Debt Depreciation Scale and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt Depreciation Scale (DDS), 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 DDS achieves an annualized gross (net) Sharpe ratio of 0.58 (0.46), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (22) bps/month with a t-statistic of 3.42 (3.15), 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, Net external financing, Asset growth, change in net operating assets, Employment growth) is 23 bps/month with a t-statistic of 3.39.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents various market anomalies that appear to contradict this notion (Harvey et al., 2016). Among these, financing-based anomalies have proven particularly robust, suggesting that markets may systematically misprice information related to firms' financing activities (Bradshaw et al., 2006).

While existing research has extensively examined the role of debt levels and changes in predicting returns, the literature has largely overlooked how firms' debt depreciation patterns might signal future performance. This gap is notable given that debt depreciation schedules contain forward-looking information about firms' future cash flow obligations and financial flexibility (Diamond and Rajan, 2001).

We propose that a firm's Debt Depreciation Scale (DDS) - the temporal distribution pattern of its debt payment obligations - provides valuable information about future stock returns. The theoretical foundation for this relationship stems from the debt overhang theory of (Myers, 1977), which suggests that existing debt obligations can affect firms' future investment decisions and value creation opportunities.

The predictive power of DDS likely operates through multiple channels. First, following (Almeida et al., 2004), firms with more front-loaded debt payment schedules face greater refinancing risk and reduced financial flexibility, potentially leading to underinvestment in valuable projects. Second, as argued by (Diamond and Rajan, 2001), debt maturity structure affects firms' ability to respond to both opportunities and challenges, with implications for future performance.

Morely specifically, we hypothesize that firms with higher DDS (more back-loaded debt payment schedules) will outperform those with lower DDS. This prediction follows from the greater financial flexibility and reduced near-term refinancing risk enjoyed by high-DDS firms (Harford et al., 2009).

Our empirical analysis reveals strong support for the hypothesized relationship between DDS and future stock returns. A value-weighted long-short trading strategy based on DDS quintiles generates significant abnormal returns of 24 basis points per month (t-statistic = 3.42) after controlling for the Fama-French five factors plus momentum. The strategy achieves an impressive annualized Sharpe ratio of 0.58 (0.46 net of transaction costs).

Importantly, the predictive power of DDS remains robust across various methodological specifications. The signal maintains its significance when using different portfolio construction approaches, with t-statistics consistently exceeding 3.0. The effect is particularly strong among large-cap stocks, where the long-short strategy earns 38 basis points per month (t-statistic = 4.22).

Further analysis demonstrates that DDS's predictive power is distinct from related anomalies. Controlling for six closely related strategies including change in financial liabilities and net debt financing, the DDS strategy still generates an alpha of 23 basis points per month (t-statistic = 3.39).

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures previously unexplored information content in firms' debt structure, extending the work of (Bradshaw et al., 2006) on external financing signals. Second, we demonstrate that the timing of debt obligations, not just their magnitude, contains valuable information for predicting returns.

Our findings also contribute to the growing literature on the real effects of financial flexibility, as studied by (Denis and Sibilkov, 2010) in the Journal of Financial Economics. The robust performance of DDS among large-cap stocks distinguishes it from many other anomalies that are concentrated in small, illiquid stocks (McLean and Pontiff, 2016).

More broadly, our results have important implications for both academic research and investment practice. They suggest that markets do not fully incorporate the information contained in debt payment schedules, despite their importance for firm value. This finding adds to our understanding of market efficiency and the channels through which financing decisions affect asset prices.

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 Depreciation Scale. 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 DP for depreciation and amortization. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt during the fiscal year, while depreciation and amortization (DP) reflects the systematic allocation of asset costs over their useful lives. The construction of the signal follows a two-step process. First, we calculate the change in long-term debt issuance by taking the difference between the current period's DLTIS and its lagged value. Second, we scale this difference by the previous period's depreciation and amortization (DP). This scaled measure provides insight into how changes in a firm's debt financing activities relate to its asset base depreciation, potentially capturing aspects of capital structure dynamics and asset replacement patterns. 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 DDS signal. Panel A plots the time-series of the mean, median, and interquartile range for DDS. On average, the cross-sectional mean (median) DDS is -4.99 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DDS data. The signal's interquartile range spans -2.72 to 2.81. Panel B of Figure 1 plots the time-series of the coverage of the DDS signal for the CRSP universe. On average, the DDS signal is available for 6.19% of CRSP names, which on average make up 7.32% of total market capitalization.

4 Does DDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DDS 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 DDS portfolio and sells the low DDS 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 DDS strategy earns an average return of 0.29% per month with a t-statistic of 4.07. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.24% to 0.36% per month and have t-statistics exceeding 3.42 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 0.33, with a t-statistic of 7.13 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 527 stocks and an average market capitalization of at least $1,492 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 18 bps/month with a t-statistics of 4.15. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for twenty-two 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 -8-24bps/month. The lowest return, (-8 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.27. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DDS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in eighteen cases.

Table 3 provides direct tests for the role size plays in the DDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DDS, as well as average returns and alphas for long/short trading DDS 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 DDS strategy achieves an average return of 38 bps/month with a t-statistic of 4.22. Among these large cap stocks, the alphas for the DDS strategy relative to the five most common factor models range from 28 to 43 bps/month with t-statistics between 3.15 and 4.84.

