Capital Stock Utilization Delta and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Capital Stock Utilization Delta (CSUD), 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 CSUD achieves an annualized gross (net) Sharpe ratio of 0.51 (0.45), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (19) bps/month with a t-statistic of 2.37 (2.39), 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), Net Payout Yield, Growth in book equity, Change in equity to assets, Share issuance (5 year), Asset growth) is 15 bps/month with a t-statistic of 1.99.

1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While many of these patterns stem from firm-specific financial ratios and market-based indicators, the role of real economic factors in driving cross-sectional return predictability remains less understood. In particular, how firms utilize their productive capacity represents a fundamental aspect of corporate decision-making that may contain valuable information about future profitability and returns.

Prior research has largely focused on capital investment levels rather than the intensity of capital utilization (Titman et al., 2004; Cooper et al., 2008). This gap is notable because utilization rates can change more rapidly than capital stock and may provide more timely signals about management's expectations and operational efficiency. Understanding how changes in capital utilization affect expected returns could shed new light on the mechanisms linking real economic decisions to asset prices.

We propose that changes in capital stock utilization (CSUD) contain predictive information about future stock returns through several economic channels. First, following (Belo et al., 2014), capacity utilization decisions reflect management's private information about future demand conditions. Increases in utilization may signal positive demand expectations that are not yet fully reflected in market prices. Second, building on (Zhang, 2005), firms face asymmetric adjustment costs in changing their capital utilization rates, with upward adjustments typically being less costly than downward adjustments.

This asymmetry creates an important dynamic: firms are more likely to increase utilization when they have strong conviction about future prospects, as the costs of later reducing utilization if needed are relatively high. Conversely, following (Cooper et al., 2021), decreases in utilization may indicate deteriorating conditions that managers, with their superior information, recognize before the market. The persistence of utilization changes also matters - temporary fluctuations likely carry less information than sustained shifts in operating intensity.

Additionally, changes in utilization rates can affect firms' operating leverage and risk profiles (Carlson et al., 2004). Higher utilization typically involves increased fixed costs, making earnings more sensitive to demand shocks. This heightened risk exposure should command a premium in equilibrium, particularly when utilization increases are driven by positive demand expectations rather than simple cost-cutting.

Our empirical analysis reveals that CSUD strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high CSUD and shorts those with low CSUD generates a monthly alpha of 19 basis points (t-statistic = 2.37) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.51, placing it in the top 7% of documented cross-sectional predictors.

Importantly, the predictive power of CSUD persists across size groups. Among the largest quintile of stocks, the long-short CSUD strategy earns a monthly alpha of 23 basis points (t-statistic = 2.32) relative to the Fama-French six-factor model. This finding suggests that the effect is not confined to small, illiquid stocks where trading costs might impede implementation.

The results remain robust after controlling for transaction costs and using alternative portfolio construction methods. The strategy's net Sharpe ratio of 0.45 ranks in the top 1% of anomalies after accounting for trading frictions. Moreover, spanning tests show that CSUD retains significant predictive power (alpha = 15 bps/month, t-statistic = 1.99) even after controlling for the six most closely related anomalies from the literature.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor based on changes in capital utilization that captures information about future returns not contained in traditional investment-based factors. While prior work by (Titman et al., 2004) and (Cooper et al., 2008) examines investment levels, we show that utilization changes provide complementary insights into firms' prospects.

Second, we extend the theoretical framework of (Zhang, 2005) and (Belo et al., 2014) by demonstrating how asymmetric adjustment costs in capacity utilization create predictable patterns in stock returns. Our findings suggest that managers' utilization decisions reveal valuable information about future cash flows that is not immediately incorporated into prices, consistent with recent work on managerial signaling by (Cooper et al., 2021).

Finally, our results have important implications for understanding the relationship between real economic decisions and asset prices. The robust predictive power of CSUD, particularly among large stocks, suggests that capacity utilization changes represent a fundamental driver of expected returns that is distinct from previously documented investment and profitability effects. This finding adds to our understanding of how operational decisions affect firm risk and expected returns.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Capital Stock Utilization Delta. 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 capital stock and item CAPXV for capital expenditure. Capital stock (CSTK) represents the firm's total capital assets, including property, plant, and equipment, while capital expenditure (CAPXV) reflects the firm's investment in long-term assets during the fiscal year.construction of the signal follows a difference-to-scale format, where we first calculate the year-over-year change in CSTK (CSTK minus its lagged value) and then divide this difference by the lagged value of CAPXV for each firm in each year of our sample. This ratio captures the relative change in a firm's capital stock relative to its recent capital investment, offering insight into how effectively the firm is utilizing and expanding its capital base. By focusing on this relationship, the signal aims to reflect aspects of capital efficiency and investment productivity in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and CAPXV to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CSUD signal. Panel A plots the time-series of the mean, median, and interquartile range for CSUD. On average, the cross-sectional mean (median) CSUD is -0.45 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input CSUD data. The signal's interquartile range spans -0.09 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the CSUD signal for the CRSP universe. On average, the CSUD signal is available for 5.87% of CRSP names, which on average make up 7.32% of total market capitalization.

4 Does CSUD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CSUD 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 CSUD portfolio and sells the low CSUD 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 CSUD strategy earns an average return of 0.31% per month with a t-statistic of 3.87. The annualized Sharpe ratio of the strategy is 0.51. The alphas range from 0.19% to 0.34% per month and have t-statistics exceeding 2.37 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 0.34, with a t-statistic of 6.36 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 526 stocks and an average market capitalization of at least $1,348 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 28 bps/month with a t-statistics of 3.46. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for fourteen 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 24-31bps/month. The lowest return, (24 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.00. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CSUD 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-four cases.

