Efficiency of Expense Allocation and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Efficiency of Expense Allocation (EEA), 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 EEA achieves an annualized gross (net) Sharpe ratio of 0.45 (0.43), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (33) bps/month with a t-statistic of 2.78 (3.21), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Analyst earnings per share, Net equity financing, Operating profitability RD adjusted, operating profits / book equity, EPS Forecast Dispersion, net income / book equity) is 24 bps/month with a t-statistic of 2.43.

1 Introduction

Market efficiency remains a central question in financial economics, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While traditional asset pricing models explain a significant portion of return variation, substantial evidence suggests that firm-specific characteristics contain additional predictive power (Harvey et al., 2016). One particularly understudied area is how firms' internal resource allocation decisions affect their market valuation and subsequent returns. Despite extensive research on corporate efficiency metrics, the link between a firm's expense allocation decisions and its stock returns remains largely unexplored.

This gap is notable given that expense allocation reflects management's strategic choices in deploying resources across different business activities. While prior research has examined broad measures of operating efficiency (Novy-Marx, 2013) and asset utilization (Hirshleifer et al., 2004), these measures may not fully capture the granular decisions firms make in allocating expenses across different operational categories. Understanding how the efficiency of expense allocation affects stock returns could provide important insights into both market efficiency and corporate decision-making.

We develop our hypothesis about the relationship between Efficiency of Expense Allocation (EEA) and stock returns based on several theoretical frameworks. First, agency theory suggests that managers may engage in inefficient expense allocation due to empire-building tendencies or personal career concerns (Jensen and Meckling, 1976). Firms with more efficient expense allocation likely have better corporate governance and monitoring mechanisms, leading to superior performance.

Second, the resource-based view of the firm indicates that competitive advantage stems from how effectively companies deploy their resources (?). Efficient expense allocation represents a capability that allows firms to maximize the productivity of their investments across different activities. This strategic capability should translate into sustained competitive advantage and superior stock returns.

Third, information processing theory suggests that the complexity of expense allocation decisions creates information asymmetry between managers and investors (Hirshleifer and Teoh, 2003). Markets may initially underreact to signals of efficient resource allocation due to limited attention or processing capacity, leading to predictable patterns in future returns as this information is gradually incorporated into prices.

Our empirical analysis reveals strong evidence that EEA predicts cross-sectional stock returns. A value-weighted long-short trading strategy based on EEA quintiles generates significant abnormal returns of 29 basis points per month (t-statistic = 2.78) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.45, placing it in the top 13% of documented return predictors.

Importantly, the predictive power of EEA remains robust after controlling for transaction costs. The strategy maintains a net Sharpe ratio of 0.43 and delivers significant risk-adjusted returns across various portfolio construction approaches. The results are particularly strong among large-cap stocks, with the long-short strategy generating monthly returns of 36 basis points (t-statistic = 2.66) in the largest size quintile.

Further tests demonstrate that EEA's predictive power is distinct from known return predictors. Controlling for the six most closely related anomalies and standard risk factors, the strategy still generates an alpha of 24 basis points per month (t-statistic = 2.43). This finding suggests that EEA captures a unique dimension of firm performance not reflected in existing measures.

Our paper makes several contributions to the asset pricing and corporate finance literature. First, we introduce a novel predictor of stock returns that captures the efficiency of firms' internal resource allocation decisions. While prior work has examined various measures of operating efficiency (Novy-Marx, 2013; Ball et al., 2015), our measure specifically focuses on the allocation of expenses across different operational categories.

Second, we extend the literature on the relationship between corporate decisions and stock returns (Titman et al., 2004; **?**). Our findings suggest that markets do not fully incorporate information about the efficiency of firms' expense allocation decisions, leading to predictable patterns in future returns. This evidence contributes to our understanding of market efficiency and information processing in financial markets.

Third, our results have important implications for both academic research and practice. For researchers, we demonstrate the importance of considering granular operational decisions when studying return predictability. For practitioners, our findings suggest that careful analysis of expense allocation efficiency can help identify profitable investment opportunities, even after accounting for transaction costs and controlling for known factors.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Efficiency of Expense Allocation 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 CAPS for capitalized software development costs and item XSGA for selling, general, and administrative expenses. Capitalized software development costs (CAPS) represent the portion of software development expenses that are capitalized rather than expensed immediately, reflecting long-term investments in software assets. Selling, general, and administrative expenses (XSGA) encompass the broad category of operational overhead costs, including marketing, office expenses, and administrative salaries. The construction of the signal follows a straightforward ratio format, where we divide CAPS by XSGA for each firm in each year of our sample. This ratio captures the relative proportion of software development costs that are capitalized compared to overall operational expenses, offering insight into how firms allocate their expenses between immediate recognition and long-term asset creation. By focusing on this relationship, the signal aims to reflect aspects of expense management and investment strategy in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both CAPS and XSGA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EEA signal. Panel A plots the time-series of the mean, median, and interquartile range for EEA. On average, the cross-sectional mean (median) EEA is -3.58 (-1.38) over the 1969 to 2023 sample, where the starting date is determined by the availability of the input EEA data. The signal's interquartile range spans -6.26 to -0.10. Panel B of Figure 1 plots the time-series of the coverage of the EEA signal for the CRSP universe. On average, the EEA signal is available for 6.35% of CRSP names, which on average make up 6.72% of total market capitalization.

