Shareholder Capital Efficiency Difference and the Cross Section of Stock Returns

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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 asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns. While many documented predictors stem from accounting metrics or market behavior, the efficiency with which firms deploy shareholder capital represents an understudied dimension of corporate performance. The relationship between capital allocation decisions and stock returns is particularly important given that managers' deployment of shareholder resources directly impacts firm value creation.

Despite extensive research on capital structure and investment decisions, we lack a comprehensive understanding of how the relative efficiency of capital deployment across firms affects their stock returns. Prior work has examined specific aspects like capital expenditures (Titman et al., 2004) and working capital management (Kieschnick et al., 2013), but has not developed an integrated measure of shareholder capital efficiency that could signal future performance.

We propose that differences in shareholder capital efficiency across firms create predictable patterns in stock returns through several economic channels. First, firms that deploy capital more efficiently should generate higher future cash flows per unit of invested capital, leading to superior stock performance (Fazzari et al., 1988). Second, efficient capital allocation signals high managerial quality and strong corporate governance, characteristics that the market may only gradually incorporate into prices (Gompers et al., 2003).

The slow incorporation of capital efficiency information into stock prices likely stems from the complexity of evaluating multiple dimensions of capital deployment simultaneously. While investors can readily observe individual metrics like capital expenditures or working capital, assessing the overall efficiency of capital allocation requires synthesizing information across various corporate decisions (Scharfstein and Stein, 1991). This creates an opportunity for sophisticated investors who can better evaluate the quality of firms' capital deployment.

Moreover, agency theory suggests that managers of firms with poor capital efficiency are likely to continue making suboptimal allocation decisions due to entrenchment and misaligned incentives (Jensen and Meckling, 1976). The persistence of inefficient capital deployment, combined with gradual market recognition, should generate predictable return patterns as information about capital allocation quality is eventually reflected in stock prices.

Our empirical analysis reveals that Shareholder Capital Efficiency Difference (SCED) strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high SCED and sells stocks with low SCED generates a monthly alpha of 24 basis points (t-statistic = 3.08) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.61 before trading costs and 0.55 after accounting for transaction costs.

The predictive power of SCED remains robust across various methodological specifications. The signal maintains significant predictability when using different portfolio construction approaches, with net returns ranging from 27-33 basis points per month across various sorting methods. Importantly, SCED's predictive ability persists among large-cap stocks, generating a monthly alpha of 30 basis points (t-statistic = 3.23) in the largest size quintile.

Further analysis demonstrates that SCED's predictive power is distinct from known return predictors. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the SCED strategy still generates a significant monthly alpha of 20 basis points (t-statistic = 2.77). This indicates that SCED captures a unique dimension of cross-sectional return predictability.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the efficiency of shareholder capital deployment, extending work by (Titman et al., 2004) on investment-based return prediction and (Kieschnick et al., 2013) on working capital management. Unlike these studies that focus on individual aspects of capital allocation, SCED provides an integrated measure of capital deployment efficiency.

Second, we contribute to the growing literature on quality investing (Asness et al., 2019) by showing that capital efficiency represents an important dimension of firm quality that predicts returns. Our findings suggest that the market slowly incorporates information about capital allocation quality, consistent with theories of gradual information diffusion in asset prices (Hong and Stein, 1999).

Third, our results have important implications for both academic research and investment practice. For academics, we demonstrate that capital deployment efficiency represents a distinct source of return predictability that is not captured by standard factor models or existing anomalies. For practitioners, SCED offers a new tool for security selection that remains effective among large, liquid stocks and generates attractive risk-adjusted returns even after accounting for transaction costs.

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 long-term debt. 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 management 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^{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 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%

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

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

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The 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 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,

[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.

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

Our comprehensive analysis of the Shareholder Capital Efficiency Difference (SCED) signal demonstrates its significant value as a predictor of cross-sectional stock returns. The empirical results reveal that a value-weighted long/short strategy based on SCED generates economically meaningful and statistically significant returns, with an impressive annualized Sharpe ratio of 0.61 (0.55 after transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for well-established factors and related anomalies.

