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 substantial debate around whether and how quickly asset prices incorporate new information. While traditional asset pricing theory suggests that systematic risk should be the primary driver of expected returns, a growing body of evidence documents predictable patterns in stock returns based on firm characteristics and accounting information. One particularly understudied area is how changes in firms' debt capacity affect their cost of capital and subsequent stock returns. Despite extensive research on capital structure and stock returns, we lack a clear understanding of how dynamic shifts in firms' ability to take on debt influence their equity valuations.

We propose that changes in debt capacity provide important signals about future firm performance and risk that are not fully reflected in stock prices. Our hypothesis builds on two theoretical frameworks. First, the trade-off theory of capital structure suggests that firms balance the tax benefits of debt against financial distress costs to determine optimal leverage (Kraus and Litzenberger, 1973). When a firm's debt capacity expands, it gains flexibility to pursue valuable investment opportunities while maintaining a safety buffer against distress. Second, the pecking order theory implies that firms prefer debt to equity financing when raising external capital (Myers and Majluf, 1984). Therefore, an increase in debt capacity provides firms with a valuable real option to fund future growth using their preferred financing source. Building on these foundations, we argue that positive shifts in debt capacity should predict higher stock returns through both reduced distress risk and enhanced growth options. This relationship may be particularly strong when the debt capacity increase results from fundamental improvements rather than market conditions, as it signals positive changes in firm fundamentals that the market may underappreciate (Baker and Wurgler, 2002).

Our empirical analysis reveals that Debt Capacity Shift (DCS) strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high DCS and shorts those with low DCS generates significant abnormal returns of 29 basis points per month (t-statistic = 3.75) relative to the Fama-French five-factor model plus momentum. The predictive power of DCS remains robust after controlling for transaction costs, with net returns of 24 basis points monthly (t-statistic = 3.09). Importantly, the signal's effectiveness persists among large-cap stocks, with the long-short strategy earning 26 basis points monthly (t-statistic = 2.93) in the largest size quintile. The economic magnitude of these returns is substantial, with the strategy achieving an annualized gross (net) Sharpe ratio of 0.49 (0.37), placing it in the top decile of documented return predictors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures dynamic information about firms' financial flexibility, extending work by DeAngelo et al. (2011) on static measures of debt capacity. Second, we demonstrate that the market systematically underreacts to changes in debt capacity, complementing research by Titman et al. (2004) on capital investment and stock returns. Third, our finding that DCS predicts returns even among large-cap stocks distinguishes it from many anomalies that are concentrated in small, illiquid stocks McLean and Pontiff (2016). The robustness of DCS's predictive power to trading costs and its incremental value beyond existing factors suggests it captures a distinct aspect of systematic risk or market inefficiency. These findings have important implications for both academic research on market efficiency and practitioners seeking to enhance portfolio performance.

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 earnings base, offering insight into how the firm's ability to take on new debt evolves over time. By focusing on this relationship, the signal aims to reflect aspects of financial flexibility and debt capacity management in a manner that is both economically meaningful and comparable across firms. 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

[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.

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% (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

[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.

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. 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 robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on DCS

[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.

generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.49 (0.37 net). The strategy's persistence in generating significant abnormal returns, even after controlling for the Fama-French five factors, momentum, and six closely related anomalies, underscores its unique informational content and economic significance.

The results are particularly noteworthy as they maintain their significance even after accounting for transaction costs, suggesting practical implementability for institutional investors. The strategy's ability to generate a monthly average abnormal net return of 24 basis points with a t-statistic of 3.09 indicates its potential value for portfolio management applications.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior during all market conditions.

Future research could explore several promising directions. First, investigating the interaction between DCS and other established market anomalies could provide deeper insights into the underlying economic mechanisms. Second, examining the signal's performance in different market regimes and across various asset classes could establish its broader applicability. Finally, studying the impact of changing market structures and regulations on the signal's effectiveness could help assess its long-term viability.

