Stock-to-Asset Spread and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock-to-Asset Spread (SAS), and its robustness in predicting returns in the cross-section of equities using the protocol proposed by Novy-Marx and Velikov (2023). A value-weighted long/short trading strategy based on SAS achieves an annualized gross (net) Sharpe ratio of 0.48 (0.42), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 25 (23) bps/month with a t-statistic of 3.13 (2.97), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net Payout Yield, Share issuance (1 year), Growth in book equity, Share issuance (5 year), Change in equity to assets, Net equity financing) is 26 bps/month with a t-statistic of 3.33.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different market conditions and methodological specifications is frequently questioned (Hou et al., 2020).

One particularly intriguing area of study involves signals derived from firms' financing decisions and capital structure choices. While extensive research has examined how firms' financing decisions reflect information about future prospects (Myers and Majluf, 1984), less attention has been paid to how the dynamic relationship between market and book values of different financing sources predicts returns.

We propose that the Stock-to-Asset Spread (SAS), defined as the difference between market-based and book-based measures of equity financing relative to total assets, captures valuable information about future stock returns. This hypothesis builds on two established theoretical frameworks. First, the market timing theory of capital structure (Baker and Wurgler, 2002) suggests that managers issue equity when they believe their stock is overvalued and repurchase when it is undervalued. Second, the q-theory of investment (Cochrane, 1988) implies that firms' financing decisions reflect their investment opportunities and expected returns.

The predictive power of SAS likely stems from its ability to capture both managerial timing of market misevaluation and fundamental changes in firms' investment opportunities. When managers believe their stock is overvalued, they are more likely to issue equity, leading to a higher SAS. Conversely, when managers view their stock as undervalued, they are more likely to repurchase shares, resulting in a lower SAS (Loughran and Ritter, 1995).

Moreover, changes in SAS may reflect managers' responses to varying investment opportunities and financing constraints. Firms with strong investment opportunities but limited internal funds may raise external equity, while those generating excess cash flow relative to investment opportunities may return capital to shareholders (Jensen and Meckling, 1976). These financing decisions should predict future returns as they reflect managers' private information about future prospects.

Our empirical analysis reveals strong evidence that SAS predicts cross-sectional stock returns. A value-weighted long-short portfolio strategy based on SAS quintiles generates a monthly alpha of 25 basis points (t-statistic = 3.13) relative to the Fama-French six-factor model. This predictive power remains robust after controlling for transaction costs, with a net alpha of 23 basis points per month (t-statistic = 2.97).

Importantly, the predictive power of SAS persists across different size segments. Among the largest quintile of stocks, the strategy achieves a monthly alpha of 28 basis points (t-statistic = 3.01), addressing concerns about implementation feasibility and market impact costs. The signal's effectiveness among large-cap stocks distinguishes it from many other documented anomalies that are concentrated in small, illiquid stocks.

Further analysis demonstrates that SAS's predictive power remains significant after controlling for related anomalies. When we control for the six most closely related anomalies and the Fama-French six factors simultaneously, the strategy maintains a significant alpha of 26 basis points per month (t-statistic = 3.33). This suggests that SAS captures unique information not contained in existing factors or anomalies.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures information about future returns through the lens of firms' financing decisions. While prior work has examined various aspects of equity financing (Baker and Wurgler, 2002; Loughran and Ritter, 1995), our measure uniquely combines market and book values to capture both mispricing and fundamental information.

Second, we demonstrate robust predictive power that survives stringent controls for transaction costs and related anomalies. Unlike many recently documented anomalies that fail to hold up to careful scrutiny (Hou et al., 2020), SAS generates significant risk-adjusted returns even after accounting for trading frictions and multiple testing concerns. The signal's effectiveness among large-cap stocks further distinguishes it from many existing anomalies.

Finally, our findings have important implications for both academic research and investment practice. For academics, our results suggest that the relationship between market and book measures of financing contains valuable information about expected returns. For practitioners, SAS represents a implementable strategy that generates significant alpha even after accounting for transaction costs.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Stock-to-Asset Spread. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK for common stock and item AOX for total assets. Common stock (CSTK) represents the total value of common shares outstanding, while total assets (AOX) provides a comprehensive measure of a firm's resources and economic scale.construction of the signal follows a difference-to-scale format, where we first calculate the change in CSTK by subtracting its lagged value, and then scale this difference by the lagged value of total assets (AOX). This spread measure captures the relative change in a firm's equity capital structure in relation to its overall asset base, offering insight into how the firm's equity financing evolves relative to its size. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financing decisions in a manner that is both scalable and interpretable. We construct this spread using end-of-fiscal-year values for both CSTK and AOX to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SAS signal. Panel A plots the time-series of the mean, median, and interquartile range for SAS. On average, the cross-sectional mean (median) SAS is -1.53 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SAS data. The signal's interquartile range spans -0.44 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SAS signal for the CRSP universe. On average, the SAS signal is available for 5.49% of CRSP names, which on average make up 6.84% of total market capitalization.

4 Does SAS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SAS using NYSE breaks. The first two lines of Panel A report monthly average excess returns for each of the five portfolios and for the long/short portfolio that buys the high SAS portfolio and sells the low SAS portfolio. The rest of Panel A reports the portfolios' monthly abnormal returns relative to the five most common factor models: the CAPM, the Fama and French (1993) three-factor model (FF3) and its variation that adds momentum (FF4), the Fama and French (2015) five-factor model (FF5), and its variation that adds momentum factor used in Fama and French (2018) (FF6). The table shows that the long/short SAS strategy earns an average return of 0.31% per month with a t-statistic of 3.63. The annualized Sharpe ratio of the strategy is 0.48. The alphas range from 0.24% to 0.38% per month and have t-statistics exceeding 3.10 everywhere. The lowest alpha is with respect to the FF5 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.27, with a t-statistic of 5.03 on the CMA factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 467 stocks and an average market capitalization of at least $1,261 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the decile sort using NYSE breakpoints and value-weighted portfolios, and equals 25 bps/month with a t-statistics of 2.53. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-one exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between 21-31bps/month. The lowest return, (21 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.10. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SAS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-three cases.

