Debt Capacity Shift and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt Capacity Shift (DCS), 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 DCS achieves an annualized gross (net) Sharpe ratio of 0.49 (0.37), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (24) bps/month with a t-statistic of 3.75 (3.09), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Change in financial liabilities, Change in net financial assets, Accruals, Book leverage (annual), Inventory Growth) is 21 bps/month with a t-statistic of 2.92.

1 Introduction

Market efficiency remains a central question in financial economics, with mounting evidence that certain firm characteristics can predict future stock returns. While many documented predictors stem from accounting information, the literature has paid relatively less attention to how changes in firms' debt capacity affect expected returns. This gap is particularly notable given the fundamental role that debt capacity plays in corporate financial flexibility and investment decisions.

Prior research shows that capital structure choices contain information about future firm prospects, but the dynamic relationship between changes in debt capacity and expected returns remains unexplored. Understanding this relationship is crucial because shifts in debt capacity may signal both changes in investment opportunities and modifications to firms' financial constraints.

We hypothesize that Debt Capacity Shift (DCS) predicts stock returns through two primary economic channels. First, following Myers and Rajan (1998), firms with expanding debt capacity gain financial flexibility, allowing them to pursue valuable investment opportunities without facing severe financing constraints. This enhanced flexibility should lead to higher expected returns as firms capitalize on growth options. Second, building on Almeida and Campello (2007), increases in debt capacity serve as collateral that reduces firms' cost of external financing, thereby increasing their ability to fund positive NPV projects.

The relationship between DCS and expected returns should be particularly pronounced when alternative financing sources are limited. Faulkender and Petersen (2006) show that firms with restricted access to public debt markets face higher costs of capital, suggesting that changes in debt capacity would have greater implications for such firms. Additionally, following Whited and Wu (2006), firms with greater financial constraints should exhibit stronger return predictability from DCS as their investment decisions are more sensitive to changes in debt capacity.

Moreover, the DCS signal should contain information beyond traditional leverage measures because it captures dynamic changes in firms' ability to raise debt rather than static leverage levels. This distinction is important because Lemmon et al. (2008) document that static leverage ratios are largely determined by time-invariant firm characteristics, whereas DCS reflects time-varying changes in firms' financial flexibility.

Our empirical analysis reveals strong evidence that DCS predicts cross-sectional stock returns. A value-weighted long-short portfolio sorting on DCS generates monthly abnormal returns of 29 basis points with a t-statistic of 3.75 relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.49, placing it in the top decile of documented return predictors.

Importantly, the predictive power of DCS remains robust after controlling for transaction costs. The strategy delivers net abnormal returns of 24 basis points per month (t-statistic = 3.09) and a net Sharpe ratio of 0.37. These findings indicate that the DCS effect is both statistically and economically significant even after accounting for implementation costs.

The return predictability is particularly strong among large-cap stocks, with the long-short strategy generating monthly returns of 26 basis points (t-statistic = 2.93) among stocks above the 80th percentile of market capitalization. This result suggests that the DCS effect is distinct from many anomalies that are concentrated in small, illiquid stocks. Moreover, the signal maintains its predictive power after controlling for six closely related anomalies, producing a monthly alpha of 21 basis points (t-statistic = 2.92).

Our paper makes several contributions to the asset pricing and corporate finance literatures. First, we introduce a novel predictor that captures dynamic changes in firms' debt capacity, extending the work of Lemmon et al. (2008) on static leverage and Almeida and Campello (2007) on financial constraints. Unlike existing measures that focus on realized financing decisions or static leverage ratios, DCS provides a forward-looking measure of changes in firms' financial flexibility.

Second, we contribute to the literature on the real effects of financial constraints by showing how changes in debt capacity affect expected returns. While Whited and Wu (2006) and Hadlock and Pierce (2010) develop measures of financial constraints, we demonstrate that changes in debt capacity contain distinct information about future stock returns. Our findings suggest that the market does not fully incorporate the implications of evolving financial flexibility for firm value.

Third, our study advances the understanding of return predictability in efficient markets. The robustness of DCS predictability among large-cap stocks and after controlling for transaction costs challenges the notion that apparent market inefficiencies are concentrated in small, illiquid stocks. These findings complement recent work by Novy-Marx and Velikov (2023) on evaluating trading strategy implementation costs and Chen and Zimmermann (2022) on documenting the factor zoo.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Debt Capacity Shift measure. 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 DLTIS for long-term debt issuance and item EBITDA for earnings before interest, taxes, depreciation, and amortization. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while EBITDA provides a measure of core operating performance by isolating operating income from non-operating expenses and tax effects. The construction of the signal follows a change-based approach, where we calculate the difference between current and previous year's DLTIS, and then scale this change by the previous year's EBITDA. This scaled difference captures the relative change in a firm's debt issuance capacity compared to its operational income base, offering insight into how the firm's ability to access debt markets evolves over time. By focusing on this relationship, the signal aims to reflect aspects of debt capacity dynamics and financial flexibility in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DCS signal. Panel A plots the time-series of the mean, median, and interquartile range for DCS. On average, the cross-sectional mean (median) DCS is 0.05 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DCS data. The signal's interquartile range spans -0.50 to 0.64. Panel B of Figure 1 plots the time-series of the coverage of the DCS signal for the CRSP universe. On average, the DCS signal is available for 6.27% of CRSP names, which on average make up 7.40% of total market capitalization.