4 Does EEA predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EEA 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 EEA portfolio and sells the low EEA 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 EEA strategy earns an average return of 0.43% per month with a t-statistic of 3.29. The annualized Sharpe ratio of the strategy is 0.45. The alphas range from 0.29% to 0.63% per month and have t-statistics exceeding 2.78 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 0.66, with a t-statistic of 13.89 on the RMW 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 517 stocks and an average market capitalization of at least $907 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 31 bps/month with a t-statistics of 2.51. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for twenty 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 28-47bps/month. The lowest return, (28 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 2.52. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EEA 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-three cases.

Table 3 provides direct tests for the role size plays in the EEA strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EEA, as well as average returns and alphas for long/short trading EEA 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 EEA strategy achieves an average return of 36 bps/month with a t-statistic of 2.66. Among these large cap stocks, the alphas for the EEA strategy relative to the five most common factor models range from 12 to 52 bps/month with t-statistics between 1.06 and 4.14.

5 How does EEA perform relative to the zoo?

Figure 2 puts the performance of EEA 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 EEA strategy falls in the distribution. The EEA strategy's gross (net) Sharpe ratio of 0.45 (0.43) is greater than 87% (99%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the EEA strategy (red line).[2] Ignoring trading costs, a $1 invested in the EEA strategy would have yielded $11.04 which ranks the EEA strategy in the top 0% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EEA strategy would have yielded $9.87 which ranks the EEA 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 EEA relative to those. Panel A shows that

[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.

the EEA strategy gross alphas fall between the 76 and 94 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 196906 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 EEA strategy has a positive net generalized alpha for five out of the five factor models. In these cases EEA ranks between the 94 and 99 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does EEA 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 EEA 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 EEA or at least to weaken the power EEA has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EEA conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EEA} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EEA} EEA_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X

[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.

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: $r_{EEA,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EEA. Stocks are finally grouped into five EEA portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EEA trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EEA 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 EEA signal in these Fama-MacBeth regressions exceed -0.26, with the minimum t-statistic occurring when controlling for Net equity financing. Controlling for all six closely related anomalies, the t-statistic on EEA is -0.10.

Similarly, Table 5 reports results from spanning tests that regress returns to the EEA 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 EEA strategy earns alphas that range from 11-35bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.10, which is achieved when controlling for Net equity financing. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EEA trading strategy achieves an alpha of 24bps/month with a t-statistic of 2.43.

7 Does EEA add relative to the whole zoo?

Finally, we can ask how much adding EEA 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 158 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 158 anomalies augmented with the EEA 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 158-anomaly combination strategy grows to $1496.56, while $1 investment in the combination strategy that includes EEA grows to $2325.82.

[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 EEA is available.

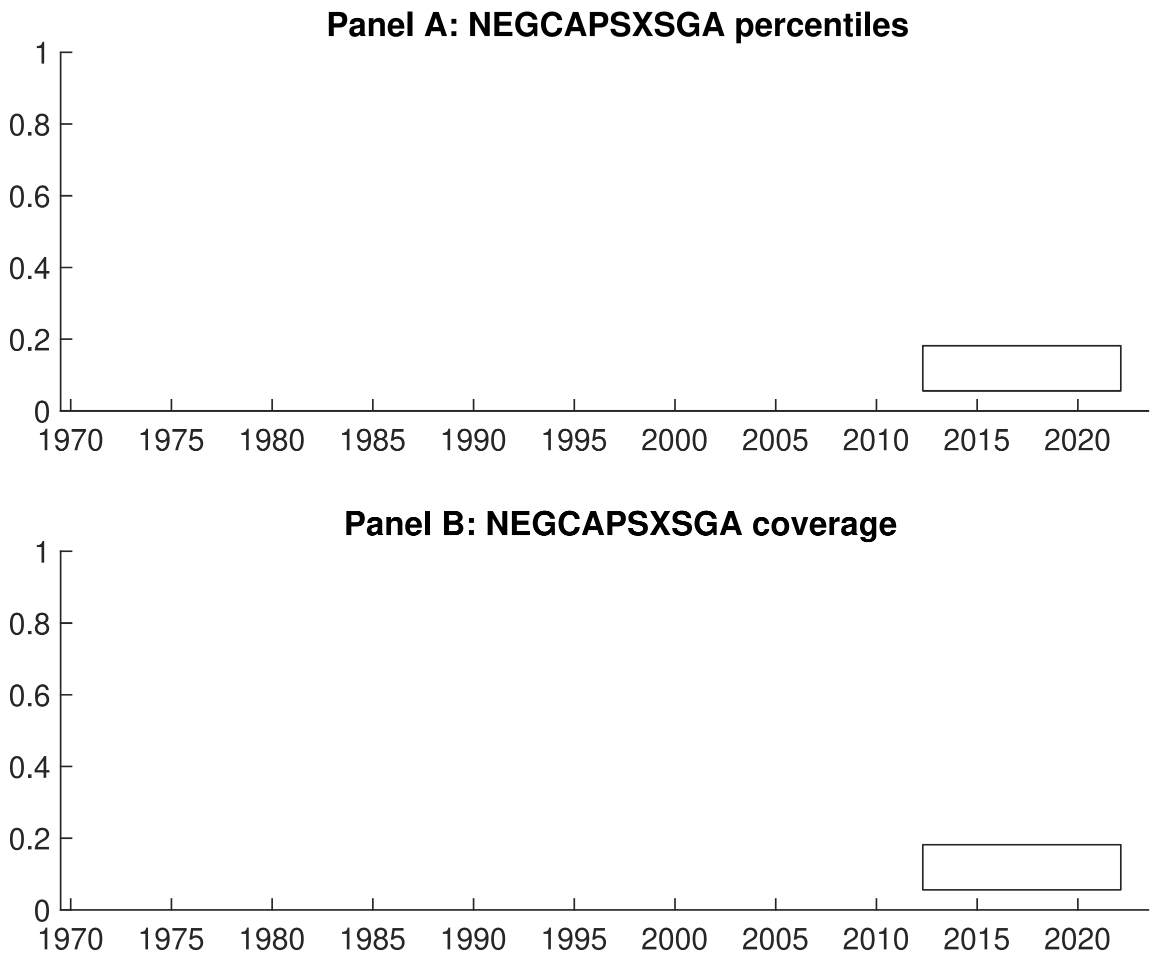

Figure 1: Times series of EEA percentiles and coverage.
This figure plots descriptive statistics for EEA. Panel A shows cross-sectional percentiles of EEA over the sample. Panel B plots the monthly coverage of EEA relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EEA. 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 196906 to 202306.

