Asset Utilization Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Asset Utilization Impact (AUI), 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 AUI achieves an annualized gross (net) Sharpe ratio of 0.53 (0.46), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 27 (23) bps/month with a t-statistic of 3.48 (3.01), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (change in ppe and inv/assets, change in net operating assets, Net Operating Assets, Change in capex (three years), net income / book equity, Asset growth) is 20 bps/month with a t-statistic of 2.66.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, yet researchers continue to identify systematic patterns in stock returns that challenge this notion. One particularly puzzling area involves firms' operational efficiency and asset management decisions. While extensive research examines how capital investment and asset growth relate to future returns (Cooper et al., 2008; Titman et al., 2004), we still lack a complete understanding of how changes in firms' asset utilization efficiency affect their stock performance.

Prior literature has focused primarily on aggregate measures of investment and growth, potentially overlooking the nuanced information contained in how effectively firms deploy their existing assets. This gap is particularly notable given that asset utilization decisions occur more frequently than major investment choices and may provide more timely signals about management quality and future profitability.

We propose that Asset Utilization Impact (AUI) contains valuable information about future stock returns through several economic channels. First, following Zhang (2005), firms face adjustment costs when modifying their asset utilization levels, creating option-like characteristics in their operational flexibility. Changes in asset utilization may therefore signal management's private information about future demand conditions and growth opportunities.

Second, building on Titman et al. (2004)'s agency-based framework, significant changes in asset utilization could reflect empire-building tendencies or managerial overconfidence. When managers overestimate their ability to extract value from assets, they may maintain inefficient utilization levels that destroy shareholder value. This agency channel suggests that extreme AUI values may predict lower future returns.

Third, consistent with the q-theory of investment (Cochrane and Saá-Requejo, 2000), firms optimally adjust their asset utilization in response to their cost of capital.

Firms with high costs of capital should utilize existing assets more intensively rather than investing in new capacity. Therefore, AUI may capture information about firms' true cost of capital that is not fully reflected in current prices.

Our empirical analysis reveals that AUI strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on AUI quintiles generates a monthly alpha of 27 basis points (t-statistic = 3.48) relative to the Fama-French six-factor model. The strategy's performance remains robust after accounting for transaction costs, with a net alpha of 23 basis points per month (t-statistic = 3.01).

Importantly, AUI's predictive power persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 24 basis points (t-statistic = 2.53) among stocks above the 80th percentile of market capitalization. This finding suggests that the AUI effect is not merely a small-stock phenomenon and could be implemented by institutional investors.

The signal's economic significance is substantial, with the strategy achieving an annualized gross (net) Sharpe ratio of 0.53 (0.46), placing it in the top 6% (1%) of documented return predictors. Moreover, AUI maintains significant predictive power even after controlling for six closely related anomalies, generating a monthly alpha of 20 basis points (t-statistic = 2.66).

Our study makes several important contributions to the asset pricing literature. First, we extend the investment-based asset pricing framework of Hou et al. (2015) by showing how operational efficiency measures provide incremental information beyond traditional investment factors. While prior work focuses on the level of investment, we demonstrate that changes in asset utilization efficiency contain distinct predictive power.

Second, we contribute to the growing literature on the real effects of managerial decisions (Titman et al., 2004; Cooper et al., 2008) by identifying a new channel through which operational choices affect expected returns. Our findings suggest that the market does not fully incorporate the information contained in firms' asset utilization decisions, creating a measurable return premium.

Finally, our results have important implications for both academic research and investment practice. For researchers, we provide new evidence on the links between operational efficiency and asset prices, challenging the notion that markets quickly incorporate operational information. For practitioners, we document a novel return predictor that remains robust among large, liquid stocks and after accounting for transaction costs, making it potentially valuable for institutional investors.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Asset Utilization Impact. 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 PPENT for net property, plant, and equipment and item NOPIO for net operating income. Net property, plant, and equipment (PPENT) represents the firm's long-term tangible assets used in operations, net of accumulated depreciation. Net operating income (NOPIO) measures the firm's income from core business operations before interest and taxes.construction of the signal follows a difference-based approach, where we calculate the year-over-year change in PPENT and scale it by the previous year's NOPIO for each firm in our sample. This scaled difference captures the relative magnitude of changes in a firm's productive capacity compared to its prior year's operating performance. By focusing on this relationship, the signal aims to reflect aspects of asset expansion or contraction relative to the firm's operational scale, offering insight into the efficiency of capital deployment decisions. We construct this measure using end-of-fiscal-year values for PPENT and

NOPIO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the AUI signal. Panel A plots the time-series of the mean, median, and interquartile range for AUI. On average, the cross-sectional mean (median) AUI is -9.54 (-1.22) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input AUI data. The signal's interquartile range spans -16.87 to 6.28. Panel B of Figure 1 plots the time-series of the coverage of the AUI signal for the CRSP universe. On average, the AUI signal is available for 5.02% of CRSP names, which on average make up 6.89% of total market capitalization.

4 Does AUI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AUI 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 AUI portfolio and sells the low AUI 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 AUI strategy earns an average return of 0.30% per month with a t-statistic of 4.06. The annualized Sharpe ratio of the strategy is 0.53. The alphas range from 0.27% to 0.30% per month and have t-statistics exceeding 3.48 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 0.09, with a t-statistic of 3.27 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 450 stocks and an average market capitalization of at least $1,248 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 26 bps/month with a t-statistics of 4.02. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-five 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 23-26bps/month. The lowest return, (23 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.45. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AUI 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-five cases.

