Asset Efficiency Margin and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Asset Efficiency Margin (AEM), 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 AEM achieves an annualized gross (net) Sharpe ratio of 0.41 (0.35), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 20 (19) bps/month with a t-statistic of 2.32 (2.18), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Net equity financing) is 24 bps/month with a t-statistic of 2.83.

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 numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different methodological approaches is frequently questioned (Hou et al., 2020).

A particularly intriguing puzzle emerges in how markets price operational efficiency. While traditional financial theory suggests that operational improvements should be quickly incorporated into stock prices, evidence indicates that markets may systematically underreact to changes in how effectively firms utilize their assets (Soliman, 2008).

We propose that Asset Efficiency Margin (AEM) captures valuable information about firms' operational effectiveness that is not immediately reflected in stock prices. Building on the q-theory of investment (Cochrane and Saá-Requejo, 2000), improvements in asset efficiency should predict higher future profitability and returns. This relationship stems from managers' optimal investment decisions - firms with increasing operational efficiency are likely to generate higher returns on future investments.

The slow incorporation of AEM information into prices can be explained through two complementary mechanisms. First, following (Hong and Stein, 1999), investors may initially underreact to complex operational information that requires sophisticated analysis to interpret. Second, institutional frictions in information processing (Cohen and Frazzini, 2008) may delay the market's recognition of efficiency improvements, particularly when they involve complex supply chain relationships.

These mechanisms suggest that AEM should predict future returns through both a cash flow channel and a discount rate channel. The cash flow channel operates through improved future profitability, while the discount rate channel reflects the gradual recognition of reduced operational risk as efficiency improvements become apparent.

Our empirical analysis reveals that AEM strongly predicts stock returns. A value-weighted long-short portfolio sorting on AEM generates an annualized Sharpe ratio of 0.41 before trading costs and 0.35 after costs. The strategy delivers monthly abnormal returns of 20 basis points relative to the Fama-French six-factor model, with a t-statistic of 2.32.

Importantly, the predictive power of AEM remains robust after controlling for size. Among the largest quintile of stocks, the AEM strategy achieves a monthly alpha of 19-25 basis points with t-statistics between 1.86 and 2.47. This indicates that the effect is not confined to small, illiquid stocks where trading costs might prohibit implementation.

The strategy's economic significance is further demonstrated by its performance relative to other documented anomalies. AEM's gross Sharpe ratio exceeds 84% of previously documented anomalies, while its net Sharpe ratio (after trading costs) outperforms 93% of competing strategies. This places AEM among the most economically meaningful return predictors in the literature.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel measure of operational efficiency that provides incremental predictive power beyond existing metrics. While prior work has examined various aspects of asset utilization (Soliman, 2008), our measure uniquely captures the dynamic relationship between efficiency improvements and returns.

Second, we provide robust evidence that markets systematically underreact to operational efficiency information, extending the literature on limited attention and information processing frictions (Hirshleifer et al., 2011). Our findings suggest that even sophisticated investors may struggle to fully incorporate complex operational information into their valuations.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the importance of considering operational metrics in asset pricing tests. For practitioners, our findings suggest profitable trading strategies that remain robust after accounting for transaction costs and are implementable even among large-cap stocks.

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 Efficiency Margin. 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 ACOX for accumulated other comprehensive income. Common stock (CSTK) represents the total par value of all common stock outstanding, while ACOX captures the cumulative change in stockholders' equity that is not reflected in retained earnings.construction of the signal follows a difference-based approach, where we calculate the year-over-year change in CSTK and scale it by the previous year's ACOX value for each firm in our sample. This scaled difference measures the relative change in common stock value against the firm's accumulated other comprehensive income, providing insight into the efficiency of asset utilization and capital structure decisions. By focusing on this relationship, the signal aims to capture aspects of equity management and financial efficiency in a manner that is both comparable across firms and interpretable over time. We construct this measure using end-of-fiscal-year values for both CSTK and ACOX to ensure consistency in our analysis.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the AEM signal. Panel A plots the time-series of the mean, median, and interquartile range for AEM. On average, the cross-sectional mean (median) AEM is -0.94 (-0.01) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input AEM data. The signal's interquartile range spans -0.80 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the AEM signal for the CRSP universe. On average, the AEM signal is available for 4.45% of CRSP names, which on average make up 5.19% of total market capitalization.

4 Does AEM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AEM 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 AEM portfolio and sells the low AEM 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 AEM strategy earns an average return of 0.27% per month with a t-statistic of 3.13. The annualized Sharpe ratio of the strategy is 0.41. The alphas range from 0.20% to 0.34% per month and have t-statistics exceeding 2.32 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 0.27, with a t-statistic of 4.69 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 405 stocks and an average market capitalization of at least $1,101 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 20 bps/month with a t-statistics of 2.35. Out of the twenty-five alphas reported in Panel A, the t-statistics for nineteen exceed two, and for ten 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 16-34bps/month. The lowest return, (16 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 1.89. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AEM 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 seventeen cases.

Table 3 provides direct tests for the role size plays in the AEM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AEM, as well as average returns and alphas for long/short trading AEM 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 AEM strategy achieves an average return of 21 bps/month with a t-statistic of 2.07. Among these large cap stocks, the alphas for the AEM strategy relative to the five most common factor models range from 19 to 25 bps/month with t-statistics between 1.86 and 2.47.