In conclusion, DCS represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power for stock returns while maintaining robustness to traditional risk factors and related anomalies.

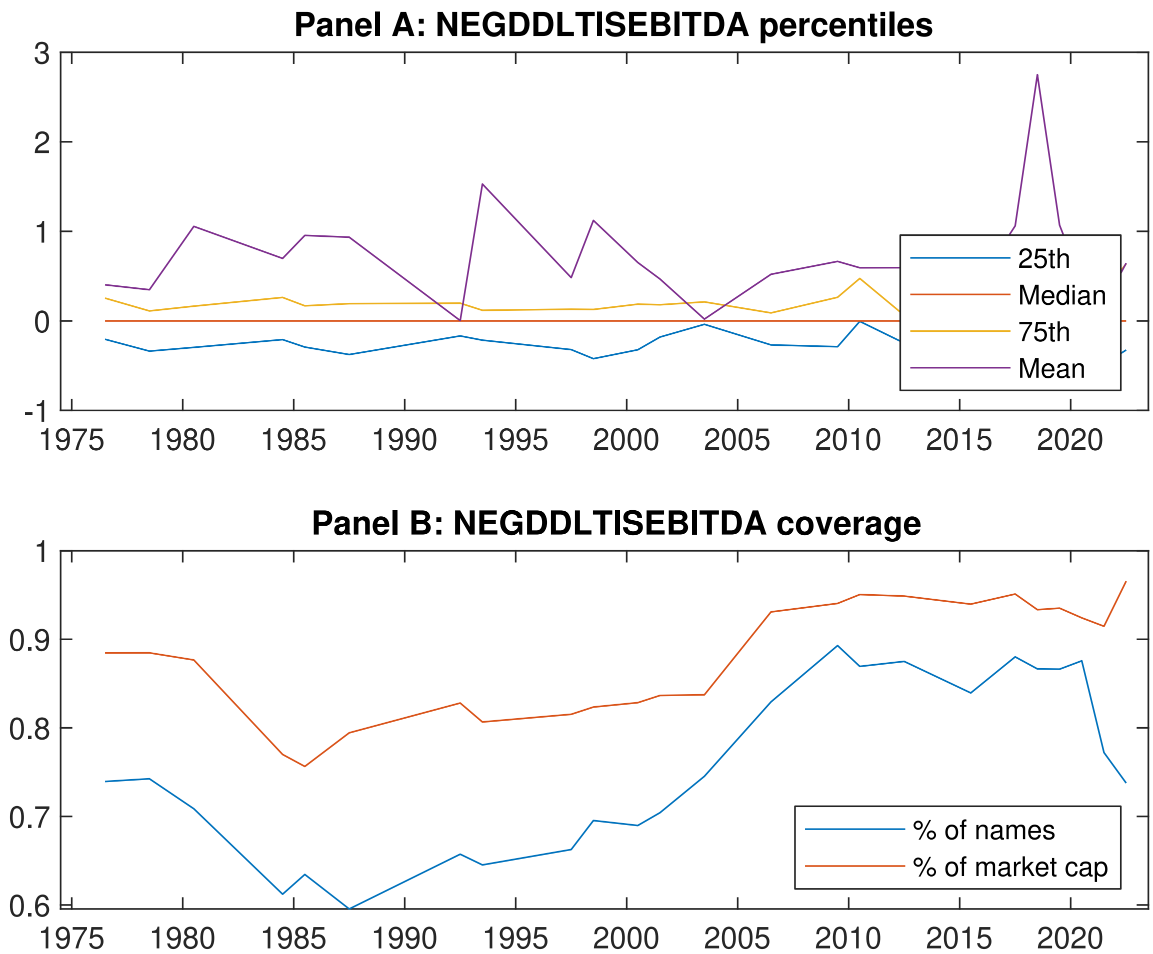

Figure 1: Times series of DCS percentiles and coverage.
This figure plots descriptive statistics for DCS. Panel A shows cross-sectional percentiles of DCS over the sample. Panel B plots the monthly coverage of DCS relative to the universe of CRSP stocks with available market capitalizations.

