Debt-Efficiency Score and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt-Efficiency Score (DES), 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 DES achieves an annualized gross (net) Sharpe ratio of 0.43 (0.32), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 16 (14) bps/month with a t-statistic of 2.30 (1.96), 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, Employment growth, Inventory Growth, Asset growth) is 16 bps/month with a t-statistic of 2.34.

1 Introduction

Market efficiency and asset pricing theory suggest that systematic patterns in stock returns should reflect underlying economic risks. However, the growing literature documenting return predictability based on firm characteristics poses a challenge to this view. While numerous studies examine how firms' financing decisions affect expected returns, the relationship between firms' operational efficiency in managing debt and subsequent stock performance remains underexplored. This gap is particularly notable given the central role of debt management in corporate financial policy and firm value creation.

Prior research has largely focused on the level or changes in debt financing (Baker and Wurgler, 2002) and investment-based explanations of the cross-section of returns (Cochrane et al., 2023). Yet these approaches may miss important information contained in how effectively firms deploy their debt financing to generate operating performance. Understanding this relationship is crucial as inefficient debt utilization could signal agency problems, operational weaknesses, or strategic mistakes that affect future profitability and returns.

We propose that a firm's Debt-Efficiency Score (DES) contains valuable information about future stock returns through multiple economic channels. First, following (Jensen, 1986), firms with poor debt efficiency may suffer from agency problems where managers fail to optimize the deployment of borrowed capital, leading to value destruction that markets only gradually recognize. This builds on evidence that market participants often underreact to complex operating information (Hirshleifer and Teoh, 2003).

Second, low debt efficiency could indicate structural problems in a firm's business model or competitive position. As (Porter and Kramer, 2011) argue, sustainable competitive advantage requires efficient deployment of all resources, including financial capital. Firms struggling to generate adequate returns on their debt may face deteriorating market positions, presaging future underperformance. This connects to research showing markets can be slow to incorporate negative information about business fundamentals (Hong and Stein, 1999).

Third, drawing on (Campbell and Shiller, 1988), debt efficiency may capture information about future cash flow risk not fully reflected in traditional measures. Firms with low debt efficiency scores face greater refinancing risk and reduced financial flexibility, potentially leading to higher required returns. This risk-based channel suggests DES may identify variation in expected returns tied to fundamental economic risks.

Our analysis reveals that DES strongly predicts the cross-section of stock returns. A value-weighted long-short portfolio strategy based on DES quintiles generates a monthly alpha of 16 basis points (t-statistic = 2.30) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.43, placing it in the top 14% of documented return predictors. These results are robust to controlling for transaction costs, with a net Sharpe ratio of 0.32.

Importantly, DES maintains significant predictive power among large-cap stocks, where many anomalies fail to generate reliable returns. In the largest size quintile, the DES long-short strategy earns a monthly alpha of 19 basis points (t-statistic = 2.15) relative to the Fama-French six-factor model. This suggests the signal captures economically meaningful information beyond well-known size effects.

The predictive power of DES remains robust when controlling for closely related anomalies. In spanning tests that include the six most related predictors (Change in financial liabilities, Net debt financing, Net external financing, Employment growth, Inventory Growth, and Asset growth) plus standard factors, DES generates a monthly alpha of 16 basis points (t-statistic = 2.34). This indicates DES captures unique information about expected returns not contained in existing measures.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures how efficiently firms utilize debt financing, extending work by (Titman and Wei, 1993) on capital structure and returns, and (Brandt and Brav, 2004) on the pricing of financing decisions. Unlike existing measures that focus on debt levels or changes, DES directly measures operational efficiency in deploying borrowed capital.

Second, we contribute to the growing literature on investment-based asset pricing pioneered by (Cochrane et al., 2023) by showing how operational efficiency in capital deployment affects required returns. Our findings suggest markets do not fully price the information contained in firms' debt management effectiveness, consistent with theories of limited attention and gradual information diffusion (Hong and Stein, 1999).

Third, our work has important implications for both academic research and investment practice. For researchers, we demonstrate the value of combining operational and financial metrics to predict returns. For practitioners, DES offers a new tool for security selection that is particularly effective among large, liquid stocks where many anomalies fail. The signal's robustness to transaction costs and effectiveness among large stocks suggests it can be profitably exploited in real-world portfolios.

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-Efficiency Score. 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 XOPR for operating income.

Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt during the fiscal year, while operating income (XOPR) measures the firm's core operational performance before interest and taxes.construction of the signal follows a change-based approach, where we first calculate the year-over-year change in DLTIS by subtracting the previous year's value from the current year's value. This difference is then scaled by the previous year's operating income (XOPR) to create our Debt-Efficiency Score. This scaling ensures comparability across firms of different sizes and operational scales. The resulting score captures the relative magnitude of changes in debt issuance compared to the firm's operational performance, providing insight into how aggressively firms are leveraging their operations through new debt. 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 DES signal. Panel A plots the time-series of the mean, median, and interquartile range for DES. On average, the cross-sectional mean (median) DES is -0.28 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DES data. The signal's interquartile range spans -0.13 to 0.13. Panel B of Figure 1 plots the time-series of the coverage of the DES signal for the CRSP universe. On average, the DES signal is available for 6.30% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does DES predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DES 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 DES portfolio and sells the low DES 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 DES strategy earns an average return of 0.21% per month with a t-statistic of 3.01. The annualized Sharpe ratio of the strategy is 0.43. The alphas range from 0.16% to 0.28% per month and have t-statistics exceeding 2.30 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 0.35, with a t-statistic of 7.49 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 554 stocks and an average market capitalization of at least $1,754 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 17 bps/month with a t-statistics of 3.48. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-four exceed two, and for sixteen 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 -9-21bps/month. The lowest return, (-9 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.38. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DES 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 DES strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DES, as well as average returns and alphas for long/short trading DES 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 DES strategy achieves an average return of 29 bps/month with a t-statistic of 3.21. Among these large cap stocks, the alphas for the DES strategy relative to the five most common factor models range from 19 to 36 bps/month with t-statistics between 2.15 and 3.98.