4 Does DCS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DCS 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 DCS portfolio and sells the low DCS 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 DCS strategy earns an average return of 0.25% per month with a t-statistic of 3.42. The annualized Sharpe ratio of the strategy is 0.49. The alphas range from 0.28% to 0.31% per month and have t-statistics exceeding 3.75 everywhere. The lowest alpha is with respect to the FF4 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 -0.06, with a t-statistic of -3.56 on the MKT 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 531 stocks and an average market capitalization of at least $1,171 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 name breakpoints and value-weighted portfolios, and equals 20 bps/month with a t-statistics of 2.74. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-five 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 -6-21bps/month. The lowest return, (-6 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.00. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DCS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the DCS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DCS, as well as average returns and alphas for long/short trading DCS 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 DCS strategy achieves an average return of 26 bps/month with a t-statistic of 2.93. Among these large cap stocks, the alphas for the DCS strategy relative to the five most common factor models range from 24 to 32 bps/month with t-statistics between 2.58 and 3.59.

5 How does DCS perform relative to the zoo?

Figure 2 puts the performance of DCS 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 DCS strategy falls in the distribution. The DCS strategy's gross (net) Sharpe ratio of 0.49 (0.37) is greater than 91% (94%) 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 DCS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the DCS strategy would have yielded \$3.29 which ranks the DCS strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DCS strategy would have yielded \$1.97 which ranks the DCS strategy in the top 6% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the DCS relative to those. Panel A shows that the DCS strategy gross alphas fall between the 57 and 78 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 197406 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 DCS strategy has a positive net generalized alpha for five out of the five factor models. In these cases DCS ranks between the 76 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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 DCS. Stocks are finally grouped into five DCS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DCS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DCS 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 DCS signal in these Fama-MacBeth regressions exceed 1.06, with the minimum t-statistic occurring when controlling for Change in financial liabilities. Controlling for all six closely related anomalies, the t-statistic on DCS is 1.78.

Similarly, Table 5 reports results from spanning tests that regress returns to the DCS 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 DCS strategy earns alphas that range from 23-29bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.07, which is achieved when controlling for Change in financial liabilities. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DCS trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.92.

7 Does DCS add relative to the whole zoo?

Finally, we can ask how much adding DCS 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 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the DCS 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 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes DCS grows to $980.45.

8 Conclusion

This study provides compelling evidence for the effectiveness of Debt Capacity Shift (DCS) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on DCS generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.49 (0.37 net). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

[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 DCS is available.

The persistence of the DCS signal's predictive power, evidenced by a monthly alpha of 21 bps (t-statistic = 2.92) after controlling for related factors, suggests that it captures unique information about firms' future performance not fully reflected in existing asset pricing factors. These results have important implications for both academic research and investment practice, offering a valuable tool for portfolio management and asset allocation decisions.

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

Future research could explore the economic mechanisms underlying the DCS signal's predictive power, its interaction with other market anomalies, and its performance in different market regimes. Additionally, investigating the signal's effectiveness in international markets and alternative asset classes could provide valuable insights into its broader applicability and robustness.

