Equity Adjustment Impact and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Equity Adjustment Impact (EAI), 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 EAI achieves an annualized gross (net) Sharpe ratio of 0.68 (0.61), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 25 (25) bps/month with a t-statistic of 3.64 (3.70), 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, Share issuance (5 year), Change in equity to assets, Momentum and LT Reversal, Net Payout Yield) is 23 bps/month with a t-statistic of 3.56.

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 (McLean and Pontiff, 2016). While many of these patterns have been attributed to either risk factors or behavioral biases, the role of accounting adjustments in asset pricing remains relatively unexplored.

Particularly intriguing is how equity-related accounting adjustments affect stock returns. While prior research has examined broad measures of equity changes (Pontiff and Woodgate, 2008), the specific impact of technical equity adjustments on future returns has received limited attention. This gap is notable given that such adjustments can significantly affect reported equity values without reflecting fundamental changes in firm operations.

We hypothesize that Equity Adjustment Impact (EAI) contains valuable information about future stock returns for several reasons. First, following (Sloan et al., 2018), accounting adjustments can create temporary disconnects between reported equity values and economic fundamentals, leading to predictable price corrections as these gaps close. The complexity of equity adjustments may cause investors to underreact to their implications, consistent with (Hirshleifer et al., 2009).

Second, equity adjustments often reflect management's private information about future firm performance. As (Daniel and Hirshleifer, 2015) argue, managers time their equity-related decisions based on their assessment of firm value relative to market prices. Technical adjustments may therefore contain subtle signals about management's expectations.

Third, the market's limited attention to technical accounting details creates potential mispricing. (Cohen and Frazzini, 2008) show that investors often fail to fully process complex financial information, particularly when it requires analyzing intricate accounting relationships. EAI captures these nuanced effects that may be overlooked by most market participants.

Our analysis reveals that EAI strongly predicts future stock returns. A value-weighted long-short strategy based on EAI quintiles generates a monthly alpha of 25 basis points (t-statistic = 3.64) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.68 before trading costs and 0.61 after costs, placing it in the top 3% of documented anomalies.

The predictive power of EAI remains robust across various methodological specifications. The signal maintains significant predictability even among large-cap stocks, with the highest size quintile generating a monthly alpha of 33 basis points (t-statistic = 3.72). This finding is particularly notable as many anomalies lose power in large, liquid stocks.

Importantly, EAI's predictive ability persists after controlling for related anomalies. When we simultaneously control for the six most closely related anomalies and the Fama-French six factors, the strategy still generates a monthly alpha of 23 basis points (t-statistic = 3.56). This indicates that EAI captures a distinct aspect of mispricing not explained by known factors.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures a previously unexplored aspect of equity accounting adjustments. While (Pontiff and Woodgate, 2008) examine aggregate equity changes and (Sloan et al., 2018) study broad accounting distortions, we isolate the specific impact of technical equity adjustments.

Second, we demonstrate that accounting complexity continues to generate mispricing in modern markets, extending the work of (Hirshleifer et al., 2009) and (Cohen and Frazzini, 2008). Our findings suggest that even sophisticated investors may struggle to fully process the implications of technical accounting adjustments, creating profitable trading opportunities.

Third, our results have important implications for market efficiency and investment practice. The robust performance of EAI, particularly among large-cap stocks, challenges the notion that anomalies are limited to small, illiquid securities. The signal's strong risk-adjusted returns after trading costs suggest that institutional investors could potentially profit from this systematic mispricing.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Equity Adjustment Impact measure. 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/ordinary stock capital and item CAPS for capital surplus/share premium reserve. Common stock capital (CSTK) represents the par or stated value of issued common stock, while capital surplus (CAPS) reflects the excess amount received over par value from the sale of common stock.construction of the signal follows a change-based approach, where we calculate the difference between the current period's CSTK and its lagged value, then scale this difference by the lagged value of CAPS. This construction captures the relative magnitude of changes in common stock capital in relation to the firm's existing capital surplus, potentially indicating significant equity-related corporate actions or adjustments. By focusing on this relationship, the signal aims to capture meaningful changes in a firm's equity structure that might signal important corporate events or strategic decisions. We construct this measure using end-of-fiscal-year values for both CSTK and CAPS to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EAI signal. Panel A plots the time-series of the mean, median, and interquartile range for EAI. On average, the cross-sectional mean (median) EAI is 0.27 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input EAI data. The signal's interquartile range spans -0.06 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the EAI signal for the CRSP universe. On average, the EAI signal is available for 6.01% of CRSP names, which on average make up 7.00% of total market capitalization.

4 Does EAI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EAI 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 EAI portfolio and sells the low EAI 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 EAI strategy earns an average return of 0.35% per month with a t-statistic of 5.16. The annualized Sharpe ratio of the strategy is 0.68. The alphas range from 0.25% to 0.38% per month and have t-statistics exceeding 3.64 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 5.75 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 553 stocks and an average market capitalization of at least $1,346 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 33 bps/month with a t-statistics of 4.43. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-five exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between 29-37bps/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 3.93. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EAI 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 EAI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EAI, as well as average returns and alphas for long/short trading EAI 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 EAI strategy achieves an average return of 33 bps/month with a t-statistic of 3.72. Among these large cap stocks, the alphas for the EAI strategy relative to the five most common factor models range from 29 to 36 bps/month with t-statistics between 3.12 and 3.94.