Table 3 provides direct tests for the role size plays in the CSUD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CSUD, as well as average returns and alphas for long/short trading CSUD 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 CSUD strategy achieves an average return of 27 bps/month with a t-statistic of 2.80. Among these large cap stocks, the alphas for the CSUD strategy relative to the five most common factor models range from 22 to 28 bps/month with t-statistics between 2.27 and 2.87.

5 How does CSUD perform relative to the zoo?

Figure 2 puts the performance of CSUD 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 CSUD strategy falls in the distribution. The CSUD strategy's gross (net) Sharpe ratio of 0.51 (0.45) is greater than 93% (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 CSUD strategy (red line).[2] Ignoring trading costs, a $1 invested in the CSUD strategy would have yielded $6.73 which ranks the CSUD strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the CSUD strategy would have yielded $4.93 which ranks the CSUD strategy in the top 2% 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 CSUD relative to those. Panel A shows that the CSUD strategy gross alphas fall between the 64 and 69 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 CSUD strategy has a positive net generalized alpha for five out of the five factor models. In these cases CSUD ranks between the 84 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does CSUD 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 CSUD 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 CSUD or at least to weaken the power CSUD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CSUD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CSUD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CSUD} CSUD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CSUD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CSUD. Stocks are finally grouped into five CSUD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CSUD trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CSUD 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 CSUD signal in these Fama-MacBeth regressions exceed 2.79, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on CSUD is 1.71.

Similarly, Table 5 reports results from spanning tests that regress returns to the CSUD 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 CSUD strategy earns alphas that range from 16-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.03, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CSUD trading strategy achieves an alpha of 15bps/month with a t-statistic of 1.99.

7 Does CSUD add relative to the whole zoo?

Finally, we can ask how much adding CSUD 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 CSUD 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 CSUD grows to $2210.06.

8 Conclusion

This study provides compelling evidence for the significance of Capital Stock Utilization Delta (CSUD) as a valuable predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on CSUD generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.51 (0.45) on a gross (net) basis. The strategy's robustness is further validated by its persistent abnormal returns when controlling for traditional risk factors and related anomalies.

Particularly noteworthy is the signal's ability to maintain significant alpha even

[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 CSUD is available.

after accounting for transaction costs and controlling for the Fama-French five-factor model plus momentum, as well as six closely related strategies from the factor zoo. The monthly alpha of 15 basis points (t-statistic = 1.99) in the presence of these controls suggests that CSUD captures unique information about future stock returns that is not fully explained by existing factors.

However, several limitations should be acknowledged. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore the signal's performance in international markets, its interaction with other established anomalies, and its underlying economic mechanisms. Additionally, investigating the signal's effectiveness across different market capitalizations and sectors could provide valuable insights for practitioners. Finally, examining how the signal's predictive power varies with market conditions and economic cycles could enhance our understanding of its practical applications in portfolio management.

