Net Asset Utilization Gap and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Net Asset Utilization Gap (NAUG), 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 NAUG achieves an annualized gross (net) Sharpe ratio of 0.58 (0.51), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 3.00 (3.07), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth) is 19 bps/month with a t-statistic of 2.63.

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 persistent patterns in stock returns that appear to contradict market efficiency (Fama and French, 2008). While many of these patterns are well-documented, the underlying economic mechanisms driving return predictability remain debated (McLean and Pontiff, 2016).

One particularly puzzling aspect is how firms' operational decisions and asset utilization patterns relate to future stock performance. While research has examined various aspects of asset efficiency (Titman et al., 1994; Cooper et al., 2008), the relationship between firms' actual asset utilization relative to their optimal capacity remains largely unexplored.

We propose that the gap between a firm's actual and potential asset utilization (Net Asset Utilization Gap, or NAUG) contains important information about future profitability and returns. This builds on theoretical work showing that capacity utilization affects firms' operating leverage and risk exposure (Carlson et al., 2004). When actual utilization falls below potential, it may signal either temporary demand weakness or management's inability to optimize operations.

The relationship between NAUG and expected returns can operate through two channels. First, following Zhang (2005), firms with low asset utilization face higher adjustment costs during economic recoveries, leading to greater systematic risk. Second, drawing on Berk et al. (1999), underutilized assets represent real options whose value depends on future growth opportunities and economic conditions.

These mechanisms suggest NAUG should predict returns cross-sectionally, with low NAUG firms earning higher subsequent returns to compensate for greater risk. The predictive power should be particularly strong among firms with high fixed costs and during periods of economic uncertainty (Kogan and Papanikolaou, 2009).

Our empirical analysis reveals that NAUG strongly predicts stock returns. A value-weighted long-short portfolio sorting on NAUG generates monthly abnormal returns of 23 basis points relative to the Fama-French six-factor model (t-statistic = 3.00). The strategy achieves an annualized gross Sharpe ratio of 0.58, placing it in the top 5% of documented return predictors.

The predictive power of NAUG is robust across various methodological choices. Using different portfolio construction approaches, the strategy consistently delivers significant abnormal returns ranging from 29-33 basis points per month net of transaction costs. Importantly, NAUG remains a significant predictor even among large-cap stocks, with the highest size quintile generating monthly abnormal returns of 30 basis points (t-statistic = 3.21).

Controlling for the six most closely related anomalies and standard risk factors simultaneously, NAUG continues to generate significant abnormal returns of 19 basis points monthly (t-statistic = 2.63). This indicates that NAUG captures unique information not contained in previously documented predictors.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel measure that captures the efficiency of firms' asset utilization decisions, extending work by Cooper et al. (2008) on asset growth and Titman et al. (1994) on capital investment. Unlike these studies, we focus specifically on the gap between actual and potential utilization.

Second, we provide new evidence on the role of operating leverage in asset pricing, complementing theoretical work by Carlson et al. (2004) and Zhang (2005). Our findings suggest that investors systematically undervalue the risk implications of asset underutilization, leading to predictable return patterns.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate that operational efficiency metrics can provide valuable insights into asset pricing. For practitioners, NAUG represents a novel signal that remains robust to transaction costs and is implementable even among large-cap stocks.

2 Data

Our study investigates the predictive power of Net Asset Utilization Gap, a financial signal derived from accounting data for cross-sectional returns. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK for common stock and item PPENT for net property, plant, and equipment. Common stock (CSTK) represents the total value of common shares outstanding, while net property, plant, and equipment (PPENT) captures the book value of a firm's fixed assets after accounting for accumulated depreciation. The construction of the signal follows a difference-in-changes approach, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year's PPENT value. Specifically, for each firm i in year t, we compute: Net Asset Utilization Gap = (CSTKi,t - CSTKi,t-1) / PPENTi,t-1. This ratio captures the relative change in equity capital relative to the firm's existing fixed asset base, potentially offering insight into how aggressively firms are expanding their equity financing relative to their productive capacity. We construct this measure using end-of-fiscal-year values for both CSTK and PPENT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the NAUG signal. Panel A plots the time-series of the mean, median, and interquartile range for NAUG. On average, the cross-sectional mean (median) NAUG is -0.07 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input NAUG data. The signal's interquartile range spans -0.02 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the NAUG signal for the CRSP universe. On average, the NAUG signal is available for 6.57% of CRSP names, which on average make up 7.85% of total market capitalization.

4 Does NAUG predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on NAUG 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 NAUG portfolio and sells the low NAUG 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 NAUG strategy earns an average return of 0.34% per month with a t-statistic of 4.38. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.23% to 0.39% per month and have t-statistics exceeding 3.00 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.32, with a t-statistic of 6.25 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 544 stocks and an average market capitalization of at least $1,444 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 32 bps/month with a t-statistics of 4.08. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-three 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 29-33bps/month. The lowest return, (29 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.63. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the NAUG 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 NAUG strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and NAUG, as well as average returns and alphas for long/short trading NAUG 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 NAUG strategy achieves an average return of 30 bps/month with a t-statistic of 3.21. Among these large cap stocks, the alphas for the NAUG strategy relative to the five most common factor models range from 25 to 33 bps/month with t-statistics between 2.64 and 3.48.

