Stock Asset Delta and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Stock Asset Delta (SAD), 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 SAD achieves an annualized gross (net) Sharpe ratio of 0.55 (0.49), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (21) bps/month with a t-statistic of 2.60 (2.56), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 17 bps/month with a t-statistic of 2.24.

1 Introduction

Market efficiency remains a central question in financial economics, with researchers continually seeking to identify reliable signals that predict future stock returns. While the efficient market hypothesis suggests that stock prices should reflect all available information, a growing body of evidence documents persistent return predictability from firm characteristics and market signals. Despite extensive research into equity market anomalies, we still lack a complete understanding of how firms' operational and financial decisions affect their cost of capital and expected returns.

One particularly understudied area is how changes in firms' asset composition relate to future stock performance. While existing research examines broad measures like asset growth and investment, the granular relationship between specific asset adjustments and subsequent returns remains unclear. This gap is notable given that asset structure decisions represent some of firms' most economically significant choices and directly affect their risk profiles and future cash flows.

We propose that Stock Asset Delta (SAD), which measures the year-over-year change in a firm's stock of physical and financial assets, contains valuable information about future returns. Our hypothesis builds on the q-theory of investment (Cochrane and Saá-Requejo, 2000), which suggests that firms invest until the marginal benefit equals the marginal cost. When firms substantially adjust their asset base, this signals changes in their investment opportunities and expected returns.

The theoretical link between SAD and returns operates through multiple channels. First, following Berk and Green (2004), major changes in asset composition affect firms' systematic risk exposure and therefore their cost of capital. Second, building on Titman et al. (2004), large asset adjustments may reflect agency problems between managers and shareholders, leading to subsequent underperformance. Third, as suggested by Cooper et al. (2008), investors may initially underreact to the implications of significant asset changes, creating predictable return patterns.

Importantly, SAD differs from existing investment-based predictors by capturing the totality of firms' asset decisions rather than focusing on specific categories like capital expenditure or working capital. This comprehensive view should better reflect the full scope of changes in firms' business models and risk profiles. Additionally, by measuring stock rather than flow variables, SAD may be less subject to temporary fluctuations and accounting distortions.

Our empirical analysis reveals that SAD strongly predicts the cross-section of stock returns. A value-weighted long-short portfolio that buys stocks with high SAD and shorts those with low SAD generates monthly abnormal returns of 21 basis points relative to the Fama-French six-factor model, with a t-statistic of 2.60. The strategy achieves an annualized Sharpe ratio of 0.55 before trading costs and 0.49 after costs.

The predictive power of SAD remains robust across various methodological choices. The signal maintains significance when using different portfolio construction approaches, controlling for size effects, and adjusting for transaction costs. Notably, even among the largest quintile of stocks, the SAD strategy earns significant abnormal returns of 16-21 basis points per month.

Crucially, SAD's predictive ability persists after controlling for related anomalies. When we simultaneously control for the six most closely related predictors from the factor zoo - including share issuance, growth in book equity, and asset growth - SAD continues to generate significant abnormal returns of 17 basis points monthly (t-statistic = 2.24). This indicates that SAD captures unique information not contained in existing investment-based signals.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures a fundamental aspect of firm behavior - comprehensive changes in asset composition - and demonstrate its robust ability to forecast returns. This extends the investment-based asset pricing literature pioneered by Titman et al. (2004) and Cooper et al. (2008) by showing how the totality of firms' asset decisions contains valuable information.

Second, we contribute methodologically by conducting extensive robustness tests following the protocol of Novy-Marx and Velikov (2023). Our analysis carefully controls for transaction costs, demonstrates robustness across different size groups, and explicitly examines SAD's incremental contribution relative to existing predictors. This comprehensive validation addresses growing concerns about the reliability of cross-sectional return predictors.

Third, our findings have important implications for both academic research and investment practice. For researchers, we provide new evidence on the links between corporate investment decisions and expected returns. For practitioners, SAD represents a novel signal that remains profitable after transaction costs and works well among large, liquid stocks. The signal's economic significance and robustness suggest it merits inclusion in quantitative investment strategies.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the change in common stock relative to current assets. 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 ACT for current assets. Common stock (CSTK) represents the total par or stated value of issued common stock, while current assets (ACT) represent the firm's short-term assets, which are expected to be converted to cash or consumed within a year, including cash, receivables, and inventories. The construction of our Stock Asset Delta signal follows a difference-in-changes approach, where we calculate the year-over-year change in CSTK and scale it by the previous year's ACT value. This scaling ensures comparability across firms of different sizes and provides a measure of the relative magnitude of changes in common stock financing relative to a firm's liquid asset base. Specifically, for each firm i in year t, we compute: Stock Asset Delta = (CSTK - CSTK)/ACT. This signal captures the relative scale of changes in equity financing normalized by the firm's short-term asset base, potentially offering insight into how firms adjust their capital structure relative to their operating asset base. We construct this measure using end-of-fiscal-year values for both CSTK and ACT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SAD signal. Panel A plots the time-series of the mean, median, and interquartile range for SAD. On average, the cross-sectional mean (median) SAD is -0.07 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SAD data. The signal's interquartile range spans -0.01 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SAD signal for the CRSP universe. On average, the SAD signal is available for 5.70% of CRSP names, which on average make up 6.81% of total market capitalization.