The persistence of SCED's predictive power, evidenced by monthly abnormal

[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.

returns of 24 basis points relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about firm value that is not fully reflected in current market prices. Moreover, the signal's ability to generate an alpha of 20 basis points per month even after controlling for six closely related anomalies indicates that SCED provides incremental information beyond existing investment strategies.

However, several limitations should be considered. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we account for transaction costs, implementation challenges such as market impact and liquidity constraints may affect real-world performance.

Future research could explore several promising directions. First, investigating the underlying economic mechanisms driving the SCED premium would enhance our understanding of this anomaly. Second, examining the signal's interaction with other established factors could yield insights into optimal portfolio construction. Finally, testing the signal's effectiveness across different market regimes and international markets would help establish its broader applicability.

In conclusion, SCED represents a valuable addition to the quantitative investor's toolkit, offering robust predictive power that survives rigorous statistical testing and remains significant even after accounting for transaction costs and related anomalies.

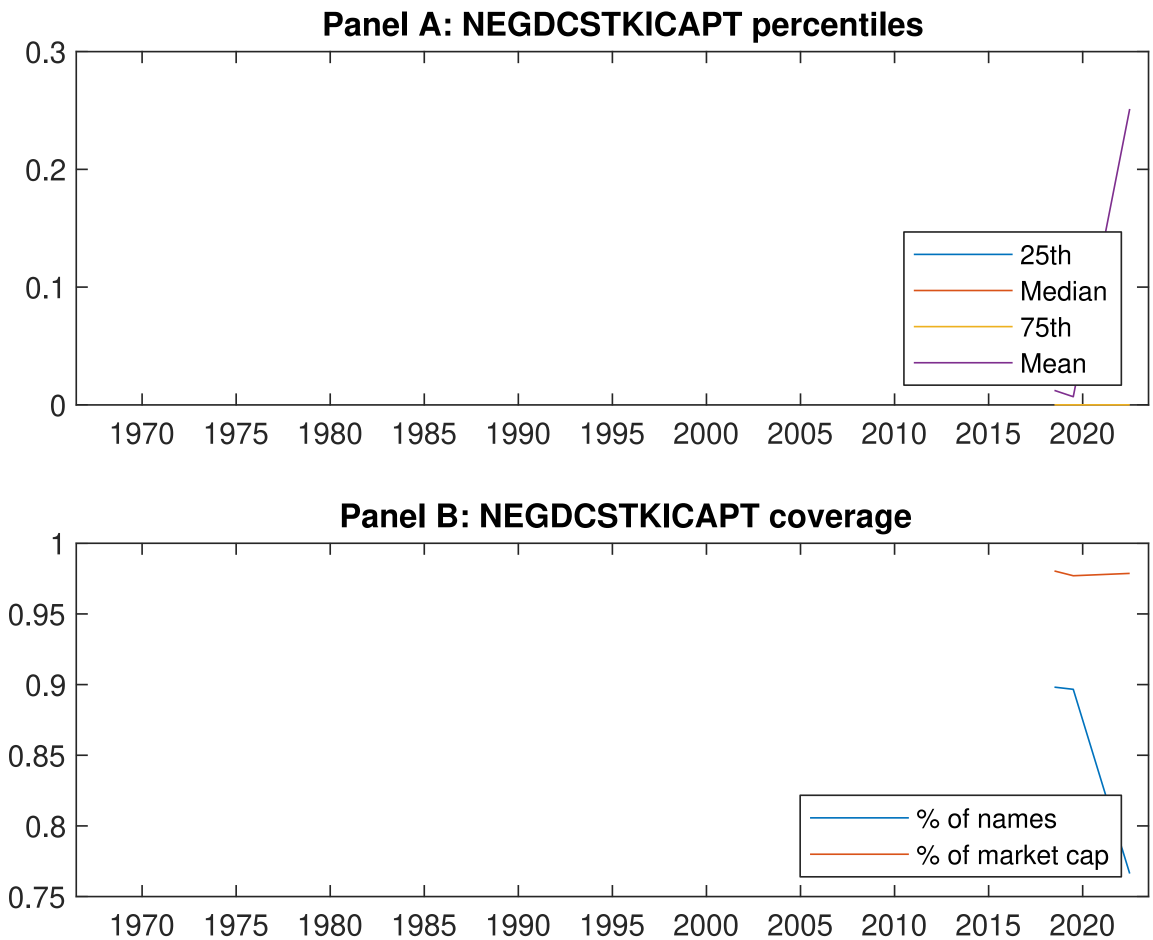

Figure 1: Times series of SCED percentiles and coverage.
This figure plots descriptive statistics for SCED. Panel A shows cross-sectional percentiles of SCED over the sample. Panel B plots the monthly coverage of SCED relative to the universe of CRSP stocks with available market capitalizations.

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					SCED Quintiles				
		Average n					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