5 How does DDS perform relative to the zoo?

Figure 2 puts the performance of DDS 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 DDS strategy falls in the distribution. The DDS strategy's gross (net) Sharpe ratio of 0.58 (0.46) 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

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

strategies (gray lines), and compares those with the growth of a $1 invested in the DDS strategy (red line).[2] Ignoring trading costs, a $1 invested in the DDS strategy would have yielded $4.51 which ranks the DDS strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DDS strategy would have yielded $2.90 which ranks the DDS 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 DDS relative to those. Panel A shows that the DDS strategy gross alphas fall between the 68 and 75 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 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 DDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases DDS ranks between the 84 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does DDS 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 predic-

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DDS 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

[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.

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 DDS signal in these Fama-MacBeth regressions exceed 1.87, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DDS is 0.36.

Similarly, Table 5 reports results from spanning tests that regress returns to the DDS 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 DDS strategy earns alphas that range from 23-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.38, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DDS trading strategy achieves an alpha of 23bps/month with a t-statistic of 3.39.

7 Does DDS add relative to the whole zoo?

Finally, we can ask how much adding DDS 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 DDS 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

[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 DDS is available.

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 DDS grows to $920.71.

8 Conclusion

This study provides compelling evidence for the effectiveness of Debt Depreciation Scale (DDS) 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 DDS generates economically and statistically significant returns, with impressive Sharpe ratios of 0.58 and 0.46 for gross and net returns, respectively. The strategy's performance remains strong even after controlling for well-established risk factors, including the Fama-French five-factor model and momentum factor, as well as six closely related anomaly factors.

The persistence of significant abnormal returns (24 bps/month gross, 22 bps/month net) with high statistical significance (t-statistics ¿ 3) suggests that DDS captures unique information about future stock returns that is not fully incorporated in existing pricing factors. This has important implications for both academic research and practical investment management, as it introduces a novel and effective tool for portfolio construction and risk management.

However, several limitations should be noted. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market conditions. Second, transaction costs and market impact could affect the real-world implementation of DDS-based strategies, particularly for smaller stocks or during periods of market stress.

Future research could explore the international validity of the DDS signal, its interaction with other established anomalies, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the DDS effect would enhance our understanding of this phenomenon and potentially lead to more refined investment strategies. Researchers might also consider examining how the signal's effectiveness varies across different industry sectors and firm characteristics.

