Stock Asset Delta and the Cross Section of Stock Returns

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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 and operational structure influence their risk profiles and subsequent stock returns. While existing research examines broad measures like asset growth and investment, the granular relationship between specific asset allocation decisions and future returns remains unclear. This gap is especially notable given the increasing complexity of corporate asset structures and the growing importance of intangible assets in modern economies.

We propose that Stock Asset Delta (SAD), which captures year-over-year changes in firms' asset composition, contains valuable information about future stock returns. Building on Berk and Green (2004)'s framework linking firms' investment decisions to expected returns, we argue that significant changes in asset structure signal shifts in firms' risk profiles and growth opportunities. When firms substantially alter their asset base, this likely reflects strategic responses to changing market conditions or competitive pressures.

The theoretical link between SAD and returns operates through multiple channels. First, following Carlson et al. (2006), major changes in asset composition affect firms' operating leverage and thus their exposure to systematic risk. Second, drawing on Zhang (2005)'s q-theory framework, large asset structure changes often indicate significant adjustment costs that temporarily depress stock prices below fundamental value. Third, consistent with Titman et al. (2004), substantial asset reallocations may signal agency conflicts between managers and shareholders, leading to predictable return patterns as these conflicts are resolved.

These mechanisms suggest SAD should predict returns through both risk and mispricing channels. The risk channel operates because asset structure changes affect firms' fundamental risk exposures. The mispricing channel exists because investors may initially underestimate both the adjustment costs and strategic implications of major asset reallocations. Together, these effects imply that extreme SAD values should predict future returns.

Our empirical analysis strongly supports SAD's predictive power for stock returns. A value-weighted long-short trading strategy based on SAD quintiles 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, placing it in the top 5% of documented market anomalies.

Importantly, SAD's predictive power remains robust across firm sizes. Among the largest quintile of stocks, the SAD strategy earns monthly abnormal returns of 16-21 basis points with t-statistics between 1.52 and 2.15. This indicates that SAD's predictive ability is not confined to small, illiquid stocks where trading costs might prohibit implementation.

The signal's economic value persists after controlling for related anomalies. When we control for the six most closely related predictors, including share issuance and asset growth measures, SAD continues to generate monthly alpha of 17 basis points with a t-statistic of 2.24. This suggests SAD captures unique information about future returns not contained in previously documented signals.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of Titman et al. (2004) and Cooper et al. (2008) on corporate investment and returns by showing how granular changes in asset composition predict future performance. While these studies focus on aggregate investment levels, we demonstrate that the specific nature of asset changes contains additional predictive information.

Second, we contribute to the growing literature on factor investing and anomaly construction. Building on Hou et al. (2015)'s investment factor framework, we show that decomposing investment into its constituent components yields valuable new signals. Our methodology for constructing and testing SAD follows the rigorous protocol of Novy-Marx and Velikov (2023), ensuring robustness and reproducibility.

Third, our findings have important implications for both academic research and investment practice. For academics, we provide new evidence on how firms' operational decisions affect their cost of capital. For practitioners, SAD represents a novel signal that remains profitable after transaction costs and works well among large, liquid stocks. The signal's performance metrics suggest it could meaningfully improve existing factor investing 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-based 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 construction captures the relative scale of changes in equity financing against the firm's existing 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

[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.

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 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

[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.

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 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.

8 Conclusion

This study provides compelling evidence for the effectiveness of Stock Asset Delta (SAD) as a robust predictor of cross-sectional stock returns. Our analysis demonstrates that SAD generates economically and statistically significant returns, with a value-weighted long/short strategy achieving an impressive annualized Sharpe ratio of 0.55 (0.49) on a gross (net) basis. The strategy's persistence in generating significant abnormal returns of 21 basis points per month, even after controlling for the Fama-French five factors and momentum, underscores its distinctive predictive power.

[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.