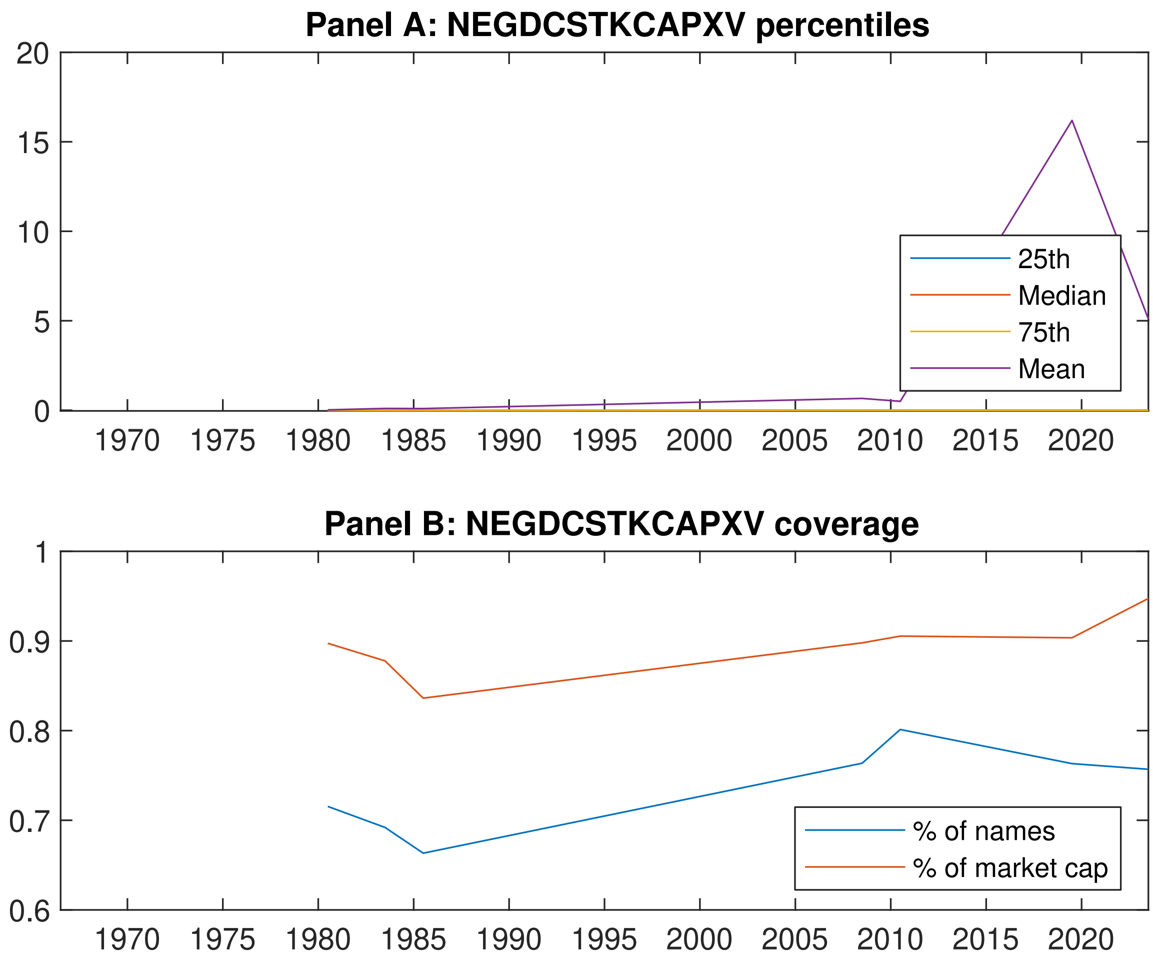

Figure 1: Times series of CSUD percentiles and coverage.
This figure plots descriptive statistics for CSUD. Panel A shows cross-sectional percentiles of CSUD over the sample. Panel B plots the monthly coverage of CSUD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CSUD. 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 CSUD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.47	0.65	0.68	0.76	0.31
	[2.48]	[2.47]	[3.37]	[4.02]	[4.50]	[3.87]
α_{CAPM}	-0.11	-0.13	0.05	0.15	0.23	0.34
	[-2.08]	[-2.70]	[0.88]	[3.07]	[4.79]	[4.24]
α_{FF3}	-0.09	-0.10	0.09	0.13	0.21	0.30
	[-1.66]	[-2.14]	[1.64]	[2.75]	[4.33]	[3.69]
α_{FF4}	-0.07	-0.06	0.10	0.08	0.19	0.26
	[-1.24]	[-1.34]	[1.95]	[1.68]	[3.94]	[3.17]
α_{FF5}	-0.11	-0.04	0.13	0.03	0.10	0.21
	[-2.02]	[-0.81]	[2.35]	[0.62]	[2.22]	[2.64]
α_{FF6}	-0.09	-0.01	0.14	-0.00	0.10	0.19
	[-1.67]	[-0.27]	[2.53]	[-0.07]	[2.15]	[2.37]
Panel B: Fama and French (2018) 6-factor model loadings for CSUD-sorted portfolios						
β_{MKT}	0.97	1.01	1.02	1.00	0.98	0.01
	[74.80]	[91.47]	[79.14]	[91.87]	[89.00]	[0.73]
β_{SMB}	0.01	0.03	0.01	-0.07	-0.01	-0.02
	[0.47]	[1.60]	[0.79]	[-4.34]	[-0.88]	[-0.82]
β_{HML}	-0.04	-0.08	-0.09	-0.01	-0.04	-0.00
	[-1.47]	[-3.75]	[-3.43]	[-0.56]	[-1.82]	[-0.05]
β_{RMW}	0.11	-0.11	-0.05	0.10	0.12	0.00
	[4.55]	[-5.03]	[-2.05]	[4.68]	[5.54]	[0.12]
β_{CMA}	-0.08	-0.07	-0.08	0.25	0.27	0.34
	[-2.06]	[-2.09]	[-2.27]	[8.22]	[8.60]	[6.36]
β_{UMD}	-0.03	-0.04	-0.02	0.05	0.00	0.03
	[-2.21]	[-3.63]	[-1.36]	[4.66]	[0.30]	[1.67]
Panel C: Average number of firms (n) and market capitalization (me)						
n	721	626	526	623	686	
me ($\$10^6$)	1530	1348	1911	2056	2252	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CSUD 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	0.31	0.34	0.30	0.26	0.21	0.19
			[3.87]	[4.24]	[3.69]	[3.17]	[2.64]	[2.37]
Quintile	NYSE	EW	0.52	0.61	0.51	0.43	0.34	0.29
			[7.13]	[8.74]	[8.36]	[7.15]	[5.97]	[5.14]
Quintile	Name	VW	0.30	0.32	0.28	0.24	0.21	0.19
			[3.74]	[3.93]	[3.42]	[2.87]	[2.59]	[2.26]
Quintile	Cap	VW	0.28	0.29	0.26	0.23	0.23	0.21
			[3.46]	[3.64]	[3.27]	[2.79]	[2.92]	[2.60]
Decile	NYSE	VW	0.35	0.38	0.30	0.26	0.29	0.26
			[3.50]	[3.82]	[3.07]	[2.58]	[2.93]	[2.58]
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	0.28	0.31	0.27	0.25	0.20	0.19
			[3.39]	[3.82]	[3.35]	[3.09]	[2.53]	[2.39]
Quintile	NYSE	EW	0.31	0.39	0.30	0.26	0.13	0.11
			[3.94]	[5.10]	[4.44]	[3.92]	[1.99]	[1.75]
Quintile	Name	VW	0.27	0.29	0.25	0.23	0.20	0.18
			[3.26]	[3.52]	[3.06]	[2.78]	[2.46]	[2.28]
Quintile	Cap	VW	0.24	0.26	0.23	0.22	0.22	0.20
			[3.00]	[3.25]	[2.93]	[2.69]	[2.74]	[2.57]
Decile	NYSE	VW	0.31	0.34	0.27	0.24	0.25	0.24
			[3.06]	[3.37]	[2.73]	[2.48]	[2.59]	[2.48]

