Asset Income Spread and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Asset Income Spread (AIS), 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 AIS achieves an annualized gross (net) Sharpe ratio of 0.36 (0.27), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (19) bps/month with a t-statistic of 3.42 (2.71), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Asset growth, Growth in book equity, Inventory Growth, Change in current operating assets, Change in equity to assets, Growth in long term operating assets) is 21 bps/month with a t-statistic of 2.89.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents various market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are related to firms' investment and growth patterns (Cooper et al., 2008; Titman et al., 2004), the underlying mechanisms driving return predictability remain debated. This paper introduces a novel predictor - the Asset Income Spread (AIS) - that captures the efficiency with which firms deploy their assets to generate income.

Prior research has focused primarily on aggregate measures of asset growth and profitability, potentially overlooking important information contained in the relationship between different types of assets and their associated income streams. The disconnect between asset allocation decisions and their income-generating effectiveness may signal agency problems or managerial mistakes that the market fails to fully price (Titman et al., 2004).

We hypothesize that AIS predicts future returns through two primary channels. First, following (Cooper et al., 2008), firms with high asset-income spreads may be engaging in empire-building or overinvestment, leading to subsequent underperformance as these inefficient investments fail to generate adequate returns. The spread between asset growth and income growth serves as a direct measure of potential agency problems, where managers pursue growth at the expense of profitability (Jensen and Meckling, 1976).

Second, building on (Hirshleifer et al., 2015), we argue that investors may systematically underreact to signals of operational inefficiency. When firms expand assets without corresponding income growth, it may indicate deteriorating business conditions or poor capital allocation decisions. However, the complexity of analyzing multiple financial statement relationships could lead to investor inattention or processing difficulties (Hirshleifer and Teoh, 2003).

Additionally, the asset-income spread may capture information about future reversals in profitability that is not fully reflected in current stock prices. Following (Fairfield et al., 2003), extreme divergences between asset and income growth rates are likely unsustainable and should predict future mean reversion in operating performance.

Our empirical analysis reveals that AIS strongly predicts future stock returns. A value-weighted long-short portfolio strategy that buys stocks with high AIS and shorts stocks with low AIS generates a monthly alpha of 24 basis points (t-statistic = 3.42) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.36, placing it in the top quartile of documented market anomalies.

Importantly, the predictive power of AIS remains robust after controlling for known determinants of the cross-section of returns. When we simultaneously control for the six most closely related anomalies and the Fama-French six factors, the strategy still earns a significant alpha of 21 basis points per month (t-statistic = 2.89). The effect is particularly strong among large-cap stocks, with the long-short strategy generating a monthly alpha of 28 basis points (t-statistic = 2.86) in the largest size quintile.

After accounting for transaction costs using the high-frequency measure of (Chen and Velikov, 2022), the strategy maintains an economically and statistically significant net alpha of 19 basis points per month (t-statistic = 2.71). This indicates that the AIS effect is implementable and robust to real-world trading frictions.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures a previously unexplored dimension of firm operating efficiency. While prior work has examined asset growth (Cooper et al., 2008) and profitability (Novy-Marx, 2013) separately, we show that the spread between these measures contains incremental information about future returns.

Second, we contribute to the literature on investor attention and processing of accounting information (Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2009). Our findings suggest that investors do not fully incorporate the implications of divergences between asset growth and income generation, consistent with theories of limited attention to complex financial relationships.

Finally, our study advances the understanding of market efficiency and anomaly persistence. The fact that AIS predicts returns even among large, liquid stocks challenges the notion that sophisticated investors should quickly arbitrage away such predictability. The robustness of our results to trading costs and various methodological choices suggests that the AIS effect represents a genuine market inefficiency with important implications for asset pricing theory and practice.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Asset Income Spread. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item ACT for current assets and item NOPIO for net operating income. Current assets (ACT) represents the firm's short-term assets, which are expected to be converted to cash or consumed within a year, including cash, receivables, and inventories. Net operating income (NOPIO) measures a company's operating performance before considering non-operating items and provides a core measure of the firm's operational efficiency. The construction of our signal follows a change-based approach, where we calculate the difference between current ACT and its lagged value, then scale this change by the lagged value of NOPIO. This scaled difference captures the relative growth in current assets compared to the firm's operational income base, potentially offering insights into changes in working capital efficiency and asset utilization patterns. By scaling the change in current assets by lagged operating income, we create a normalized measure that allows for meaningful comparison across firms of different sizes and across different time periods. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the AIS signal. Panel A plots the time-series of the mean, median, and interquartile range for AIS. On average, the cross-sectional mean (median) AIS is -18.87 (-1.91) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input AIS data. The signal's interquartile range spans -33.13 to 22.50. Panel B of Figure 1 plots the time-series of the coverage of the AIS signal for the CRSP universe. On average, the AIS signal is available for 4.82% of CRSP names, which on average make up 6.48% of total market capitalization.

4 Does AIS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AIS 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 AIS portfolio and sells the low AIS 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 AIS strategy earns an average return of 0.20% per month with a t-statistic of 2.75. The annualized Sharpe ratio of the strategy is 0.36. The alphas range from 0.20% to 0.24% per month and have t-statistics exceeding 2.87 everywhere. The lowest alpha is with respect to the FF3 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 0.22, with a t-statistic of 4.62 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 407 stocks and an average market capitalization of at least $1,310 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

19 bps/month with a t-statistics of 2.55. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 1-20bps/month. The lowest return, (1 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.15. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AIS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-one cases, and significantly expands the achievable frontier in nineteen cases.