5 How does NAUG perform relative to the zoo?

Figure 2 puts the performance of NAUG 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 NAUG strategy falls in the distribution. The NAUG strategy's gross (net) Sharpe ratio of 0.58 (0.51) is greater than 95% (99%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the

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

NAUG strategy (red line).[2] Ignoring trading costs, a $1 invested in the NAUG strategy would have yielded $8.43 which ranks the NAUG strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the NAUG strategy would have yielded $6.26 which ranks the NAUG strategy in the top 0% 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 NAUG relative to those. Panel A shows that the NAUG strategy gross alphas fall between the 70 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 196606 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The NAUG strategy has a positive net generalized alpha for five out of the five factor models. In these cases NAUG ranks between the 87 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does NAUG 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

[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.

more likely to be formed on the basis of signals with higher absolute correlations. Figure 5 plots a name histogram of the correlations of NAUG 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 NAUG or at least to weaken the power NAUG has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of NAUG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NAUG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NAUG} NAUG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{NAUG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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. Then, within each quintile, we sort stocks into quintiles based on NAUG. Stocks are finally grouped into five NAUG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NAUG trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on NAUG 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

[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.

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 NAUG signal in these Fama-MacBeth regressions exceed 3.49, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on NAUG is 1.98.

Similarly, Table 5 reports results from spanning tests that regress returns to the NAUG 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 NAUG strategy earns alphas that range from 20-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.66, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the NAUG trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.63.

7 Does NAUG add relative to the whole zoo?

Finally, we can ask how much adding NAUG 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 NAUG 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,

[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 NAUG is available.

and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, \$1 investment in the 155-anomaly combination strategy grows to \$2333.55, while \$1 investment in the combination strategy that includes NAUG grows to \$2313.16.

8 Conclusion

This study provides compelling evidence for the effectiveness of Net Asset Utilization Gap (NAUG) 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 NAUG delivers economically and statistically significant results, with an impressive annualized Sharpe ratio and consistent abnormal returns even after controlling for well-known risk factors.

Particularly noteworthy is the signal's persistence in generating significant alpha (19 bps/month) even when controlling for the Fama-French five-factor model, momentum factor, and six closely related strategies from the factor zoo. This robust performance suggests that NAUG captures unique information about future stock returns that is not fully explained by existing factors.

The practical implications of these findings are significant for investment professionals and portfolio managers. The signal's ability to generate attractive risk-adjusted returns, even after accounting for transaction costs, suggests its potential value in real-world portfolio management applications.

However, several limitations should be noted. First, the study's findings may be sensitive to the specific time period examined. Second, the implementation costs might vary across different market environments and investor scales. Future research could explore the signal's effectiveness in international markets, its interaction with other established factors, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the NAUG premium would provide valuable insights into its persistence and reliability.

Overall, this research contributes to the growing literature on return predictability and suggests that NAUG represents a valuable addition to the toolkit of quantitative investors and researchers in asset pricing.

