Net Asset Impact to Depreciation and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Net Asset Impact to Depreciation (NAID), 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 NAID achieves an annualized gross (net) Sharpe ratio of 0.45 (0.41), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (25) bps/month with a t-statistic of 2.98 (2.60), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Total accruals, Size, Price, Advertising Expense, Abnormal Accruals, Past trading volume) is 21 bps/month with a t-statistic of 2.23.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional asset pricing models assume that publicly available accounting information is fully reflected in stock prices, a growing body of evidence suggests that certain accounting-based signals can predict future returns (Richardson et al., 2010). This predictability poses a challenge to market efficiency and raises questions about how investors process complex accounting information.

One particularly understudied area is how investors interpret the relationship between firms' depreciation policies and their net asset positions. While depreciation directly affects reported earnings and book values, its economic significance extends beyond pure accounting effects to reflect management's assessment of asset productivity and replacement needs (Beaver, 1998). This disconnect between accounting treatment and economic reality creates potential opportunities for sophisticated investors to identify mispriced securities.

We hypothesize that the ratio of net asset impact to depreciation (NAID) contains valuable information about future stock returns for several reasons. First, following (Zhang, 2013), firms with higher NAID ratios likely have greater operational flexibility, as their net asset positions are less constrained by accumulated depreciation. This flexibility should be particularly valuable during economic downturns, suggesting these firms may have lower systematic risk.

Second, building on (Titman and Jegadeesh, 1994), we argue that NAID captures information about management's investment efficiency. A high NAID indicates that management has maintained productive capacity while controlling depreciation costs, potentially signaling superior capital allocation skills. This efficiency should translate into higher future profitability and returns (Fama and French, 2006).

Third, behavioral finance theory suggests that investors may struggle to fully process the implications of complex accounting relationships (Hirshleifer, 2001). The interaction between net assets and depreciation involves multiple financial statement items and requires sophisticated analysis to interpret correctly. This complexity creates an opportunity for informed investors to profit from others' limited attention.

Our empirical analysis reveals strong support for NAID's predictive power. A value-weighted long-short trading strategy based on NAID quintiles generates significant abnormal returns of 29 basis points per month (t-statistic = 2.98) relative to the Fama-French five-factor model plus momentum. The strategy's economic significance is substantial, with an annualized Sharpe ratio of 0.45 before trading costs and 0.41 after costs.

Importantly, NAID's predictive ability remains robust after controlling for known return predictors. When we include the six most closely related anomalies (Total accruals, Size, Price, Advertising Expense, Abnormal Accruals, and Past trading volume), the strategy still earns a significant alpha of 21 basis points per month (t-statistic = 2.23). This persistence suggests NAID captures unique information not reflected in existing factors.

The signal's effectiveness extends across the size spectrum, though with varying magnitude. Among the largest quintile of stocks, NAID generates monthly alphas between 18 and 34 basis points with respect to standard factor models. This finding indicates that the anomaly is not confined to small, illiquid stocks where implementation might be challenging.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of (Sloan, 1996) on accounting-based anomalies by identifying a novel signal that captures information about asset efficiency and management skill. Unlike traditional accrual measures, NAID specifically focuses on the relationship between productive assets and their depreciation patterns.

Second, we contribute to the growing literature on investment-based asset pricing

(Zhang, 2013) by showing how depreciation policies contain information about firms' real investment opportunities and constraints. Our findings suggest that accounting choices related to fixed assets have important implications for expected returns, beyond their direct effects on reported earnings.

Finally, our work adds to the empirical asset pricing literature by documenting a robust new return predictor that survives the rigorous testing protocol of (Novy-Marx and Velikov, 2023). The fact that NAID generates significant risk-adjusted returns even after accounting for transaction costs and controlling for known anomalies suggests it captures a distinct dimension of cross-sectional return predictability. These findings have important implications for both academic research on market efficiency and practical applications 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 Net Asset Impact to Depreciation ratio. 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 AOLOCH for other changes in assets and liabilities and item DPACT for depreciation and amortization. AOLOCH captures the net changes in various assets and liabilities not accounted for elsewhere in the cash flow statement, representing adjustments that affect a company's operational position. DPACT, meanwhile, represents the total depreciation and amortization expenses recognized during the accounting period, reflecting the systematic allocation of asset costs over their useful lives. The construction of the signal follows a straightforward ratio format, where we divide AOLOCH by DPACT for each firm in each year of our sample. This ratio provides insight into how changes in a firm's asset and liability position relate to its depreciation expenses, potentially capturing aspects of asset management efficiency and accounting quality. By examining this relationship, the signal aims to reflect the relative magnitude of operational adjustments against the baseline depreciation costs, offering a perspective on asset utilization and operational dynamics. We construct this ratio using end-of-fiscal-year values for both AOLOCH and DPACT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the NAID signal. Panel A plots the time-series of the mean, median, and interquartile range for NAID. On average, the cross-sectional mean (median) NAID is -0.11 (-0.00) over the 1989 to 2023 sample, where the starting date is determined by the availability of the input NAID data. The signal's interquartile range spans -0.26 to 0.17. Panel B of Figure 1 plots the time-series of the coverage of the NAID signal for the CRSP universe. On average, the NAID signal is available for 6.84% of CRSP names, which on average make up 7.62% of total market capitalization.