Table 3 provides direct tests for the role size plays in the AIS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AIS, as well as average returns and alphas for long/short trading AIS 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 AIS strategy achieves an average return of 23 bps/month with a t-statistic of 2.25. Among these large cap stocks, the alphas for the AIS strategy relative to the five most common factor models range from 24 to 30 bps/month with t-statistics between 2.41 and 3.06.

5 How does AIS perform relative to the zoo?

Figure 2 puts the performance of AIS 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 AIS strategy falls in the distribution. The AIS strategy's gross (net) Sharpe ratio of 0.36 (0.27) is greater than 77% (88%) 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 AIS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the AIS strategy would have yielded \$2.63 which ranks the AIS strategy in the top 10% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the AIS strategy would have yielded \$1.60 which ranks the AIS strategy in the top 8% 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 AIS relative to those. Panel A shows that the AIS strategy gross alphas fall between the 48 and 75 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196506 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity

[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.

set for an investor having access to the Fama-French three-factor (six-factor) model. The AIS strategy has a positive net generalized alpha for five out of the five factor models. In these cases AIS ranks between the 66 and 84 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does AIS 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 AIS with 208 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 AIS or at least to weaken the power AIS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of AIS conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AIS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AIS} AIS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{AIS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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

[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.

constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 208 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on AIS. Stocks are finally grouped into five AIS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AIS trading strategies conditioned on each of the 208 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AIS 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 AIS signal in these Fama-MacBeth regressions exceed 0.80, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on AIS is 1.20.

Similarly, Table 5 reports results from spanning tests that regress returns to the AIS 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 AIS strategy earns alphas that range from 22-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.14, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AIS trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.89.

7 Does AIS add relative to the whole zoo?

Finally, we can ask how much adding AIS 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 AIS 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 $3027.42, while $1 investment in the combination strategy that includes AIS grows to $2968.35.

8 Conclusion

This study provides compelling evidence for the significance of Asset Income Spread (AIS) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on AIS generates economically and statistically significant returns, even after accounting for transaction costs and controlling for well-known risk factors. The strategy's ability to maintain significant alpha when tested against both the Fama-French five-factor model plus momentum, and an expanded model including six closely related anomalies, underscores its distinctive nature and incremental predictive power.

The empirical results reveal that AIS-based strategies achieve impressive risk-adjusted performance, with annualized Sharpe ratios of 0.36 (gross) and 0.27 (net). The persistence of abnormal returns, even after accounting for transaction costs, suggests that the signal could be valuable for practical implementation in invest-

[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 AIS is available.

ment strategies. The robust t-statistics across various specifications provide strong statistical support for the signal's predictive capabilities.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across different market regimes. Future research could explore the signal's performance in international markets, its interaction with other established anomalies, and its behavior during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the AIS effect could provide valuable insights into asset pricing theory.

In conclusion, our findings contribute to the growing literature on return predictability and suggest that AIS represents a meaningful addition to the investment practitioner's toolkit, while also opening new avenues for academic research in asset pricing.