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

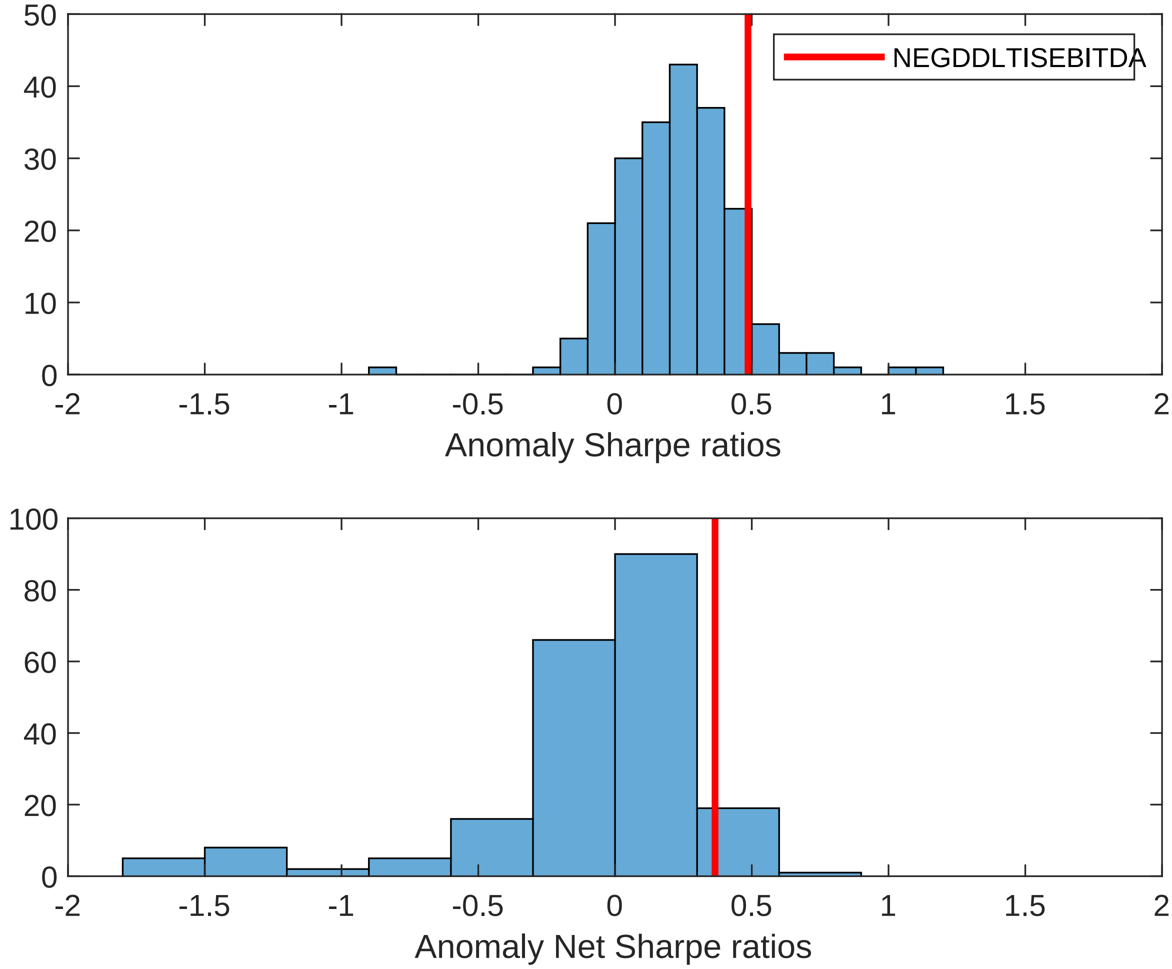

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DCS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

