Debt Surplus Delta and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt Surplus Delta (DSD), 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 DSD achieves an annualized gross (net) Sharpe ratio of 0.53 (0.44), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (20) bps/month with a t-statistic of 2.92 (2.75), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in financial liabilities, Net debt financing, Investment to revenue, Book leverage (annual), Inventory Growth, Accruals) is 19 bps/month with a t-statistic of 2.65.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns (Harvey et al., 2016). While extensive research has documented various accounting-based signals, the role of changes in firms' debt structure remains incompletely understood. Despite the theoretical importance of capital structure decisions, empirical evidence on how dynamic adjustments in debt levels affect expected returns has been mixed (Welch and Goyal, 2008).

This gap is particularly notable given that debt financing decisions directly affect firms' risk profiles and future investment opportunities. While prior work has examined static leverage levels (George et al., 2010) and aggregate credit growth (Baron and Xiong, 2017), the predictive power of firm-specific changes in debt relative to industry peers - what we term the 'Debt Surplus Delta' (DSD) - has not been systematically investigated.

We develop three hypotheses linking DSD to future returns based on established theoretical frameworks. First, following Myers and Majluf (1984), firms that increase debt more than industry peers may be signaling negative private information about future prospects, as managers prefer debt to equity only when they believe their shares are undervalued. This information hypothesis predicts lower returns following high DSD.

Second, building on Jensen and Meckling (1976), excess debt growth may indicate agency problems where managers engage in empire-building at the expense of shareholders. When firms take on more debt than peers, it could reflect overinvestment in negative NPV projects, suggesting lower future profitability and returns.

Third, the risk-based explanation draws on Gomes and Schmid (2010), who show that higher leverage increases equity risk premiums through operating leverage effects. Firms with positive DSD face greater financial distress risk relative to peers, potentially commanding higher expected returns. However, this mechanical effect may be dominated by the negative signals from the information and agency channels.

Our empirical analysis reveals that DSD strongly predicts future returns in the cross-section. A value-weighted long-short portfolio that buys stocks with high DSD and shorts those with low DSD generates monthly abnormal returns of 22 basis points (t-statistic = 2.92) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.53 before trading costs and 0.44 after costs.

Importantly, the predictive power of DSD persists among large-cap stocks, with the long-short strategy earning monthly abnormal returns of 27 basis points (t-statistic = 3.06) in the largest size quintile. This suggests the effect is not driven by small, illiquid stocks. The signal's robustness is further demonstrated by its significant alpha of 19 basis points monthly (t-statistic = 2.65) when controlling for six closely related anomalies and common factors.

Cross-sectional tests reveal that DSD's predictive power remains significant after controlling for known determinants of returns including size, book-to-market, momentum, and other leverage-based measures. The effect is particularly strong among firms with high institutional ownership and analyst coverage, consistent with the information-based explanation.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel measure of abnormal debt growth that captures firm-specific variation relative to industry peers. While prior work like George et al. (2010) examines static leverage levels and Baron and Xiong (2017) studies aggregate credit expansion, DSD provides new insights into the asset pricing implications of dynamic capital structure decisions.

Second, we contribute to the growing literature on the 'factor zoo' (Cochrane and Piazzesi, 2005; Harvey et al., 2016) by documenting a robust return predictor that survives stringent controls and trading cost adjustments. Our findings suggest that debt structure changes contain unique information not captured by existing factors. The signal's effectiveness among large, liquid stocks distinguishes it from many previously documented anomalies.

Third, our results inform the broader debate on market efficiency and the channels through which financing decisions affect asset prices. The evidence supports theories emphasizing the role of information asymmetry and agency costs in capital structure choices, while challenging purely risk-based explanations. These findings have important implications for both academic research on market efficiency and practitioners' portfolio strategies.

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 Surplus Delta 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 CAPS for capitalization. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while capitalization (CAPS) measures the total value of a company's outstanding shares of stock. The construction of the signal follows a difference-based approach, where we first calculate the change in DLTIS by subtracting its lagged value from the current value, and then scale this difference by the lagged value of CAPS for each firm in each year of our sample. This scaled difference captures the relative change in debt issuance relative to the firm's market capitalization, offering insight into the dynamics of corporate financing decisions and capital structure changes. By focusing on this relationship, the signal aims to reflect aspects of debt management and financing policy in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both DLTIS and CAPS to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DSD signal. Panel A plots the time-series of the mean, median, and interquartile range for DSD. On average, the cross-sectional mean (median) DSD is -2.15 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DSD data. The signal's interquartile range spans -0.44 to 0.32. Panel B of Figure 1 plots the time-series of the coverage of the DSD signal for the CRSP universe. On average, the DSD signal is available for 5.72% of CRSP names, which on average make up 6.57% of total market capitalization.

4 Does DSD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DSD 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 DSD portfolio and sells the low DSD 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 DSD strategy earns an average return of 0.28% per month with a t-statistic of 3.74. The annualized

Sharpe ratio of the strategy is 0.53. The alphas range from 0.22% to 0.31% per month and have t-statistics exceeding 2.92 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 0.23, with a t-statistic of 4.58 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 476 stocks and an average market capitalization of at least $1,584 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 NYSE breakpoints and equal-weighted portfolios, and equals 23 bps/month with a t-statistics of 4.97. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for nineteen 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 1-23bps/month. The lowest return, (1 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.23. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DSD trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in eighteen cases.