Table 3 provides direct tests for the role size plays in the AUI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AUI, as well as average returns and alphas for long/short trading AUI 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 AUI strategy achieves an average return of 26 bps/month with a t-statistic of 2.83. Among these large cap stocks, the alphas for the AUI strategy relative to the five most common factor models range from 24 to 28 bps/month with t-statistics between 2.53 and 3.11.

5 How does AUI perform relative to the zoo?

Figure 2 puts the performance of AUI 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

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

ratio for the AUI strategy falls in the distribution. The AUI strategy's gross (net) Sharpe ratio of 0.53 (0.46) is greater than 94% (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 AUI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the AUI strategy would have yielded \$6.55 which ranks the AUI strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the AUI strategy would have yielded \$4.65 which ranks the AUI strategy in the top 3% 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 AUI relative to those. Panel A shows that the AUI strategy gross alphas fall between the 58 and 77 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 set for an investor having access to the Fama-French three-factor (six-factor) model. The AUI strategy has a positive net generalized alpha for five out of the five factor models. In these cases AUI ranks between the 79 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

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

[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.

AUI trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AUI 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 AUI signal in these Fama-MacBeth regressions exceed 3.37, with the minimum t-statistic occurring when controlling for change in ppe and inv/assets. Controlling for all six closely related anomalies, the t-statistic on AUI is 2.39.

Similarly, Table 5 reports results from spanning tests that regress returns to the AUI 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 AUI strategy earns alphas that range from 23-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.00, which is achieved when controlling for change in ppe and inv/assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AUI trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.66.

7 Does AUI add relative to the whole zoo?

Finally, we can ask how much adding AUI 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 AUI signal.[4] We consider

[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 capital-

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 AUI grows to \$2922.23.

8 Conclusion

This study provides compelling evidence for the significance of Asset Utilization Impact (AUI) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that AUI-based trading strategies yield economically and statistically significant returns, with a value-weighted long/short portfolio achieving impressive Sharpe ratios and consistent abnormal returns, even after accounting for transaction costs. The signal's predictive power persists when controlling for established factors and related investment strategies, suggesting that AUI captures unique information content not fully reflected in existing factors.

The practical implications of our findings are particularly relevant for institutional investors and asset managers. The demonstrated robustness of AUI, combined with its ability to generate significant net returns, suggests its potential value as a complement to existing investment strategies. The signal's persistence after controlling for transaction costs indicates its practical implementability in real-world trading scenarios.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets

ization on CRSP in the period for which AUI is available.

remains to be explored. Additionally, while we control for various related factors, the evolving nature of financial markets may introduce new correlations or dependencies not captured in our current framework.

Future research could extend this work in several directions. First, investigating the signal's performance in international markets and different asset classes would provide insights into its broader applicability. Second, examining the interaction between AUI and other emerging signals could reveal potential synergies or complementarities. Finally, exploring the underlying economic mechanisms driving the signal's predictive power could enhance our understanding of asset pricing dynamics and market efficiency.