5 How does DES perform relative to the zoo?

Figure 2 puts the performance of DES 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 DES strategy falls in the distribution. The DES strategy's gross (net) Sharpe ratio of 0.43 (0.32) is greater than 86% (93%) 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 DES strategy (red line).[2] Ignoring trading costs, a \$1 invested in the DES strategy would have yielded \$2.45 which ranks the DES strategy in the top 8% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DES strategy would have yielded \$1.52 which ranks the DES strategy in the top 7% 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 DES relative to those. Panel A shows that

[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.

the DES strategy gross alphas fall between the 51 and 67 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 DES strategy has a positive net generalized alpha for five out of the five factor models. In these cases DES ranks between the 72 and 85 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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: $r_{DES,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DES. Stocks are finally grouped into five DES portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DES trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DES 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 DES signal in these Fama-MacBeth regressions exceed -0.30, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DES is -0.77.

Similarly, Table 5 reports results from spanning tests that regress returns to the DES 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 DES strategy earns alphas that range from 15-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.20, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DES trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.34.

7 Does DES add relative to the whole zoo?

Finally, we can ask how much adding DES 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 DES 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 DES grows to $949.76.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Debt-Efficiency Score (DES) 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 DES generates economically meaningful and statistically significant returns, with an annualized gross Sharpe ratio of 0.43 (0.32 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

[4] We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capitalization on CRSP in the period for which DES is available.

The persistence of the DES signal's predictive power, even after accounting for transaction costs and various risk factors, suggests that it captures a distinct aspect of firm performance that is not fully reflected in existing pricing factors. This has important implications for both academic research and practical investment management, as it provides a novel tool for portfolio construction and risk management.

However, several limitations should be noted. First, our analysis focuses on a specific time period and market context, which may not fully represent future market conditions. Second, the implementation of the strategy requires regular portfolio rebalancing, which could pose challenges for investors with limited trading capabilities or in less liquid market segments.

Future research could explore several promising directions. First, investigating the underlying economic mechanisms driving the DES signal's predictive power would enhance our understanding of this anomaly. Second, examining the signal's effectiveness in international markets and different asset classes could test its broader applicability. Finally, studying potential interactions between DES and other established factors could yield insights into optimal factor combination strategies.

In conclusion, while the DES signal demonstrates significant promise as a return predictor, continued research is needed to fully understand its theoretical foundations and practical applications across different market contexts.