Table 3 provides direct tests for the role size plays in the SAS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SAS, as well as average returns and alphas for long/short trading SAS strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80^{th} NYSE percentile), the SAS strategy achieves an average return of 27 bps/month with a t-statistic of 2.85. Among these large cap stocks, the alphas for the SAS strategy relative to the five most common factor models range from 26 to 32 bps/month with t-statistics between 2.78 and 3.39.

5 How does SAS perform relative to the zoo?

Figure 2 puts the performance of SAS in context, showing the long/short strategy performance relative to other strategies in the "factor zoo." It shows Sharpe ratio histograms, both for gross and net returns (Panel A and B, respectively), for 212 documented anomalies in the zoo.[1] The vertical red line shows where the Sharpe ratio for the SAS strategy falls in the distribution. The SAS strategy's gross (net) Sharpe ratio of 0.48 (0.42) is greater than 90% (98%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the SAS strategy (red line).[2] Ignoring trading costs, a $1 invested in the SAS strategy would have yielded $6.21 which ranks the SAS strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SAS strategy would have yielded $4.54 which ranks the SAS strategy in the top 2% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the SAS relative to those. Panel A shows that the SAS strategy gross alphas fall between the 66 and 75 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196606 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The SAS strategy has a positive net generalized alpha for five out of the five factor models. In these cases SAS ranks between the 84 and 91 percentiles in terms of how

[1] The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

[2] The figure assumes an initial investment of $1 in T-bills and $1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

much it could have expanded the achievable investment frontier.

6 Does SAS add relative to related anomalies?

With so many anomalies, it is possible that any proposed, new cross-sectional predictor is just capturing some combination of known predictors. It is consequently natural to investigate to what extent the proposed predictor adds additional predictive power beyond the most closely related anomalies. Closely related anomalies are more likely to be formed on the basis of signals with higher absolute correlations. Figure 5 plots a name histogram of the correlations of SAS with 209 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price SAS or at least to weaken the power SAS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SAS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SAS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SAS} SAS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SAS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SAS. Stocks are finally grouped into

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

five SAS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SAS trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SAS and the six anomalies most closely-related to it. The six most-closely related anomalies are picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. Controlling for each of these signals at a time, the t-statistics on the SAS signal in these Fama-MacBeth regressions exceed 1.39, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SAS is 1.64.

Similarly, Table 5 reports results from spanning tests that regress returns to the SAS strategy onto the returns of the six most closely-related anomalies and the six Fama-French factors. Controlling for the six most-closely related anomalies individually, the SAS strategy earns alphas that range from 22-31bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.85, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SAS trading strategy achieves an alpha of 26bps/month with a t-statistic of 3.33.

7 Does SAS add relative to the whole zoo?

Finally, we can ask how much adding SAS to the entire factor zoo could improve investment performance. Figure 8 plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the SAS signal.[4] We consider one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes SAS grows to $2166.45.

[4] We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capitalization on CRSP in the period for which SAS is available.