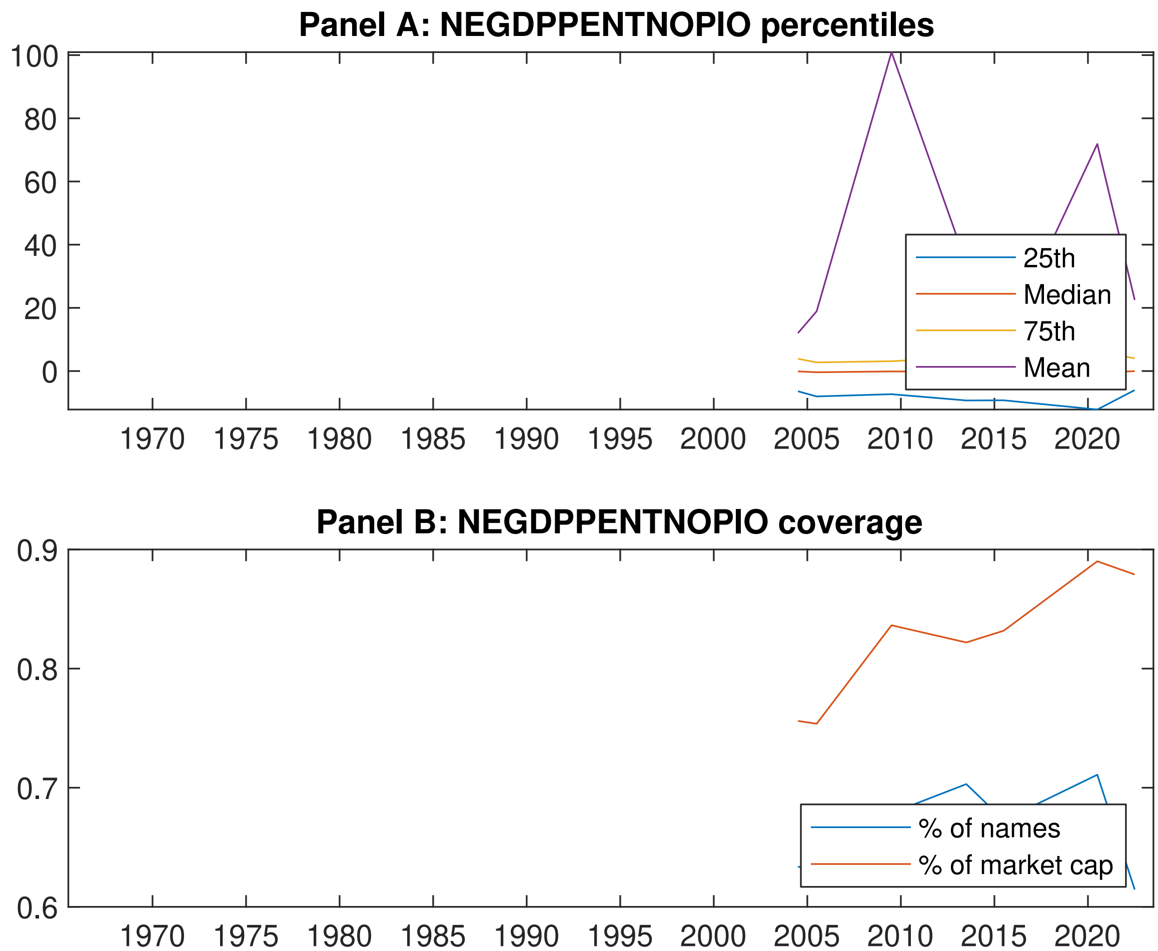

Figure 1: Times series of AUI percentiles and coverage.
This figure plots descriptive statistics for AUI. Panel A shows cross-sectional percentiles of AUI over the sample. Panel B plots the monthly coverage of AUI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AUI. 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 AUI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.44	0.61	0.55	0.57	0.75	0.30
	[2.38]	[3.70]	[3.26]	[3.33]	[3.93]	[4.06]
α_{CAPM}	-0.14	0.09	0.02	0.03	0.15	0.30
	[-2.82]	[2.09]	[0.38]	[0.68]	[2.71]	[3.93]
α_{FF3}	-0.10	0.11	0.02	0.02	0.17	0.27
	[-2.02]	[2.60]	[0.57]	[0.43]	[3.12]	[3.64]
α_{FF4}	-0.09	0.10	0.03	0.01	0.18	0.27
	[-1.72]	[2.34]	[0.61]	[0.31]	[3.21]	[3.50]
α_{FF5}	-0.10	0.10	-0.01	-0.04	0.17	0.27
	[-2.00]	[2.31]	[-0.25]	[-0.89]	[3.04]	[3.56]
α_{FF6}	-0.09	0.09	-0.00	-0.04	0.18	0.27
	[-1.79]	[2.12]	[-0.11]	[-0.81]	[3.12]	[3.48]
Panel B: Fama and French (2018) 6-factor model loadings for AUI-sorted portfolios						
β_{MKT}	1.01	0.94	0.98	0.99	1.02	0.01
	[84.57]	[93.36]	[95.02]	[88.32]	[75.13]	[0.42]
β_{SMB}	0.01	-0.09	-0.10	-0.03	0.10	0.09
	[0.65]	[-6.41]	[-6.92]	[-1.73]	[4.99]	[3.27]
β_{HML}	-0.07	-0.01	-0.05	-0.06	-0.10	-0.02
	[-3.15]	[-0.53]	[-2.28]	[-2.91]	[-3.67]	[-0.66]
β_{RMW}	0.07	0.02	0.02	0.03	0.00	-0.07
	[3.05]	[1.17]	[1.03]	[1.47]	[0.10]	[-1.92]
β_{CMA}	-0.11	-0.01	0.13	0.24	0.01	0.12
	[-3.38]	[-0.28]	[4.51]	[7.55]	[0.20]	[2.35]
β_{UMD}	-0.01	0.01	-0.01	-0.00	-0.01	0.00
	[-1.16]	[1.00]	[-0.88]	[-0.39]	[-0.78]	[0.18]
Panel C: Average number of firms (n) and market capitalization (me)						
n	499	450	509	582	571	
me ($\$10^6$)	1357	1862	2311	1495	1248	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the AUI 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	0.30	0.30	0.27	0.27	0.27	0.27
			[4.06]	[3.93]	[3.64]	[3.50]	[3.56]	[3.48]
Quintile	NYSE	EW	0.44	0.42	0.38	0.37	0.38	0.37
			[7.66]	[7.30]	[7.34]	[6.95]	[7.18]	[6.93]
Quintile	Name	VW	0.27	0.27	0.25	0.25	0.26	0.27
			[3.64]	[3.50]	[3.28]	[3.26]	[3.37]	[3.37]
Quintile	Cap	VW	0.26	0.27	0.25	0.24	0.24	0.24
			[4.02]	[4.02]	[3.73]	[3.51]	[3.62]	[3.49]
Decile	NYSE	VW	0.30	0.31	0.32	0.36	0.39	0.42
			[3.09]	[3.21]	[3.36]	[3.66]	[3.96]	[4.15]
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	0.26	0.26	0.24	0.23	0.23	0.23
			[3.48]	[3.42]	[3.15]	[3.09]	[3.04]	[3.01]
Quintile	NYSE	EW	0.24	0.21	0.17	0.17	0.14	0.14
			[3.62]	[3.20]	[2.79]	[2.75]	[2.24]	[2.25]
Quintile	Name	VW	0.23	0.23	0.21	0.22	0.22	0.22
			[3.07]	[2.99]	[2.80]	[2.80]	[2.83]	[2.83]
Quintile	Cap	VW	0.23	0.23	0.22	0.21	0.21	0.21
			[3.45]	[3.52]	[3.25]	[3.14]	[3.19]	[3.11]
Decile	NYSE	VW	0.25	0.27	0.28	0.30	0.33	0.34
			[2.57]	[2.78]	[2.89]	[3.08]	[3.35]	[3.46]