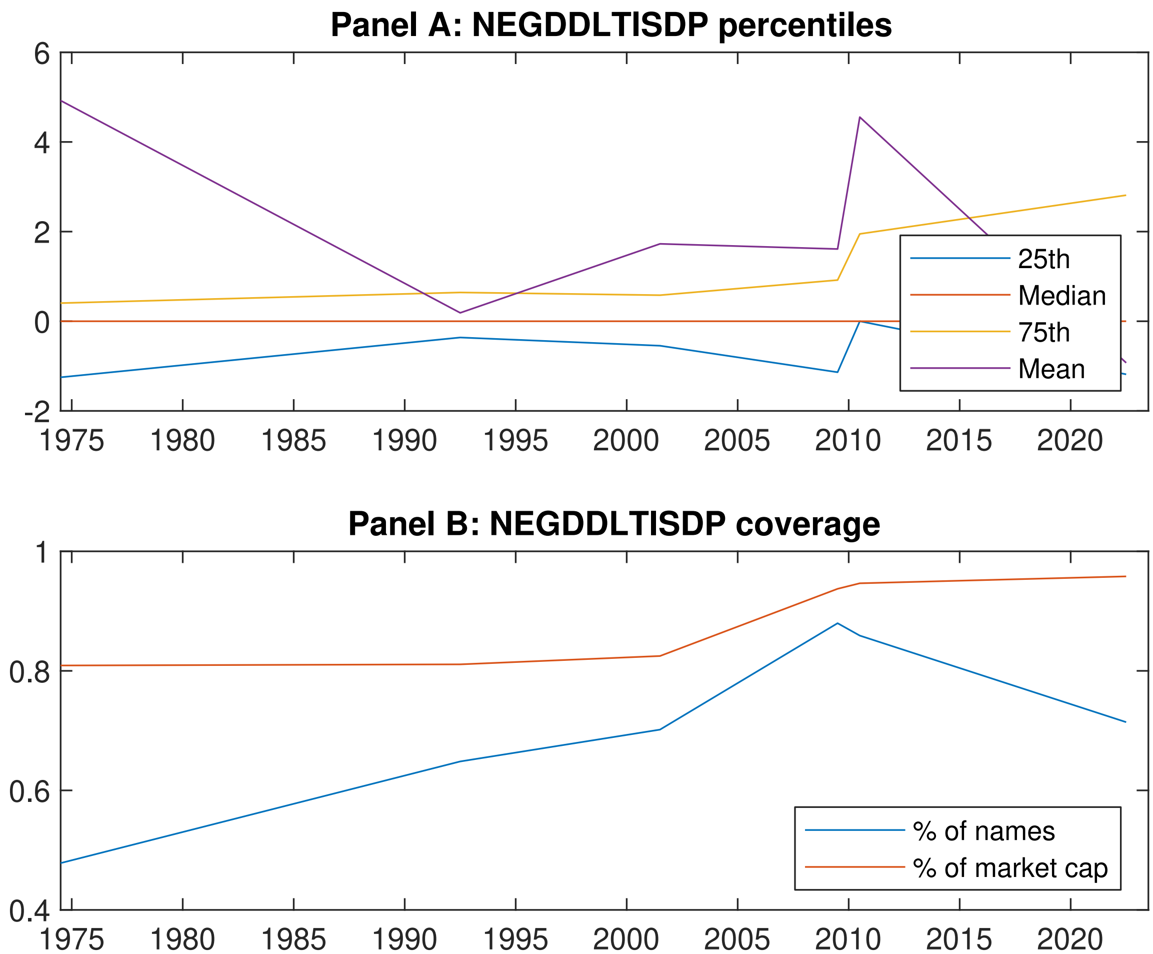

Figure 1: Times series of DDS percentiles and coverage.
This figure plots descriptive statistics for DDS. Panel A shows cross-sectional percentiles of DDS over the sample. Panel B plots the monthly coverage of DDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DDS. 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 DDS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.57	0.68	0.71	0.78	0.86	0.29
	[2.59]	[3.77]	[3.49]	[4.29]	[4.29]	[4.07]
α_{CAPM}	-0.20	0.05	0.01	0.15	0.16	0.36
	[-3.55]	[1.09]	[0.16]	[2.93]	[3.15]	[5.13]
α_{FF3}	-0.23	0.03	0.07	0.15	0.13	0.36
	[-4.24]	[0.59]	[1.32]	[2.86]	[2.67]	[5.19]
α_{FF4}	-0.18	0.03	0.12	0.11	0.12	0.30
	[-3.36]	[0.75]	[2.15]	[2.08]	[2.31]	[4.29]
α_{FF5}	-0.19	-0.05	0.13	0.03	0.09	0.27
	[-3.50]	[-1.25]	[2.22]	[0.62]	[1.70]	[3.94]
α_{FF6}	-0.16	-0.04	0.16	0.01	0.08	0.24
	[-2.96]	[-0.95]	[2.74]	[0.27]	[1.55]	[3.42]
Panel B: Fama and French (2018) 6-factor model loadings for DDS-sorted portfolios						
β_{MKT}	1.09	0.97	0.97	0.97	1.03	-0.06
	[89.25]	[97.28]	[73.48]	[84.98]	[87.30]	[-3.87]
β_{SMB}	0.09	-0.12	-0.00	-0.02	0.13	0.04
	[4.82]	[-7.65]	[-0.14]	[-1.29]	[7.23]	[1.66]
β_{HML}	0.15	0.07	-0.16	-0.09	0.01	-0.15
	[6.53]	[3.82]	[-6.16]	[-3.92]	[0.24]	[-4.84]
β_{RMW}	0.06	0.14	-0.04	0.11	0.07	0.01
	[2.46]	[7.09]	[-1.50]	[4.98]	[2.86]	[0.23]
β_{CMA}	-0.24	0.11	-0.11	0.28	0.09	0.33
	[-6.86]	[3.73]	[-2.90]	[8.35]	[2.50]	[7.13]
β_{UMD}	-0.05	-0.02	-0.05	0.03	0.01	0.06
	[-4.17]	[-2.21]	[-3.86]	[2.62]	[1.01]	[3.96]
Panel C: Average number of firms (n) and market capitalization (me)						
n	674	527	1055	576	648	
me ($\$10^6$)	1579	2730	2124	2684	1492	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DDS 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	0.29	0.36	0.36	0.30	0.27	0.24
			[4.07]	[5.13]	[5.19]	[4.29]	[3.94]	[3.42]
Quintile	NYSE	EW	0.18	0.22	0.20	0.19	0.18	0.17
			[4.15]	[4.86]	[4.56]	[4.16]	[4.05]	[3.86]
Quintile	Name	VW	0.26	0.31	0.32	0.28	0.26	0.24
			[3.66]	[4.49]	[4.64]	[4.00]	[3.80]	[3.47]
Quintile	Cap	VW	0.29	0.34	0.35	0.30	0.25	0.23
			[4.20]	[4.96]	[5.13]	[4.37]	[3.71]	[3.31]
Decile	NYSE	VW	0.25	0.33	0.31	0.21	0.17	0.11
			[2.52]	[3.24]	[3.07]	[2.11]	[1.70]	[1.14]
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	0.32	0.32	0.28	0.25	0.22
			[3.22]	[4.45]	[4.50]	[4.05]	[3.46]	[3.15]
Quintile	NYSE	EW	-0.08					
			[-1.27]					
Quintile	Name	VW	0.20	0.27	0.27	0.25	0.23	0.21
			[2.80]	[3.76]	[3.89]	[3.57]	[3.23]	[2.99]
Quintile	Cap	VW	0.24	0.30	0.31	0.28	0.23	0.21
			[3.43]	[4.37]	[4.50]	[4.13]	[3.33]	[3.07]
Decile	NYSE	VW	0.18	0.27	0.26	0.20	0.15	0.11
			[1.81]	[2.68]	[2.54]	[2.03]	[1.49]	[1.13]