Table 3: Conditional sort on size and CSUD

This table presents results for conditional double sorts on size and CSUD. 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 CSUD. 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 CSUD and short stocks with low CSUD .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

Size quintiles	CSUD Quintiles (L)	(2)	(3)	(4)	(H)	CSUD Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.38	0.64	0.87	0.96	1.00	0.62	0.69	0.58	0.51	0.39	0.35
	[1.33]	[2.33]	[3.25]	[3.60]	[4.00]	[6.34]	[7.25]	[6.78]	[5.95]	[4.73]	[4.22]
(2)	0.46	0.65	0.87	0.90	0.94	0.48	0.55	0.42	0.37	0.28	0.26
	[1.85]	[2.63]	[3.44]	[3.80]	[4.10]	[4.85]	[5.69]	[4.78]	[4.16]	[3.27]	[2.90]
(3)	0.59	0.66	0.74	0.84	0.93	0.34	0.39	0.31	0.28	0.22	0.21
	[2.67]	[2.98]	[3.13]	[3.88]	[4.52]	[4.00]	[4.65]	[3.85]	[3.40]	[2.72]	[2.48]
(4)	0.52	0.59	0.80	0.79	0.81	0.29	0.33	0.25	0.23	0.08	0.08
	[2.55]	[2.83]	[3.68]	[3.95]	[4.24]	[3.57]	[4.12]	[3.31]	[3.01]	[1.06]	[1.05]
(5)	0.47	0.48	0.55	0.50	0.73	0.27	0.28	0.25	0.22	0.24	0.23
	[2.69]	[2.55]	[2.99]	[2.87]	[4.40]	[2.80]	[2.87]	[2.57]	[2.27]	[2.52]	[2.32]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	CSUD Quintiles, Average n (L)	(2)	(3)	(4)	(H)	CSUD Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	350	350	349	347	349	25	29	35	26	25
(2)	99	98	98	98	98	49	50	50	50	50
(3)	72	71	71	71	71	87	85	88	88	89
(4)	62	61	61	62	62	189	188	196	198	200
(5)	57	57	56	56	56	1306	1316	1596	1465	1615

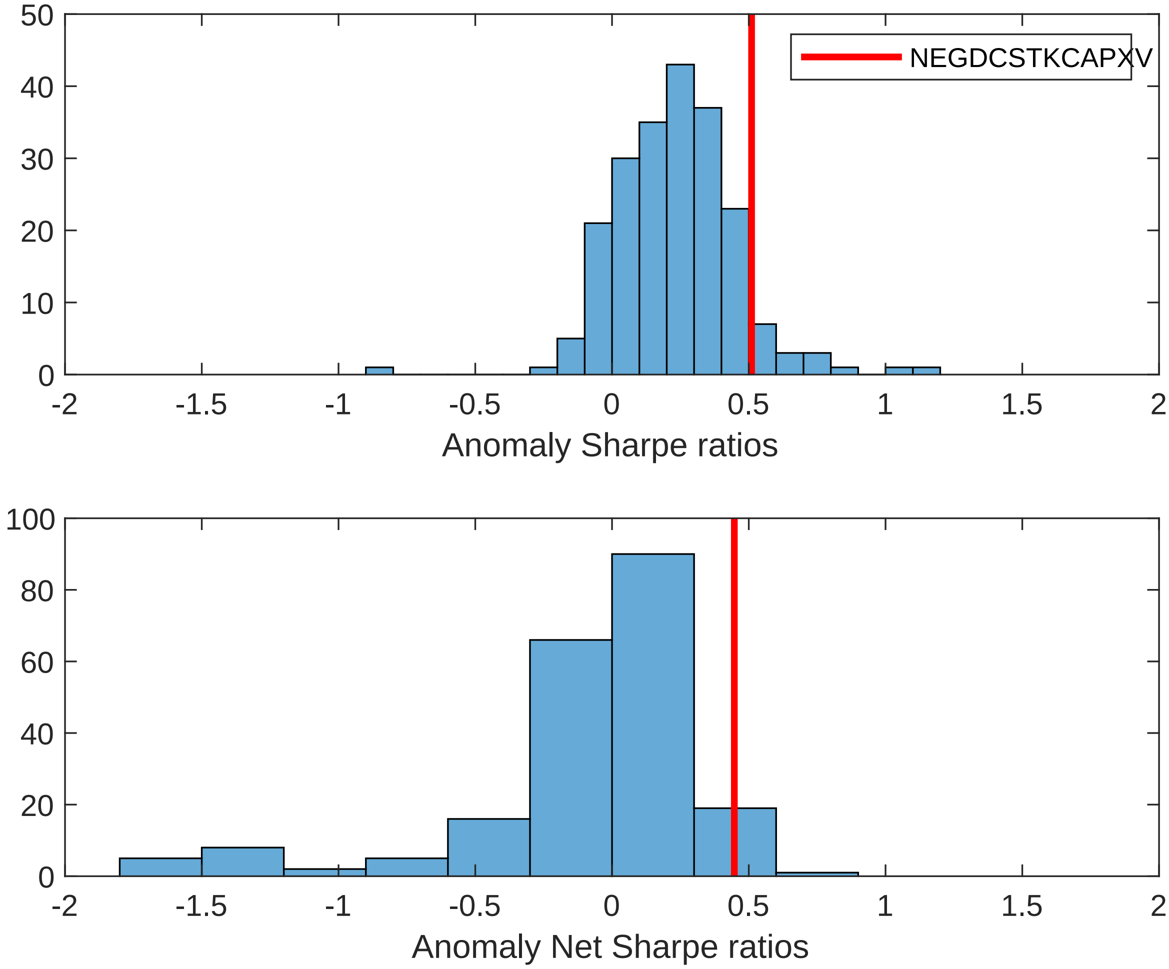

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CSUD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