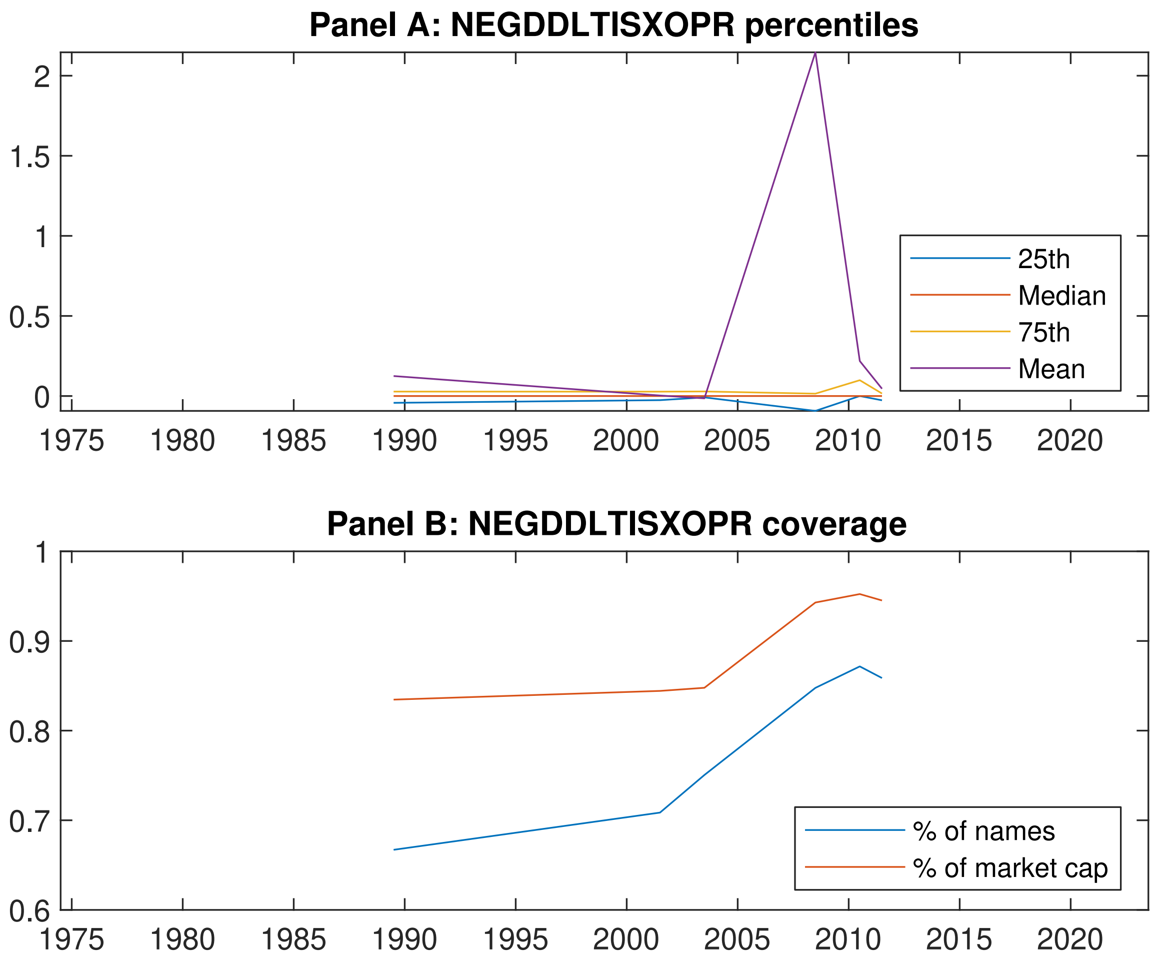


Figure 1: Times series of DES percentiles and coverage.
This figure plots descriptive statistics for DES. Panel A shows cross-sectional percentiles of DES over the sample. Panel B plots the monthly coverage of DES relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DES. 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 DES-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.55	0.70	0.69	0.80	0.76	0.21
	[2.65]	[3.83]	[3.37]	[4.38]	[3.91]	[3.01]
α_{CAPM}	-0.18	0.07	-0.02	0.17	0.08	0.26
	[-3.39]	[1.29]	[-0.31]	[3.33]	[1.66]	[3.74]
α_{FF3}	-0.22	0.04	0.04	0.16	0.06	0.28
	[-4.27]	[0.86]	[0.77]	[3.22]	[1.25]	[4.00]
α_{FF4}	-0.19	0.07	0.09	0.11	0.06	0.25
	[-3.67]	[1.47]	[1.61]	[2.27]	[1.18]	[3.50]
α_{FF5}	-0.15	-0.05	0.08	0.07	0.02	0.17
	[-3.02]	[-1.00]	[1.43]	[1.35]	[0.32]	[2.47]
α_{FF6}	-0.14	-0.02	0.11	0.04	0.02	0.16
	[-2.72]	[-0.37]	[1.97]	[0.81]	[0.40]	[2.30]
Panel B: Fama and French (2018) 6-factor model loadings for DES-sorted portfolios						
β_{MKT}	1.05	0.98	0.99	0.97	1.02	-0.04
	[89.40]	[93.53]	[78.05]	[85.07]	[85.62]	[-2.21]
β_{SMB}	0.01	-0.11	0.04	0.01	0.02	0.01
	[0.73]	[-7.09]	[1.92]	[0.51]	[1.06]	[0.25]
β_{HML}	0.18	0.06	-0.15	-0.05	-0.02	-0.20
	[8.03]	[3.09]	[-6.37]	[-2.08]	[-0.68]	[-6.43]
β_{RMW}	-0.04	0.17	0.01	0.12	0.03	0.06
	[-1.58]	[8.13]	[0.32]	[5.19]	[1.08]	[1.97]
β_{CMA}	-0.19	0.11	-0.12	0.17	0.16	0.35
	[-5.51]	[3.62]	[-3.16]	[5.08]	[4.61]	[7.49]
β_{UMD}	-0.02	-0.05	-0.05	0.05	-0.01	0.02
	[-2.08]	[-4.85]	[-4.06]	[4.10]	[-0.59]	[1.10]
Panel C: Average number of firms (n) and market capitalization (me)						
n	656	554	1088	609	630	
me ($\$10^6$)	1797	2611	2057	2556	1754	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DES 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	0.21	0.26	0.28	0.25	0.17	0.16
			[3.01]	[3.74]	[4.00]	[3.50]	[2.47]	[2.30]
Quintile	NYSE	EW	0.17	0.19	0.19	0.18	0.17	0.17
			[3.48]	[4.01]	[3.85]	[3.63]	[3.48]	[3.41]
Quintile	Name	VW	0.19	0.23	0.25	0.21	0.17	0.15
			[2.74]	[3.41]	[3.71]	[3.07]	[2.60]	[2.27]
Quintile	Cap	VW	0.26	0.30	0.32	0.27	0.20	0.17
			[3.66]	[4.36]	[4.62]	[3.83]	[2.94]	[2.54]
Decile	NYSE	VW	0.27	0.37	0.36	0.27	0.22	0.17
			[2.94]	[4.02]	[3.91]	[2.98]	[2.46]	[1.94]
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	0.16	0.22	0.24	0.22	0.15	0.14
			[2.24]	[3.15]	[3.36]	[3.11]	[2.16]	[1.96]
Quintile	NYSE	EW	-0.09					
			[-1.38]					
Quintile	Name	VW	0.13	0.19	0.21	0.19	0.15	0.13
			[1.95]	[2.84]	[3.07]	[2.76]	[2.19]	[1.93]
Quintile	Cap	VW	0.21	0.27	0.28	0.25	0.18	0.16
			[2.93]	[3.78]	[3.98]	[3.59]	[2.59]	[2.30]
Decile	NYSE	VW	0.21	0.31	0.31	0.26	0.20	0.16
			[2.24]	[3.40]	[3.29]	[2.82]	[2.18]	[1.85]