4 Does NAID predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on NAID 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 NAID portfolio and sells the low NAID 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 NAID strategy earns an average return of 0.26% per month with a t-statistic of 2.67. The annualized Sharpe ratio of the strategy is 0.45. The alphas range from 0.26% to 0.32% per month and have t-statistics exceeding 2.78 everywhere. The lowest alpha is with respect to the FF4 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 -0.14, with a t-statistic of -4.00 on the SMB 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 551 stocks and an average market capitalization of at least $2,481 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 NYSE breakpoints and equal-weighted portfolios, and equals 26 bps/month with a t-statistics of 4.06. Out of the twenty-five alphas reported in

Panel A, the t-statistics for twenty-five exceed two, and for seventeen 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 4-34bps/month. The lowest return, (4 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.53. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the NAID trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-four cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the NAID strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and NAID, as well as average returns and alphas for long/short trading NAID 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 NAID strategy achieves an average return of 24 bps/month with a t-statistic of 1.84. Among these large cap stocks, the alphas for the NAID strategy relative to the five most common factor models range from 18 to 34 bps/month with t-statistics between 1.38 and 2.67.

5 How does NAID perform relative to the zoo?

Figure 2 puts the performance of NAID 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 NAID strategy falls in the distribution. The NAID strategy's gross (net) Sharpe ratio of 0.45 (0.41) is greater than 88% (97%) 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 NAID strategy (red line).[2] Ignoring trading costs, a \$1 invested in the NAID strategy would have yielded \$1.55 which ranks the NAID strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the NAID strategy would have yielded \$1.29 which ranks the NAID strategy in the top 4% 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 NAID relative to those. Panel A shows that the NAID strategy gross alphas fall between the 56 and 78 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 198906 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 NAID strategy has a positive net generalized alpha for five out of the five factor models. In these cases NAID ranks between the 77 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does NAID 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 NAID with 210 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 NAID or at least to weaken the power NAID has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of NAID conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NAID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NAID} NAID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{NAID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts,

[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.

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 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on NAID. Stocks are finally grouped into five NAID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NAID trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on NAID 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 NAID signal in these Fama-MacBeth regressions exceed 1.72, with the minimum t-statistic occurring when controlling for Total accruals. Controlling for all six closely related anomalies, the t-statistic on NAID is 1.65.

Similarly, Table 5 reports results from spanning tests that regress returns to the NAID 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 NAID strategy earns alphas that range from 21-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.22, which is achieved when controlling for Total accruals. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the NAID trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.23.

7 Does NAID add relative to the whole zoo?

Finally, we can ask how much adding NAID 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 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the NAID 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 159-anomaly combination strategy grows to $42.41, while $1 investment in the combination strategy that includes NAID grows to $42.73.

8 Conclusion

This study provides compelling evidence for the predictive power of Net Asset Impact to Depreciation (NAID) in forecasting cross-sectional stock returns. Our findings demonstrate that NAID-based trading strategies yield economically and statistically significant returns, with a value-weighted long/short portfolio generating an impressive annualized Sharpe ratio of 0.45 (0.41 after transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for well-established factor models and related anomalies.

The persistence of NAID's predictive ability, evidenced by monthly abnormal

[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 NAID is available.

returns of 29 basis points (25 basis points net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about firm value that is not fully reflected in market prices. Furthermore, the signal's continued significance after controlling for six closely related anomalies indicates that NAID provides distinct insights beyond existing financial metrics.

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, while we account for transaction costs, the implementation challenges in different market conditions and for investors with varying capital constraints deserve further investigation.

Future research could extend this work by examining NAID's performance across different market regimes, investigating its interaction with other accounting-based signals, and exploring its effectiveness in international markets. Additionally, studying the underlying economic mechanisms driving NAID's predictive power could provide valuable insights for both academics and practitioners.

In conclusion, NAID represents a promising addition to the quantitative investor's toolkit, offering meaningful predictive power that remains robust to common risk factors and related anomalies. These findings contribute to our understanding of market efficiency and asset pricing, while opening new avenues for future research in financial economics.