Table 3 provides direct tests for the role size plays in the DSD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DSD, as well as average returns and alphas for long/short trading DSD 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 DSD strategy achieves an average return of 27 bps/month with a t-statistic of 3.06. Among these large cap stocks, the alphas for the DSD strategy relative to the five most common factor models range from 19 to 31 bps/month with t-statistics between 2.08 and 3.51.

5 How does DSD perform relative to the zoo?

Figure 2 puts the performance of DSD 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 DSD strategy falls in the distribution. The DSD strategy's gross (net) Sharpe ratio of 0.53 (0.44) is greater than 95% (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 DSD strategy (red line).[2] Ignoring trading costs, a $1 invested in the DSD strategy would have yielded $3.94 which ranks the DSD strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DSD strategy would have yielded $2.73 which ranks the DSD strategy in the top 3% 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 DSD relative to those. Panel A shows that the DSD strategy gross alphas fall between the 58 and 71 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 DSD strategy has a positive net generalized alpha for five out of the five factor models. In these cases DSD ranks between the 79 and 87 percentiles in terms of how

[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.

much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DSD 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 DSD signal in these Fama-MacBeth regressions exceed 0.49, with the minimum t-statistic occurring when controlling for Net debt financing. Controlling for all six closely related anomalies, the t-statistic on DSD is 0.44.

Similarly, Table 5 reports results from spanning tests that regress returns to the DSD 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 DSD strategy earns alphas that range from 20-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.75, which is achieved when controlling for Net debt financing. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DSD trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.65.

7 Does DSD add relative to the whole zoo?

Finally, we can ask how much adding DSD 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 DSD 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 DSD grows to \$903.72.

8 Conclusion

This study provides compelling evidence for the effectiveness of Debt Surplus Delta (DSD) 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 DSD generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.53 (0.44 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factor models and related anomalies from the factor zoo.

The persistence of DSD's predictive power, evidenced by monthly abnormal returns of 22 basis points (20 bps net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about firm fundamentals that is not fully incorporated into stock prices. Furthermore, the signal's ability to generate an alpha of 19 bps per month even after controlling for six closely related strategies indicates that DSD provides incremental information

[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 DSD is available.

beyond existing financial indicators.

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, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore the application of DSD in international markets, its interaction with other market anomalies, and its performance during specific market conditions. Additionally, investigating the underlying economic mechanisms driving the DSD effect could provide valuable insights for both academics and practitioners. As markets continue to evolve and trading strategies become more sophisticated, understanding the robustness and limitations of signals like DSD becomes increasingly important for portfolio management and risk assessment.