5 How does AEM perform relative to the zoo?

Figure 2 puts the performance of AEM 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 AEM strategy falls in the distribution. The AEM strategy's gross (net) Sharpe ratio of 0.41 (0.35) is greater than 84% (93%) of anomaly Sharpe ratios,

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

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 AEM strategy (red line).[2] Ignoring trading costs, a \$1 invested in the AEM strategy would have yielded \$4.72 which ranks the AEM strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the AEM strategy would have yielded \$3.33 which ranks the AEM 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 AEM relative to those. Panel A shows that the AEM strategy gross alphas fall between the 64 and 71 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 AEM strategy has a positive net generalized alpha for five out of the five factor models. In these cases AEM ranks between the 81 and 87 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 AEM 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 AEM 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 AEM or at least to weaken the power AEM has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of AEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AEM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AEM} AEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AEM. Stocks are finally grouped into five AEM 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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AEM 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 AEM signal in these Fama-MacBeth regressions exceed 0.68, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on AEM is 1.10.

Similarly, Table 5 reports results from spanning tests that regress returns to the AEM 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 AEM strategy earns alphas that range from 17-29bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.01, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AEM trading strategy achieves an alpha of 24bps/month with a t-statistic of 2.83.

7 Does AEM add relative to the whole zoo?

Finally, we can ask how much adding AEM 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 AEM signal.[4] We consider one different methods for combining signals.

[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 AEM is available.

Panel A shows results using “Average rank” as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes AEM grows to $1892.32.