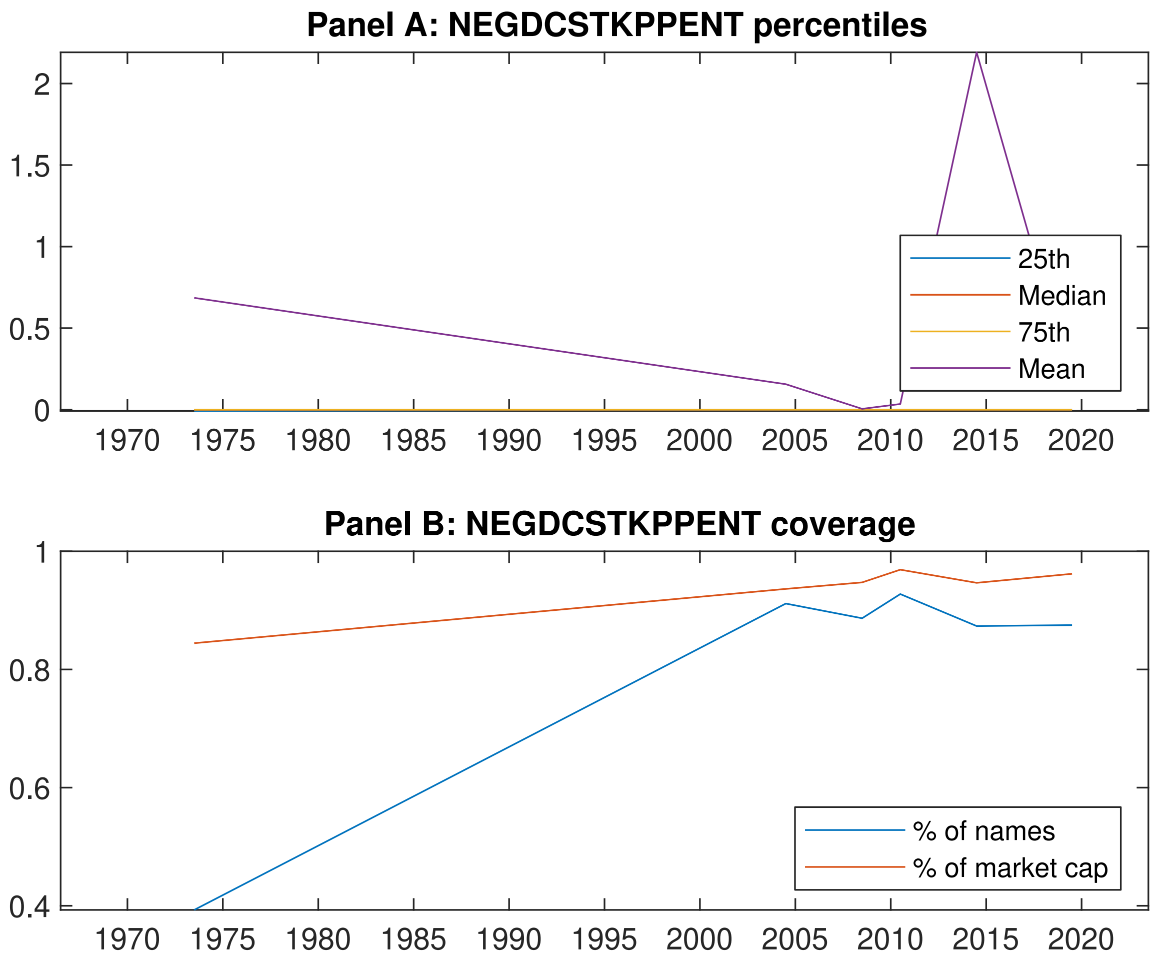

Figure 1: Times series of NAUG percentiles and coverage.
This figure plots descriptive statistics for NAUG. Panel A shows cross-sectional percentiles of NAUG over the sample. Panel B plots the monthly coverage of NAUG relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on NAUG. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 196606 to 202306.

Panel A: Excess returns and alphas on NAUG-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.42	0.51	0.65	0.69	0.76	0.34
	[2.31]	[2.71]	[3.51]	[4.13]	[4.54]	[4.38]
α_{CAPM}	-0.15	-0.08	0.07	0.17	0.24	0.39
	[-2.97]	[-1.87]	[1.38]	[3.60]	[5.14]	[4.98]
α_{FF3}	-0.14	-0.07	0.08	0.13	0.19	0.34
	[-2.83]	[-1.57]	[1.58]	[3.07]	[4.47]	[4.41]
α_{FF4}	-0.12	-0.03	0.10	0.09	0.17	0.30
	[-2.34]	[-0.71]	[1.95]	[2.03]	[3.98]	[3.82]
α_{FF5}	-0.16	0.01	0.09	0.04	0.10	0.26
	[-3.05]	[0.26]	[1.68]	[0.90]	[2.36]	[3.34]
α_{FF6}	-0.14	0.04	0.10	0.01	0.09	0.23
	[-2.68]	[0.81]	[1.95]	[0.23]	[2.19]	[3.00]
Panel B: Fama and French (2018) 6-factor model loadings for NAUG-sorted portfolios						
β_{MKT}	0.99	1.00	1.00	0.99	0.99	-0.01
	[82.06]	[96.11]	[82.92]	[100.33]	[98.27]	[-0.43]
β_{SMB}	0.01	0.03	0.02	-0.07	-0.02	-0.03
	[0.61]	[1.80]	[1.21]	[-4.86]	[-1.44]	[-1.20]
β_{HML}	0.02	-0.01	-0.02	0.04	0.04	0.02
	[0.97]	[-0.65]	[-0.69]	[1.91]	[2.01]	[0.46]
β_{RMW}	0.11	-0.13	0.03	0.10	0.12	0.01
	[4.82]	[-6.37]	[1.33]	[5.01]	[6.27]	[0.25]
β_{CMA}	-0.11	-0.12	-0.06	0.23	0.21	0.32
	[-3.22]	[-4.13]	[-1.82]	[8.13]	[7.41]	[6.25]
β_{UMD}	-0.03	-0.04	-0.02	0.04	0.01	0.04
	[-2.34]	[-3.67]	[-1.93]	[4.46]	[0.94]	[2.08]
Panel C: Average number of firms (n) and market capitalization (me)						
n	876	682	544	685	768	
me ($\$10^6$)	1730	1444	1974	2193	2417	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the NAUG strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 196606 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.34	0.39	0.34	0.30	0.26	0.23
			[4.38]	[4.98]	[4.41]	[3.82]	[3.34]	[3.00]
Quintile	NYSE	EW	0.51	0.59	0.50	0.42	0.35	0.29
			[7.29]	[9.09]	[8.76]	[7.46]	[6.44]	[5.51]
Quintile	Name	VW	0.35	0.39	0.34	0.29	0.27	0.24
			[4.42]	[4.88]	[4.37]	[3.67]	[3.48]	[3.04]
Quintile	Cap	VW	0.32	0.36	0.32	0.28	0.28	0.25
			[4.08]	[4.57]	[4.12]	[3.51]	[3.62]	[3.22]
Decile	NYSE	VW	0.37	0.43	0.35	0.28	0.32	0.27
			[3.88]	[4.49]	[3.77]	[2.95]	[3.44]	[2.85]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.30	0.35	0.31	0.29	0.24	0.23
			[3.89]	[4.53]	[4.05]	[3.75]	[3.23]	[3.07]
Quintile	NYSE	EW	0.31	0.38	0.30	0.25	0.14	0.12
			[4.05]	[5.31]	[4.69]	[4.10]	[2.34]	[2.02]
Quintile	Name	VW	0.31	0.36	0.32	0.29	0.27	0.25
			[3.93]	[4.49]	[4.05]	[3.70]	[3.40]	[3.18]
Quintile	Cap	VW	0.29	0.33	0.29	0.27	0.27	0.25
			[3.63]	[4.17]	[3.77]	[3.47]	[3.46]	[3.26]
Decile	NYSE	VW	0.33	0.39	0.32	0.28	0.30	0.27
			[3.43]	[4.09]	[3.49]	[3.07]	[3.21]	[2.97]

Table 3: Conditional sort on size and NAUG

This table presents results for conditional double sorts on size and NAUG. 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 NAUG. 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 NAUG and short stocks with low NAUG .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

