Equity Impact Scale and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Equity Impact Scale (EIS), 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 EIS achieves an annualized gross (net) Sharpe ratio of 0.38 (0.31), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (19) bps/month with a t-statistic of 2.85 (2.42), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Growth in book equity, Change in equity to assets, Asset growth, Off season long-term reversal, Inventory Growth, change in ppe and inv/assets) is 18 bps/month with a t-statistic of 2.36.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Fama and French, 2008; Stambaugh and Yuan, 2017). While hundreds of return predictors have been documented in the academic literature, understanding which signals truly capture distinct economic mechanisms remains a central challenge in asset pricing research.

One particularly understudied aspect of firm behavior is how companies manage and scale their equity capital base over time. While research has examined specific corporate actions like share issuance (Pontiff and Woodgate, 2008) and stock splits (Ikenberry et al., 1996), we lack a comprehensive framework for understanding how firms' broader equity management decisions affect expected returns.

We propose that a firm's Equity Impact Scale (EIS) - a novel measure capturing the aggregate effect of all equity-related corporate actions - provides valuable information about future stock returns. The theoretical motivation draws on both the q-theory of investment (Cochrane and Saá-Requejo, 2000) and behavioral models of investor attention (Hirshleifer and Teoh, 2003). When firms actively manage their equity through issuance, repurchases, splits, and other actions, they reveal private information about growth opportunities and internal valuations.

Specifically, we hypothesize that firms with high EIS scores are signaling confidence in their future prospects through equity-expanding actions, while low EIS firms may be indicating concerns through equity-contracting behavior. This information may be overlooked by investors due to the complexity of tracking and aggregating multiple types of equity actions (Cohen and Frazzini, 2008).

Moreover, the q-theory framework suggests that firms optimally adjust their equity base in response to investment opportunities and costs of capital (Li and Whited, 2016). Therefore, EIS may capture information about expected returns through its relationship with firms' optimal investment and financing decisions. This mechanism operates distinctly from previously documented effects related to specific corporate actions.

Our empirical analysis reveals that EIS strongly predicts the cross-section of stock returns. A value-weighted long-short portfolio that buys stocks with high EIS and shorts those with low EIS generates monthly abnormal returns of 22 basis points (t-statistic = 2.92) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.38 before trading costs and 0.31 after costs.

Importantly, the predictive power of EIS remains robust after controlling for known return predictors. The strategy's alpha relative to the six most closely related anomalies from the factor zoo (Growth in book equity, Change in equity to assets, Asset growth, Off season long-term reversal, Inventory Growth, and change in PPE and inventory/assets) is 18 basis points per month (t-statistic = 2.36).

The effect is particularly strong among large-cap stocks, with the long-short strategy generating monthly returns of 20 basis points (t-statistic = 2.01) among stocks above the 80th percentile of market capitalization. This suggests that the EIS effect is distinct from many anomalies that are concentrated in small, illiquid stocks.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel return predictor that aggregates information from multiple equity-related corporate actions into a single measure. This extends prior work examining isolated corporate events (Pontiff and Woodgate, 2008; Ikenberry et al., 1996) by providing a unified framework for understanding how firms' equity management decisions affect expected returns.

Second, we demonstrate that EIS captures unique information not contained in existing factors or anomalies. Our signal's performance ranks in the top quintile among over 200 documented anomalies, with particularly strong results after accounting for transaction costs. This suggests that EIS identifies a distinct economic mechanism affecting stock returns.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we provide new evidence on how corporate actions reveal information about expected returns. For practitioners, we document a novel signal that remains profitable after transaction costs and works well among large, liquid stocks. The broader implications suggest that comprehensive measures of corporate behavior can provide valuable insights beyond examining isolated corporate events.

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 Impact Scale. 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 SEQ for stockholders' equity and item NOPIO for the number of shares outstanding. Stockholders' equity (SEQ) represents the total equity of a company's shareholders, including common stock, preferred stock, capital surplus, and retained earnings. The number of shares outstanding (NOPIO) provides the total count of shares issued by the company and held by shareholders. The construction of the signal follows a difference-in-equity approach, where we calculate the change in SEQ from one period to the next and scale this difference by the lagged number of shares outstanding. Specifically, for each firm in each period, we subtract the previous period's SEQ from the current period's SEQ and divide this difference by the previous period's NOPIO. This scaled difference captures the per-share change in equity value, potentially reflecting the impact of various corporate actions and performance outcomes on shareholder wealth. We construct this measure using end-of-fiscal-year values for both SEQ and NOPIO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EIS signal. Panel A plots the time-series of the mean, median, and interquartile range for EIS. On average, the cross-sectional mean (median) EIS is -15.76 (-2.60) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input EIS data. The signal's interquartile range spans -35.98 to 23.78. Panel B of Figure 1 plots the time-series of the coverage of the EIS signal for the CRSP universe. On average, the EIS signal is available for 4.86% of CRSP names, which on average make up 6.78% of total market capitalization.

4 Does EIS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EIS 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 EIS portfolio and sells the low EIS 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 EIS strategy earns an average return of 0.22% per month with a t-statistic of 2.92. The annualized Sharpe ratio of the strategy is 0.38. The alphas range from 0.21% to 0.25% per month and have t-statistics exceeding 2.77 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 -0.10, with a t-statistic of -2.75 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 427 stocks and an average market capitalization of at least $1,505 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 16 bps/month with a t-statistics of 2.25. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for thirteen 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 10-23bps/month. The lowest return, (10 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.48. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EIS 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 eighteen cases.