5 How does EAI perform relative to the zoo?

Figure 2 puts the performance of EAI 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 EAI strategy falls in the distribution. The EAI strategy's gross (net) Sharpe ratio of 0.68 (0.61) is greater than 97% (100%) 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 EAI strategy (red line).[2] Ignoring trading costs, a $1 invested in the EAI strategy would have yielded $9.63 which ranks the EAI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EAI strategy would have yielded $7.21 which ranks the EAI 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 EAI relative to those. Panel A shows that the EAI strategy gross alphas fall between the 72 and 78 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 EAI strategy has a positive net generalized alpha for five out of the five factor models. In these cases EAI ranks between the 87 and 92 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 EAI 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 EAI 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 EAI or at least to weaken the power EAI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EAI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EAI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EAI} EAI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EAI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EAI. Stocks are finally grouped into five EAI 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.

EAI trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EAI 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 EAI signal in these Fama-MacBeth regressions exceed 0.22, with the minimum t-statistic occurring when controlling for Share issuance (1 year). Controlling for all six closely related anomalies, the t-statistic on EAI is 0.43.

Similarly, Table 5 reports results from spanning tests that regress returns to the EAI 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 EAI strategy earns alphas that range from 23-27bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.37, which is achieved when controlling for Share issuance (1 year). Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EAI trading strategy achieves an alpha of 23bps/month with a t-statistic of 3.56.

7 Does EAI add relative to the whole zoo?

Finally, we can ask how much adding EAI 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 EAI 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 EAI 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 EAI grows to $2546.15.

