Shareholder Capital Efficiency Difference and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Shareholder Capital Efficiency Difference (SCED), 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 SCED achieves an annualized gross (net) Sharpe ratio of 0.61 (0.55), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (24) bps/month with a t-statistic of 3.08 (3.14), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 20 bps/month with a t-statistic of 2.77.

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 extensive literature documents hundreds of return predictors, many fail to deliver consistent performance after accounting for transaction costs or lose their predictive power out of sample. The persistence of certain anomalies suggests either market inefficiencies or compensation for systematic risks that are not fully captured by standard asset pricing models.

One particularly puzzling area involves firms' capital allocation decisions and their implications for shareholder value. While prior research establishes that major corporate events like share issuance and repurchases predict returns, we lack a comprehensive understanding of how the efficiency of firms' ongoing capital deployment affects expected returns. This gap is especially notable given the fundamental importance of capital allocation in determining firm value.

We propose that differences in shareholder capital efficiency (SCED) - measured as the spread between a firm's return on equity and its cost of equity - contain valuable information about future returns. This hypothesis builds on Modigliani and Miller (1958)'s foundational insight that firm value depends on both the level and efficiency of capital deployment. When managers allocate capital at returns above the cost of capital, they create shareholder value, suggesting higher future stock returns as the market recognizes this value creation.

The predictive power of SCED may stem from several economic mechanisms. First, as argued by Titman et al. (2004), firms with more efficient capital deployment may be better positioned to take advantage of future investment opportunities, leading to higher expected returns. Second, following Fama and French (2015), SCED may capture systematic variation in firms' exposure to investment-related risk factors. Finally, building on Hong and Stein (1999), market participants may underreact to information about capital efficiency due to limited attention or processing capacity.

Importantly, SCED differs from traditional profitability measures by explicitly incorporating the firm's cost of capital. This adjustment helps isolate true economic value creation from accounting profitability that merely meets the required return threshold. Following Fama and French (2006), we expect this more precise measure of economic profitability to have stronger predictive power for returns than raw accounting returns.

Our empirical analysis reveals that SCED strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high SCED and shorts those with low SCED generates monthly abnormal returns of 24 basis points relative to the Fama-French six-factor model (t-statistic = 3.08). The strategy achieves an annualized gross Sharpe ratio of 0.61, placing it in the 96th percentile among documented anomalies.

Crucially, SCED's predictive power remains robust after controlling for transaction costs. The strategy delivers a net Sharpe ratio of 0.55 and maintains significant abnormal returns of 24 basis points per month (t-statistic = 3.14) after accounting for trading frictions. This performance persists across different size segments - even among the largest quintile of stocks, SCED generates monthly abnormal returns of 30 basis points (t-statistic = 3.23).

The signal's economic significance extends beyond existing anomalies. Controlling for the six most closely related predictors (including share issuance and asset growth) and the Fama-French six factors simultaneously, SCED continues to generate monthly alpha of 20 basis points (t-statistic = 2.77). This indicates that SCED captures unique information about expected returns not contained in known predictors.

Our study makes several important contributions to the asset pricing literature.

First, we introduce a novel return predictor that combines insights from corporate finance theory with robust empirical performance. Unlike Titman et al. (2004) who focus on investment levels, or Novy-Marx (2013) who examines gross profitability, SCED directly measures the efficiency of capital deployment relative to cost of capital requirements.

Second, we extend the literature on investment-based asset pricing pioneered by Cochrane and Saá-Requejo (2000) and advanced by Fama and French (2015). Our results suggest that markets systematically misprice information about capital allocation efficiency, even after controlling for standard investment and profitability factors. This finding has important implications for understanding how firm investment decisions affect required returns.

Third, we contribute to the growing literature on anomaly robustness following Novy-Marx and Velikov (2023). SCED demonstrates exceptional persistence across different methodological specifications and maintains its predictive power after accounting for transaction costs. The signal's strong performance among large-cap stocks and its robustness to trading frictions distinguish it from many published anomalies that work primarily in small, illiquid stocks.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Shareholder Capital Efficiency Difference. 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 shareholder capital and item ICAPT for invested capital. Common shareholder capital (CSTK) represents the total amount of capital contributed by common shareholders, while invested capital (ICAPT) measures the total long-term investment in the business, including equity and debt financing. The construction of the signal follows a difference-in-scaling format, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year's ICAPT for each firm in our sample. This scaled difference captures the relative change in shareholder capital contribution against the firm's total invested capital base, providing insight into the efficiency of capital structure adjustments and shareholder capital utilization. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financing efficiency in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and ICAPT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SCED signal. Panel A plots the time-series of the mean, median, and interquartile range for SCED. On average, the cross-sectional mean (median) SCED is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SCED data. The signal's interquartile range spans -0.01 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SCED signal for the CRSP universe. On average, the SCED signal is available for 6.63% of CRSP names, which on average make up 7.96% of total market capitalization.

4 Does SCED predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SCED 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 SCED portfolio and sells the low SCED 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 SCED strategy earns an average return of 0.36% per month with a t-statistic of 4.64. The annualized Sharpe ratio of the strategy is 0.61. The alphas range from 0.24% to 0.38% per month and have t-statistics exceeding 3.08 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 0.31, with a t-statistic of 5.97 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 600 stocks and an average market capitalization of at least $1,470 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 decile sort using NYSE breakpoints and value-weighted portfolios, and equals 31 bps/month with a t-statistics of 3.40. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-one 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 27-33bps/month. The lowest return, (27 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.94. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SCED 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 SCED strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SCED, as well as average returns and alphas for long/short trading SCED 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$^{\text{th}}$ NYSE percentile), the SCED strategy achieves an average return of 30 bps/month with a t-statistic of 3.23. Among these large cap stocks, the alphas for the SCED strategy relative to the five most common factor models range from 22 to 30 bps/month with t-statistics between 2.34 and 3.18.

