Acquisitions Efficiency Ratio and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Acquisitions Efficiency Ratio (AER), 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 AER achieves an annualized gross (net) Sharpe ratio of 0.32 (0.22), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 15 (9) bps/month with a t-statistic of 2.13 (1.29), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Asset growth, Change in current operating assets, Change in current operating liabilities, Change in Net Noncurrent Op Assets, Growth in book equity, Inventory Growth) is 16 bps/month with a t-statistic of 2.26.

1 Introduction

Market efficiency and asset pricing models remain central topics in financial economics, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While hundreds of potential predictors have been documented in the literature (Harvey et al., 2016), many fail to survive careful scrutiny of their robustness and economic significance (Hou et al., 2020). A key challenge in this domain is identifying signals that are both theoretically motivated and empirically robust.

One understudied area in the cross-sectional prediction literature is the efficiency with which firms deploy capital through acquisitions. While extensive research has examined the market reaction to merger announcements (**?**) and long-run post-merger performance (**?**), less attention has been paid to how a firm's historical acquisition efficiency relates to its future stock returns.

We hypothesize that firms' Acquisition Efficiency Ratio (AER) contains valuable information about future returns through several economic channels. First, following Jensen and Meckling (1976), managers with better track records of value-creating acquisitions likely have superior capital allocation skills and stronger corporate governance, leading to better future investment decisions. Second, building on **?**, firms with historically efficient acquisitions may have developed valuable organizational capabilities in target selection, due diligence, and post-merger integration.

The relationship between AER and future returns may also reflect market underreaction to the persistence of managerial skill in acquisitions. While the market responds to individual merger announcements (**?**), investors may underestimate the extent to which past acquisition efficiency predicts future value creation. This builds on evidence of investor underreaction to complex signals documented by **?**.

Additionally, AER may capture information about agency costs and corporate governance quality that is not fully reflected in stock prices. Firms with poor acquisition track records often suffer from empire-building tendencies and weak board oversight (Masulis et al., 2012), suggesting that AER could serve as a proxy for broader governance issues that affect future performance.

Our empirical analysis reveals that AER strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on AER quintiles generates a monthly alpha of 15 basis points (t-statistic = 2.13) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.32, placing it in the top third of documented cross-sectional predictors.

The predictive power of AER remains robust after controlling for transaction costs and various portfolio construction approaches. Using the methodology of Novy-Marx and Velikov (2023), we find that the strategy delivers a net alpha of 9 basis points per month (t-statistic = 1.29) after accounting for trading frictions. Importantly, the signal's predictive ability persists among large-cap stocks, with the long-short strategy generating a monthly alpha of 24 basis points (t-statistic = 2.57) in the largest size quintile.

Further tests demonstrate that AER's predictive power is distinct from related anomalies. Controlling for the six most closely related predictors from the factor zoo, including asset growth and investment-based signals, the strategy maintains a significant alpha of 16 basis points per month (t-statistic = 2.26). This suggests that AER captures a unique dimension of cross-sectional return predictability.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures information about managerial skill and corporate governance through the lens of acquisition efficiency. This extends work by **?** on merger characteristics and Masulis et al. (2012) on corporate governance by showing how historical acquisition performance contains valuable information for future stock returns.

Second, we contribute to the growing literature on investment-based return predictability ?. While previous research has focused on aggregate investment levels or specific types of investment, our findings highlight the importance of considering the efficiency of major corporate investments in predicting returns. The robust performance of AER among large-cap stocks also addresses concerns about the implementability of investment-based trading strategies.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining corporate actions through the lens of efficiency rather than just scale or frequency. For practitioners, our findings suggest that historical acquisition efficiency provides an economically meaningful signal for portfolio formation that is robust to transaction costs and works well among liquid 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 Acquisitions Efficiency Ratio. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item AQC for acquisition expenditures and item ACT for current assets. Acquisition expenditures (AQC) represent cash outflows and other assets used for merger and acquisition activities, including the purchase price and related costs of acquiring other companies or business units. Current assets (ACT) represent the firm's short-term assets, which are expected to be converted to cash or consumed within a year, including cash, receivables, and inventories. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's acquisition expenditures (AQC) and its lagged value, then scale this difference by lagged current assets (ACT). This ratio captures the relative change in acquisition activities relative to the firm's asset base, offering insight into the intensity and efficiency of a firm's acquisition strategy. By focusing on this relationship, the signal aims to reflect aspects of corporate growth strategy and capital allocation efficiency in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the AER signal. Panel A plots the time-series of the mean, median, and interquartile range for AER. On average, the cross-sectional mean (median) AER is -0.23 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input AER data. The signal's interquartile range spans -0.02 to 0.02. Panel B of Figure 1 plots the time-series of the coverage of the AER signal for the CRSP universe. On average, the AER signal is available for 5.41% of CRSP names, which on average make up 5.55% of total market capitalization.

4 Does AER predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AER 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 AER portfolio and sells the low AER 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 AER strategy earns an average return of 0.15% per month with a t-statistic of 2.26. The annualized Sharpe ratio of the strategy is 0.32. The alphas range from 0.14% to 0.17% per month and have t-statistics exceeding 2.08 everywhere. The lowest alpha is with respect to the FF3 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.06, with a t-statistic of 1.79 on the HML 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 475 stocks and an average market capitalization of at least $1,130 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 name breakpoints and value-weighted portfolios, and equals 11 bps/month with a t-statistics of 1.74. Out of the twenty-five alphas reported in

Panel A, the t-statistics for thirteen exceed two, and for 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 1-14bps/month. The lowest return, (1 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.22. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AER trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-one cases, and significantly expands the achievable frontier in one cases.