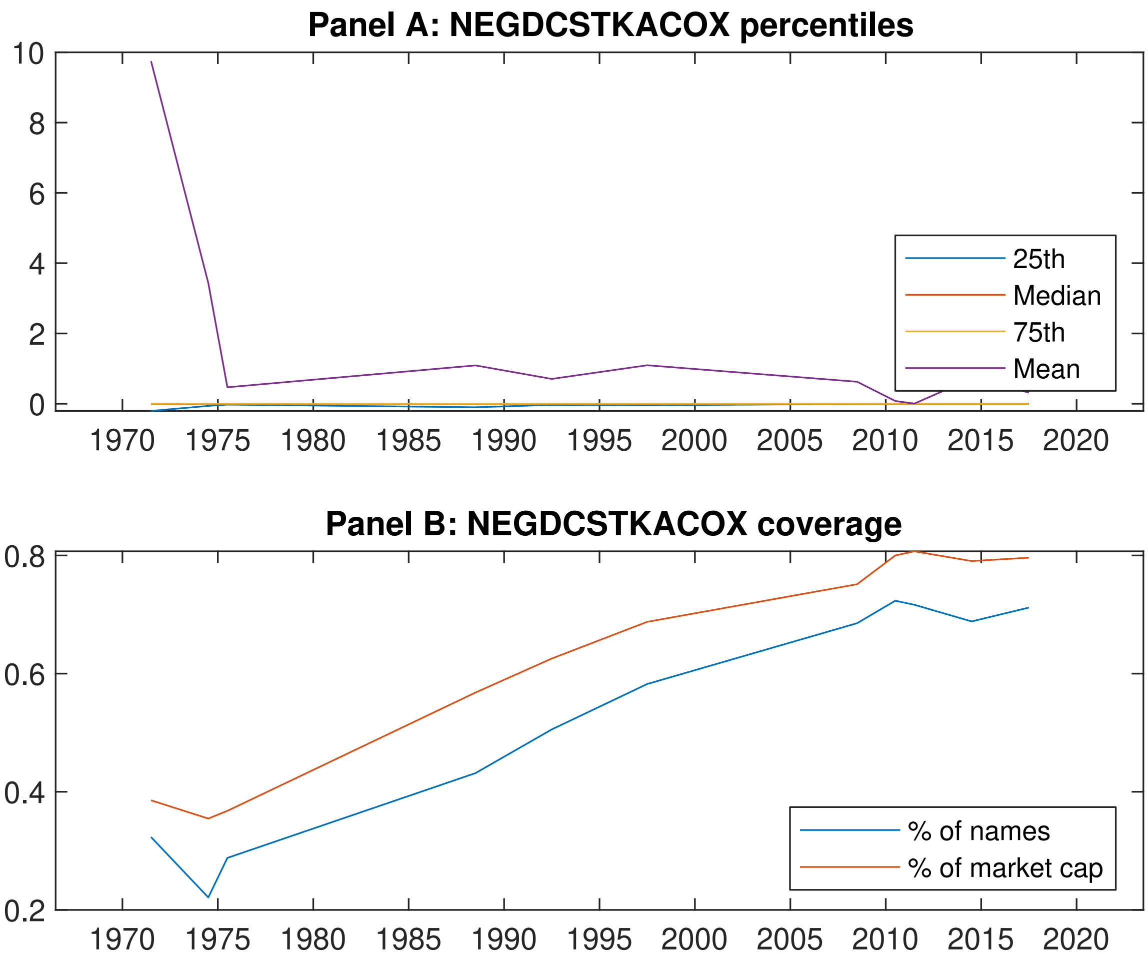


Figure 1: Times series of AEM percentiles and coverage.
This figure plots descriptive statistics for AEM. Panel A shows cross-sectional percentiles of AEM over the sample. Panel B plots the monthly coverage of AEM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AEM. 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 AEM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.48	0.51	0.65	0.74	0.75	0.27
	[2.51]	[2.61]	[3.29]	[4.37]	[4.41]	[3.13]
α_{CAPM}	-0.11	-0.10	0.04	0.22	0.23	0.34
	[-1.77]	[-1.59]	[0.62]	[3.85]	[4.06]	[3.90]
α_{FF3}	-0.08	-0.05	0.10	0.22	0.21	0.28
	[-1.23]	[-0.86]	[1.76]	[3.77]	[3.73]	[3.33]
α_{FF4}	-0.07	-0.03	0.10	0.15	0.19	0.27
	[-1.16]	[-0.60]	[1.86]	[2.70]	[3.41]	[3.07]
α_{FF5}	-0.12	0.04	0.11	0.07	0.09	0.21
	[-1.98]	[0.71]	[2.03]	[1.31]	[1.58]	[2.41]
α_{FF6}	-0.12	0.04	0.12	0.03	0.09	0.20
	[-1.88]	[0.77]	[2.07]	[0.63]	[1.55]	[2.32]
Panel B: Fama and French (2018) 6-factor model loadings for AEM-sorted portfolios						
β_{MKT}	1.03	1.01	1.02	0.98	0.97	-0.05
	[69.56]	[73.96]	[75.96]	[75.90]	[74.98]	[-2.59]
β_{SMB}	0.03	0.07	0.06	0.01	0.03	-0.00
	[1.52]	[3.39]	[2.99]	[0.33]	[1.57]	[-0.10]
β_{HML}	-0.09	-0.09	-0.14	-0.09	-0.07	0.03
	[-3.34]	[-3.52]	[-5.48]	[-3.59]	[-2.76]	[0.65]
β_{RMW}	0.14	-0.14	0.02	0.20	0.18	0.04
	[4.99]	[-5.28]	[0.80]	[7.83]	[7.08]	[0.88]
β_{CMA}	-0.01	-0.15	-0.10	0.29	0.26	0.27
	[-0.32]	[-4.01]	[-2.67]	[7.81]	[7.09]	[4.69]
β_{UMD}	-0.01	-0.01	-0.01	0.06	0.00	0.01
	[-0.54]	[-0.46]	[-0.44]	[4.59]	[0.08]	[0.43]
Panel C: Average number of firms (n) and market capitalization (me)						
n	542	504	405	464	487	
me ($\$10^6$)	1275	1101	1732	1679	1986	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the AEM 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	0.27	0.34	0.28	0.27	0.21	0.20
			[3.13]	[3.90]	[3.33]	[3.07]	[2.41]	[2.32]
Quintile	NYSE	EW	0.55	0.64	0.56	0.49	0.40	0.36
			[7.18]	[8.81]	[8.37]	[7.44]	[6.25]	[5.67]
Quintile	Name	VW	0.26	0.31	0.25	0.23	0.19	0.18
			[2.90]	[3.49]	[2.89]	[2.57]	[2.14]	[1.98]
Quintile	Cap	VW	0.20	0.26	0.24	0.20	0.19	0.17
			[2.35]	[3.06]	[2.74]	[2.30]	[2.17]	[1.90]
Decile	NYSE	VW	0.26	0.27	0.22	0.20	0.19	0.18
			[2.29]	[2.45]	[1.93]	[1.73]	[1.68]	[1.58]

Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.23	0.30	0.25	0.25	0.19	0.19
			[2.67]	[3.47]	[2.97]	[2.86]	[2.20]	[2.18]
Quintile	NYSE	EW	0.34	0.43	0.34	0.32	0.18	0.17
			[4.15]	[5.34]	[4.75]	[4.37]	[2.57]	[2.45]
Quintile	Name	VW	0.22	0.28	0.23	0.22	0.17	0.17
			[2.45]	[3.12]	[2.60]	[2.45]	[1.96]	[1.92]
Quintile	Cap	VW	0.16	0.23	0.20	0.18	0.17	0.15
			[1.89]	[2.66]	[2.36]	[2.13]	[1.94]	[1.79]
Decile	NYSE	VW	0.21	0.23	0.18	0.17	0.16	0.15
			[1.88]	[2.04]	[1.60]	[1.51]	[1.39]	[1.37]

Table 3: Conditional sort on size and AEM

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

		AEM Quintiles					AEM Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.36	0.73	0.88	1.00	1.00	0.64	0.70	0.62	0.57	0.43	0.40
		[1.26]	[2.62]	[3.26]	[3.61]	[3.92]	[6.20]	[6.96]	[6.51]	[5.88]	[4.70]	[4.34]
	(2)	0.54	0.74	0.83	0.97	0.86	0.32	0.41	0.29	0.27	0.17	0.16
		[2.06]	[2.85]	[3.25]	[3.92]	[3.67]	[3.01]	[3.90]	[2.98]	[2.67]	[1.74]	[1.63]
	(3)	0.65	0.66	0.86	0.84	0.94	0.29	0.35	0.27	0.28	0.23	0.24
		[2.80]	[2.71]	[3.55]	[3.75]	[4.40]	[2.96]	[3.58]	[2.87]	[2.90]	[2.32]	[2.40]
	(4)	0.51	0.58	0.81	0.82	0.82	0.31	0.36	0.27	0.25	0.14	0.14
		[2.34]	[2.59]	[3.65]	[3.83]	[4.08]	[3.26]	[3.76]	[2.93]	[2.74]	[1.52]	[1.51]
	(5)	0.52	0.47	0.54	0.52	0.73	0.21	0.25	0.22	0.21	0.19	0.19
		[2.84]	[2.39]	[2.80]	[2.97]	[4.34]	[2.07]	[2.47]	[2.16]	[2.07]	[1.86]	[1.85]