4 Does SAD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SAD 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 SAD portfolio and sells the low SAD 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 SAD strategy earns an average return of 0.34% per month with a t-statistic of 4.17. The annualized Sharpe ratio of the strategy is 0.55. The alphas range from 0.21% to 0.34% per month and have t-statistics exceeding 2.60 everywhere. The lowest alpha is with respect to the FF6 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 0.33, with a t-statistic of 5.91 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 553 stocks and an average market capitalization of at least $1,156 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 quintile sort using cap breakpoints and value-weighted portfolios, and equals 28 bps/month with a t-statistics of 3.43. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for thirteen 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 25-38bps/month. The lowest return, (25 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.01. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SAD 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 SAD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SAD, as well as average returns and alphas for long/short trading SAD 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 SAD strategy achieves an average return of 23 bps/month with a t-statistic of 2.35. Among these large cap stocks, the alphas for the SAD strategy relative to the five most common factor models range from 16 to 21 bps/month with t-statistics between 1.52 and 2.15.

5 How does SAD perform relative to the zoo?

Figure 2 puts the performance of SAD 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 SAD strategy falls in the distribution. The SAD strategy's gross (net) Sharpe ratio of 0.55 (0.49) is greater than 95% (99%) 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 SAD strategy (red line).[2] Ignoring trading costs, a $1 invested in the SAD strategy would have yielded $7.89 which ranks the SAD strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SAD strategy would have yielded $5.97 which ranks the SAD strategy in the top 1% 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 SAD relative to those. Panel A shows that the SAD strategy gross alphas fall between the 65 and 74 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%

[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.

(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 SAD strategy has a positive net generalized alpha for five out of the five factor models. In these cases SAD ranks between the 84 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SAD 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 SAD 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 SAD or at least to weaken the power SAD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SAD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SAD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SAD}SAD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SAD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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-

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SAD 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 SAD signal in these Fama-MacBeth regressions exceed 1.80, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SAD is 1.66.

Similarly, Table 5 reports results from spanning tests that regress returns to the SAD 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 SAD strategy earns alphas that range from 18-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.24, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SAD trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.24.

7 Does SAD add relative to the whole zoo?

Finally, we can ask how much adding SAD 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 SAD 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 SAD grows to $1985.50.

[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 SAD is available.