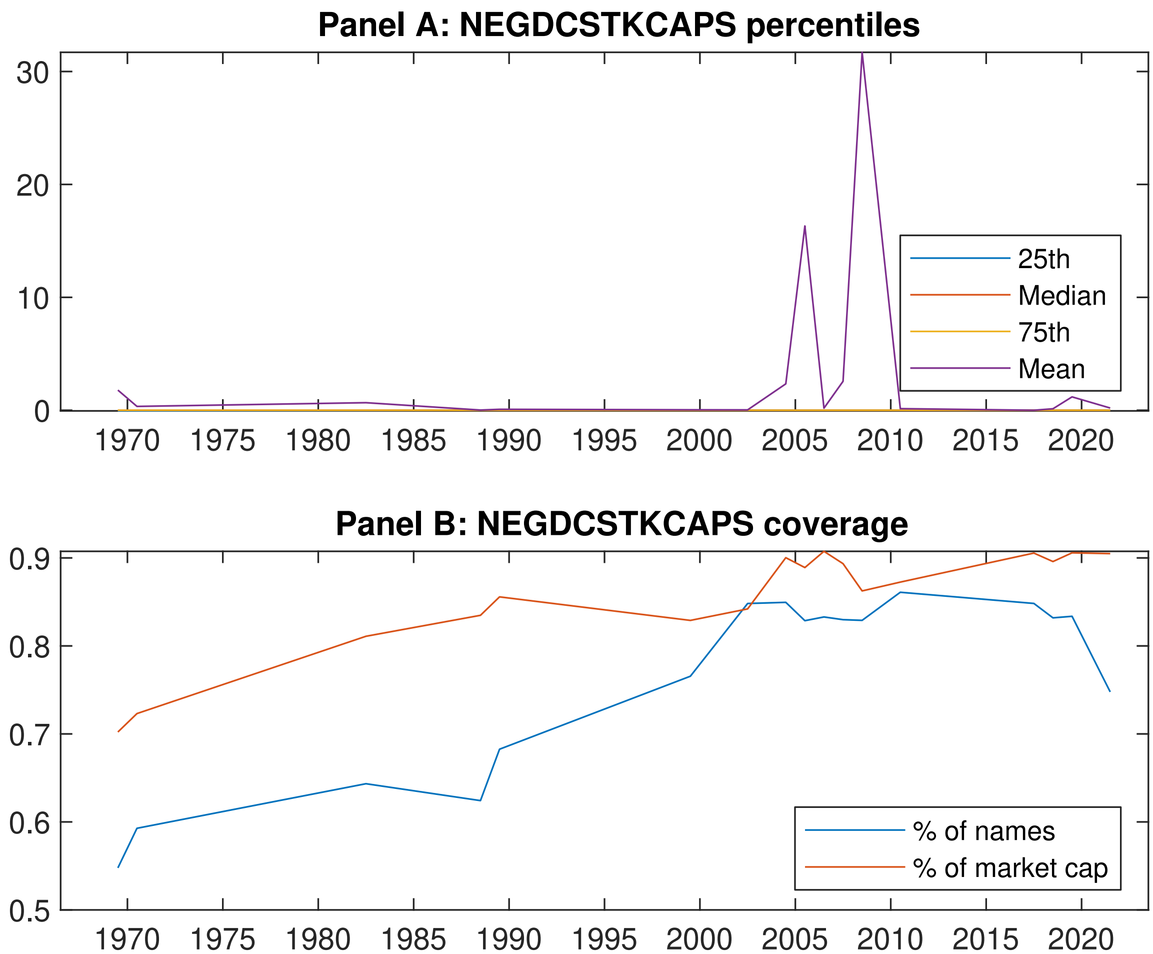

Figure 1: Times series of EAI percentiles and coverage.
This figure plots descriptive statistics for EAI. Panel A shows cross-sectional percentiles of EAI over the sample. Panel B plots the monthly coverage of EAI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EAI. 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 EAI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40	0.45	0.67	0.68	0.76	0.35
	[2.24]	[2.33]	[3.41]	[3.92]	[4.39]	[5.16]
α_{CAPM}	-0.17	-0.16	0.06	0.14	0.22	0.38
	[-3.60]	[-3.04]	[1.01]	[2.75]	[4.44]	[5.62]
α_{FF3}	-0.20	-0.14	0.10	0.10	0.18	0.38
	[-4.39]	[-2.75]	[1.78]	[2.00]	[3.84]	[5.48]
α_{FF4}	-0.16	-0.08	0.12	0.05	0.17	0.33
	[-3.49]	[-1.60]	[2.08]	[0.99]	[3.63]	[4.76]
α_{FF5}	-0.20	-0.05	0.17	0.03	0.08	0.28
	[-4.29]	[-0.98]	[2.94]	[0.65]	[1.83]	[4.08]
α_{FF6}	-0.17	-0.01	0.18	-0.00	0.09	0.25
	[-3.62]	[-0.18]	[3.10]	[-0.05]	[1.88]	[3.64]
Panel B: Fama and French (2018) 6-factor model loadings for EAI-sorted portfolios						
β_{MKT}	1.00	1.03	1.01	1.02	1.01	0.00
	[93.45]	[85.50]	[73.65]	[89.81]	[91.99]	[0.08]
β_{SMB}	-0.01	-0.01	0.06	-0.05	-0.04	-0.03
	[-0.50]	[-0.76]	[2.86]	[-2.83]	[-2.28]	[-1.20]
β_{HML}	0.11	0.00	-0.13	0.11	0.04	-0.07
	[5.10]	[0.09]	[-4.78]	[5.14]	[1.73]	[-2.20]
β_{RMW}	0.06	-0.13	-0.15	0.08	0.14	0.08
	[2.90]	[-5.62]	[-5.74]	[3.75]	[6.54]	[2.47]
β_{CMA}	-0.07	-0.15	-0.04	0.11	0.20	0.27
	[-2.24]	[-4.45]	[-0.91]	[3.29]	[6.37]	[5.75]
β_{UMD}	-0.05	-0.06	-0.02	0.05	-0.01	0.04
	[-4.62]	[-5.40]	[-1.27]	[4.74]	[-0.48]	[2.72]
Panel C: Average number of firms (n) and market capitalization (me)						
n	553	674	646	668	714	
me ($\$10^6$)	1441	1346	1924	2050	2217	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EAI 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	0.35	0.38	0.38	0.33	0.28	0.25
			[5.16]	[5.62]	[5.48]	[4.76]	[4.08]	[3.64]
Quintile	NYSE	EW	0.51	0.53	0.49	0.44	0.44	0.40
			[8.05]	[8.34]	[8.17]	[7.23]	[7.26]	[6.64]
Quintile	Name	VW	0.33	0.37	0.35	0.31	0.25	0.23
			[4.90]	[5.43]	[5.18]	[4.54]	[3.75]	[3.39]
Quintile	Cap	VW	0.33	0.35	0.35	0.29	0.32	0.27
			[4.43]	[4.66]	[4.64]	[3.80]	[4.14]	[3.54]
Decile	NYSE	VW	0.41	0.43	0.41	0.36	0.40	0.37
			[4.72]	[4.88]	[4.68]	[4.10]	[4.50]	[4.09]

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	0.32	0.35	0.34	0.32	0.27	0.25
			[4.61]	[5.14]	[5.00]	[4.65]	[3.95]	[3.70]
Quintile	NYSE	EW	0.32	0.34	0.30	0.27	0.23	0.21
			[4.62]	[4.83]	[4.45]	[4.08]	[3.51]	[3.26]
Quintile	Name	VW	0.30	0.34	0.32	0.30	0.25	0.23
			[4.35]	[4.95]	[4.72]	[4.41]	[3.66]	[3.45]
Quintile	Cap	VW	0.29	0.32	0.32	0.29	0.30	0.27
			[3.93]	[4.25]	[4.22]	[3.79]	[3.92]	[3.59]
Decile	NYSE	VW	0.37	0.39	0.38	0.35	0.37	0.36
			[4.24]	[4.49]	[4.31]	[4.03]	[4.23]	[4.03]

Table 3: Conditional sort on size and EAI

This table presents results for conditional double sorts on size and EAI. 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 EAI. 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 EAI and short stocks with low EAI .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	EAI Quintiles (L)	(2)	(3)	(4)	(H)	EAI Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.49	0.61	0.79	0.93	0.95	0.46	0.48	0.45	0.39	0.39	0.34
	[2.02]	[2.20]	[2.88]	[3.62]	[3.95]	[6.78]	[6.98]	[6.63]	[5.67]	[5.61]	[4.95]
(2)	0.67	0.57	0.84	0.86	0.94	0.27	0.29	0.25	0.18	0.22	0.17
	[2.94]	[2.32]	[3.38]	[3.55]	[4.15]	[3.31]	[3.51]	[3.04]	[2.25]	[2.59]	[2.03]
(3)	0.60	0.58	0.70	0.86	0.91	0.30	0.32	0.31	0.28	0.29	0.27
	[2.86]	[2.53]	[3.01]	[3.92]	[4.40]	[4.23]	[4.39]	[4.19]	[3.78]	[3.88]	[3.59]
(4)	0.51	0.59	0.72	0.86	0.81	0.30	0.31	0.28	0.25	0.19	0.17
	[2.60]	[2.77]	[3.30]	[4.17]	[4.21]	[4.21]	[4.41]	[3.96]	[3.46]	[2.61]	[2.35]
(5)	0.37	0.52	0.49	0.54	0.71	0.33	0.35	0.36	0.29	0.34	0.29
	[2.08]	[2.84]	[2.48]	[3.03]	[4.11]	[3.72]	[3.88]	[3.94]	[3.12]	[3.69]	[3.08]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EAI Quintiles, Average n (L)	(2)	(3)	(4)	(H)	EAI Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	362	360	360	358	359	31	31	36	27	27
(2)	103	102	102	101	102	53	53	53	52	53
(3)	74	73	73	73	73	91	88	90	92	92
(4)	61	61	61	61	61	190	188	196	199	202
(5)	55	55	55	55	55	1150	1355	1568	1433	1630

