Debt Impact Efficiency Score and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Debt Impact Efficiency Score (DIES), 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 DIES achieves an annualized gross (net) Sharpe ratio of 0.41 (0.30), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (18) bps/month with a t-statistic of 2.74 (2.24), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Change in financial liabilities, Change in net financial assets, Investment to revenue, Accruals, Sales growth over inventory growth) is 17 bps/month with a t-statistic of 2.16.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While many of these patterns are related to firms' financing decisions and capital structure (Baker and Wurgler, 2002), the complex interactions between debt financing choices and future stock performance remain incompletely understood. In particular, the literature has not fully explored how the efficiency with which firms deploy debt financing affects subsequent returns.

Prior research has focused primarily on the level of leverage (George and Hwang, 2010) or changes in debt (Bradshaw et al., 2006) rather than examining how effectively firms utilize debt financing to generate value. This gap is notable given that similar firms can experience vastly different outcomes from comparable levels of debt financing, suggesting that the efficiency of debt deployment may contain important information about future performance.

We propose that the Debt Impact Efficiency Score (DIES) captures meaningful variation in how effectively firms convert debt financing into productive assets and future cash flows. Building on Myers (1977)'s framework of debt overhang and investment efficiency, we argue that firms with higher DIES are better at avoiding both underinvestment and overinvestment problems associated with debt financing. These firms should experience superior future performance as their debt-financed investments generate higher returns.

The theoretical link between DIES and future returns operates through multiple channels. First, following Jensen (1986), firms with higher DIES likely have better governance mechanisms that prevent managers from pursuing value-destroying investments with debt proceeds. Second, as shown by Rajan and Zingales (1995), firms that use debt more efficiently face lower costs of capital and have greater financial flexibility. Third, consistent with Titman (1984), efficient debt deployment signals management quality and helps firms maintain valuable relationships with stakeholders.

These mechanisms suggest that DIES contains information about future firm performance not fully reflected in current prices. While market participants can observe raw debt levels and changes, the efficiency of debt deployment is more difficult to evaluate, potentially leading to systematic mispricing. This creates an opportunity for DIES to predict future returns as the market gradually recognizes firms' differential abilities to generate value from debt financing.

Our empirical analysis reveals that DIES strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high DIES and shorts those with low DIES generates a monthly alpha of 21 basis points (t-statistic = 2.74) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.41, placing it in the top quintile of documented return predictors.

The predictive power of DIES remains robust after controlling for size. Among the largest quintile of stocks by market capitalization, the DIES strategy earns a monthly alpha of 20 basis points (t-statistic = 2.28) relative to the Fama-French six-factor model. This indicates that the DIES effect is not confined to small, illiquid stocks where trading costs might impede implementation.

Most importantly, DIES continues to generate significant abnormal returns even after controlling for the six most closely related anomalies from the literature. In spanning tests that include both the Fama-French factors and these related anomalies, the DIES strategy produces a monthly alpha of 17 basis points (t-statistic = 2.16). This demonstrates that DIES captures a distinct dimension of mispricing not explained by previously documented effects.

Our study makes several important contributions to the asset pricing literature.

First, we introduce a novel measure that quantifies how efficiently firms deploy debt financing, extending prior work by Bradshaw et al. (2006) and George and Hwang (2010) that focused primarily on debt levels rather than deployment efficiency. Second, we demonstrate that this efficiency metric contains valuable information about future stock returns that is incremental to known predictors.

Third, our findings contribute to the growing literature on investment-based asset pricing pioneered by Cochrane and Saá-Requejo (2000). While prior studies have examined investment efficiency broadly, we specifically isolate the efficiency of debt-financed investment and show its importance for asset prices. This helps bridge the gap between capital structure research in corporate finance and cross-sectional asset pricing.

Finally, our results have important implications for both academic research and investment practice. For academics, we provide new evidence on how financing decisions affect asset prices through their impact on investment efficiency. For practitioners, we document a novel signal that can be used to enhance portfolio selection, particularly among large-cap stocks where many traditional anomalies have limited power.

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 Impact 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 OIADP for operating income before depreciation. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt during the reporting period, while operating income before depreciation (OIADP) measures a firm's core operational profitability before accounting for depreciation expenses.construction of the signal follows a difference-scaling approach, where we first calculate the change in long-term debt issuance by subtracting the previous period's DLTIS from the current period's value, and then scale this difference by the previous period's operating income (OIADP). This scaled difference captures the relative magnitude of changes in debt financing against the firm's operational income capacity, offering insight into how efficiently the firm utilizes new debt relative to its earnings power. By focusing on this relationship, the signal aims to reflect aspects of financial leverage and operational efficiency in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DIES signal. Panel A plots the time-series of the mean, median, and interquartile range for DIES. On average, the cross-sectional mean (median) DIES is -0.59 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DIES data. The signal's interquartile range spans -0.60 to 0.74. Panel B of Figure 1 plots the time-series of the coverage of the DIES signal for the CRSP universe. On average, the DIES signal is available for 6.30% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does DIES predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DIES 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 DIES portfolio and sells the low DIES 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 DIES strategy earns an average return of 0.22% per month with a t-statistic of 2.89. The annualized Sharpe ratio of the strategy is 0.41. The alphas range from 0.21% to 0.26% per month and have t-statistics exceeding 2.74 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 -0.15, with a t-statistic of -4.35 on the HML 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 541 stocks and an average market capitalization of at least $1,166 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 10 bps/month with a t-statistics of 2.42. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for nine 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 -15-18bps/month. The lowest return, (-15 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -2.55. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DIES trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in fifteen cases.