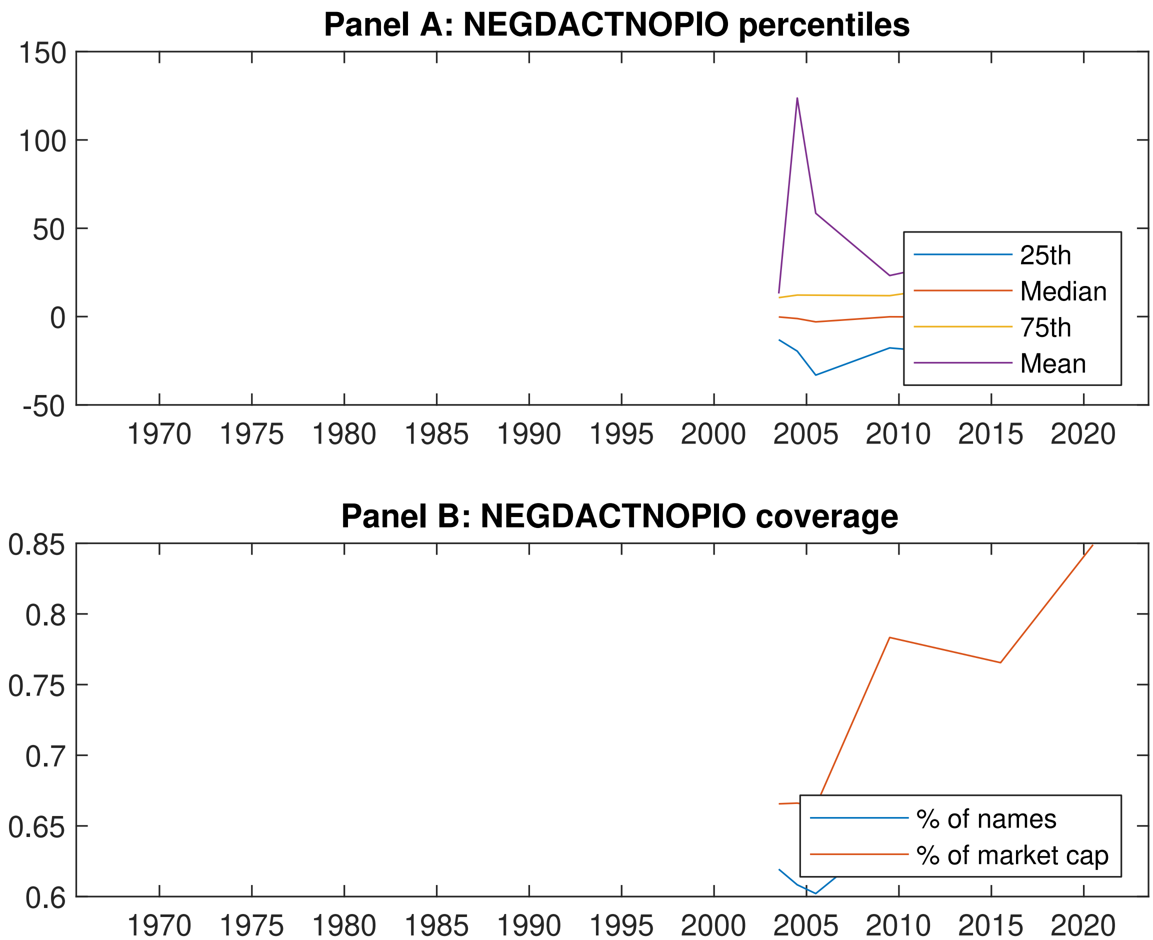

Figure 1: Times series of AIS percentiles and coverage.
This figure plots descriptive statistics for AIS. Panel A shows cross-sectional percentiles of AIS over the sample. Panel B plots the monthly coverage of AIS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AIS. 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 196506 to 202306.

Panel A: Excess returns and alphas on AIS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.59	0.55	0.51	0.59	0.79	0.20
	[2.92]	[3.11]	[3.23]	[3.74]	[4.18]	[2.75]
α_{CAPM}	-0.04	-0.01	0.02	0.11	0.20	0.24
	[-0.69]	[-0.13]	[0.41]	[1.93]	[3.43]	[3.39]
α_{FF3}	0.05	0.03	0.02	0.07	0.25	0.20
	[0.91]	[0.73]	[0.41]	[1.30]	[4.55]	[2.87]
α_{FF4}	0.04	0.04	-0.00	0.08	0.27	0.23
	[0.76]	[0.76]	[-0.06]	[1.56]	[4.89]	[3.24]
α_{FF5}	0.07	0.02	-0.07	-0.00	0.29	0.22
	[1.48]	[0.32]	[-1.51]	[-0.05]	[5.20]	[3.07]
α_{FF6}	0.06	0.02	-0.08	0.02	0.31	0.24
	[1.26]	[0.37]	[-1.72]	[0.37]	[5.44]	[3.42]
Panel B: Fama and French (2018) 6-factor model loadings for AIS-sorted portfolios						
β_{MKT}	1.04	0.98	0.93	0.94	0.99	-0.05
	[87.19]	[83.43]	[81.92]	[80.29]	[74.21]	[-3.08]
β_{SMB}	0.12	0.02	-0.11	-0.13	0.07	-0.05
	[6.72]	[1.22]	[-6.72]	[-7.84]	[3.38]	[-2.09]
β_{HML}	-0.19	-0.11	-0.01	0.01	-0.18	0.01
	[-8.12]	[-4.86]	[-0.46]	[0.35]	[-7.03]	[0.20]
β_{RMW}	0.04	0.07	0.15	0.01	-0.11	-0.15
	[1.80]	[3.17]	[6.92]	[0.33]	[-4.11]	[-4.54]
β_{CMA}	-0.21	-0.03	0.15	0.33	0.01	0.22
	[-6.11]	[-0.80]	[4.69]	[9.83]	[0.36]	[4.62]
β_{UMD}	0.02	-0.00	0.02	-0.03	-0.02	-0.04
	[1.30]	[-0.36]	[1.45]	[-2.69]	[-1.88]	[-2.42]
Panel C: Average number of firms (n) and market capitalization (me)						
n	590	458	407	450	597	
me ($\$10^6$)	1448	1624	1834	1452	1310	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the AIS 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 196506 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	0.20	0.24	0.20	0.23	0.22	0.24
			[2.75]	[3.39]	[2.87]	[3.24]	[3.07]	[3.42]
Quintile	NYSE	EW	0.23	0.24	0.20	0.20	0.22	0.22
			[4.80]	[5.00]	[4.36]	[4.20]	[4.77]	[4.65]
Quintile	Name	VW	0.25	0.29	0.27	0.30	0.30	0.32
			[3.24]	[3.76]	[3.51]	[3.88]	[3.82]	[4.15]
Quintile	Cap	VW	0.19	0.26	0.21	0.22	0.23	0.24
			[2.55]	[3.56]	[2.90]	[3.01]	[3.31]	[3.44]
Decile	NYSE	VW	0.22	0.25	0.24	0.26	0.29	0.31
			[2.31]	[2.66]	[2.50]	[2.64]	[3.05]	[3.15]
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	0.15	0.20	0.16	0.18	0.17	0.19
			[2.08]	[2.75]	[2.29]	[2.53]	[2.48]	[2.71]
Quintile	NYSE	EW	0.01	0.03				
			[0.15]	[0.49]				
Quintile	Name	VW	0.20	0.24	0.22	0.24	0.24	0.26
			[2.57]	[3.11]	[2.88]	[3.13]	[3.18]	[3.37]
Quintile	Cap	VW	0.15	0.22	0.17	0.18	0.19	0.20
			[1.98]	[3.03]	[2.42]	[2.52]	[2.80]	[2.94]
Decile	NYSE	VW	0.16	0.20	0.19	0.20	0.23	0.23
			[1.71]	[2.07]	[1.92]	[2.03]	[2.35]	[2.42]

Table 3: Conditional sort on size and AIS

This table presents results for conditional double sorts on size and AIS. 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 AIS. 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 AIS and short stocks with low AIS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