Table 3: Conditional sort on size and DDS

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

	DDS Quintiles					DDS Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.72	0.92	1.00	0.98	0.79	0.07	0.09	0.06	0.04	0.02	0.01
	[2.61]	[3.32]	[3.61]	[3.44]	[2.77]	[0.74]	[0.96]	[0.65]	[0.38]	[0.22]	[0.10]
(2)	0.76	0.98	0.84	0.96	0.89	0.13	0.17	0.14	0.13	0.10	0.10
	[2.84]	[3.85]	[3.29]	[3.82]	[3.51]	[1.60]	[2.12]	[1.87]	[1.68]	[1.33]	[1.25]
(3)	0.85	0.82	0.87	0.87	0.96	0.10	0.16	0.16	0.13	0.16	0.14
	[3.38]	[3.69]	[3.56]	[3.88]	[4.07]	[1.30]	[2.07]	[2.05]	[1.59]	[2.06]	[1.75]
(4)	0.73	0.84	0.87	0.79	0.90	0.17	0.20	0.19	0.18	0.14	0.14
	[3.24]	[3.95]	[3.86]	[3.72]	[4.18]	[2.21]	[2.69]	[2.55]	[2.33]	[1.82]	[1.74]
(5)	0.48	0.63	0.64	0.69	0.86	0.38	0.42	0.43	0.35	0.33	0.28
	[2.33]	[3.48]	[3.29]	[3.68]	[4.38]	[4.22]	[4.61]	[4.84]	[3.90]	[3.70]	[3.15]

Panel B: Portfolio average number of firms and market capitalization

	DDS Quintiles: Average n					DDS Quintiles: Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	393	393	393	393	390	36	33	32	33	35
(2)	107	106	106	107	106	58	60	57	60	59
(3)	76	76	75	76	76	104	104	100	102	104
(4)	63	63	64	64	63	221	228	219	226	220
(5)	58	58	58	58	58	1378	1941	1796	2043	1361