Table 3 provides direct tests for the role size plays in the DIES strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DIES, as well as average returns and alphas for long/short trading DIES 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$^{\text{th}}$ NYSE percentile), the DIES strategy achieves an average return of 25 bps/month with a t-statistic of 2.83. Among these large cap stocks, the alphas for the DIES strategy relative to the five most common factor models range from 20 to 29 bps/month with t-statistics between 2.28 and 3.33.

5 How does DIES perform relative to the zoo?

Figure 2 puts the performance of DIES 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 DIES strategy falls in the distribution. The DIES strategy's gross (net) Sharpe ratio of 0.41 (0.30) is greater than 83% (90%) 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 DIES strategy (red line).[2] Ignoring trading costs, a $1 invested in the DIES strategy would have yielded $2.57 which ranks the DIES strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DIES strategy would have yielded $1.50 which ranks the DIES 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 DIES relative to those. Panel A shows

[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.

that the DIES strategy gross alphas fall between the 48 and 70 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 DIES strategy has a positive net generalized alpha for five out of the five factor models. In these cases DIES ranks between the 65 and 83 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DIES 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 DIES signal in these Fama-MacBeth regressions exceed 0.06, with the minimum t-statistic occurring when controlling for Change in financial liabilities. Controlling for all six closely related anomalies, the t-statistic on DIES is 0.45.

Similarly, Table 5 reports results from spanning tests that regress returns to the DIES 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 DIES strategy earns alphas that range from 17-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.20, which is achieved when controlling for Change in financial liabilities. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the

DIES trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.16.

7 Does DIES add relative to the whole zoo?

Finally, we can ask how much adding DIES 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 DIES 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 DIES grows to $1029.71.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Debt Impact Efficiency Score (DIES) 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 DIES generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.41 (0.30 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal

[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 DIES is available.

returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

The persistence of alpha in both gross and net returns (21 and 18 bps/month, respectively) suggests that DIES captures unique information about firm value that is not fully reflected in current market prices or explained by well-known risk 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 considered. 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 DIES-based strategies, particularly for smaller, less liquid stocks.

Future research could explore the international validity of DIES, its interaction with other established market anomalies, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the DIES premium would enhance our understanding of this signal's predictive power. Finally, examining how the signal's effectiveness varies across different market segments and firm characteristics could yield valuable insights for practical applications.