Table 3: Conditional sort on size and DES

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

	DES Quintiles					DES Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.68	0.93	0.99	1.03	0.73	0.05	0.06	0.04	0.03	0.05	0.04
	[2.47]	[3.39]	[3.58]	[3.47]	[2.66]	[0.63]	[0.82]	[0.59]	[0.45]	[0.66]	[0.56]
(2)	0.75	0.98	0.82	0.98	0.86	0.11	0.15	0.12	0.12	0.09	0.09
	[2.80]	[3.82]	[3.26]	[3.89]	[3.40]	[1.37]	[1.86]	[1.52]	[1.47]	[1.15]	[1.16]
(3)	0.79	0.86	0.86	0.94	0.88	0.09	0.14	0.15	0.11	0.13	0.11
	[3.19]	[3.82]	[3.53]	[4.14]	[3.79]	[1.16]	[1.82]	[1.95]	[1.43]	[1.69]	[1.36]
(4)	0.72	0.83	0.90	0.83	0.86	0.13	0.16	0.15	0.13	0.09	0.09
	[3.25]	[3.85]	[3.99]	[3.87]	[3.98]	[1.71]	[2.01]	[1.93]	[1.69]	[1.15]	[1.06]
(5)	0.45	0.69	0.63	0.73	0.74	0.29	0.34	0.36	0.30	0.22	0.19
	[2.17]	[3.84]	[3.10]	[3.89]	[3.85]	[3.21]	[3.79]	[3.98]	[3.28]	[2.50]	[2.15]

Panel B: Portfolio average number of firms and market capitalization

	DES Quintiles					DES Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	398	399	399	399	396	38	33	33	33	36
(2)	108	108	108	108	108	60	60	58	61	60
(3)	77	77	77	77	77	106	106	102	105	105
(4)	64	65	65	65	64	224	232	222	230	222
(5)	59	59	59	59	59	1477	1953	1741	1994	1484

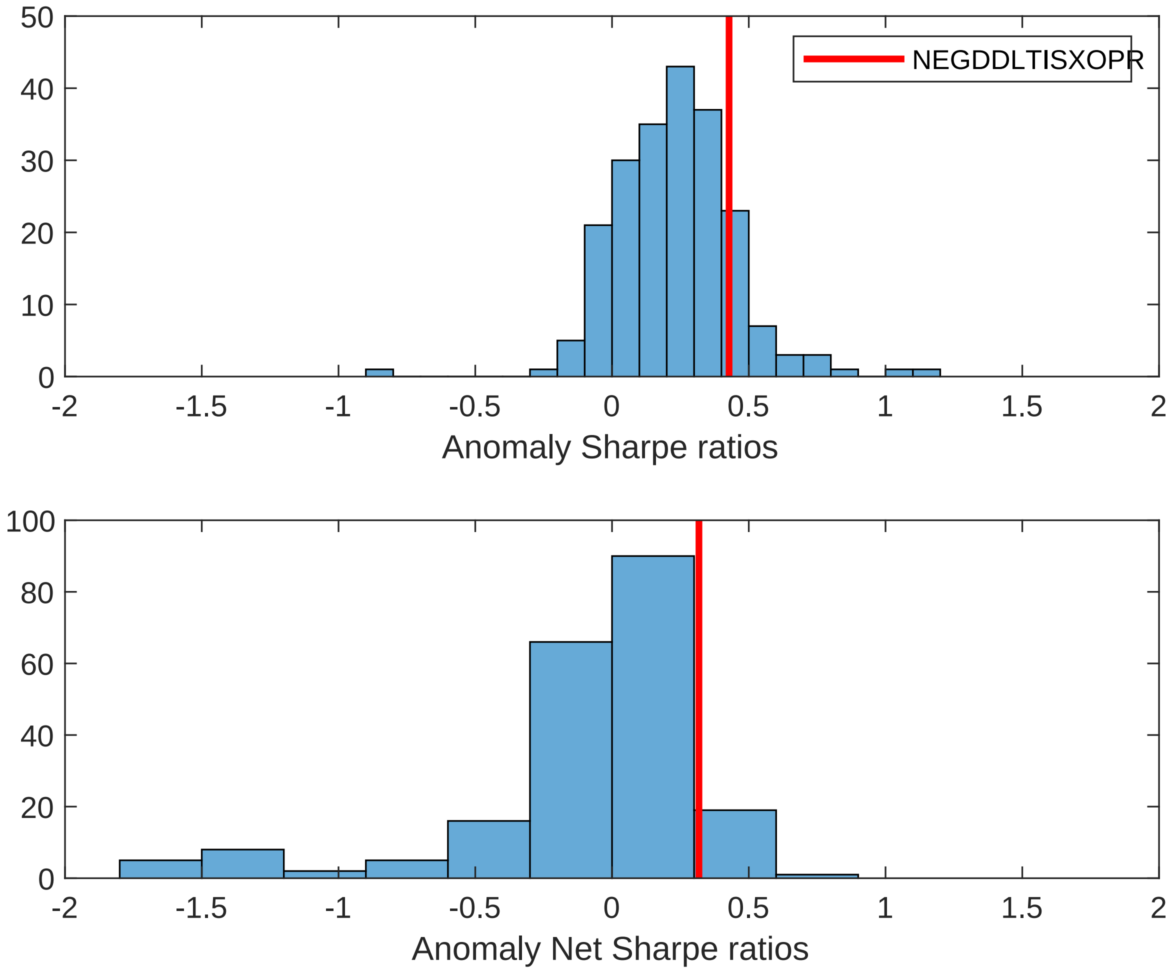


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DES with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