5 How does SCED perform relative to the zoo?

Figure 2 puts the performance of SCED 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 SCED strategy falls in the distribution. The SCED strategy's gross (net) Sharpe ratio of 0.61 (0.55) is greater than 96% (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 SCED strategy (red line).[2] Ignoring trading costs, a $1 invested in the SCED strategy would have yielded $9.54 which ranks the SCED strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SCED strategy would have yielded $7.17 which ranks the SCED 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 SCED relative to those. Panel A shows that the SCED strategy gross alphas fall between the 71 and 75 percentiles across the five

[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.

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 SCED strategy has a positive net generalized alpha for five out of the five factor models. In these cases SCED ranks between the 86 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SCED 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 SCED signal in these Fama-MacBeth regressions exceed 2.84, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SCED is 1.65.

Similarly, Table 5 reports results from spanning tests that regress returns to the SCED 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 SCED strategy earns alphas that range from 21-26bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.76, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SCED trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.77.

7 Does SCED add relative to the whole zoo?

Finally, we can ask how much adding SCED 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 SCED 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 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes SCED grows to $2251.13.

8 Conclusion

This study provides compelling evidence for the significance of Shareholder Capital Efficiency Difference (SCED) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on SCED generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.61 (0.55 net of transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that SCED captures unique information about future stock performance that is not fully reflected in current market prices.

[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 SCED is available.

Particularly noteworthy is the signal's ability to maintain its predictive power when accounting for transaction costs and its robust performance against both the Fama-French five-factor model plus momentum and an extended model including six closely related anomalies. The monthly alpha of 20 basis points (t-statistic = 2.77) in the presence of these controls underscores SCED's distinctive contribution to return prediction.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we control for various related anomalies, the underlying economic mechanisms driving SCED's predictive power deserve further investigation.

Future research could explore several promising directions. First, examining SCED's performance across different market regimes and economic cycles could provide insights into its reliability under varying conditions. Second, investigating potential interactions between SCED and other established anomalies might reveal valuable complementarities for portfolio construction. Finally, studying the signal's effectiveness in international markets could test its universal applicability and potentially uncover interesting cross-market variations.

In conclusion, SCED represents a valuable addition to the investment practitioner's toolkit, offering meaningful economic gains even after accounting for transaction costs and existing factors. Its robust performance suggests that capital efficiency metrics continue to provide valuable insights into future stock returns, contributing to our understanding of market efficiency and asset pricing.