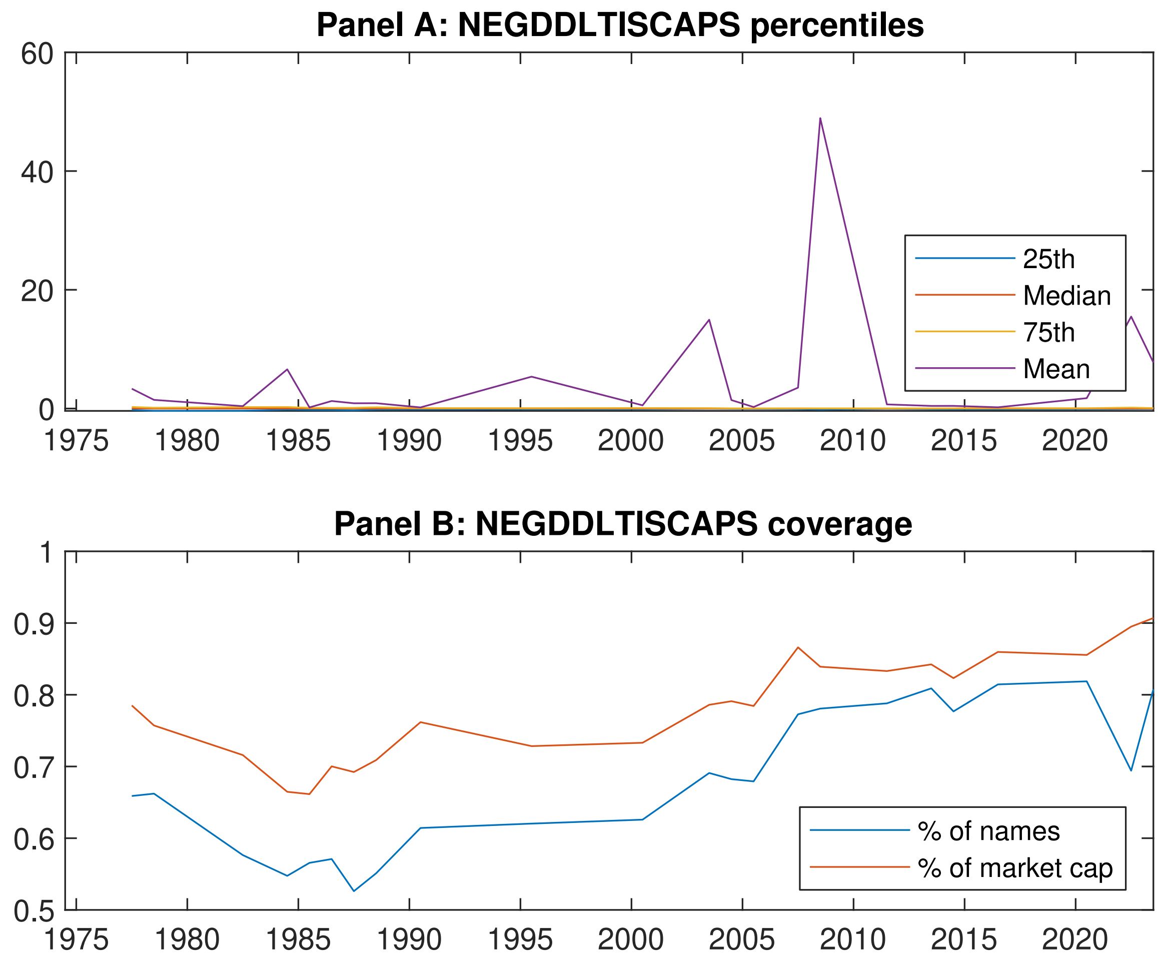


Figure 1: Times series of DSD percentiles and coverage.
This figure plots descriptive statistics for DSD. Panel A shows cross-sectional percentiles of DSD over the sample. Panel B plots the monthly coverage of DSD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DSD. 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 DSD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.62	0.67	0.65	0.72	0.90	0.28
	[3.11]	[3.41]	[3.04]	[3.85]	[4.65]	[3.74]
α_{CAPM}	-0.07	-0.02	-0.08	0.07	0.23	0.30
	[-1.22]	[-0.45]	[-1.16]	[1.41]	[4.40]	[4.02]
α_{FF3}	-0.11	-0.04	-0.01	0.06	0.20	0.31
	[-1.99]	[-0.97]	[-0.22]	[1.19]	[3.90]	[4.21]
α_{FF4}	-0.09	-0.01	0.07	0.05	0.15	0.24
	[-1.59]	[-0.34]	[1.07]	[1.07]	[3.01]	[3.31]
α_{FF5}	-0.17	-0.03	0.12	0.02	0.09	0.26
	[-3.08]	[-0.57]	[1.84]	[0.43]	[1.80]	[3.49]
α_{FF6}	-0.15	-0.01	0.16	0.02	0.07	0.22
	[-2.71]	[-0.18]	[2.66]	[0.44]	[1.34]	[2.92]
Panel B: Fama and French (2018) 6-factor model loadings for DSD-sorted portfolios						
β_{MKT}	1.04	1.02	0.99	0.97	1.03	-0.02
	[82.03]	[99.82]	[69.26]	[83.03]	[89.71]	[-0.96]
β_{SMB}	-0.00	-0.06	0.01	0.01	0.06	0.06
	[-0.20]	[-3.69]	[0.42]	[0.66]	[3.25]	[2.34]
β_{HML}	0.10	0.11	-0.14	-0.02	-0.02	-0.13
	[4.31]	[5.47]	[-5.10]	[-1.03]	[-0.95]	[-3.87]
β_{RMW}	0.17	0.02	-0.16	0.03	0.13	-0.04
	[6.74]	[0.98]	[-5.72]	[1.15]	[5.62]	[-1.26]
β_{CMA}	-0.00	-0.08	-0.20	0.11	0.22	0.23
	[-0.09]	[-2.79]	[-4.86]	[3.31]	[6.70]	[4.58]
β_{UMD}	-0.04	-0.03	-0.08	-0.00	0.04	0.08
	[-2.73]	[-2.98]	[-5.89]	[-0.09]	[3.54]	[4.42]
Panel C: Average number of firms (n) and market capitalization (me)						
n	491	564	1052	620	476	
me ($\$10^6$)	1652	2398	1828	2256	1584	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DSD 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	0.28	0.30	0.31	0.24	0.26	0.22
			[3.74]	[4.02]	[4.21]	[3.31]	[3.49]	[2.92]
Quintile	NYSE	EW	0.23	0.25	0.24	0.22	0.20	0.19
			[4.97]	[5.50]	[5.21]	[4.74]	[4.39]	[4.20]
Quintile	Name	VW	0.24	0.28	0.28	0.22	0.21	0.17
			[3.63]	[4.16]	[4.18]	[3.32]	[3.06]	[2.56]
Quintile	Cap	VW	0.23	0.26	0.27	0.22	0.22	0.19
			[3.24]	[3.65]	[3.84]	[3.04]	[3.11]	[2.63]
Decile	NYSE	VW	0.24	0.28	0.27	0.25	0.20	0.19
			[2.79]	[3.29]	[3.19]	[2.85]	[2.27]	[2.14]
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	0.23	0.26	0.27	0.24	0.23	0.20
			[3.07]	[3.52]	[3.66]	[3.21]	[3.07]	[2.75]
Quintile	NYSE	EW	0.01	0.04	0.02	0.02		
			[0.23]	[0.65]	[0.34]	[0.26]		
Quintile	Name	VW	0.20	0.25	0.25	0.22	0.18	0.16
			[2.92]	[3.63]	[3.63]	[3.20]	[2.68]	[2.38]
Quintile	Cap	VW	0.18	0.23	0.24	0.21	0.20	0.17
			[2.57]	[3.16]	[3.29]	[2.89]	[2.68]	[2.39]
Decile	NYSE	VW	0.19	0.24	0.23	0.21	0.16	0.15
			[2.20]	[2.73]	[2.65]	[2.47]	[1.81]	[1.70]