Table 3 provides direct tests for the role size plays in the AER strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AER, as well as average returns and alphas for long/short trading AER 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 AER strategy achieves an average return of 20 bps/month with a t-statistic of 2.24. Among these large cap stocks, the alphas for the AER strategy relative to the five most common factor models range from 21 to 24 bps/month with t-statistics between 2.23 and 2.57.

5 How does AER perform relative to the zoo?

Figure 2 puts the performance of AER 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 AER strategy falls in the distribution. The AER strategy's gross (net) Sharpe ratio of 0.32 (0.22) is greater than 67% (81%) 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 AER strategy (red line).[2] Ignoring trading costs, a \$1 invested in the AER strategy would have yielded \$1.20 which ranks the AER strategy in the top 14% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the AER strategy would have yielded \$0.67 which ranks the AER strategy in the top 12% 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 AER relative to those. Panel A shows that the AER strategy gross alphas fall between the 34 and 61 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 197406 to 202306 sample. For example, 45%

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

[2] The figure assumes an initial investment of \$1 in T-bills and \$1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The AER strategy has a positive net generalized alpha for five out of the five factor models. In these cases AER ranks between the 56 and 71 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does AER 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 AER 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 AER or at least to weaken the power AER has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of AER conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AER} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AER}AER_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AER,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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-

[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.

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 AER. Stocks are finally grouped into five AER portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AER trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AER 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 AER signal in these Fama-MacBeth regressions exceed -1.28, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on AER is -0.19.

Similarly, Table 5 reports results from spanning tests that regress returns to the AER 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 AER strategy earns alphas that range from 15-17bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.09, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AER trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.26.

7 Does AER add relative to the whole zoo?

Finally, we can ask how much adding AER 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 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the AER signal.[4] We consider one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes AER grows to $974.52.

8 Conclusion

This study provides evidence that the Acquisitions Efficiency Ratio (AER) serves as a meaningful predictor of stock returns, though with moderate economic significance. Our analysis demonstrates that a value-weighted long/short strategy based on AER generates positive abnormal returns, achieving an annualized gross Sharpe ratio of 0.32 (0.22 net of transaction costs). The signal's predictive power remains robust even after controlling for established factors and related anomalies, as evidenced by the significant alpha of 16 bps per month (t-statistic = 2.26) when accounting for the Fama-French five factors, momentum, and six closely related strategies.

[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 AER is available.

However, the practical implementation of this signal presents certain challenges, as indicated by the reduction in performance metrics when considering transaction costs. The decline in Sharpe ratio and statistical significance of abnormal returns after accounting for costs suggests that careful consideration must be given to implementation strategies in real-world applications.

Several limitations of this study warrant mention. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains unexplored. Second, the study period may not capture all market conditions, potentially limiting the generalizability of our findings.

Future research could extend this work in several directions. Investigation of the signal's performance in international markets would provide insights into its global applicability. Additionally, examining the interaction between AER and other established signals could reveal potential complementarities or substitution effects. Finally, exploring the underlying economic mechanisms driving the AER's predictive power could enhance our understanding of corporate acquisition efficiency and its relationship with stock returns.