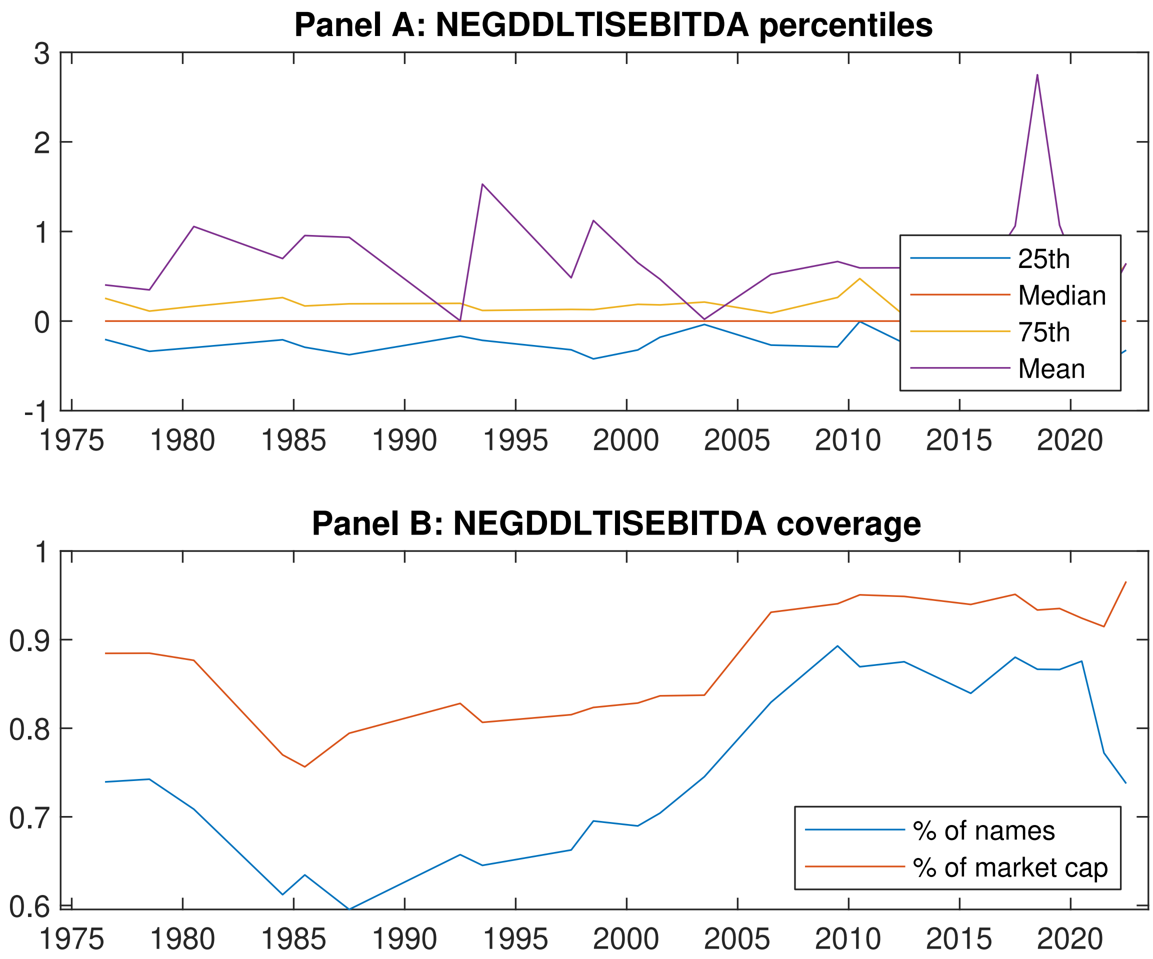

Figure 1: Times series of DCS percentiles and coverage.
This figure plots descriptive statistics for DCS. Panel A shows cross-sectional percentiles of DCS over the sample. Panel B plots the monthly coverage of DCS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DCS. 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 197406 to 202306.

Panel A: Excess returns and alphas on DCS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.55	0.66	0.71	0.80	0.81	0.25
	[2.49]	[3.61]	[3.55]	[4.42]	[3.82]	[3.42]
α_{CAPM}	-0.22	0.02	0.02	0.17	0.07	0.29
	[-3.70]	[0.50]	[0.31]	[3.73]	[1.28]	[3.95]
α_{FF3}	-0.25	-0.01	0.07	0.17	0.05	0.31
	[-4.39]	[-0.37]	[1.30]	[3.77]	[0.97]	[4.15]
α_{FF4}	-0.22	-0.00	0.11	0.13	0.06	0.28
	[-3.76]	[-0.10]	[2.14]	[2.89]	[1.13]	[3.75]
α_{FF5}	-0.24	-0.06	0.09	0.08	0.07	0.30
	[-4.01]	[-1.53]	[1.58]	[1.89]	[1.22]	[4.00]
α_{FF6}	-0.21	-0.05	0.12	0.06	0.07	0.29
	[-3.61]	[-1.24]	[2.17]	[1.41]	[1.33]	[3.75]
Panel B: Fama and French (2018) 6-factor model loadings for DCS-sorted portfolios						
β_{MKT}	1.10	0.98	0.98	0.96	1.04	-0.06
	[81.27]	[103.30]	[77.27]	[96.12]	[82.29]	[-3.56]
β_{SMB}	0.14	-0.12	-0.00	-0.05	0.19	0.05
	[6.54]	[-8.21]	[-0.06]	[-3.07]	[9.66]	[1.91]
β_{HML}	0.09	0.13	-0.15	-0.04	-0.01	-0.10
	[3.44]	[7.20]	[-6.12]	[-1.92]	[-0.52]	[-3.04]
β_{RMW}	0.05	0.10	0.02	0.09	-0.03	-0.08
	[1.93]	[5.25]	[0.62]	[4.76]	[-1.21]	[-2.37]
β_{CMA}	-0.12	0.04	-0.05	0.16	0.01	0.14
	[-3.16]	[1.53]	[-1.30]	[5.60]	[0.31]	[2.67]
β_{UMD}	-0.04	-0.02	-0.06	0.04	-0.01	0.03
	[-2.94]	[-2.16]	[-4.37]	[3.60]	[-0.89]	[1.64]
Panel C: Average number of firms (n) and market capitalization (me)						
n	677	531	1069	577	664	
me ($\$10^6$)	1198	2988	2310	3056	1171	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DCS 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 197406 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	0.25	0.29	0.31	0.28	0.30	0.29
			[3.42]	[3.95]	[4.15]	[3.75]	[4.00]	[3.75]
Quintile	NYSE	EW	0.20	0.22	0.22	0.21	0.22	0.22
			[4.65]	[5.12]	[5.12]	[4.71]	[5.13]	[4.89]
Quintile	Name	VW	0.20	0.25	0.27	0.24	0.24	0.23
			[2.74]	[3.36]	[3.63]	[3.27]	[3.23]	[3.05]
Quintile	Cap	VW	0.23	0.27	0.29	0.25	0.22	0.20
			[3.67]	[4.27]	[4.59]	[3.92]	[3.41]	[3.06]
Decile	NYSE	VW	0.28	0.32	0.33	0.31	0.34	0.34
			[2.96]	[3.33]	[3.42]	[3.23]	[3.52]	[3.40]
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	0.19	0.24	0.25	0.24	0.25	0.24
			[2.57]	[3.20]	[3.35]	[3.16]	[3.26]	[3.09]
Quintile	NYSE	EW	-0.06					
			[-1.00]					
Quintile	Name	VW	0.14	0.20	0.21	0.20	0.20	0.19
			[1.88]	[2.68]	[2.89]	[2.73]	[2.64]	[2.48]
Quintile	Cap	VW	0.18	0.23	0.25	0.23	0.19	0.17
			[2.86]	[3.59]	[3.84]	[3.51]	[2.89]	[2.64]
Decile	NYSE	VW	0.21	0.25	0.25	0.25	0.26	0.26
			[2.14]	[2.57]	[2.64]	[2.56]	[2.69]	[2.61]

Table 3: Conditional sort on size and DCS

This table presents results for conditional double sorts on size and DCS. 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 DCS. 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 DCS and short stocks with low DCS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197406 to 202306.