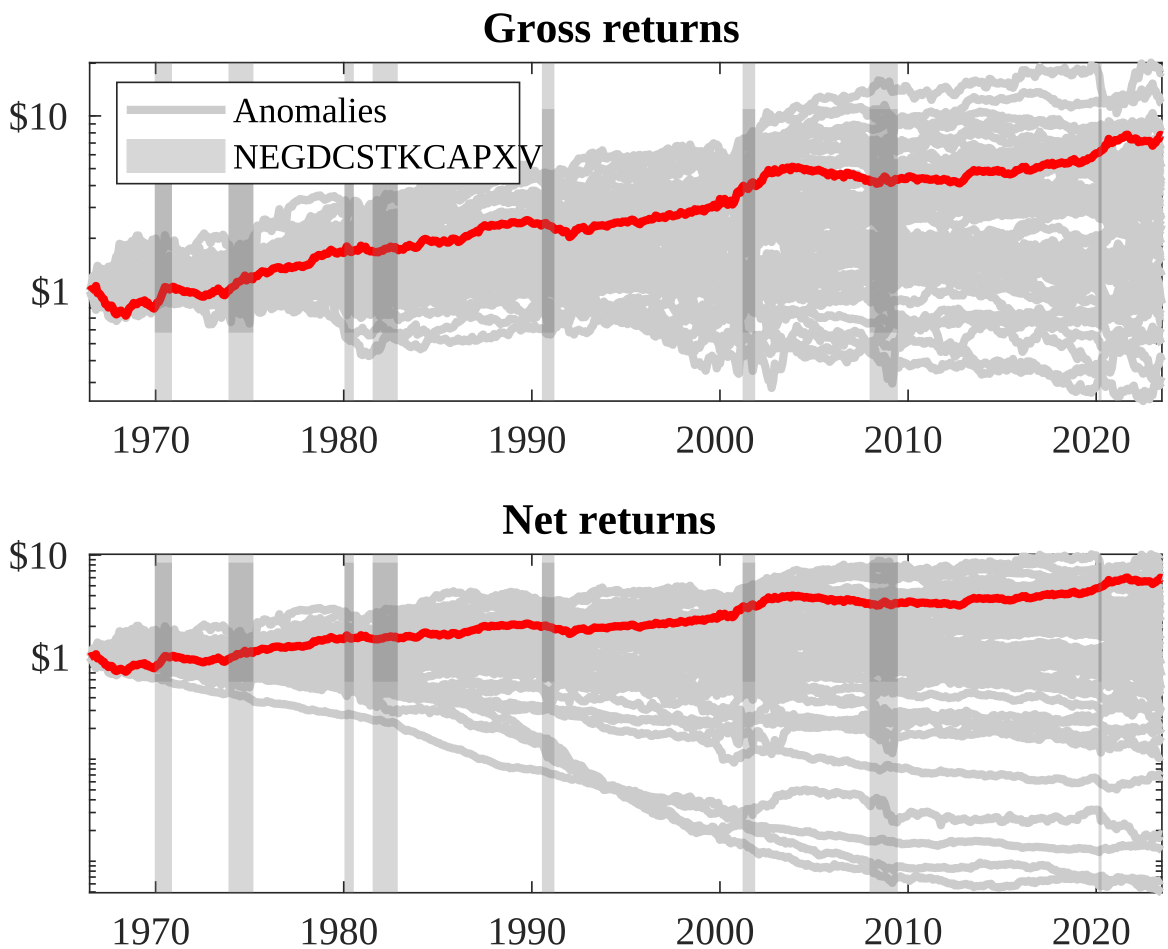

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CSUD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