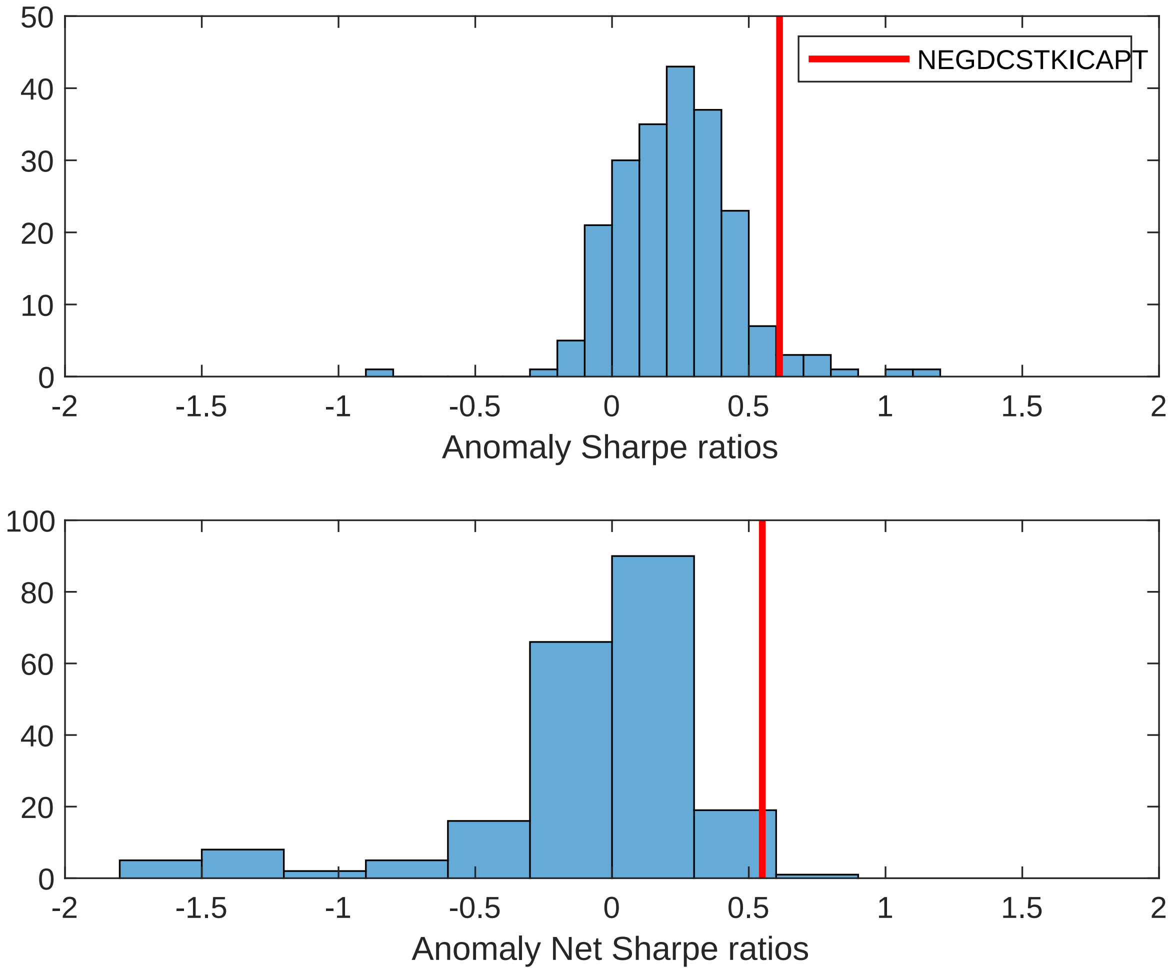

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SCED with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