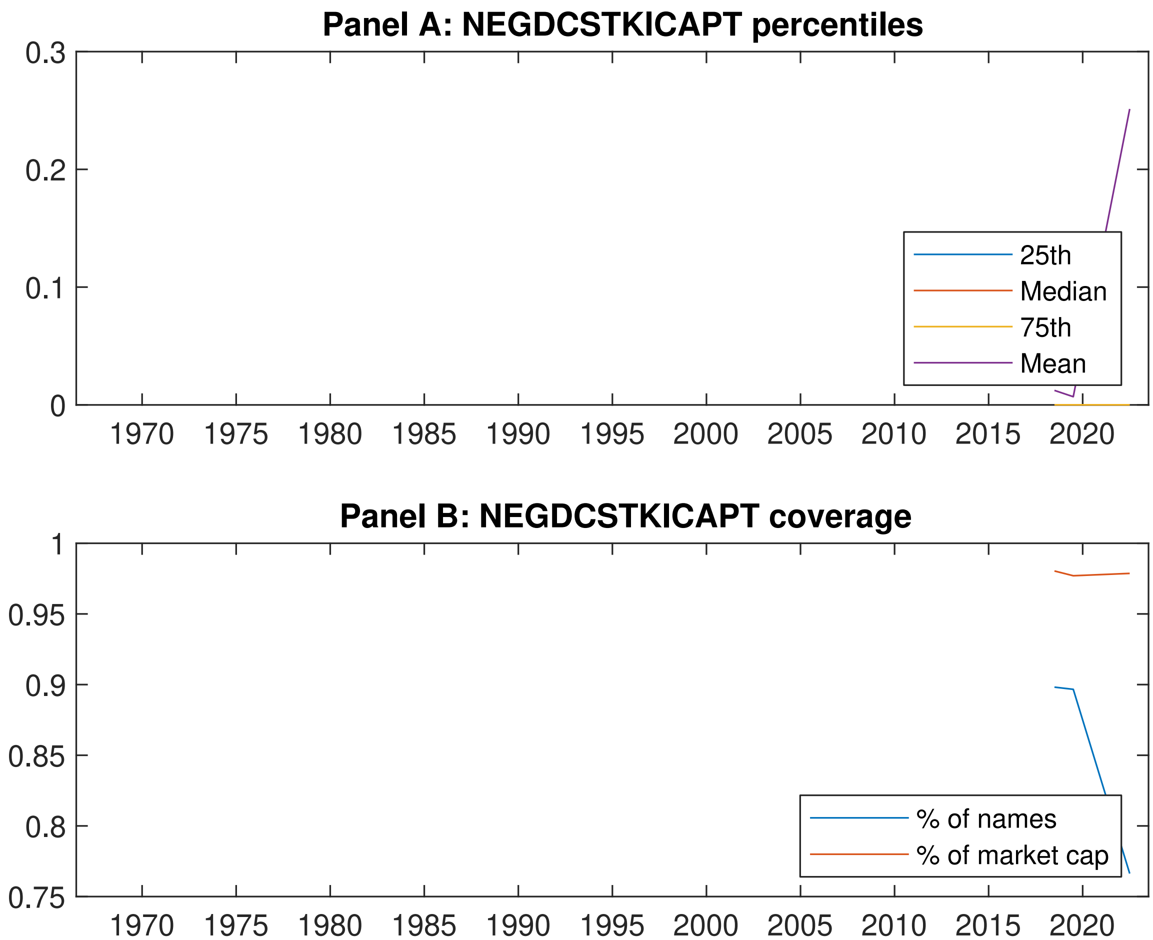

Figure 1: Times series of SCED percentiles and coverage.
This figure plots descriptive statistics for SCED. Panel A shows cross-sectional percentiles of SCED over the sample. Panel B plots the monthly coverage of SCED relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SCED. 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 SCED-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.52	0.65	0.67	0.77	0.36
	[2.29]	[2.77]	[3.43]	[3.93]	[4.55]	[4.64]
α_{CAPM}	-0.15	-0.08	0.05	0.14	0.24	0.38
	[-2.83]	[-1.68]	[1.07]	[2.84]	[5.06]	[4.96]
α_{FF3}	-0.15	-0.07	0.07	0.10	0.19	0.34
	[-2.87]	[-1.45]	[1.36]	[2.25]	[4.30]	[4.40]
α_{FF4}	-0.13	-0.04	0.10	0.05	0.17	0.30
	[-2.43]	[-0.78]	[1.95]	[1.18]	[3.82]	[3.83]
α_{FF5}	-0.17	0.00	0.10	0.01	0.09	0.26
	[-3.23]	[0.04]	[1.90]	[0.29]	[2.20]	[3.41]
α_{FF6}	-0.15	0.02	0.12	-0.02	0.09	0.24
	[-2.88]	[0.45]	[2.33]	[-0.43]	[2.03]	[3.08]
Panel B: Fama and French (2018) 6-factor model loadings for SCED-sorted portfolios						
β_{MKT}	0.97	1.02	1.01	1.01	0.99	0.01
	[79.03]	[95.37]	[83.82]	[97.56]	[96.46]	[0.70]
β_{SMB}	-0.02	0.02	0.04	-0.07	-0.01	0.00
	[-0.97]	[1.05]	[2.53]	[-4.92]	[-0.94]	[0.13]
β_{HML}	0.05	-0.00	-0.05	0.06	0.05	0.00
	[2.11]	[-0.13]	[-2.00]	[3.04]	[2.76]	[0.12]
β_{RMW}	0.12	-0.11	-0.04	0.10	0.12	0.00
	[5.11]	[-5.09]	[-1.63]	[5.10]	[6.24]	[0.04]
β_{CMA}	-0.10	-0.10	-0.04	0.18	0.21	0.31
	[-2.79]	[-3.39]	[-1.18]	[6.26]	[7.32]	[5.97]
β_{UMD}	-0.03	-0.03	-0.04	0.05	0.01	0.04
	[-2.13]	[-2.77]	[-2.95]	[4.79]	[1.00]	[2.00]
Panel C: Average number of firms (n) and market capitalization (me)						
n	794	718	600	702	780	
me ($\$10^6$)	1726	1470	2031	2277	2430	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SCED 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	0.36	0.38	0.34	0.30	0.26	0.24
			[4.64]	[4.96]	[4.40]	[3.83]	[3.41]	[3.08]
Quintile	NYSE	EW	0.53	0.60	0.52	0.44	0.39	0.34
			[8.46]	[10.04]	[9.52]	[8.28]	[7.46]	[6.61]
Quintile	Name	VW	0.34	0.36	0.32	0.29	0.26	0.24
			[4.45]	[4.59]	[4.10]	[3.68]	[3.31]	[3.08]
Quintile	Cap	VW	0.32	0.33	0.30	0.25	0.27	0.24
			[4.03]	[4.17]	[3.77]	[3.14]	[3.47]	[3.04]
Decile	NYSE	VW	0.31	0.32	0.26	0.22	0.25	0.22
			[3.40]	[3.49]	[2.85]	[2.34]	[2.76]	[2.39]

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	0.31	0.29	0.25	0.24
			[4.17]	[4.53]	[4.06]	[3.78]	[3.30]	[3.14]
Quintile	NYSE	EW	0.33	0.38	0.31	0.27	0.18	0.16
			[4.72]	[5.75]	[5.08]	[4.55]	[3.03]	[2.73]
Quintile	Name	VW	0.31	0.33	0.29	0.28	0.25	0.24
			[3.96]	[4.17]	[3.76]	[3.55]	[3.18]	[3.06]
Quintile	Cap	VW	0.28	0.30	0.27	0.24	0.26	0.24
			[3.58]	[3.76]	[3.41]	[3.10]	[3.28]	[3.06]
Decile	NYSE	VW	0.27	0.28	0.23	0.21	0.22	0.21
			[2.94]	[3.07]	[2.52]	[2.26]	[2.43]	[2.29]