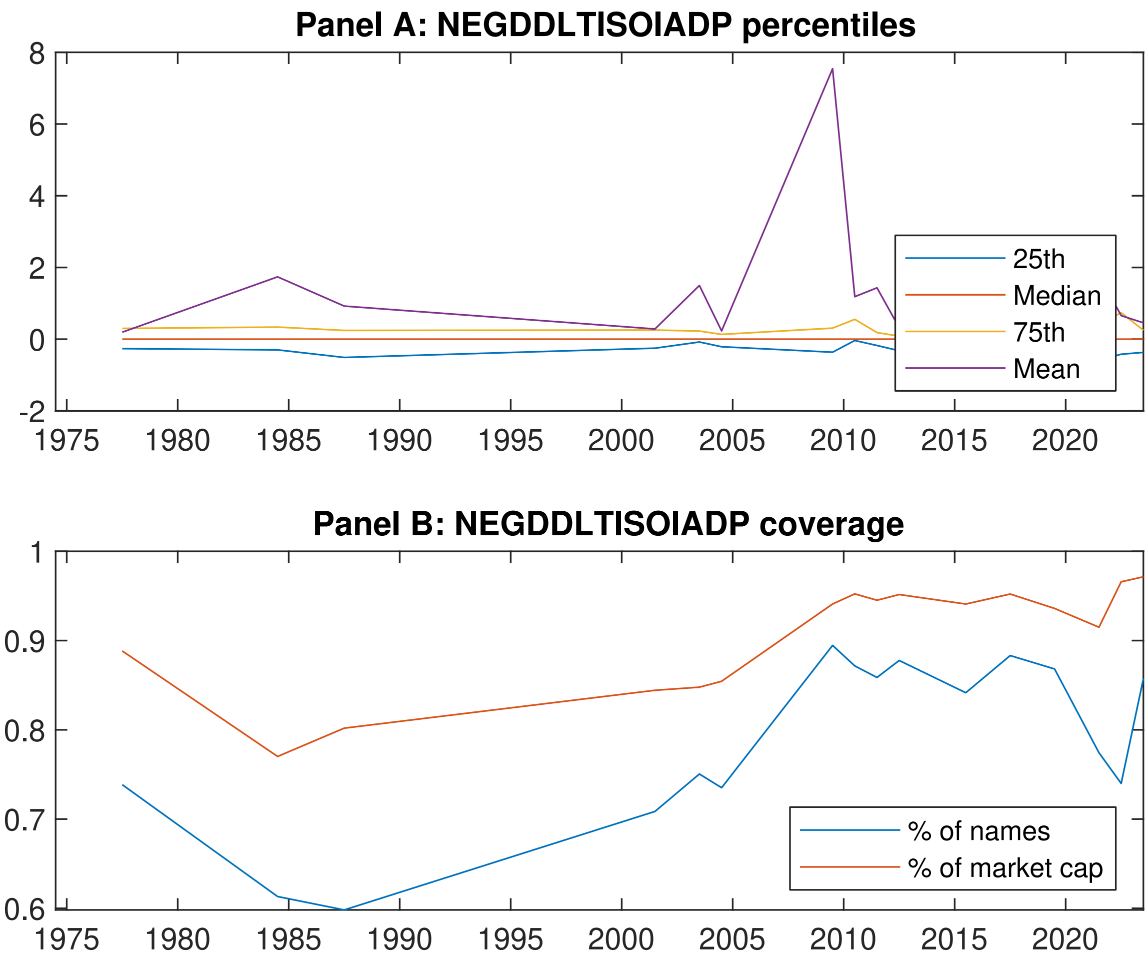

Figure 1: Times series of DIES percentiles and coverage.
This figure plots descriptive statistics for DIES. Panel A shows cross-sectional percentiles of DIES over the sample. Panel B plots the monthly coverage of DIES relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DIES. 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 DIES-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.58	0.65	0.71	0.80	0.80	0.22
	[2.64]	[3.53]	[3.57]	[4.50]	[3.70]	[2.89]
α_{CAPM}	-0.18	0.01	0.02	0.18	0.05	0.23
	[-3.06]	[0.21]	[0.35]	[4.04]	[0.84]	[3.06]
α_{FF3}	-0.23	-0.03	0.07	0.18	0.03	0.26
	[-4.00]	[-0.73]	[1.32]	[4.03]	[0.57]	[3.44]
α_{FF4}	-0.20	-0.01	0.10	0.15	0.03	0.23
	[-3.49]	[-0.15]	[2.00]	[3.32]	[0.43]	[2.96]
α_{FF5}	-0.21	-0.08	0.09	0.09	0.02	0.23
	[-3.70]	[-1.80]	[1.77]	[2.13]	[0.32]	[3.02]
α_{FF6}	-0.20	-0.05	0.12	0.08	0.02	0.21
	[-3.39]	[-1.30]	[2.22]	[1.80]	[0.27]	[2.74]
Panel B: Fama and French (2018) 6-factor model loadings for DIES-sorted portfolios						
β_{MKT}	1.09	0.98	0.98	0.95	1.08	-0.01
	[81.32]	[101.71]	[79.72]	[95.63]	[76.57]	[-0.65]
β_{SMB}	0.16	-0.12	-0.01	-0.04	0.15	-0.01
	[7.73]	[-8.20]	[-0.76]	[-2.59]	[6.97]	[-0.30]
β_{HML}	0.11	0.13	-0.13	-0.04	-0.03	-0.15
	[4.47]	[7.00]	[-5.33]	[-2.14]	[-1.29]	[-4.35]
β_{RMW}	0.06	0.10	-0.00	0.10	-0.01	-0.06
	[2.11]	[5.39]	[-0.18]	[4.97]	[-0.26]	[-1.78]
β_{CMA}	-0.12	0.04	-0.06	0.17	0.08	0.20
	[-3.07]	[1.44]	[-1.78]	[5.81]	[1.95]	[3.82]
β_{UMD}	-0.03	-0.04	-0.04	0.02	0.01	0.04
	[-2.23]	[-3.84]	[-3.36]	[2.44]	[0.36]	[1.95]
Panel C: Average number of firms (n) and market capitalization (me)						
n	665	541	1082	597	652	
me ($\$10^6$)	1166	3002	2366	3045	1196	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DIES 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	0.22	0.23	0.26	0.23	0.23	0.21
			[2.89]	[3.06]	[3.44]	[2.96]	[3.02]	[2.74]
Quintile	NYSE	EW	0.10	0.11	0.11	0.11	0.12	0.12
			[2.42]	[2.57]	[2.63]	[2.54]	[2.79]	[2.76]
Quintile	Name	VW	0.19	0.22	0.25	0.21	0.20	0.18
			[2.71]	[3.16]	[3.48]	[2.99]	[2.80]	[2.54]
Quintile	Cap	VW	0.22	0.25	0.27	0.23	0.19	0.17
			[3.57]	[4.04]	[4.32]	[3.71]	[3.05]	[2.75]
Decile	NYSE	VW	0.25	0.25	0.24	0.25	0.20	0.21
			[2.47]	[2.40]	[2.35]	[2.38]	[1.85]	[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	0.19	0.21	0.19	0.19	0.18
			[2.09]	[2.44]	[2.73]	[2.50]	[2.45]	[2.24]
Quintile	NYSE	EW	-0.15					
			[-2.55]					
Quintile	Name	VW	0.13	0.18	0.19	0.18	0.16	0.15
			[1.86]	[2.46]	[2.71]	[2.47]	[2.23]	[2.02]
Quintile	Cap	VW	0.17	0.21	0.23	0.21	0.17	0.15
			[2.76]	[3.38]	[3.59]	[3.29]	[2.58]	[2.35]
Decile	NYSE	VW	0.18	0.19	0.18	0.18	0.13	0.14
			[1.72]	[1.78]	[1.71]	[1.75]	[1.24]	[1.27]