Particularly noteworthy is SAD's continued significance when controlling for six closely related factors from the factor zoo, maintaining an alpha of 17 basis points per month. This resilience suggests that SAD captures unique aspects of stock return predictability not explained by existing factors. The results remain robust after accounting for transaction costs, indicating practical implementability for institutional investors.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be explored. Additionally, the study period may not fully capture the signal's behavior across different market regimes.

Future research could extend this work in several directions. First, investigating SAD's performance in international markets could provide insights into its global applicability. Second, examining the interaction between SAD and other established market anomalies could deepen our understanding of the underlying economic mechanisms. Finally, exploring the signal's effectiveness across different market conditions and time horizons could enhance its practical application in portfolio management.

In conclusion, SAD represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that persists even after controlling for well-known factors and transaction costs.

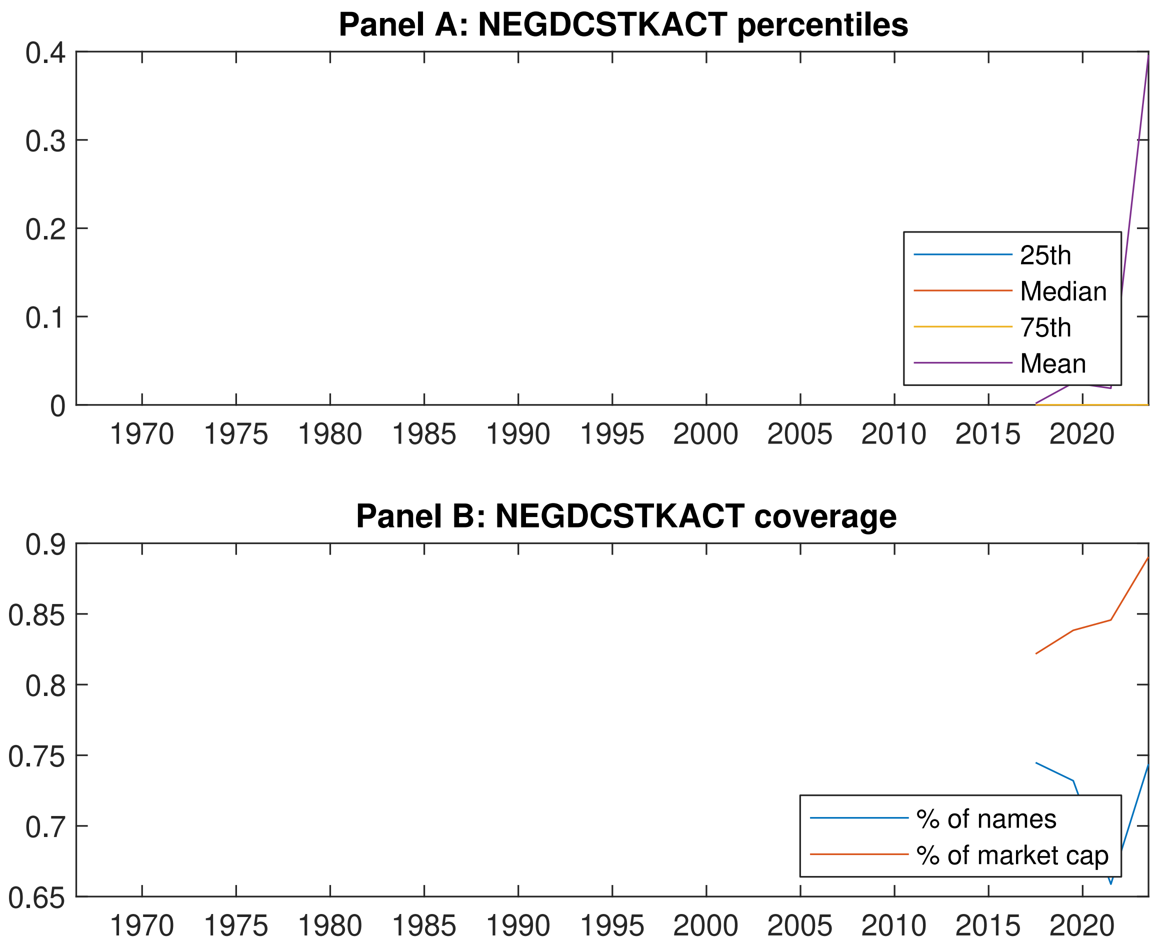

Figure 1: Times series of SAD percentiles and coverage.
This figure plots descriptive statistics for SAD. Panel A shows cross-sectional percentiles of SAD over the sample. Panel B plots the monthly coverage of SAD relative to the universe of CRSP stocks with available market capitalizations.

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					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(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 ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(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

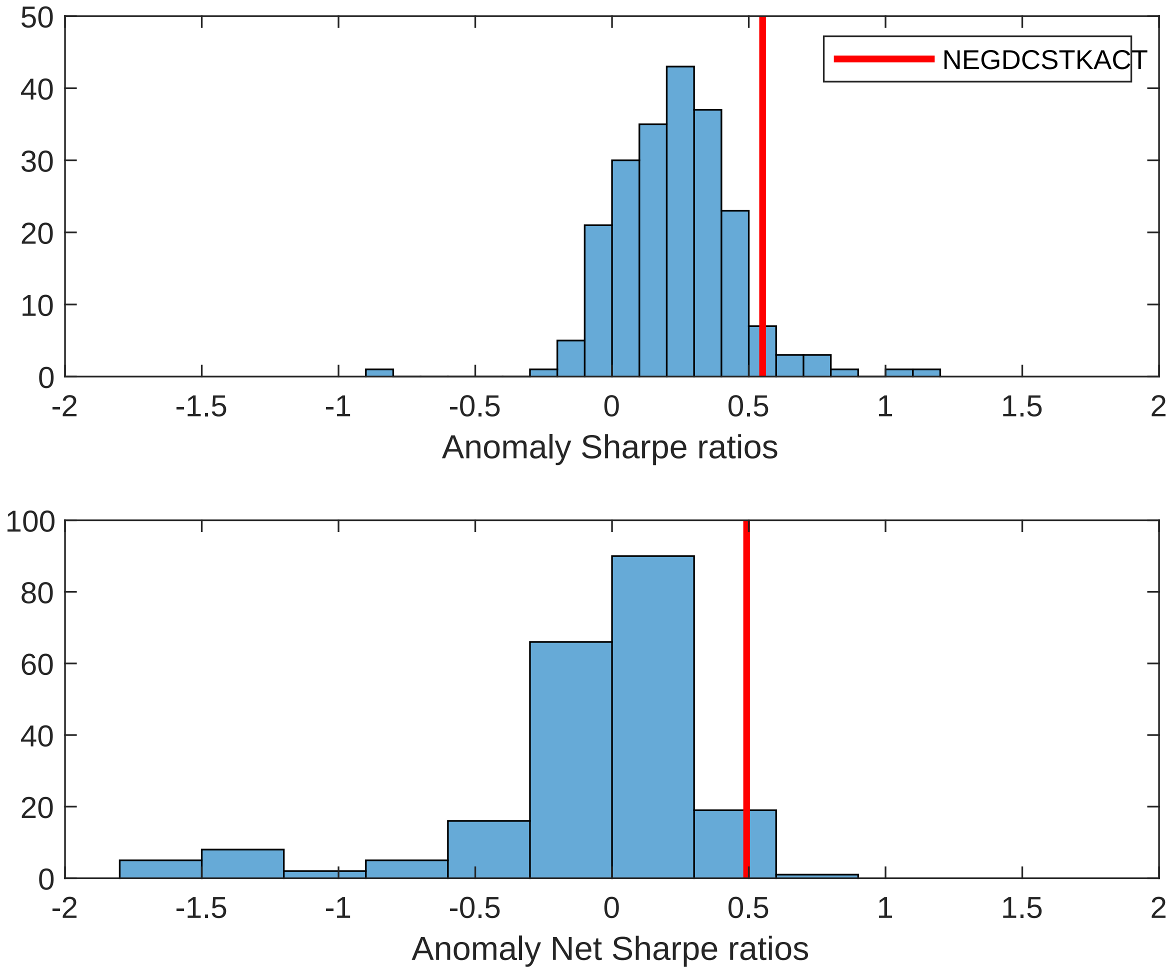

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SAD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