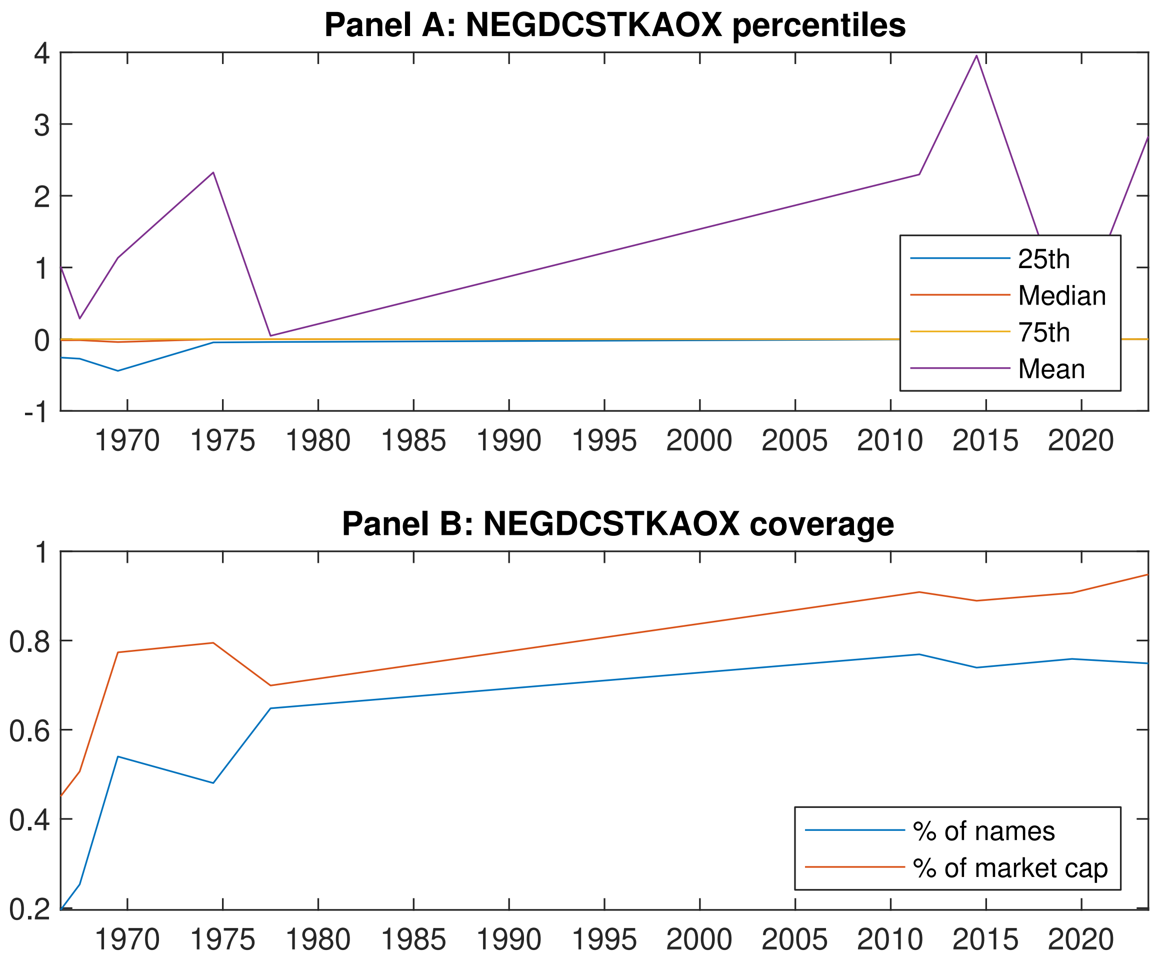

Figure 1: Times series of SAS percentiles and coverage.
This figure plots descriptive statistics for SAS. Panel A shows cross-sectional percentiles of SAS over the sample. Panel B plots the monthly coverage of SAS relative to the universe of CRSP stocks with available market capitalizations.

Table 1: Basic sort: VW, quintile, NYSE-breaks

This table reports average excess returns and alphas for portfolios sorted on SAS. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 196606 to 202306.

Panel A: Excess returns and alphas on SAS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.48	0.50	0.64	0.68	0.79	0.31
	[2.51]	[2.57]	[3.33]	[3.92]	[4.64]	[3.63]
α_{CAPM}	-0.12	-0.11	0.04	0.14	0.26	0.38
	[-2.13]	[-2.23]	[0.73]	[2.70]	[5.20]	[4.58]
α_{FF3}	-0.07	-0.08	0.07	0.11	0.23	0.29
	[-1.23]	[-1.59]	[1.27]	[2.29]	[4.63]	[3.74]
α_{FF4}	-0.07	-0.06	0.10	0.07	0.21	0.29
	[-1.38]	[-1.16]	[1.93]	[1.41]	[4.33]	[3.64]
α_{FF5}	-0.12	-0.02	0.08	0.01	0.12	0.24
	[-2.29]	[-0.45]	[1.47]	[0.19]	[2.59]	[3.10]
α_{FF6}	-0.12	-0.01	0.11	-0.02	0.12	0.25
	[-2.34]	[-0.21]	[1.99]	[-0.35]	[2.58]	[3.13]
Panel B: Fama and French (2018) 6-factor model loadings for SAS-sorted portfolios						
β_{MKT}	1.04	1.02	1.03	1.02	0.98	-0.05
	[82.54]	[88.60]	[81.34]	[88.01]	[86.96]	[-2.88]
β_{SMB}	0.06	0.06	0.01	-0.07	-0.00	-0.06
	[3.16]	[3.34]	[0.49]	[-4.44]	[-0.09]	[-2.18]
β_{HML}	-0.14	-0.08	-0.09	0.03	-0.01	0.13
	[-5.87]	[-3.79]	[-3.53]	[1.49]	[-0.55]	[3.61]
β_{RMW}	0.16	-0.08	-0.00	0.15	0.13	-0.03
	[6.71]	[-3.59]	[-0.15]	[6.54]	[5.91]	[-0.93]
β_{CMA}	-0.02	-0.09	-0.02	0.19	0.25	0.27
	[-0.58]	[-2.78]	[-0.55]	[5.89]	[7.68]	[5.03]
β_{UMD}	0.01	-0.02	-0.04	0.04	-0.00	-0.01
	[0.52]	[-1.59]	[-3.49]	[3.61]	[-0.16]	[-0.45]
Panel C: Average number of firms (n) and market capitalization (me)						
n	727	568	467	581	623	
me ($\$10^6$)	1474	1261	2014	2052	2231	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SAS strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 196606 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.31	0.38	0.29	0.29	0.24	0.25
			[3.63]	[4.58]	[3.74]	[3.64]	[3.10]	[3.13]
Quintile	NYSE	EW	0.51	0.61	0.51	0.44	0.35	0.31
			[6.60]	[8.51]	[8.23]	[7.14]	[5.98]	[5.26]
Quintile	Name	VW	0.31	0.36	0.27	0.27	0.25	0.25
			[3.62]	[4.24]	[3.39]	[3.27]	[3.03]	[3.01]
Quintile	Cap	VW	0.28	0.34	0.27	0.26	0.25	0.25
			[3.34]	[4.13]	[3.46]	[3.19]	[3.20]	[3.07]
Decile	NYSE	VW	0.25	0.30	0.21	0.20	0.23	0.23
			[2.53]	[3.08]	[2.21]	[2.09]	[2.44]	[2.36]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.27	0.34	0.27	0.27	0.22	0.23
			[3.17]	[4.16]	[3.46]	[3.44]	[2.86]	[2.97]
Quintile	NYSE	EW	0.31	0.40	0.30	0.27	0.13	0.12
			[3.64]	[5.01]	[4.39]	[3.93]	[2.01]	[1.86]
Quintile	Name	VW	0.27	0.32	0.25	0.25	0.22	0.23
			[3.15]	[3.83]	[3.11]	[3.07]	[2.73]	[2.82]
Quintile	Cap	VW	0.24	0.31	0.25	0.24	0.23	0.23
			[2.90]	[3.76]	[3.17]	[3.05]	[3.00]	[2.98]
Decile	NYSE	VW	0.21	0.27	0.19	0.18	0.20	0.21
			[2.10]	[2.72]	[1.99]	[1.93]	[2.11]	[2.16]