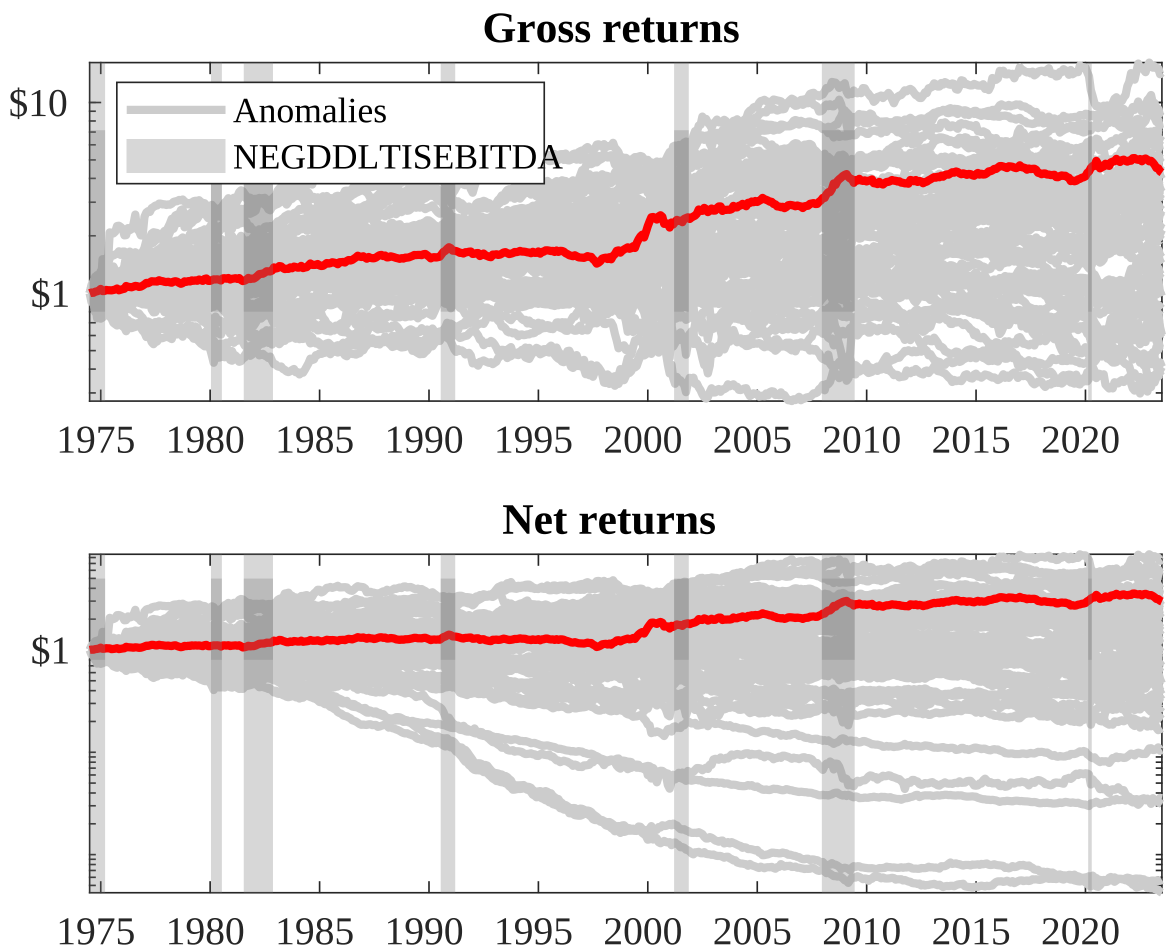

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DCS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