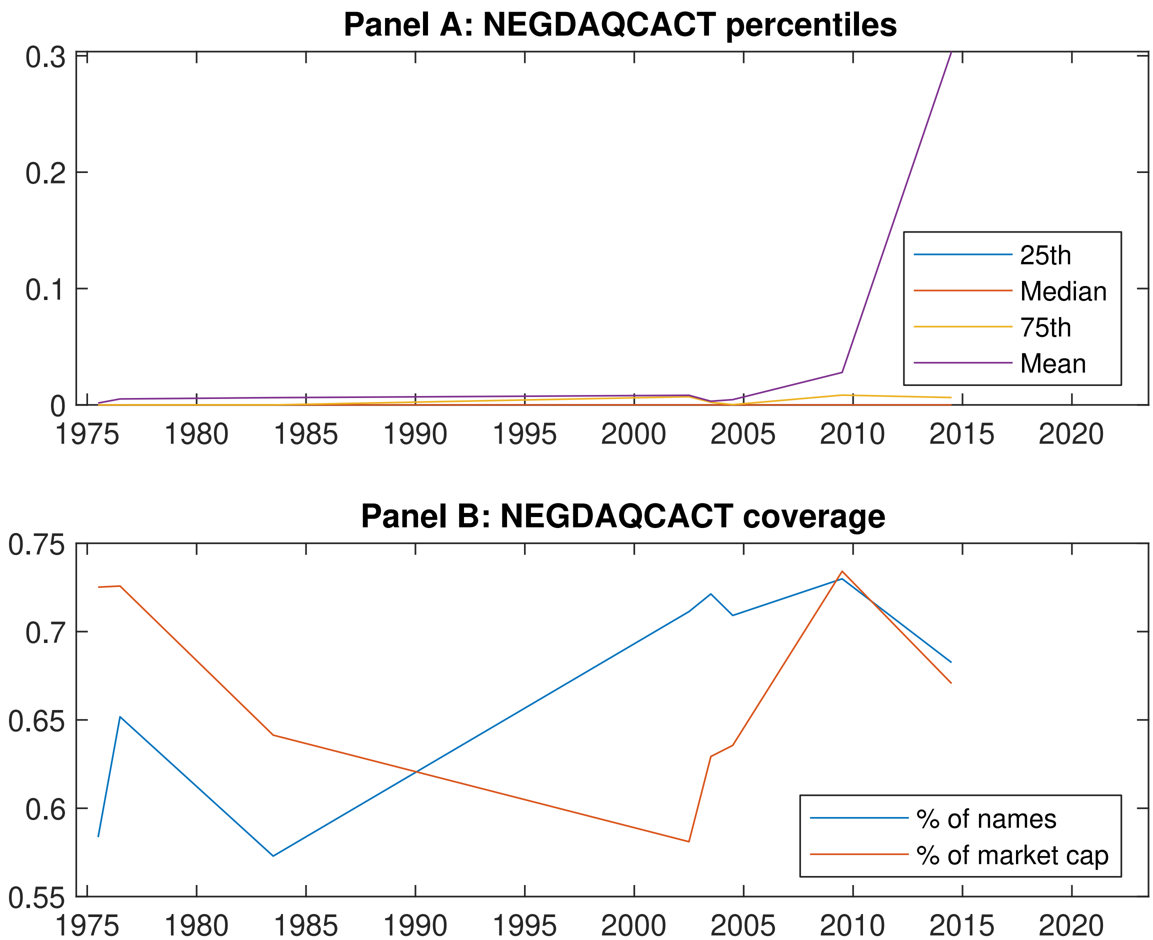


Figure 1: Times series of AER percentiles and coverage.
This figure plots descriptive statistics for AER. Panel A shows cross-sectional percentiles of AER over the sample. Panel B plots the monthly coverage of AER relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AER. 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 197406 to 202306.

Panel A: Excess returns and alphas on AER-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.59	0.79	0.63	0.71	0.74	0.15
	[2.96]	[4.06]	[3.27]	[3.49]	[3.83]	[2.26]
α_{CAPM}	-0.10	0.12	-0.03	0.01	0.07	0.17
	[-1.75]	[2.13]	[-0.48]	[0.11]	[1.33]	[2.46]
α_{FF3}	-0.08	0.13	-0.02	0.04	0.07	0.14
	[-1.33]	[2.43]	[-0.29]	[0.69]	[1.28]	[2.09]
α_{FF4}	-0.07	0.13	-0.04	0.06	0.08	0.15
	[-1.26]	[2.39]	[-0.66]	[1.08]	[1.43]	[2.14]
α_{FF5}	-0.16	0.07	-0.04	0.04	-0.02	0.15
	[-2.96]	[1.20]	[-0.58]	[0.76]	[-0.38]	[2.08]
α_{FF6}	-0.15	0.07	-0.05	0.06	-0.00	0.15
	[-2.76]	[1.32]	[-0.82]	[1.07]	[-0.08]	[2.13]
Panel B: Fama and French (2018) 6-factor model loadings for AER-sorted portfolios						
β_{MKT}	1.00	1.00	0.95	1.01	1.00	-0.01
	[77.86]	[77.64]	[65.93]	[76.68]	[83.20]	[-0.32]
β_{SMB}	0.07	0.01	0.13	0.03	0.03	-0.03
	[3.32]	[0.38]	[5.74]	[1.28]	[1.74]	[-1.35]
β_{HML}	-0.13	-0.11	-0.08	-0.15	-0.07	0.06
	[-5.24]	[-4.43]	[-2.76]	[-5.82]	[-3.22]	[1.79]
β_{RMW}	0.19	0.09	0.03	-0.04	0.15	-0.04
	[7.35]	[3.71]	[1.04]	[-1.67]	[6.22]	[-1.25]
β_{CMA}	0.08	0.13	0.01	0.08	0.14	0.06
	[2.24]	[3.52]	[0.36]	[2.17]	[4.10]	[1.26]
β_{UMD}	-0.02	-0.01	0.03	-0.03	-0.03	-0.01
	[-1.36]	[-0.93]	[1.84]	[-2.37]	[-2.22]	[-0.56]
Panel C: Average number of firms (n) and market capitalization (me)						
n	479	646	802	660	475	
me ($\$10^6$)	1528	1893	1130	1705	1571	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the AER 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 197406 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	0.15	0.17	0.14	0.15	0.15	0.15
			[2.26]	[2.46]	[2.09]	[2.14]	[2.08]	[2.13]
Quintile	NYSE	EW	0.23	0.23	0.21	0.20	0.20	0.19
			[4.97]	[4.89]	[4.56]	[4.19]	[4.18]	[3.99]
Quintile	Name	VW	0.11	0.12	0.10	0.12	0.12	0.14
			[1.74]	[1.88]	[1.60]	[1.87]	[1.88]	[2.08]
Quintile	Cap	VW	0.12	0.13	0.10	0.12	0.12	0.13
			[1.57]	[1.73]	[1.38]	[1.50]	[1.55]	[1.64]
Decile	NYSE	VW	0.19	0.24	0.21	0.18	0.17	0.15
			[2.16]	[2.67]	[2.38]	[1.97]	[1.88]	[1.67]
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	0.11	0.12	0.10	0.10	0.08	0.09
			[1.55]	[1.74]	[1.42]	[1.48]	[1.20]	[1.29]
Quintile	NYSE	EW	0.01	0.01				
			[0.22]	[0.22]				
Quintile	Name	VW	0.07	0.08	0.06	0.08	0.07	0.08
			[1.02]	[1.22]	[0.97]	[1.16]	[1.05]	[1.20]
Quintile	Cap	VW	0.07	0.08	0.06	0.07	0.06	0.07
			[0.95]	[1.08]	[0.78]	[0.87]	[0.75]	[0.85]
Decile	NYSE	VW	0.14	0.18	0.16	0.14	0.12	0.11
			[1.52]	[2.06]	[1.82]	[1.61]	[1.35]	[1.22]

Table 3: Conditional sort on size and AER

This table presents results for conditional double sorts on size and AER. 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 AER. 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 AER and short stocks with low AER .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197406 to 202306.