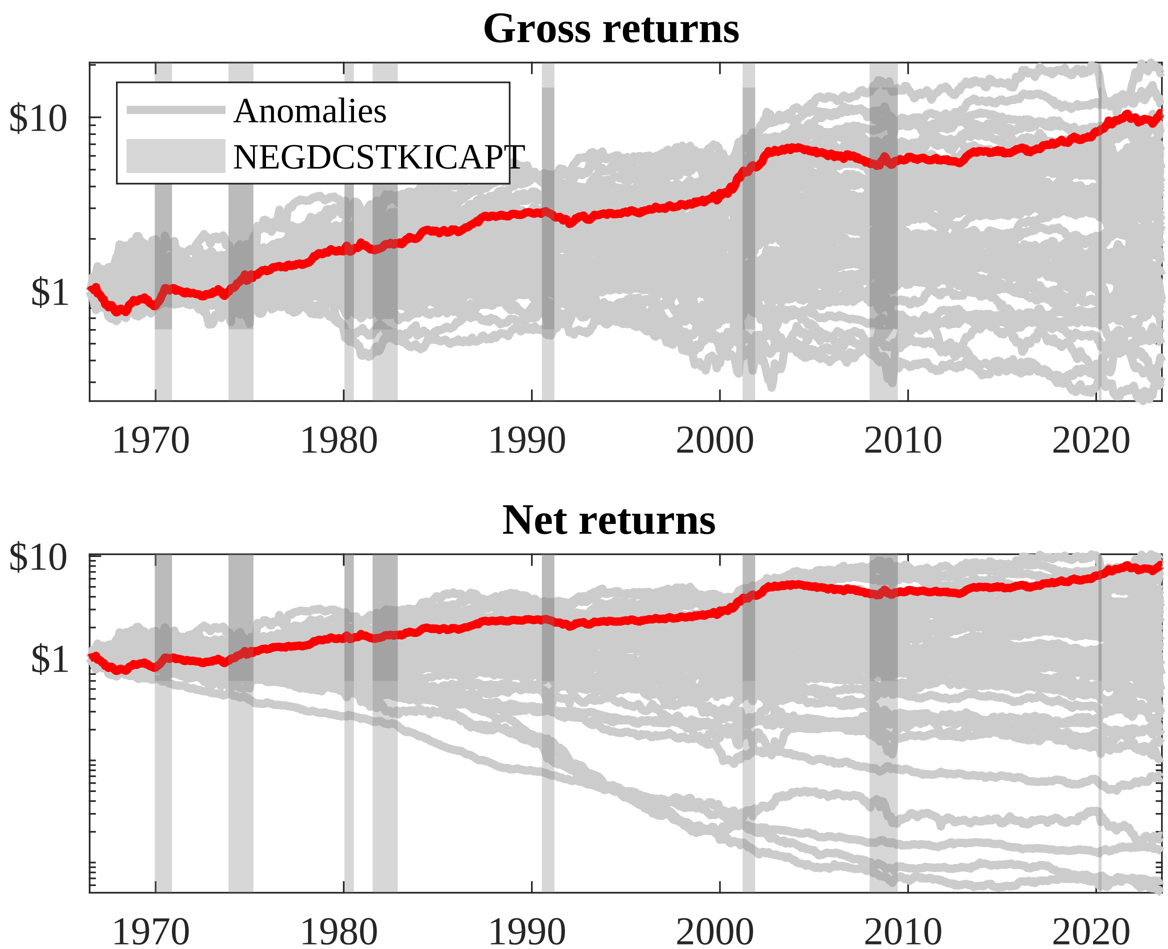

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SCED trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