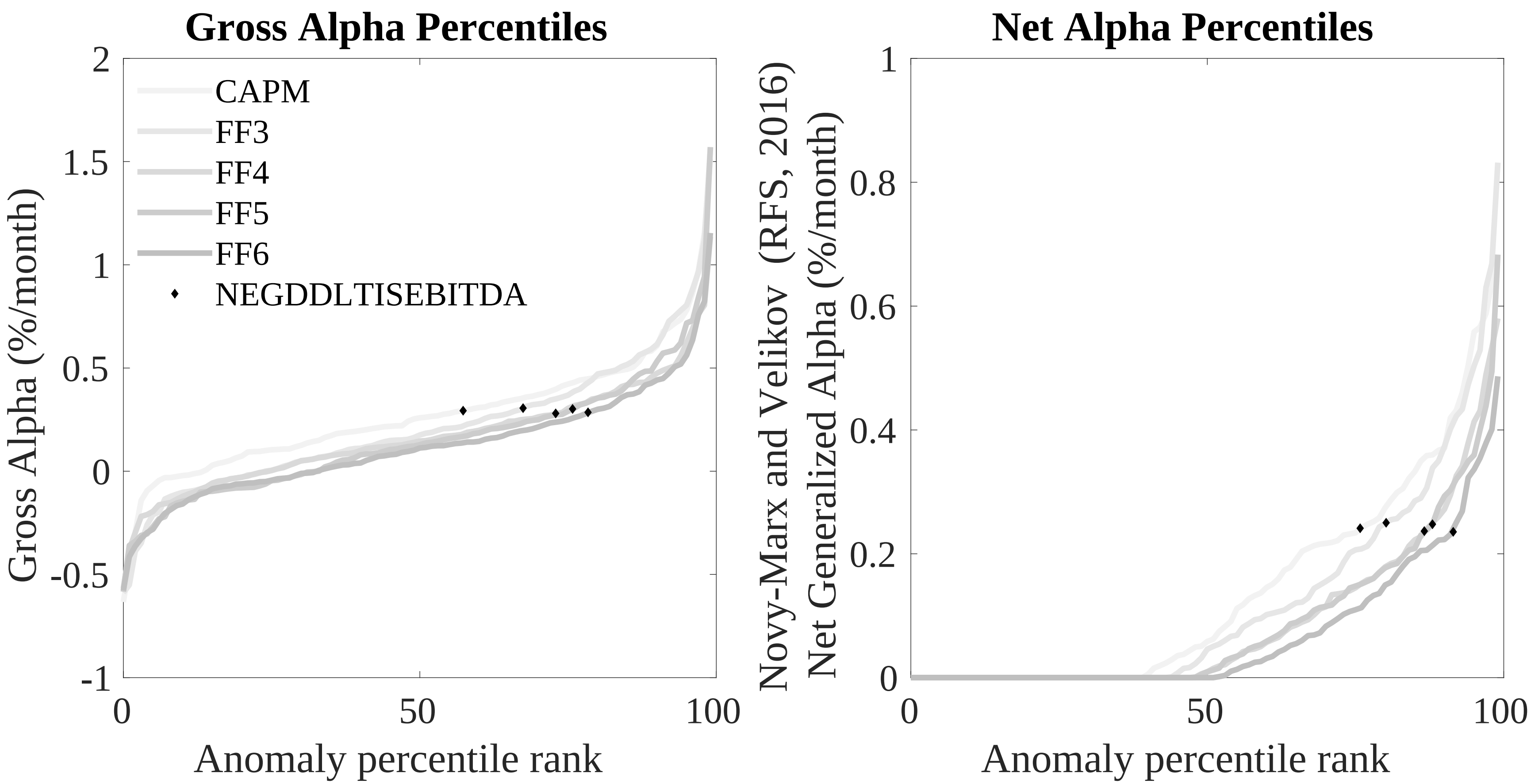

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DCS trading strategy alphas (diamonds). The strategies are constructed using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