Table 3 provides direct tests for the role size plays in the EIS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EIS, as well as average returns and alphas for long/short trading EIS 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 EIS strategy achieves an average return of 20 bps/month with a t-statistic of 2.01. Among these large cap stocks, the alphas for the EIS strategy relative to the five most common factor models range from 18 to 25 bps/month with t-statistics between 1.91 and 2.53.

5 How does EIS perform relative to the zoo?

Figure 2 puts the performance of EIS 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 EIS strategy falls in the distribution. The EIS strategy's gross (net) Sharpe ratio of 0.38 (0.31) is greater than 81% (91%) 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 EIS strategy (red line).[2] Ignoring trading costs, a $1 invested in the EIS strategy would have yielded $3.31 which ranks the EIS strategy in the top 10% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EIS strategy would have yielded $2.19 which ranks the EIS strategy in the top 6% 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 EIS relative to those. Panel A shows that the EIS strategy gross alphas fall between the 49 and 71 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196506 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 EIS strategy has a positive net generalized alpha for five out of the five factor models. In these cases EIS ranks between the 69 and 83 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does EIS 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 EIS 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 EIS or at least to weaken the power EIS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EIS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EIS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EIS} EIS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EIS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on EIS. Stocks are finally grouped into five EIS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EIS trading

[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.

strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EIS 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 EIS signal in these Fama-MacBeth regressions exceed 1.69, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on EIS is 1.38.

Similarly, Table 5 reports results from spanning tests that regress returns to the EIS 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 EIS strategy earns alphas that range from 20-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.59, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EIS trading strategy achieves an alpha of 18bps/month with a t-statistic of 2.36.

7 Does EIS add relative to the whole zoo?

Finally, we can ask how much adding EIS 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 EIS 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 EIS 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 \$3027.42, while \$1 investment in the combination strategy that includes EIS grows to \$3233.01.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Equity Impact Scale (EIS) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on EIS generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.38 (0.31 net). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

The persistence of the signal's predictive power, evidenced by monthly abnormal gross returns of 22 bps (19 bps net) with strong statistical significance, suggests that EIS captures unique information about future stock returns that is not fully reflected in existing factors. This has important implications for both academic research and practical investment management, as it introduces a novel tool for portfolio construction and risk management.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, transaction costs and market impact could affect the strategy's realworld implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore the signal's performance in different market regimes, its interaction with other established factors, and its effectiveness in international markets. Additionally, investigating the underlying economic mechanisms driving the EIS effect could provide valuable insights into market efficiency and asset pricing theory. Finally, examining the signal's robustness across different asset classes could further validate its utility in investment decision-making.