Table 3: Conditional sort on size and DIES

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

	DIES Quintiles					DIES Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.79	0.84	0.96	0.98	0.78	-0.01	0.00	0.00	-0.02	0.05	0.03
	[2.90]	[2.99]	[3.48]	[3.32]	[2.87]	[-0.11]	[0.04]	[0.06]	[-0.25]	[0.70]	[0.43]
(2)	0.82	0.90	0.82	0.94	0.90	0.08	0.12	0.10	0.10	0.11	0.11
	[3.09]	[3.58]	[3.23]	[3.72]	[3.52]	[1.10]	[1.50]	[1.26]	[1.31]	[1.35]	[1.38]
(3)	0.87	0.86	0.87	0.85	0.89	0.02	0.05	0.06	0.06	0.09	0.09
	[3.50]	[3.86]	[3.56]	[3.81]	[3.72]	[0.26]	[0.62]	[0.79]	[0.72]	[1.17]	[1.08]
(4)	0.66	0.87	0.89	0.80	0.92	0.26	0.28	0.30	0.25	0.33	0.30
	[2.84]	[4.17]	[4.00]	[3.85]	[4.11]	[3.25]	[3.55]	[3.73]	[3.16]	[4.07]	[3.63]
(5)	0.52	0.63	0.63	0.74	0.76	0.25	0.26	0.29	0.26	0.21	0.20
	[2.56]	[3.48]	[3.12]	[4.01]	[3.84]	[2.83]	[2.94]	[3.33]	[2.99]	[2.40]	[2.28]

Panel B: Portfolio average number of firms and market capitalization

	DIES Quintiles: Average n					DIES Quintiles: Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	398	398	399	399	397	37	33	33	34	36
(2)	108	108	108	108	108	60	61	58	60	60
(3)	77	77	77	77	77	105	107	102	104	105
(4)	64	65	65	65	64	222	233	222	233	220
(5)	59	59	59	59	59	1273	2053	1873	2131	1320

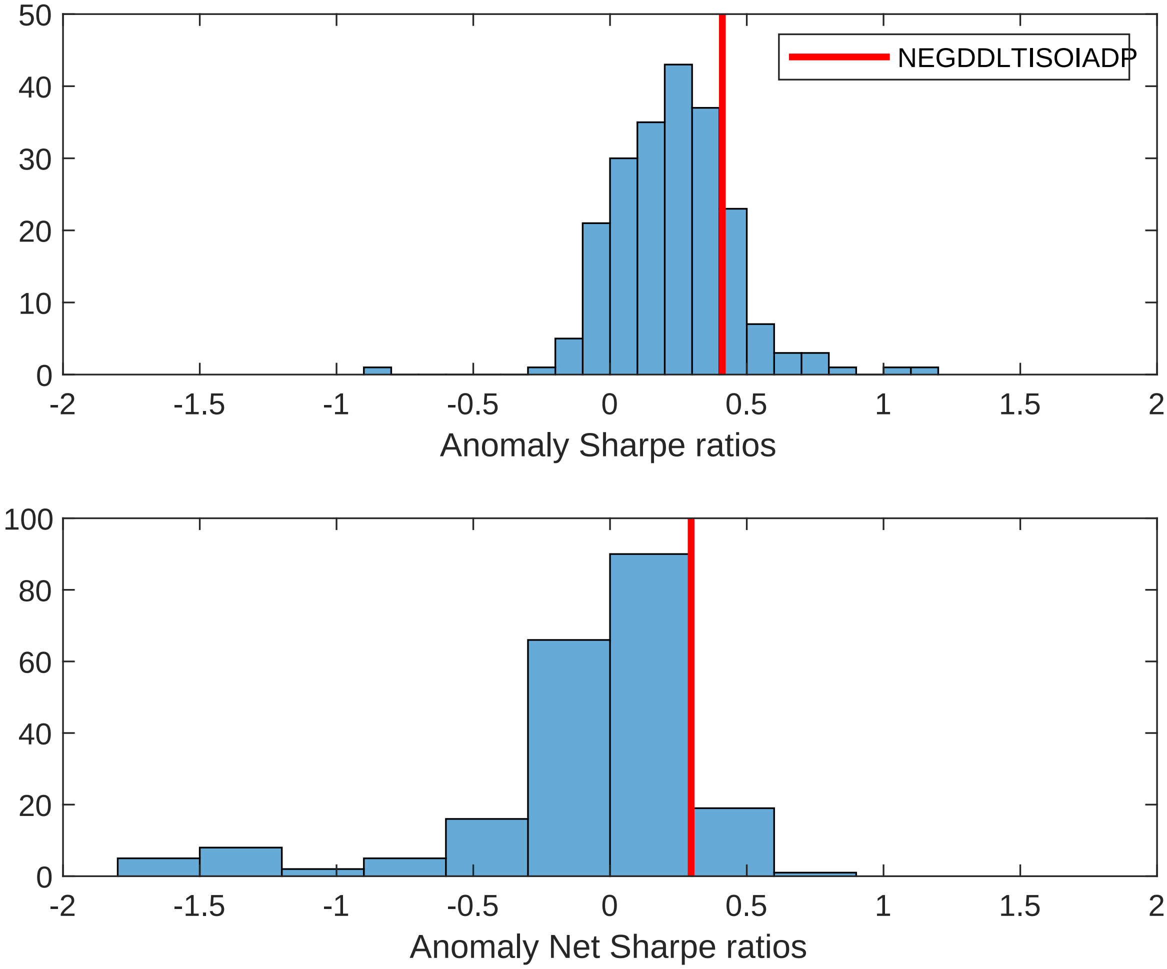

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIES with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