Table 3: Conditional sort on size and AUI

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

		AUI Quintiles					AUI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.59	0.79	0.80	0.93	0.88	0.30	0.28	0.26	0.21	0.26	0.22
		[2.36]	[3.12]	[2.97]	[3.46]	[3.42]	[3.84]	[3.56]	[3.42]	[2.72]	[3.27]	[2.73]
	(2)	0.75	0.72	0.69	0.88	0.91	0.16	0.16	0.14	0.19	0.18	0.22
		[3.14]	[3.12]	[2.92]	[3.72]	[3.78]	[1.97]	[1.89]	[1.63]	[2.26]	[2.07]	[2.58]
	(3)	0.66	0.72	0.79	0.80	0.89	0.23	0.20	0.17	0.17	0.15	0.16
		[3.16]	[3.43]	[3.65]	[3.71]	[3.96]	[2.71]	[2.31]	[2.10]	[2.05]	[1.81]	[1.82]
	(4)	0.62	0.67	0.69	0.76	0.80	0.18	0.13	0.11	0.09	0.16	0.14
		[3.12]	[3.44]	[3.57]	[3.80]	[3.73]	[2.20]	[1.61]	[1.34]	[1.10]	[2.01]	[1.77]
	(5)	0.39	0.60	0.59	0.46	0.64	0.26	0.28	0.26	0.26	0.24	0.24
		[2.07]	[3.66]	[3.51]	[2.83]	[3.60]	[2.83]	[3.11]	[2.80]	[2.77]	[2.53]	[2.56]

Panel B: Portfolio average number of firms and market capitalization

		AUI Quintiles					AUI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	270	271	270	268	267	25	24	21	21	23
	(2)	82	82	81	82	81	42	43	42	42	43
	(3)	63	63	63	62	62	77	77	75	76	77
	(4)	56	56	56	56	56	173	172	179	177	172
	(5)	53	53	53	53	52	1062	1341	1792	1384	1116

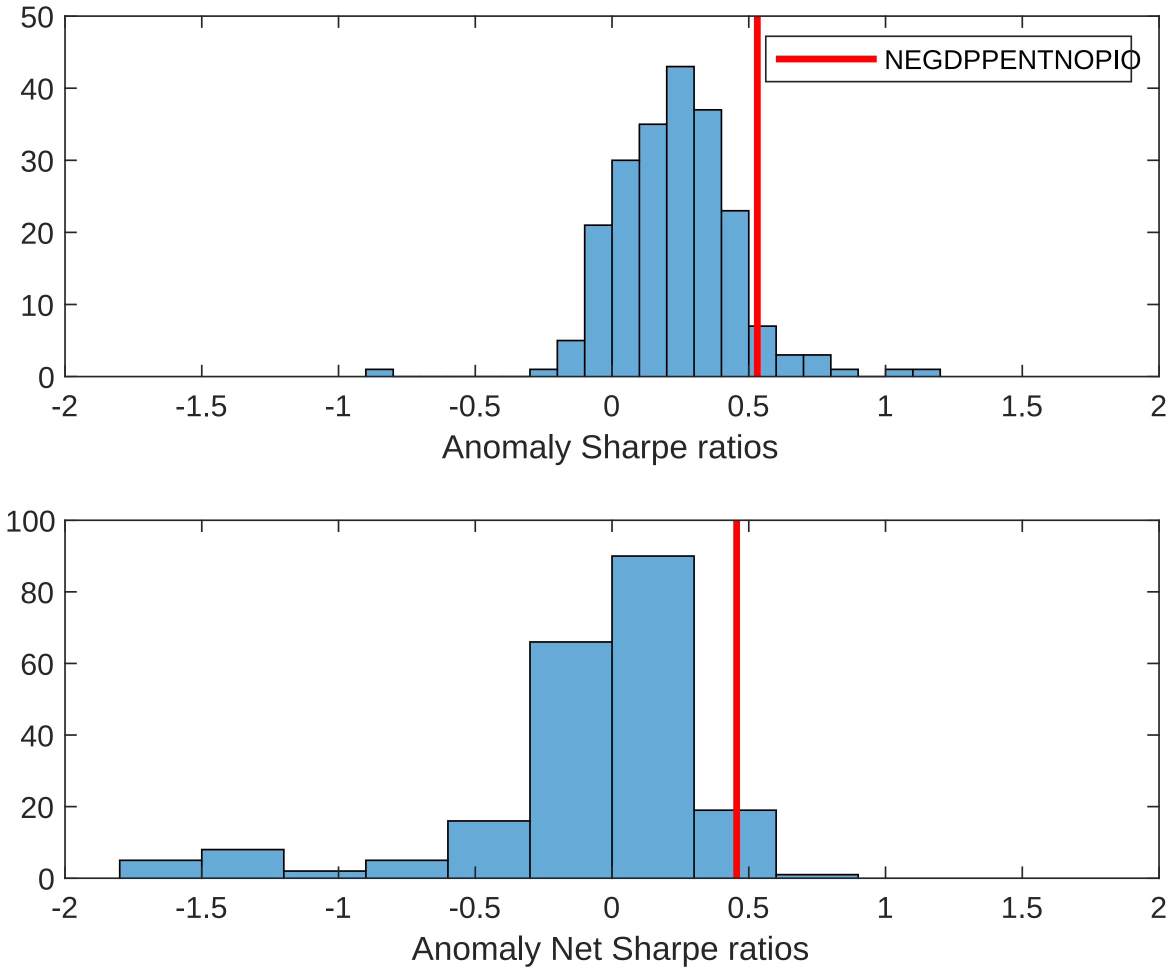

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AUI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