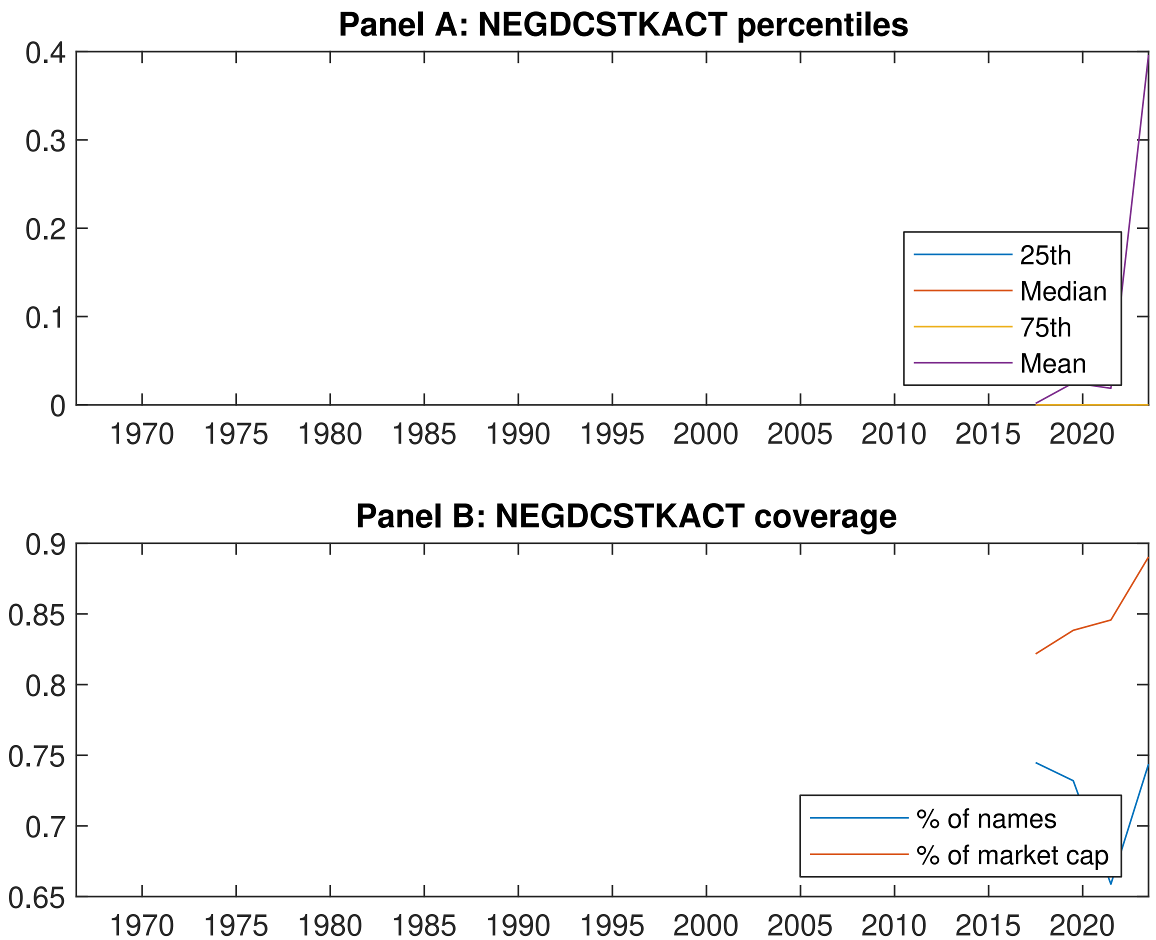


Figure 1: Times series of SAD percentiles and coverage.
This figure plots descriptive statistics for SAD. Panel A shows cross-sectional percentiles of SAD over the sample. Panel B plots the monthly coverage of SAD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SAD. 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 SAD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.48	0.66	0.71	0.77	0.34
	[2.54]	[2.44]	[3.45]	[4.23]	[4.60]	[4.17]
α_{CAPM}	-0.09	-0.13	0.07	0.19	0.25	0.34
	[-1.66]	[-2.30]	[1.13]	[3.57]	[4.87]	[4.23]
α_{FF3}	-0.08	-0.08	0.13	0.19	0.23	0.31
	[-1.48]	[-1.46]	[2.35]	[3.52]	[4.46]	[3.83]
α_{FF4}	-0.08	-0.05	0.15	0.12	0.21	0.29
	[-1.36]	[-0.91]	[2.72]	[2.27]	[4.01]	[3.46]
α_{FF5}	-0.11	0.00	0.17	0.07	0.12	0.22
	[-1.88]	[0.04]	[3.00]	[1.30]	[2.36]	[2.75]
α_{FF6}	-0.10	0.02	0.19	0.02	0.11	0.21
	[-1.77]	[0.35]	[3.25]	[0.44]	[2.24]	[2.60]
Panel B: Fama and French (2018) 6-factor model loadings for SAD-sorted portfolios						
β_{MKT}	0.93	1.02	0.99	0.98	0.97	0.03
	[68.48]	[78.65]	[73.48]	[81.92]	[82.22]	[1.71]
β_{SMB}	-0.03	0.04	0.08	-0.03	0.00	0.03
	[-1.59]	[2.03]	[3.92]	[-1.96]	[0.05]	[1.15]
β_{HML}	-0.00	-0.13	-0.20	-0.07	-0.06	-0.06
	[-0.12]	[-5.11]	[-7.69]	[-2.98]	[-2.71]	[-1.55]
β_{RMW}	0.09	-0.14	-0.09	0.13	0.12	0.03
	[3.42]	[-5.63]	[-3.35]	[5.70]	[5.37]	[0.85]
β_{CMA}	-0.03	-0.11	-0.01	0.27	0.29	0.33
	[-0.87]	[-2.92]	[-0.30]	[7.95]	[8.74]	[5.91]
β_{UMD}	-0.01	-0.03	-0.03	0.07	0.01	0.02
	[-0.59]	[-2.11]	[-1.87]	[5.87]	[0.66]	[0.81]
Panel C: Average number of firms (n) and market capitalization (me)						
n	604	645	553	604	664	
me ($\$10^6$)	1452	1156	1779	1792	2087	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SAD 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	0.34	0.34	0.31	0.29	0.22	0.21
			[4.17]	[4.23]	[3.83]	[3.46]	[2.75]	[2.60]
Quintile	NYSE	EW	0.58	0.65	0.57	0.49	0.41	0.36
			[8.08]	[9.22]	[8.58]	[7.52]	[6.46]	[5.76]
Quintile	Name	VW	0.33	0.34	0.31	0.29	0.23	0.23
			[4.15]	[4.20]	[3.83]	[3.53]	[2.88]	[2.77]
Quintile	Cap	VW	0.28	0.27	0.26	0.22	0.21	0.19
			[3.43]	[3.28]	[3.10]	[2.56]	[2.51]	[2.17]
Decile	NYSE	VW	0.33	0.29	0.26	0.21	0.20	0.17
			[3.22]	[2.85]	[2.59]	[2.06]	[1.93]	[1.60]
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	0.30	0.31	0.28	0.27	0.22	0.21
			[3.73]	[3.83]	[3.48]	[3.31]	[2.66]	[2.56]
Quintile	NYSE	EW	0.38	0.44	0.36	0.32	0.19	0.18
			[4.82]	[5.65]	[4.99]	[4.54]	[2.85]	[2.63]
Quintile	Name	VW	0.29	0.31	0.28	0.27	0.22	0.22
			[3.70]	[3.80]	[3.47]	[3.34]	[2.75]	[2.68]
Quintile	Cap	VW	0.25	0.24	0.23	0.21	0.20	0.18
			[3.01]	[2.91]	[2.74]	[2.46]	[2.37]	[2.15]
Decile	NYSE	VW	0.29	0.25	0.23	0.20	0.18	0.16
			[2.84]	[2.48]	[2.26]	[1.99]	[1.77]	[1.57]

Table 3: Conditional sort on size and SAD

This table presents results for conditional double sorts on size and SAD. 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 SAD. 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 SAD and short stocks with low SAD .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