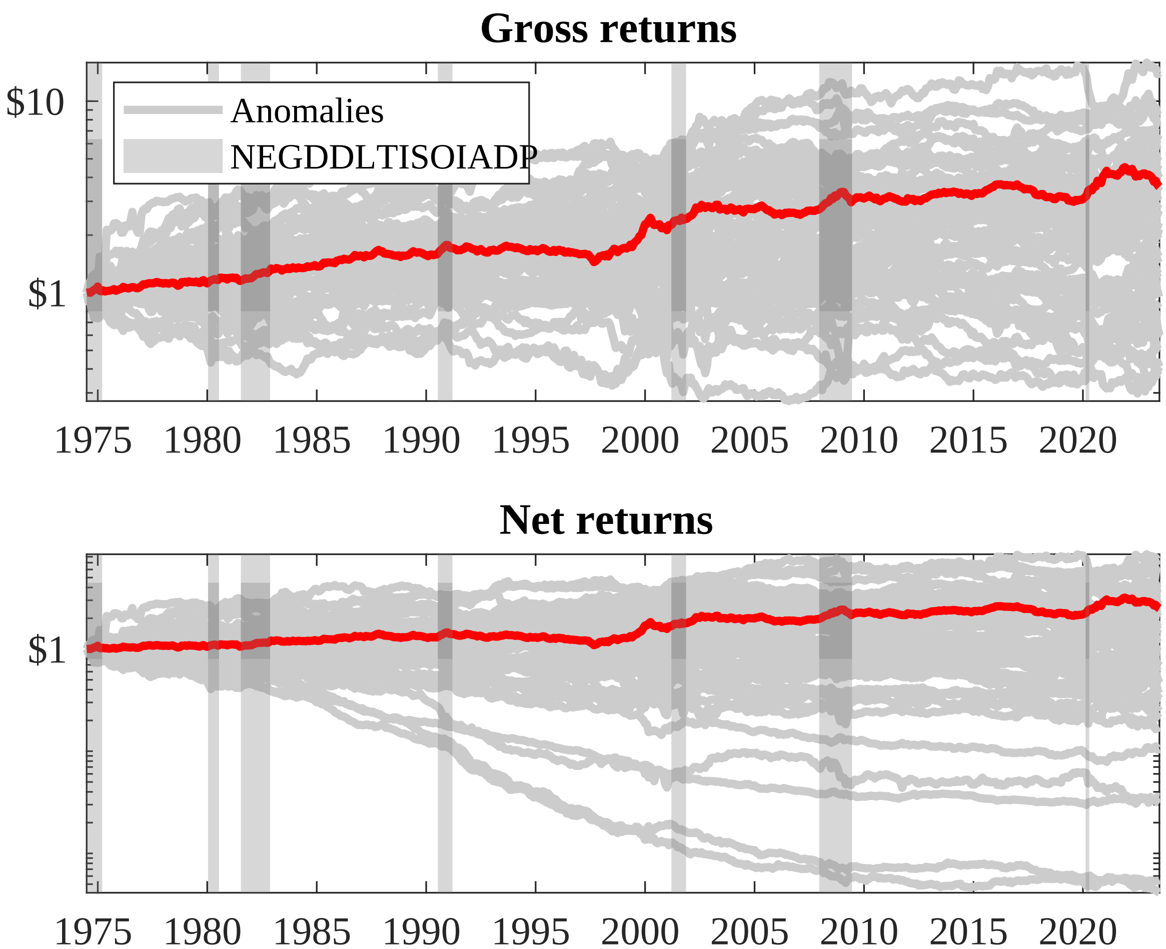

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIES trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