Panel A: Excess returns and alphas on EEA-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.30	0.52	0.69	0.61	0.73	0.43
	[1.33]	[2.56]	[3.41]	[3.21]	[4.44]	[3.29]
α_{CAPM}	-0.36	-0.10	0.07	0.03	0.24	0.60
	[-4.07]	[-1.85]	[1.22]	[0.53]	[4.13]	[5.00]
α_{FF3}	-0.39	-0.09	0.12	0.04	0.24	0.63
	[-4.51]	[-1.78]	[1.99]	[0.76]	[4.33]	[5.54]
α_{FF4}	-0.38	-0.05	0.14	0.08	0.20	0.58
	[-4.33]	[-0.98]	[2.24]	[1.51]	[3.61]	[5.05]
α_{FF5}	-0.26	0.01	0.17	-0.00	0.05	0.31
	[-3.04]	[0.15]	[2.84]	[-0.02]	[0.97]	[2.96]
α_{FF6}	-0.26	0.04	0.18	0.03	0.03	0.29
	[-3.01]	[0.68]	[2.95]	[0.61]	[0.63]	[2.78]
Panel B: Fama and French (2018) 6-factor model loadings for EEA-sorted portfolios						
β_{MKT}	1.10	1.02	1.04	1.01	0.93	-0.17
	[54.79]	[85.70]	[72.12]	[85.73]	[81.75]	[-6.99]
β_{SMB}	0.14	0.10	-0.01	-0.02	-0.04	-0.18
	[4.88]	[5.69]	[-0.63]	[-0.96]	[-2.30]	[-5.11]
β_{HML}	0.10	-0.02	-0.08	-0.05	-0.10	-0.20
	[2.52]	[-0.90]	[-2.73]	[-2.09]	[-4.80]	[-4.33]
β_{RMW}	-0.30	-0.20	-0.07	0.14	0.36	0.66
	[-7.55]	[-8.61]	[-2.45]	[5.98]	[16.35]	[13.89]
β_{CMA}	-0.09	-0.07	-0.11	-0.01	0.24	0.33
	[-1.49]	[-2.14]	[-2.72]	[-0.32]	[7.40]	[4.69]
β_{UMD}	0.00	-0.04	-0.01	-0.05	0.03	0.02
	[0.07]	[-3.56]	[-0.96]	[-4.28]	[2.29]	[1.01]
Panel C: Average number of firms (n) and market capitalization (me)						
n	951	812	616	517	591	
me ($\$10^6$)	907	1734	2051	1888	2198	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EEA 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 196906 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	0.43	0.60	0.63	0.58	0.31	0.29
			[3.29]	[5.00]	[5.54]	[5.05]	[2.96]	[2.78]
Quintile	NYSE	EW	0.39	0.51	0.50	0.41	0.28	0.22
			[3.61]	[5.01]	[5.26]	[4.34]	[3.22]	[2.56]
Quintile	Name	VW	0.49	0.67	0.71	0.68	0.41	0.41
			[3.54]	[5.16]	[5.77]	[5.44]	[3.59]	[3.52]
Quintile	Cap	VW	0.31	0.48	0.48	0.45	0.14	0.15
			[2.51]	[4.33]	[4.60]	[4.30]	[1.57]	[1.60]
Decile	NYSE	VW	0.50	0.69	0.72	0.69	0.48	0.47
			[3.46]	[5.23]	[5.65]	[5.30]	[3.86]	[3.74]
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	0.42	0.59	0.61	0.59	0.36	0.33
			[3.18]	[4.90]	[5.34]	[5.11]	[3.40]	[3.21]
Quintile	NYSE	EW	0.28	0.38	0.35	0.31	0.16	0.13
			[2.52]	[3.63]	[3.69]	[3.24]	[1.79]	[1.47]
Quintile	Name	VW	0.47	0.66	0.68	0.67	0.46	0.44
			[3.41]	[5.07]	[5.58]	[5.44]	[3.93]	[3.81]
Quintile	Cap	VW	0.29	0.47	0.46	0.44	0.19	0.18
			[2.40]	[4.18]	[4.38]	[4.25]	[2.07]	[1.99]
Decile	NYSE	VW	0.47	0.68	0.70	0.69	0.52	0.50
			[3.31]	[5.14]	[5.50]	[5.35]	[4.13]	[4.00]

Table 3: Conditional sort on size and EEA

This table presents results for conditional double sorts on size and EEA. 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 EEA. 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 EEA and short stocks with low EEA .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196906 to 202306.