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

	AIS Quintiles					AIS Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.57	0.84	0.91	0.87	0.79	0.22	0.23	0.22	0.16	0.25	0.20
	[2.15]	[3.35]	[3.58]	[3.27]	[2.94]	[2.98]	[3.01]	[2.91]	[2.15]	[3.23]	[2.59]
(2)	0.66	0.80	0.86	0.85	0.77	0.11	0.14	0.11	0.18	0.14	0.20
	[2.60]	[3.41]	[3.73]	[3.67]	[3.17]	[1.29]	[1.53]	[1.22]	[2.04]	[1.59]	[2.23]
(3)	0.69	0.79	0.81	0.77	0.75	0.06	0.09	0.04	0.06	0.01	0.04
	[2.92]	[3.65]	[3.96]	[3.77]	[3.36]	[0.68]	[1.06]	[0.44]	[0.70]	[0.16]	[0.43]
(4)	0.65	0.69	0.64	0.76	0.83	0.18	0.18	0.14	0.13	0.16	0.15
	[2.98]	[3.44]	[3.31]	[4.11]	[3.81]	[2.26]	[2.34]	[1.74]	[1.57]	[1.99]	[1.86]
(5)	0.52	0.50	0.46	0.54	0.75	0.23	0.30	0.24	0.26	0.26	0.28
	[2.58]	[2.82]	[2.88]	[3.39]	[4.18]	[2.25]	[3.06]	[2.41]	[2.66]	[2.61]	[2.86]

Panel B: Portfolio average number of firms and market capitalization

	AIS Quintiles: Average n					AIS Quintiles: Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	260	261	259	258	258	22	23	21	20	21
(2)	79	79	79	78	78	40	41	40	40	40
(3)	60	60	60	60	60	72	72	72	71	72
(4)	54	53	53	53	53	163	163	164	164	164
(5)	50	50	49	50	49	1020	1253	1582	1268	1060

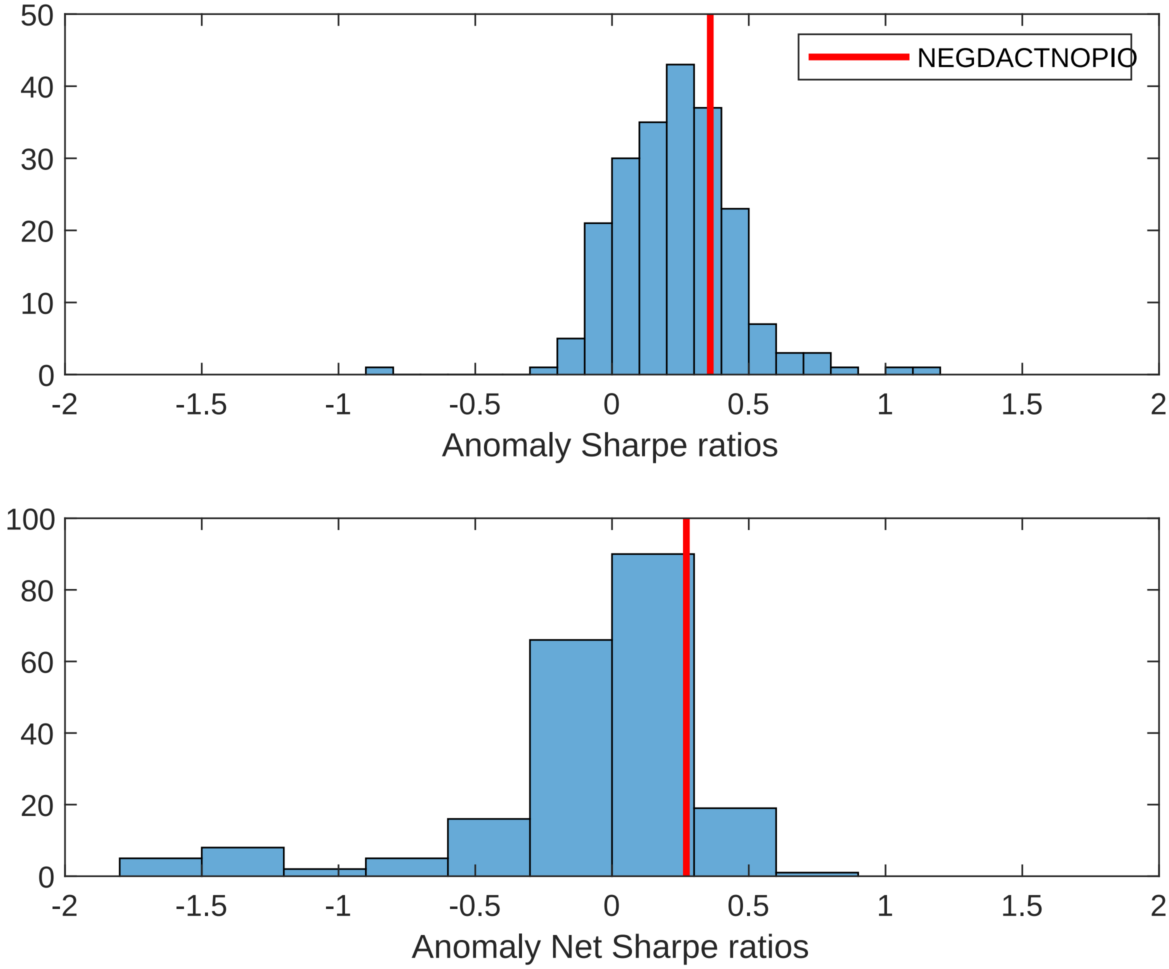

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AIS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