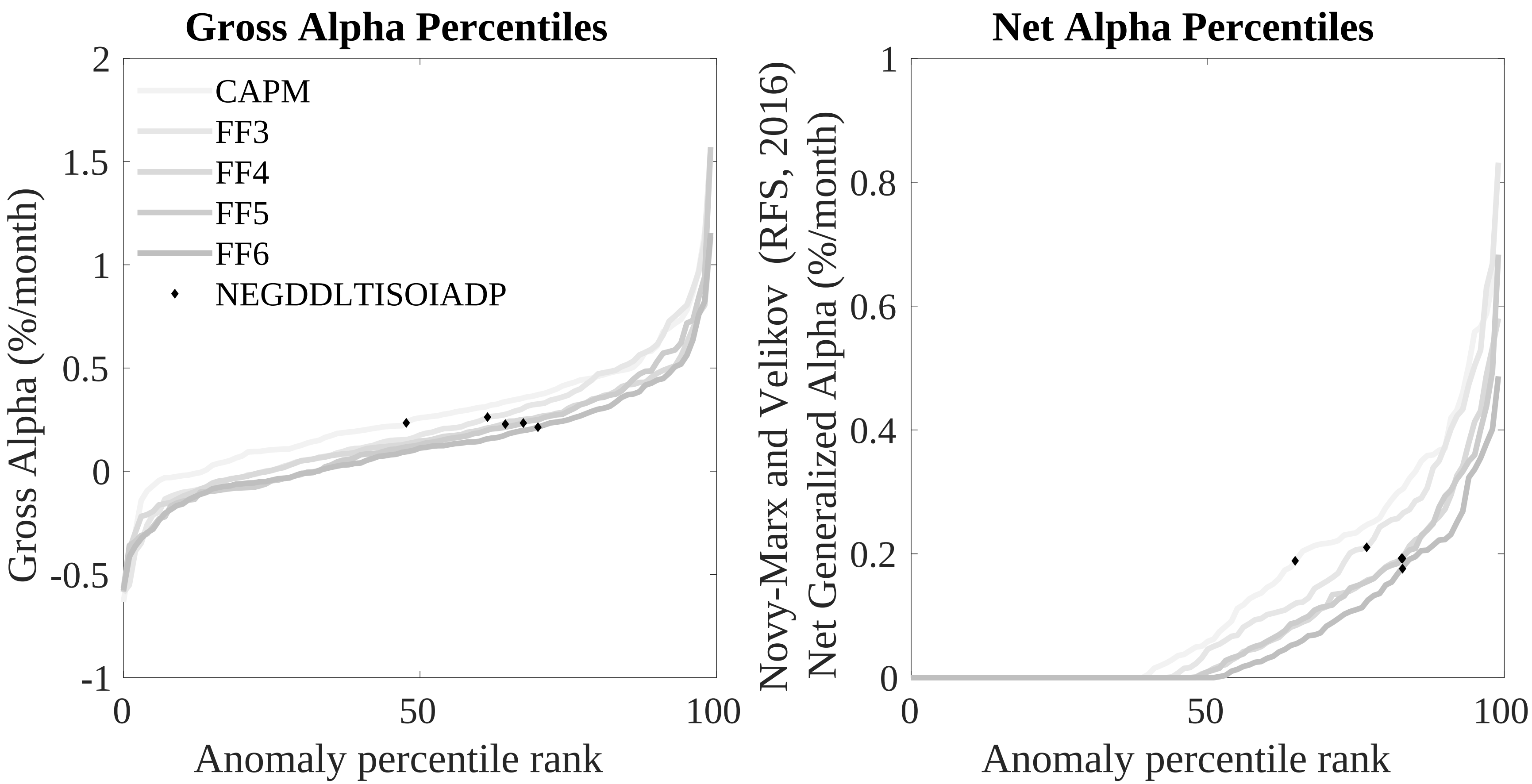

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DIES trading strategy alphas (diamonds). The strategies are constructed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

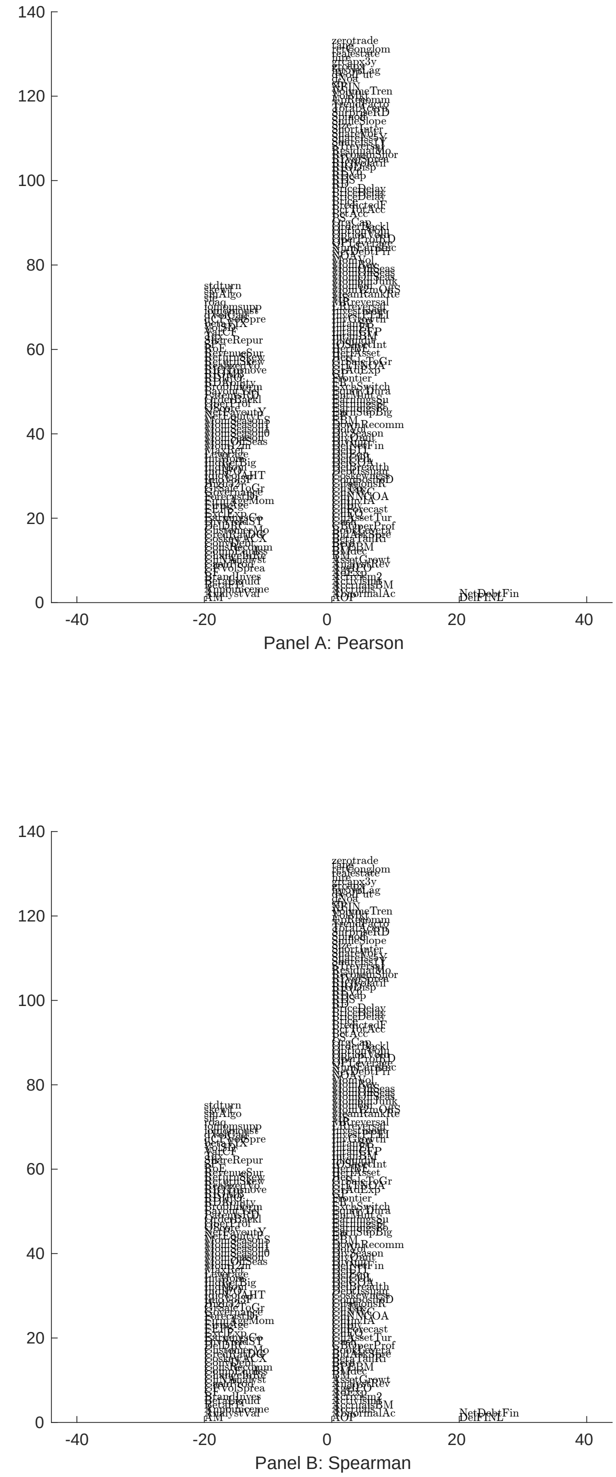

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DIES. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