Size quintiles	NAUG Quintiles (L)	(2)	(3)	(4)	(H)	NAUG Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.44	0.66	0.83	0.97	0.98	0.53	0.61	0.54	0.47	0.39	0.34
	[1.64]	[2.51]	[3.22]	[3.83]	[4.10]	[6.48]	[7.66]	[7.30]	[6.32]	[5.36]	[4.72]
(2)	0.48	0.71	0.84	0.90	0.95	0.47	0.53	0.42	0.36	0.31	0.27
	[2.00]	[2.97]	[3.47]	[3.92]	[4.24]	[5.08]	[5.91]	[5.04]	[4.28]	[3.67]	[3.19]
(3)	0.58	0.62	0.79	0.80	0.93	0.35	0.40	0.33	0.31	0.24	0.23
	[2.65]	[2.80]	[3.45]	[3.80]	[4.58]	[4.28]	[5.00]	[4.35]	[3.95]	[3.08]	[2.90]
(4)	0.50	0.59	0.81	0.79	0.81	0.31	0.37	0.29	0.27	0.12	0.13
	[2.40]	[2.80]	[3.84]	[4.00]	[4.28]	[3.78]	[4.63]	[3.91]	[3.64]	[1.73]	[1.75]
(5)	0.42	0.51	0.50	0.55	0.72	0.30	0.33	0.29	0.25	0.28	0.25
	[2.35]	[2.73]	[2.83]	[3.19]	[4.31]	[3.21]	[3.48]	[3.07]	[2.66]	[2.92]	[2.64]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	NAUG Quintiles, Average n (L)	(2)	(3)	(4)	(H)	NAUG Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	393	393	392	390	391	32	35	40	30	30
(2)	111	111	110	110	111	56	56	57	56	57
(3)	81	80	80	80	80	97	95	97	98	99
(4)	67	67	67	67	67	201	203	210	213	214
(5)	61	61	61	61	61	1370	1411	1693	1566	1745

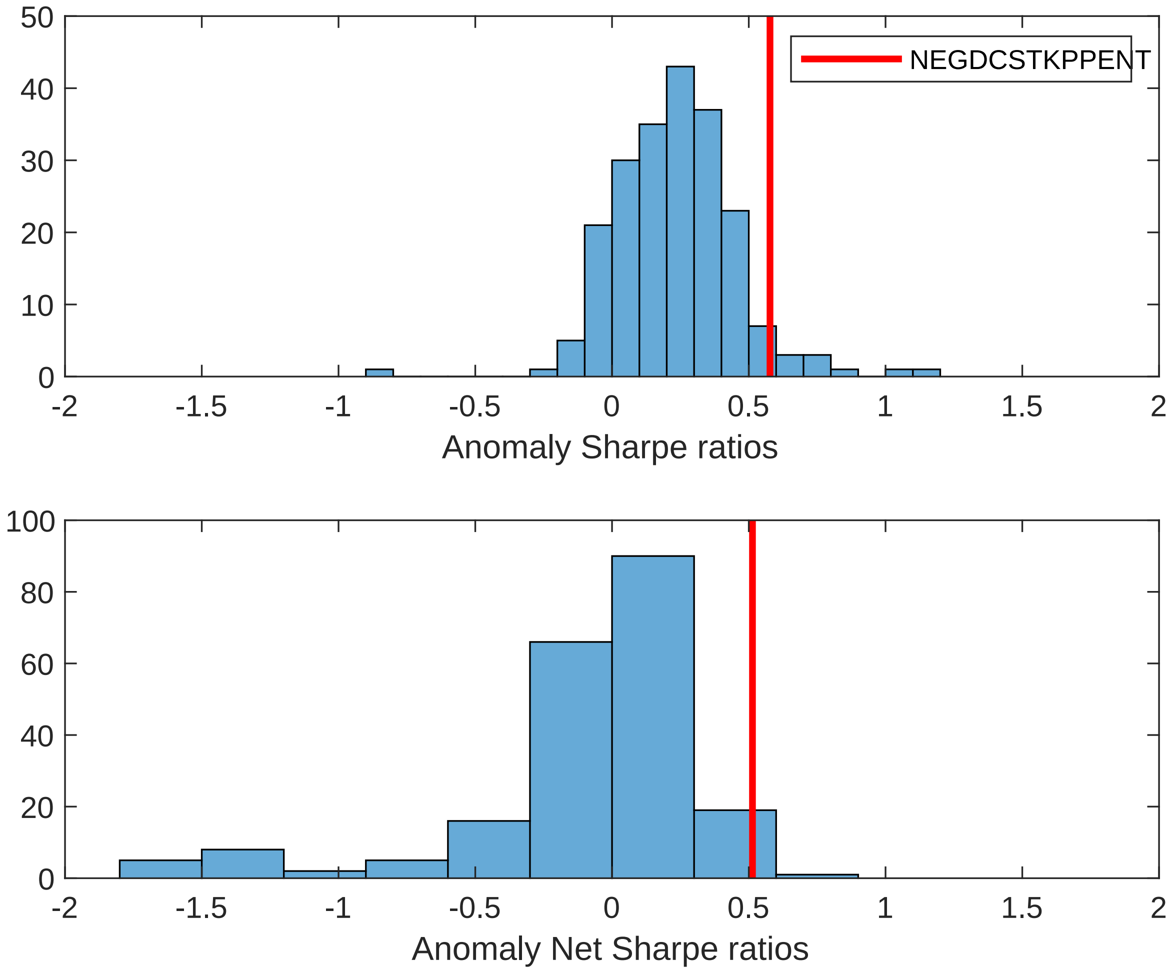

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the NAUG with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