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

	EEA Quintiles					EEA Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.12	0.44	0.76	0.79	0.88	0.76	0.86	0.81	0.80	0.67	0.66
	[0.40]	[1.61]	[2.88]	[3.20]	[3.56]	[5.59]	[6.51]	[6.19]	[5.95]	[5.13]	[5.01]
(2)	0.41	0.68	0.79	0.88	0.70	0.29	0.40	0.37	0.39	0.16	0.19
	[1.49]	[2.58]	[3.24]	[3.67]	[3.02]	[2.37]	[3.48]	[3.19]	[3.29]	[1.46]	[1.69]
(3)	0.47	0.57	0.79	0.81	0.81	0.34	0.47	0.45	0.48	0.21	0.25
	[1.78]	[2.30]	[3.26]	[3.57]	[3.87]	[2.74]	[4.03]	[3.92]	[4.08]	[1.95]	[2.27]
(4)	0.38	0.68	0.80	0.79	0.75	0.36	0.51	0.50	0.47	0.31	0.30
	[1.53]	[2.77]	[3.53]	[3.56]	[3.80]	[2.99]	[4.43]	[4.37]	[4.03]	[2.74]	[2.62]
(5)	0.36	0.51	0.60	0.63	0.72	0.36	0.52	0.52	0.46	0.14	0.12
	[1.66]	[2.49]	[3.09]	[3.39]	[4.34]	[2.66]	[4.12]	[4.14]	[3.62]	[1.24]	[1.06]

Panel B: Portfolio average number of firms and market capitalization

	EEA Quintiles					EEA Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	406	407	410	412	412	30	32	35	35	36
(2)	109	109	108	109	109	55	55	55	56	56
(3)	73	73	73	74	74	90	90	93	93	93
(4)	56	56	57	57	57	176	180	188	186	189
(5)	49	49	49	49	49	853	1543	1627	1330	1605

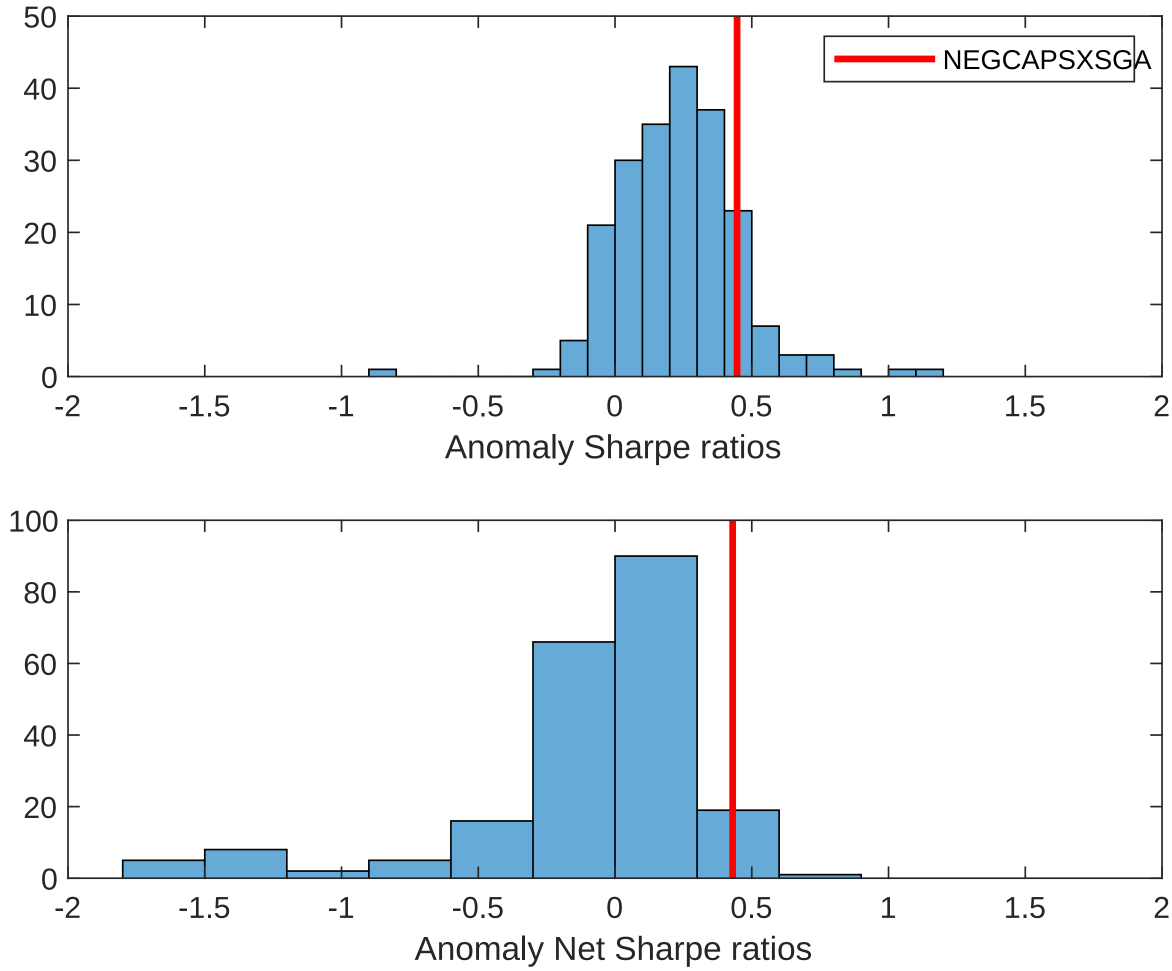

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EEA with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