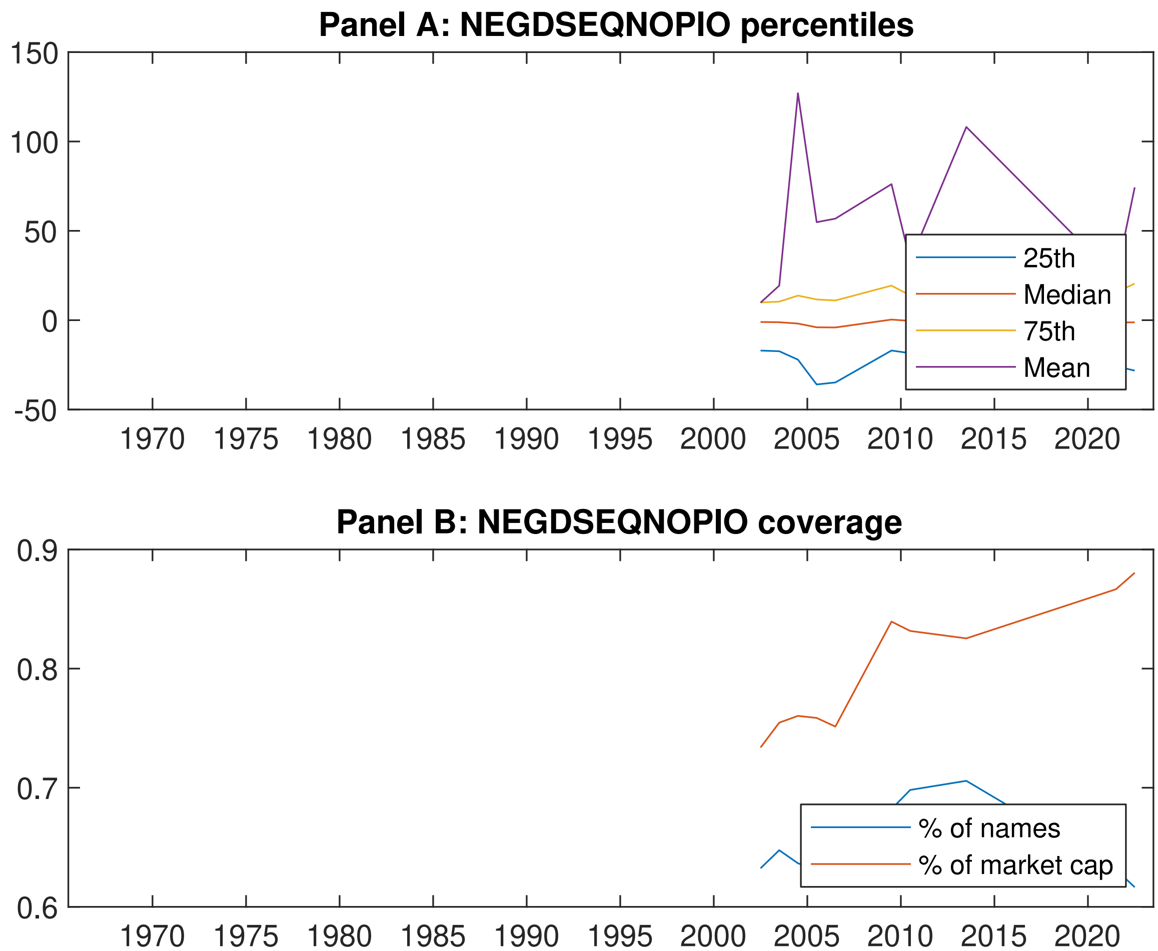

Figure 1: Times series of EIS percentiles and coverage.
This figure plots descriptive statistics for EIS. Panel A shows cross-sectional percentiles of EIS over the sample. Panel B plots the monthly coverage of EIS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EIS. 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 196506 to 202306.

Panel A: Excess returns and alphas on EIS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.48	0.56	0.53	0.64	0.70	0.22
	[2.42]	[3.26]	[3.32]	[3.85]	[3.70]	[2.92]
α_{CAPM}	-0.14	0.02	0.03	0.13	0.11	0.25
	[-2.71]	[0.38]	[0.67]	[2.22]	[1.90]	[3.31]
α_{FF3}	-0.07	0.06	0.00	0.09	0.15	0.21
	[-1.48]	[1.28]	[0.07]	[1.62]	[2.59]	[2.81]
α_{FF4}	-0.06	0.07	-0.01	0.09	0.15	0.22
	[-1.29]	[1.49]	[-0.22]	[1.51]	[2.68]	[2.77]
α_{FF5}	-0.04	0.04	-0.09	-0.01	0.18	0.22
	[-0.84]	[0.86]	[-1.99]	[-0.26]	[3.17]	[2.86]
α_{FF6}	-0.04	0.05	-0.09	-0.00	0.19	0.22
	[-0.77]	[1.05]	[-2.02]	[-0.09]	[3.21]	[2.85]
Panel B: Fama and French (2018) 6-factor model loadings for EIS-sorted portfolios						
β_{MKT}	1.04	0.95	0.96	0.99	1.01	-0.04
	[92.18]	[90.79]	[91.73]	[78.26]	[72.94]	[-1.98]
β_{SMB}	0.04	-0.02	-0.11	-0.12	0.05	0.01
	[2.68]	[-1.27]	[-7.45]	[-6.42]	[2.60]	[0.30]
β_{HML}	-0.16	-0.07	0.05	-0.01	-0.13	0.04
	[-7.45]	[-3.37]	[2.41]	[-0.54]	[-4.75]	[1.01]
β_{RMW}	0.00	0.10	0.13	0.06	-0.10	-0.10
	[0.21]	[4.76]	[6.25]	[2.32]	[-3.53]	[-2.75]
β_{CMA}	-0.14	-0.07	0.19	0.39	0.00	0.14
	[-4.30]	[-2.52]	[6.55]	[10.98]	[0.02]	[2.63]
β_{UMD}	-0.00	-0.01	0.00	-0.01	-0.01	-0.00
	[-0.33]	[-1.24]	[0.34]	[-1.04]	[-0.51]	[-0.18]
Panel C: Average number of firms (n) and market capitalization (me)						
n	580	470	427	487	612	
me ($\$10^6$)	1520	1700	1822	1753	1505	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EIS 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 196506 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	0.22	0.25	0.21	0.22	0.22	0.22
			[2.92]	[3.31]	[2.81]	[2.77]	[2.86]	[2.85]
Quintile	NYSE	EW	0.30	0.31	0.26	0.23	0.28	0.25
			[5.40]	[5.37]	[4.86]	[4.27]	[5.28]	[4.81]
Quintile	Name	VW	0.27	0.29	0.27	0.26	0.32	0.31
			[3.36]	[3.57]	[3.33]	[3.14]	[3.78]	[3.61]
Quintile	Cap	VW	0.16	0.21	0.16	0.16	0.17	0.17
			[2.25]	[2.88]	[2.28]	[2.20]	[2.42]	[2.38]
Decile	NYSE	VW	0.23	0.26	0.26	0.28	0.35	0.36
			[2.26]	[2.54]	[2.60]	[2.71]	[3.40]	[3.44]
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	0.18	0.22	0.18	0.18	0.18	0.19
			[2.35]	[2.79]	[2.35]	[2.35]	[2.38]	[2.42]
Quintile	NYSE	EW	0.10	0.10	0.06	0.04	0.04	0.04
			[1.48]	[1.59]	[0.90]	[0.73]	[0.70]	[0.62]
Quintile	Name	VW	0.23	0.25	0.24	0.23	0.27	0.26
			[2.80]	[3.06]	[2.86]	[2.77]	[3.22]	[3.15]
Quintile	Cap	VW	0.13	0.17	0.13	0.13	0.14	0.14
			[1.72]	[2.39]	[1.86]	[1.83]	[2.01]	[2.05]
Decile	NYSE	VW	0.18	0.22	0.22	0.23	0.28	0.29
			[1.75]	[2.12]	[2.17]	[2.26]	[2.80]	[2.83]

Table 3: Conditional sort on size and EIS

This table presents results for conditional double sorts on size and EIS. 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 EIS. 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 EIS and short stocks with low EIS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