Table 3: Conditional sort on size and SCED

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

		SCED Quintiles					SCED Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.43	0.63	0.86	0.92	0.97	0.54	0.60	0.54	0.47	0.42	0.37
		[1.63]	[2.39]	[3.30]	[3.67]	[4.01]	[7.11]	[8.02]	[7.57]	[6.59]	[5.87]	[5.22]
	(2)	0.53	0.63	0.91	0.86	0.95	0.42	0.47	0.38	0.33	0.31	0.27
		[2.27]	[2.58]	[3.72]	[3.73]	[4.25]	[4.85]	[5.52]	[4.70]	[3.99]	[3.72]	[3.27]
	(3)	0.56	0.64	0.79	0.79	0.94	0.38	0.41	0.36	0.35	0.32	0.31
		[2.64]	[2.86]	[3.41]	[3.74]	[4.65]	[5.16]	[5.52]	[4.95]	[4.64]	[4.22]	[4.06]
	(4)	0.50	0.60	0.79	0.80	0.81	0.31	0.35	0.28	0.26	0.13	0.13
		[2.48]	[2.88]	[3.67]	[4.03]	[4.28]	[4.01]	[4.57]	[3.92]	[3.53]	[1.88]	[1.77]
	(5)	0.42	0.50	0.50	0.55	0.72	0.30	0.30	0.27	0.22	0.27	0.23
		[2.44]	[2.61]	[2.74]	[3.16]	[4.30]	[3.23]	[3.18]	[2.85]	[2.34]	[2.81]	[2.44]

Panel B: Portfolio average number of firms and market capitalization

		SCED Quintiles Average n					SCED Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	397	397	396	394	395	32	34	41	30	30
	(2)	112	112	111	111	111	57	57	58	56	57
	(3)	82	81	80	81	81	99	96	99	100	101
	(4)	68	68	68	68	68	205	206	213	216	217
	(5)	62	62	62	62	62	1420	1404	1732	1609	1765

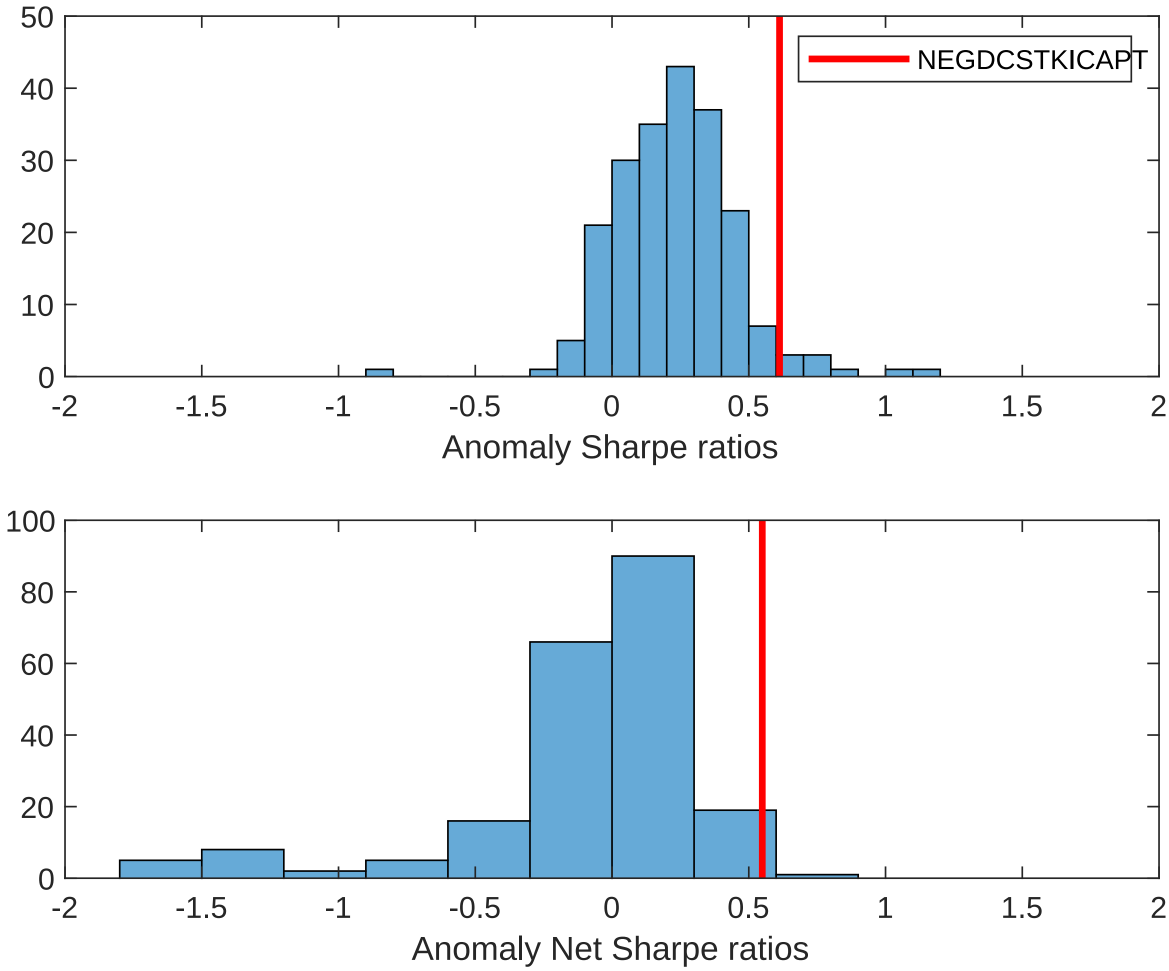

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SCED with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