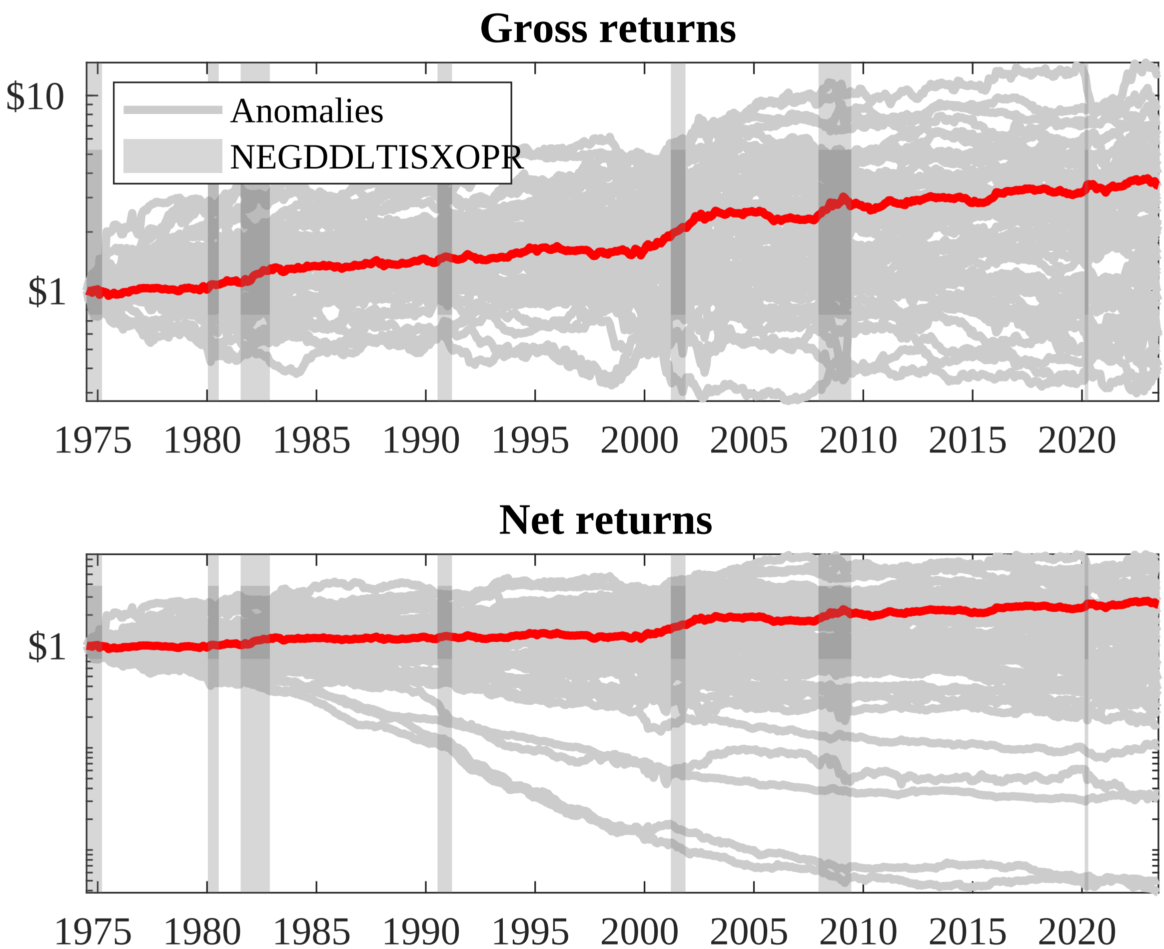


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DES trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