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

Size quintiles	EIS Quintiles (L)	(2)	(3)	(4)	(H)	EIS Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.54	0.88	0.85	0.93	0.76	0.22	0.21	0.18	0.15	0.22	0.19
	[2.05]	[3.51]	[3.47]	[3.40]	[2.75]	[2.71]	[2.51]	[2.12]	[1.74]	[2.54]	[2.20]
(2)	0.71	0.78	0.79	0.79	0.91	0.19	0.20	0.19	0.22	0.24	0.26
	[2.86]	[3.39]	[3.48]	[3.38]	[3.62]	[2.06]	[2.11]	[2.03]	[2.24]	[2.52]	[2.69]
(3)	0.67	0.82	0.76	0.74	0.84	0.16	0.18	0.14	0.14	0.12	0.12
	[2.93]	[3.85]	[3.78]	[3.59]	[3.71]	[1.99]	[2.19]	[1.67]	[1.61]	[1.37]	[1.38]
(4)	0.58	0.62	0.68	0.75	0.88	0.30	0.30	0.25	0.22	0.24	0.23
	[2.69]	[3.15]	[3.71]	[3.91]	[4.04]	[3.71]	[3.58]	[2.99]	[2.64]	[2.95]	[2.70]
(5)	0.46	0.44	0.50	0.63	0.65	0.20	0.25	0.18	0.18	0.21	0.21
	[2.33]	[2.55]	[3.09]	[3.98]	[3.60]	[2.01]	[2.53]	[1.91]	[1.89]	[2.18]	[2.17]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EIS Quintiles, Average n (L)	(2)	(3)	(4)	(H)	EIS Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	266	267	268	264	262	24	24	22	21	22
(2)	80	80	81	80	80	42	42	43	42	43
(3)	62	62	62	62	62	77	77	77	77	77
(4)	55	55	55	55	55	175	175	177	177	174
(5)	52	52	52	52	52	1107	1292	1578	1547	1190

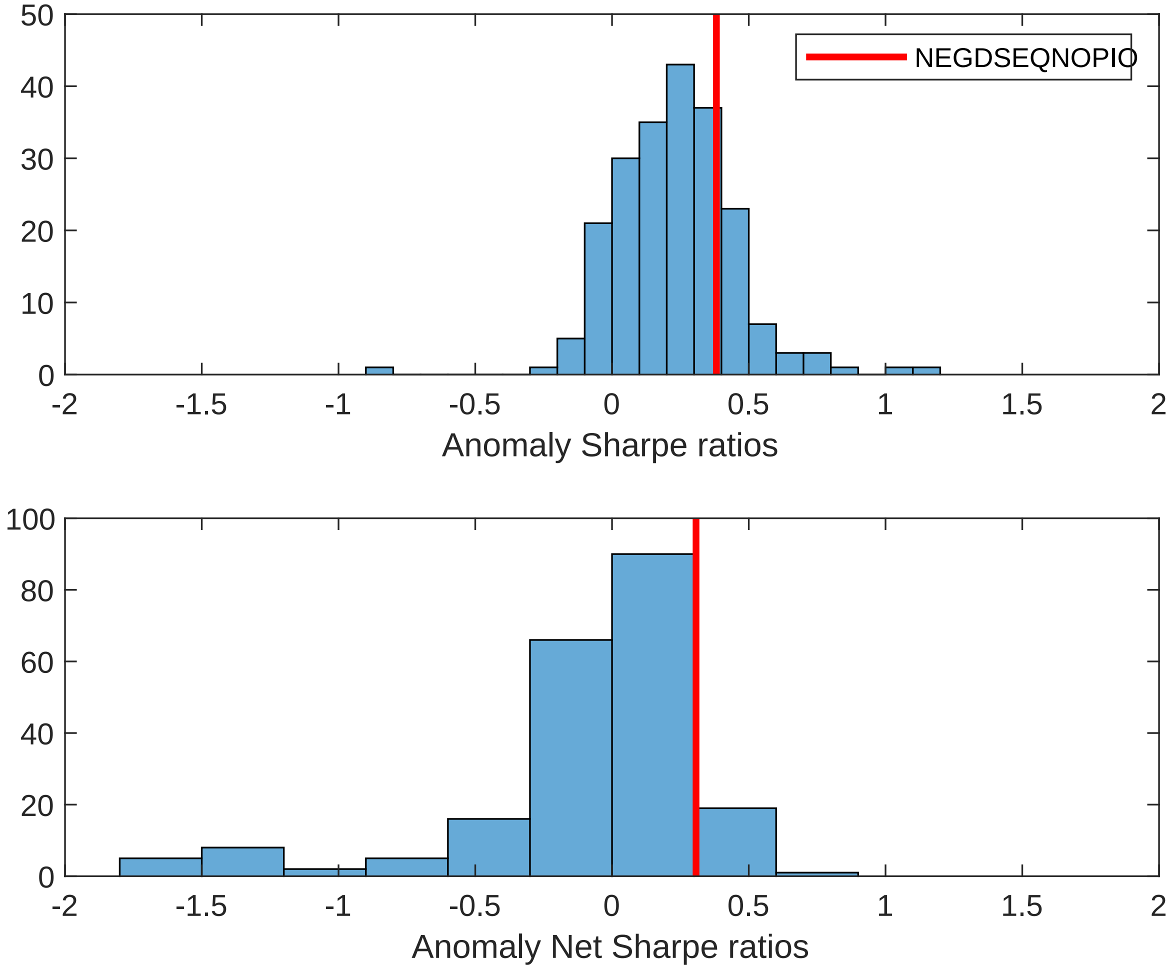

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EIS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