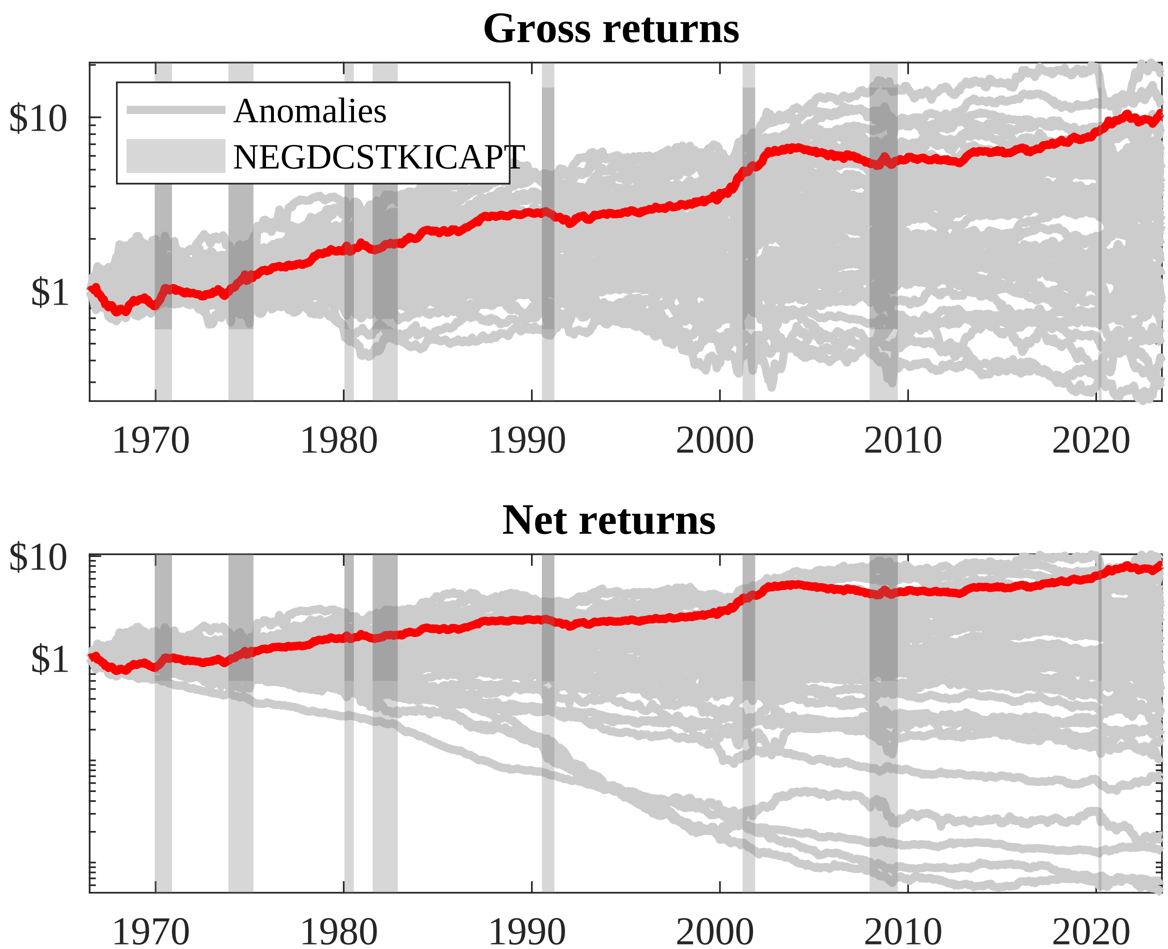

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SCED trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