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

		AER Quintiles					AER Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.74	0.98	0.93	0.89	0.98	0.24	0.26	0.25	0.18	0.16	0.12
		[2.66]	[3.48]	[3.21]	[3.02]	[3.31]	[2.03]	[2.14]	[2.07]	[1.45]	[1.34]	[0.99]
	(2)	0.85	0.83	0.91	0.93	0.95	0.10	0.10	0.06	0.03	0.01	-0.01
		[3.27]	[3.20]	[3.42]	[3.51]	[3.63]	[1.23]	[1.25]	[0.78]	[0.41]	[0.13]	[-0.10]
	(3)	0.90	0.82	0.86	0.95	0.88	-0.01	-0.03	-0.07	-0.06	-0.05	-0.04
		[3.77]	[3.37]	[3.55]	[3.95]	[3.64]	[-0.18]	[-0.35]	[-0.87]	[-0.70]	[-0.62]	[-0.50]
	(4)	0.84	0.84	0.86	0.91	0.87	0.03	0.02	0.02	0.04	0.01	0.02
		[3.80]	[3.65]	[3.84]	[4.00]	[3.95]	[0.43]	[0.31]	[0.28]	[0.46]	[0.10]	[0.26]
	(5)	0.51	0.78	0.60	0.64	0.71	0.20	0.23	0.21	0.22	0.24	0.24
		[2.53]	[4.03]	[3.22]	[3.24]	[3.66]	[2.24]	[2.48]	[2.23]	[2.31]	[2.50]	[2.57]

Panel B: Portfolio average number of firms and market capitalization

		AER Quintiles Average n					AER Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	358	355	356	356	356	35	27	26	27	33
	(2)	94	95	94	94	94	52	51	50	51	52
	(3)	64	64	64	64	64	87	85	85	87	88
	(4)	52	53	52	53	53	188	192	183	190	189
	(5)	45	45	45	45	45	1087	1434	1048	1287	1194

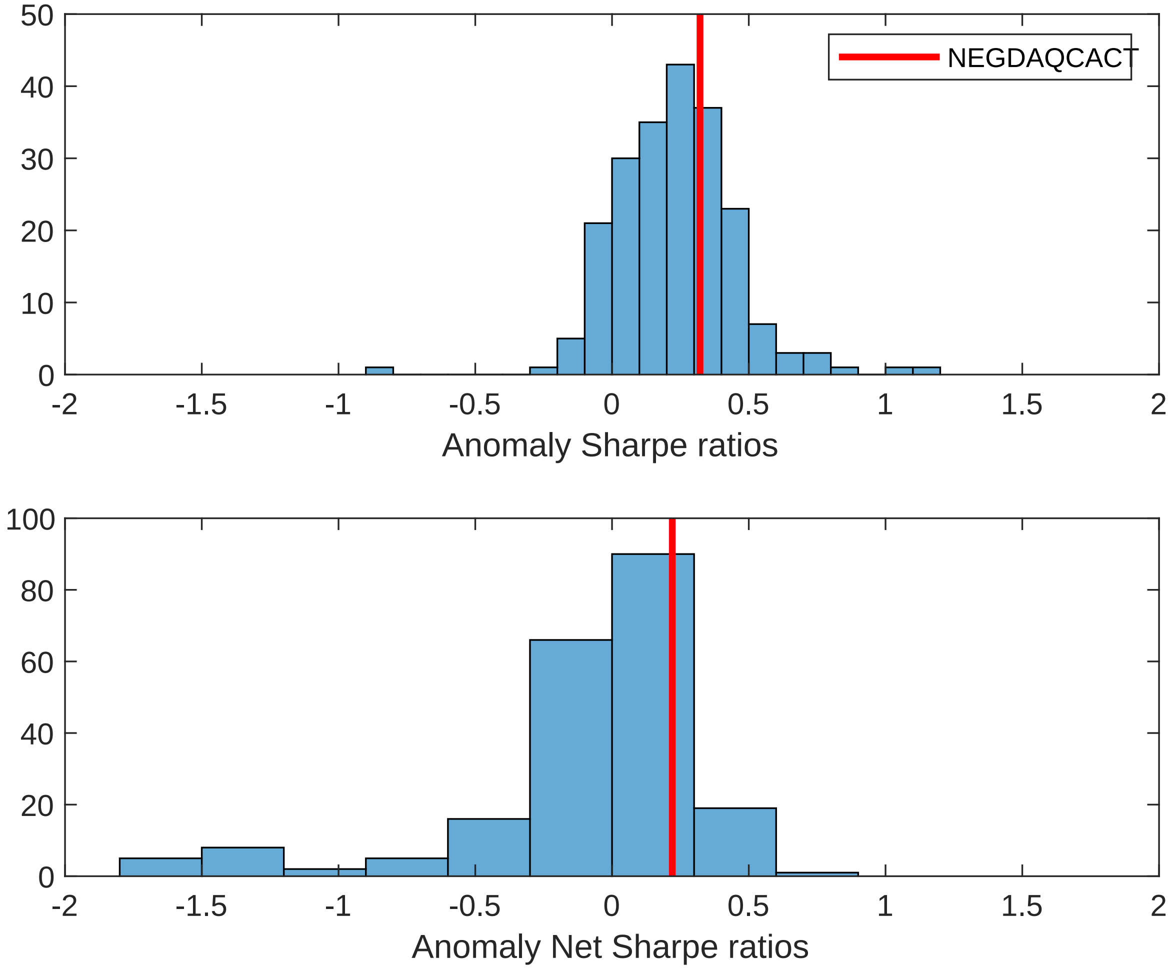


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AER with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