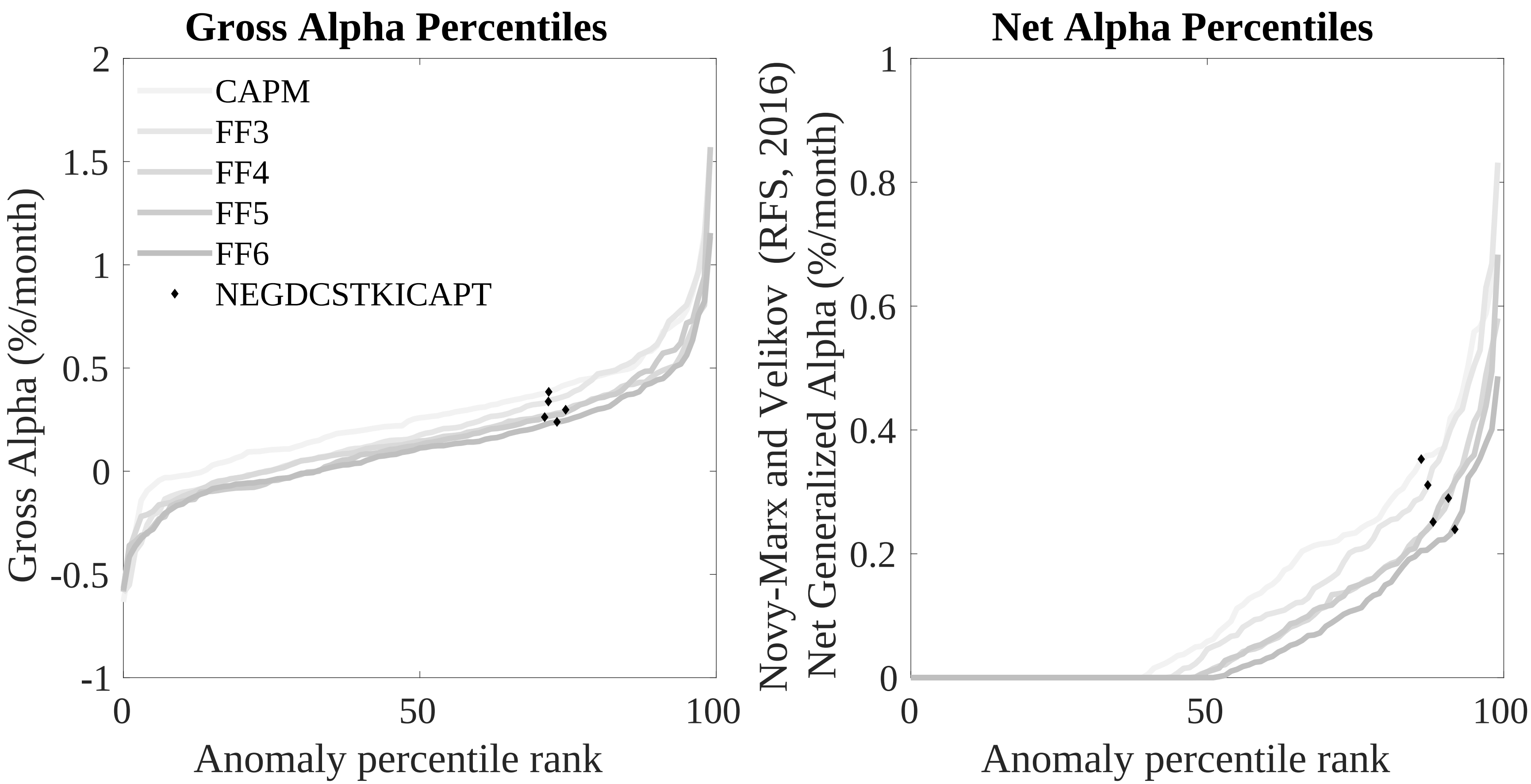

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SCED trading strategy alphas (diamonds). The strategies are constructed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