	SAD Quintiles					SAD Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.32	0.66	0.88	0.96	0.96	0.64	0.71	0.64	0.58	0.49	0.46
	[1.13]	[2.36]	[3.23]	[3.60]	[3.84]	[7.30]	[8.24]	[7.78]	[6.99]	[6.11]	[5.61]
(2)	0.53	0.64	0.86	0.87	0.93	0.40	0.46	0.36	0.33	0.26	0.24
	[2.16]	[2.52]	[3.36]	[3.62]	[4.05]	[4.43]	[5.16]	[4.24]	[3.83]	[2.99]	[2.79]
(3)	0.58	0.61	0.80	0.80	0.92	0.34	0.36	0.30	0.30	0.23	0.24
	[2.76]	[2.59]	[3.34]	[3.64]	[4.45]	[4.11]	[4.33]	[3.66]	[3.67]	[2.73]	[2.84]
(4)	0.49	0.63	0.75	0.85	0.81	0.32	0.33	0.27	0.25	0.11	0.11
	[2.51]	[2.89]	[3.42]	[4.16]	[4.24]	[3.98]	[4.05]	[3.45]	[3.07]	[1.46]	[1.36]
(5)	0.48	0.45	0.54	0.56	0.72	0.23	0.21	0.21	0.18	0.18	0.16
	[2.94]	[2.38]	[2.83]	[3.20]	[4.35]	[2.35]	[2.15]	[2.08]	[1.74]	[1.72]	[1.52]

Panel B: Portfolio average number of firms and market capitalization

	SAD Quintiles: Average n					SAD Quintiles: Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	342	342	343	340	341	25	27	34	25	24
(2)	95	94	94	93	94	47	47	47	47	47
(3)	68	68	68	67	68	82	79	81	82	83
(4)	58	58	58	58	59	177	174	180	183	185
(5)	53	53	53	53	53	1211	1143	1476	1258	1503

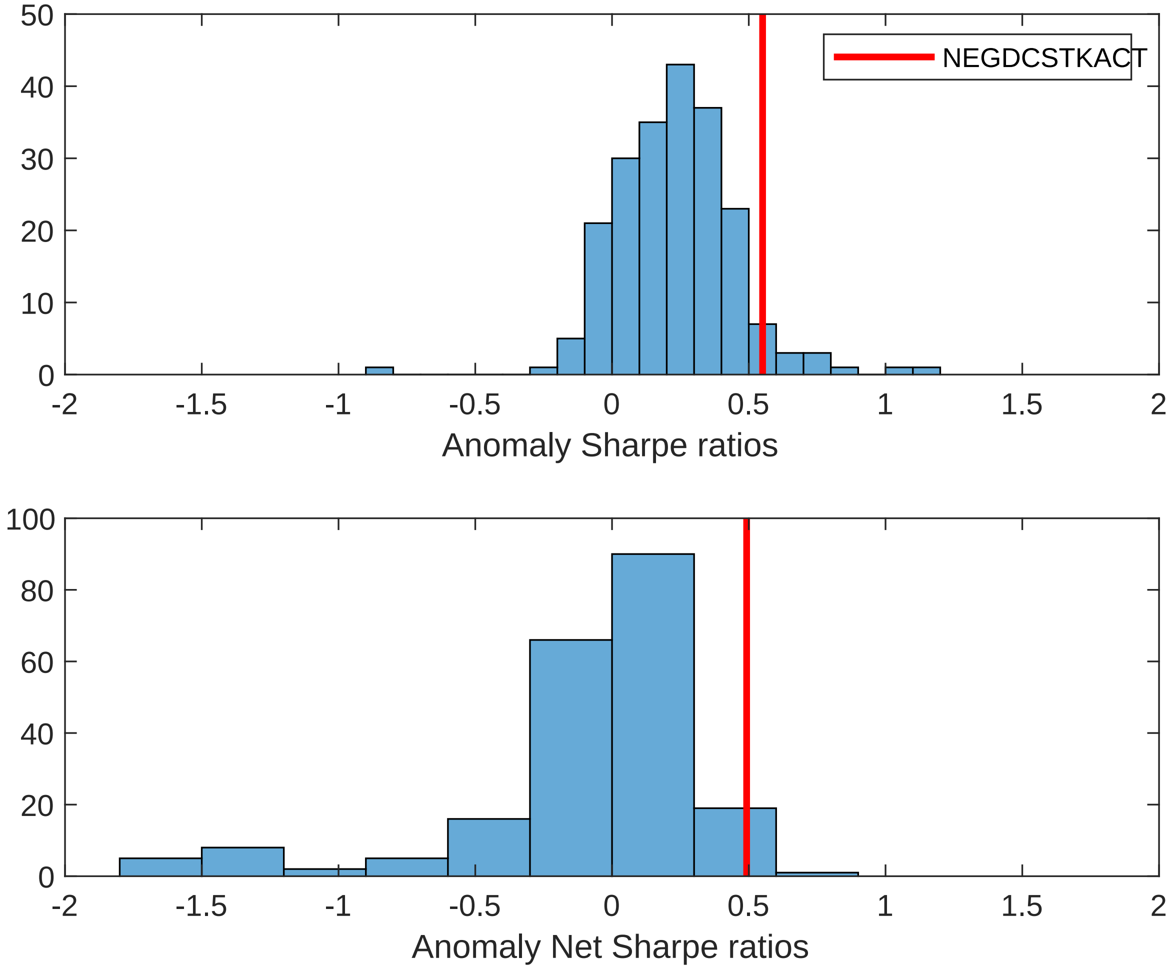


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SAD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