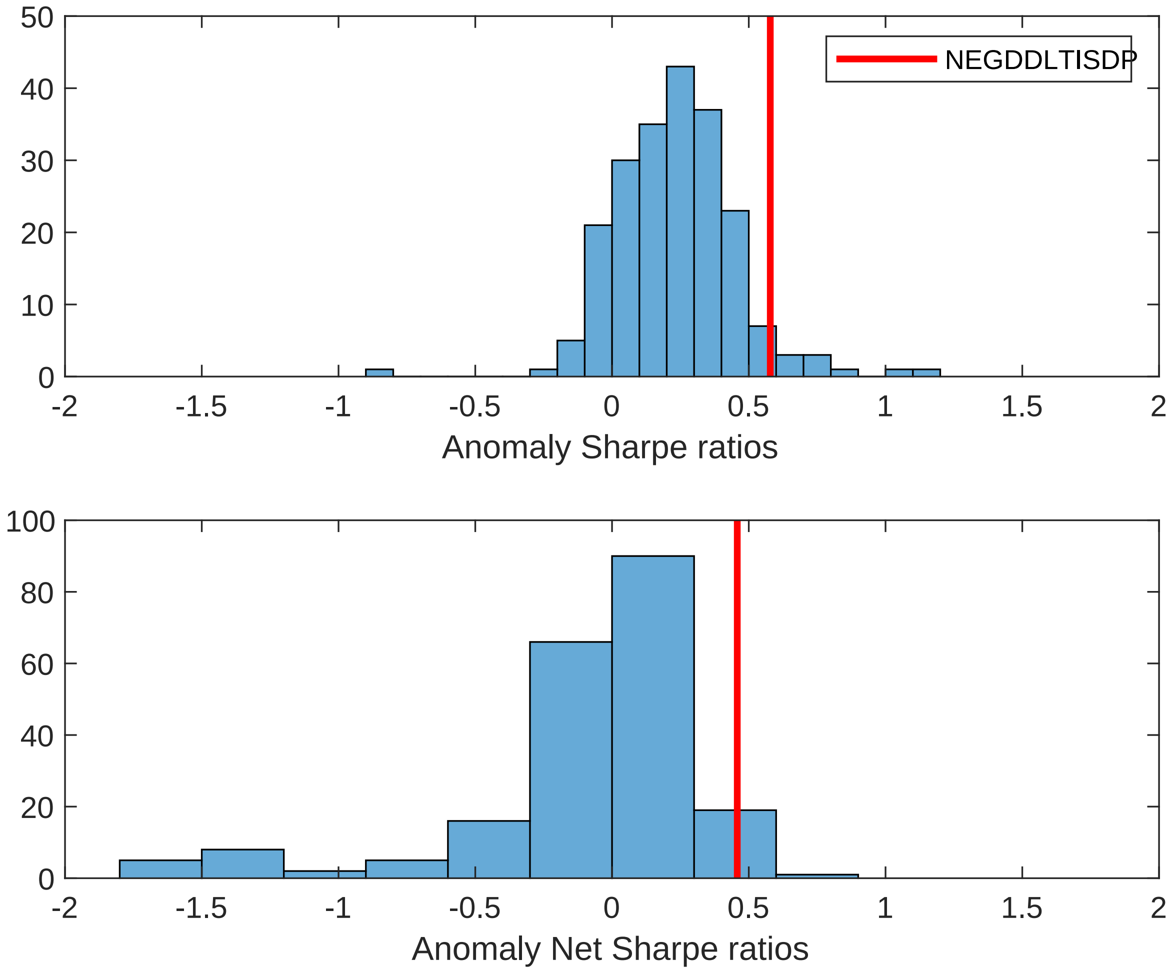

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

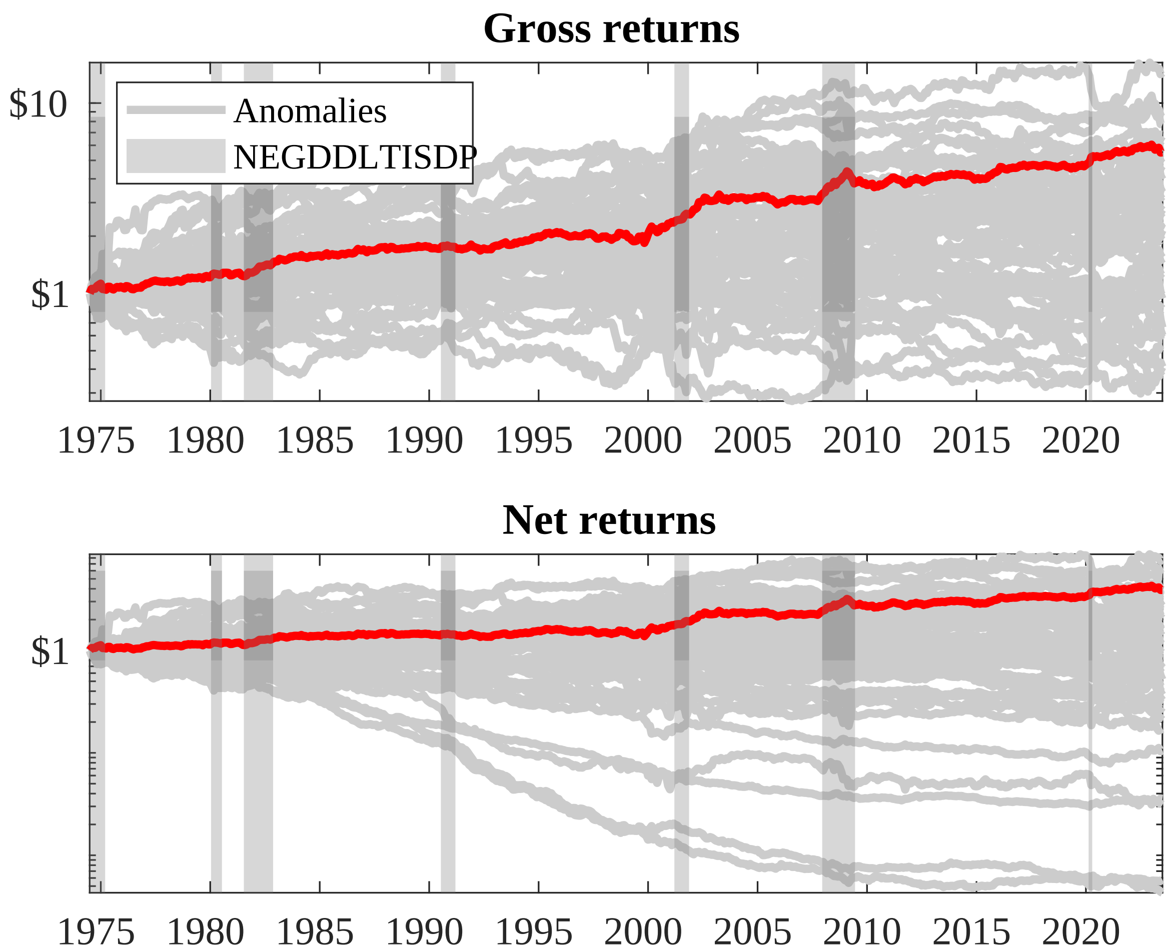

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