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

		DCS Quintiles					DCS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.69	0.90	0.96	1.01	0.78	0.09	0.10	0.09	0.05	0.07	0.04
		[2.52]	[3.22]	[3.49]	[3.44]	[2.86]	[1.21]	[1.28]	[1.15]	[0.63]	[0.85]	[0.53]
	(2)	0.75	0.96	0.81	0.98	0.89	0.14	0.17	0.14	0.15	0.15	0.16
		[2.82]	[3.83]	[3.21]	[3.89]	[3.44]	[1.95]	[2.25]	[1.91]	[2.00]	[2.04]	[2.11]
	(3)	0.81	0.89	0.83	0.90	0.91	0.09	0.14	0.14	0.12	0.16	0.14
		[3.23]	[4.00]	[3.37]	[4.08]	[3.79]	[1.18]	[1.71]	[1.68]	[1.42]	[1.89]	[1.69]
	(4)	0.65	0.88	0.88	0.80	0.93	0.29	0.32	0.33	0.31	0.35	0.34
		[2.80]	[4.20]	[3.96]	[3.82]	[4.24]	[3.74]	[4.12]	[4.32]	[3.94]	[4.48]	[4.21]
	(5)	0.49	0.64	0.63	0.74	0.75	0.26	0.29	0.32	0.30	0.25	0.24
		[2.37]	[3.58]	[3.14]	[4.01]	[3.80]	[2.93]	[3.27]	[3.59]	[3.26]	[2.71]	[2.58]

Panel B: Portfolio average number of firms and market capitalization

		DCS Quintiles					DCS Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	397	398	398	398	395	36	34	33	34	35
	(2)	108	108	107	108	107	59	61	58	60	60
	(3)	76	76	76	76	76	105	106	102	104	104
	(4)	64	64	64	64	64	220	232	221	230	220
	(5)	58	59	59	59	59	1285	2053	1867	2106	1300

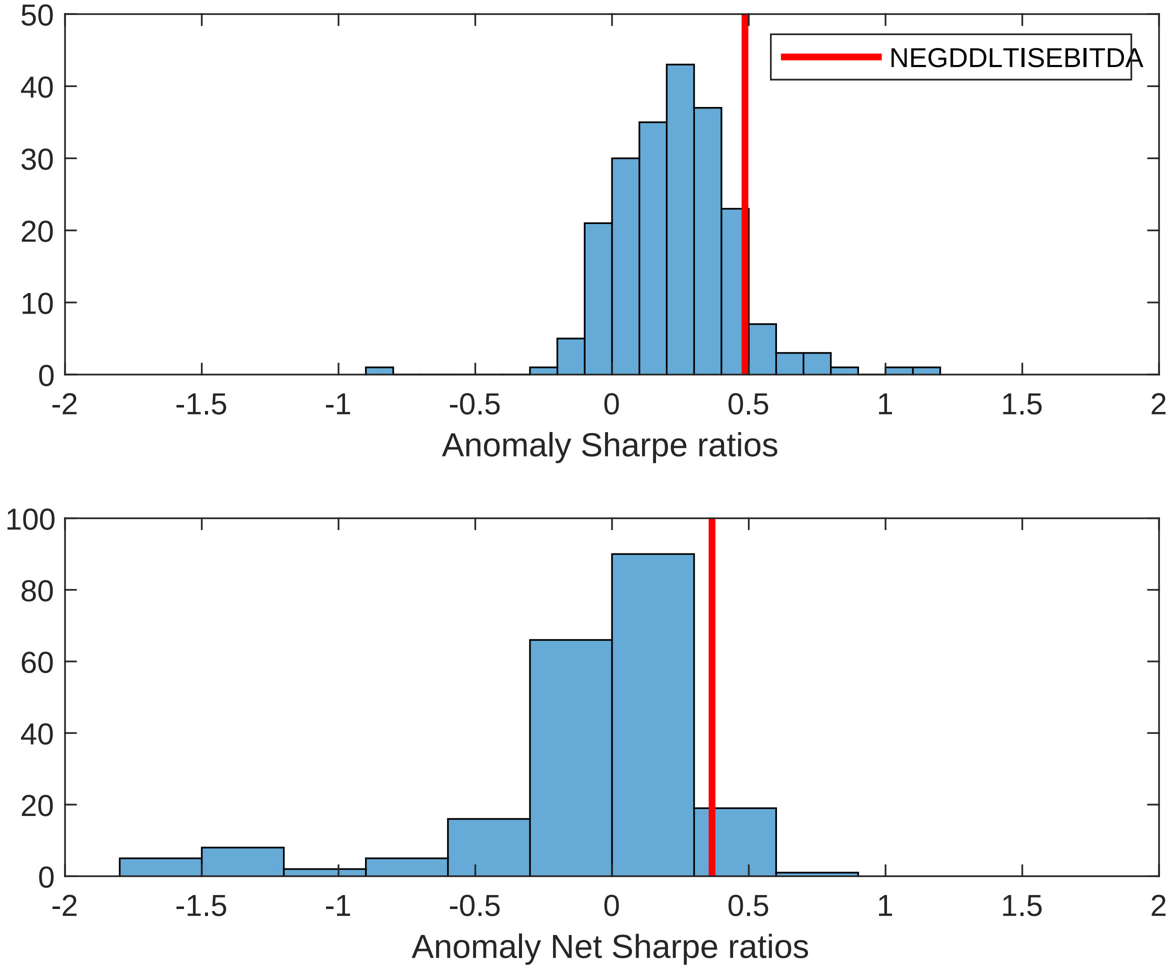

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DCS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