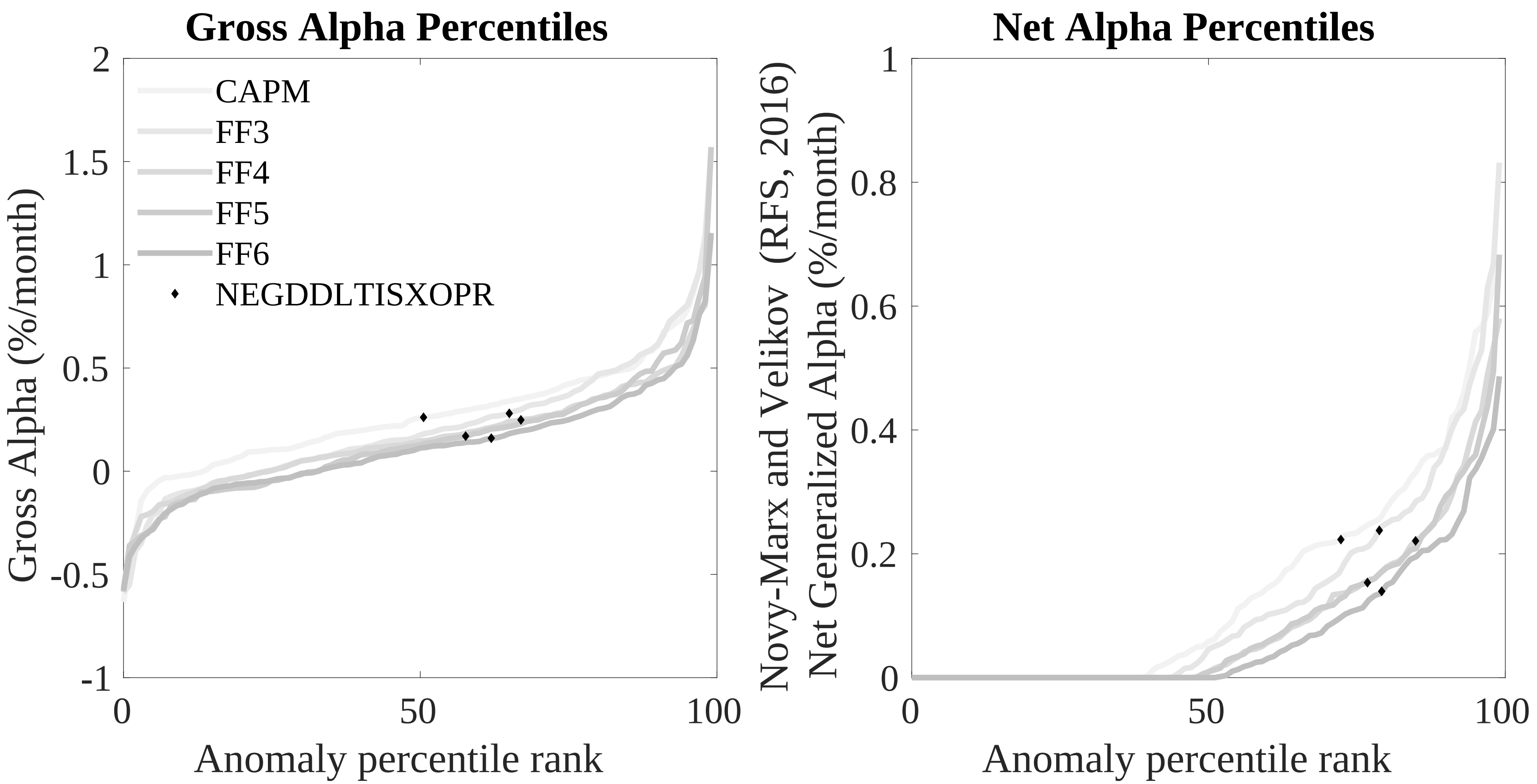
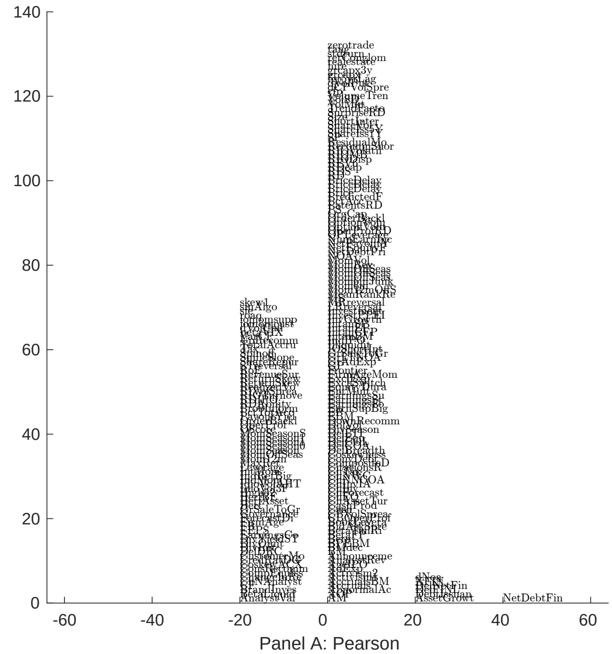


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DES trading strategy alphas (diamonds). The strategies are constructed using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



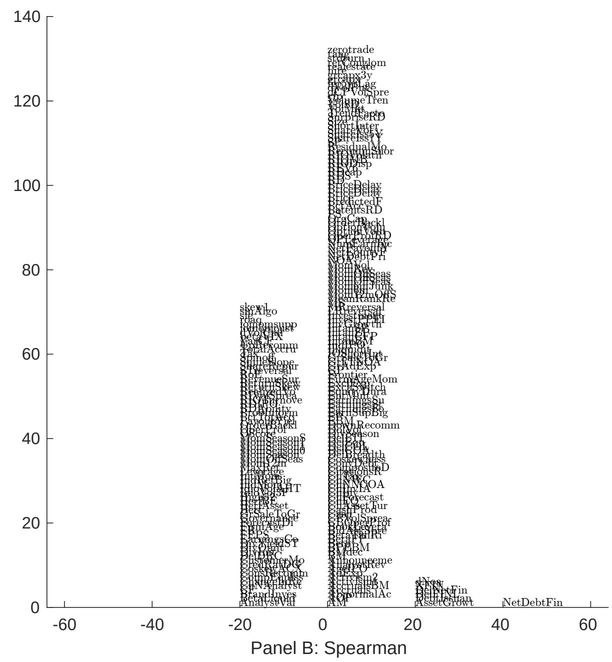


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DES. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