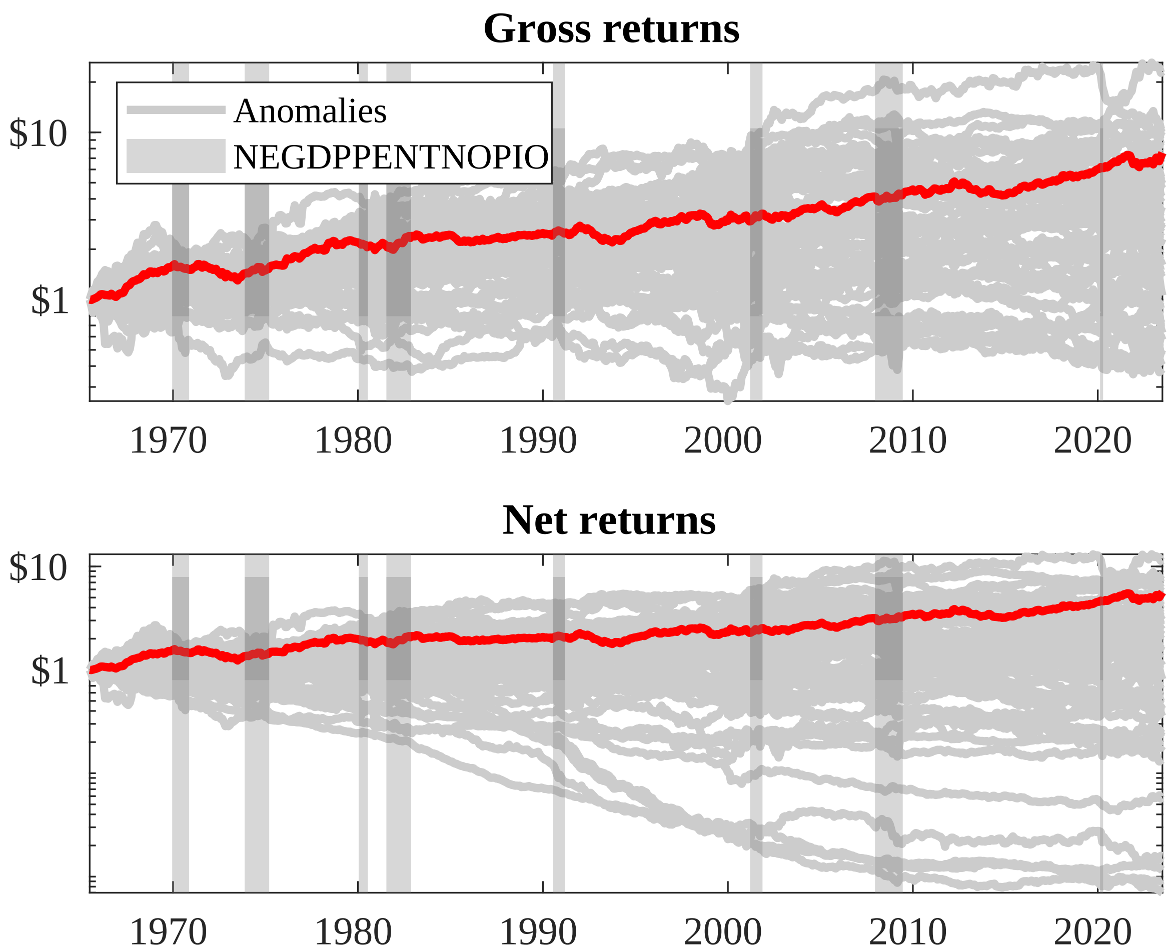

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AUI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