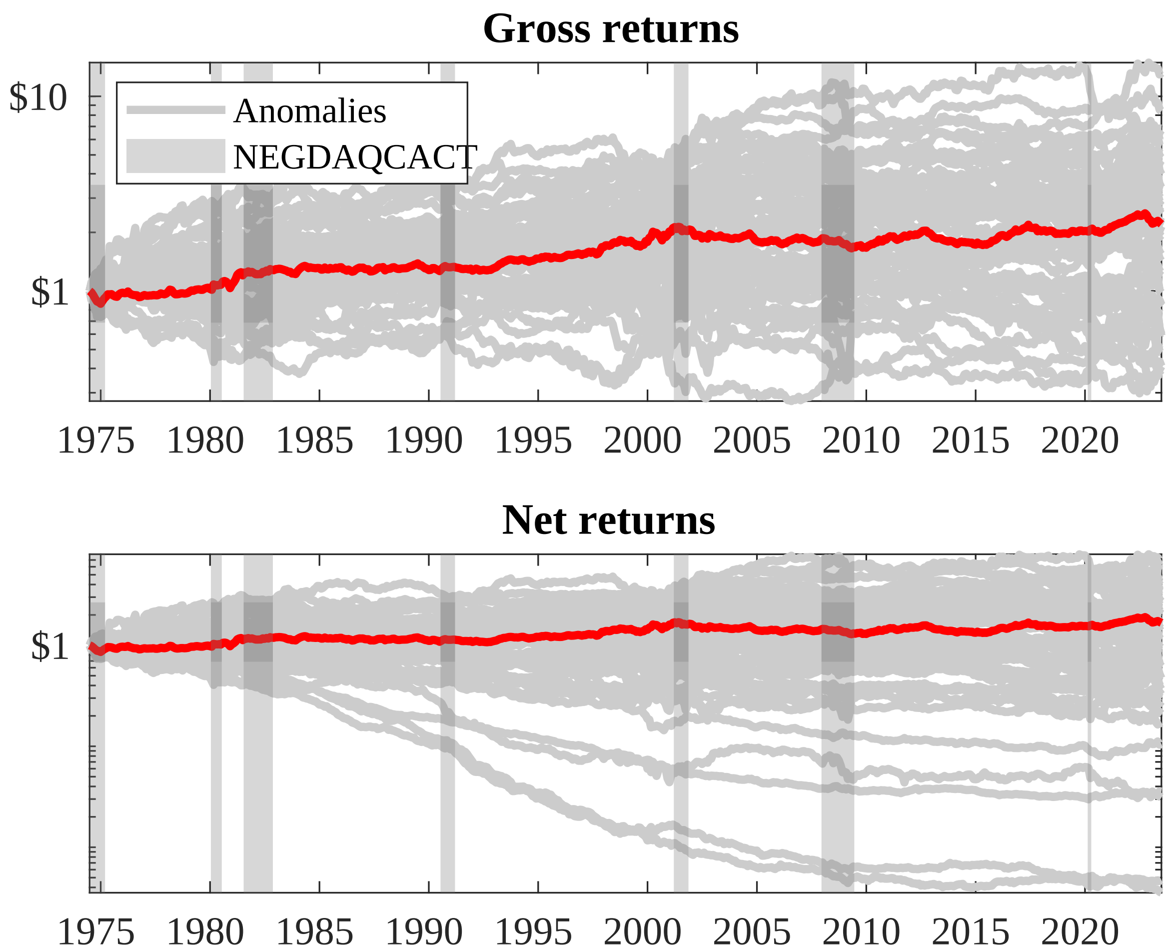


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AER trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