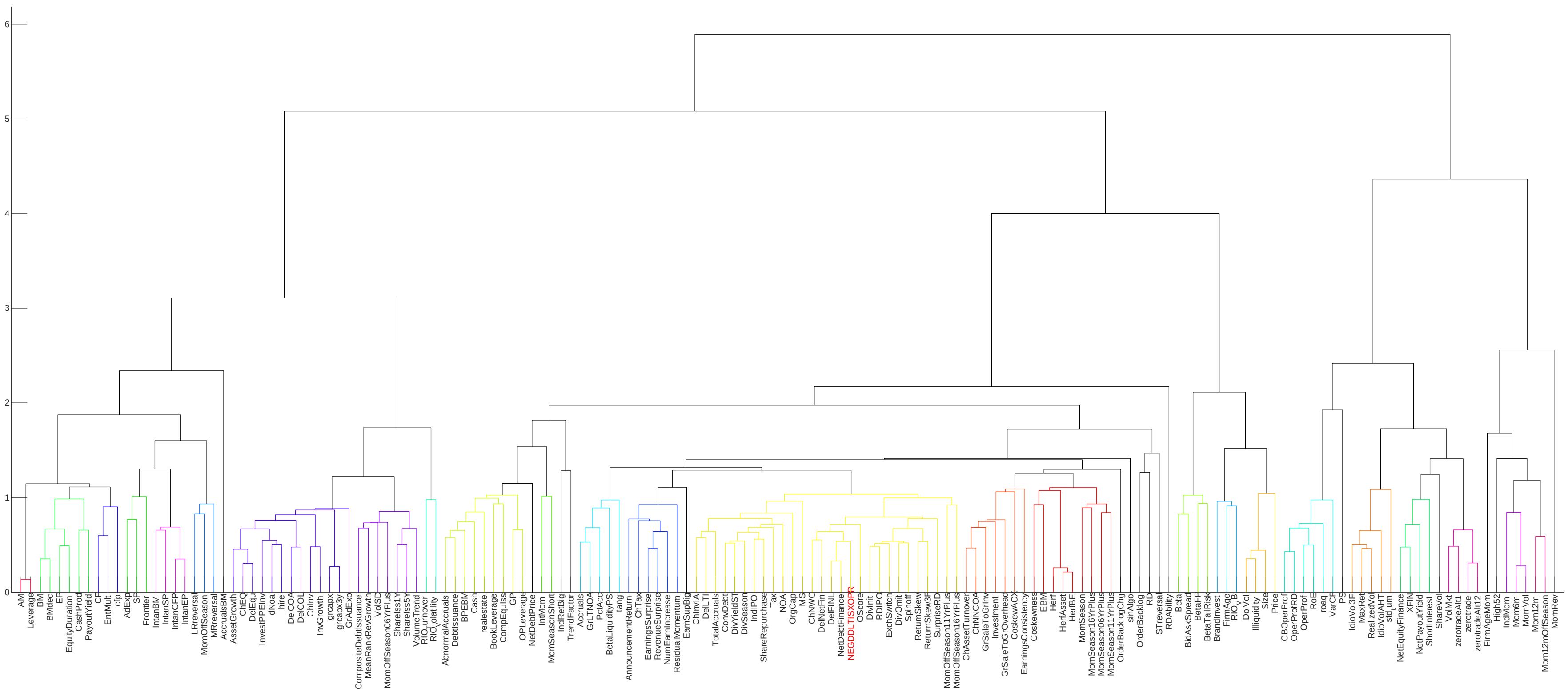


Figure 6: Agglomerative hierarchical cluster plot

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

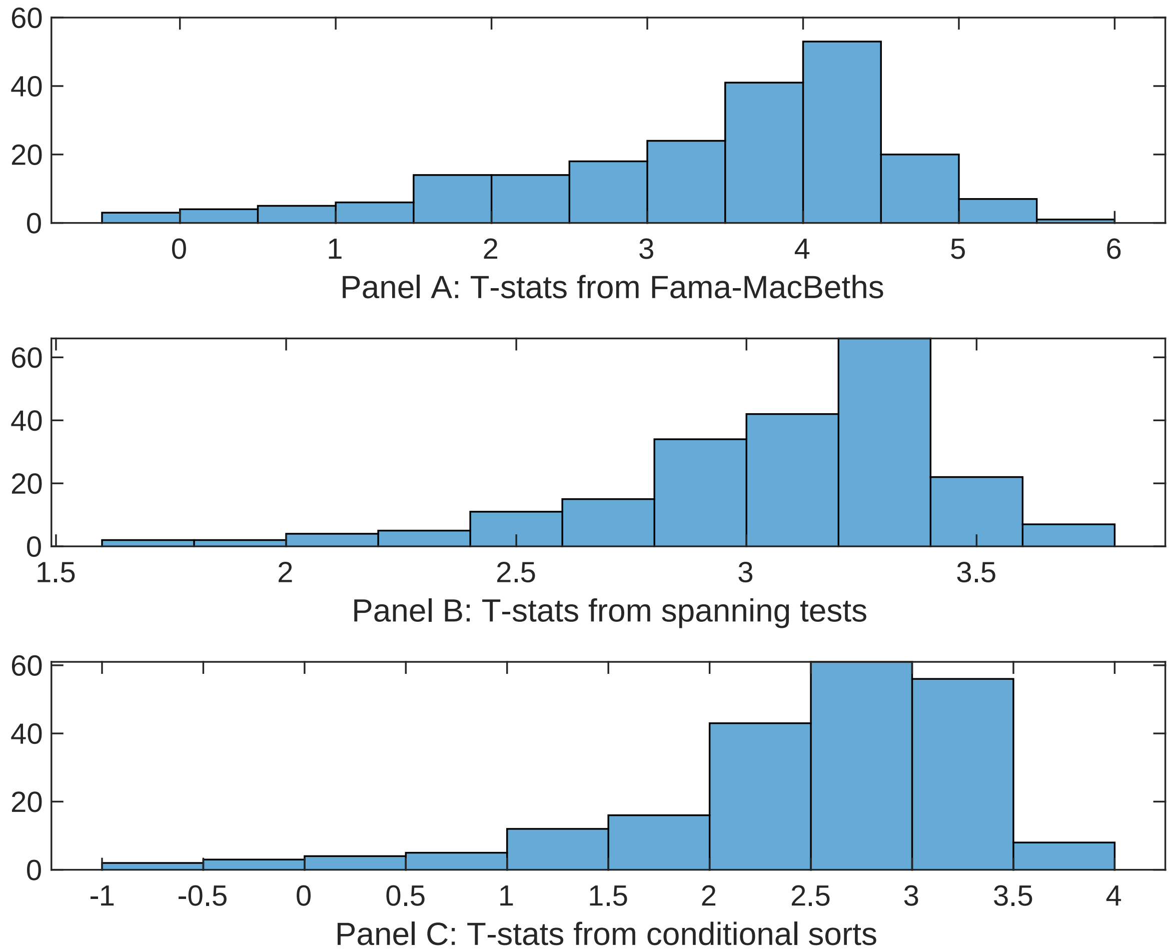


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DES conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DES} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DES} DES_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DES,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DES. Stocks are finally grouped into five DES portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DES 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 DES. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DES} DES_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Employment growth, Inventory Growth, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.14	0.14	0.14	0.14	0.14	0.15	0.15
	[5.52]	[5.49]	[5.85]	[5.50]	[5.46]	[5.96]	[5.80]
DES	0.12	0.17	0.66	0.15	0.23	-0.14	-0.50
	[0.03]	[0.37]	[1.44]	[3.23]	[3.56]	[-0.30]	[-0.77]
Anomaly 1	0.17						-0.61
	[9.40]						[-1.33]
Anomaly 2		0.20					0.11
		[9.20]					[1.70]
Anomaly 3			0.19				0.97
			[6.21]				[1.76]
Anomaly 4				0.92			0.47
				[6.13]			[0.34]
Anomaly 5					0.39		0.76
					[6.79]		[1.36]
Anomaly 6						0.11	0.75
						[9.38]	[3.90]