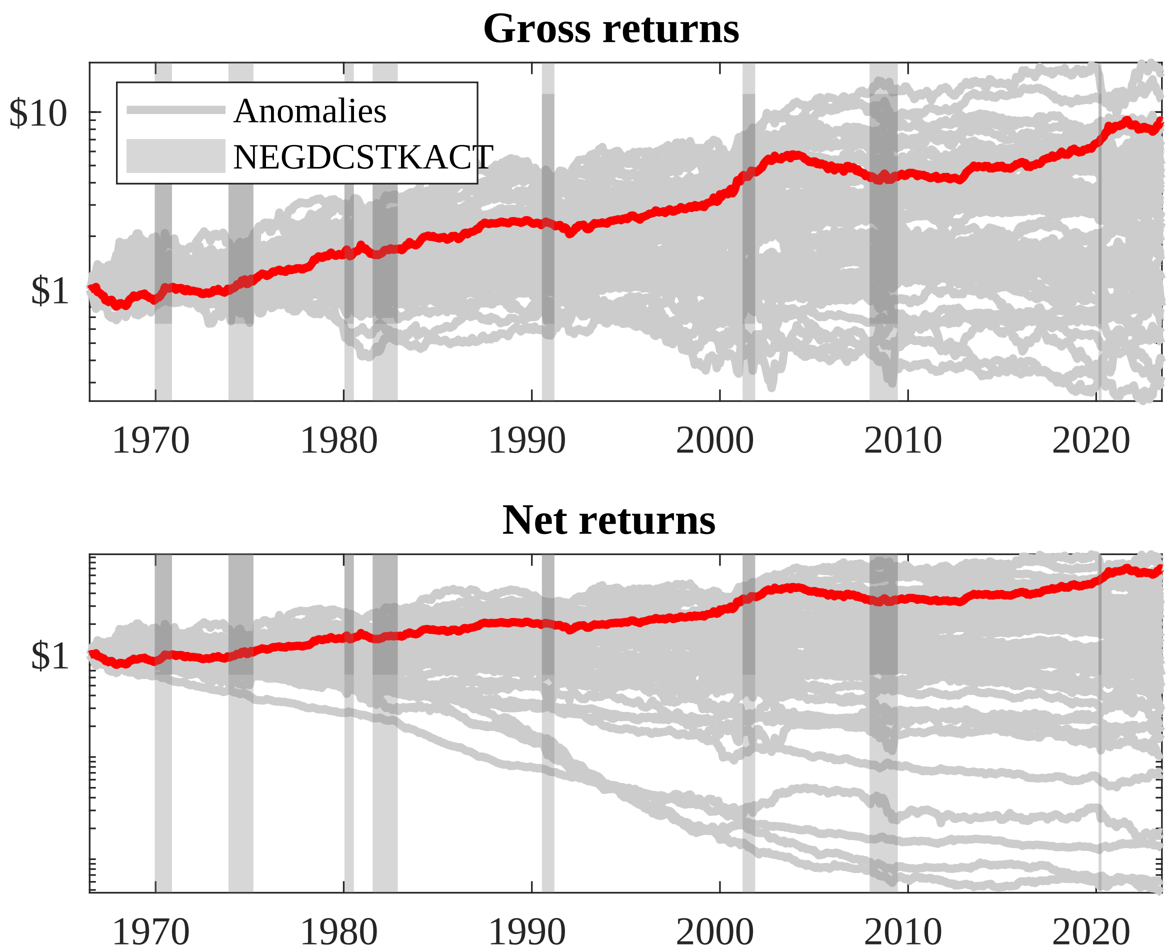


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SAD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

