Patel
Ludmila Skulkina
Josh Yafa
Greg Brandes
Paresh Desai
Bala Gorthi
Frank McCreary
Snehal Patel
Steven Sun
Ivan Yi
James Chen
David Garnett
Tim Henning
Shanu Nigam
Narasimham Seshadri
Jason Wingo

2005–2006*
Albert Tsao
Daphne Kelley
Howard Shen
Matthew Gregory
Scott Warner
Arthur Hovsepian
Daniel Jacobsen
Howard Wang
Philip Lee
Turan Malhotra
Betty Chen
David Speaker
Josh Neumann
P.J. DuWors
Venkat Balakrishnan

2004–2005*
Jim Adams
Allan Cheng
Todd Dubester
Brian Horner
Anne Leung
Hiroshi Watanabe
Jon Burningham
Michael Chien
Eric Ellingsen
Susan Huang
Greg Robitshek
Kejian Wu
Betty Chen
David DeWolf
Joe Gubler
Natalia Kanevsky
Christina Um

2003–2004*

Nicolas Amato	Daniel Bryant	Lucia Buzdugan
Chris Campbell	Elizaveta Fridman	David DeWolf
Bejamin Lavine	Rui Matos	Jay Meldreum
Brian Horner	Oleg Melnikov	Natalia Kanevsky
Tom Moro	Loren Sageser	Nicholas Seet
Peter Sengelmann	Jianhua Shao	Pavel Sokolov
Amy Yeshurun		

2002–2003*

Kahlil Andrews	Tim Ascough	Jonathan Bailly
Erik Bernhardt	David DeWolf	James Capizzi
Eric Ellingsen	Brian Hsieh	Robert Huntsman
Robert Kramer	Ning Liu	Brian Mech
Rebecca Rhodes	Thomas Stevens	Li Tang
David Yagiela	Lori Zarutsky	

2001–2002*

Robert Bergquist	Tim Byun	Lynn Douglass
Daniel Duke	Chris Gourrier	John Karambelas
Mark Laulainen	Daniel Lo	Francisco Lopez
Clifford Ma	David Stankey	Warren Suh
Michael Taila	Jorge Thiermann	Benjamin Wei

* These classes did not invest real assets because the ASAM had not yet been funded. Instead, in their pursuit of knowledge, they invested play money and paved the way for all future ASAM Fellows.

UCLA Anderson School of Management