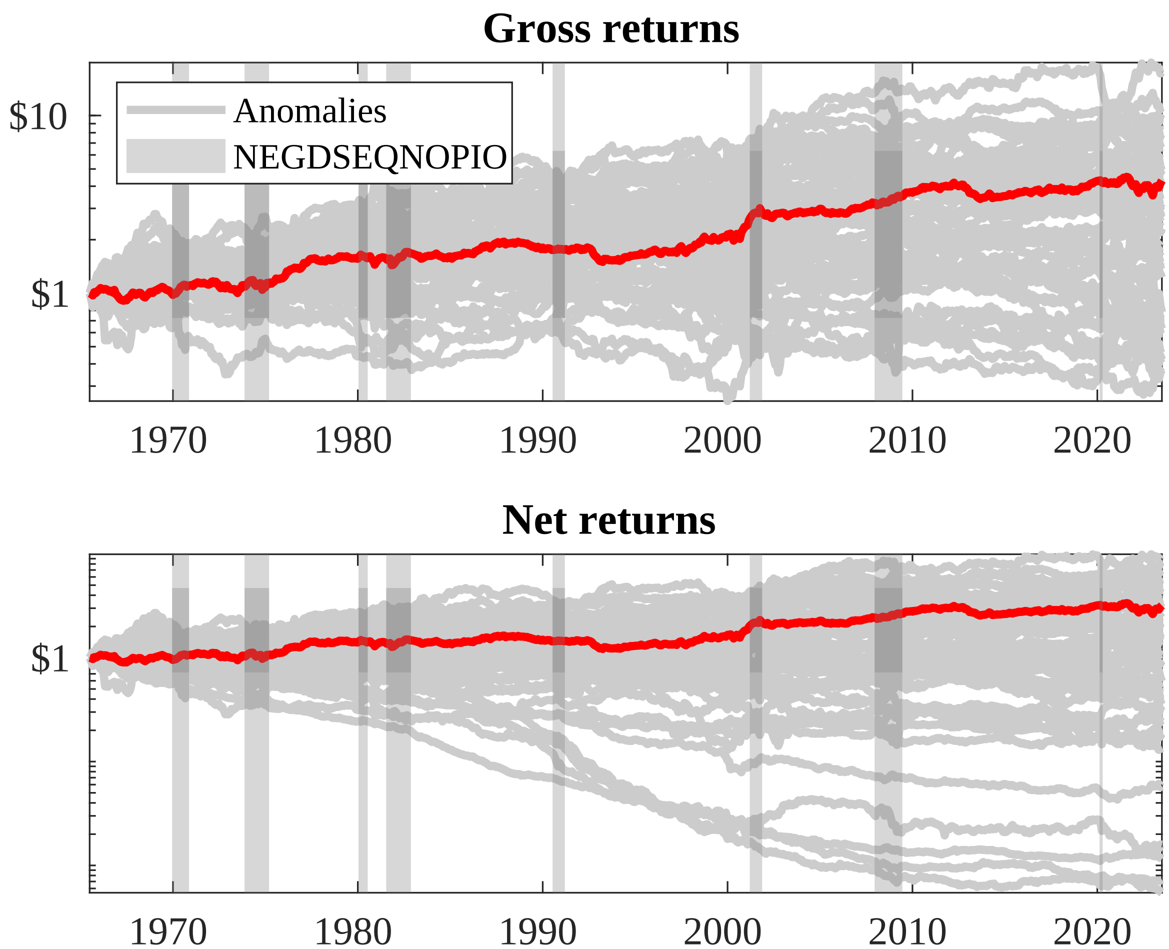

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EIS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