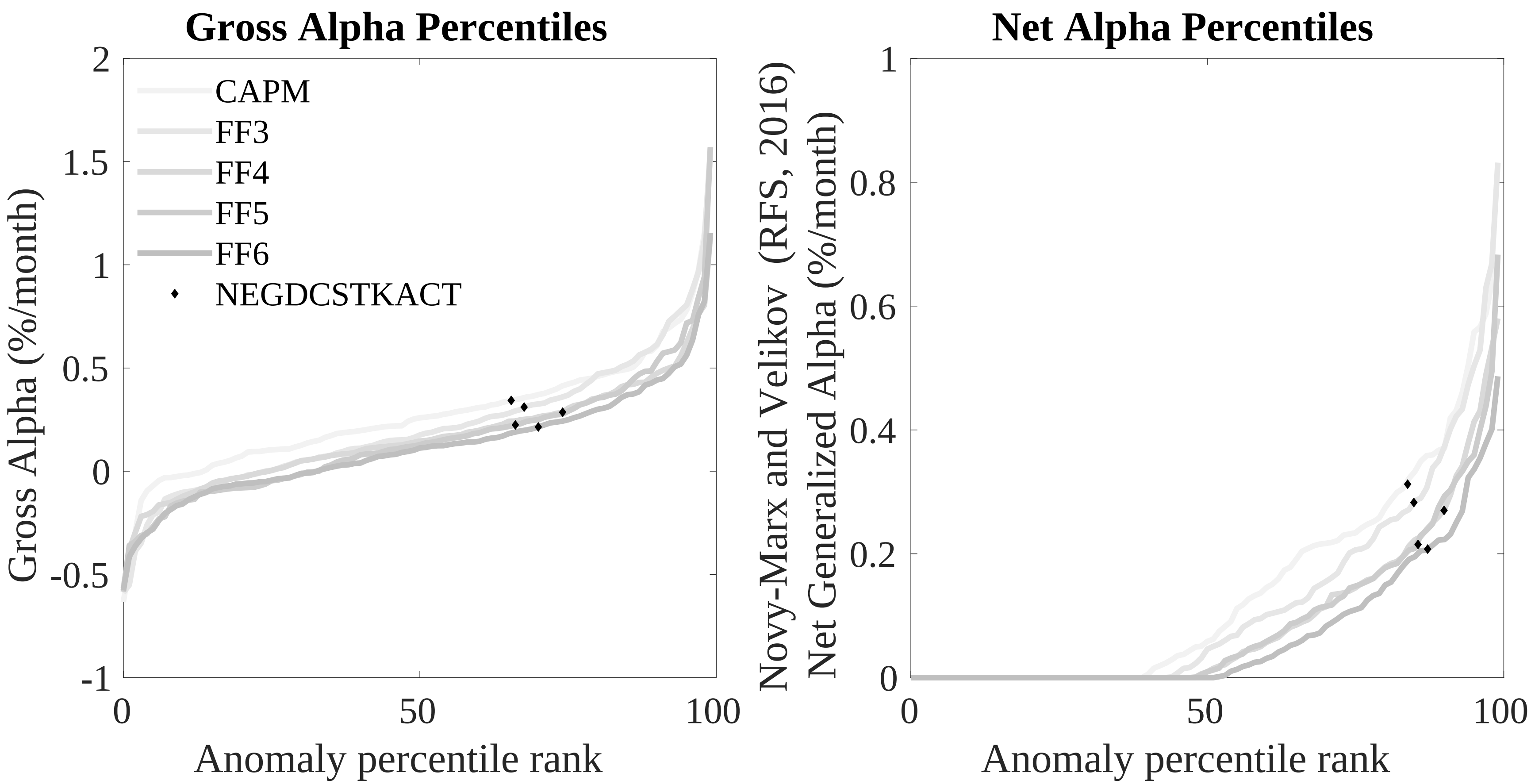
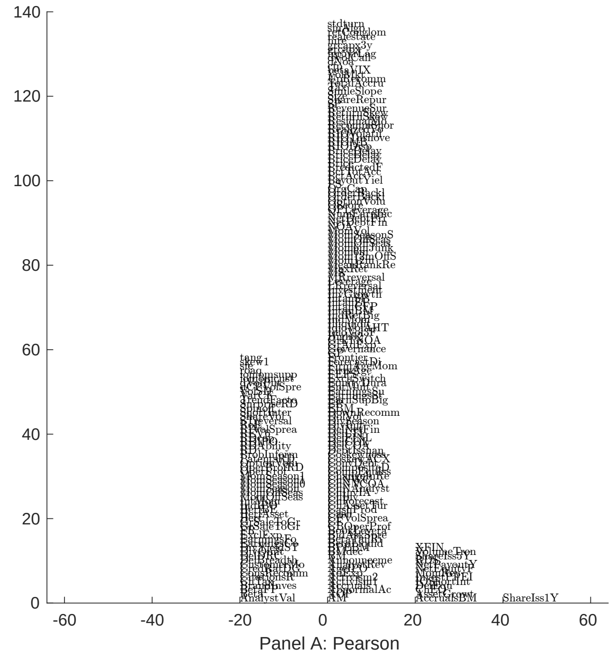


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SAD trading strategy alphas (diamonds). The strategies are constructed using 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.



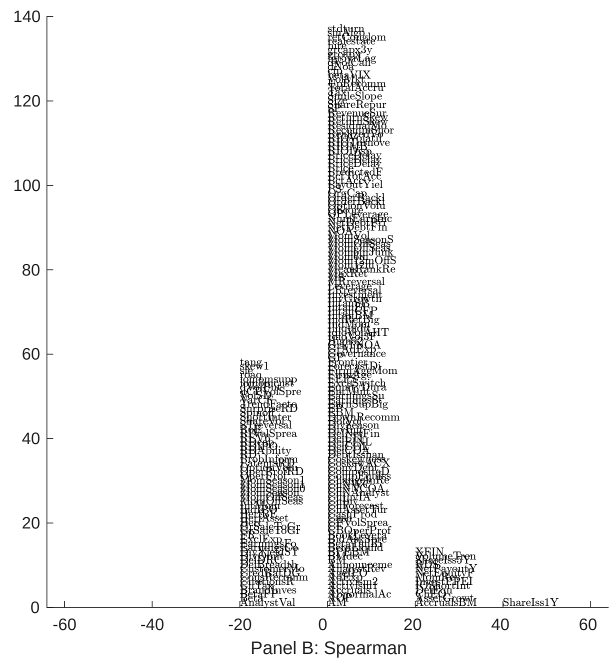


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SAD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