Panel B: Portfolio average number of firms and market capitalization

		AEM Quintiles					AEM Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	263	263	263	261	262	23	25	30	22	22
	(2)	77	77	77	76	77	43	44	44	44	44
	(3)	55	55	54	54	55	75	73	75	77	77
	(4)	46	45	46	46	46	160	160	166	168	171
	(5)	41	41	41	41	41	1085	1133	1393	1205	1414

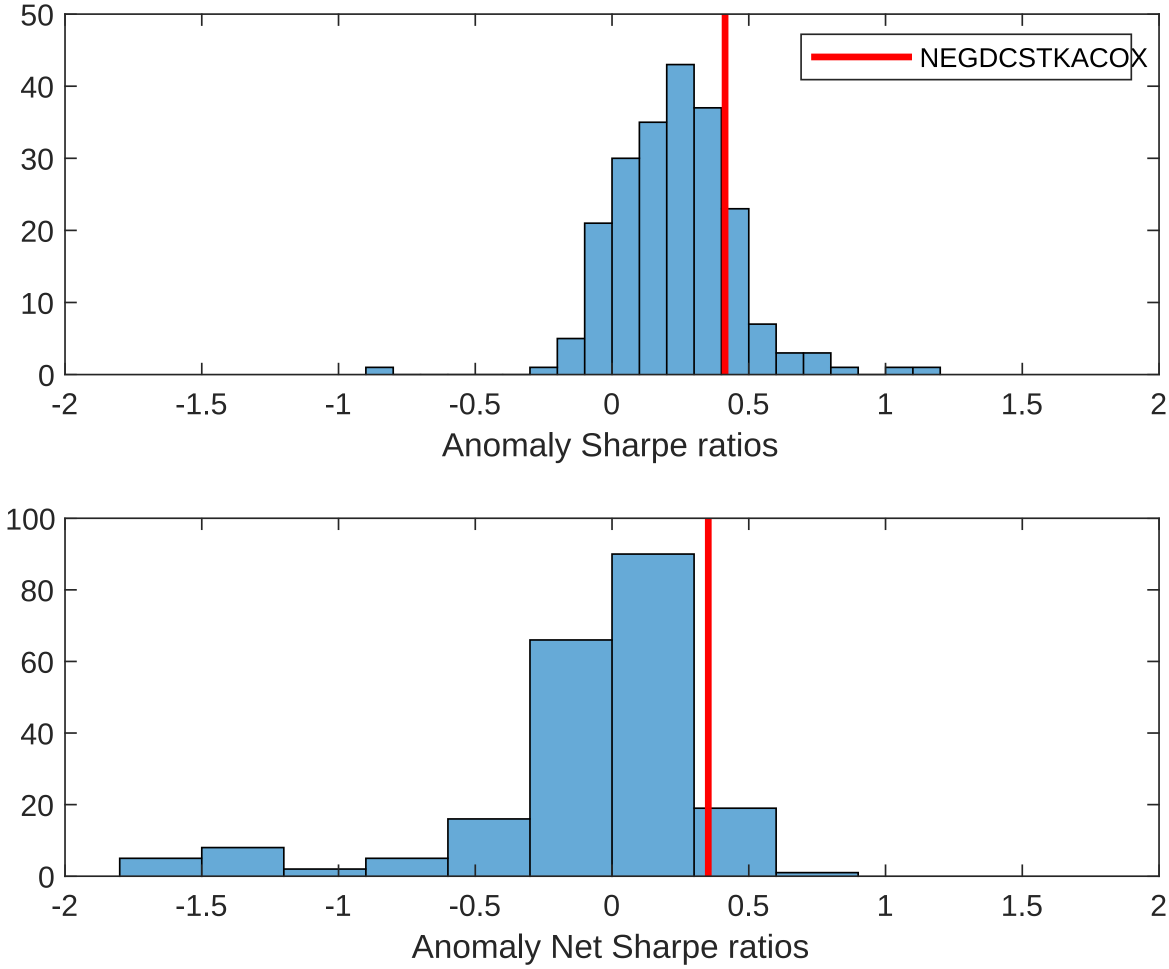


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AEM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