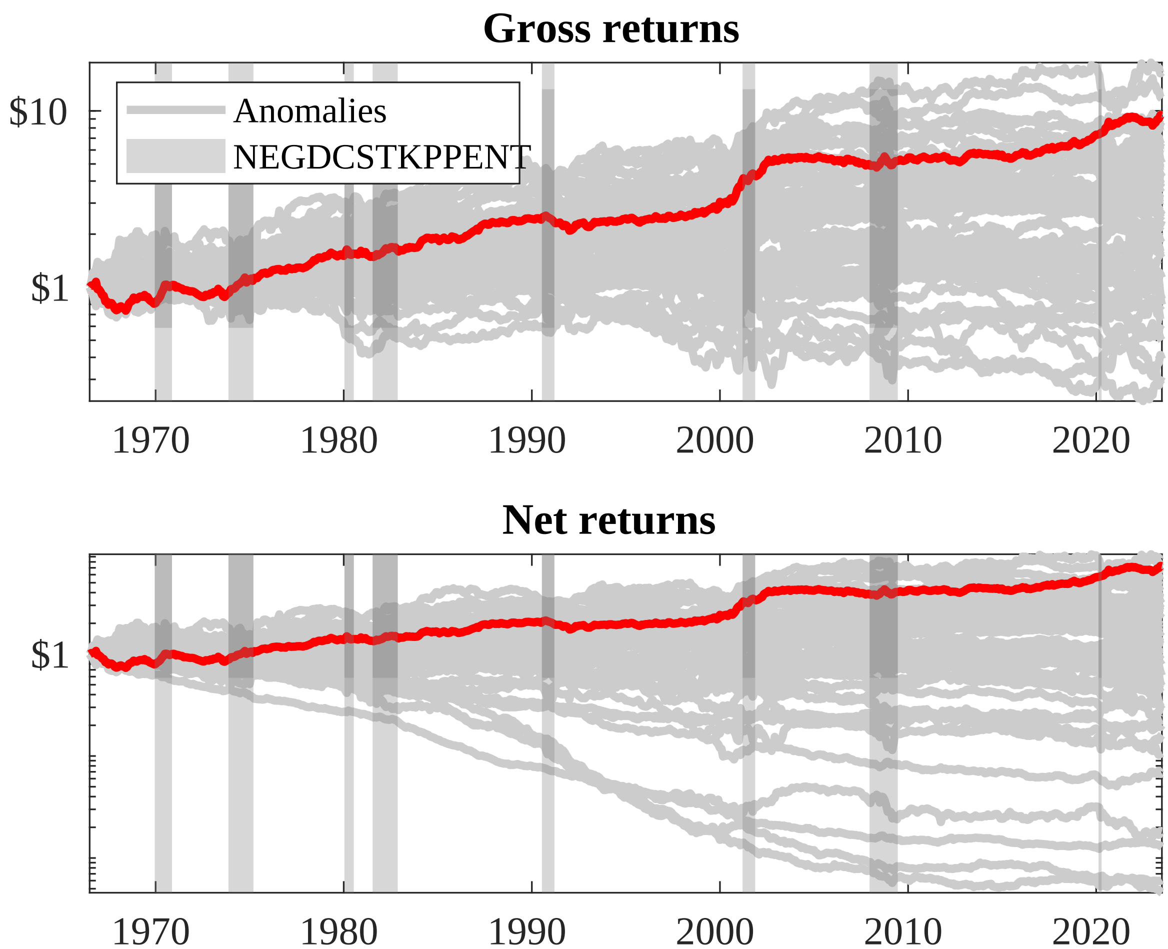

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the NAUG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