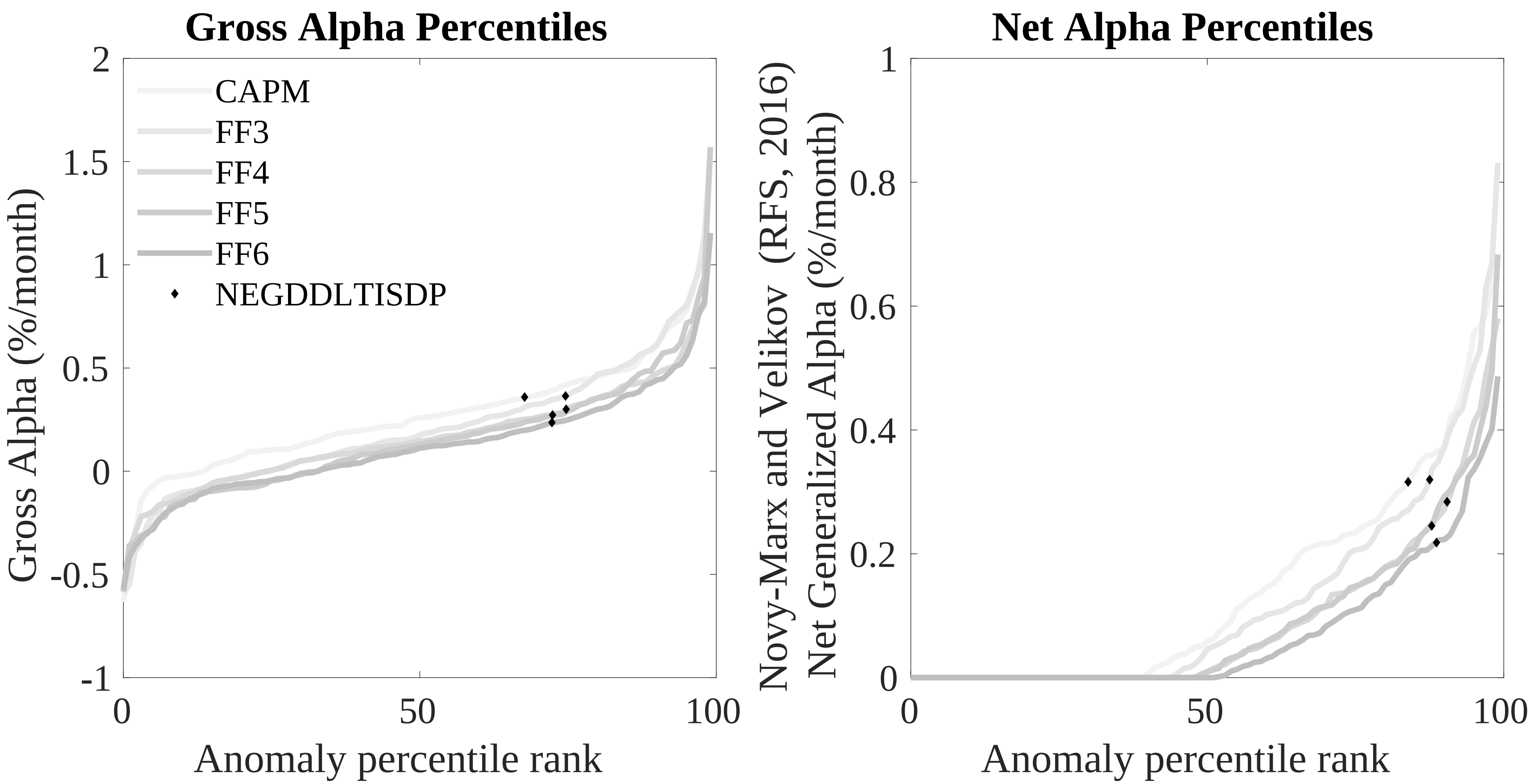

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DDS trading strategy alphas (diamonds). The strategies are constructed using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