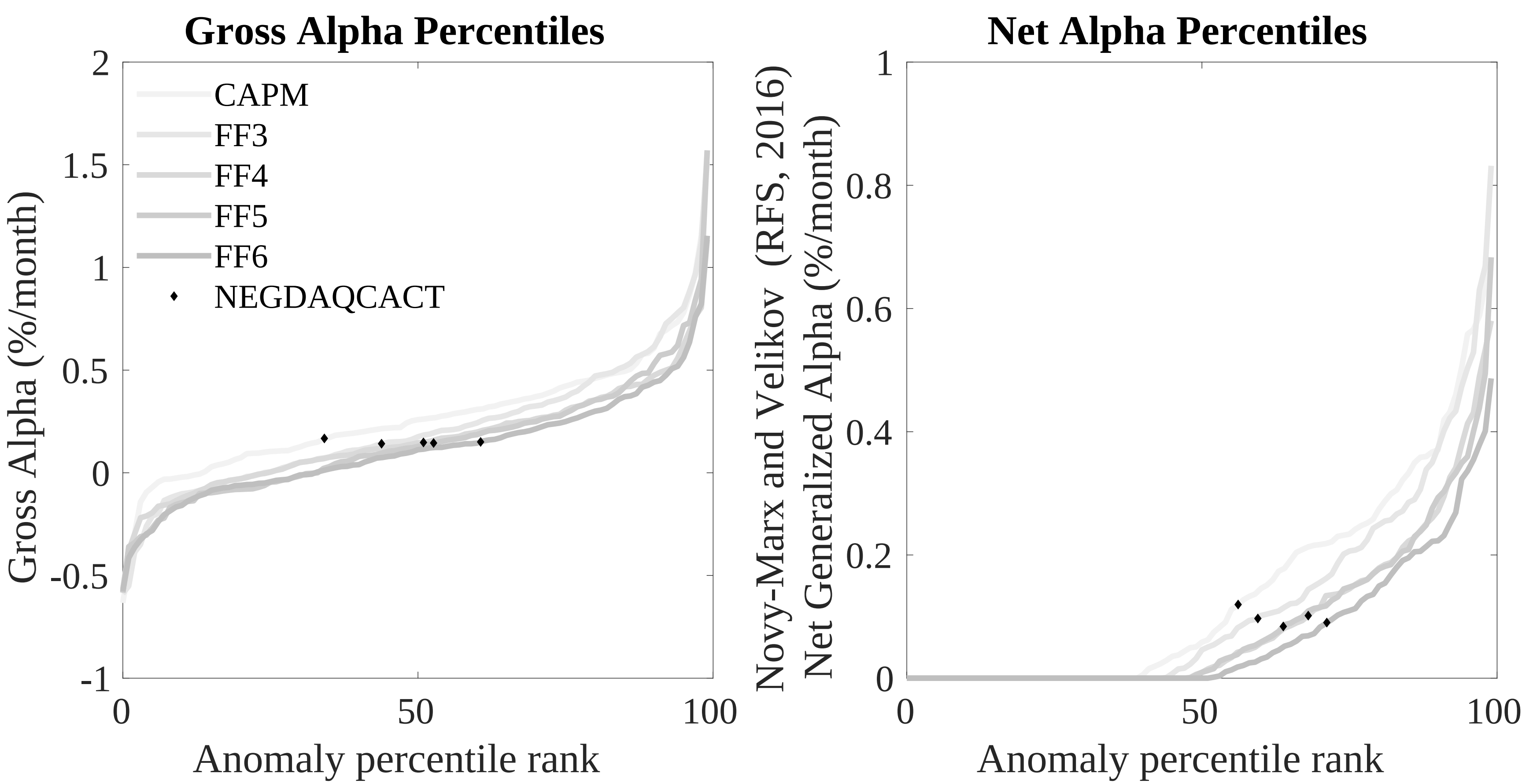
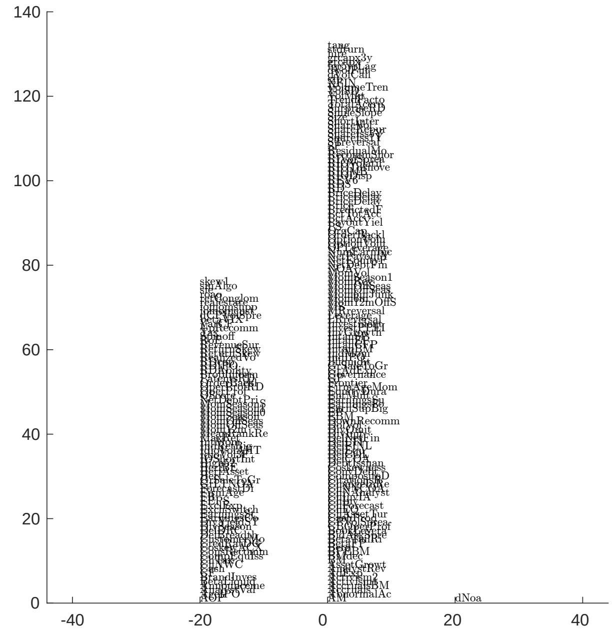
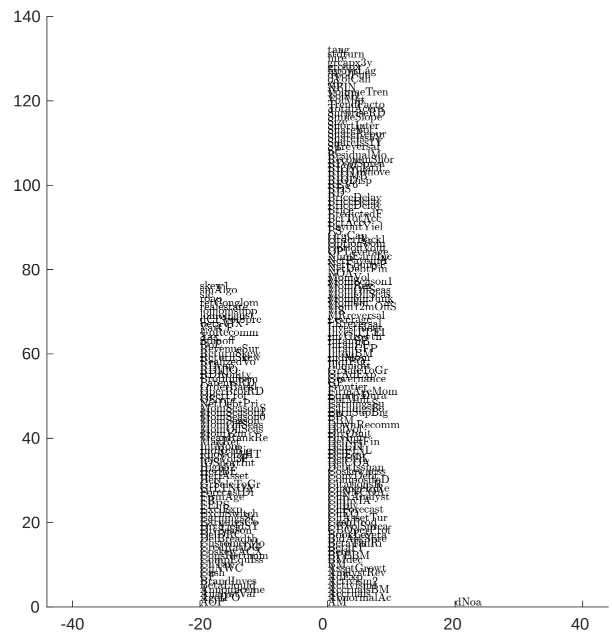


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AER trading strategy alphas (diamonds). The strategies are constructed using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