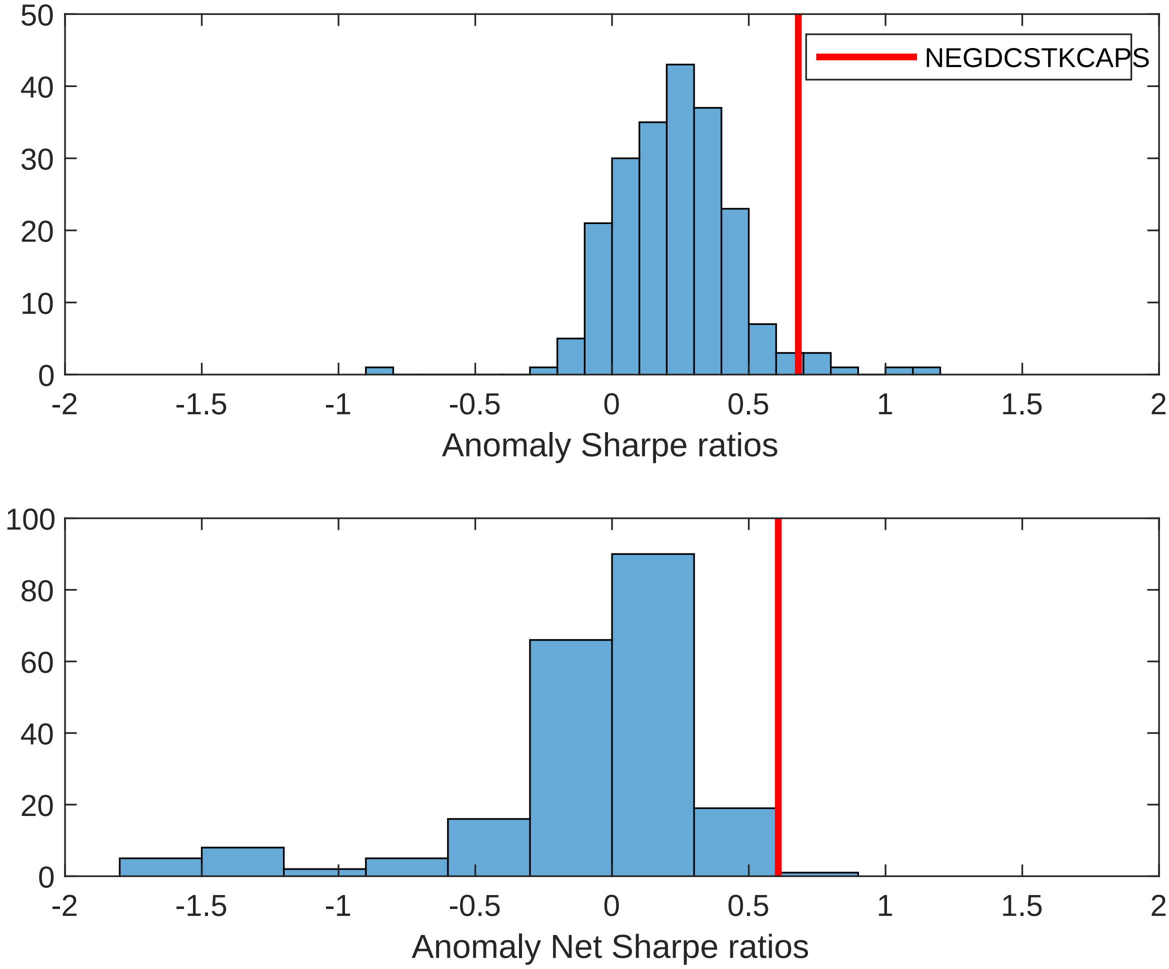

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EAI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