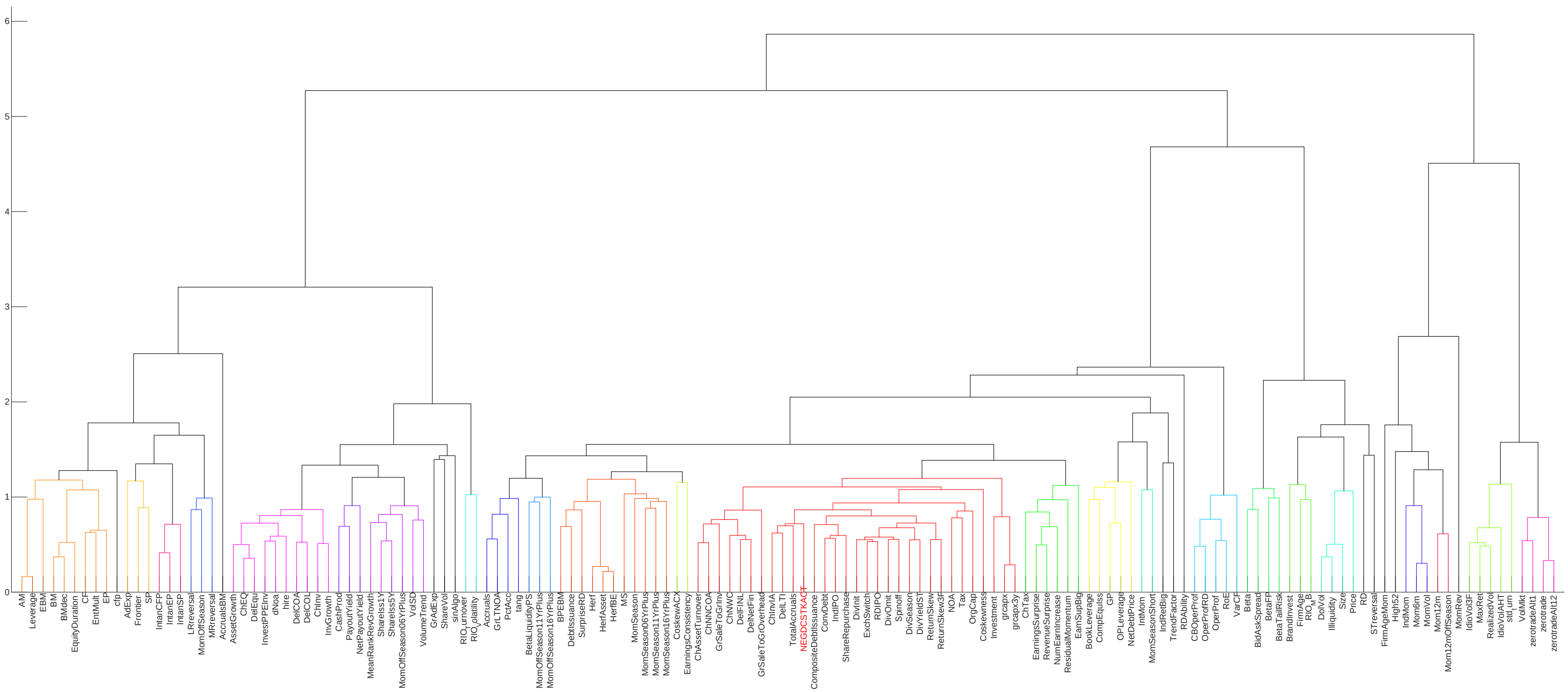


Figure 6: Agglomerative hierarchical cluster plot

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

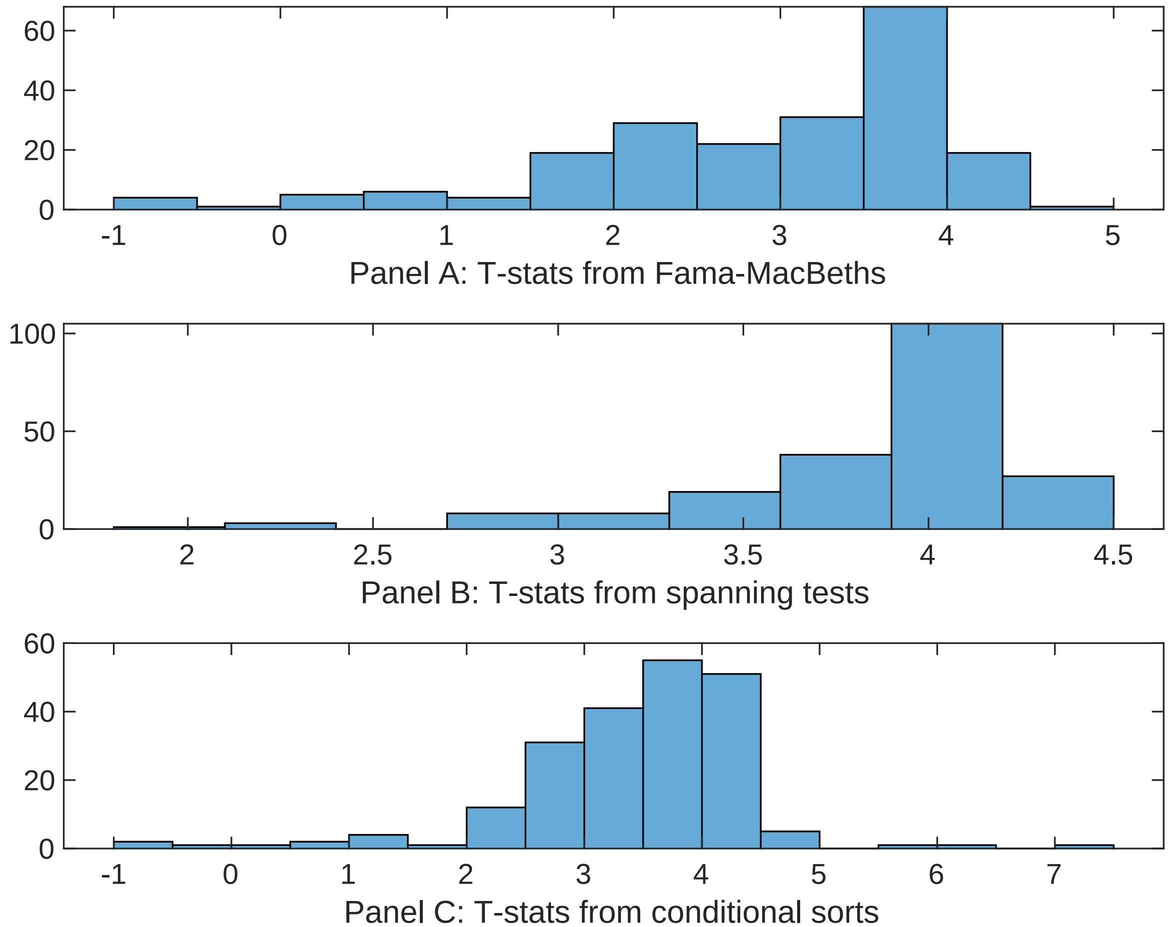


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SAD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SAD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SAD} SAD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SAD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SAD. Stocks are finally grouped into five SAD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SAD 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 SAD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SAD} SAD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. 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	0.13	0.18	0.12	0.13	0.13	0.14	0.13
	[5.46]	[7.13]	[5.19]	[5.84]	[5.38]	[5.83]	[5.20]
SAD	0.15	0.12	0.87	0.15	0.13	0.98	0.79
	[3.35]	[2.66]	[1.80]	[3.67]	[3.00]	[2.25]	[1.66]
Anomaly 1	0.27						0.96
	[5.73]						[2.38]
Anomaly 2		0.49					-0.43
		[4.38]					[-0.29]
Anomaly 3			0.28				0.23
			[2.48]				[2.14]
Anomaly 4				0.32			0.31
				[3.38]			[0.35]
Anomaly 5					0.15		-0.99
					[4.20]		[-0.18]
Anomaly 6						0.11	0.72