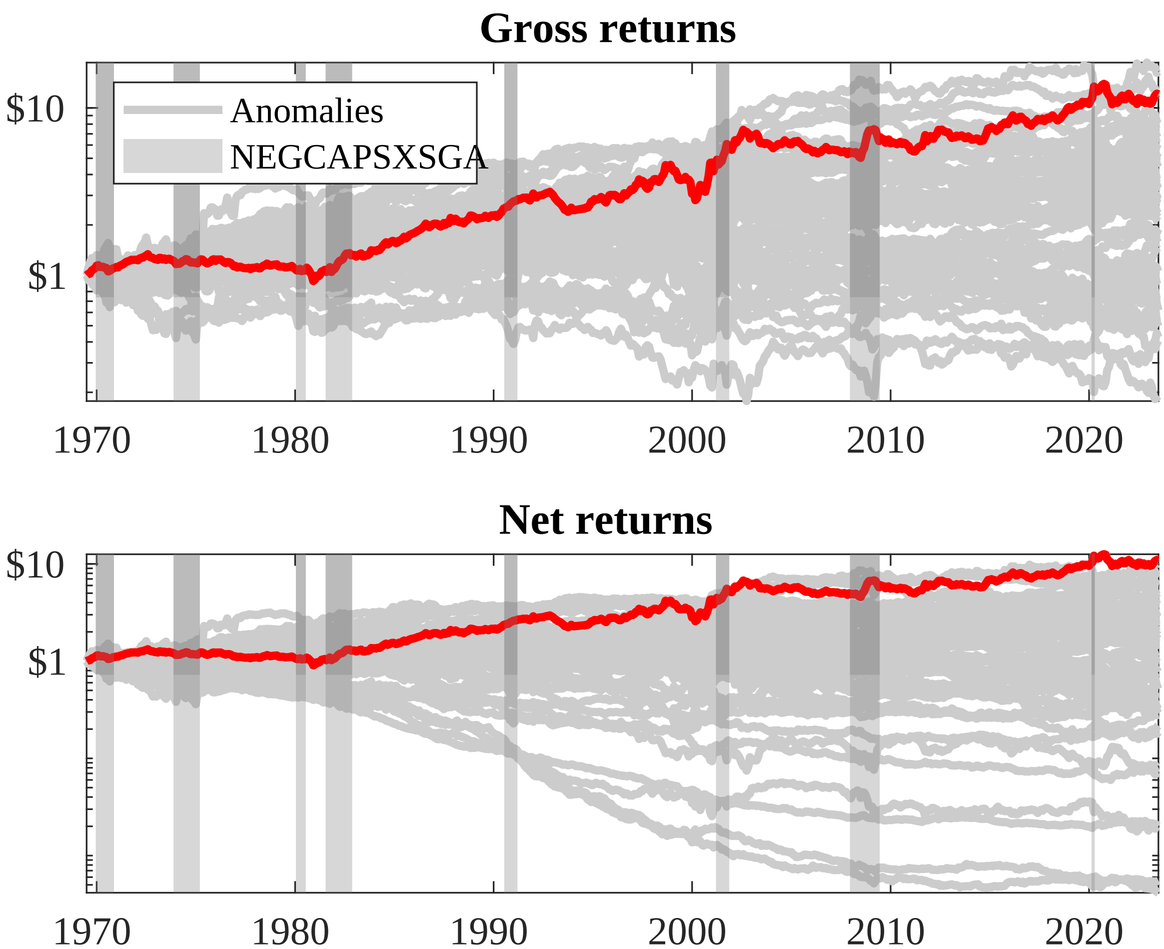

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EEA trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