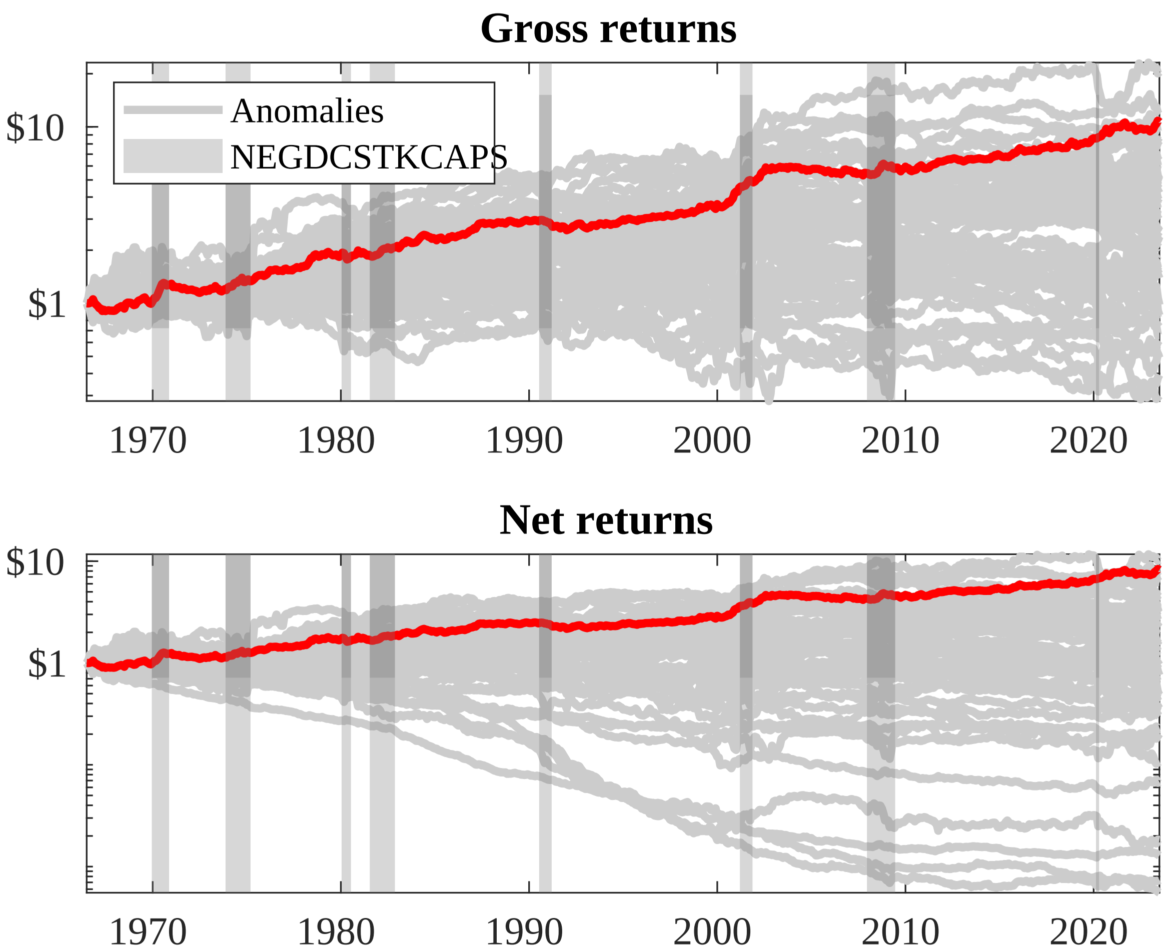

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EAI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