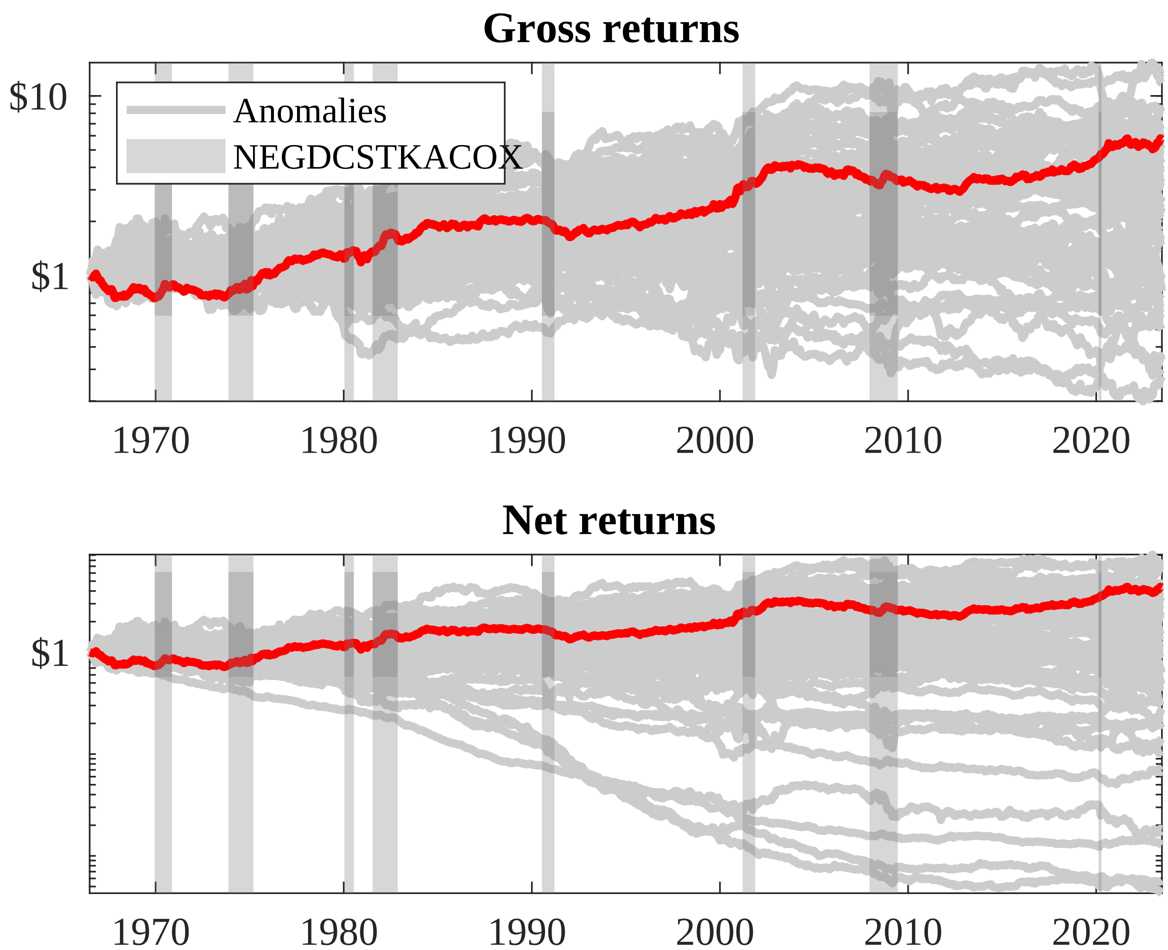


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AEM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