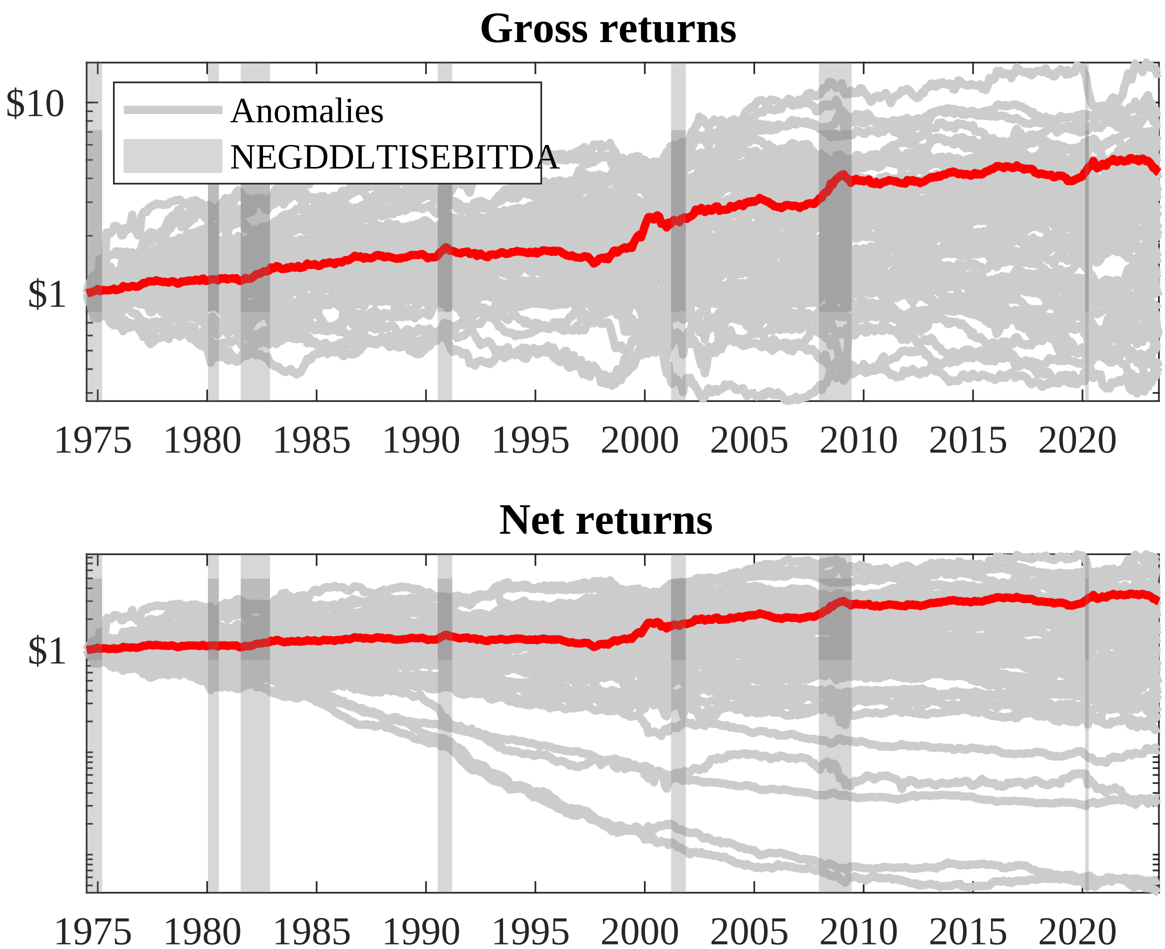

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DCS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