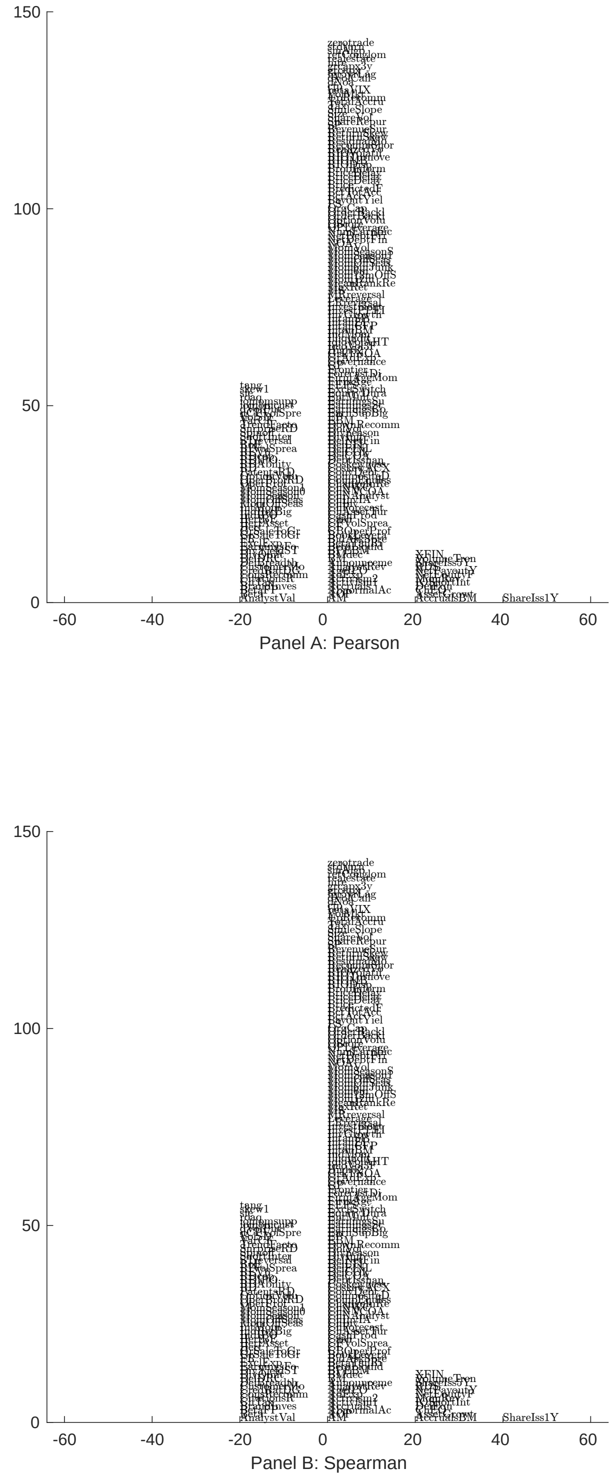

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SCED. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