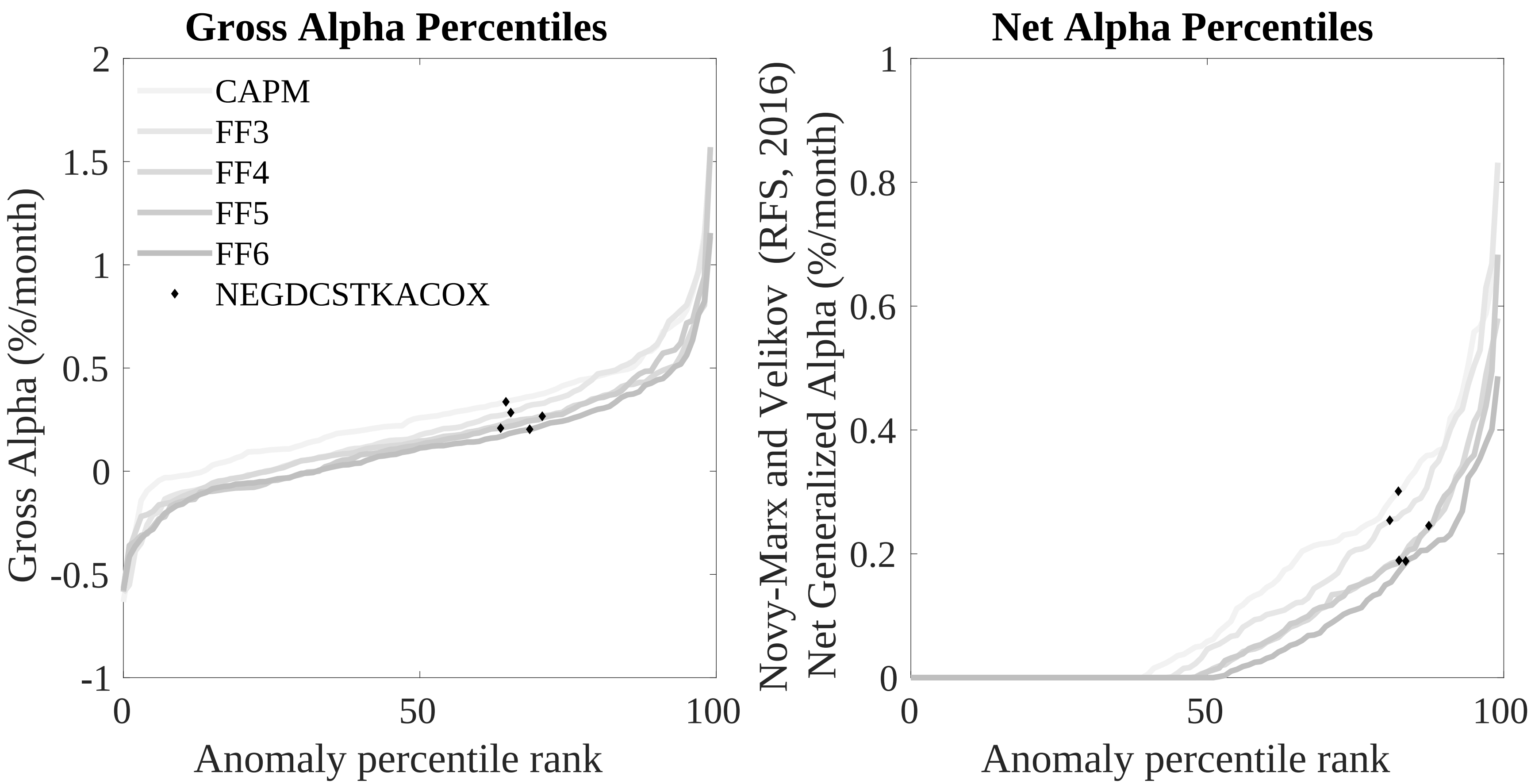
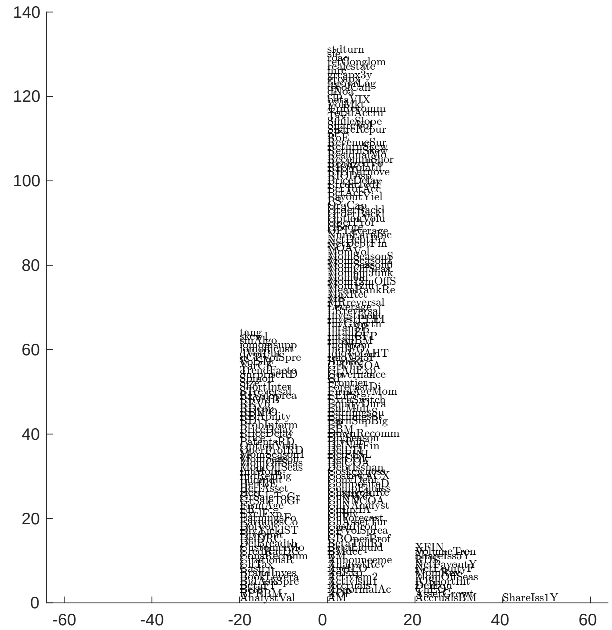
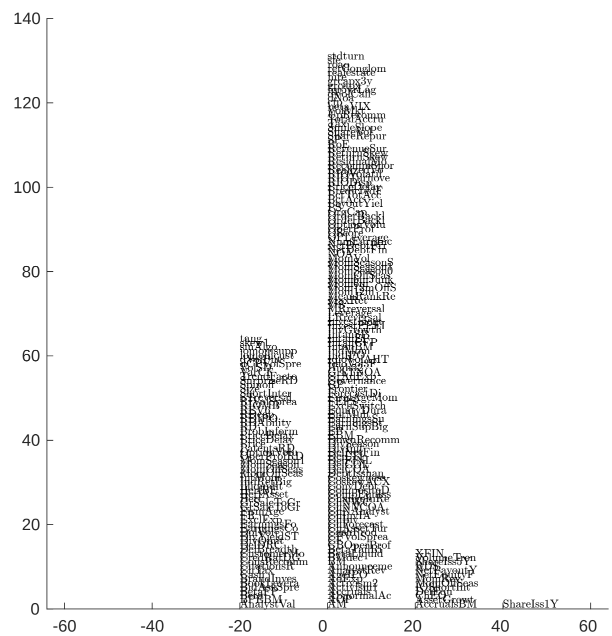


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AEM trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