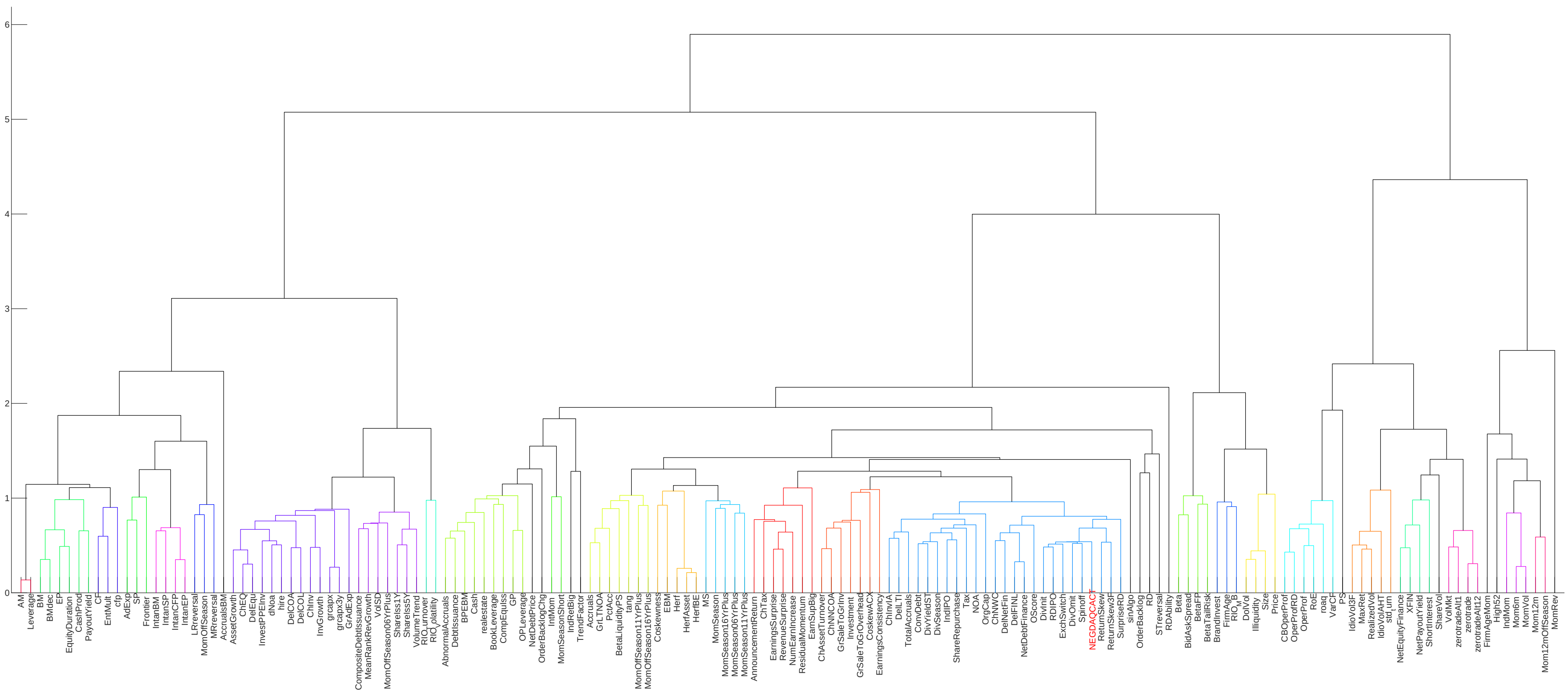


Figure 6: Agglomerative hierarchical cluster plot

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

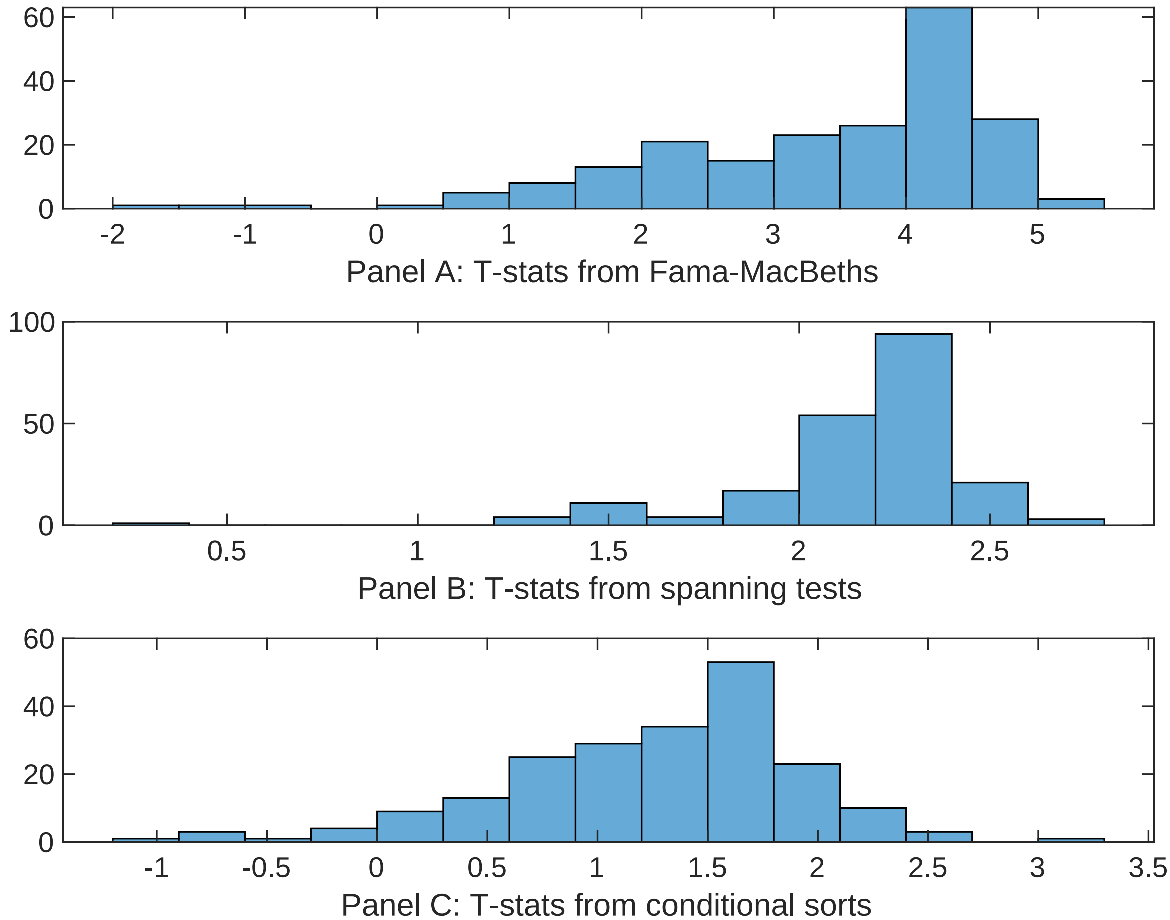


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AER conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AER} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AER} AER_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AER,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AER. Stocks are finally grouped into five AER portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AER 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 AER. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AER} AER_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Asset growth, Change in current operating assets, Change in current operating liabilities, Change in Net Noncurrent Op Assets, Growth in book equity, Inventory 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 197406 to 202306.

Intercept	0.15	0.14	0.14	0.14	0.19	0.14	0.16
	[5.89]	[5.51]	[5.44]	[5.28]	[7.02]	[5.47]	[5.70]
AER	-0.11	0.22	0.27	0.31	0.27	0.28	-0.18
	[-1.28]	[2.79]	[3.43]	[3.82]	[3.46]	[2.97]	[-0.19]
Anomaly 1	0.11						0.66
	[8.98]						[5.11]
Anomaly 2		0.23					0.91
		[6.78]					[2.41]
Anomaly 3			0.24				0.23
			[5.98]				[0.44]
Anomaly 4				0.83			0.57
				[3.85]			[1.98]
Anomaly 5					0.48		0.87
					[5.06]		[0.97]
Anomaly 6						0.41	0.94