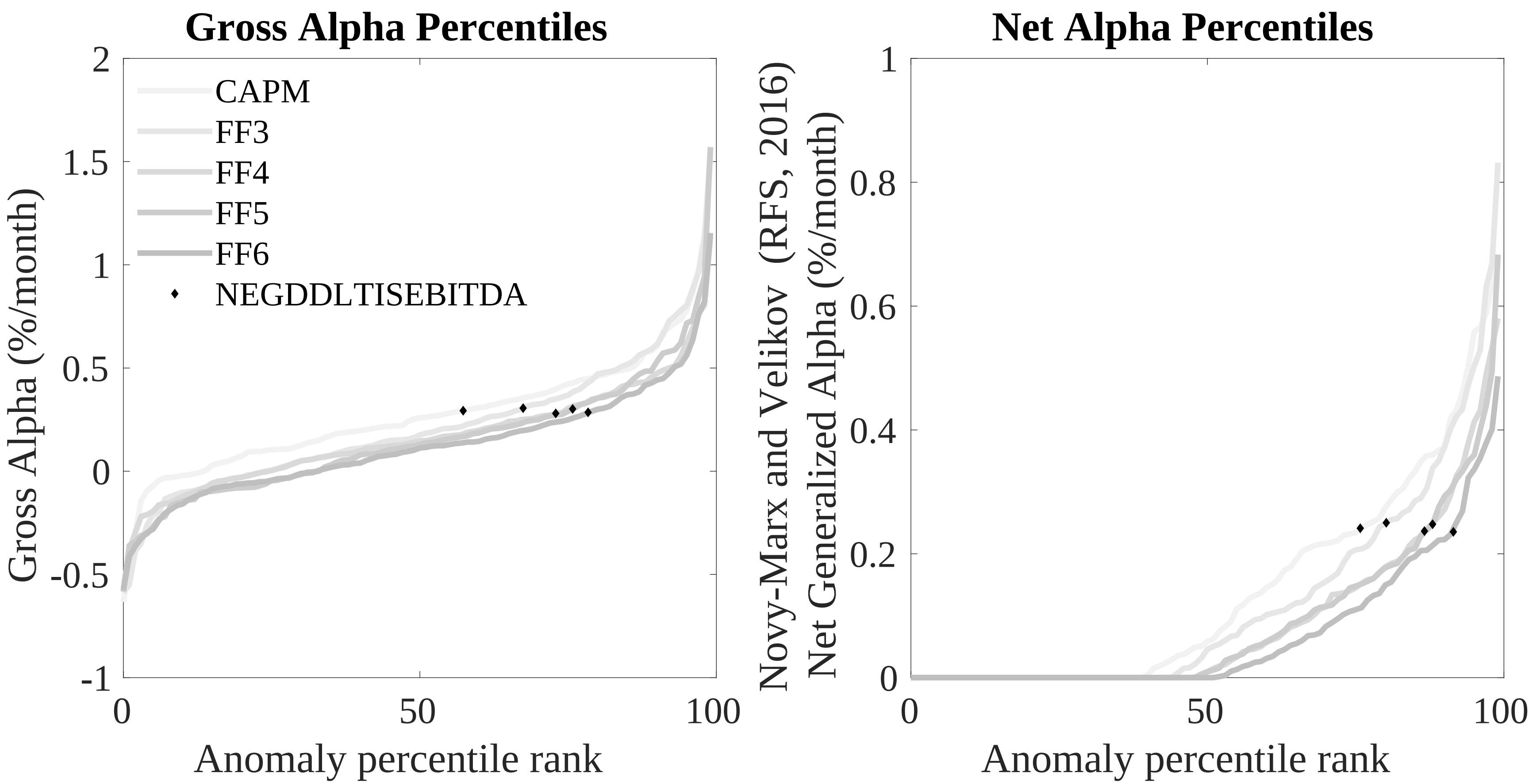

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DCS trading strategy alphas (diamonds). The strategies are constructed using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

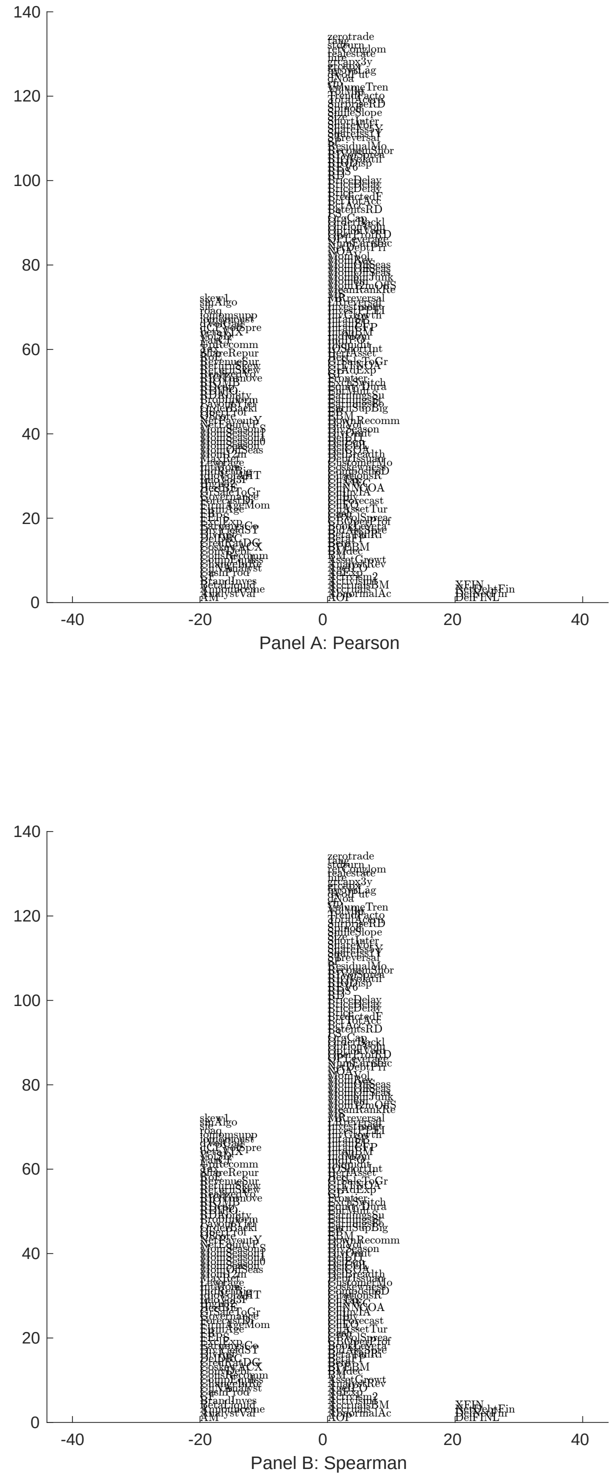

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DCS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