Table 3: Conditional sort on size and SAS

This table presents results for conditional double sorts on size and SAS. In each month, stocks are first sorted into quintiles based on size using NYSE breakpoints. Then, within each size quintile, stocks are further sorted based on SAS. Finally, they are grouped into twenty-five portfolios based on the intersection of the two sorts. Panel A presents the average returns to the 25 portfolios, as well as strategies that go long stocks with high SAS and short stocks with low SAS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

Panel A: portfolio average returns and time-series regression results

		SAS Quintiles					SAS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.39	0.72	0.86	0.94	0.95	0.56	0.64	0.54	0.50	0.37	0.35
		[1.36]	[2.60]	[3.19]	[3.53]	[3.81]	[5.77]	[6.72]	[6.32]	[5.80]	[4.49]	[4.23]
	(2)	0.50	0.68	0.82	0.96	0.93	0.43	0.52	0.38	0.36	0.28	0.27
		[1.91]	[2.64]	[3.27]	[3.98]	[3.98]	[4.40]	[5.44]	[4.56]	[4.21]	[3.34]	[3.18]
	(3)	0.65	0.62	0.82	0.88	0.94	0.28	0.36	0.25	0.25	0.17	0.18
		[2.76]	[2.58]	[3.43]	[3.91]	[4.41]	[3.07]	[4.00]	[3.02]	[2.98]	[2.03]	[2.11]
	(4)	0.50	0.62	0.83	0.87	0.84	0.34	0.42	0.30	0.27	0.17	0.16
		[2.24]	[2.76]	[3.79]	[4.15]	[4.24]	[3.69]	[4.74]	[3.82]	[3.45]	[2.21]	[2.08]
	(5)	0.51	0.52	0.41	0.57	0.78	0.27	0.32	0.26	0.26	0.28	0.28
		[2.76]	[2.68]	[2.21]	[3.23]	[4.67]	[2.85]	[3.39]	[2.78]	[2.75]	[3.01]	[3.02]

Panel B: Portfolio average number of firms and market capitalization

		SAS Quintiles					SAS Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	326	326	326	324	325	25	29	33	25	24
	(2)	94	93	93	93	93	48	49	50	48	49
	(3)	67	66	66	66	66	85	83	85	87	87
	(4)	56	56	56	56	56	183	183	192	192	195
	(5)	52	52	52	52	52	1268	1334	1614	1462	1602

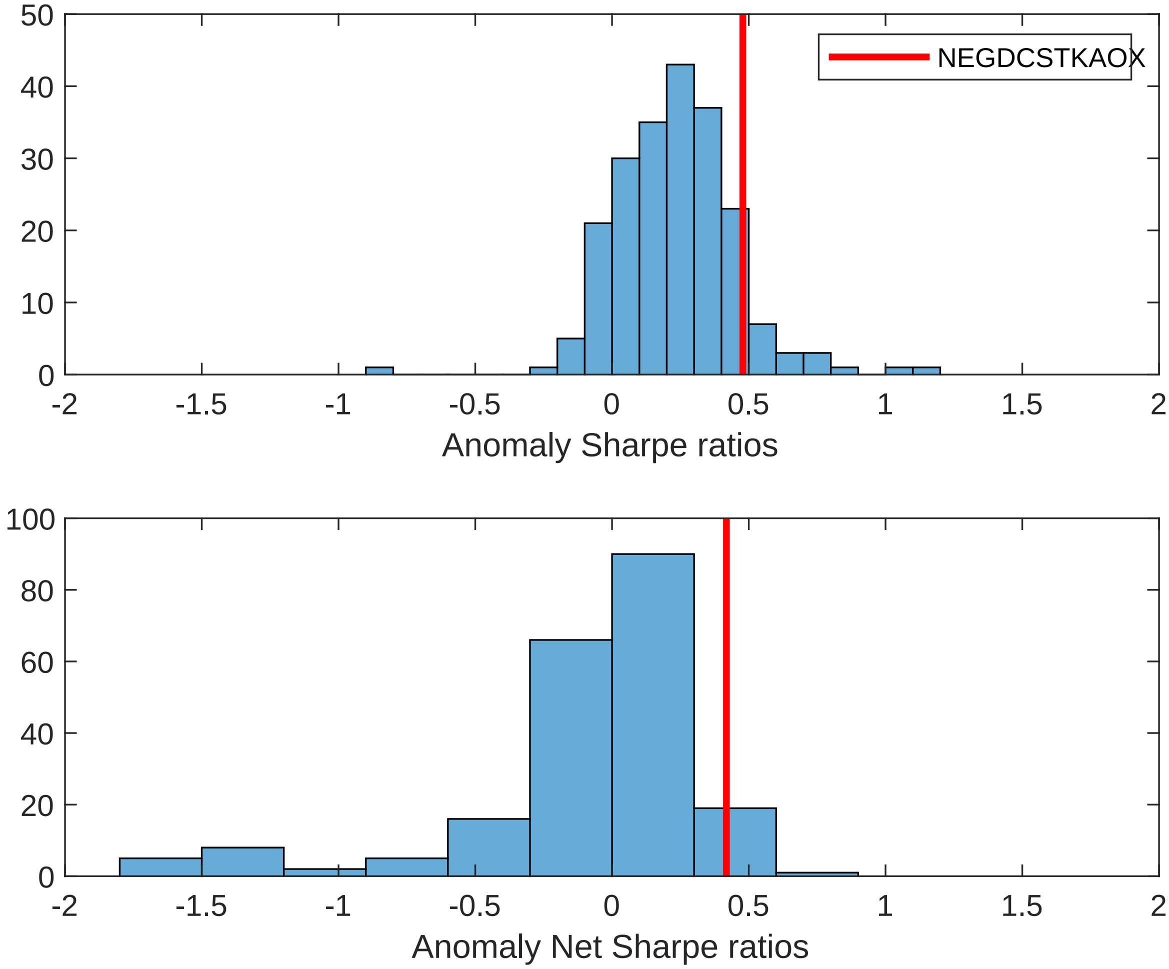

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SAS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