Table 3: Conditional sort on size and DSD

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

Size quintiles	DSD Quintiles (L)	(2)	(3)	(4)	(H)	DSD Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.80	0.77	0.98	0.82	0.90	0.11	0.13	0.11	0.05	0.06	0.03
	[3.04]	[2.60]	[3.50]	[2.72]	[3.29]	[1.12]	[1.29]	[1.08]	[0.53]	[0.61]	[0.30]
(2)	0.83	0.92	0.83	0.94	0.90	0.07	0.11	0.08	0.06	0.06	0.05
	[3.21]	[3.46]	[3.18]	[3.56]	[3.63]	[0.92]	[1.41]	[1.10]	[0.83]	[0.73]	[0.58]
(3)	0.79	0.91	0.81	0.84	0.94	0.15	0.19	0.18	0.15	0.16	0.13
	[3.24]	[3.85]	[3.19]	[3.58]	[4.03]	[1.96]	[2.47]	[2.38]	[1.87]	[1.99]	[1.69]
(4)	0.72	0.92	0.86	0.81	0.85	0.13	0.14	0.13	0.10	0.10	0.08
	[3.28]	[4.19]	[3.75]	[3.68]	[3.96]	[1.67]	[1.88]	[1.72]	[1.33]	[1.20]	[0.98]
(5)	0.58	0.55	0.61	0.68	0.85	0.27	0.29	0.31	0.23	0.23	0.19
	[2.95]	[2.79]	[2.95]	[3.48]	[4.49]	[3.06]	[3.30]	[3.51]	[2.66]	[2.60]	[2.08]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	DSD Quintiles, Average n (L)	(2)	(3)	(4)	(H)	DSD Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	363	362	363	362	361	36	29	30	29	34
(2)	99	98	99	98	99	56	55	54	56	56
(3)	69	69	69	69	69	96	98	93	95	96
(4)	58	58	58	58	58	209	212	203	210	207
(5)	53	53	53	53	53	1419	1758	1455	1726	1408

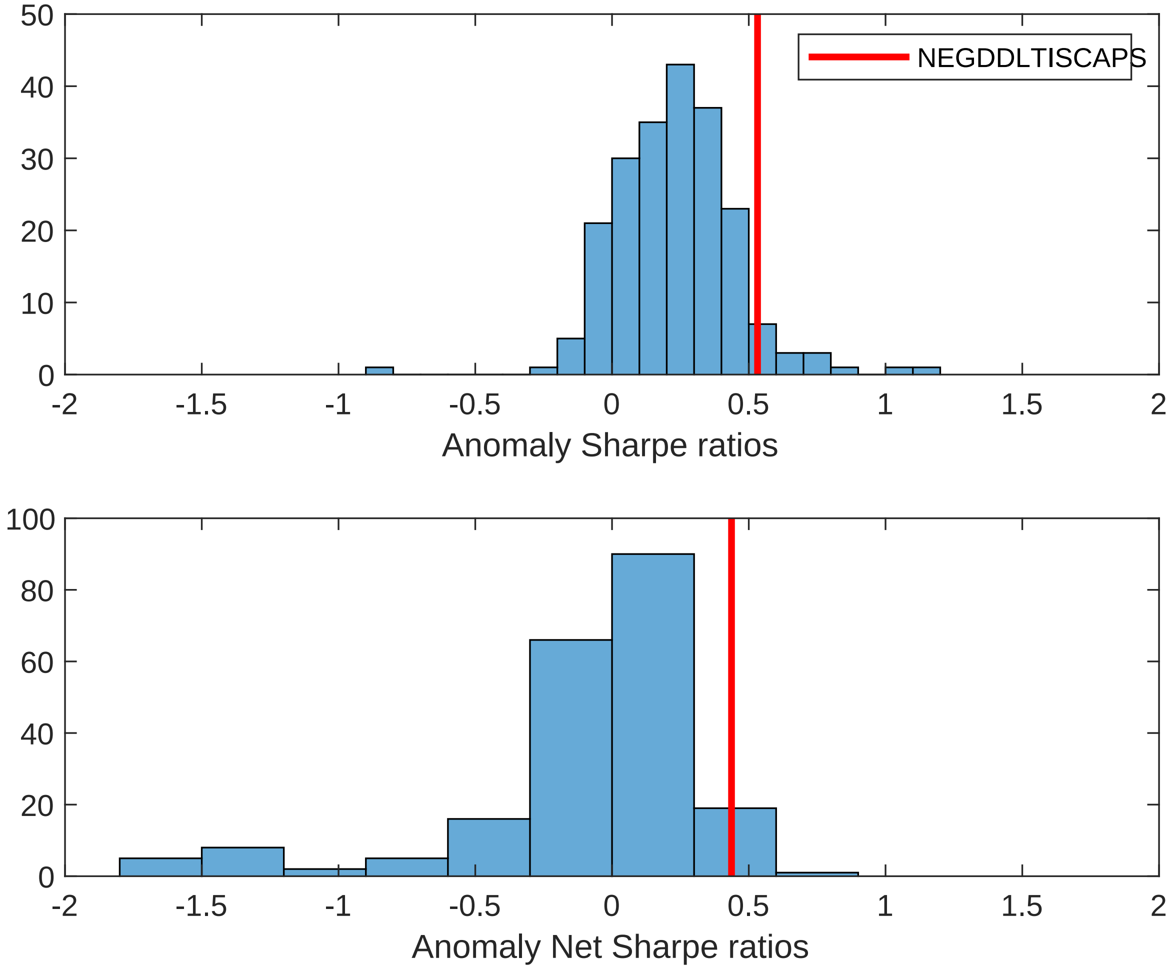


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DSD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