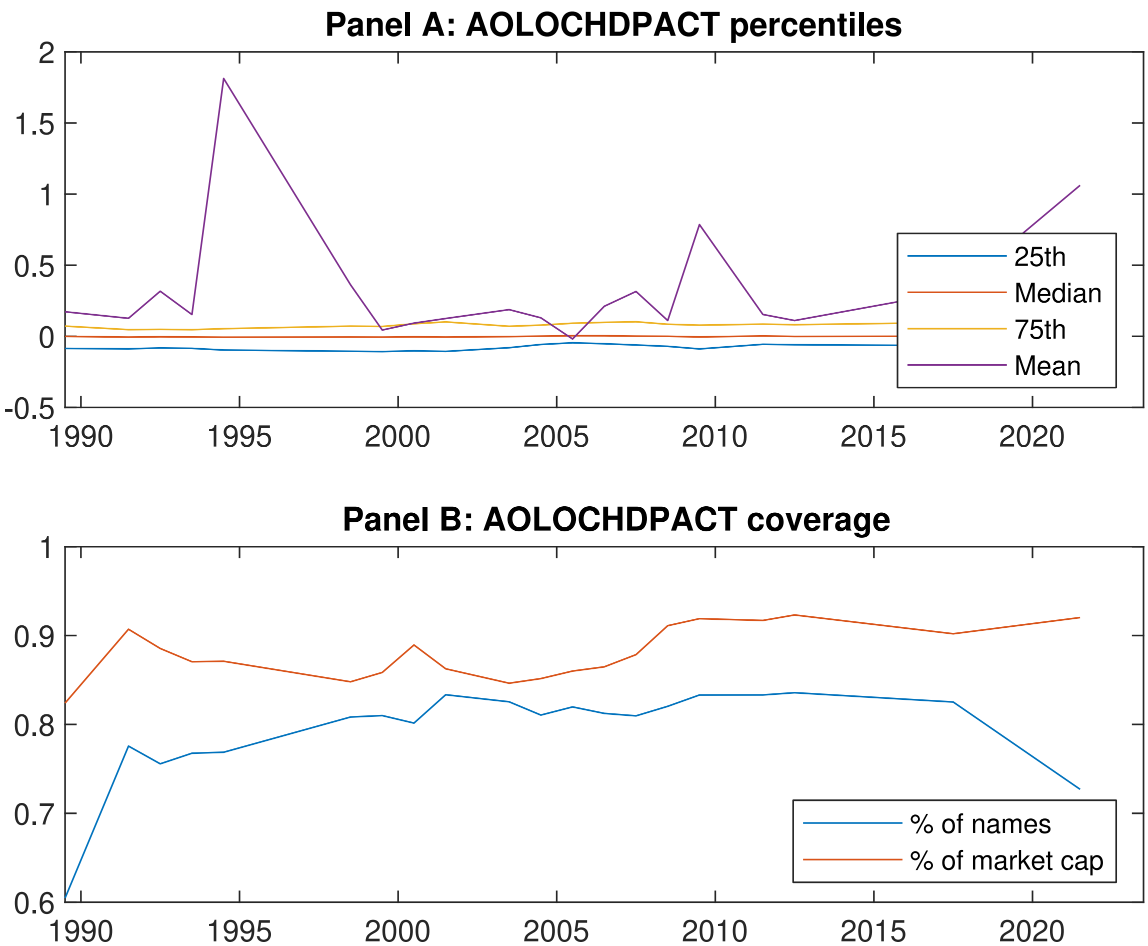


Figure 1: Times series of NAID percentiles and coverage.
This figure plots descriptive statistics for NAID. Panel A shows cross-sectional percentiles of NAID over the sample. Panel B plots the monthly coverage of NAID relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on NAID. 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 198906 to 202306.

Panel A: Excess returns and alphas on NAID-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.62	0.60	0.71	0.69	0.88	0.26
	[2.41]	[2.83]	[3.61]	[3.40]	[3.52]	[2.67]
α_{CAPM}	-0.18	-0.05	0.12	0.06	0.10	0.28
	[-2.57]	[-0.85]	[1.59]	[1.02]	[1.44]	[2.92]
α_{FF3}	-0.16	-0.06	0.08	0.06	0.14	0.30
	[-2.43]	[-0.91]	[1.24]	[0.98]	[2.34]	[3.20]
α_{FF4}	-0.11	-0.04	0.08	0.04	0.15	0.26
	[-1.72]	[-0.57]	[1.16]	[0.70]	[2.46]	[2.78]
α_{FF5}	-0.07	-0.17	-0.08	-0.06	0.25	0.32
	[-1.05]	[-2.71]	[-1.19]	[-1.11]	[4.28]	[3.33]
α_{FF6}	-0.04	-0.14	-0.07	-0.07	0.25	0.29
	[-0.56]	[-2.30]	[-1.09]	[-1.17]	[4.21]	[2.98]
Panel B: Fama and French (2018) 6-factor model loadings for NAID-sorted portfolios						
β_{MKT}	1.06	0.96	0.91	0.95	1.04	-0.02
	[66.14]	[61.74]	[57.96]	[67.59]	[70.57]	[-1.01]
β_{SMB}	0.11	0.01	-0.02	-0.01	-0.03	-0.14
	[4.61]	[0.46]	[-0.92]	[-0.68]	[-1.44]	[-4.00]
β_{HML}	-0.08	-0.14	0.04	-0.11	-0.09	-0.00
	[-2.97]	[-5.12]	[1.41]	[-4.68]	[-3.42]	[-0.11]
β_{RMW}	-0.14	0.11	0.24	0.14	-0.10	0.04
	[-4.73]	[4.07]	[8.32]	[5.60]	[-3.67]	[0.92]
β_{CMA}	-0.07	0.27	0.21	0.22	-0.27	-0.20
	[-1.70]	[7.08]	[5.26]	[6.19]	[-7.31]	[-3.37]
β_{UMD}	-0.06	-0.05	-0.01	0.01	0.00	0.06
	[-3.96]	[-3.35]	[-0.75]	[0.53]	[0.23]	[2.82]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1029	638	551	623	1000	
me (\$$10^6$)	2481	2502	2735	2980	4000	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the NAID 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 198906 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	0.26	0.28	0.30	0.26	0.32	0.29
			[2.67]	[2.92]	[3.20]	[2.78]	[3.33]	[2.98]
Quintile	NYSE	EW	0.26	0.28	0.29	0.23	0.28	0.23
			[4.06]	[4.51]	[4.68]	[3.80]	[4.35]	[3.71]
Quintile	Name	VW	0.37	0.40	0.42	0.38	0.49	0.44
			[3.34]	[3.53]	[3.99]	[3.57]	[4.51]	[4.13]
Quintile	Cap	VW	0.29	0.27	0.30	0.27	0.38	0.34
			[2.77]	[2.56]	[2.92]	[2.57]	[3.63]	[3.28]
Decile	NYSE	VW	0.33	0.34	0.38	0.36	0.45	0.42
			[2.57]	[2.67]	[3.15]	[2.93]	[3.78]	[3.53]
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	0.23	0.24	0.25	0.23	0.27	0.25
			[2.39]	[2.50]	[2.70]	[2.44]	[2.82]	[2.60]
Quintile	NYSE	EW	0.04	0.06	0.06	0.02	0.01	
			[0.53]	[0.71]	[0.72]	[0.33]	[0.08]	
Quintile	Name	VW	0.34	0.35	0.37	0.34	0.42	0.40
			[3.06]	[3.12]	[3.46]	[3.22]	[3.92]	[3.70]
Quintile	Cap	VW	0.27	0.24	0.25	0.23	0.32	0.30
			[2.53]	[2.22]	[2.48]	[2.28]	[3.13]	[2.93]
Decile	NYSE	VW	0.29	0.30	0.32	0.31	0.39	0.37
			[2.30]	[2.34]	[2.68]	[2.56]	[3.26]	[3.12]

Table 3: Conditional sort on size and NAID

This table presents results for conditional double sorts on size and NAID. 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 NAID. 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 NAID and short stocks with low NAID .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198906 to 202306.