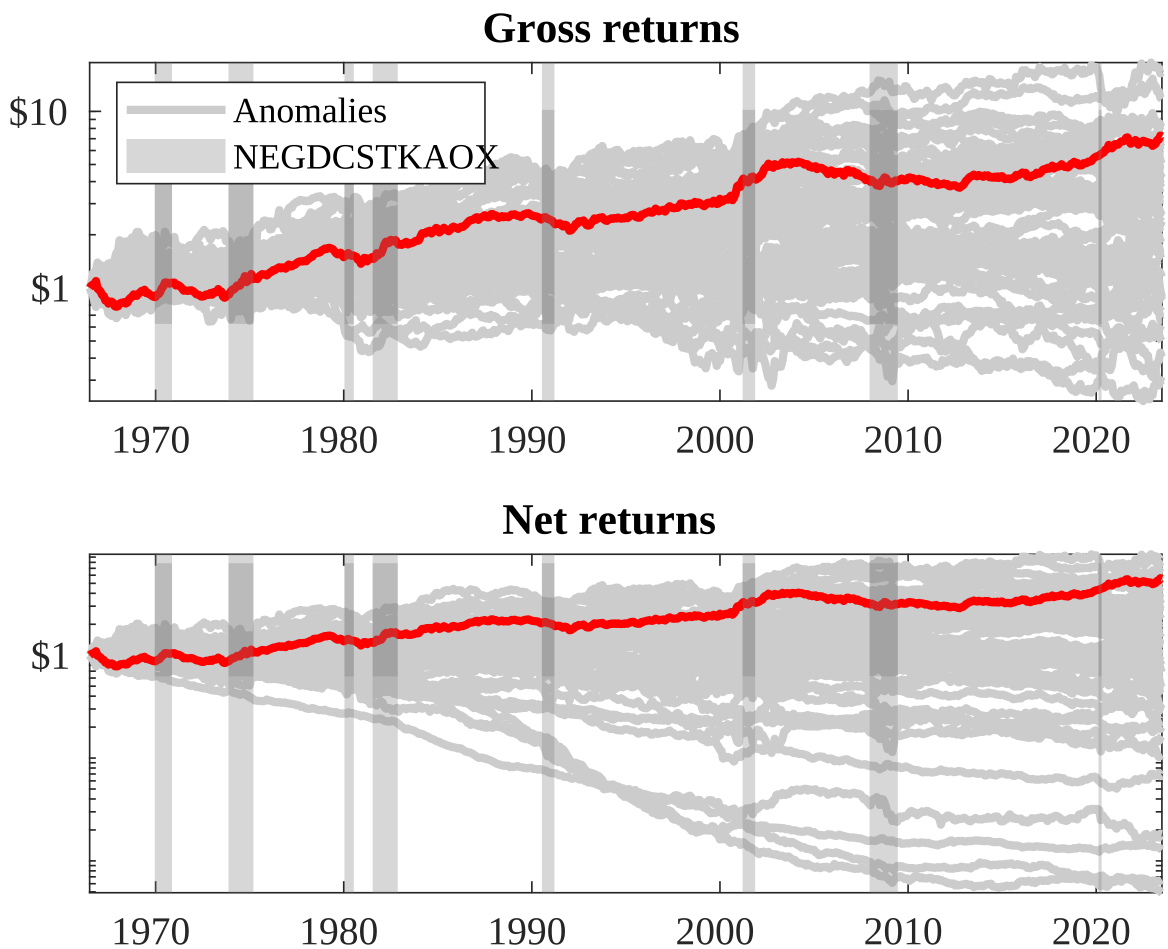

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SAS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel B plots results for net strtaegy returns.