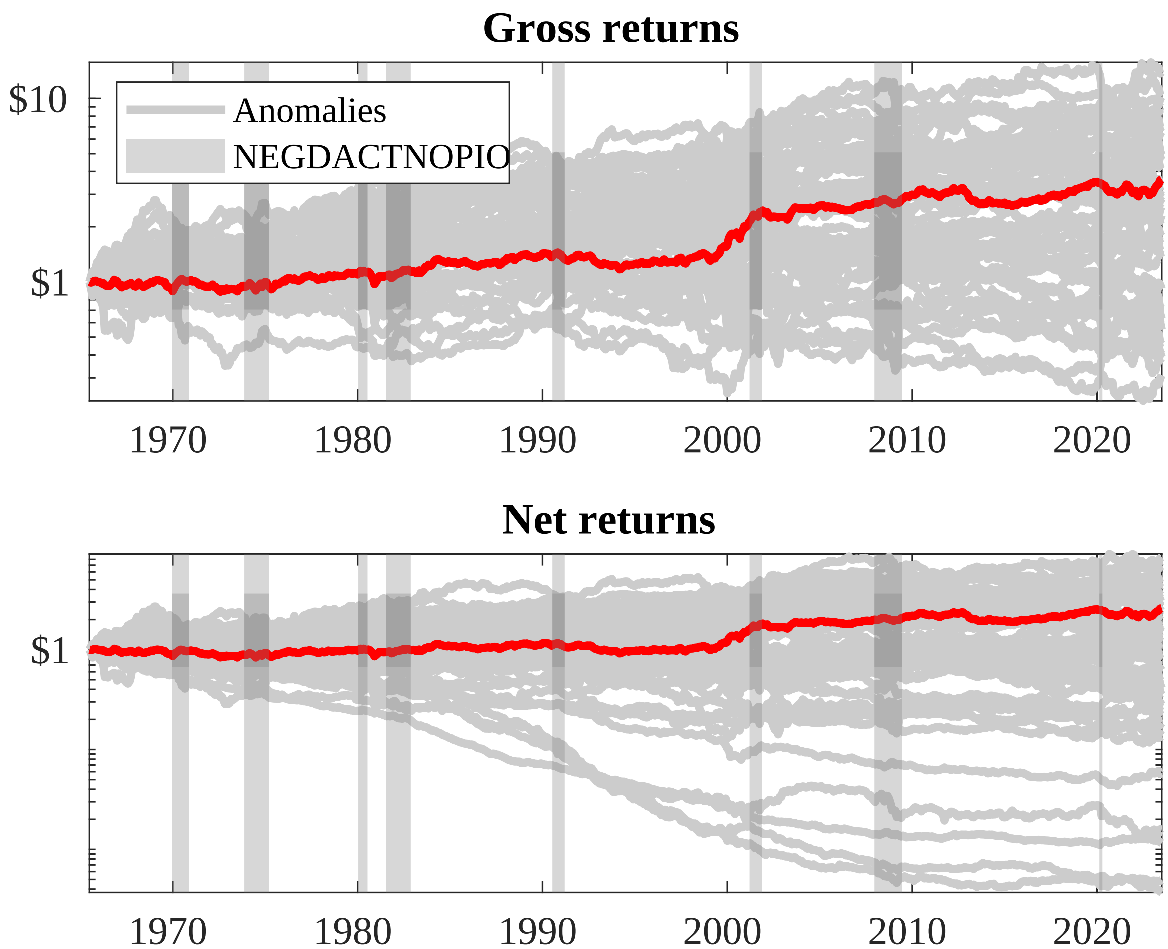

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AIS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