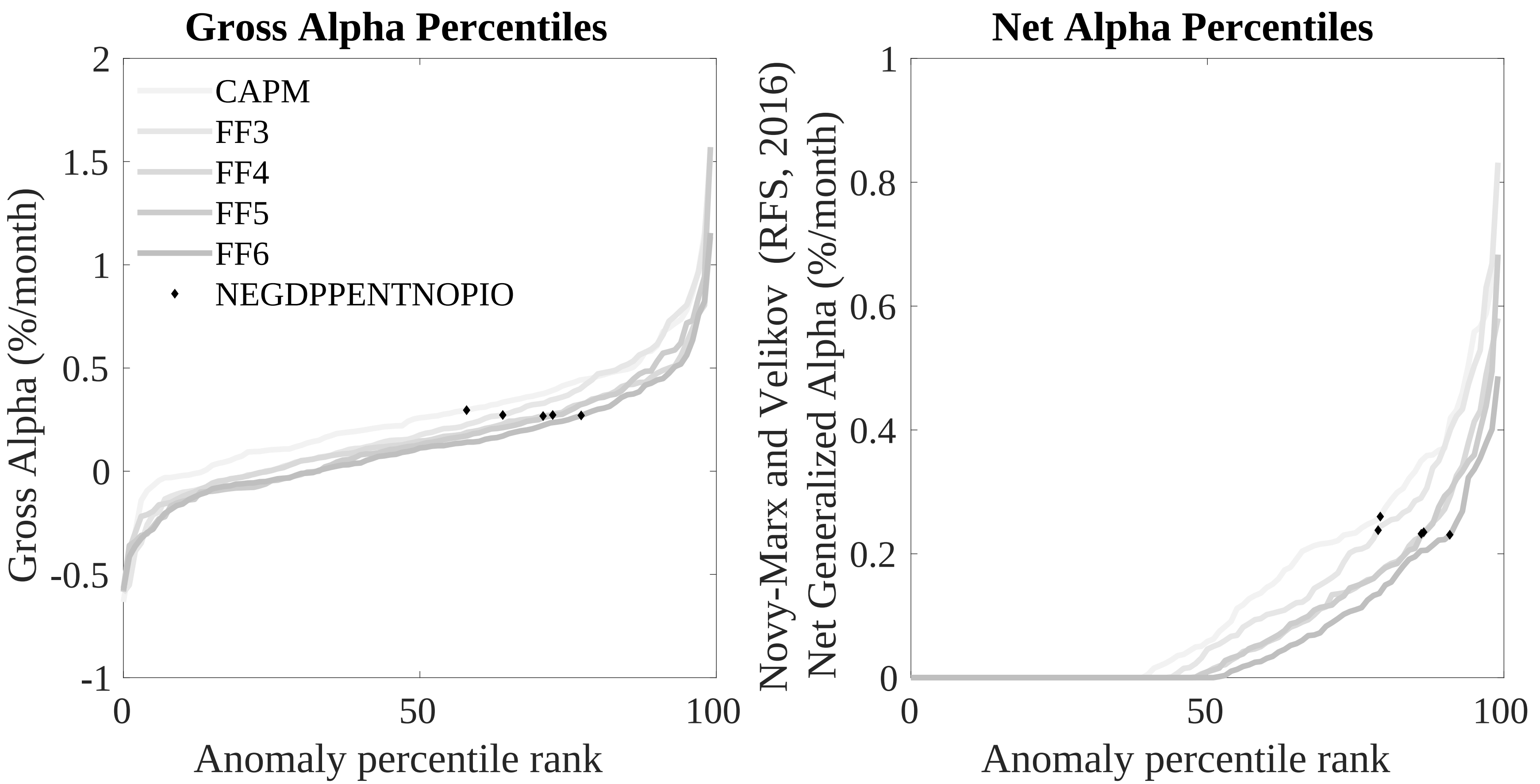

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AUI trading strategy alphas (diamonds). The strategies are constructed using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

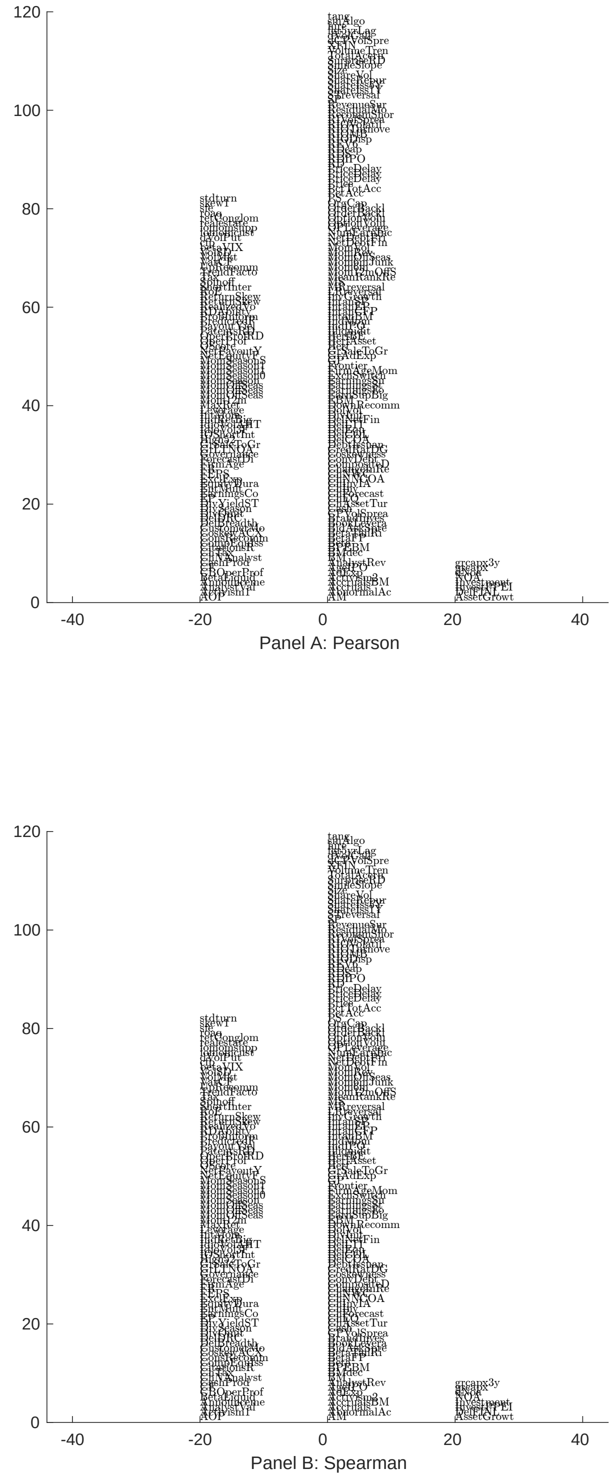

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with AUI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