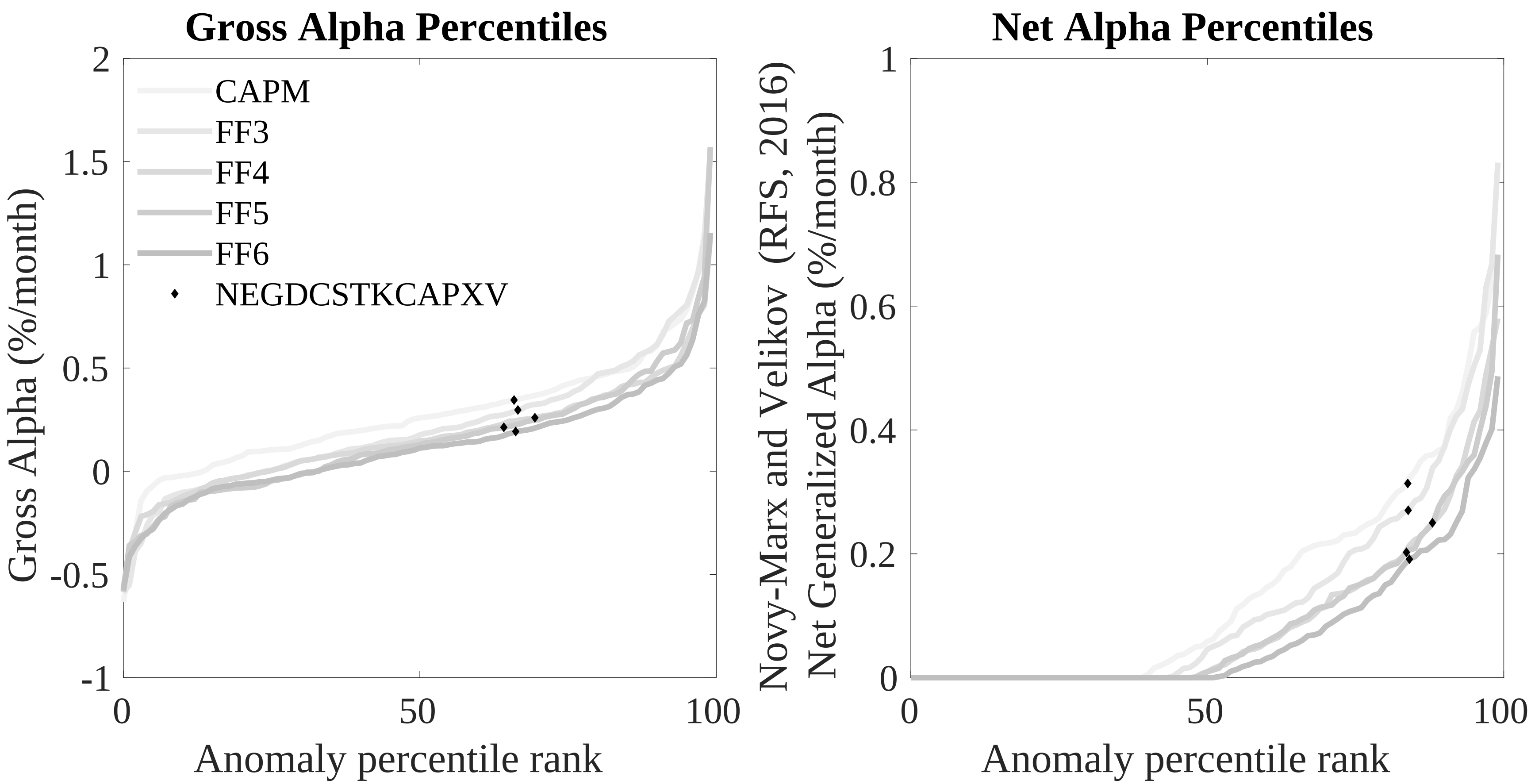

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CSUD trading strategy alphas (diamonds). The strategies are constructed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

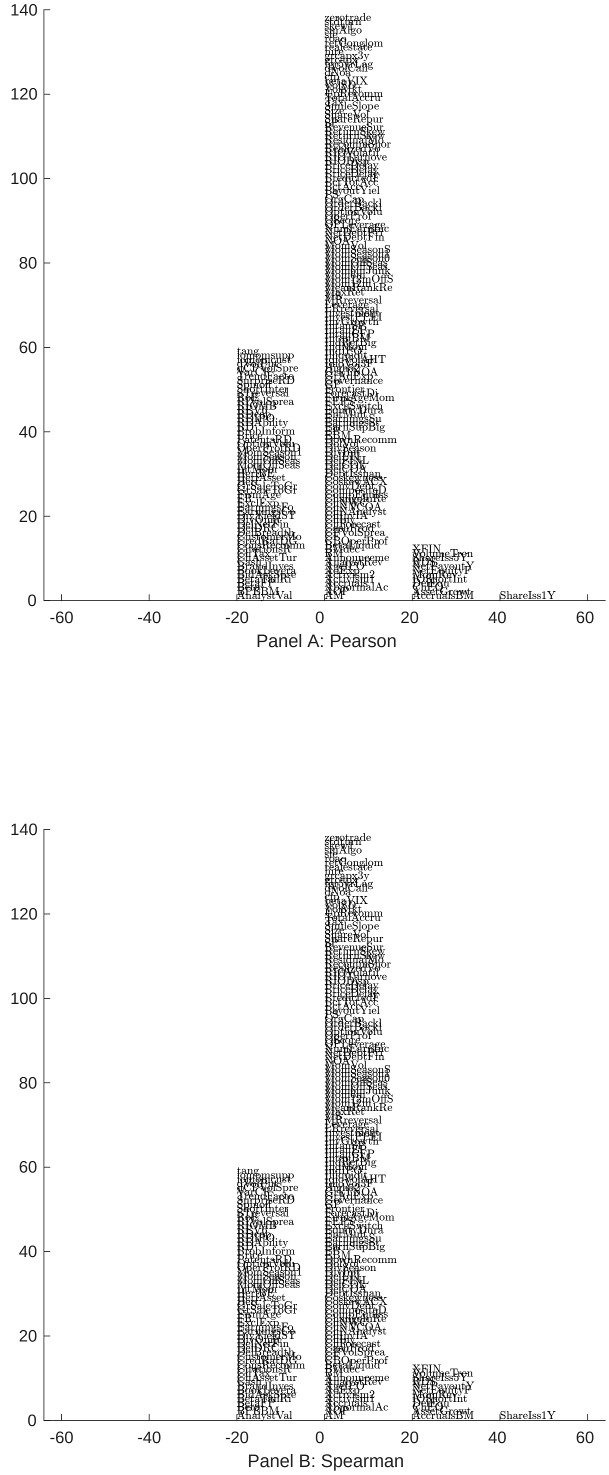

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with CSUD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