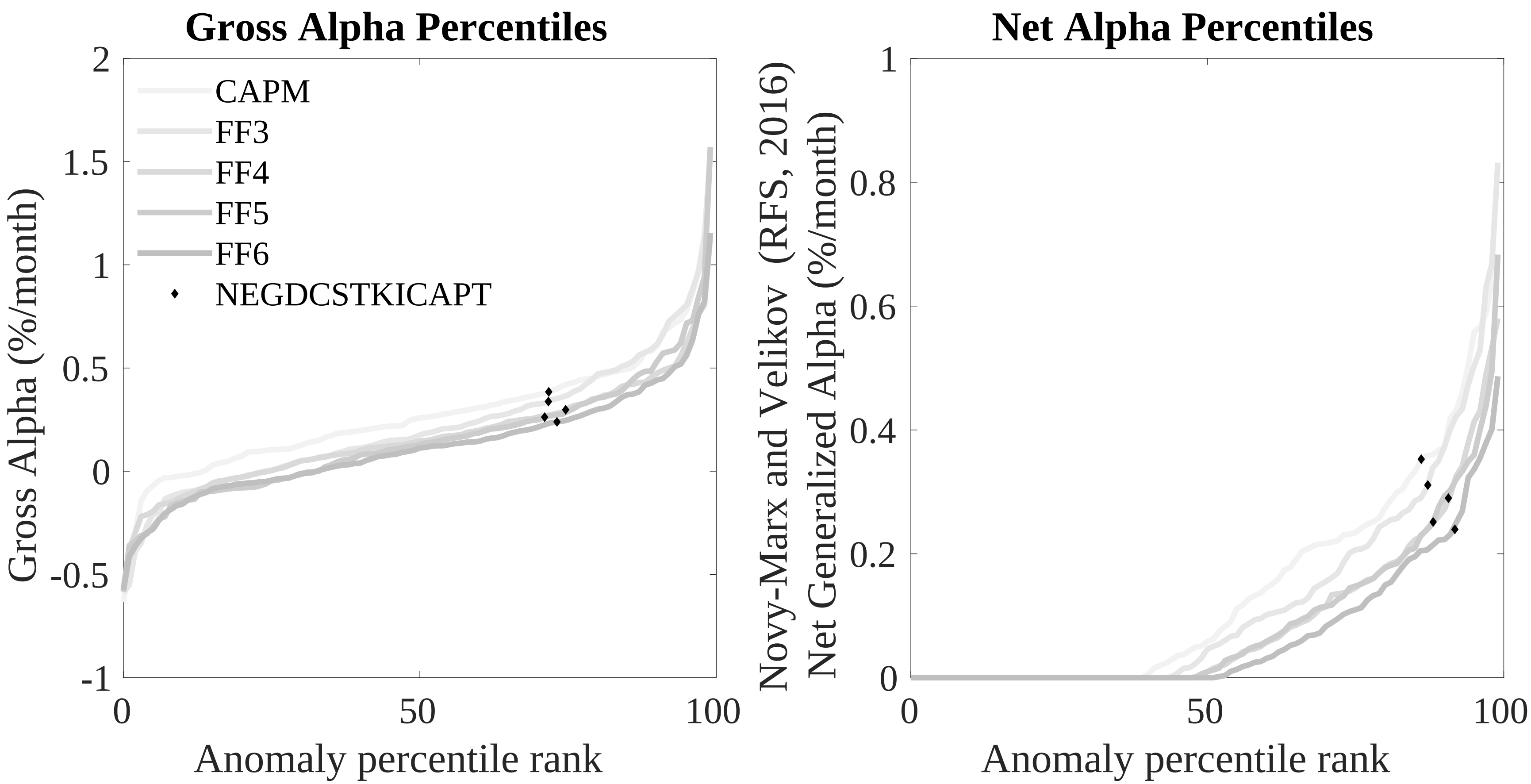

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SCED trading strategy alphas (diamonds). The strategies are constructed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

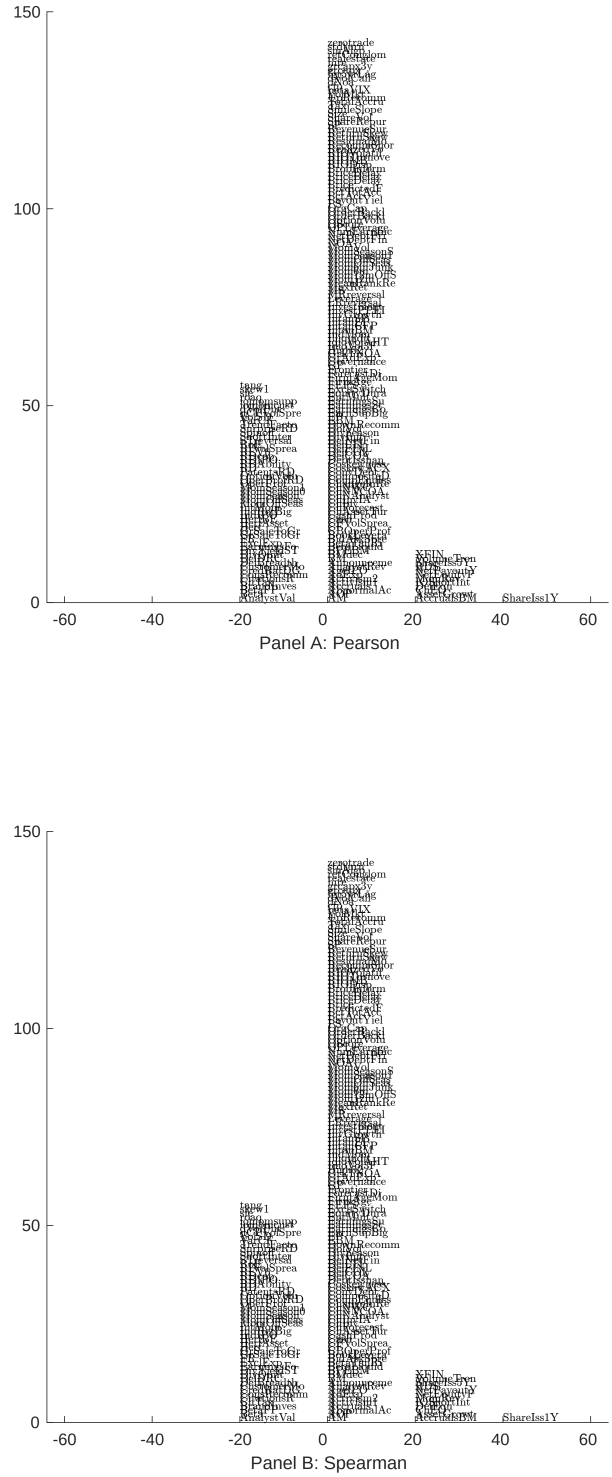

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SCED. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