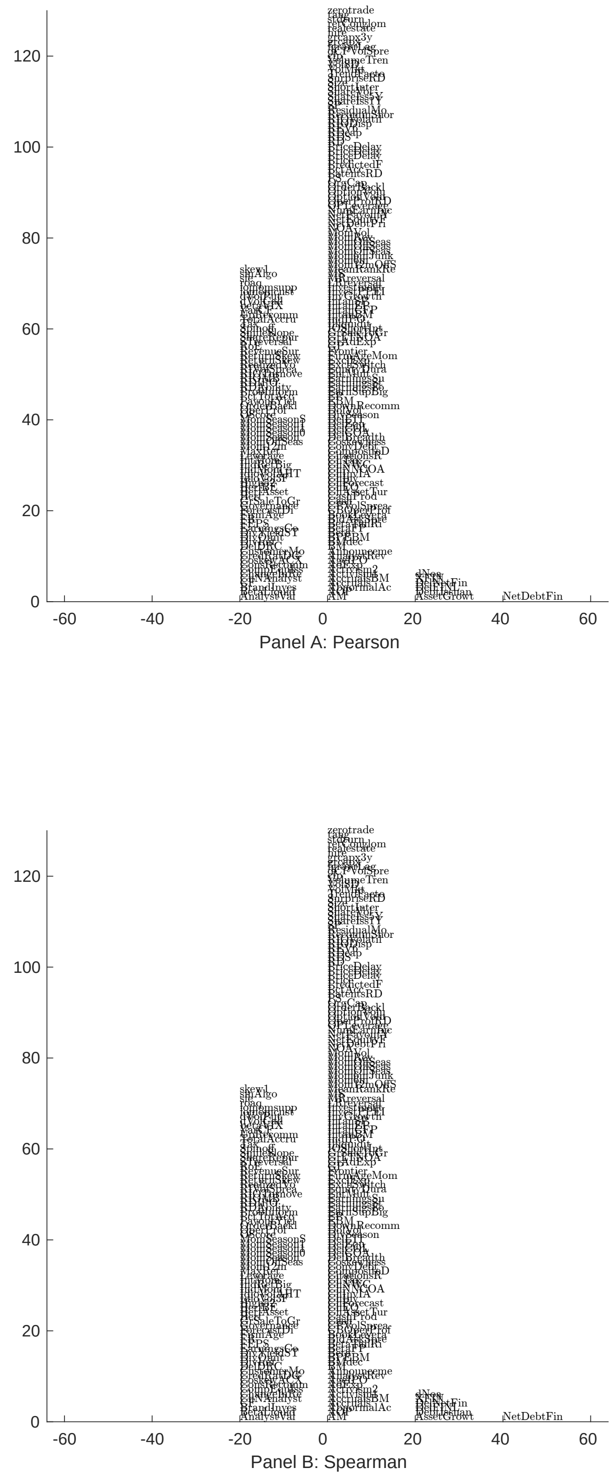

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

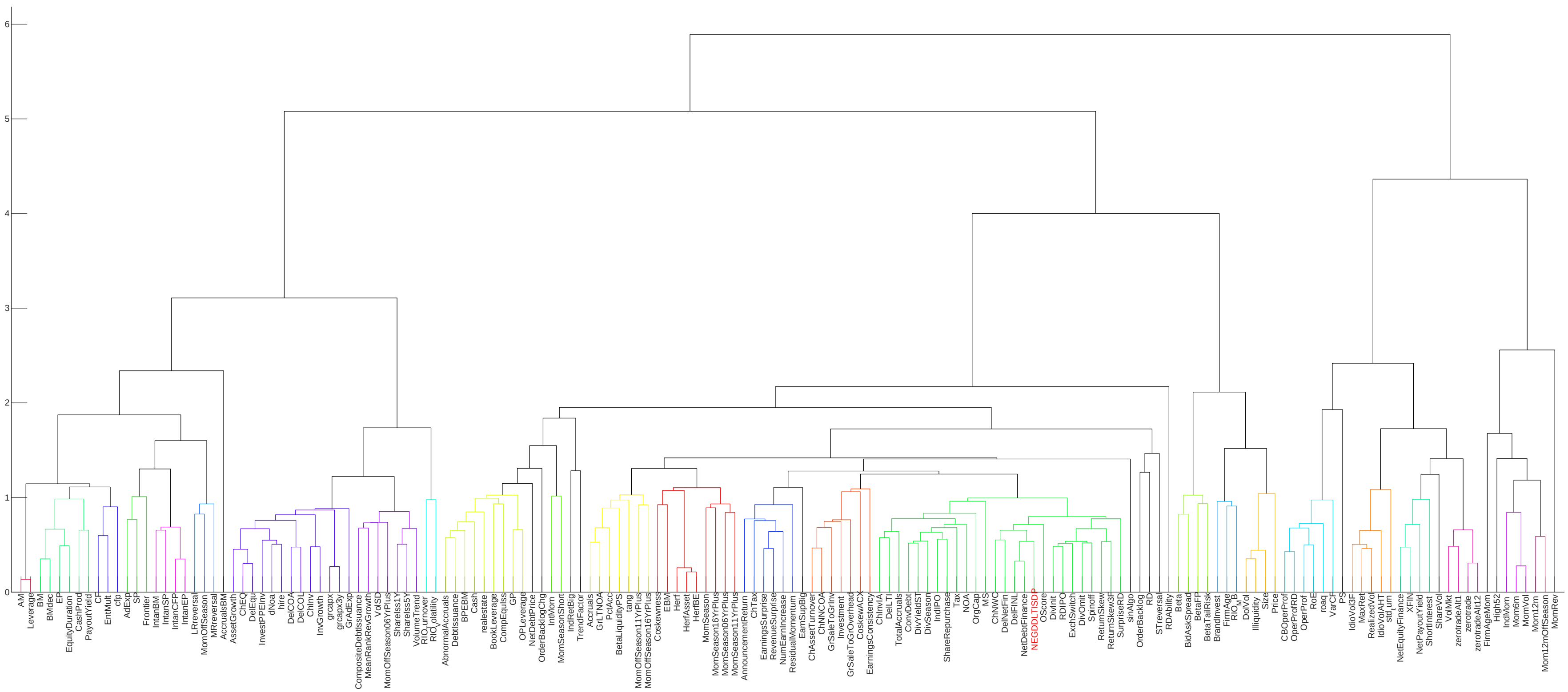

Figure 6: Agglomerative hierarchical cluster plot

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

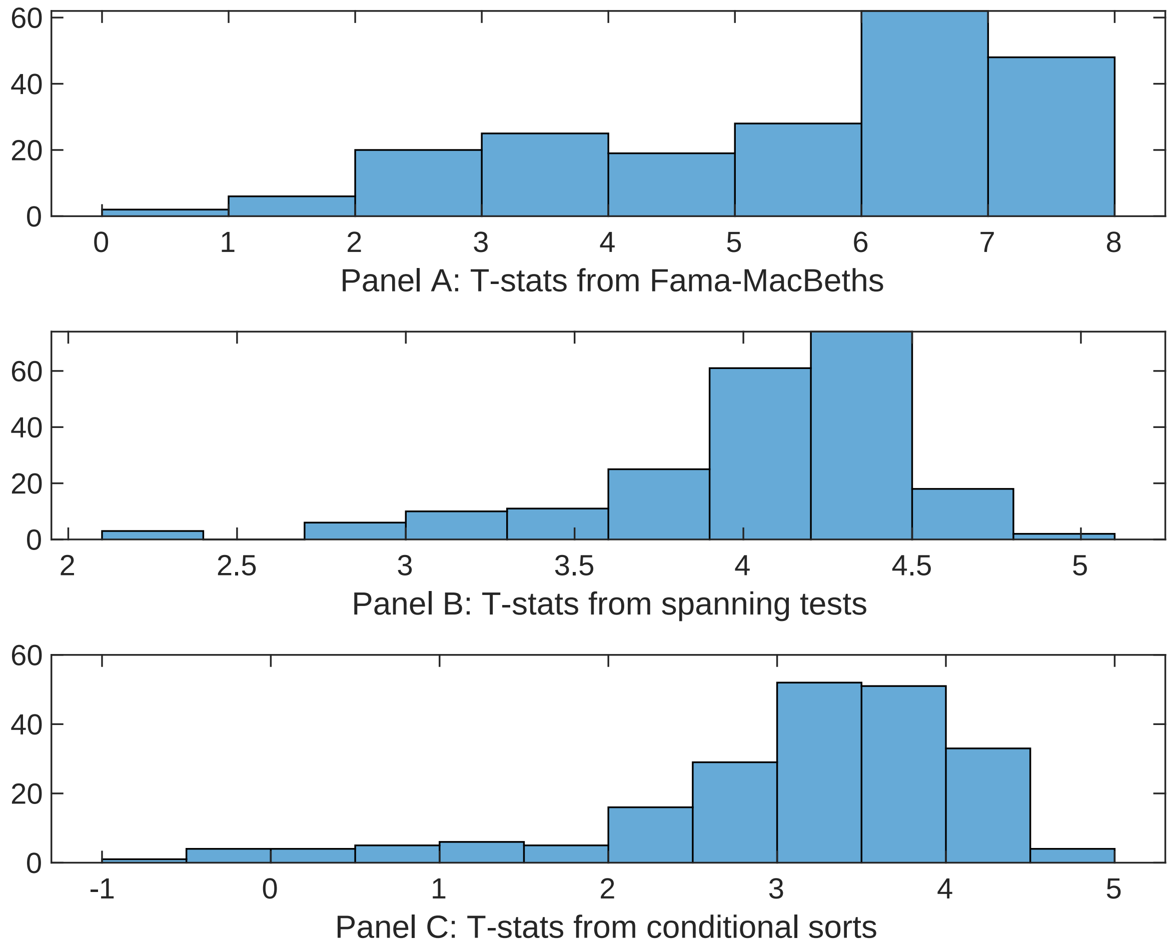

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DDS} DDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DDS. Stocks are finally grouped into five DDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DDS 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 DDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DDS} DDS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, change in net operating assets, Employment 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	0.14	0.15	0.14	0.14	0.15
	[5.55]	[5.52]	[5.89]	[5.98]	[5.84]	[5.52]	[6.12]
DDS	0.45	0.56	0.74	0.39	0.37	0.11	0.73
	[2.30]	[2.82]	[3.63]	[1.87]	[1.91]	[5.67]	[0.36]
Anomaly 1	0.17						-0.35
	[9.16]						[-0.91]
Anomaly 2		0.19					0.46
		[8.55]					[0.85]
Anomaly 3			0.18				0.78
			[6.01]				[1.54]
Anomaly 4				0.11			0.50
				[8.99]			[2.94]
Anomaly 5					0.14		0.65
					[9.99]		[4.27]
Anomaly 6						0.91	0.96