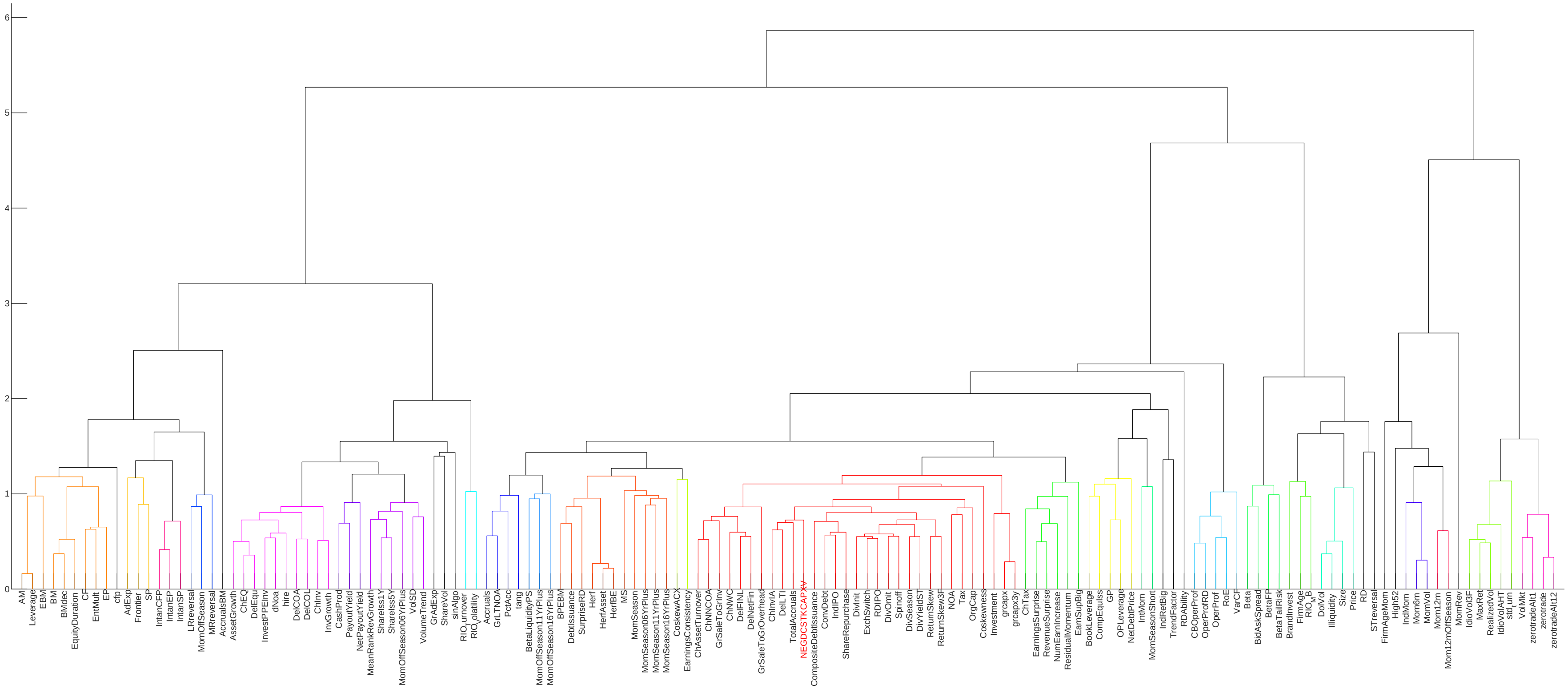

Figure 6: Agglomerative hierarchical cluster plot

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

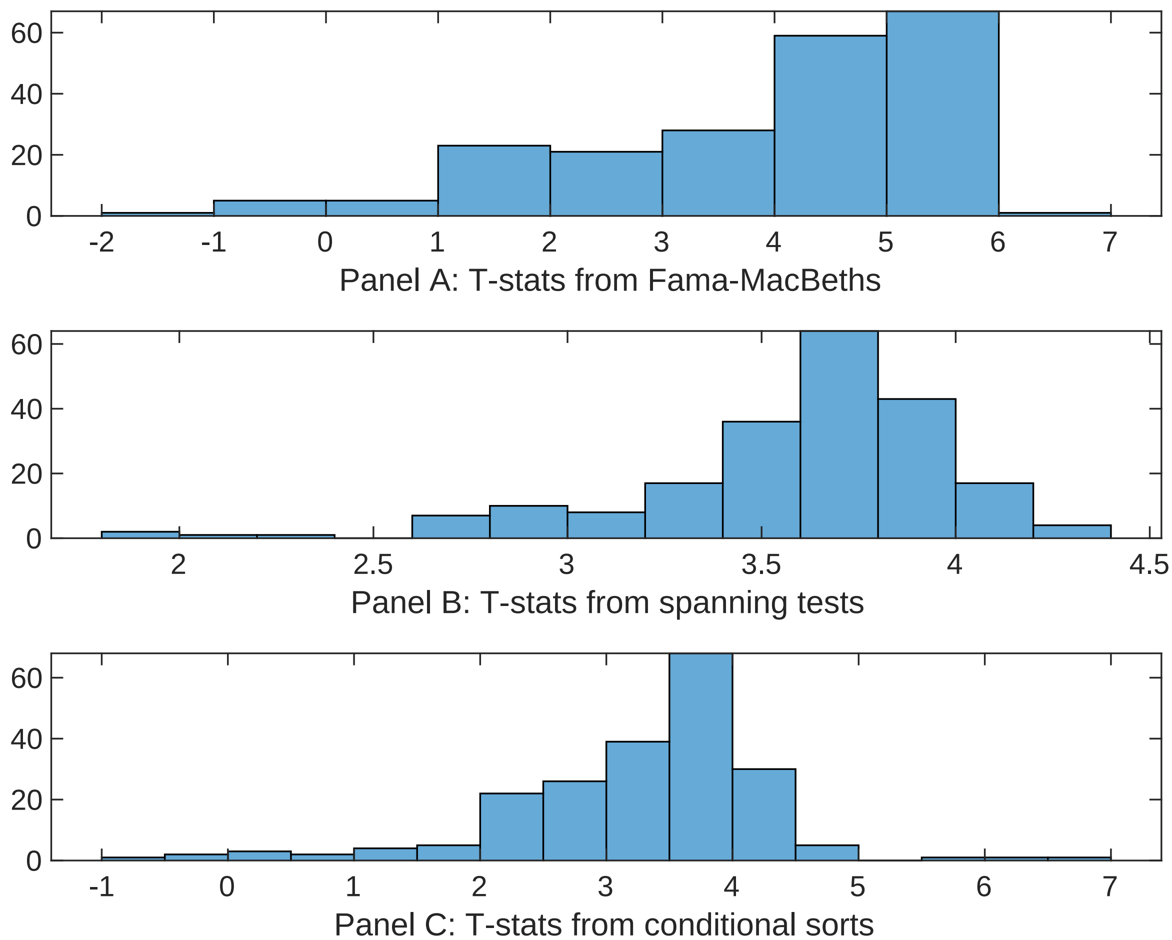

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CSUD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CSUD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CSUD} CSUD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CSUD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CSUD. Stocks are finally grouped into five CSUD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CSUD 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 CSUD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CSUD} CSUD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Change in equity to assets, Share issuance (5 year), 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	0.12	0.18	0.13	0.13	0.13	0.13
	[5.49]	[5.23]	[7.04]	[5.41]	[5.90]	[5.86]	[5.13]
CSUD	0.18	0.10	0.18	0.17	0.18	0.14	0.67
	[4.73]	[2.79]	[4.96]	[4.74]	[4.38]	[3.80]	[1.71]
Anomaly 1	0.26						0.11
	[5.55]						[2.61]
Anomaly 2		0.27					0.23
		[2.38]					[2.12]
Anomaly 3			0.49				0.23
			[4.36]				[0.01]
Anomaly 4				0.14			-0.22
				[3.97]			[-0.39]
Anomaly 5					0.34		0.38
					[3.62]		[0.43]
Anomaly 6						0.10	0.68
						[8.59]	[6.35]