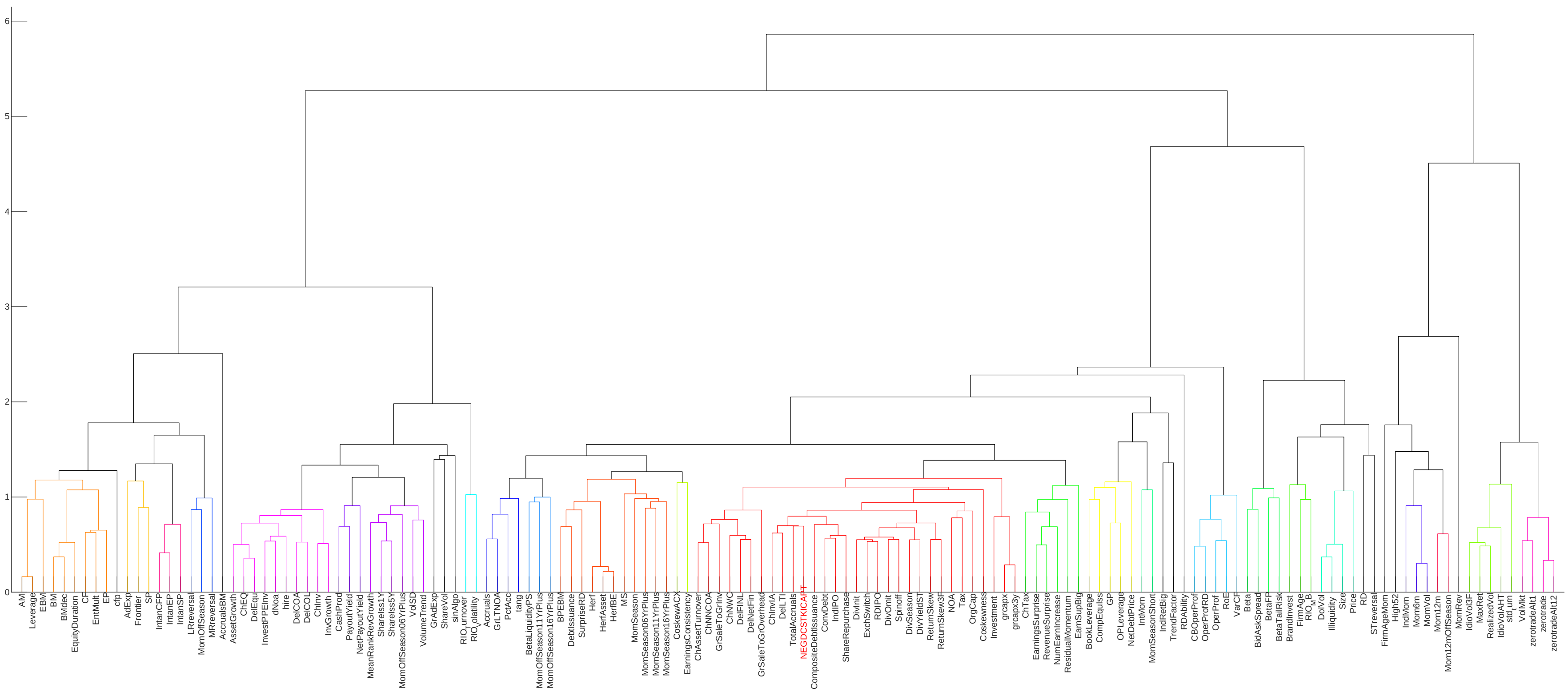

Figure 6: Agglomerative hierarchical cluster plot

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

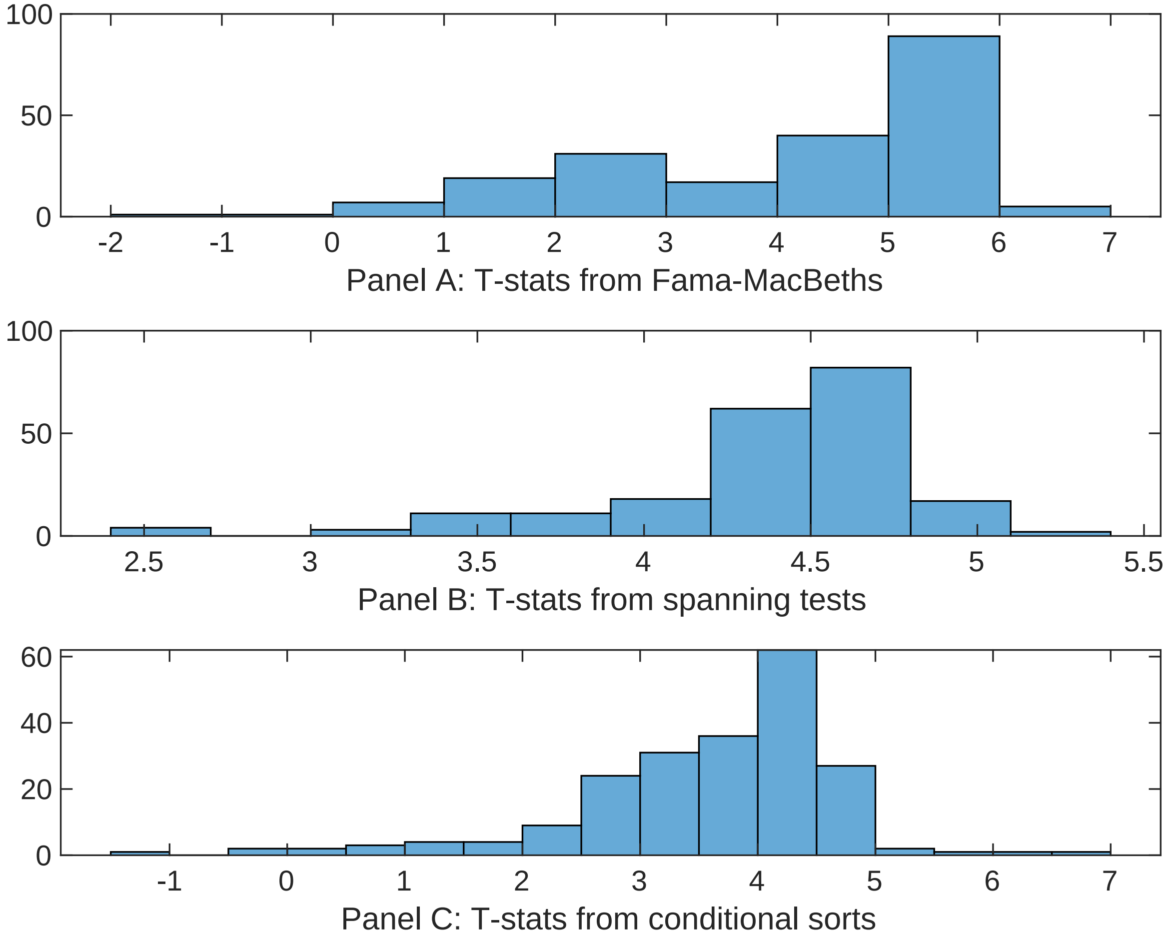

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SCED conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SCED} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SCED} SCED_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SCED,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SCED. Stocks are finally grouped into five SCED portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SCED 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 SCED. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SCED} SCED_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.13	0.17	0.12	0.13	0.12	0.13	0.13
	[5.68]	[7.24]	[5.25]	[6.05]	[5.57]	[6.05]	[5.15]
SCED	0.39	0.31	0.25	0.40	0.35	0.28	0.14
	[5.02]	[4.33]	[2.84]	[5.12]	[4.71]	[3.76]	[1.65]
Anomaly 1	0.26						0.99
	[5.81]						[2.47]
Anomaly 2		0.47					-0.65
		[4.35]					[-0.04]
Anomaly 3			0.27				0.23
			[2.47]				[2.13]
Anomaly 4				0.37			0.39
				[4.30]			[0.43]
Anomaly 5					0.14		-0.18
					[4.04]		[-0.32]
Anomaly 6						0.10	0.68