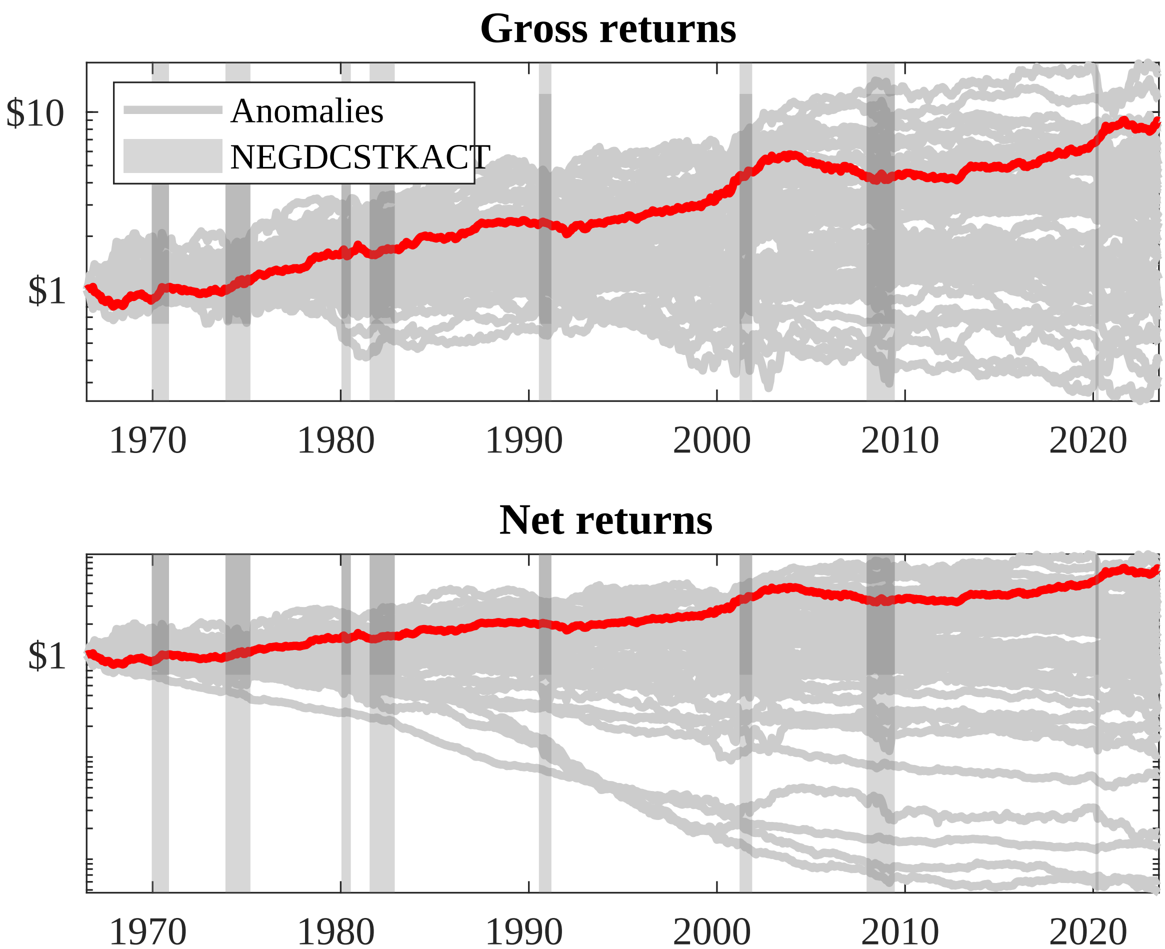

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SAD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