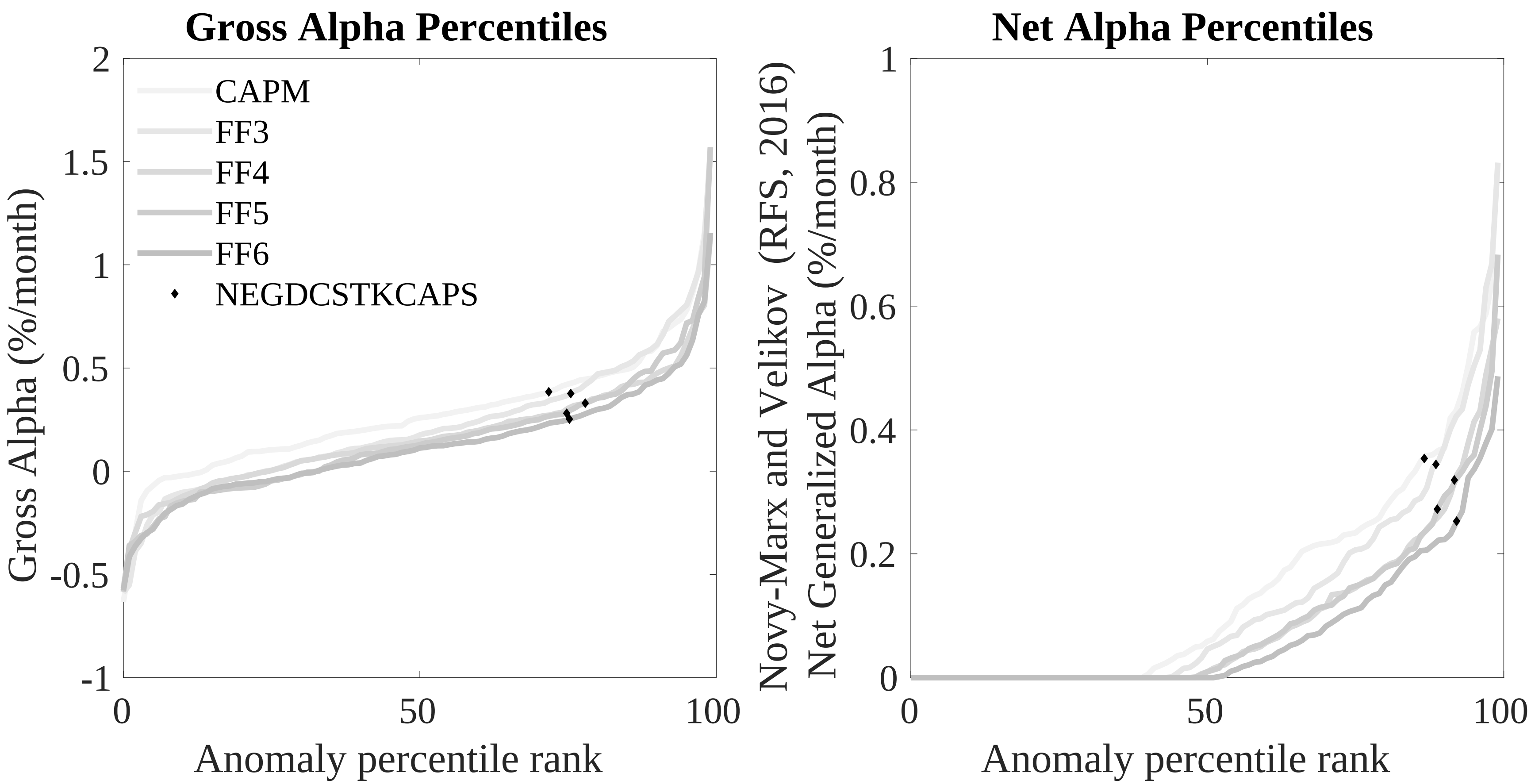

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EAI trading strategy alphas (diamonds). The strategies are constructed using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

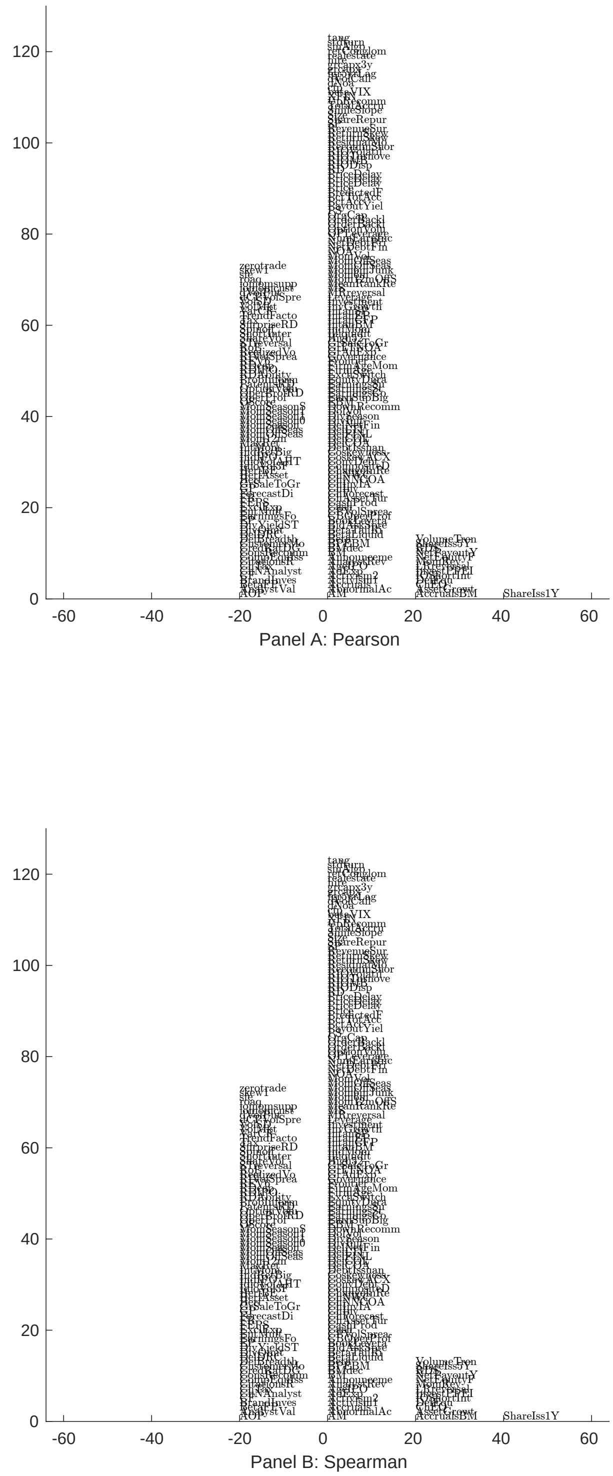

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with EAI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