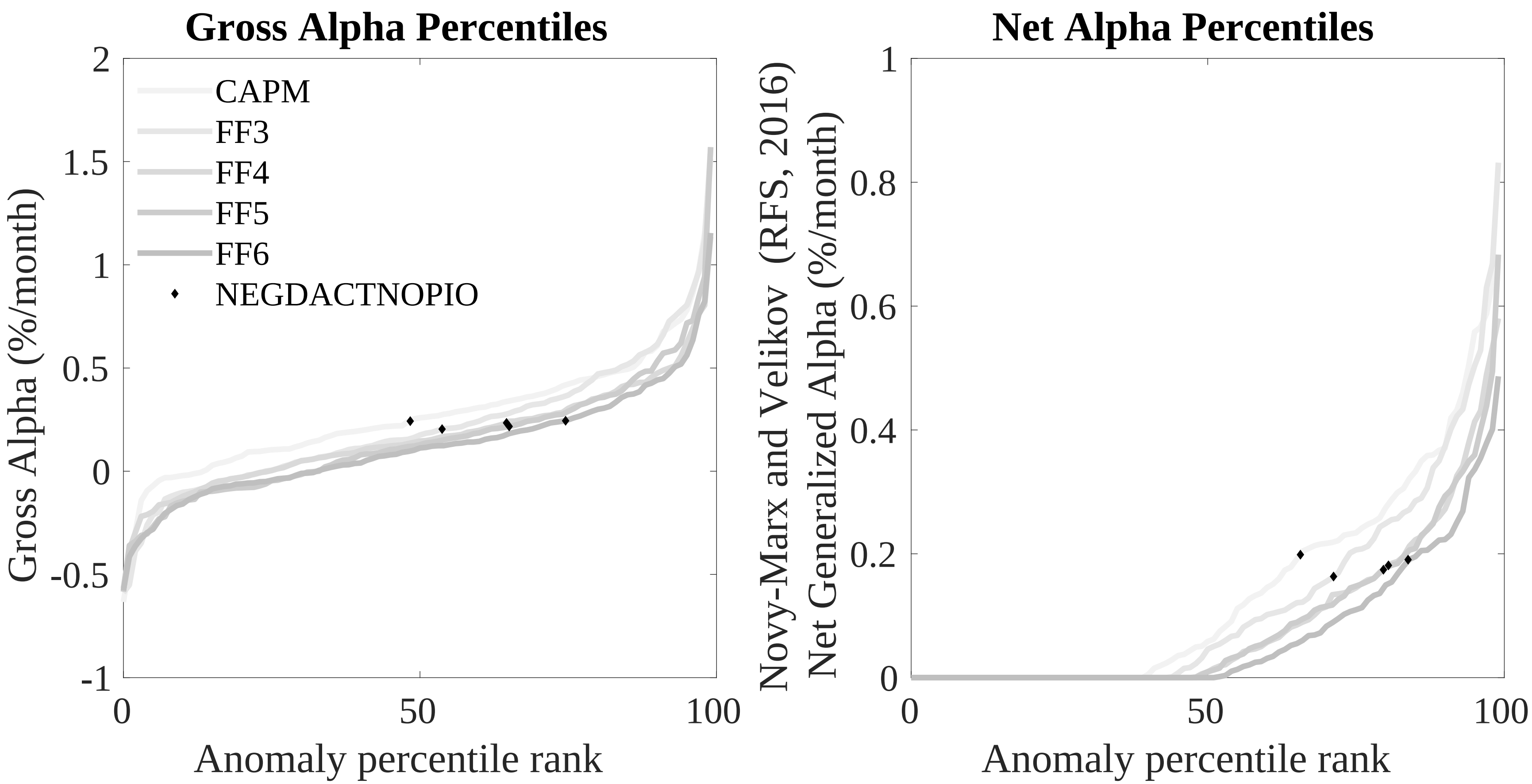

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AIS trading strategy alphas (diamonds). The strategies are constructed using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

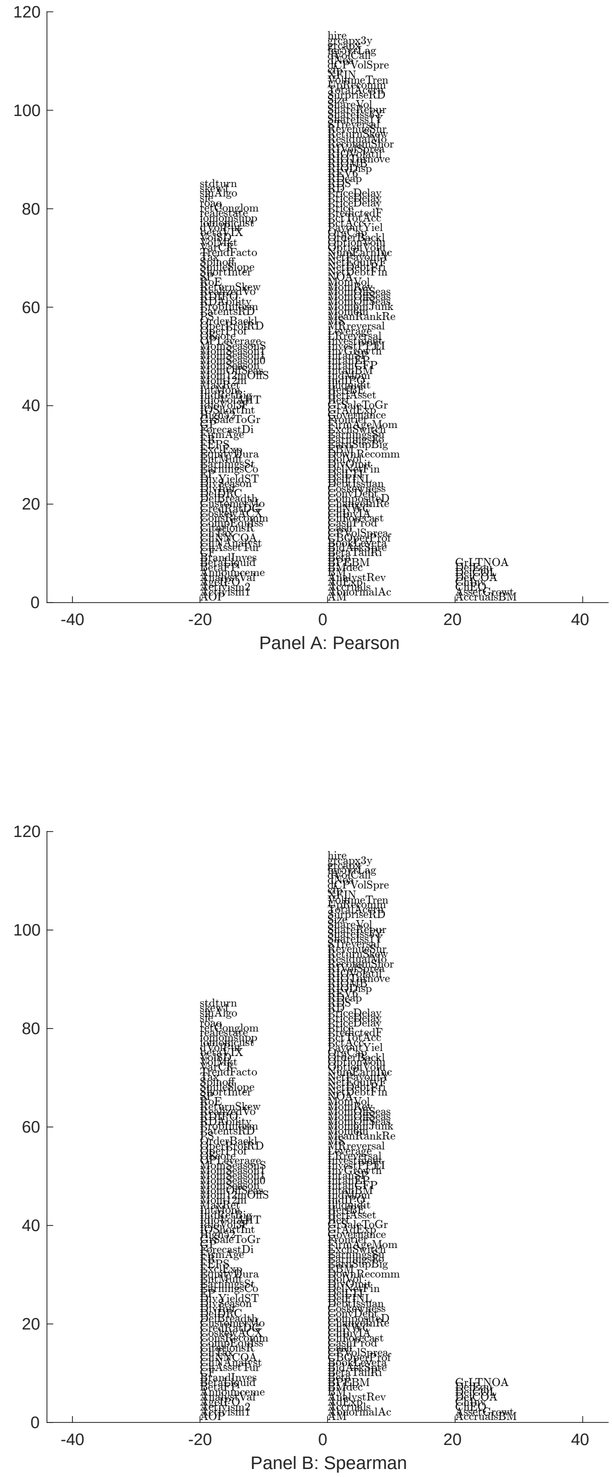

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 208 filtered anomaly signals with AIS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