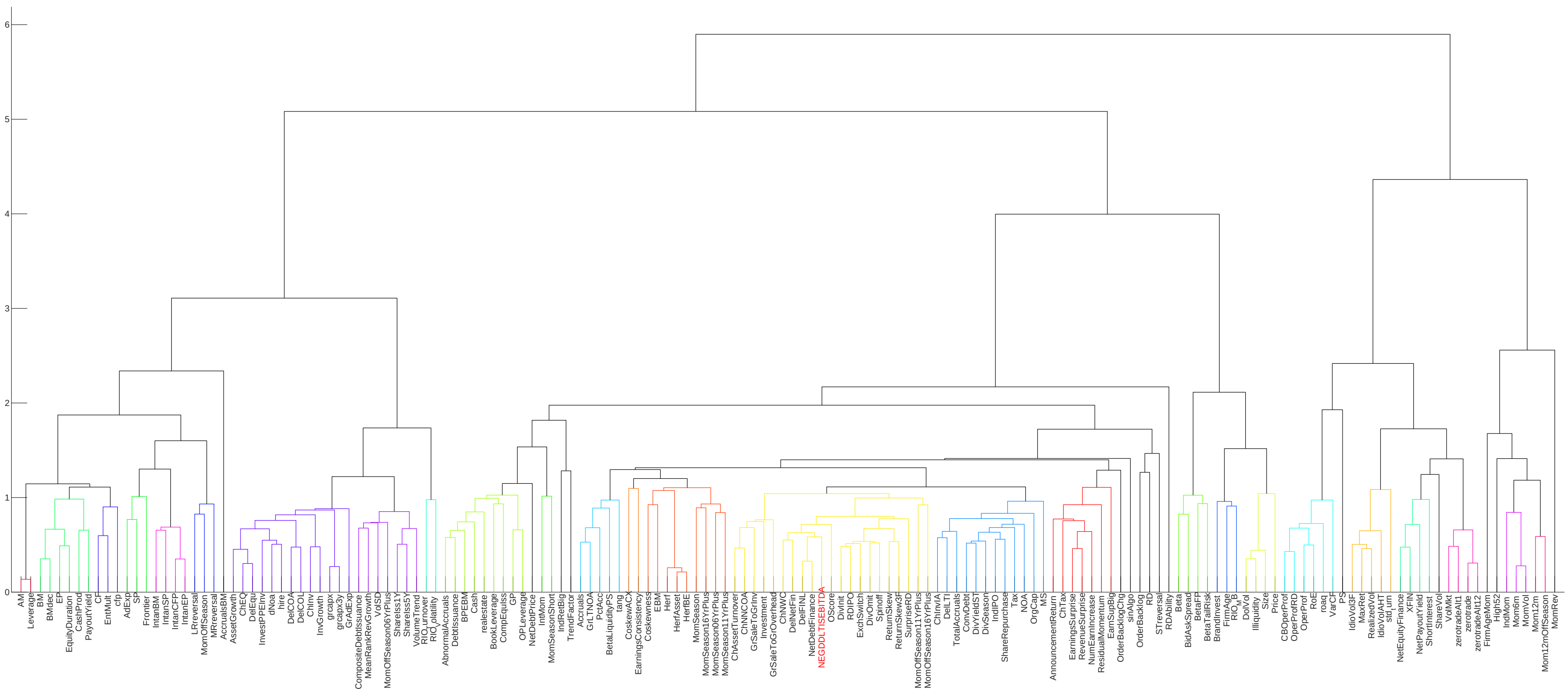

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

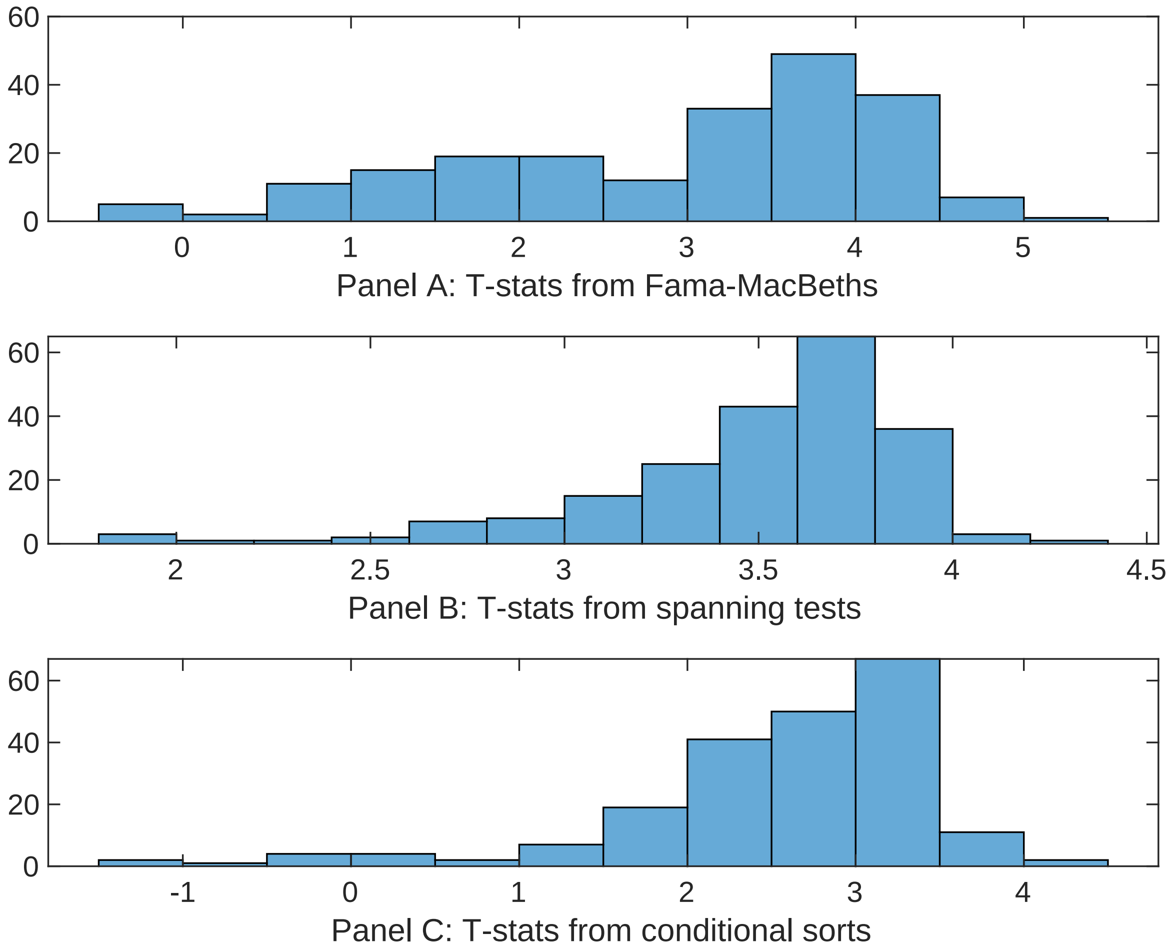

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DCS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DCS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DCS} DCS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DCS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DCS. Stocks are finally grouped into five DCS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DCS 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 DCS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DCS} DCS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net debt financing, Change in financial liabilities, Change in net financial assets, Accruals, Book leverage (annual), Inventory 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 197406 to 202306.

Intercept	0.14	0.14	0.13	0.13	0.14	0.14	0.14
	[5.48]	[5.52]	[5.38]	[5.16]	[5.41]	[5.45]	[5.64]
DCS	0.91	0.77	0.17	0.24	0.28	0.30	0.15
	[1.23]	[1.06]	[2.36]	[3.25]	[3.87]	[3.55]	[1.78]
Anomaly 1	0.20						0.17
	[9.08]						[3.95]
Anomaly 2		0.18					0.98
		[9.41]					[1.97]
Anomaly 3			0.73				-0.10
			[4.81]				[-3.24]
Anomaly 4				0.14			0.92
				[4.51]			[2.49]
Anomaly 5					0.11		0.69
					[1.17]		[0.62]
Anomaly 6						0.40	0.24
						[7.06]	[4.14]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	0	0	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 DCS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DCS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Net debt financing, Change in financial liabilities, Change in net financial assets, Accruals, Book leverage (annual), Inventory 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 197406 to 202306.