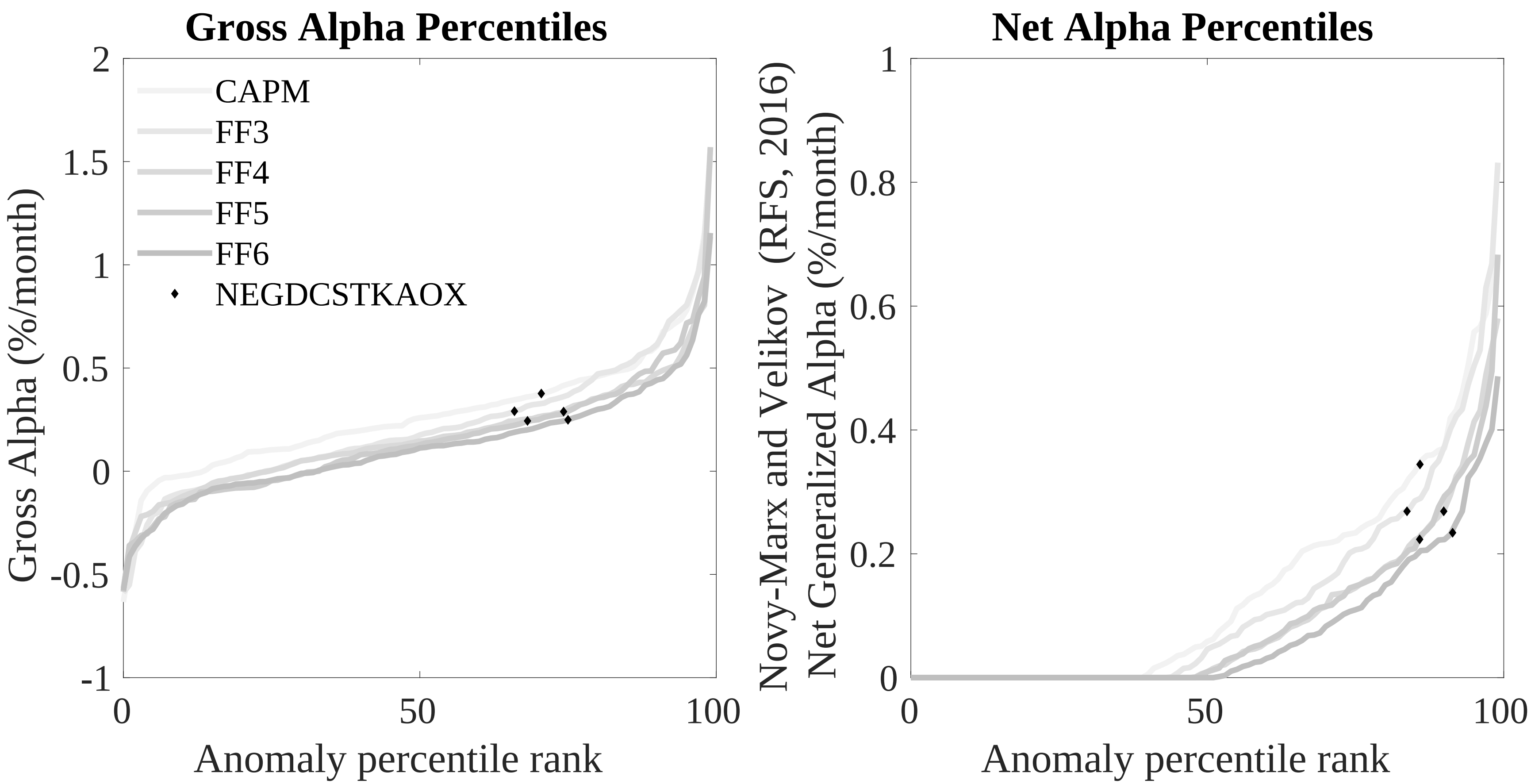

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SAS trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.

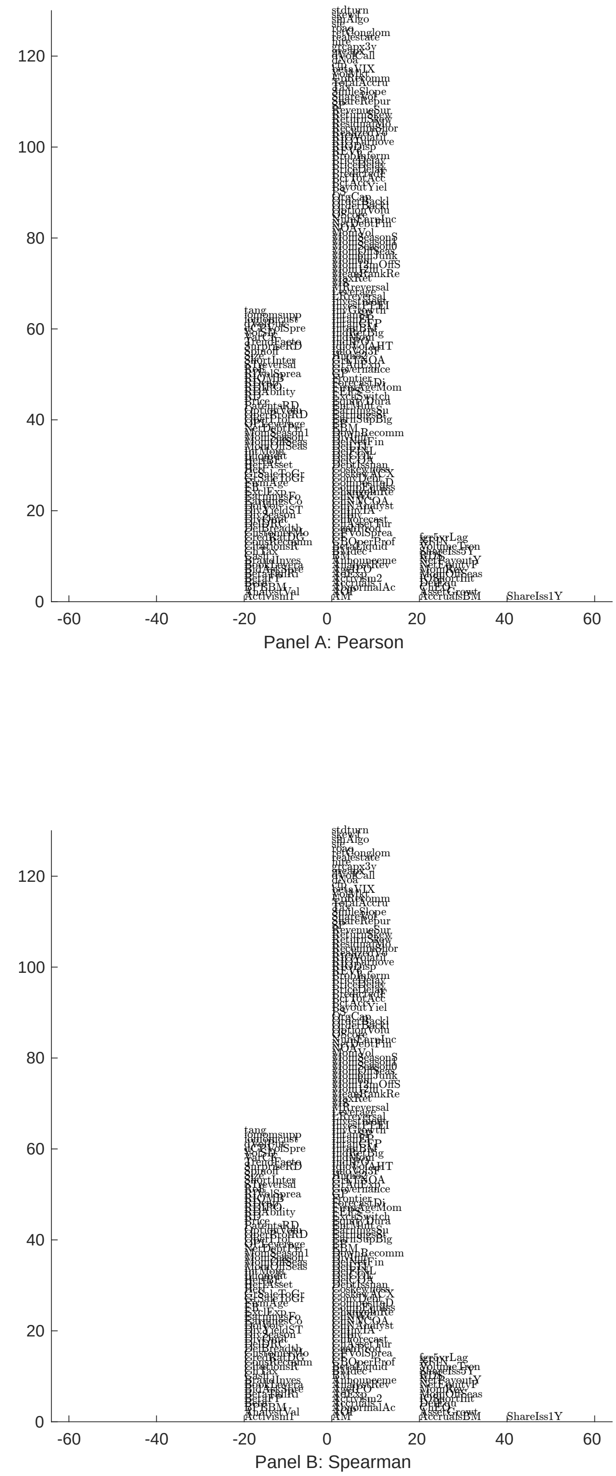

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SAS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