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

		NAID Quintiles					NAID Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.39	0.79	0.95	1.00	0.61	0.22	0.24	0.23	0.18	0.26	0.21
		[1.01]	[2.33]	[2.78]	[2.99]	[1.64]	[2.03]	[2.18]	[2.11]	[1.62]	[2.21]	[1.83]
	(2)	0.60	0.78	0.87	0.83	0.65	0.04	0.13	0.13	0.10	0.09	0.07
		[1.71]	[2.61]	[3.04]	[2.82]	[1.97]	[0.37]	[1.13]	[1.13]	[0.83]	[0.76]	[0.56]
	(3)	0.66	0.76	0.81	0.80	0.85	0.19	0.19	0.20	0.20	0.30	0.29
		[2.08]	[2.76]	[3.12]	[3.03]	[2.69]	[1.72]	[1.65]	[1.80]	[1.74]	[2.59]	[2.46]
	(4)	0.75	0.77	0.80	0.75	0.96	0.21	0.21	0.26	0.21	0.39	0.34
		[2.64]	[3.09]	[3.34]	[3.07]	[3.27]	[1.89]	[1.82]	[2.52]	[2.03]	[3.70]	[3.25]
	(5)	0.67	0.49	0.73	0.70	0.91	0.24	0.18	0.22	0.19	0.34	0.31
		[2.82]	[2.35]	[3.80]	[3.37]	[3.44]	[1.84]	[1.38]	[1.69]	[1.45]	[2.67]	[2.39]

Panel B: Portfolio average number of firms and market capitalization

		NAID Quintiles					NAID Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	419	422	423	422	418	44	48	47	46	47
	(2)	126	127	127	127	126	82	85	86	86	84
	(3)	85	86	86	86	85	141	145	145	145	145
	(4)	71	72	72	72	72	306	317	316	317	319
	(5)	63	64	64	64	64	2195	2078	2370	2637	2466

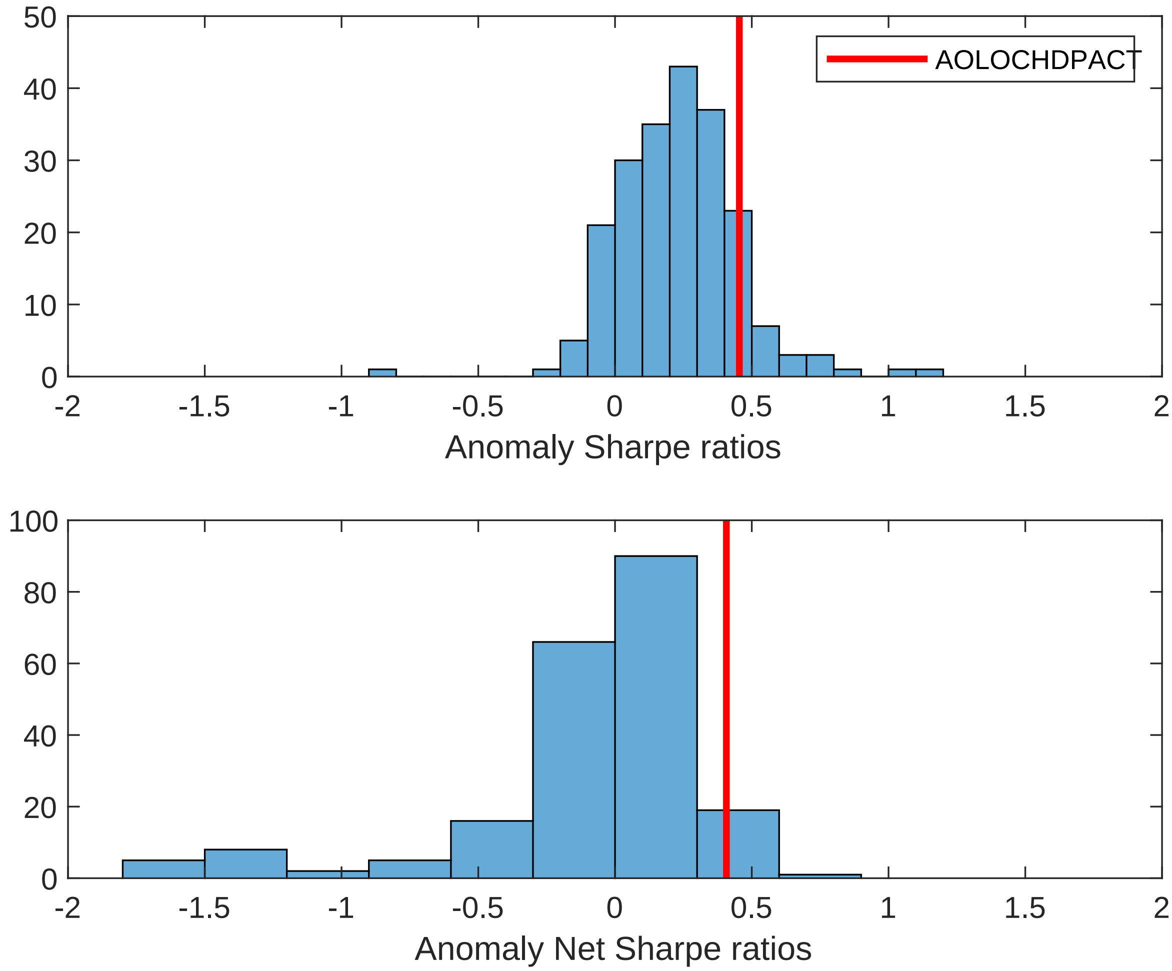


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the NAID with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