# months	679	679	684	684	679	684	679
$\bar{R}^2(\%)$	0	1	0	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 CSUD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CSUD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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), Net Payout Yield, Growth in book equity, Change in equity to assets, Share issuance (5 year), 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	0.17	0.19	0.19	0.21	0.16	0.20	0.15
	[2.14]	[2.31]	[2.47]	[2.64]	[2.03]	[2.45]	[1.99]
Anomaly 1	24.70						17.53
	[6.06]						[3.72]
Anomaly 2		13.78					2.72
		[4.41]					[0.76]
Anomaly 3			35.05				38.16
			[8.06]				[5.99]
Anomaly 4				20.16			-7.47
				[4.73]			[-1.25]
Anomaly 5					9.12		-4.40
					[2.15]		[-0.98]
Anomaly 6						4.89	-16.53
						[0.91]	[-2.94]
mkt	3.43	3.80	2.60	1.13	2.90	1.47	4.15
	[1.83]	[1.97]	[1.41]	[0.60]	[1.48]	[0.76]	[2.17]
smb	-0.72	0.91	-3.29	-2.43	-2.08	-2.55	0.22
	[-0.27]	[0.33]	[-1.23]	[-0.88]	[-0.75]	[-0.90]	[0.08]
hml	-2.56	-4.63	-3.97	-2.41	-1.65	-0.01	-4.39
	[-0.70]	[-1.19]	[-1.11]	[-0.65]	[-0.42]	[-0.00]	[-1.14]
rmw	-7.57	-7.19	2.19	2.36	-1.04	0.26	-4.31
	[-1.95]	[-1.75]	[0.61]	[0.63]	[-0.27]	[0.07]	[-1.01]
cma	22.59	24.56	-0.68	13.11	32.29	28.17	16.11
	[3.93]	[4.12]	[-0.10]	[1.88]	[5.68]	[3.31]	[1.94]
umd	3.06	4.54	2.83	3.81	3.51	3.32	2.14
	[1.66]	[2.42]	[1.55]	[2.02]	[1.86]	[1.73]	[1.17]
# months	680	680	684	684	680	684	680
$\bar{R}^2$(%)	17	15	18	13	13	11	22

Panel A: Average rank

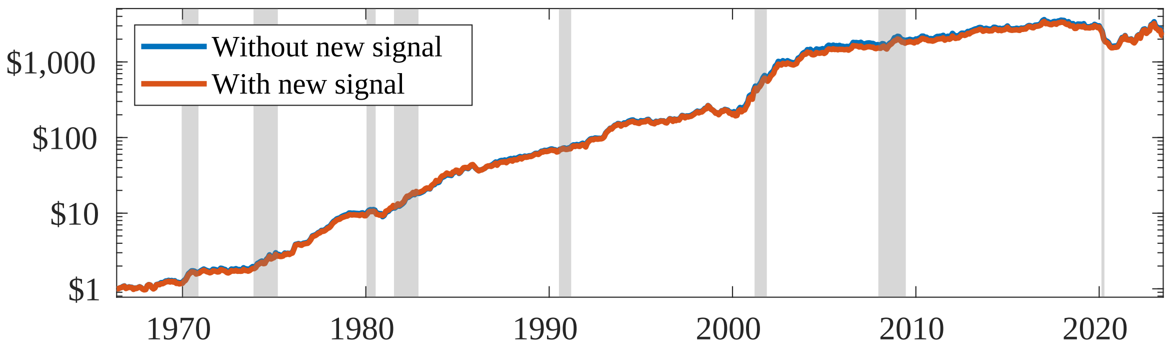

Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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