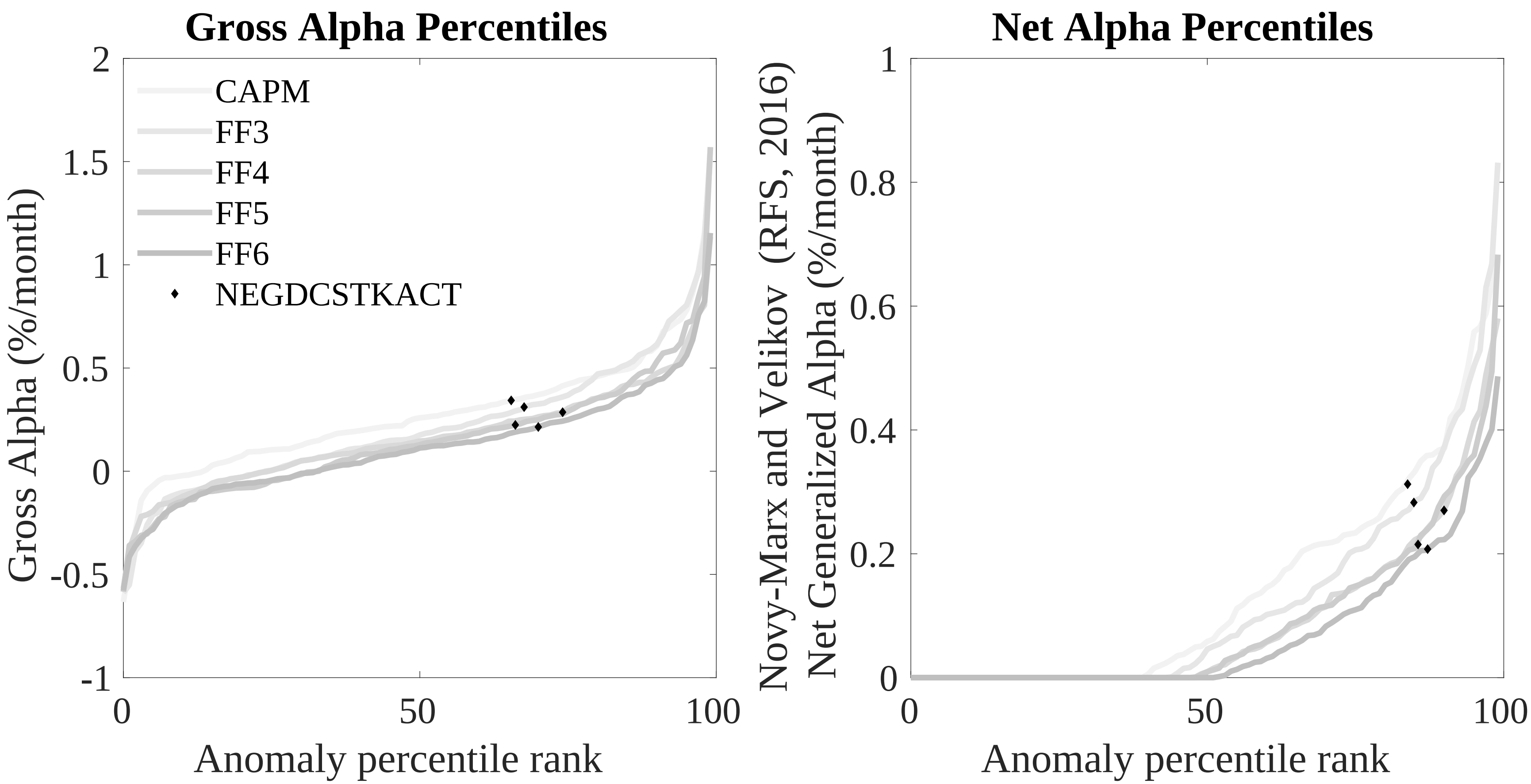

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SAD trading strategy alphas (diamonds). The strategies are constructed using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