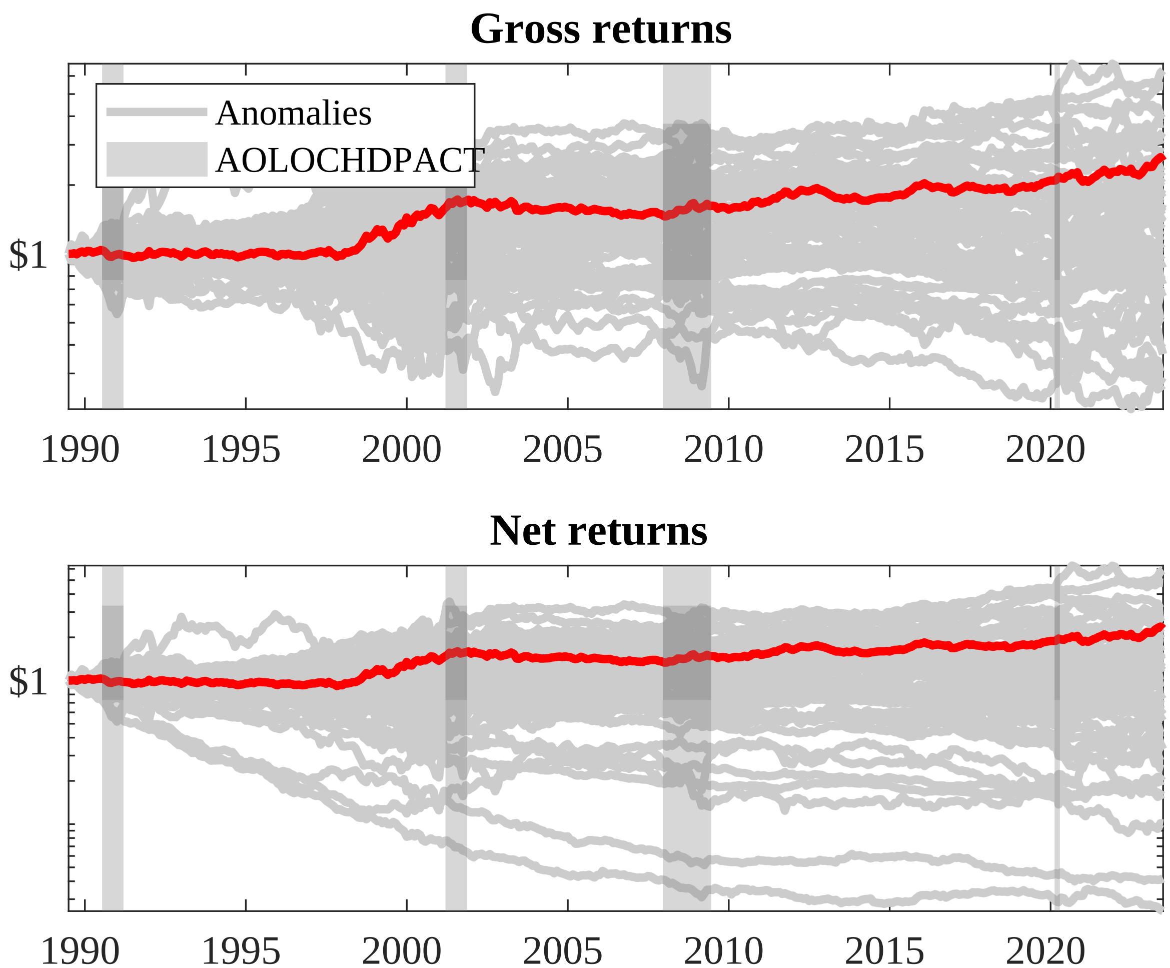


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the NAID trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