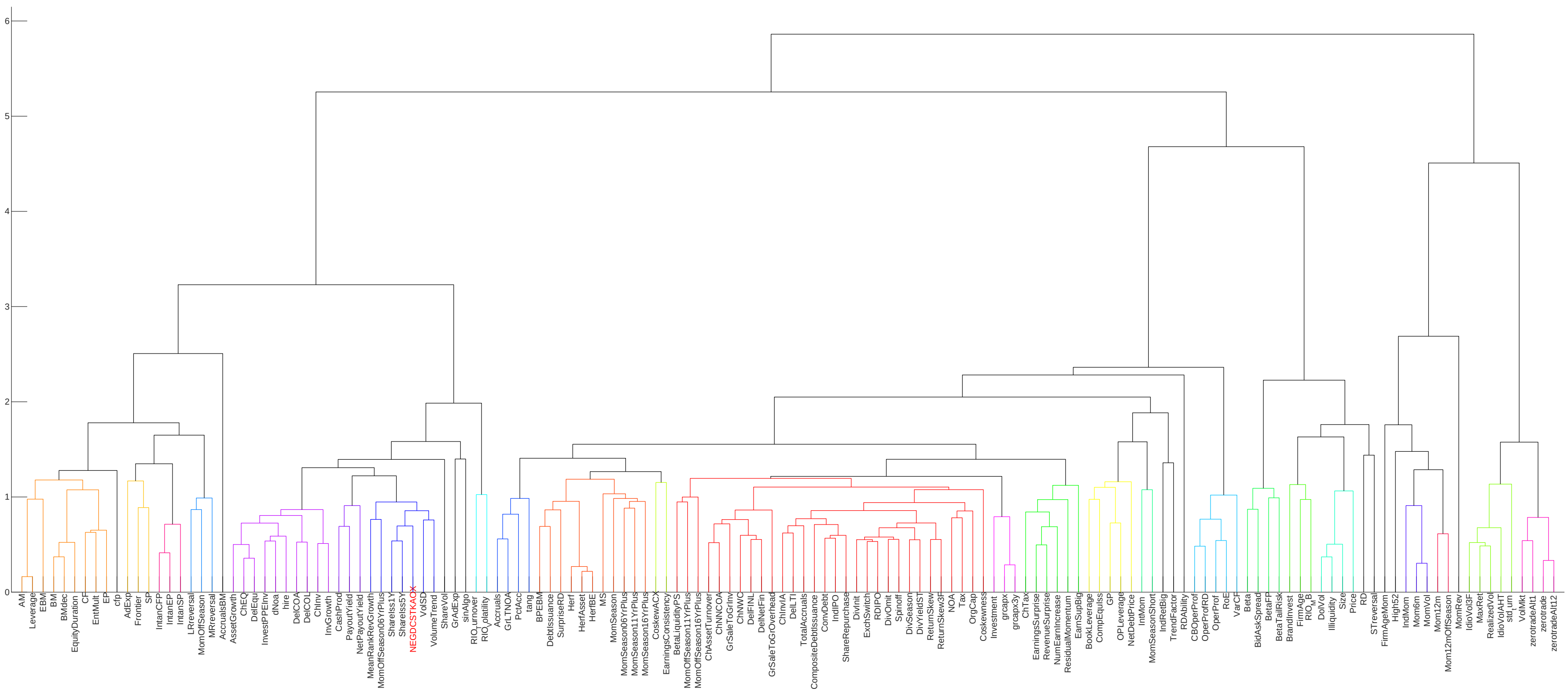

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

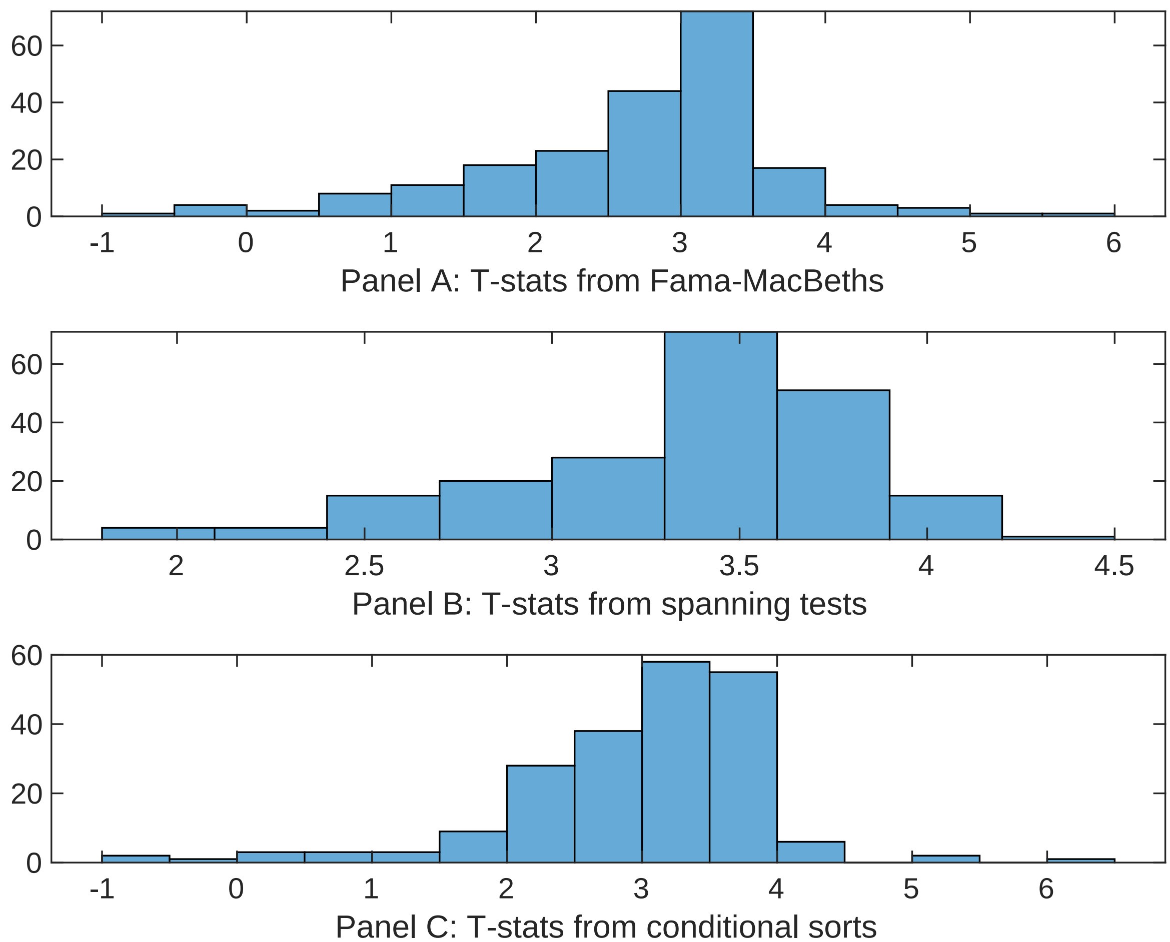

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SAS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SAS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SAS} SAS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SAS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SAS. Stocks are finally grouped into five SAS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SAS trading strategies conditioned on each of the 209 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies

This table presents Fama-MacBeth results of returns on SAS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SAS} SAS_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net Payout Yield, Share issuance (1 year), Growth in book equity, Share issuance (5 year), Change in equity to assets, Net equity financing. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.12	0.13	0.19	0.13	0.13	0.13	0.14
	[5.14]	[5.43]	[7.19]	[5.80]	[5.40]	[5.33]	[5.06]
SAS	0.29	0.58	0.45	0.67	0.53	0.53	0.34
	[1.39]	[2.77]	[2.27]	[3.32]	[2.45]	[2.73]	[1.64]
Anomaly 1	0.33						0.20
	[3.24]						[4.01]
Anomaly 2		0.27					0.88
		[6.01]					[2.08]
Anomaly 3			0.54				0.58
			[5.18]				[0.04]
Anomaly 4				0.37			0.98
				[3.96]			[1.06]
Anomaly 5					0.17		0.81
					[4.83]		[1.31]
Anomaly 6						0.15	-0.78
						[2.31]	[-0.94]