						[6.93]	[1.48]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	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 AER trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AER} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Asset growth, Change in current operating assets, Change in current operating liabilities, Change in Net Noncurrent Op Assets, Growth in book equity, Inventory 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 197406 to 202306.

Intercept	0.15	0.15	0.17	0.16	0.15	0.15	0.16
	[2.17]	[2.15]	[2.39]	[2.28]	[2.09]	[2.12]	[2.26]
Anomaly 1	14.50						9.62
	[3.19]						[1.75]
Anomaly 2		4.46					-0.07
		[1.25]					[-0.02]
Anomaly 3			6.70				0.09
			[2.02]				[0.02]
Anomaly 4				-12.04			-11.22
				[-3.75]			[-3.38]
Anomaly 5					9.50		4.29
					[2.43]		[0.99]
Anomaly 6						4.28	2.92
						[1.54]	[0.99]
mkt	-0.89	-1.01	-1.20	-0.92	-0.55	-1.06	-0.78
	[-0.55]	[-0.62]	[-0.74]	[-0.57]	[-0.34]	[-0.65]	[-0.49]
smb	-4.93	-2.62	-3.15	-2.92	-3.91	-3.03	-3.84
	[-1.95]	[-1.01]	[-1.26]	[-1.18]	[-1.56]	[-1.20]	[-1.45]
hml	4.48	3.29	2.33	5.52	4.07	4.92	4.50
	[1.45]	[0.96]	[0.69]	[1.80]	[1.30]	[1.58]	[1.27]
rmw	-3.38	-2.93	-3.80	-1.87	-3.34	-2.88	-1.45
	[-1.06]	[-0.90]	[-1.18]	[-0.58]	[-1.04]	[-0.89]	[-0.44]
cma	-11.98	3.67	2.16	5.62	-3.12	2.27	-13.10
	[-1.63]	[0.72]	[0.43]	[1.21]	[-0.52]	[0.43]	[-1.74]
umd	-0.46	-0.84	-0.61	0.50	-1.18	-1.45	0.47
	[-0.28]	[-0.51]	[-0.37]	[0.30]	[-0.73]	[-0.88]	[0.28]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	4	2	3	4	3	3	5

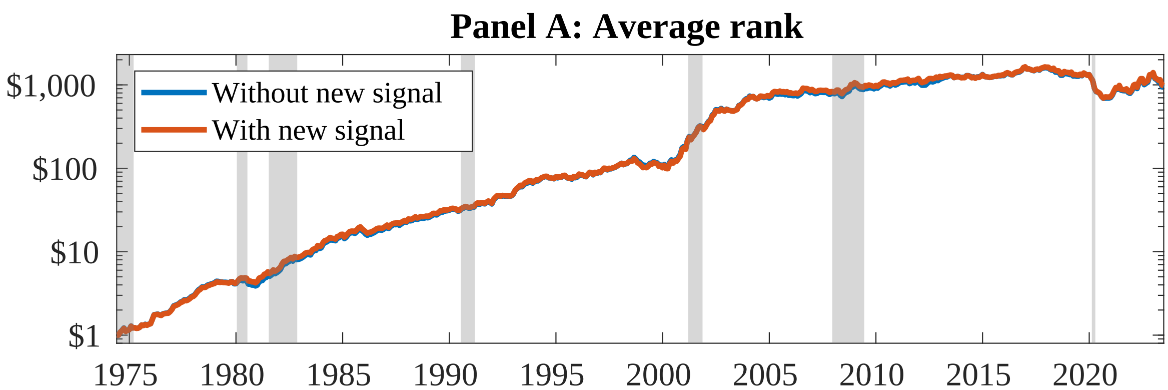


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines indicate combination trading strategies that utilize the 156 anomalies as well as AER. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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