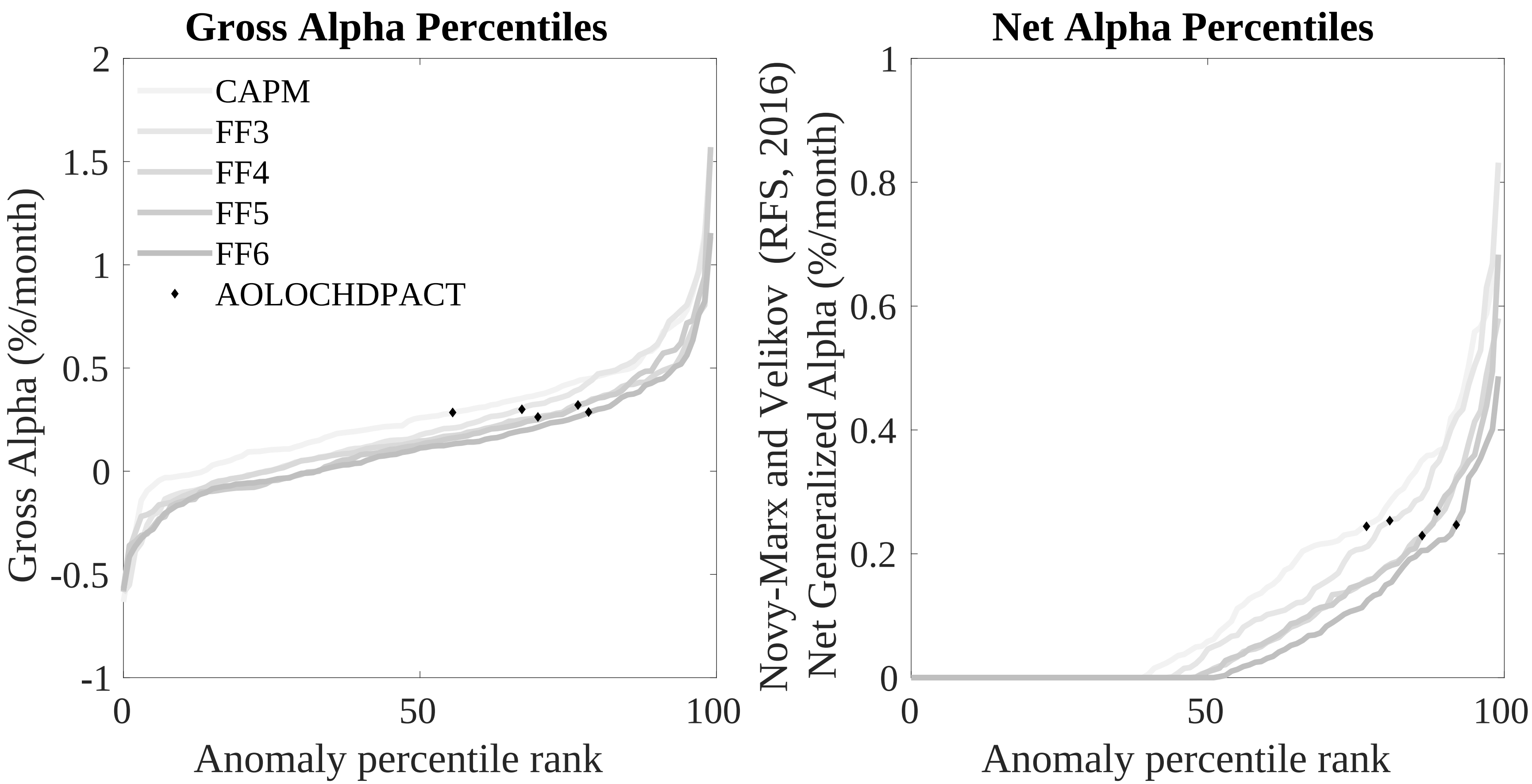
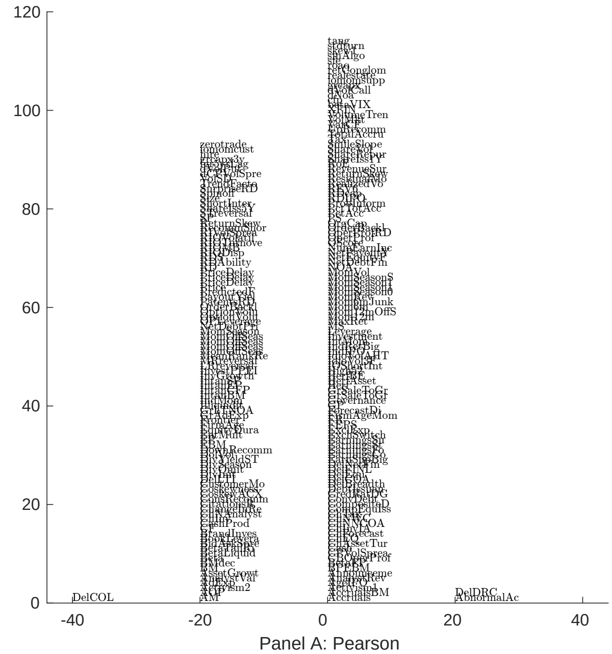


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the NAID trading strategy alphas (diamonds). The strategies are constructed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



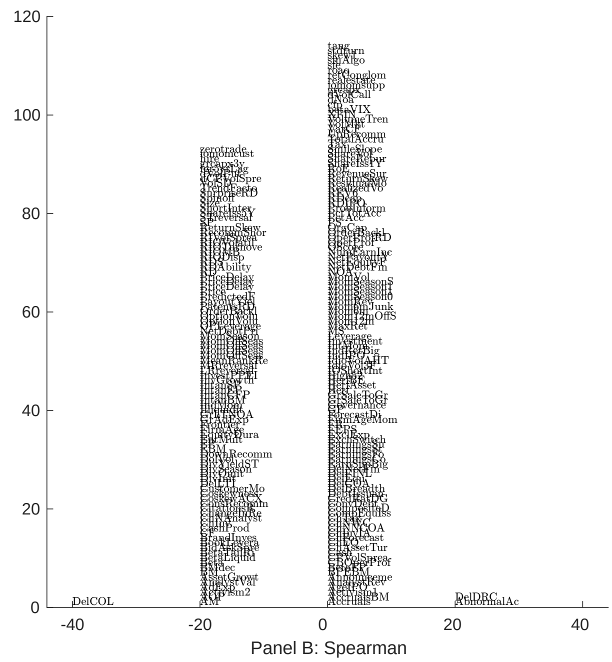


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with NAID. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