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

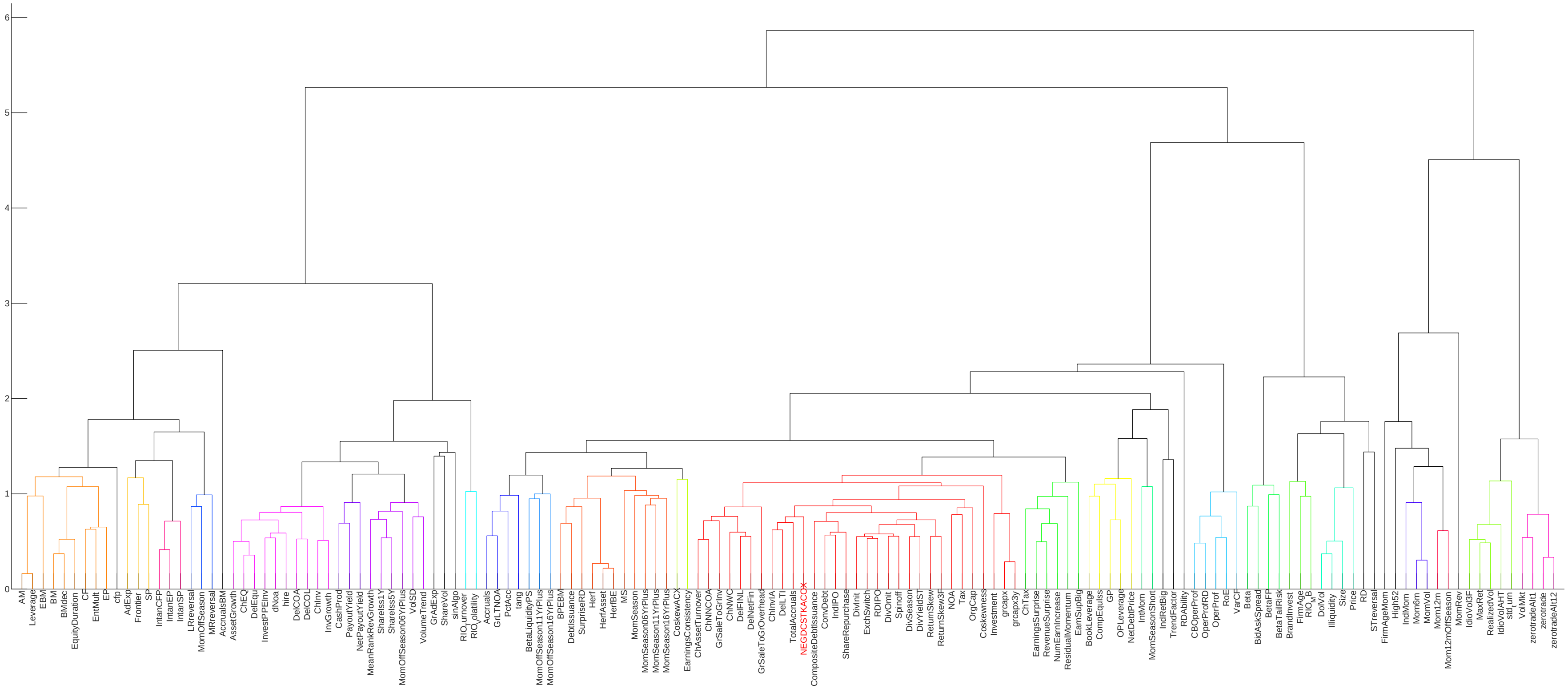


Figure 6: Agglomerative hierarchical cluster plot

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

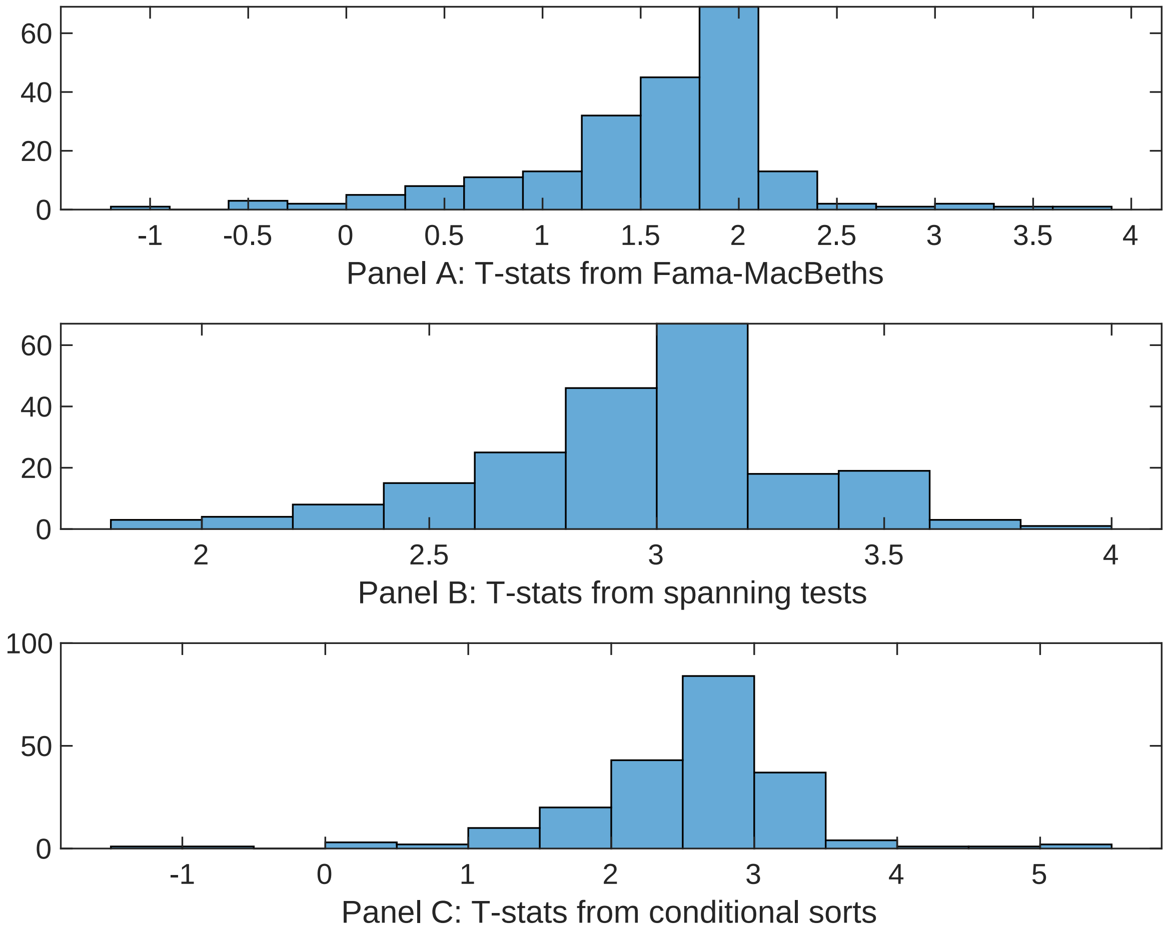


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AEM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AEM} AEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AEM. Stocks are finally grouped into five AEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AEM 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 AEM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AEM} AEM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Net equity financing. 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	0.19	0.12	0.13	0.13	0.13	0.16
	[5.46]	[7.26]	[5.21]	[5.78]	[5.42]	[5.21]	[6.20]
AEM	0.44	0.35	0.20	0.58	0.35	0.41	0.34
	[1.42]	[1.16]	[0.68]	[1.92]	[1.05]	[1.26]	[1.10]
Anomaly 1	0.28						0.11
	[5.67]						[2.34]
Anomaly 2		0.55					0.28
		[5.16]					[2.01]
Anomaly 3			0.28				0.16
			[2.64]				[2.99]
Anomaly 4				0.30			0.60
				[3.00]			[0.61]
Anomaly 5					0.17		0.26
					[4.83]		[0.43]
Anomaly 6						0.16	-0.87
						[2.49]	[-1.05]