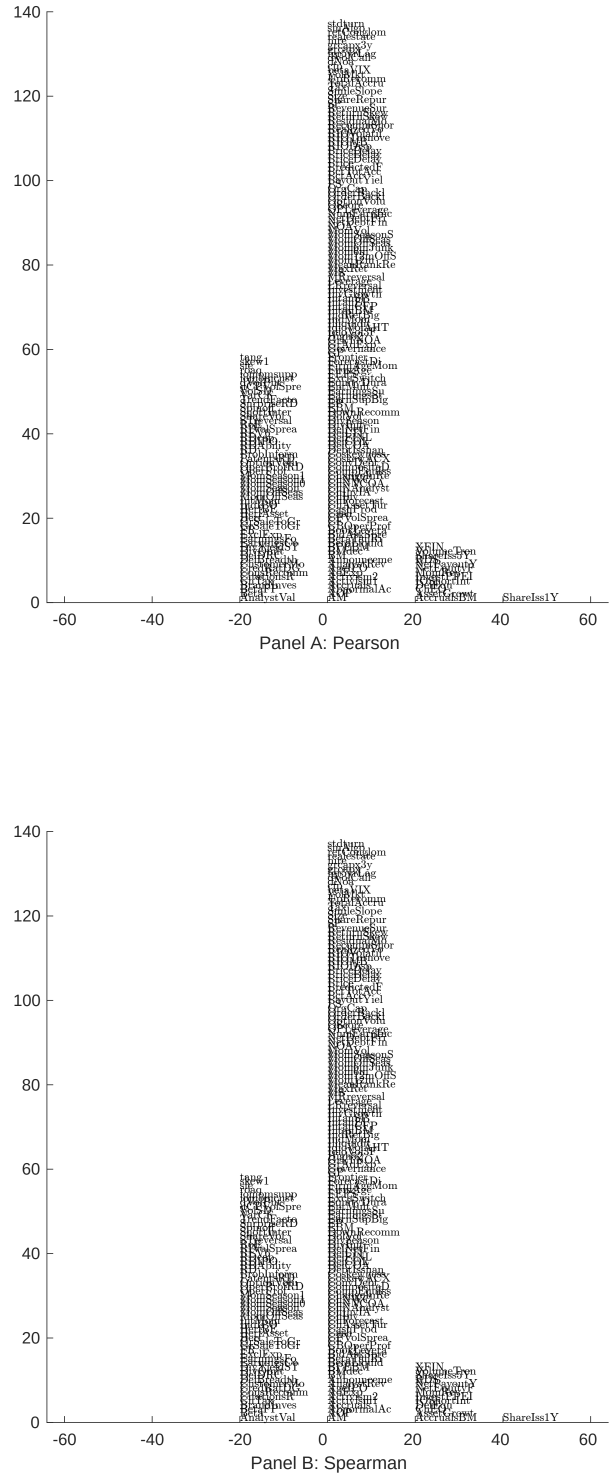

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SAD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