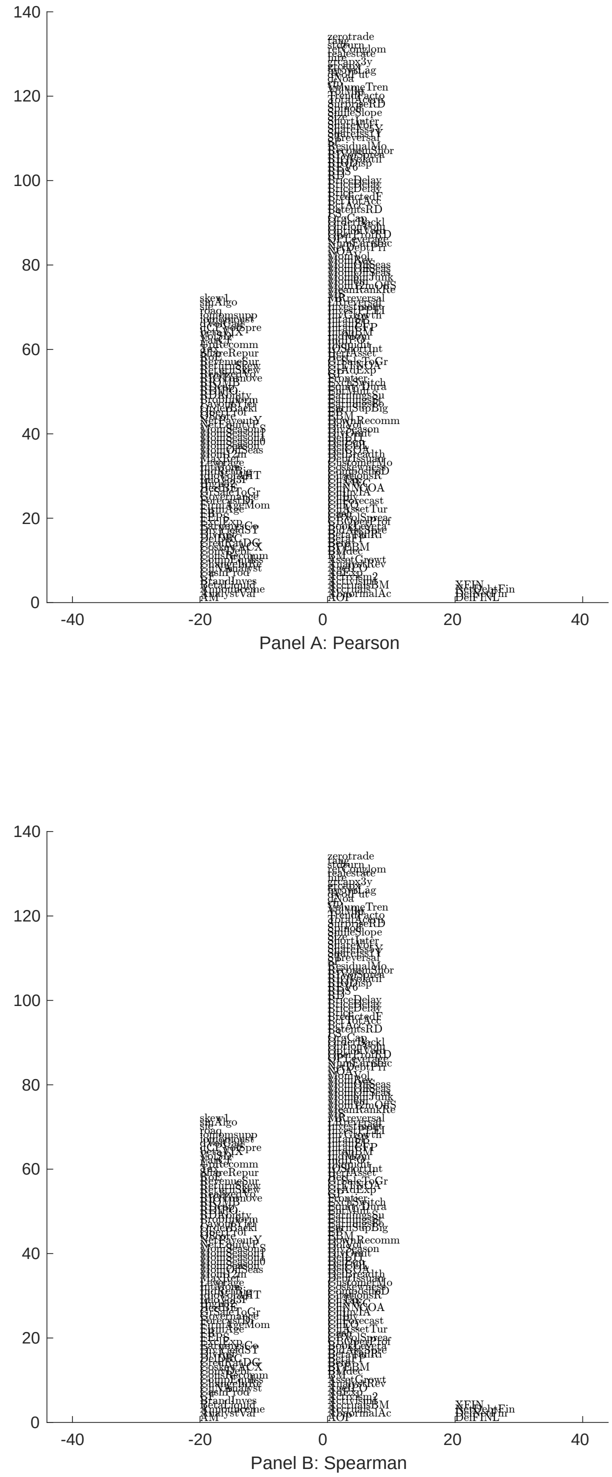

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DCS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