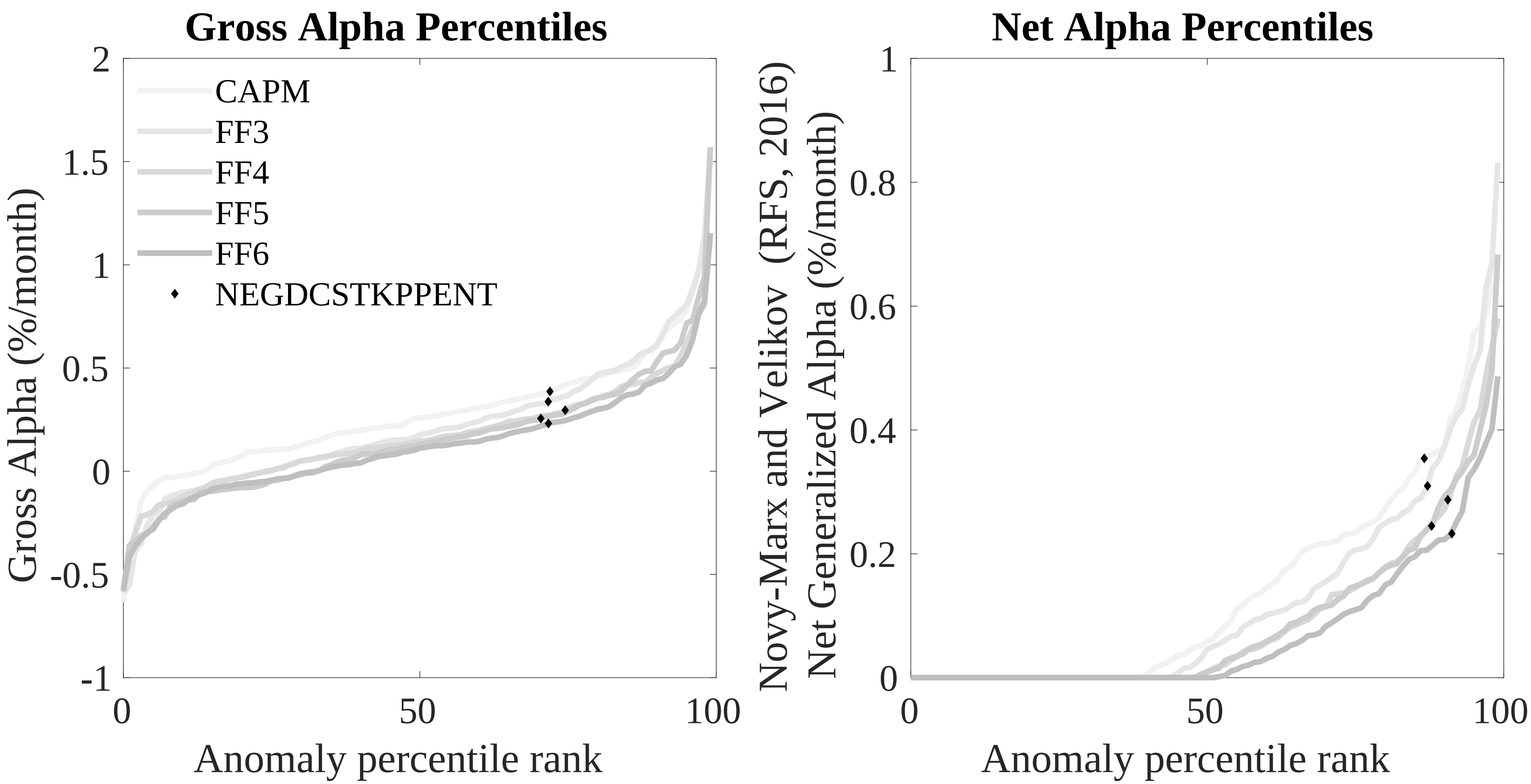

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the NAUG trading strategy alphas (diamonds). The strategies are constructed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

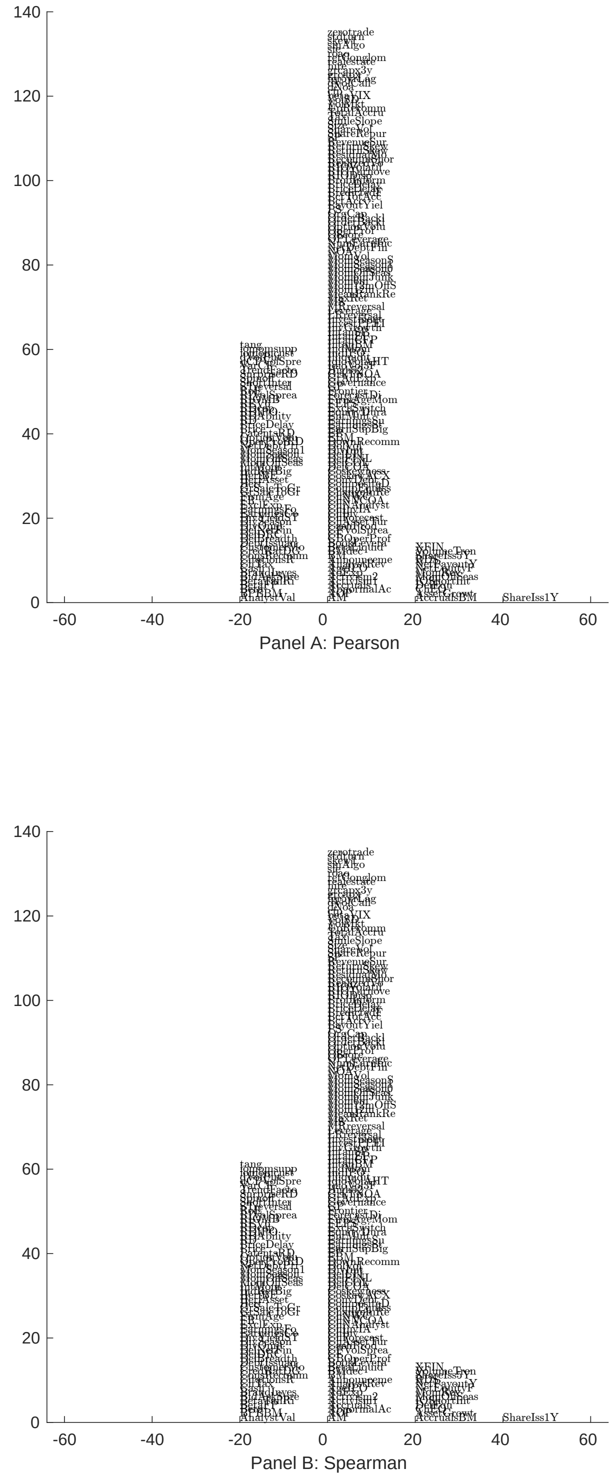

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with NAUG. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