Intercept	0.27	0.27	0.23	0.26	0.27	0.29	0.21
	[3.67]	[3.66]	[3.07]	[3.38]	[3.54]	[3.83]	[2.92]
Anomaly 1	25.46						20.98
	[6.05]						[3.71]
Anomaly 2		22.65					-3.77
		[5.12]					[-0.61]
Anomaly 3			24.26				14.89
			[6.35]				[3.43]
Anomaly 4				10.96			1.74
				[3.59]			[0.52]
Anomaly 5					12.36		10.20
					[4.43]		[3.21]
Anomaly 6						4.80	4.97
						[1.58]	[1.73]
mkt	-6.09	-5.81	-6.05	-5.30	-4.64	-6.21	-4.93
	[-3.56]	[-3.37]	[-3.55]	[-3.01]	[-2.63]	[-3.53]	[-2.90]
smb	3.30	2.98	7.15	6.76	3.61	5.49	4.89
	[1.24]	[1.10]	[2.69]	[2.47]	[1.34]	[2.00]	[1.74]
hml	-9.38	-8.59	-10.60	-6.77	-0.46	-9.87	-2.33
	[-2.86]	[-2.59]	[-3.23]	[-1.97]	[-0.12]	[-2.92]	[-0.61]
rmw	-10.73	-10.39	-5.03	-5.23	-5.48	-8.00	-3.96
	[-3.14]	[-3.01]	[-1.46]	[-1.45]	[-1.55]	[-2.27]	[-1.10]
cma	6.49	5.47	19.81	9.34	12.87	8.74	7.96
	[1.28]	[1.05]	[3.91]	[1.81]	[2.55]	[1.51]	[1.32]
umd	0.95	0.85	2.27	2.40	2.93	2.59	0.59
	[0.54]	[0.47]	[1.31]	[1.35]	[1.67]	[1.44]	[0.33]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	12	10	12	8	9	7	17

Panel A: Average rank

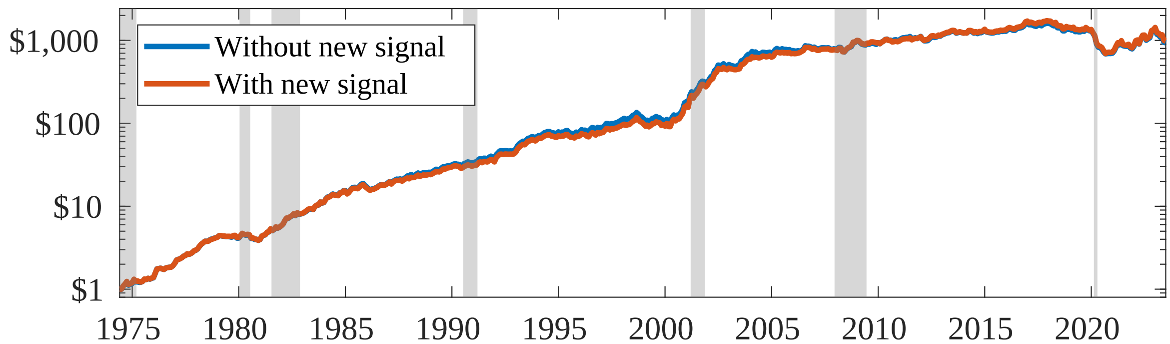

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines indicate combination trading strategies that utilize the 156 anomalies as well as DCS. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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