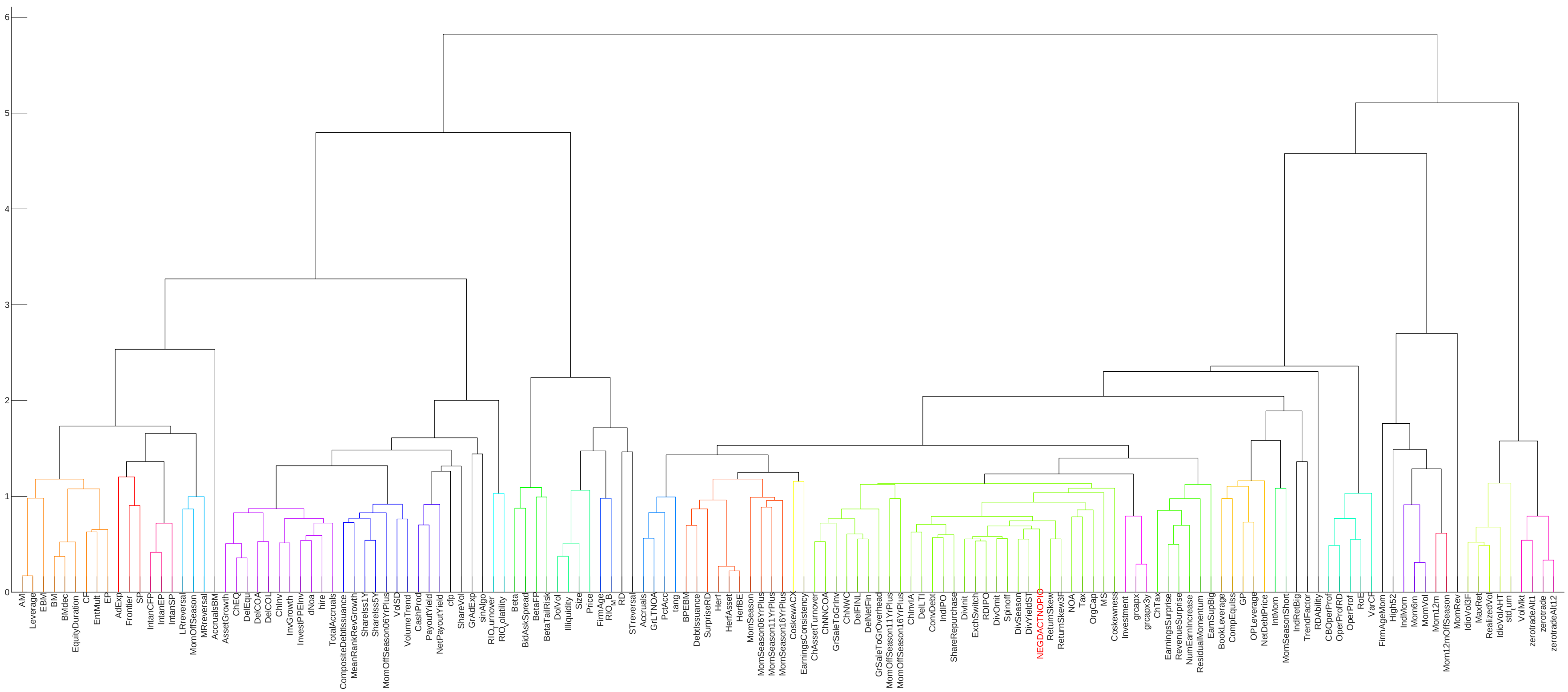

Figure 6: Agglomerative hierarchical cluster plot

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

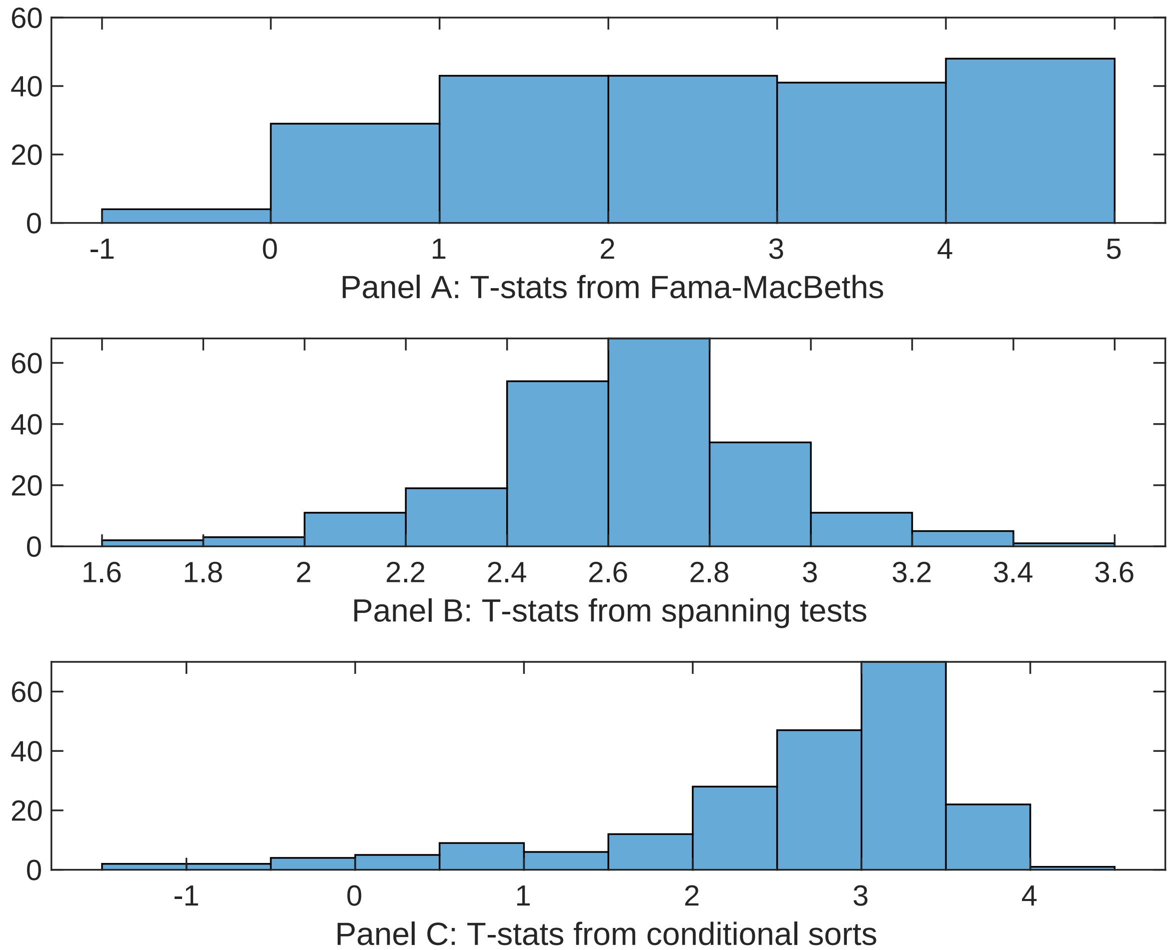

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AIS conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AIS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AIS} AIS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{AIS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on AIS. Stocks are finally grouped into five AIS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AIS trading strategies conditioned on each of the 208 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on AIS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AIS} AIS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Asset growth, Growth in book equity, Inventory Growth, Change in current operating assets, Change in equity to assets, Growth in long term operating assets. 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 196506 to 202306.