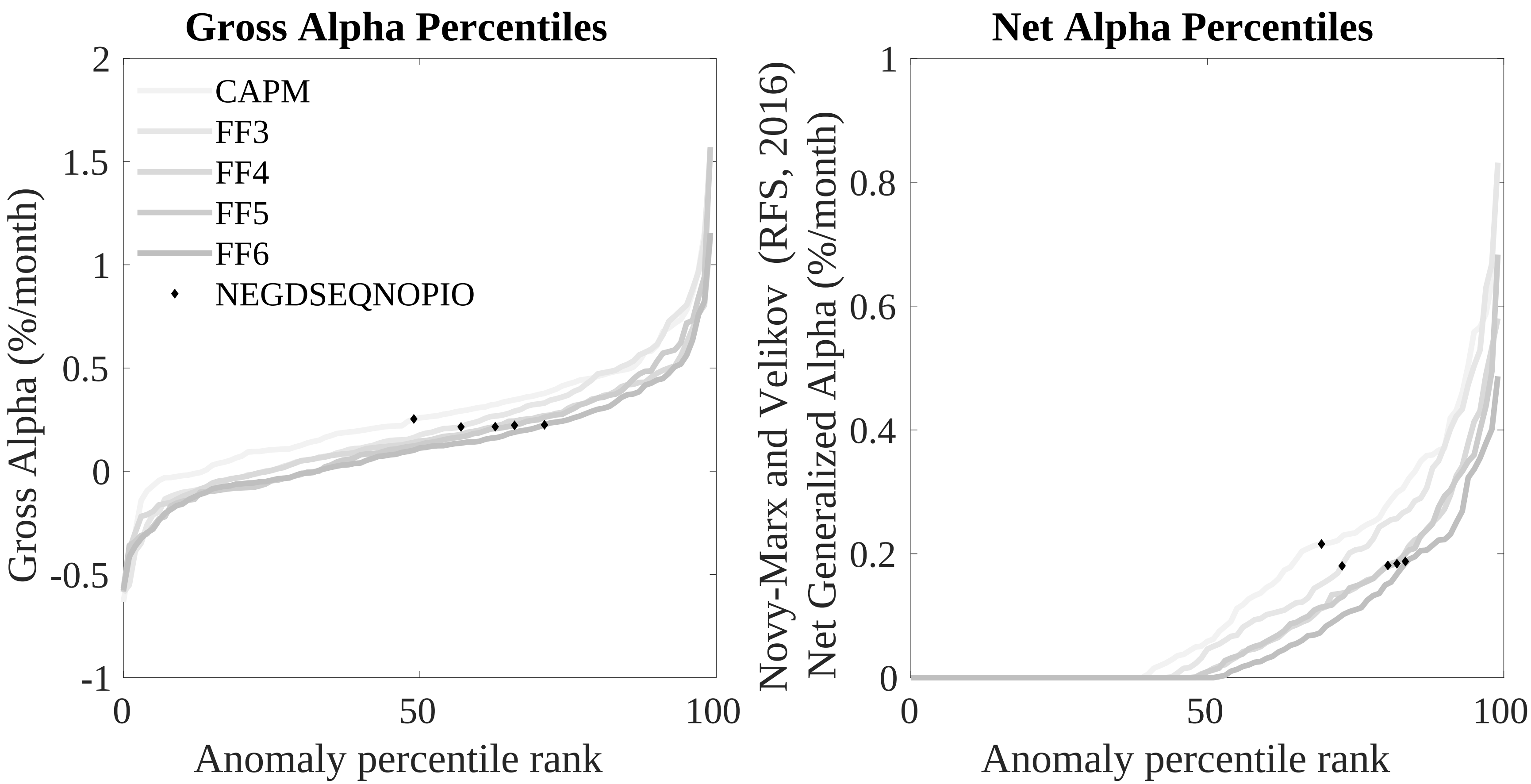

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EIS trading strategy alphas (diamonds). The strategies are constructed using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

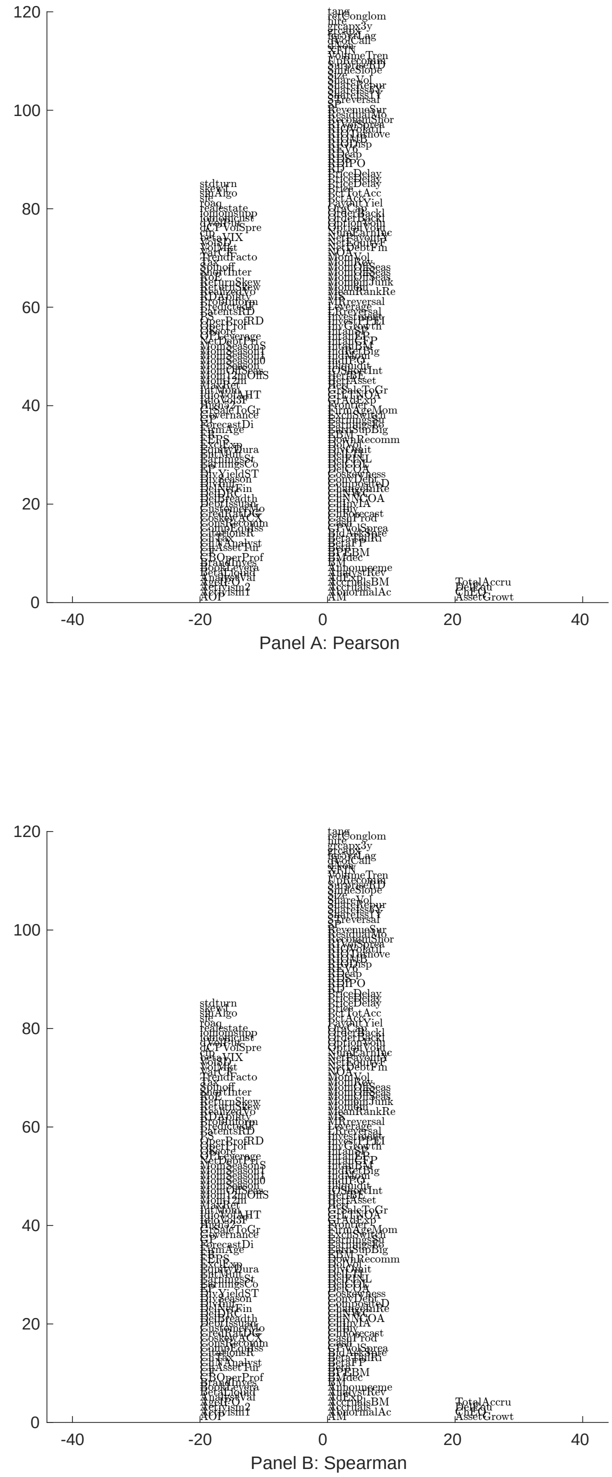

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with EIS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