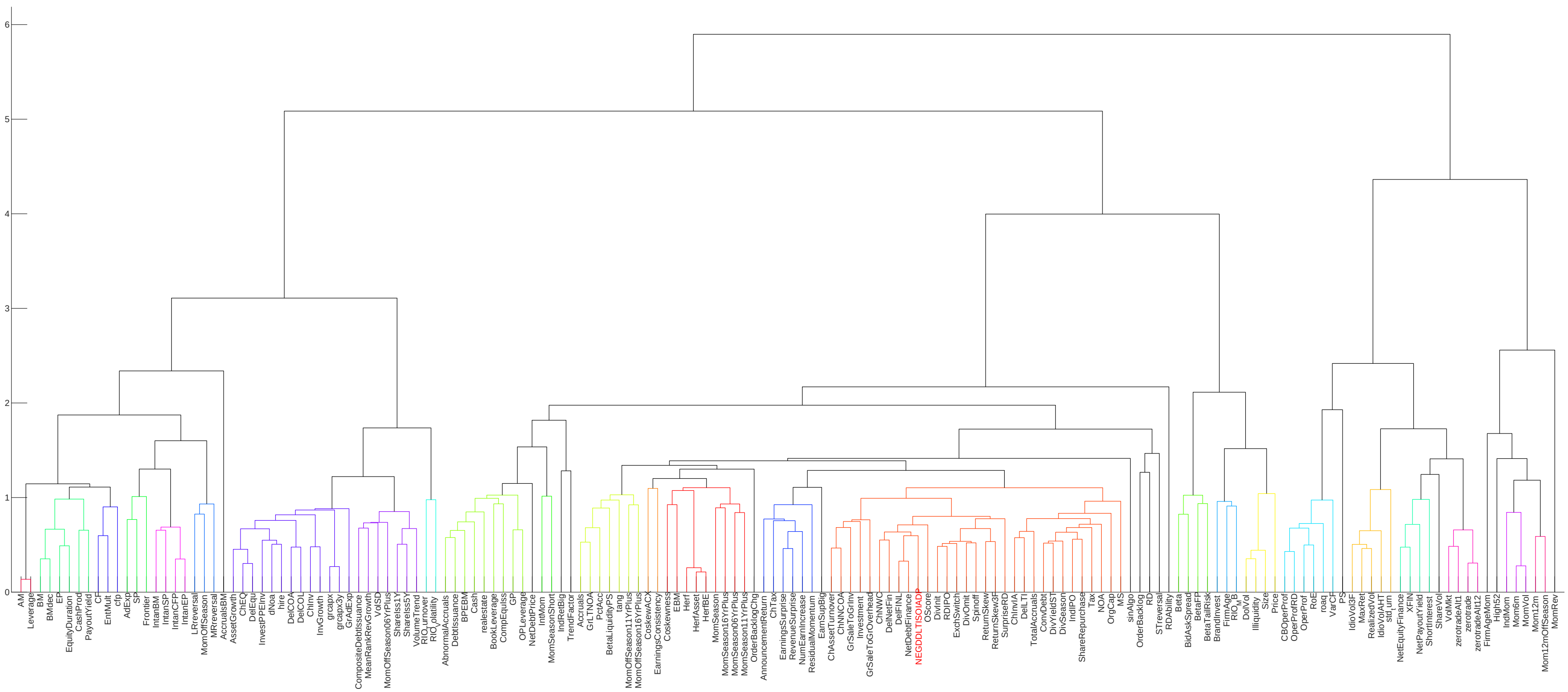

Figure 6: Agglomerative hierarchical cluster plot

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

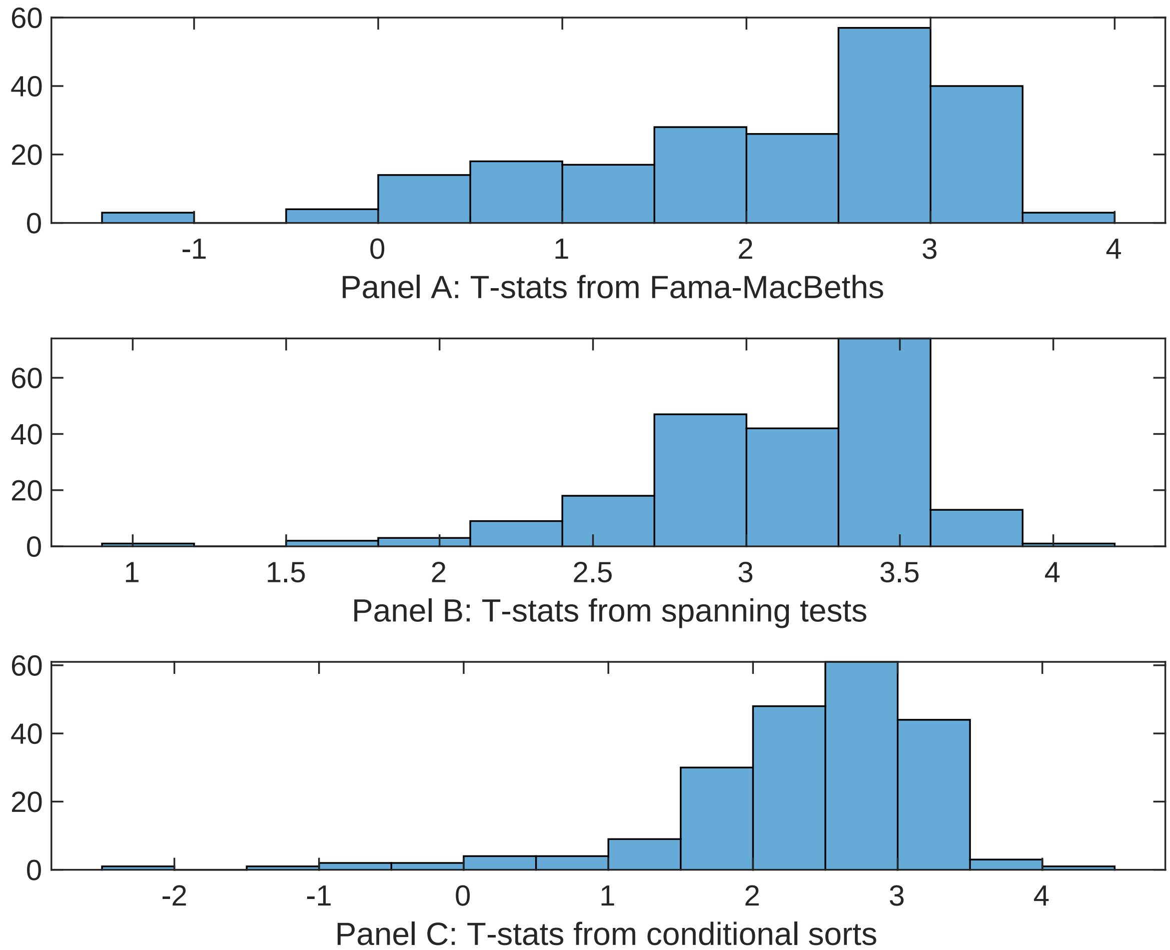

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DIES conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIES} from Fama-MacBeth regressions of the form $r_{i,t}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

Intercept	0.14	0.14	0.13	0.16	0.13	0.13	0.15
	[5.48]	[5.52]	[5.38]	[6.35]	[5.15]	[5.36]	[6.13]
DIES	0.17	0.25	0.50	0.12	0.89	0.12	0.20
	[0.42]	[0.06]	[1.24]	[2.68]	[2.23]	[2.71]	[0.45]
Anomaly 1	0.21						0.94
	[9.25]						[2.20]
Anomaly 2		0.18					0.15
		[9.64]					[2.99]
Anomaly 3			0.76				-0.86
			[5.00]				[-2.74]
Anomaly 4				0.24			0.18
				[5.47]			[3.79]
Anomaly 5					0.14		0.11
					[4.57]		[2.84]
Anomaly 6						0.14	0.92
						[4.81]	[2.86]
# 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 DIES trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DIES} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Net debt financing, Change in financial liabilities, Change in net financial assets, Investment to revenue, Accruals, Sales growth over inventory growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.21	0.21	0.17	0.21	0.20	0.22	0.17
	[2.69]	[2.68]	[2.20]	[2.72]	[2.59]	[2.80]	[2.16]