# months	679	684	679	679	684	615	607
$\bar{R}^2(\%)$	0	0	1	0	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the AEM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AEM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Net equity financing. 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	0.18	0.20	0.20	0.17	0.23	0.29	0.24
	[2.09]	[2.43]	[2.33]	[2.01]	[2.73]	[3.17]	[2.83]
Anomaly 1	28.41						10.37
	[6.52]						[1.88]
Anomaly 2		41.27					31.28
		[8.90]					[4.41]
Anomaly 3			18.19				8.47
			[5.46]				[1.88]
Anomaly 4				21.12			7.55
				[4.70]			[1.51]
Anomaly 5					31.67		3.18
					[7.03]		[0.47]
Anomaly 6						11.29	-9.06
						[2.69]	[-1.80]
mkt	-2.95	-3.83	-2.19	-2.33	-5.69	-4.88	-3.62
	[-1.47]	[-1.95]	[-1.06]	[-1.12]	[-2.84]	[-2.17]	[-1.67]
smb	1.69	-1.38	3.94	-0.79	-0.51	6.41	-0.68
	[0.59]	[-0.48]	[1.33]	[-0.27]	[-0.18]	[1.79]	[-0.20]
hml	0.14	-1.78	-3.25	-2.24	-0.97	2.05	-6.76
	[0.04]	[-0.47]	[-0.78]	[-0.54]	[-0.25]	[0.50]	[-1.61]
rmw	-5.91	5.44	-6.83	-0.62	6.43	-1.31	2.55
	[-1.42]	[1.42]	[-1.56]	[-0.15]	[1.64]	[-0.27]	[0.52]
cma	13.56	-13.88	13.91	20.59	-5.89	14.16	-19.34
	[2.21]	[-1.92]	[2.19]	[3.42]	[-0.80]	[2.11]	[-2.51]
umd	0.80	0.48	2.67	1.24	1.90	0.35	0.86
	[0.40]	[0.25]	[1.33]	[0.62]	[0.95]	[0.17]	[0.43]
# months	680	684	680	680	684	618	614
$\bar{R}^2(\%)$	17	20	16	15	16	10	22

Panel A: Average rank

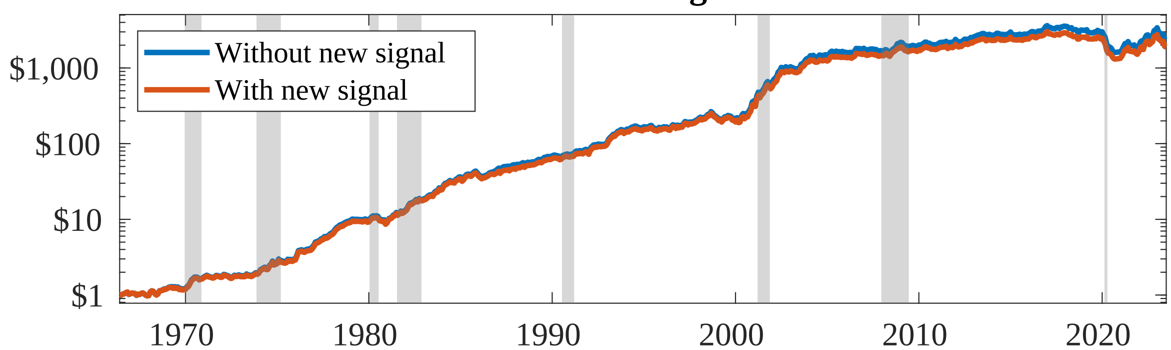


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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