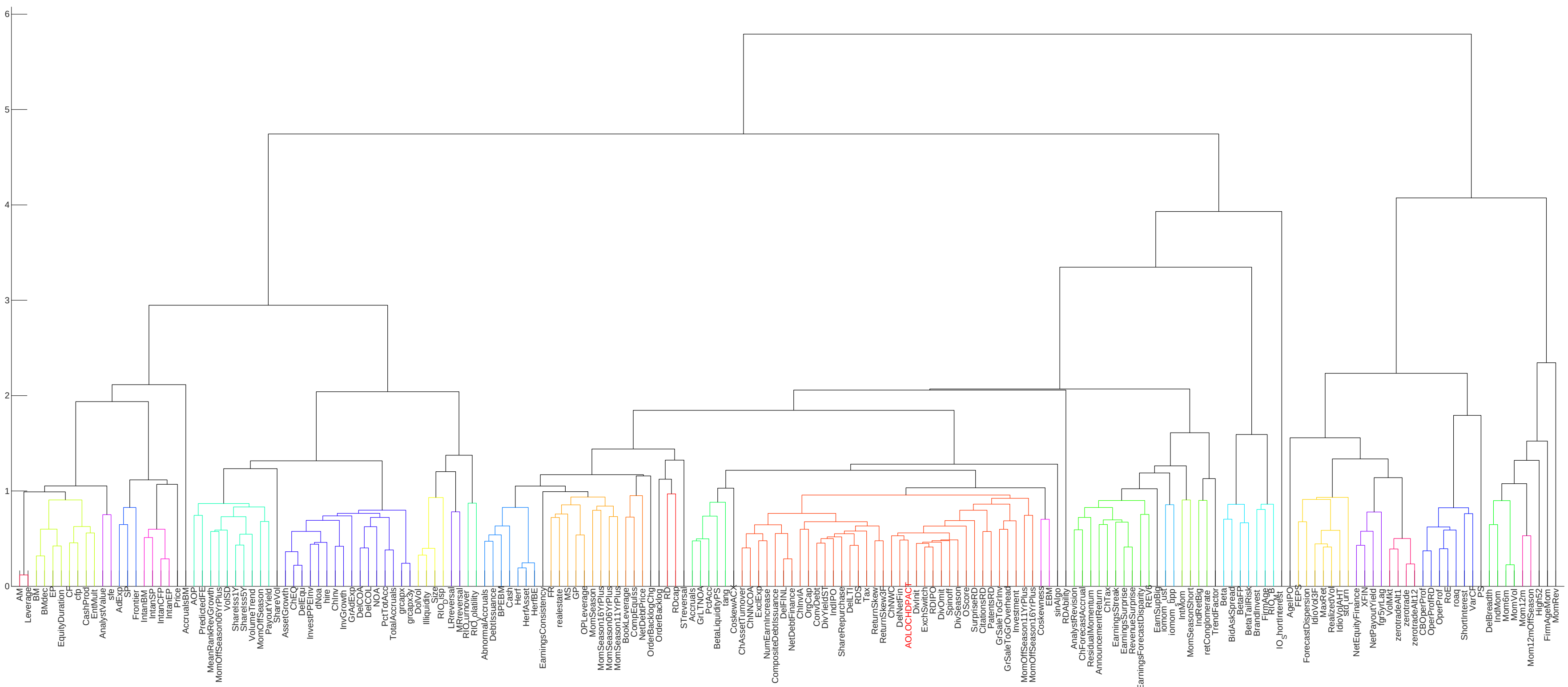


Figure 6: Agglomerative hierarchical cluster plot

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

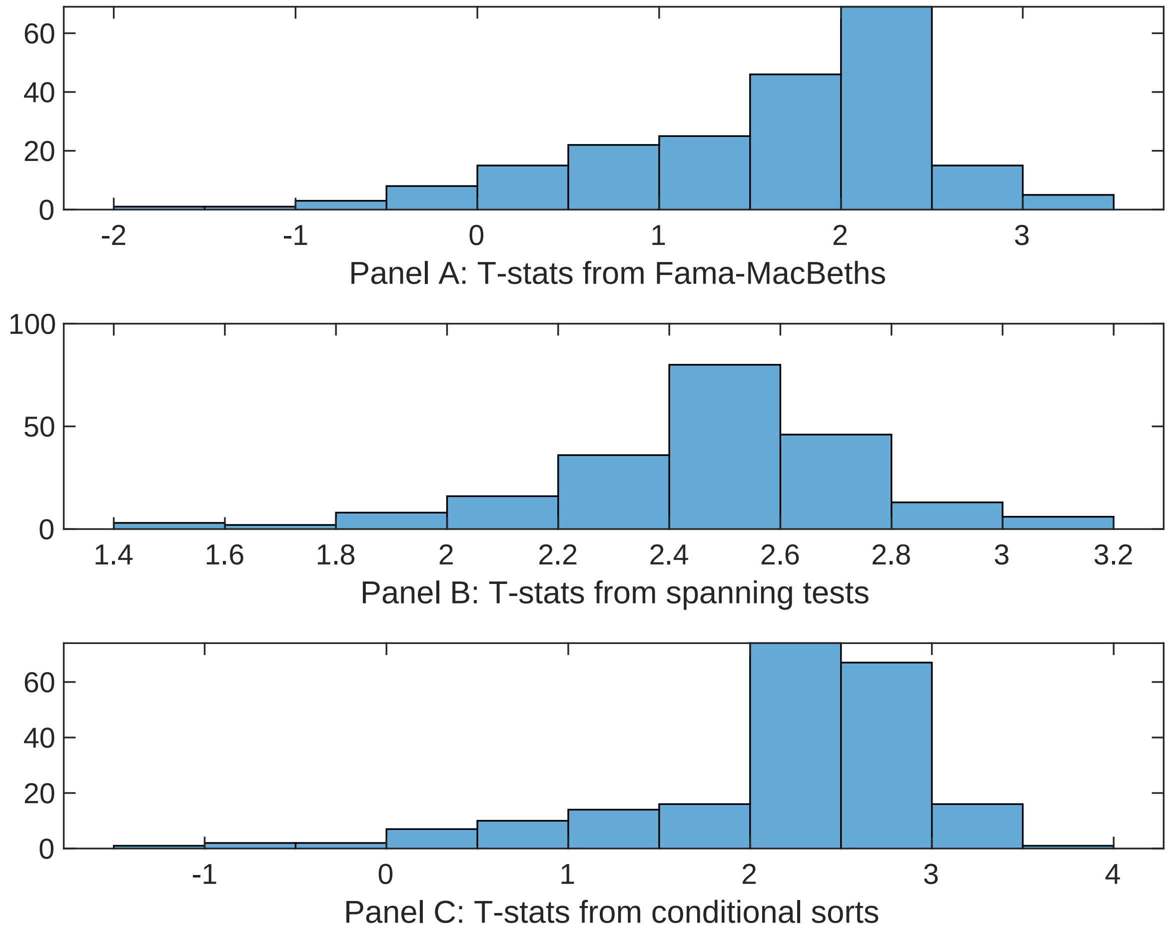


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of NAID conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NAID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NAID} NAID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{NAID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 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 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on NAID. Stocks are finally grouped into five NAID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NAID trading strategies conditioned on each of the 210 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on NAID. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{NAID} NAID_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Total accruals, Size, Price, Advertising Expense, Abnormal Accruals, Past trading volume. 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 198906 to 202306.

Intercept	0.11	0.11	0.12	0.10	0.12	0.13	0.13
	[3.83]	[3.43]	[3.09]	[3.36]	[3.81]	[3.75]	[3.85]
NAID	0.28	0.35	0.39	0.60	0.35	0.40	0.52
	[1.72]	[2.29]	[2.67]	[2.02]	[2.11]	[2.63]	[1.65]
Anomaly 1	0.56						0.58
	[1.98]						[2.03]
Anomaly 2		0.11					-0.16
		[0.68]					[-1.26]
Anomaly 3			0.73				-0.44
			[1.31]				[-0.06]
Anomaly 4				0.78			-0.42
				[0.11]			[-0.64]
Anomaly 5					-0.56		-0.57
					[-0.19]		[-1.57]
Anomaly 6						0.89	0.87
						[2.66]	[2.02]