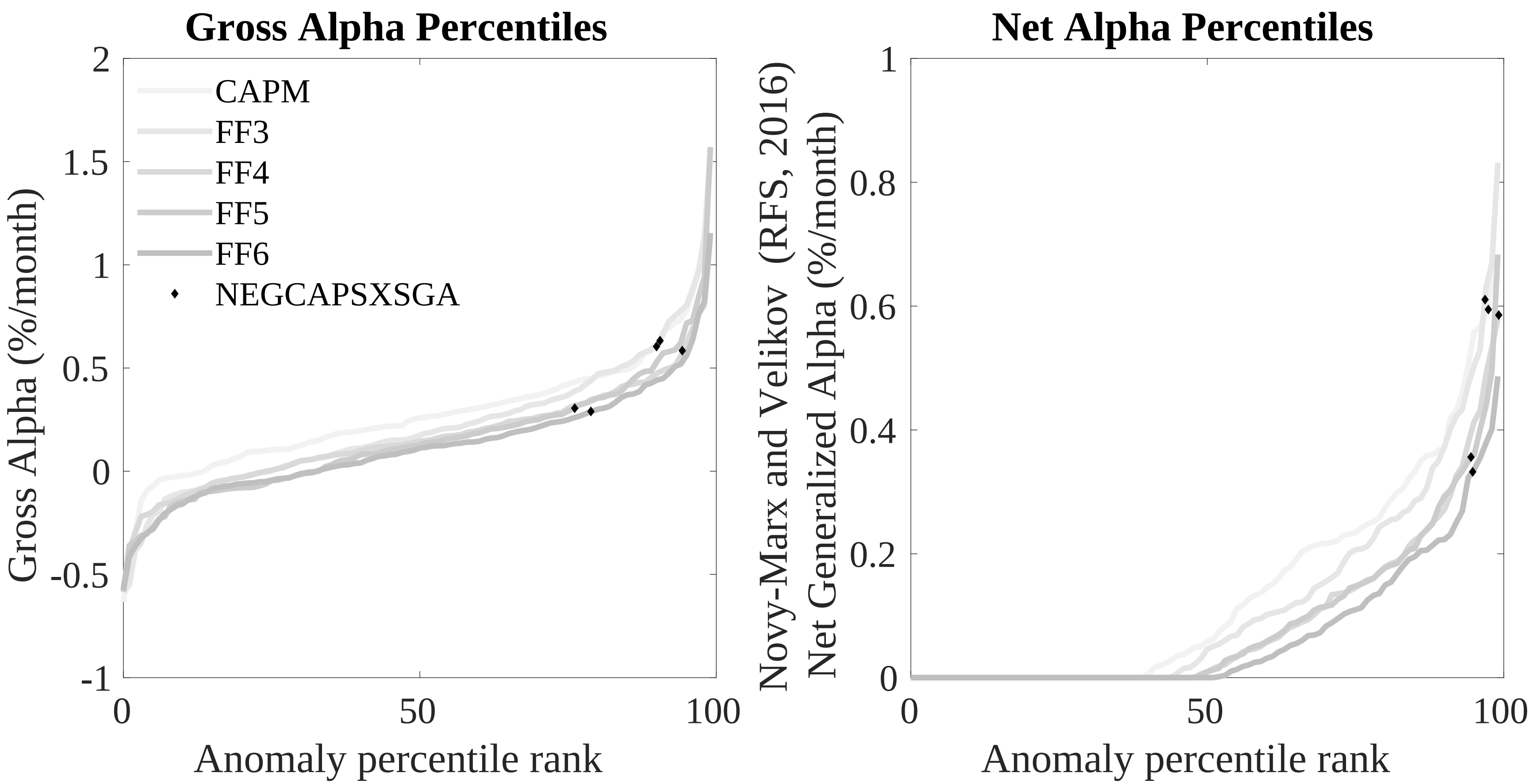

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EEA trading strategy alphas (diamonds). The strategies are constructed using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

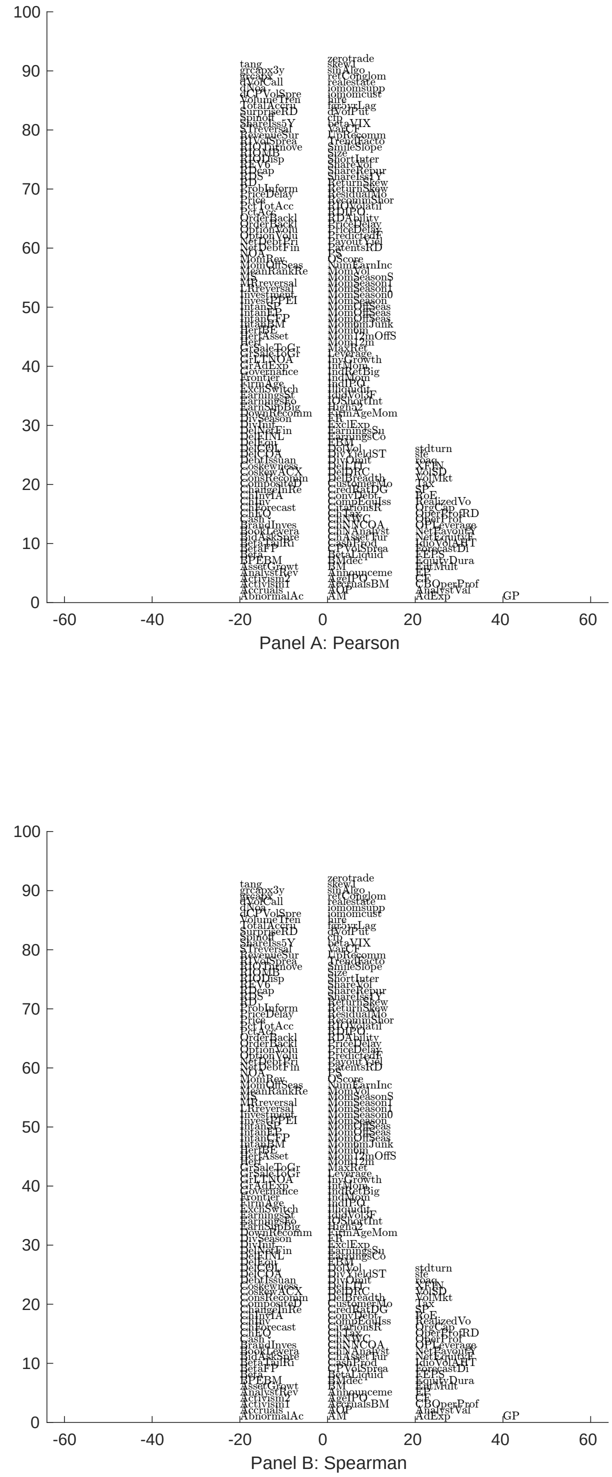

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with EEA. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