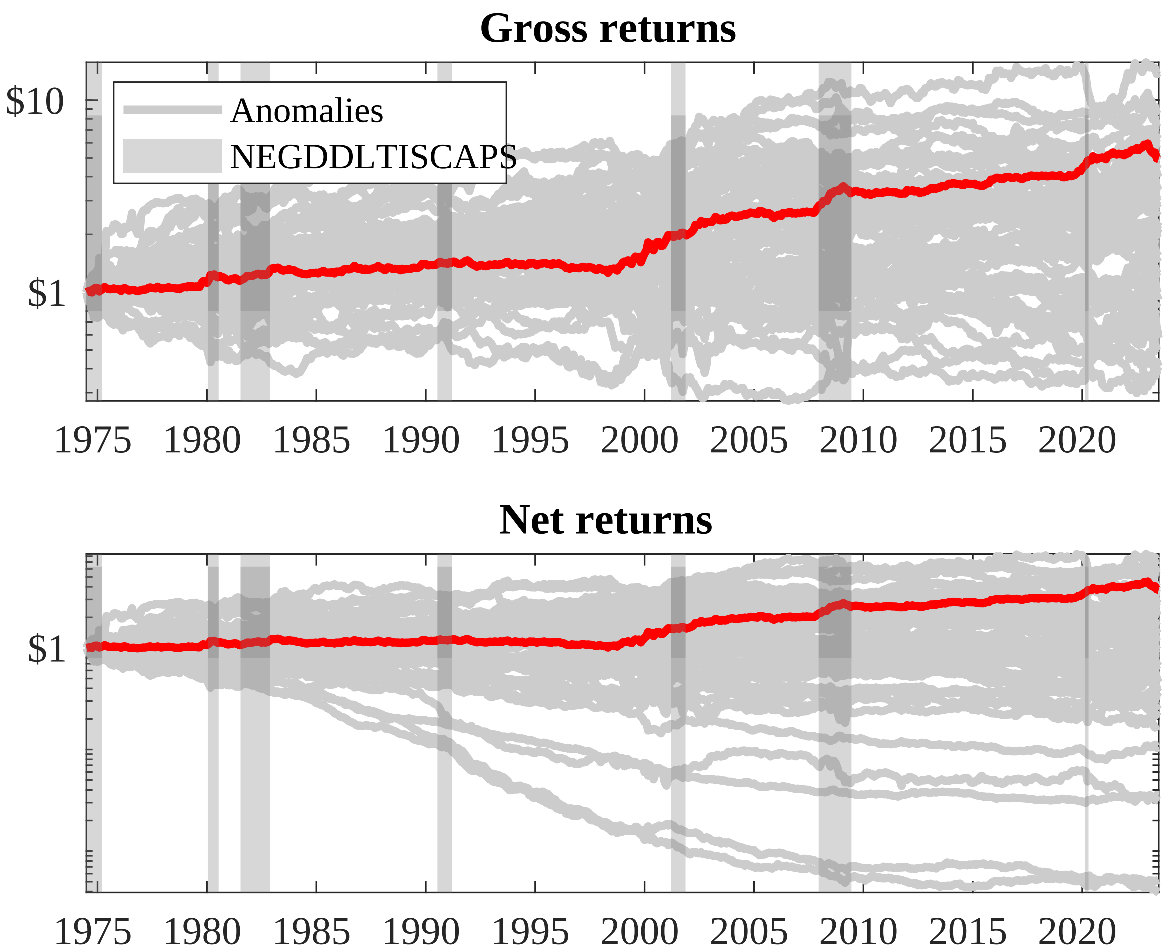


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DSD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