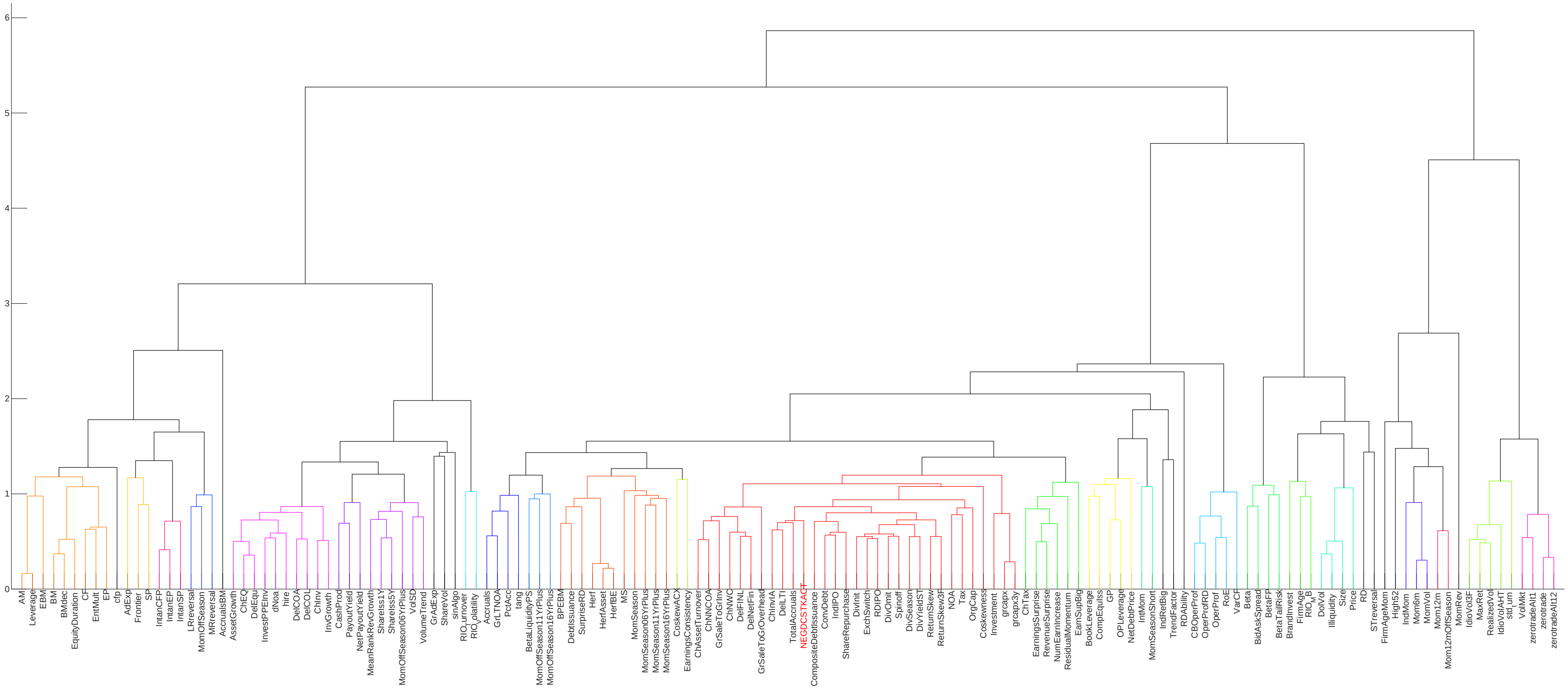

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

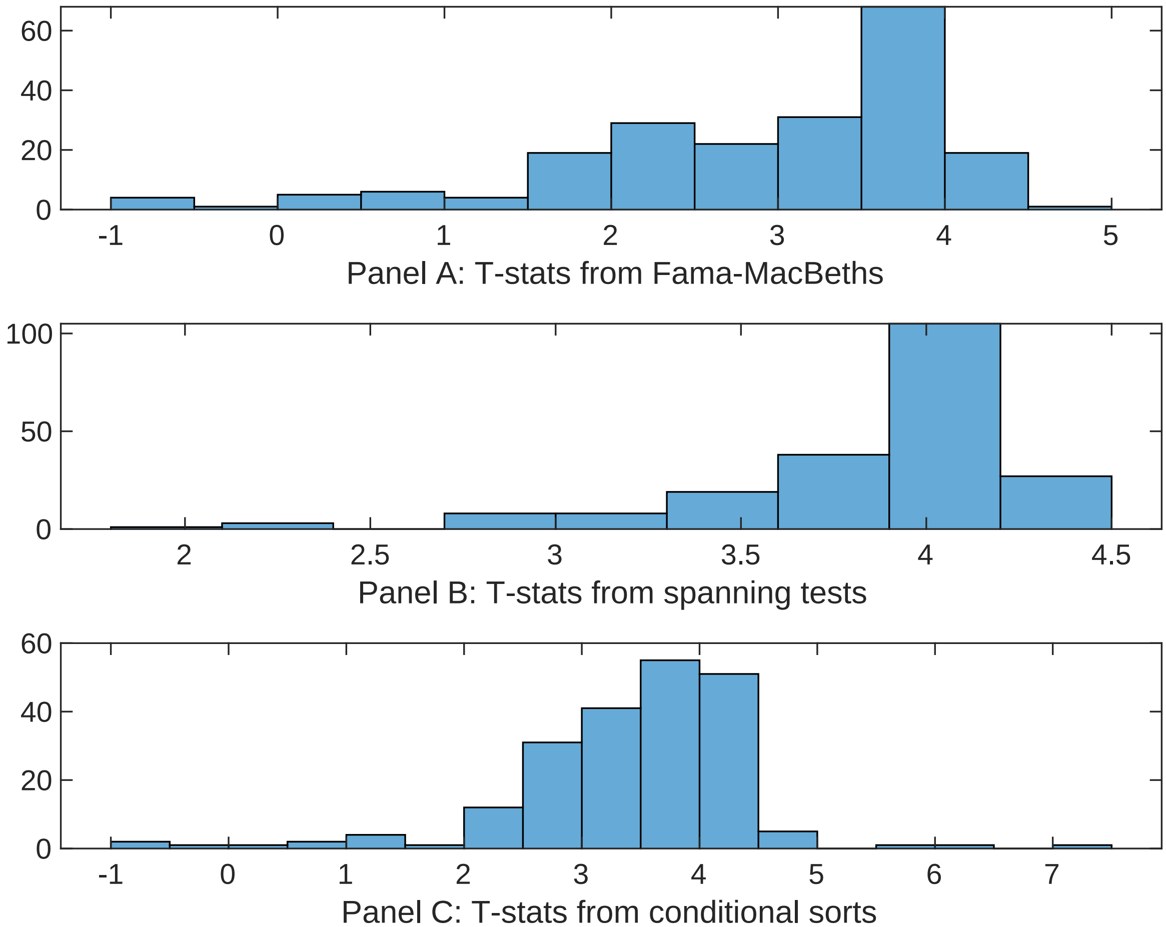

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SAD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SAD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