						[8.86]	[6.48]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SCED trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SCED} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.22	0.24	0.24	0.21	0.26	0.25	0.20
	[2.90]	[3.22]	[3.11]	[2.76]	[3.37]	[3.14]	[2.77]
Anomaly 1	27.40						18.09
	[7.12]						[4.10]
Anomaly 2		36.11					39.26
		[8.77]					[6.57]
Anomaly 3			15.99				3.84
			[5.40]				[1.15]
Anomaly 4				14.81			0.82
				[3.69]			[0.19]
Anomaly 5					20.54		-9.14
					[5.06]		[-1.64]
Anomaly 6						3.64	-18.57
						[0.71]	[-3.52]
mkt	3.57	2.62	4.09	3.53	1.11	1.45	4.97
	[2.02]	[1.50]	[2.23]	[1.90]	[0.62]	[0.79]	[2.78]
smb	1.99	-0.61	3.92	0.08	0.28	0.28	2.80
	[0.78]	[-0.24]	[1.49]	[0.03]	[0.11]	[0.10]	[1.08]
hml	-2.36	-3.37	-4.96	-2.86	-1.73	0.77	-5.85
	[-0.68]	[-0.99]	[-1.35]	[-0.77]	[-0.49]	[0.22]	[-1.63]
rmw	-9.00	1.76	-8.98	-2.74	1.91	-0.21	-6.85
	[-2.45]	[0.52]	[-2.31]	[-0.76]	[0.54]	[-0.06]	[-1.71]
cma	17.70	-5.18	19.32	26.64	9.28	26.24	12.56
	[3.26]	[-0.81]	[3.42]	[4.95]	[1.40]	[3.23]	[1.62]
umd	3.44	3.28	5.13	3.91	4.28	3.73	2.47
	[1.98]	[1.90]	[2.89]	[2.19]	[2.39]	[2.04]	[1.43]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	18	19	15	13	13	10	24

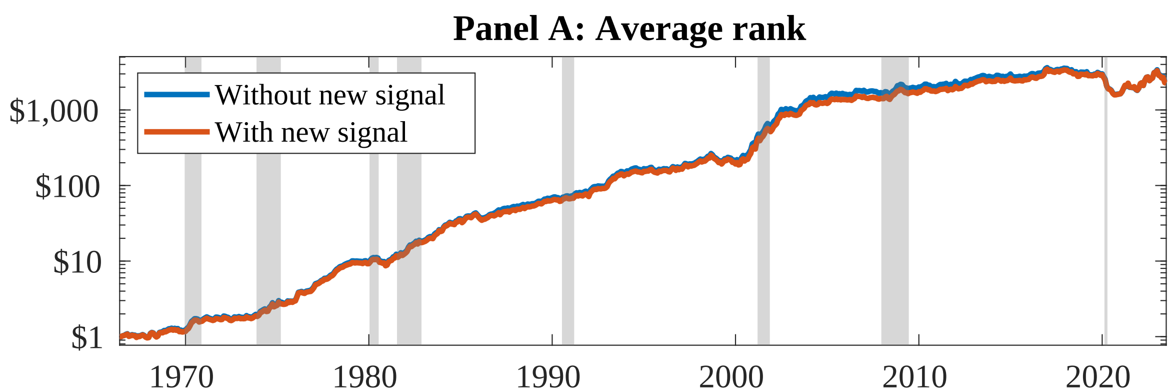

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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