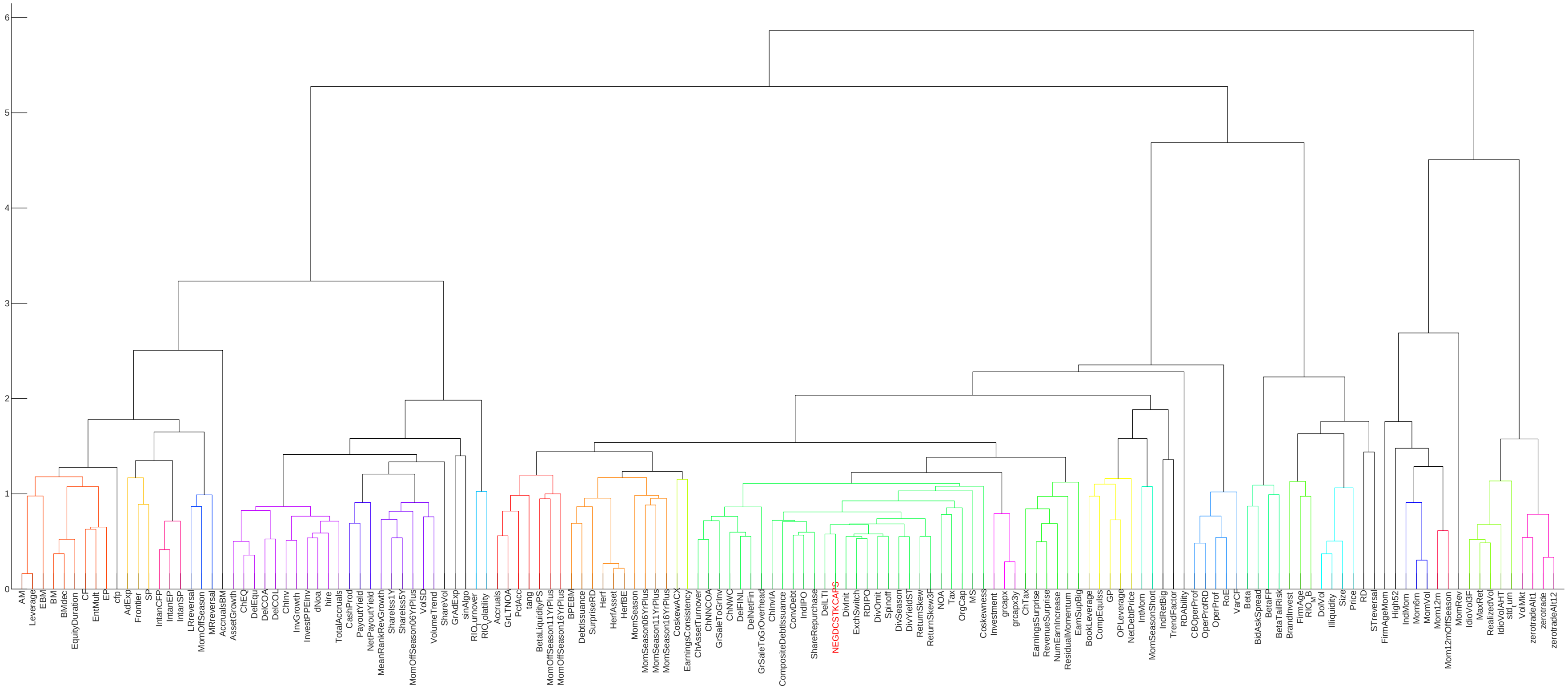

Figure 6: Agglomerative hierarchical cluster plot

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

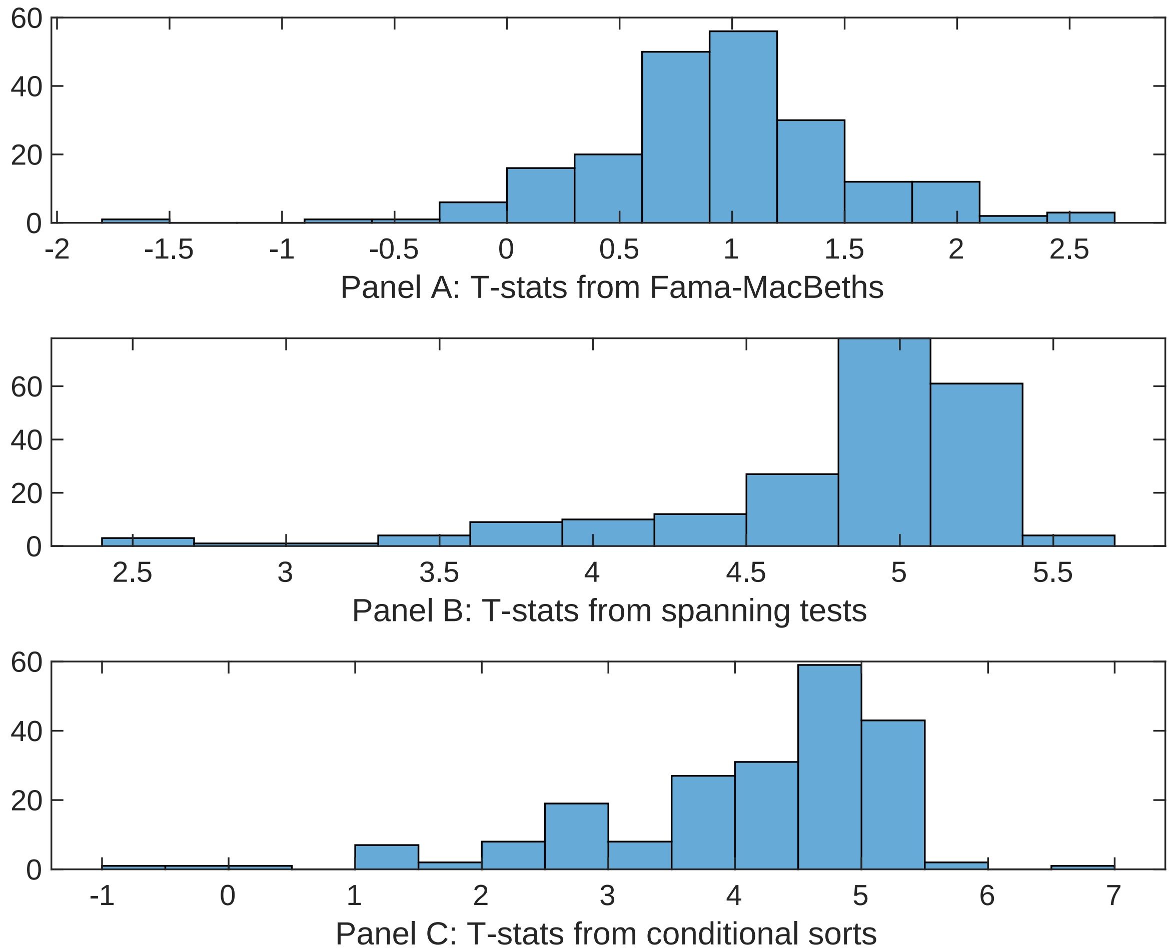

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EAI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EAI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EAI} EAI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EAI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EAI. Stocks are finally grouped into five EAI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EAI 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 EAI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EAI} EAI_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Share issuance (5 year), Change in equity to assets, Momentum and LT Reversal, Net Payout Yield. 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	0.18	0.13	0.12	0.33	0.12	0.12
	[5.47]	[7.22]	[5.83]	[5.40]	[0.96]	[5.09]	[2.76]
EAI	0.13	0.27	0.64	0.41	0.74	0.43	0.30
	[0.22]	[0.47]	[1.00]	[0.69]	[1.70]	[0.52]	[0.43]
Anomaly 1	0.28						-0.77
	[5.97]						[-0.44]
Anomaly 2		0.51					0.55
		[4.63]					[2.32]
Anomaly 3			0.37				0.12
			[4.20]				[0.28]
Anomaly 4				0.16			-0.16
				[4.44]			[-1.99]
Anomaly 5					0.11		0.11
					[4.24]		[3.43]
Anomaly 6						0.30	0.23
						[2.64]	[2.47]