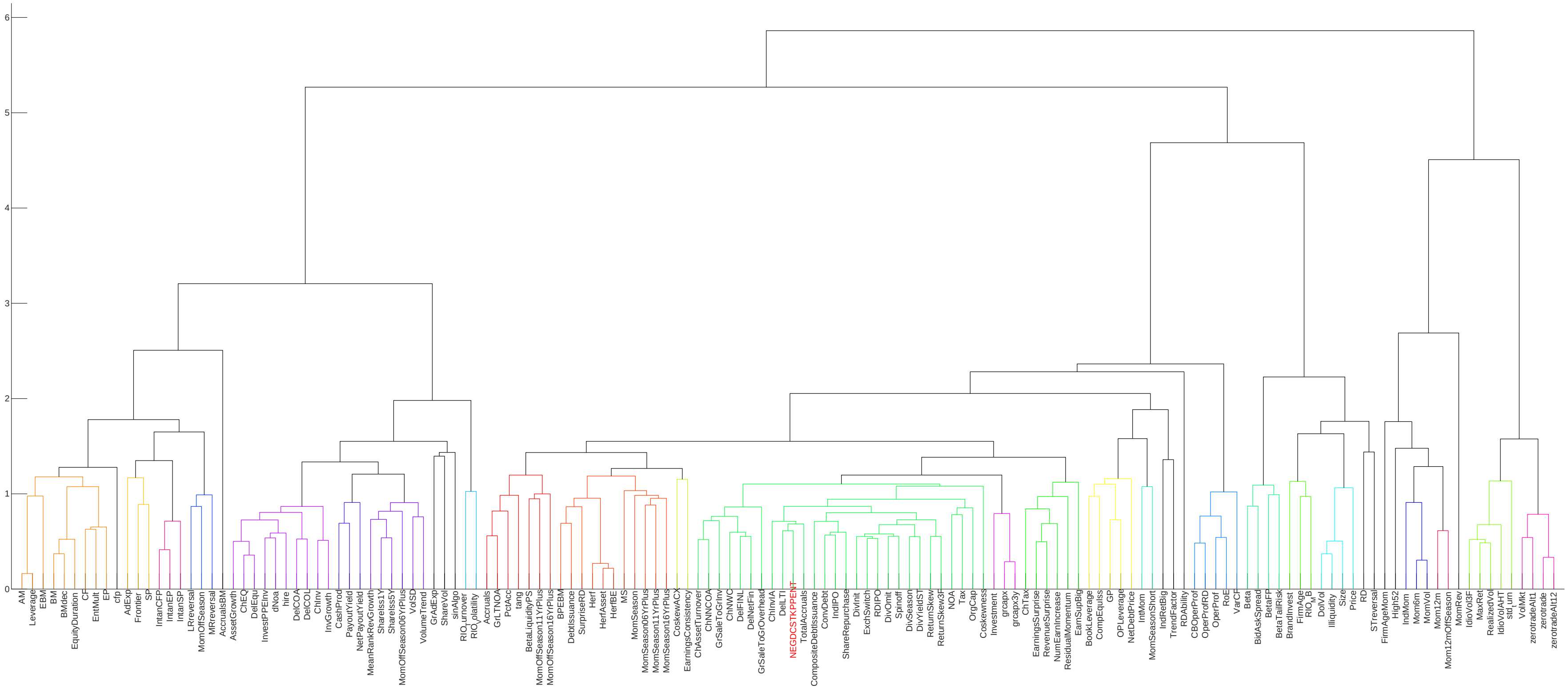

Figure 6: Agglomerative hierarchical cluster plot

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

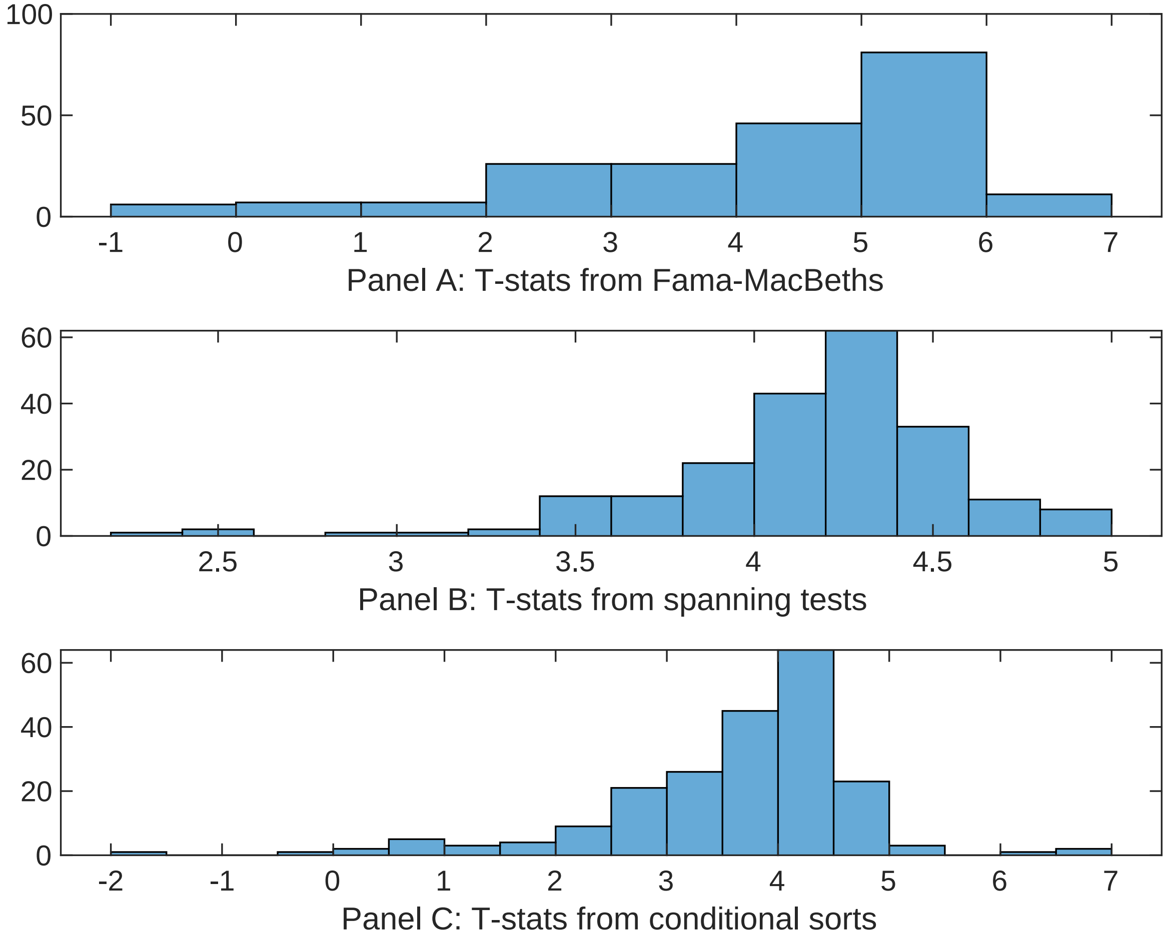

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of NAUG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NAUG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NAUG} NAUG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{NAUG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 NAUG. Stocks are finally grouped into five NAUG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NAUG 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 NAUG. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{NAUG} NAUG_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.13	0.12	0.18	0.13	0.13	0.13	0.13
	[5.66]	[5.25]	[7.24]	[6.03]	[5.58]	[6.04]	[5.13]
NAUG	0.90	0.60	0.84	0.81	0.86	0.66	0.36
	[5.34]	[3.49]	[5.66]	[4.68]	[5.58]	[4.37]	[1.98]
Anomaly 1	0.26						0.10
	[5.81]						[2.48]
Anomaly 2		0.28					0.23
		[2.54]					[2.15]
Anomaly 3			0.48				0.11
			[4.46]				[0.01]
Anomaly 4				0.37			0.44
				[4.34]			[0.49]
Anomaly 5					0.15		-0.18
					[4.20]		[-0.32]
Anomaly 6						0.10	0.68
						[8.90]	[6.48]