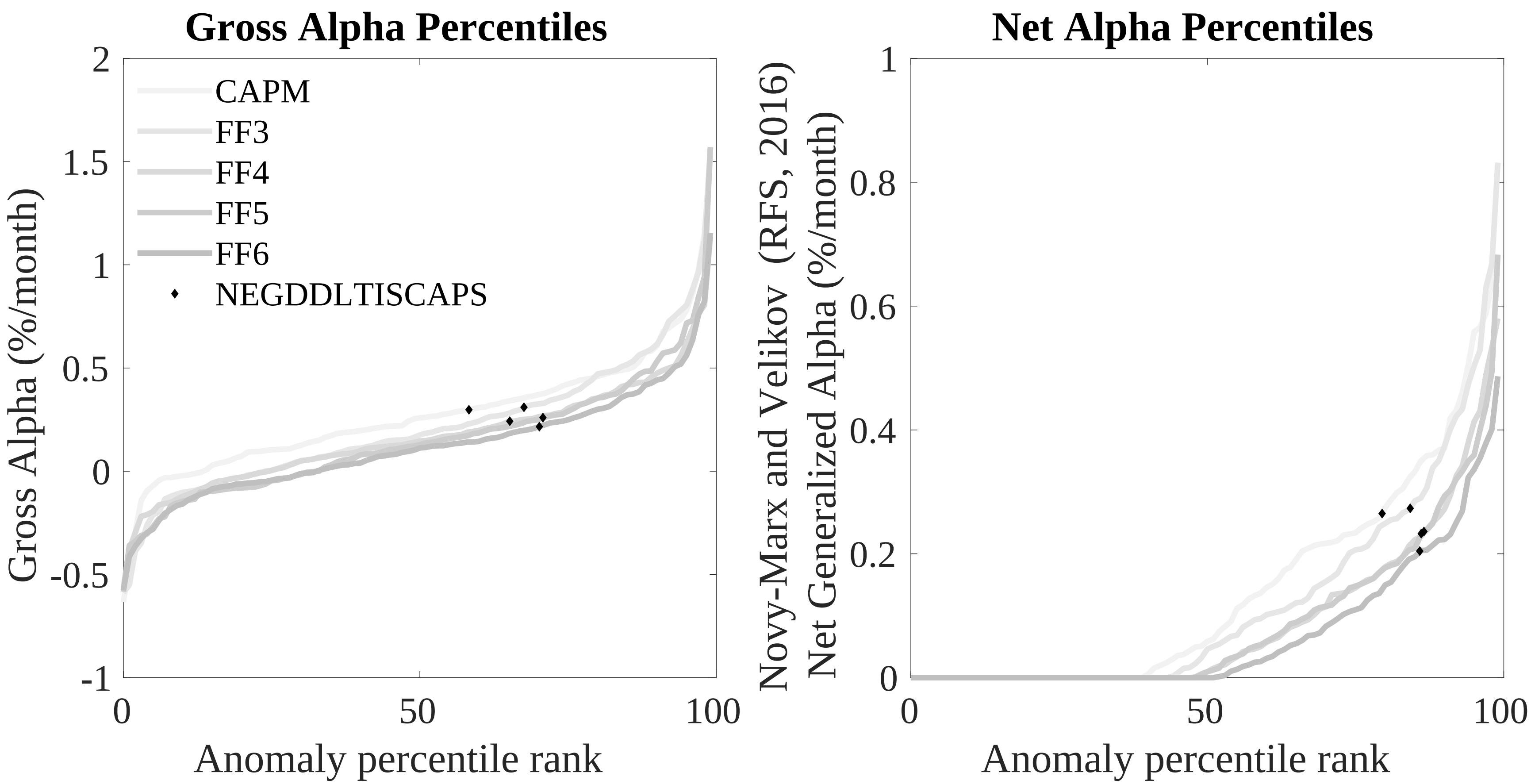
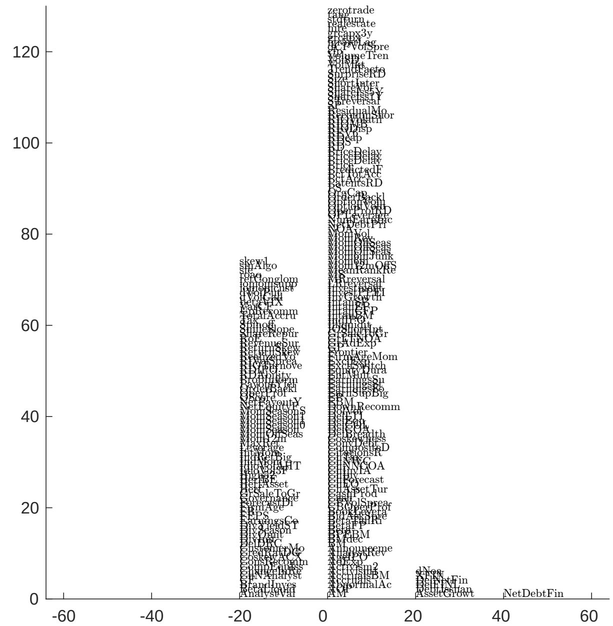
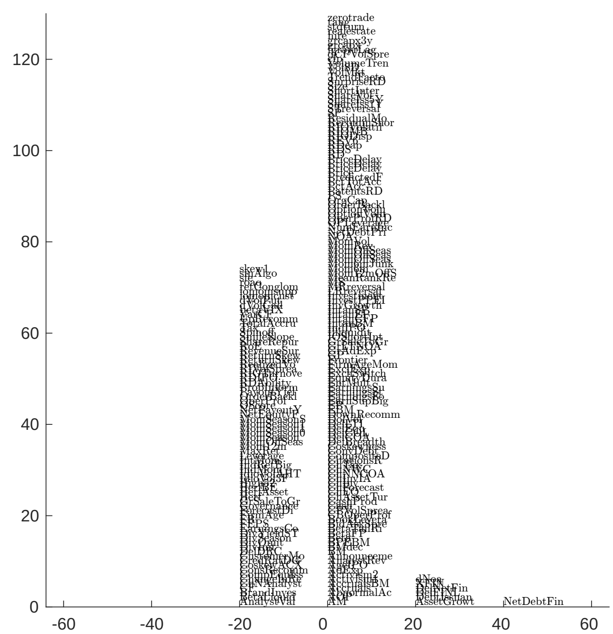


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DSD trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