# 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 DES trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DES} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Employment growth, Inventory Growth, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.15	0.15	0.16	0.20	0.17	0.17	0.16
	[2.20]	[2.24]	[2.26]	[2.83]	[2.44]	[2.45]	[2.34]
Anomaly 1	25.64						18.18
	[6.43]						[3.39]
Anomaly 2		23.07					7.79
		[6.01]					[1.47]
Anomaly 3			12.44				8.59
			[3.52]				[2.30]
Anomaly 4				11.46			7.47
				[2.95]			[1.85]
Anomaly 5					6.04		3.85
					[2.19]		[1.36]
Anomaly 6						6.91	-3.35
						[1.52]	[-0.70]
mkt	-3.43	-3.74	-2.06	-3.51	-3.90	-3.71	-2.33
	[-2.21]	[-2.40]	[-1.24]	[-2.20]	[-2.43]	[-2.31]	[-1.43]
smb	-1.85	-1.10	4.45	0.95	1.06	-0.25	2.12
	[-0.76]	[-0.45]	[1.64]	[0.38]	[0.43]	[-0.10]	[0.75]
hml	-18.16	-19.13	-18.05	-21.48	-19.64	-19.68	-18.88
	[-6.07]	[-6.38]	[-5.86]	[-6.82]	[-6.38]	[-6.37]	[-6.14]
rmw	4.59	4.67	-0.90	6.97	7.38	6.58	0.20
	[1.48]	[1.49]	[-0.24]	[2.19]	[2.30]	[2.06]	[0.05]
cma	25.44	28.07	25.65	23.45	28.60	25.37	14.08
	[5.41]	[6.05]	[4.94]	[4.01]	[5.44]	[3.46]	[1.89]
umd	-0.67	-0.09	1.75	1.23	1.24	2.07	-1.47
	[-0.42]	[-0.06]	[1.09]	[0.76]	[0.76]	[1.27]	[-0.89]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	19	18	15	14	14	13	20

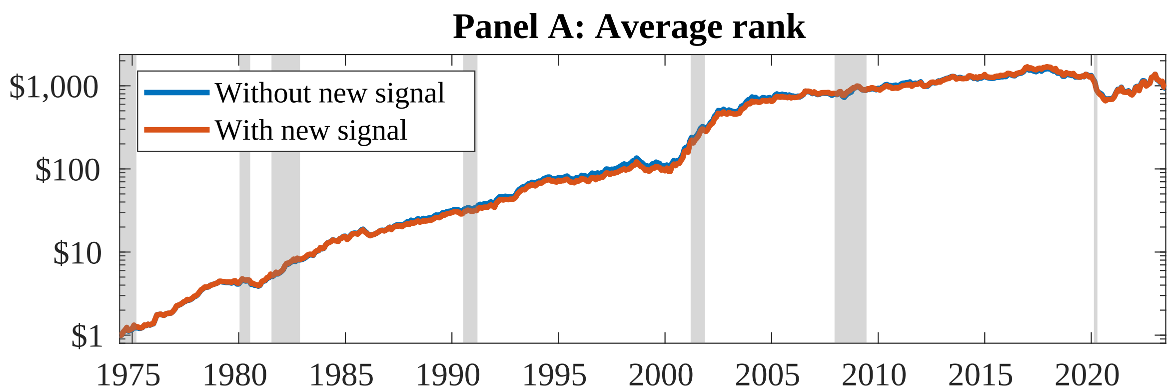


Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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