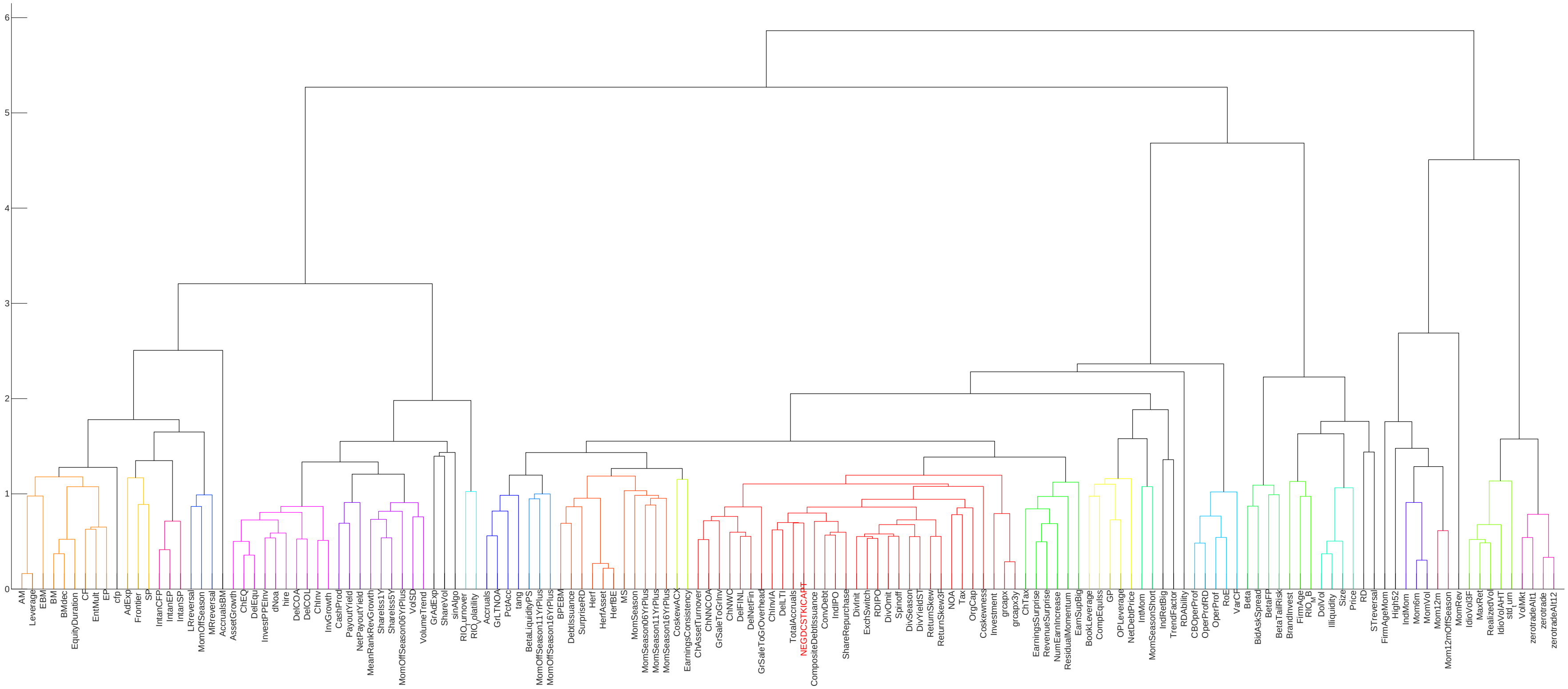

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

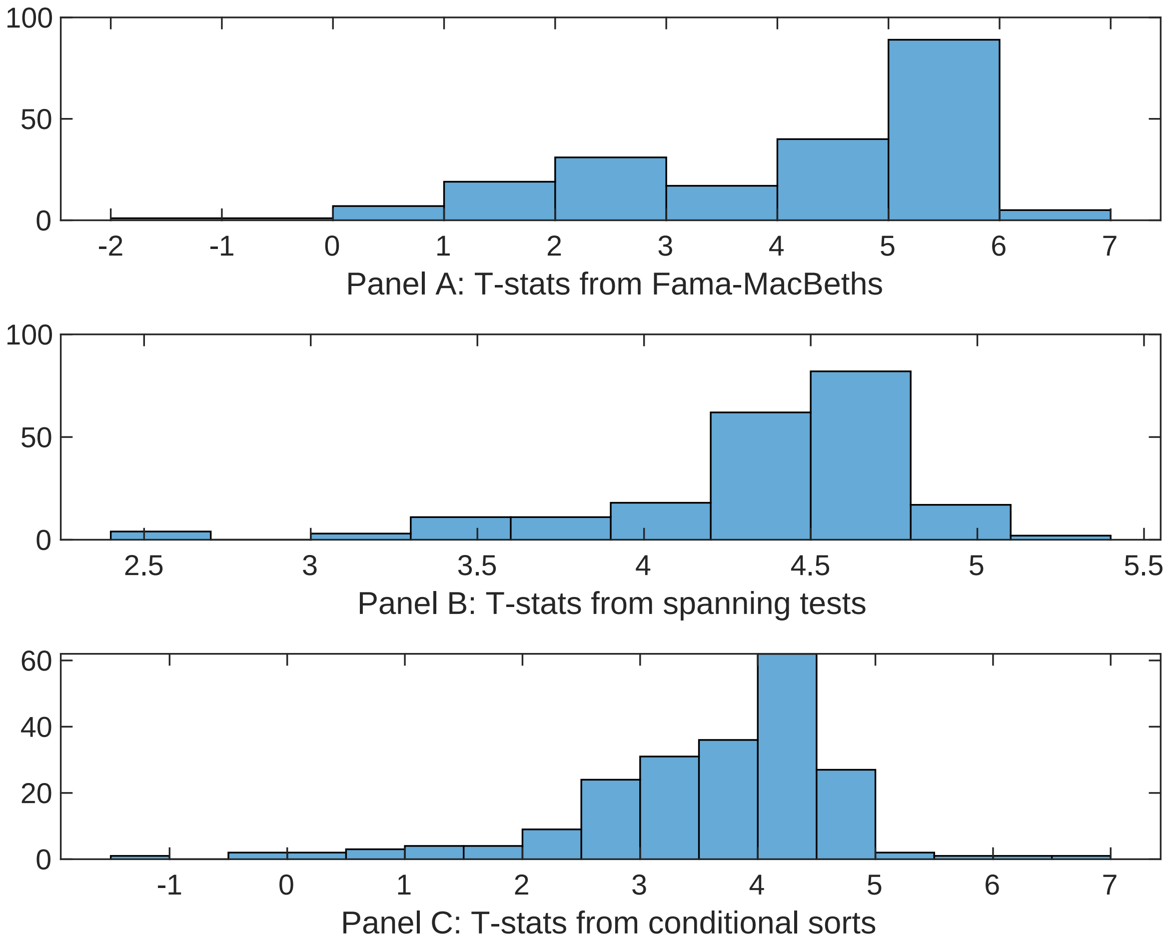

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SCED conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SCED} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