# months	679	679	684	679	684	618	610
$\bar{R}^2(\%)$	1	0	0	0	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SAS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SAS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Net Payout Yield, Share issuance (1 year), Growth in book equity, Share issuance (5 year), Change in equity to assets, Net equity financing. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.25	0.22	0.25	0.22	0.28	0.31	0.26
	[3.27]	[2.97]	[3.33]	[2.85]	[3.59]	[3.68]	[3.33]
Anomaly 1	19.95						9.16
	[6.70]						[2.24]
Anomaly 2		28.70					12.06
		[7.36]					[2.41]
Anomaly 3			37.84				26.02
			[9.02]				[4.06]
Anomaly 4				20.95			7.66
				[5.18]			[1.69]
Anomaly 5					27.67		1.69
					[6.77]		[0.28]
Anomaly 6						13.38	-6.41
						[3.50]	[-1.41]
mkt	-2.05	-3.04	-4.04	-2.46	-5.72	-3.71	-2.30
	[-1.11]	[-1.69]	[-2.27]	[-1.31]	[-3.14]	[-1.81]	[-1.17]
smb	-1.42	-3.95	-6.90	-6.43	-6.08	1.74	-4.77
	[-0.54]	[-1.53]	[-2.68]	[-2.42]	[-2.30]	[0.54]	[-1.53]
hml	6.52	10.62	9.15	8.34	10.07	13.48	4.91
	[1.76]	[3.03]	[2.65]	[2.22]	[2.84]	[3.66]	[1.29]
rmw	-14.83	-12.99	-1.67	-7.57	-0.90	-8.47	-6.46
	[-3.80]	[-3.49]	[-0.48]	[-2.08]	[-0.25]	[-1.91]	[-1.45]
cma	11.53	12.46	-11.39	19.71	-2.64	10.91	-17.72
	[2.03]	[2.26]	[-1.74]	[3.64]	[-0.39]	[1.79]	[-2.55]
umd	1.06	-0.94	-1.22	-0.48	0.04	-0.68	-0.11
	[0.59]	[-0.53]	[-0.69]	[-0.27]	[0.02]	[-0.35]	[-0.06]
# months	680	680	684	680	684	618	614
$\bar{R}^2$(%)	28	29	29	26	26	19	30

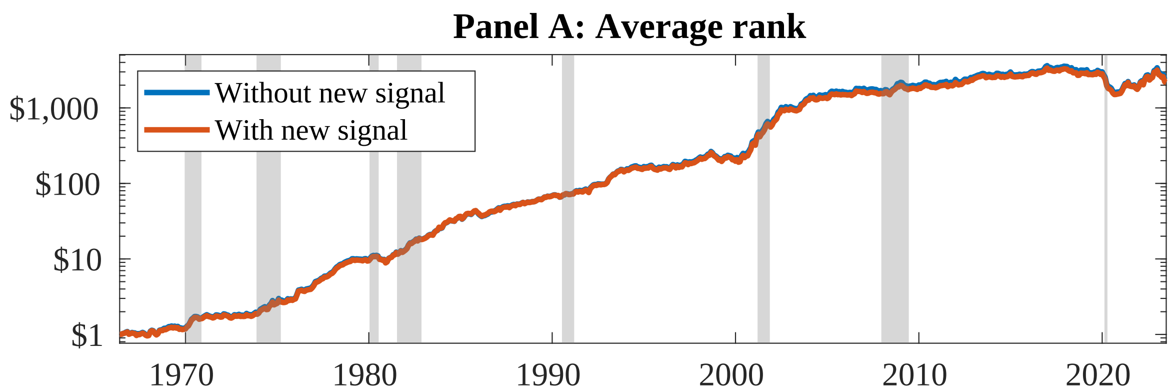

Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines indicate combination trading strategies that utilize the 155 anomalies as well as SAS. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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