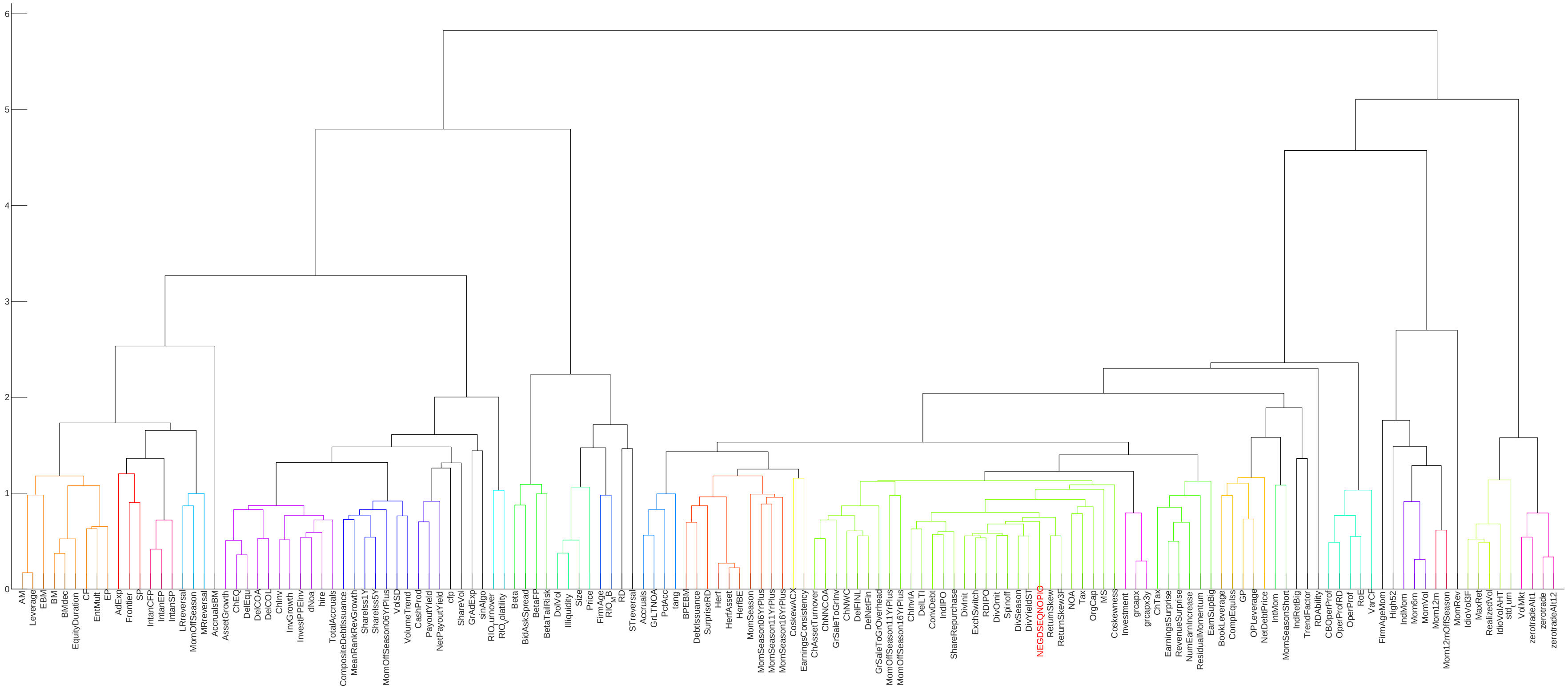

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

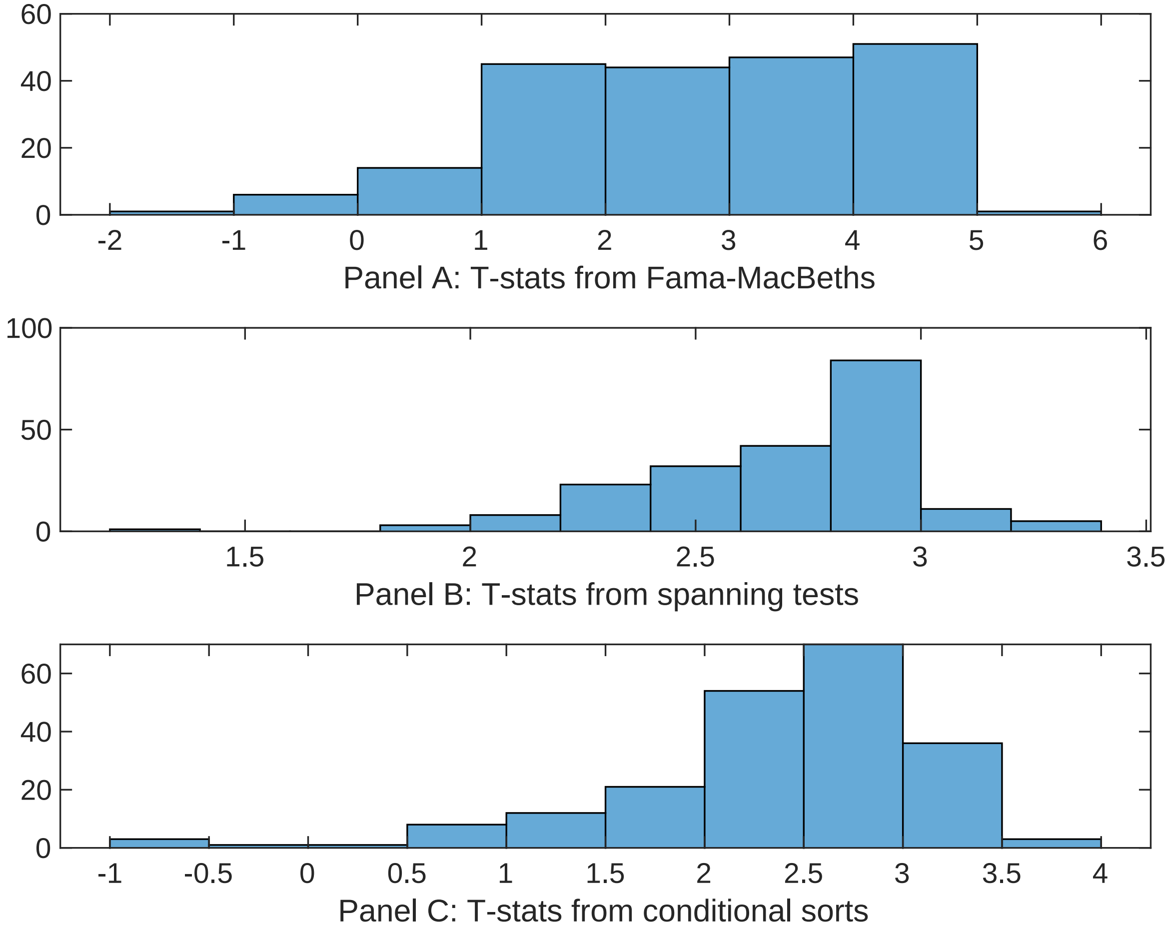

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EIS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EIS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EIS} EIS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EIS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EIS. Stocks are finally grouped into five EIS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EIS 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 EIS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EIS} EIS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Change in equity to assets, Asset growth, Off season long-term reversal, Inventory Growth, change in ppe and inv/assets. 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 196506 to 202306.

Intercept	0.17	0.12	0.13	0.13	0.12	0.13	0.13
	[7.05]	[5.49]	[5.90]	[6.10]	[5.43]	[5.87]	[6.47]
EIS	0.30	0.32	0.22	0.33	0.44	0.29	0.18
	[2.41]	[2.60]	[1.69]	[2.63]	[3.16]	[2.18]	[1.38]
Anomaly 1	0.46						-0.53
	[4.05]						[-0.41]
Anomaly 2		0.15					-0.37
		[4.08]					[-0.80]
Anomaly 3			0.97				0.45
			[7.94]				[3.53]
Anomaly 4				0.14			0.11
				[5.66]			[5.02]
Anomaly 5					0.29		0.48
					[5.38]		[0.79]
Anomaly 6						0.16	0.52
						[7.69]	[1.90]