						[5.95]	[0.76]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the DDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Net external financing, Asset growth, change in net operating assets, Employment 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	0.23	0.23	0.23	0.25	0.25	0.25	0.23
	[3.38]	[3.40]	[3.40]	[3.56]	[3.52]	[3.60]	[3.39]
Anomaly 1	21.65						16.10
	[5.42]						[2.93]
Anomaly 2		21.31					9.84
		[5.57]					[1.85]
Anomaly 3			12.28				8.80
			[3.50]				[2.35]
Anomaly 4				3.11			-0.45
				[0.69]			[-0.09]
Anomaly 5					0.99		-8.11
					[0.24]		[-1.81]
Anomaly 6						2.13	1.22
						[0.55]	[0.31]
mkt	-6.08	-6.34	-4.68	-6.33	-6.34	-6.30	-4.94
	[-3.91]	[-4.08]	[-2.84]	[-3.97]	[-3.97]	[-3.94]	[-3.03]
smb	1.90	2.41	7.79	3.52	3.85	3.93	4.56
	[0.78]	[1.00]	[2.89]	[1.40]	[1.56]	[1.59]	[1.61]
hml	-13.43	-14.23	-13.14	-14.60	-14.56	-14.85	-12.07
	[-4.48]	[-4.76]	[-4.30]	[-4.76]	[-4.71]	[-4.73]	[-3.90]
rmw	-0.62	-0.71	-6.32	1.04	1.05	1.10	-6.46
	[-0.20]	[-0.23]	[-1.67]	[0.33]	[0.33]	[0.35]	[-1.71]
cma	24.70	26.45	23.68	28.03	31.16	29.95	23.60
	[5.24]	[5.72]	[4.60]	[3.85]	[5.62]	[5.12]	[3.16]
umd	4.38	4.72	6.42	6.58	6.42	6.35	4.27
	[2.71]	[2.95]	[4.02]	[4.06]	[3.97]	[3.91]	[2.61]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	21	22	19	18	17	17	23

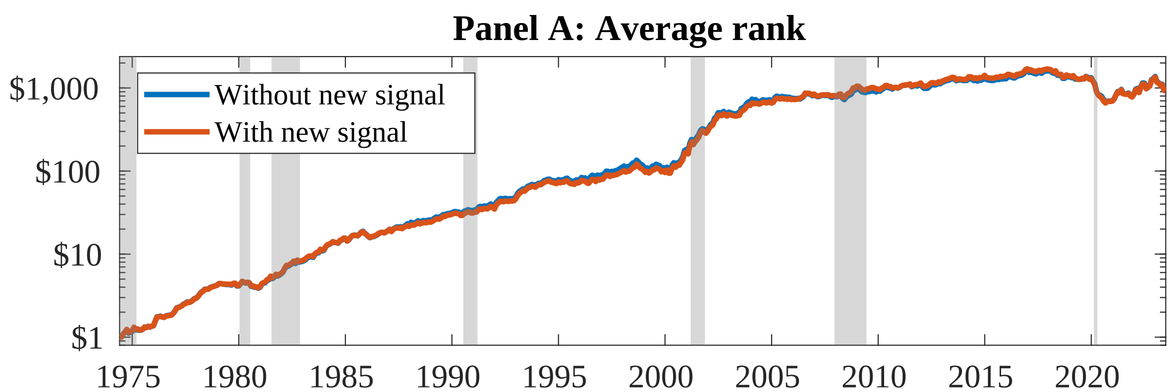

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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