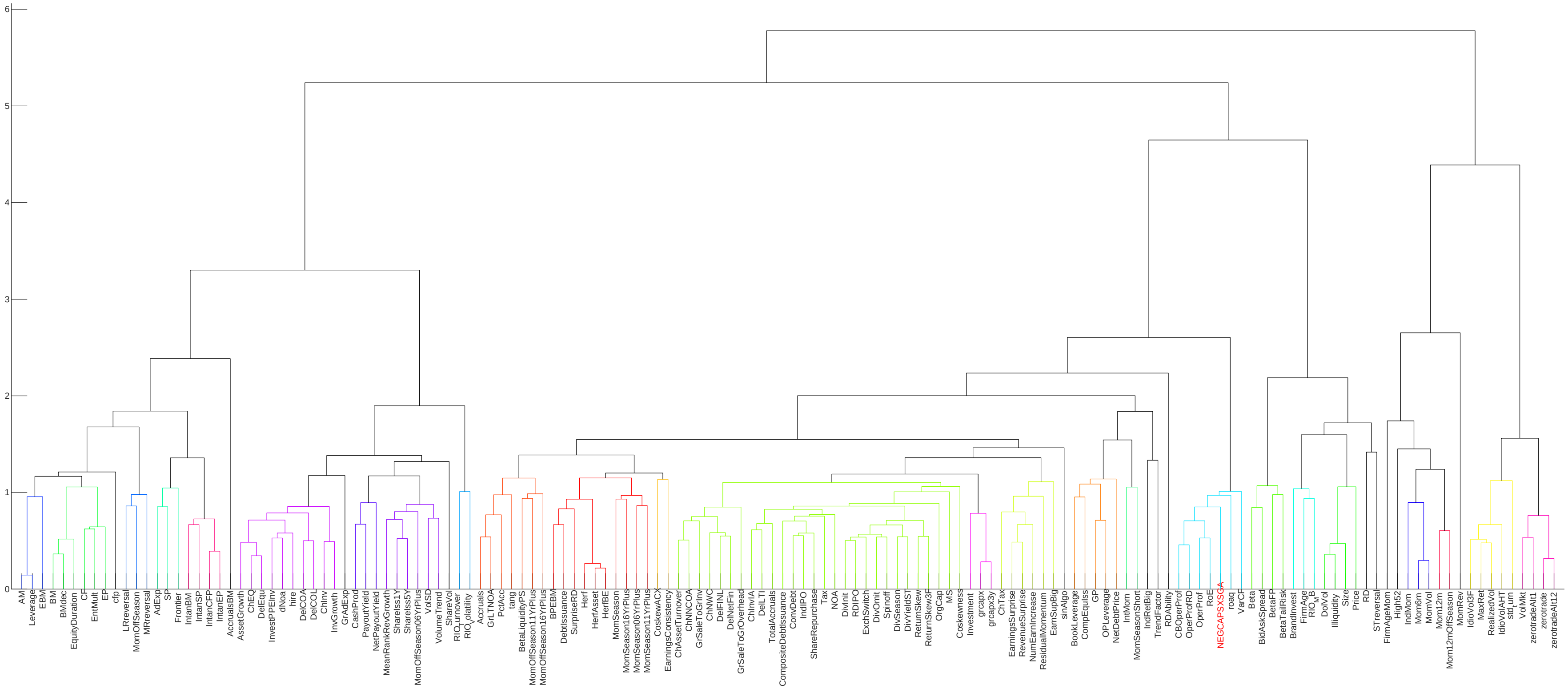

Figure 6: Agglomerative hierarchical cluster plot

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

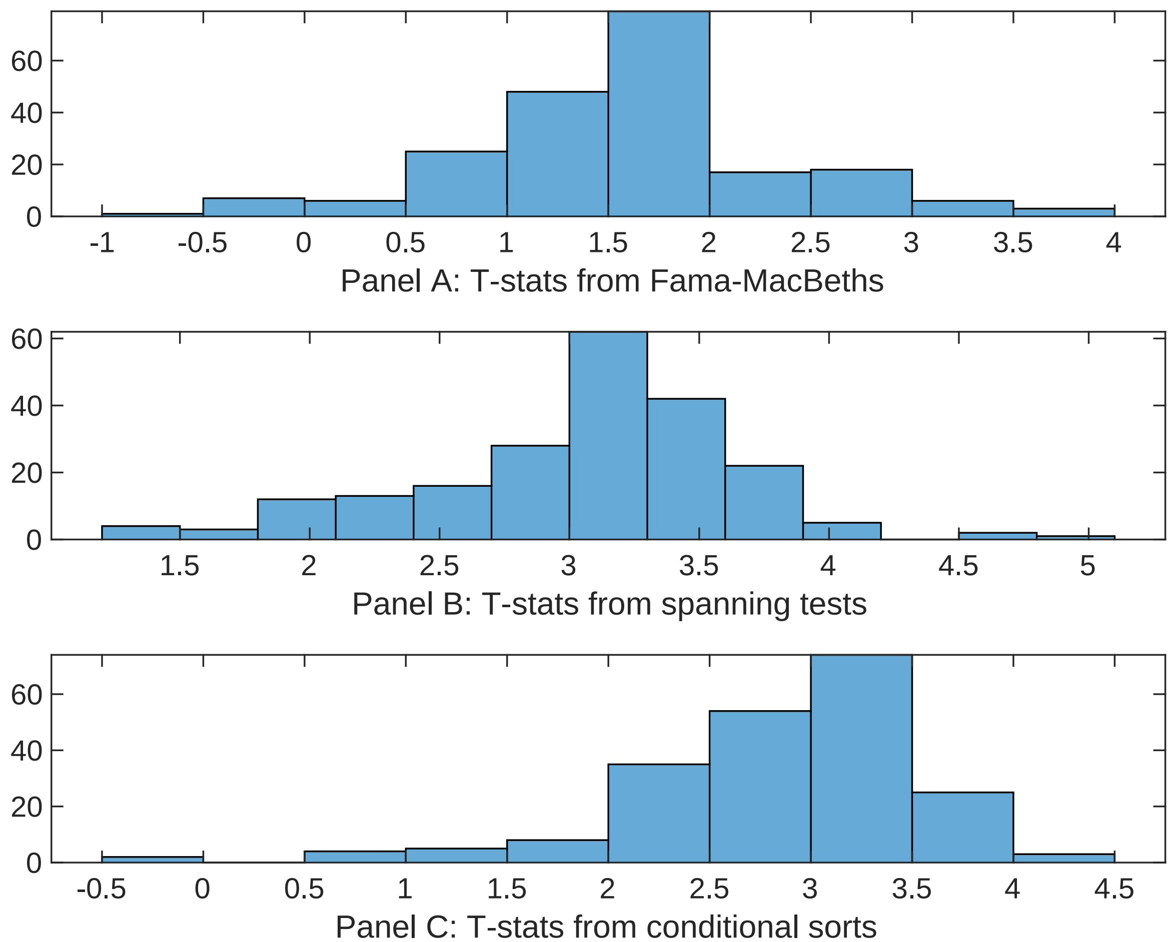

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EEA conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EEA} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EEA} EEA_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EEA,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EEA. Stocks are finally grouped into five EEA portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EEA 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 EEA. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EEA} EEA_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Analyst earnings per share, Net equity financing, Operating profitability RD adjusted, operating profits / book equity, EPS Forecast Dispersion, net income / book equity. 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 196906 to 202306.

Intercept	0.11	0.13	0.10	0.10	0.12	0.12	0.10
	[3.79]	[5.26]	[3.68]	[4.11]	[5.19]	[4.85]	[3.72]
EEA	0.28	-0.30	0.73	0.31	0.13	0.19	-0.15
	[1.94]	[-0.26]	[0.61]	[2.55]	[0.85]	[1.67]	[-0.10]
Anomaly 1	0.76						-0.22
	[1.29]						[-0.50]
Anomaly 2		0.20					0.40
		[3.18]					[0.83]
Anomaly 3			0.14				0.91
			[3.47]				[2.04]
Anomaly 4				0.41			0.26
				[3.57]			[1.62]
Anomaly 5					0.26		0.25
					[1.44]		[1.79]
Anomaly 6						0.12	-0.25
						[0.79]	[-1.37]