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

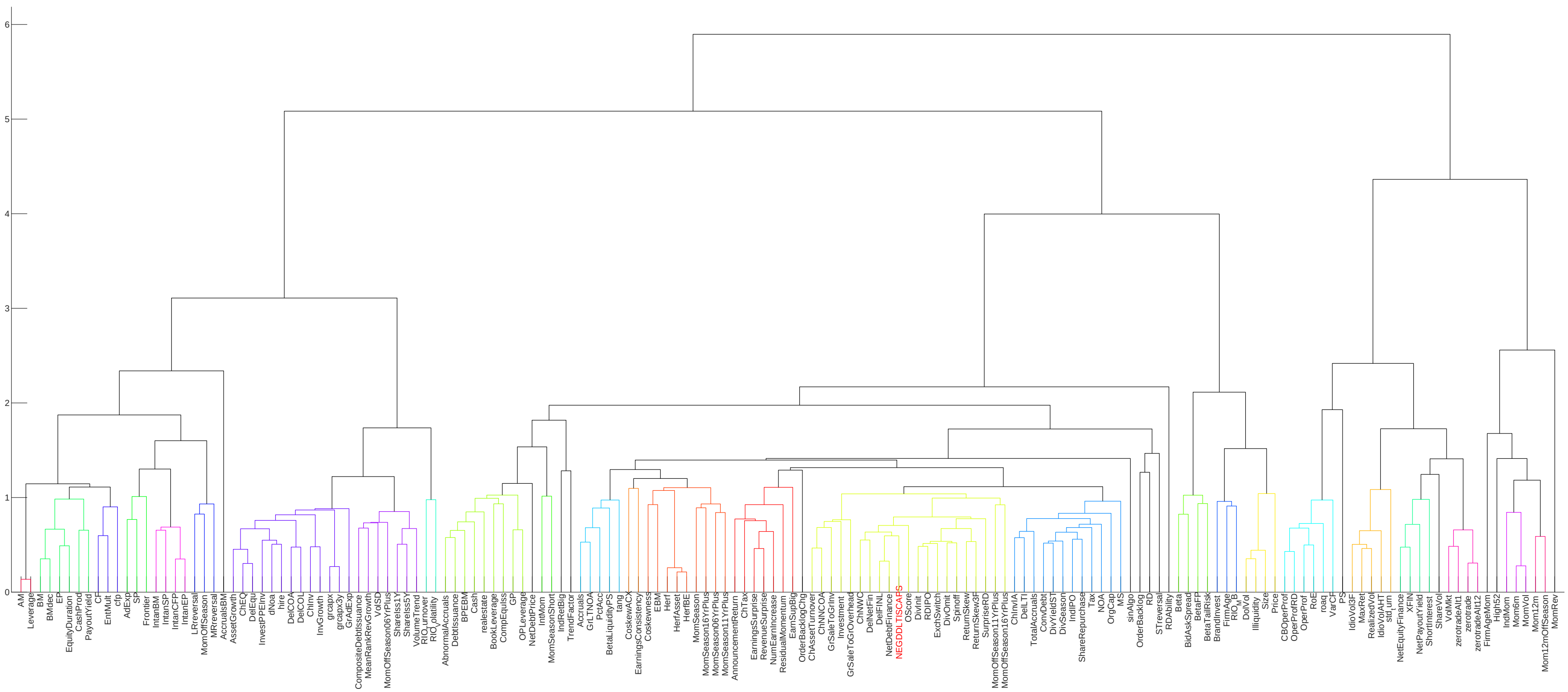


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

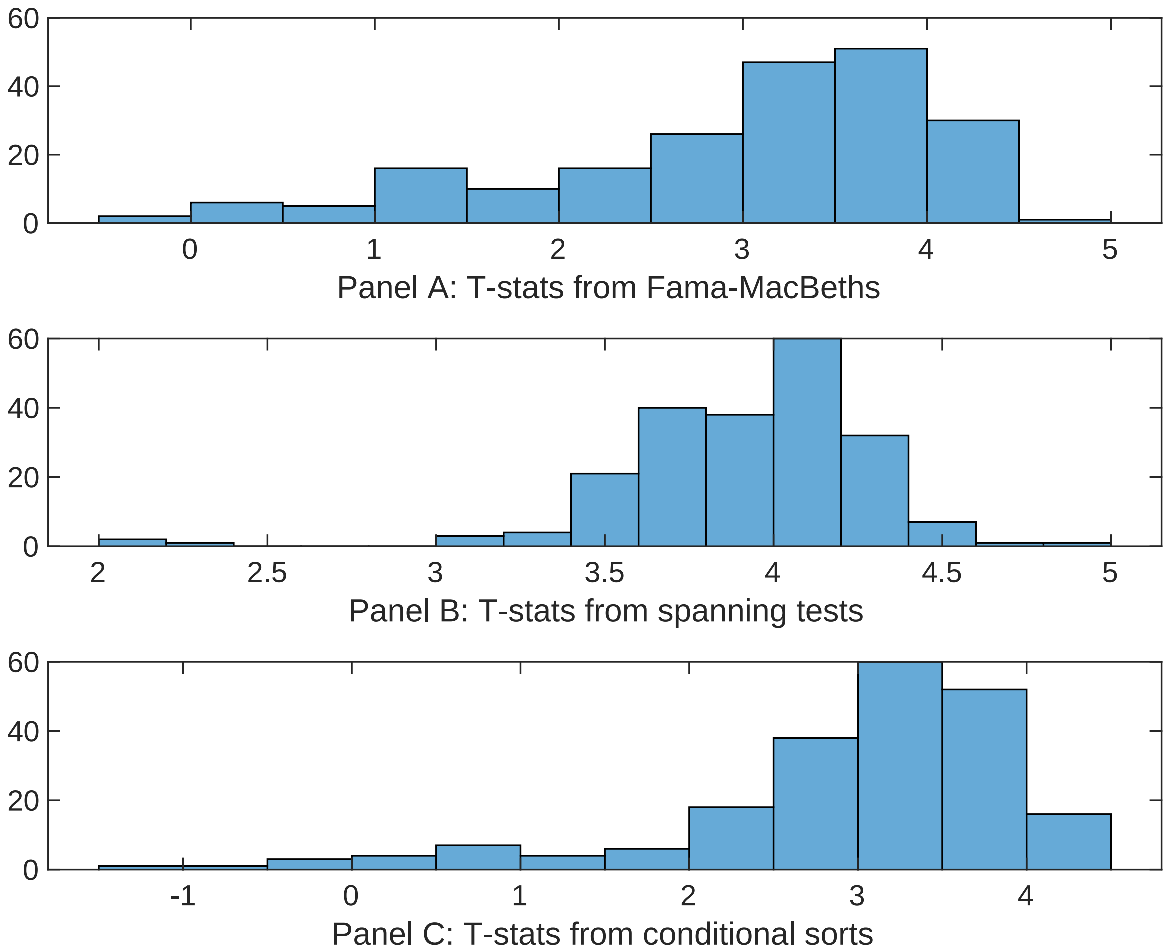


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DSD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DSD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DSD} DSD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DSD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DSD. Stocks are finally grouped into five DSD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DSD 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 DSD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DSD} DSD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Investment to revenue, Book leverage (annual), Inventory Growth, Accruals. 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	0.16	0.14	0.14	0.13	0.16
	[5.45]	[5.41]	[6.31]	[5.36]	[5.38]	[5.09]	[6.48]
DSD	0.34	0.27	0.15	0.19	0.17	0.18	0.31
	[0.59]	[0.49]	[3.06]	[3.66]	[2.46]	[3.42]	[0.44]
Anomaly 1	0.18						-0.37
	[9.34]						[-0.08]
Anomaly 2		0.21					0.14
		[8.80]					[2.79]
Anomaly 3			0.25				0.21
			[5.43]				[4.03]
Anomaly 4				0.13			0.49
				[1.43]			[0.42]
Anomaly 5					0.41		0.25
					[7.07]		[3.79]
Anomaly 6						0.14	0.74
						[4.42]	[1.88]