# months	679	684	679	684	619	679	491
$\bar{R}^2(\%)$	0	0	0	0	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the EAI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EAI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Share issuance (5 year), Change in equity to assets, Momentum and LT Reversal, Net Payout Yield. 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	0.24	0.25	0.23	0.27	0.23	0.25	0.23
	[3.62]	[3.77]	[3.45]	[3.90]	[3.37]	[3.70]	[3.56]
Anomaly 1	28.69						20.79
	[8.45]						[5.31]
Anomaly 2		26.45					20.70
		[7.06]					[3.98]
Anomaly 3			20.54				10.10
			[5.80]				[2.68]
Anomaly 4				14.69			-12.00
				[4.02]			[-2.42]
Anomaly 5					3.54		3.55
					[4.04]		[4.27]
Anomaly 6						13.13	1.95
						[4.94]	[0.66]
mkt	2.30	1.06	2.84	-0.04	0.67	2.33	4.33
	[1.47]	[0.67]	[1.73]	[-0.03]	[0.41]	[1.42]	[2.71]
smb	-1.27	-3.59	-3.71	-2.93	-3.68	0.17	-4.39
	[-0.56]	[-1.56]	[-1.59]	[-1.24]	[-1.55]	[0.07]	[-1.89]
hml	-9.77	-9.63	-11.92	-8.39	-6.46	-10.94	-14.90
	[-3.20]	[-3.12]	[-3.62]	[-2.65]	[-2.06]	[-3.31]	[-4.63]
rmw	-1.75	9.12	3.75	9.19	9.11	0.38	-1.32
	[-0.54]	[2.94]	[1.18]	[2.88]	[2.89]	[0.11]	[-0.37]
cma	11.58	-0.03	18.98	10.93	23.17	16.22	-1.46
	[2.42]	[-0.01]	[4.00]	[1.83]	[4.93]	[3.20]	[-0.25]
umd	4.17	4.17	4.62	4.89	1.18	5.69	0.18
	[2.71]	[2.65]	[2.93]	[3.03]	[0.65]	[3.56]	[0.10]
# months	680	684	680	684	680	680	680
$\bar{R}^2$(%)	18	15	13	10	11	12	23

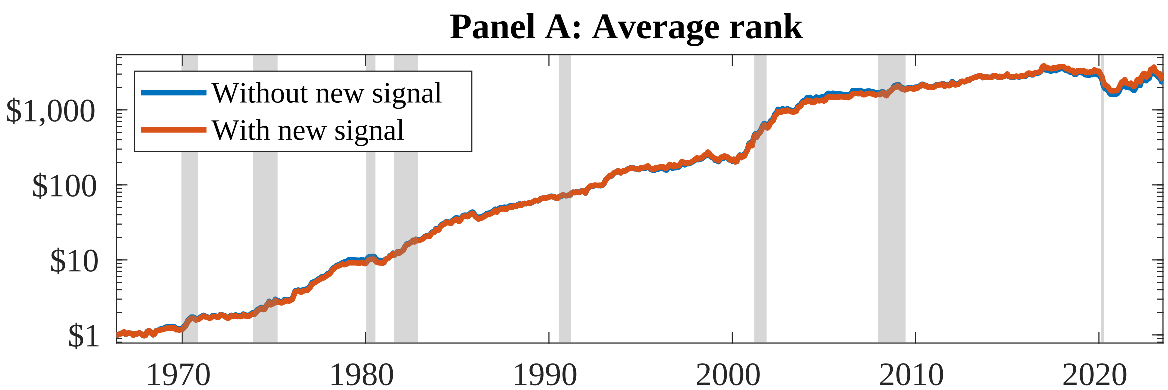

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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