# months	679	679	684	679	684	684	679
$\bar{R}^2(\%)$	0	1	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 NAUG trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{NAUG} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.21	0.23	0.23	0.20	0.25	0.24	0.19
	[2.79]	[3.00]	[3.14]	[2.66]	[3.25]	[3.07]	[2.63]
Anomaly 1	25.12						16.36
	[6.53]						[3.72]
Anomaly 2		15.37					4.81
		[5.22]					[1.45]
Anomaly 3			35.64				42.62
			[8.70]				[7.16]
Anomaly 4				12.25			-1.16
				[3.06]			[-0.28]
Anomaly 5					17.69		-14.28
					[4.36]		[-2.57]
Anomaly 6						3.88	-17.10
						[0.76]	[-3.26]
mkt	1.38	1.95	0.57	1.19	-0.88	-0.59	2.92
	[0.78]	[1.07]	[0.33]	[0.64]	[-0.49]	[-0.32]	[1.64]
smb	-1.61	0.27	-4.19	-3.24	-3.26	-3.33	-0.65
	[-0.63]	[0.10]	[-1.66]	[-1.23]	[-1.25]	[-1.24]	[-0.25]
hml	-0.75	-3.44	-2.14	-0.78	-0.19	1.93	-3.93
	[-0.22]	[-0.94]	[-0.64]	[-0.21]	[-0.06]	[0.55]	[-1.10]
rmw	-7.55	-7.95	2.43	-1.53	2.31	0.47	-6.09
	[-2.06]	[-2.06]	[0.72]	[-0.43]	[0.65]	[0.13]	[-1.53]
cma	20.09	20.99	-3.54	28.81	13.42	27.13	14.88
	[3.71]	[3.74]	[-0.55]	[5.37]	[2.02]	[3.36]	[1.92]
umd	3.69	5.29	3.45	4.12	4.36	3.91	2.63
	[2.12]	[2.99]	[2.01]	[2.31]	[2.43]	[2.14]	[1.53]
# months	680	680	684	680	684	684	680
$\bar{R}^2(\%)$	20	18	22	16	15	13	26

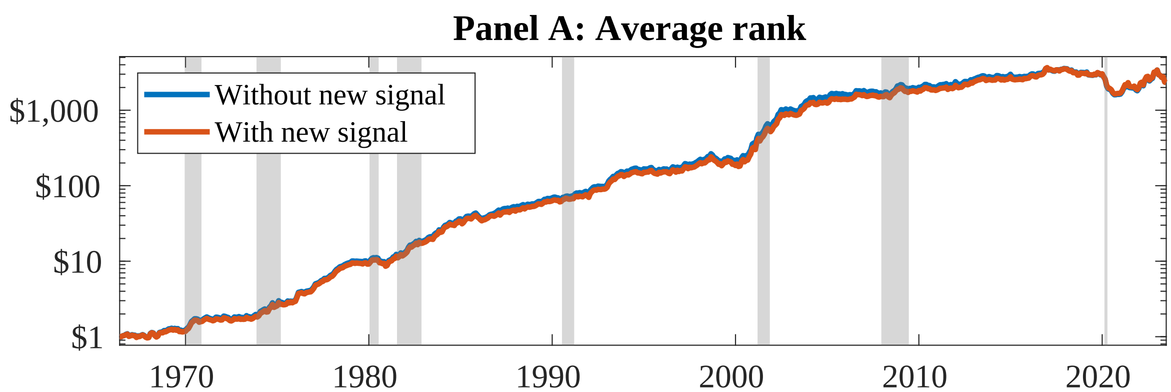

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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