SCED} SCED_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

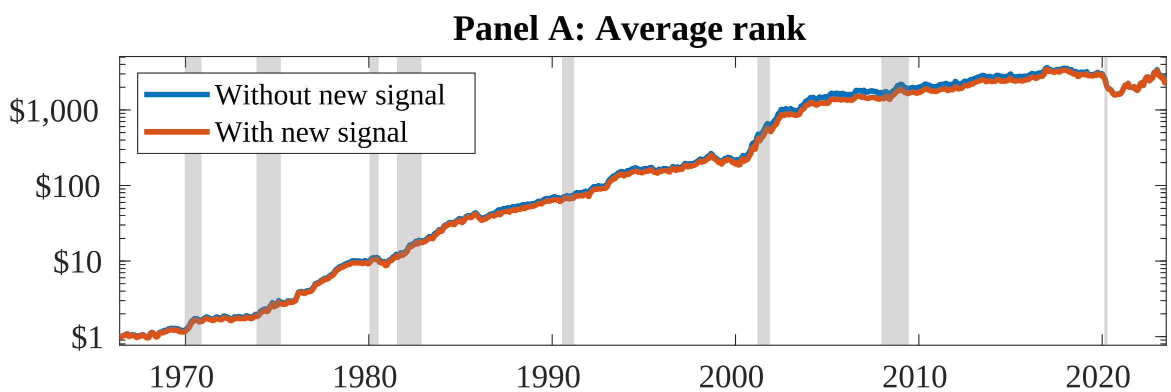

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines 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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