# months	564	618	643	643	564	648	564
$\bar{R}^2(\%)$	2	1	1	1	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the EEA trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EEA} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Analyst earnings per share, Net equity financing, Operating profitability RD adjusted, operating profits / book equity, EPS Forecast Dispersion, net income / book equity. 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 196906 to 202306.

Intercept	0.33	0.33	0.11	0.23	0.35	0.28	0.24
	[3.01]	[3.23]	[1.10]	[2.28]	[3.48]	[2.76]	[2.43]
Anomaly 1	16.03						-10.51
	[3.62]						[-2.46]
Anomaly 2		41.30					27.26
		[8.88]					[5.56]
Anomaly 3			36.48				31.98
			[8.44]				[6.14]
Anomaly 4				28.21			-6.40
				[5.92]			[-1.09]
Anomaly 5					34.95		26.55
					[10.99]		[7.69]
Anomaly 6						38.77	2.47
						[6.81]	[0.36]
mkt	-17.24	-10.76	-10.35	-13.30	-11.14	-11.31	-5.02
	[-6.16]	[-4.32]	[-4.21]	[-5.39]	[-4.37]	[-4.49]	[-1.96]
smb	-17.84	-5.38	-4.42	-9.74	-11.43	-4.78	-2.58
	[-3.62]	[-1.36]	[-1.17]	[-2.59]	[-2.87]	[-1.20]	[-0.58]
hml	-24.79	-24.10	-8.07	-16.76	-19.91	-15.70	-9.28
	[-4.83]	[-5.37]	[-1.72]	[-3.62]	[-4.34]	[-3.43]	[-1.95]
rmw	44.30	39.81	41.35	40.84	30.06	31.51	13.69
	[6.49]	[7.38]	[7.56]	[6.35]	[5.54]	[4.54]	[1.91]
cma	34.22	10.63	35.19	31.62	32.29	40.92	19.93
	[4.54]	[1.43]	[5.18]	[4.53]	[4.70]	[5.90]	[2.68]
umd	1.93	2.18	-1.44	-0.25	-2.15	1.49	-0.82
	[0.71]	[0.94]	[-0.61]	[-0.10]	[-0.88]	[0.64]	[-0.34]
# months	565	618	644	644	565	648	565
$\bar{R}^2(\%)$	51	52	49	47	58	48	64

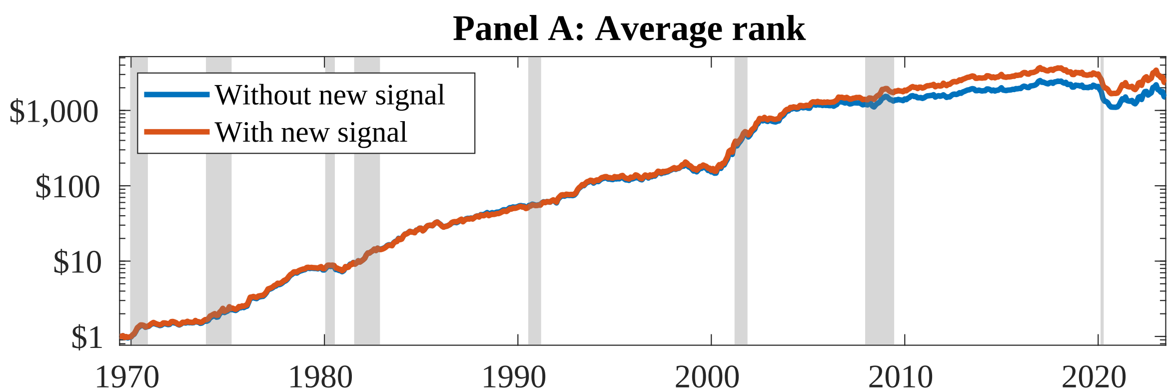

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 158 anomalies. The red solid lines indicate combination trading strategies that utilize the 158 anomalies as well as EEA. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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