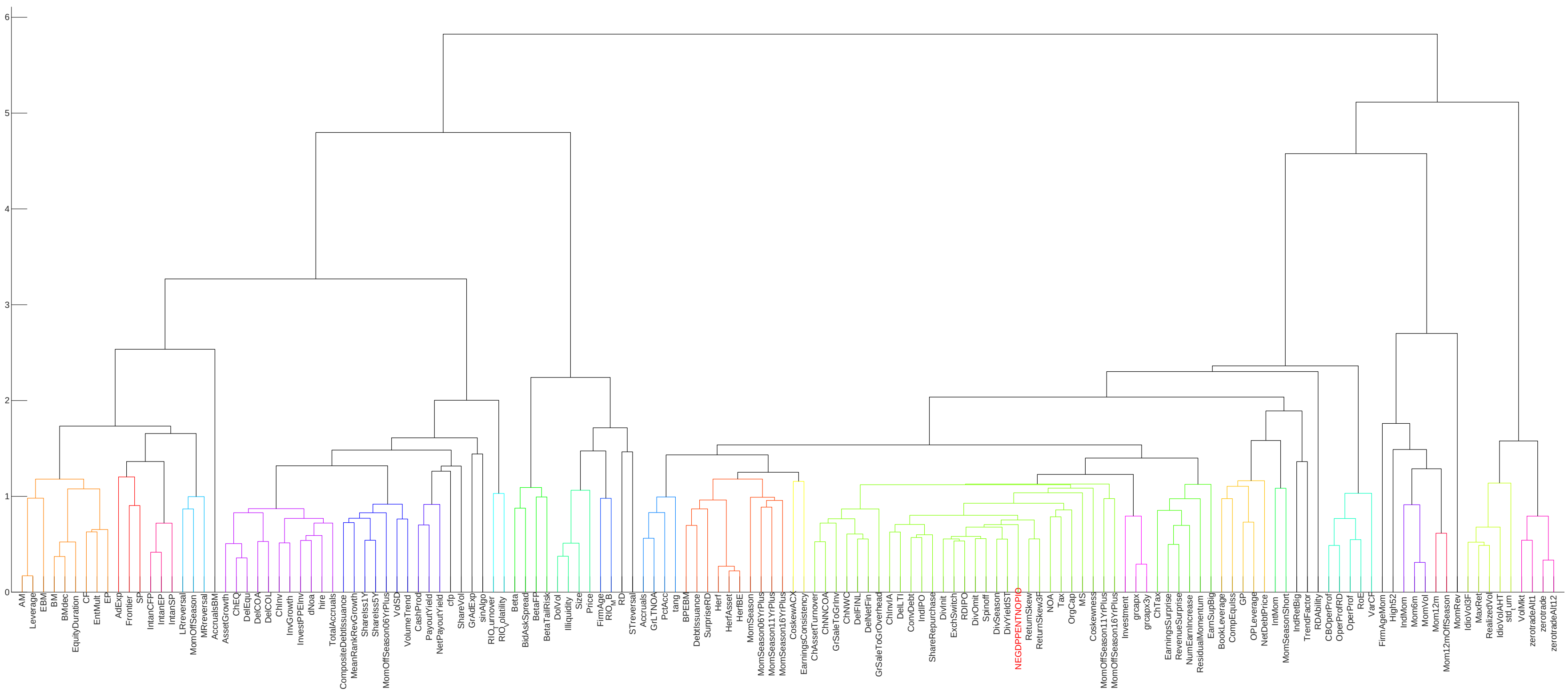

Figure 6: Agglomerative hierarchical cluster plot

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

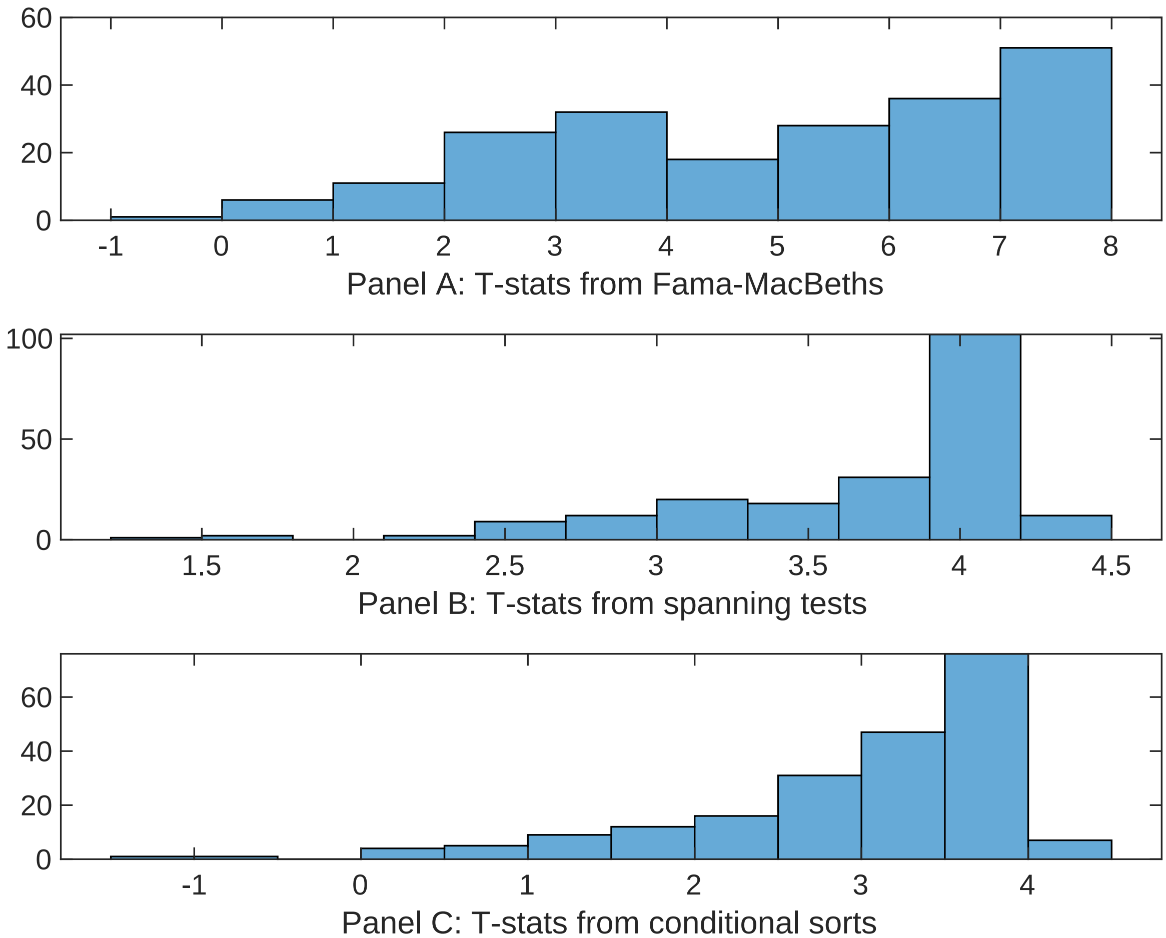

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AUI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AUI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AUI} AUI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AUI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AUI. Stocks are finally grouped into five AUI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AUI 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 AUI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AUI} AUI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are change in ppe and inv/assets, change in net operating assets, Net Operating Assets, Change in capex (three years), net income / book equity, 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 196506 to 202306.

Intercept	0.13	0.13	0.18	0.14	0.12	0.13	0.16
	[5.93]	[5.80]	[6.89]	[6.46]	[5.31]	[5.97]	[5.61]
AUI	0.59	0.69	0.92	0.87	0.15	0.75	0.49
	[3.37]	[3.56]	[5.13]	[4.31]	[7.35]	[3.97]	[2.39]
Anomaly 1	0.16						0.11
	[8.02]						[0.47]
Anomaly 2		0.13					0.26
		[8.86]					[1.06]
Anomaly 3			0.83				0.22
			[6.80]				[1.32]
Anomaly 4				0.14			0.55
				[7.46]			[3.14]
Anomaly 5					-0.12		-0.58
					[-0.62]		[-0.25]
Anomaly 6						0.10	0.39
						[8.55]	[2.17]