# 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 DSD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DSD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Change in financial liabilities, Net debt financing, Investment to revenue, Book leverage (annual), Inventory Growth, Accruals. 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	0.21	0.21	0.22	0.20	0.23	0.21	0.19
	[2.90]	[2.91]	[2.93]	[2.75]	[3.04]	[2.82]	[2.65]
Anomaly 1	14.77						0.84
	[3.40]						[0.14]
Anomaly 2		14.95					14.87
		[3.59]					[2.66]
Anomaly 3			6.68				5.67
			[2.30]				[1.98]
Anomaly 4				11.70			13.89
				[4.31]			[4.43]
Anomaly 5					4.70		4.62
					[1.60]		[1.61]
Anomaly 6						4.71	-4.72
						[1.58]	[-1.40]
mkt	-1.63	-1.81	-2.00	-0.44	-1.93	-1.47	-0.81
	[-0.96]	[-1.07]	[-1.17]	[-0.26]	[-1.13]	[-0.85]	[-0.48]
smb	4.93	5.25	5.07	4.93	6.73	7.01	2.33
	[1.86]	[1.99]	[1.89]	[1.88]	[2.53]	[2.61]	[0.84]
hml	-11.55	-12.09	-11.75	-3.53	-12.45	-11.01	-2.70
	[-3.54]	[-3.72]	[-3.58]	[-0.93]	[-3.79]	[-3.26]	[-0.71]
rmw	-5.19	-5.28	-3.49	-1.04	-3.41	-2.59	-2.08
	[-1.53]	[-1.56]	[-1.03]	[-0.30]	[-1.00]	[-0.73]	[-0.59]
cma	17.06	18.15	21.32	21.85	17.79	20.40	14.66
	[3.32]	[3.60]	[4.30]	[4.46]	[3.17]	[4.03]	[2.58]
umd	6.10	6.30	6.62	7.43	7.09	7.25	5.21
	[3.46]	[3.61]	[3.75]	[4.36]	[4.06]	[4.18]	[2.93]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	12	12	11	13	10	10	15

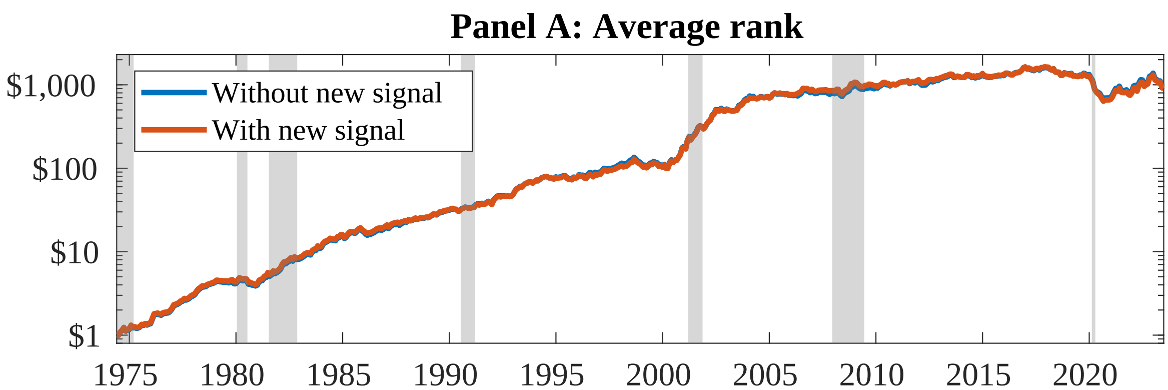


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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