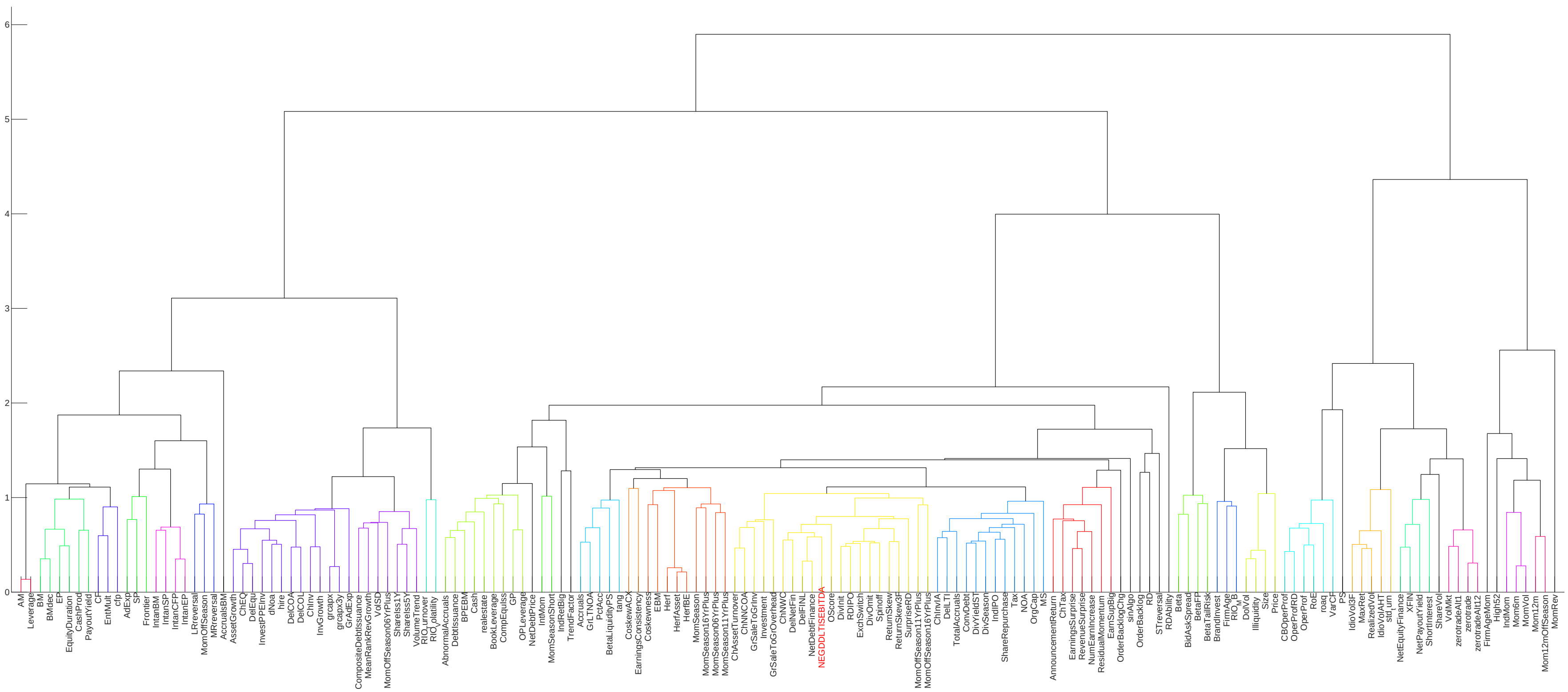

Figure 6: Agglomerative hierarchical cluster plot

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

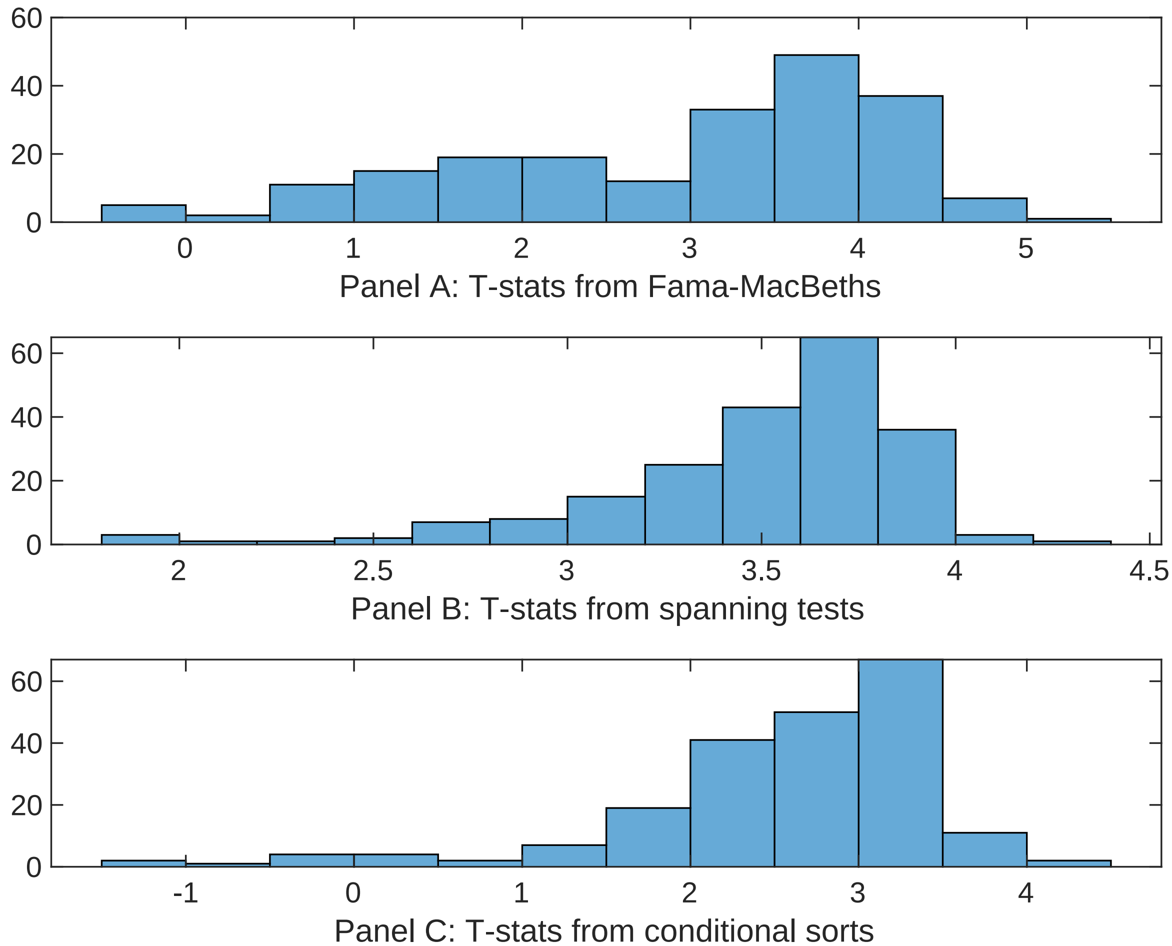

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DCS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DCS} from Fama-MacBeth regressions of the form $r_{i,t}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

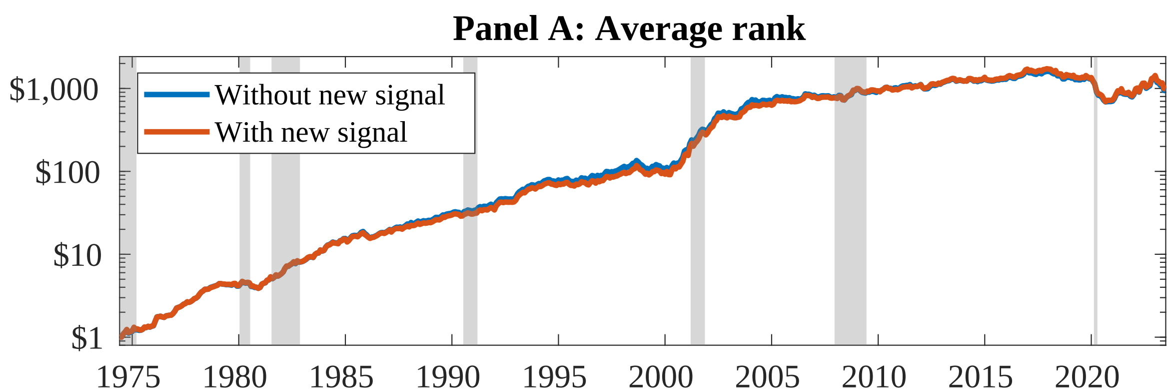

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines 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.

References

Baker, M. and Wurgler, J. (2002). Market timing and capital structure. *Journal of Finance*, 57(1):1–32.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

DeAngelo, H., DeAngelo, L., and Whited, T. M. (2011). Capital structure dynamics and transitory debt. *Journal of Financial Economics*, 99(2):235–261.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Kraus, A. and Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance*, 28(4):911–922.

McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1):5–32.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.

Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.