# months	408	408	408	403	408	403	403
$\bar{R}^2(\%)$	0	0	1	1	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the NAID trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{NAID} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Total accruals, Size, Price, Advertising Expense, Abnormal Accruals, Past trading volume. 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 198906 to 202306.

Intercept	0.27	0.28	0.27	0.27	0.21	0.28	0.21
	[2.89]	[2.87]	[2.78]	[2.83]	[2.22]	[2.93]	[2.23]
Anomaly 1	-16.37						-14.19
	[-3.60]						[-3.09]
Anomaly 2		-2.94					-3.60
		[-0.56]					[-0.37]
Anomaly 3			3.40				6.21
			[0.94]				[1.31]
Anomaly 4				-4.66			-3.35
				[-1.60]			[-1.18]
Anomaly 5					16.93		18.21
					[3.95]		[4.26]
Anomaly 6						-13.22	-9.37
						[-2.02]	[-0.92]
mkt	-1.79	-2.14	-2.40	-1.65	-3.29	-4.95	-6.70
	[-0.77]	[-0.88]	[-0.98]	[-0.70]	[-1.39]	[-1.75]	[-2.21]
smb	-15.22	-10.96	-17.35	-11.34	-15.25	-1.38	-6.78
	[-4.52]	[-1.61]	[-3.67]	[-3.14]	[-4.55]	[-0.20]	[-0.97]
hml	-2.33	-0.54	-1.24	2.37	1.52	4.01	5.65
	[-0.57]	[-0.13]	[-0.30]	[0.56]	[0.37]	[0.90]	[1.21]
rmw	0.55	3.45	6.33	5.39	6.10	4.22	7.18
	[0.13]	[0.77]	[1.30]	[1.24]	[1.44]	[0.99]	[1.42]
cma	-8.38	-19.98	-20.43	-19.45	-15.31	-20.79	-6.18
	[-1.25]	[-3.36]	[-3.43]	[-3.19]	[-2.57]	[-3.48]	[-0.91]
umd	4.76	5.69	8.63	4.83	5.40	4.73	4.76
	[2.26]	[2.34]	[2.73]	[2.04]	[2.61]	[2.07]	[1.45]
# months	408	408	408	404	408	404	404
$\bar{R}^2(\%)$	15	12	12	12	16	13	19

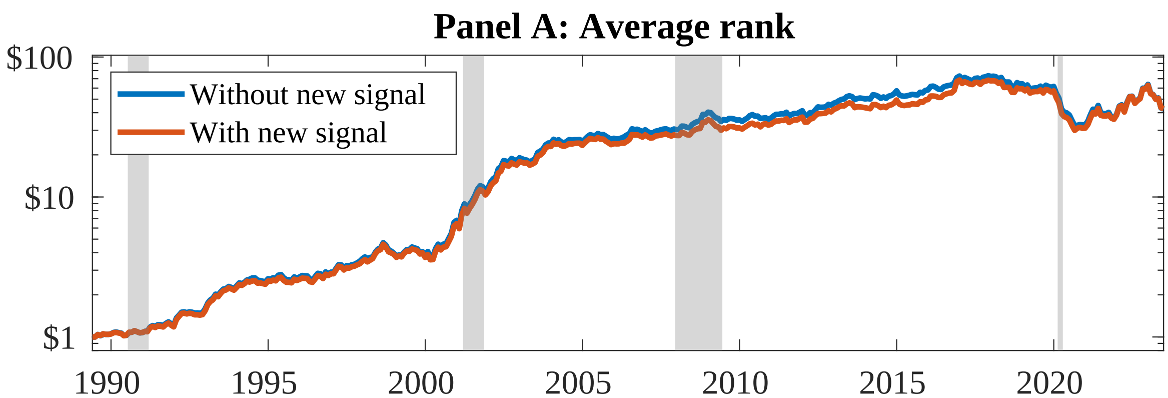


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as NAID. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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