Anomaly 1	24.27						14.15
	[5.62]						[2.47]
Anomaly 2		23.28					5.00
		[5.15]					[0.80]
Anomaly 3			20.78				11.29
			[5.27]				[2.51]
Anomaly 4				10.07			6.35
				[3.32]			[2.09]
Anomaly 5					6.53		0.74
					[2.08]		[0.24]
Anomaly 6						11.88	7.49
						[3.50]	[2.21]
mkt	-1.06	-0.78	-1.03	-1.35	-0.59	-1.38	-1.33
	[-0.61]	[-0.44]	[-0.59]	[-0.76]	[-0.33]	[-0.78]	[-0.76]
smb	-2.70	-3.16	0.76	-2.86	-0.03	-1.42	-2.69
	[-0.99]	[-1.15]	[0.28]	[-1.02]	[-0.01]	[-0.52]	[-0.93]
hml	-14.21	-13.37	-15.28	-13.72	-12.75	-14.18	-13.65
	[-4.22]	[-3.94]	[-4.51]	[-3.99]	[-3.60]	[-4.14]	[-3.97]
rmw	-8.59	-8.39	-3.51	-5.76	-4.58	-7.87	-6.45
	[-2.45]	[-2.38]	[-0.99]	[-1.62]	[-1.23]	[-2.20]	[-1.73]
cma	13.13	11.60	25.17	18.35	17.16	18.85	16.05
	[2.52]	[2.17]	[4.81]	[3.53]	[3.22]	[3.64]	[2.81]
umd	1.65	1.39	2.98	2.27	3.26	2.19	-0.16
	[0.91]	[0.76]	[1.67]	[1.23]	[1.79]	[1.19]	[-0.08]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	10	9	10	7	6	7	13

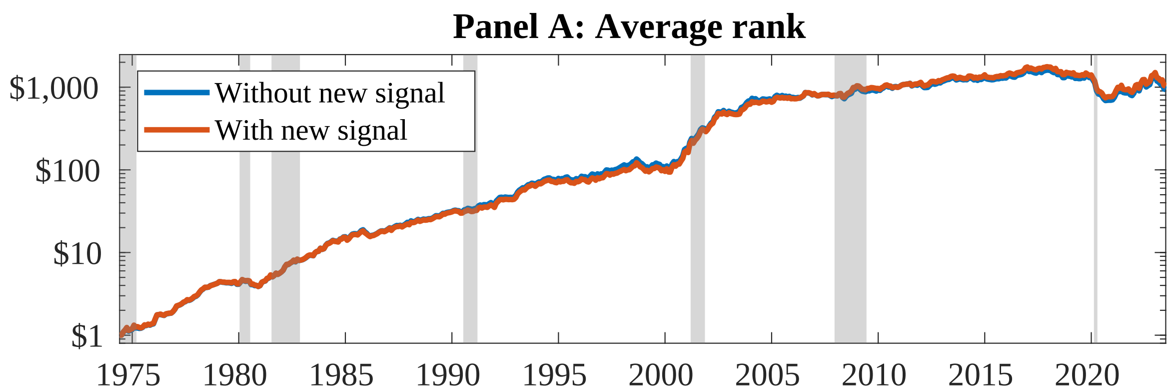

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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