# months	696	696	696	691	696	696	691
$\bar{R}^2(\%)$	0	0	0	1	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the EIS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EIS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Growth in book equity, Change in equity to assets, Asset growth, Off season long-term reversal, Inventory Growth, change in ppe and inv/assets. 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 196506 to 202306.

Intercept	0.22	0.25	0.23	0.20	0.21	0.23	0.18
	[2.97]	[3.18]	[2.94]	[2.59]	[2.69]	[2.92]	[2.36]
Anomaly 1	33.93						39.61
	[8.07]						[6.32]
Anomaly 2		22.01					-1.14
		[5.35]					[-0.20]
Anomaly 3			2.77				-18.38
			[0.53]				[-3.31]
Anomaly 4				7.49			1.77
				[2.69]			[0.64]
Anomaly 5					9.79		4.40
					[2.46]		[1.10]
Anomaly 6						2.14	0.47
						[0.57]	[0.12]
mkt	-2.28	-3.73	-3.37	-2.22	-3.14	-3.43	-1.54
	[-1.27]	[-2.03]	[-1.80]	[-1.18]	[-1.68]	[-1.83]	[-0.85]
smb	-0.48	0.35	0.51	-0.72	1.99	0.71	1.26
	[-0.19]	[0.13]	[0.19]	[-0.26]	[0.73]	[0.26]	[0.46]
hml	0.09	1.40	4.18	0.15	3.63	4.06	-1.30
	[0.03]	[0.39]	[1.16]	[0.04]	[1.01]	[1.12]	[-0.35]
rmw	-8.80	-8.46	-10.72	-10.12	-8.93	-10.68	-7.15
	[-2.52]	[-2.35]	[-2.94]	[-2.81]	[-2.41]	[-2.93]	[-2.02]
cma	-20.19	-9.55	9.93	11.75	6.91	11.67	-3.76
	[-3.09]	[-1.42]	[1.21]	[2.15]	[1.18]	[1.94]	[-0.46]
umd	-0.57	0.51	-0.11	0.42	-0.81	-0.23	-1.39
	[-0.32]	[0.28]	[-0.06]	[0.23]	[-0.44]	[-0.12]	[-0.78]
# months	696	696	696	692	696	696	692
$\bar{R}^2(\%)$	13	9	5	7	6	5	15

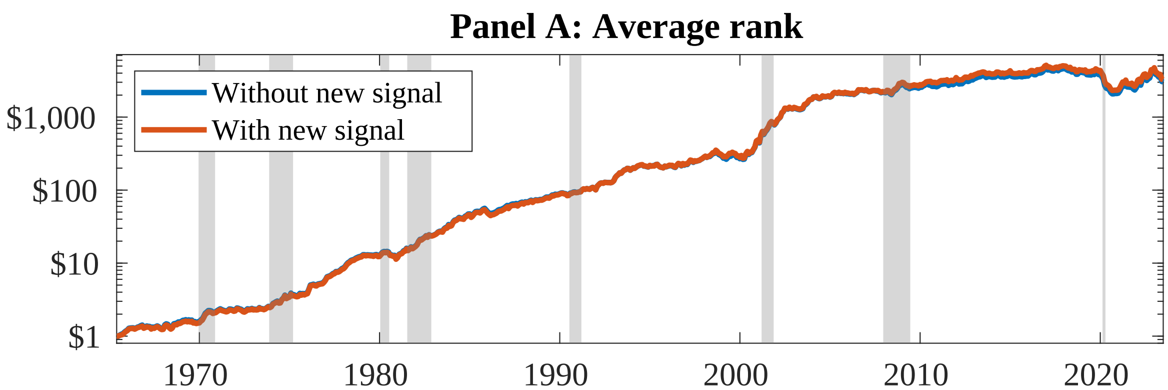

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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