Intercept	0.13	0.17	0.12	0.13	0.12	0.12	0.13
	[5.95]	[7.06]	[5.48]	[5.57]	[5.47]	[5.26]	[6.34]
AIS	0.82	0.30	0.22	0.19	0.28	0.40	0.13
	[0.80]	[2.71]	[2.12]	[1.86]	[2.51]	[3.77]	[1.20]
Anomaly 1	0.10						0.79
	[8.77]						[7.65]
Anomaly 2		0.45					-0.24
		[4.10]					[-0.18]
Anomaly 3			0.35				0.11
			[6.71]				[1.84]
Anomaly 4				0.22			0.94
				[6.80]			[0.24]
Anomaly 5					0.14		0.26
					[4.05]		[0.51]
Anomaly 6						0.64	-0.23
						[2.56]	[-0.91]
# months	696	696	696	696	696	696	696
$\bar{R}^2(\%)$	0	0	0	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 AIS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AIS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Asset growth, Growth in book equity, Inventory Growth, Change in current operating assets, Change in equity to assets, Growth in long term operating assets. 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 196506 to 202306.

Intercept	0.25	0.25	0.22	0.25	0.25	0.23	0.21
	[3.47]	[3.45]	[3.14]	[3.48]	[3.55]	[3.28]	[2.89]
Anomaly 1	1.14						-7.63
	[0.24]						[-1.46]
Anomaly 2		13.18					12.00
		[3.34]					[2.02]
Anomaly 3			12.93				12.07
			[3.60]				[3.03]
Anomaly 4				2.68			-3.05
				[0.76]			[-0.75]
Anomaly 5					7.99		1.35
					[2.11]		[0.24]
Anomaly 6						10.08	8.03
						[3.05]	[2.40]
mkt	-4.97	-4.55	-4.66	-5.01	-5.10	-4.15	-3.64
	[-2.94]	[-2.70]	[-2.78]	[-2.96]	[-3.02]	[-2.44]	[-2.15]
smb	-5.10	-5.48	-3.38	-4.45	-5.14	-3.12	-2.36
	[-2.05]	[-2.25]	[-1.37]	[-1.75]	[-2.11]	[-1.25]	[-0.89]
hml	1.09	-0.50	0.26	0.11	0.09	1.67	0.57
	[0.33]	[-0.15]	[0.08]	[0.03]	[0.03]	[0.52]	[0.16]
rmw	-15.42	-14.67	-13.06	-15.05	-14.60	-12.41	-10.38
	[-4.67]	[-4.47]	[-3.92]	[-4.51]	[-4.41]	[-3.62]	[-2.99]
cma	20.21	8.58	13.14	20.11	13.29	18.83	9.24
	[2.71]	[1.40]	[2.48]	[3.89]	[2.15]	[3.89]	[1.20]
umd	-3.89	-4.07	-4.72	-3.82	-3.67	-3.69	-4.99
	[-2.32]	[-2.46]	[-2.83]	[-2.28]	[-2.20]	[-2.22]	[-2.93]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	13	14	14	13	13	14	16

Panel A: Average rank

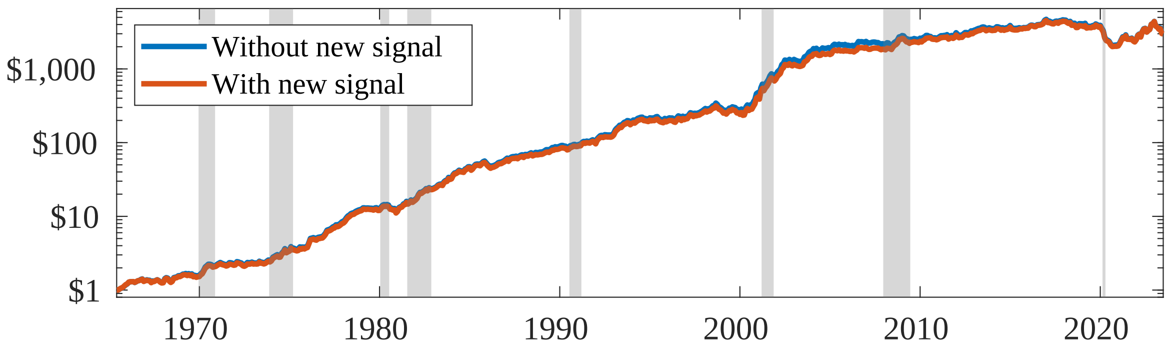

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

References

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63(4):1609–1651.

DellaVigna, S. and Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *Journal of Finance*, 64(2):709–749.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fairfield, P. M., Whisenant, J. S., and Yohn, T. L. (2003). Accrued earnings and growth: Implications for future profitability and market mispricing. *The Accounting Review*, 78(1):353–371.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Hirshleifer, D., Li, J., and Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics*, 76:87–106.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper.*

Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.