SAD} SAD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

Panel A: Average rank

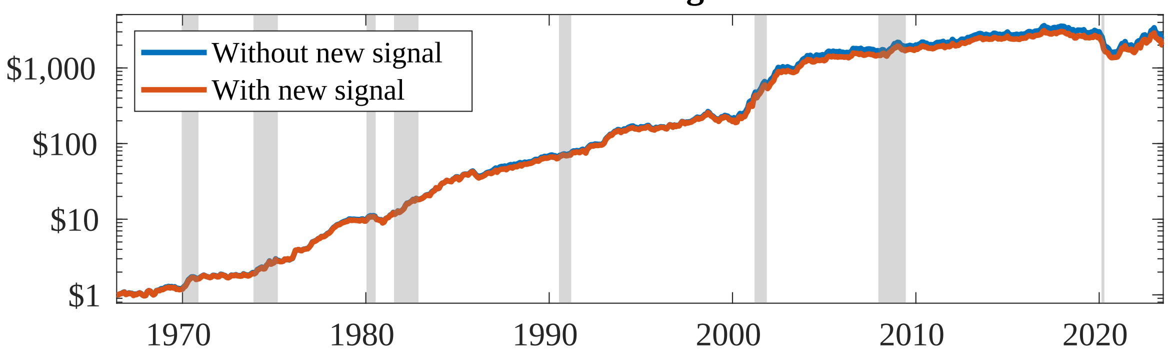

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines 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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