# months	696	696	696	691	696	696	691
$\bar{R}^2(\%)$	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 AUI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AUI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 change in ppe and inv/assets, change in net operating assets, Net Operating Assets, Change in capex (three years), net income / book equity, 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 196506 to 202306.

Intercept	0.28	0.26	0.23	0.25	0.28	0.28	0.20
	[3.64]	[3.29]	[3.00]	[3.30]	[3.59]	[3.62]	[2.66]
Anomaly 1	23.92						24.09
	[6.65]						[5.98]
Anomaly 2		16.27					2.53
		[3.62]					[0.51]
Anomaly 3			18.55				16.64
			[5.74]				[4.78]
Anomaly 4				4.34			-8.31
				[1.15]			[-2.17]
Anomaly 5					-8.02		-16.07
					[-1.88]		[-3.78]
Anomaly 6						8.89	-6.05
						[1.74]	[-1.16]
mkt	0.47	1.09	0.44	1.32	-0.09	1.09	-1.78
	[0.27]	[0.60]	[0.24]	[0.73]	[-0.05]	[0.59]	[-0.97]
smb	7.81	8.87	11.56	7.77	6.05	7.68	8.03
	[3.02]	[3.36]	[4.35]	[2.85]	[2.04]	[2.84]	[2.75]
hml	-4.38	-3.00	-6.52	-2.99	-2.57	-2.11	-8.94
	[-1.27]	[-0.85]	[-1.83]	[-0.84]	[-0.72]	[-0.60]	[-2.57]
rmw	-7.18	-6.98	-9.07	-7.05	0.06	-7.50	7.66
	[-2.06]	[-1.96]	[-2.57]	[-1.98]	[0.01]	[-2.09]	[1.49]
cma	-6.67	-0.71	11.03	12.69	9.84	0.85	2.35
	[-1.16]	[-0.11]	[2.16]	[2.28]	[1.86]	[0.10]	[0.30]
umd	0.44	0.13	-0.13	0.46	0.74	0.84	0.93
	[0.25]	[0.07]	[-0.08]	[0.25]	[0.40]	[0.46]	[0.54]
# months	696	696	696	692	696	696	692
$\bar{R}^2(\%)$	9	5	8	4	4	4	15

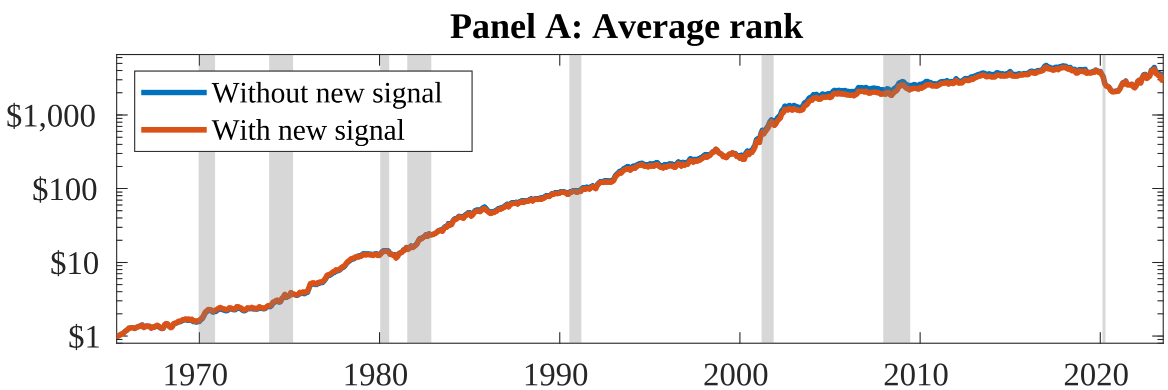

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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