						[8.84]	[6.93]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the SAD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SAD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. 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	0.19	0.21	0.20	0.18	0.23	0.22	0.17
	[2.35]	[2.67]	[2.52]	[2.24]	[2.87]	[2.66]	[2.24]
Anomaly 1	26.79						17.79
	[6.53]						[3.73]
Anomaly 2		34.93					33.34
		[7.91]					[5.17]
Anomaly 3			14.54				1.82
			[4.61]				[0.51]
Anomaly 4				14.60			1.36
				[3.42]			[0.30]
Anomaly 5					22.29		-3.07
					[5.17]		[-0.51]
Anomaly 6						6.04	-15.60
						[1.11]	[-2.74]
mkt	5.70	4.68	6.05	5.67	3.19	3.56	6.62
	[3.02]	[2.50]	[3.10]	[2.87]	[1.66]	[1.83]	[3.42]
smb	5.04	2.35	6.76	3.17	3.17	2.96	5.31
	[1.86]	[0.87]	[2.41]	[1.13]	[1.14]	[1.03]	[1.89]
hml	-8.32	-9.49	-10.39	-8.84	-8.22	-5.59	-11.33
	[-2.26]	[-2.61]	[-2.65]	[-2.23]	[-2.20]	[-1.48]	[-2.92]
rmw	-5.68	4.70	-5.03	0.41	5.08	2.76	-2.29
	[-1.45]	[1.29]	[-1.21]	[0.11]	[1.35]	[0.73]	[-0.53]
cma	19.92	-2.29	22.39	28.62	9.18	25.05	11.97
	[3.44]	[-0.33]	[3.72]	[5.01]	[1.30]	[2.90]	[1.42]
umd	1.46	1.23	3.04	1.92	2.28	1.76	0.71
	[0.79]	[0.66]	[1.60]	[1.01]	[1.19]	[0.90]	[0.38]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	13	14	10	9	9	6	17

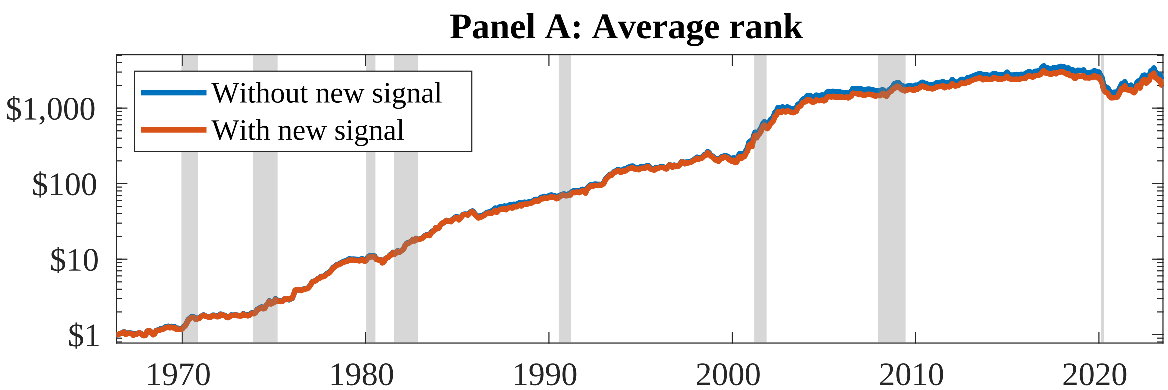


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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