Debt Funding Efficiency and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt Funding Efficiency (DFE), 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 DFE achieves an annualized gross (net) Sharpe ratio of 0.57 (0.45), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 20 (17) bps/month with a t-statistic of 2.92 (2.49), 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, Employment growth, change in net operating assets) is 20 bps/month with a t-statistic of 2.91.

1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all 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 (Hou et al., 2020). While many of these anomalies are related to firms' financing decisions and capital structure choices (Titman et al., 1993; Bradshaw et al., 2006), the role of debt funding efficiency in asset pricing remains relatively unexplored.

Prior research has established that firms' financing decisions contain information about future stock returns, particularly through channels such as external financing (Bradshaw et al., 2006) and debt issuance (Spiess and Affleck-Graves, 1999). However, these studies primarily focus on the quantity rather than the quality of debt financing. This creates an important gap in our understanding of how the efficiency with which firms deploy debt capital affects their market valuation.

We hypothesize that Debt Funding Efficiency (DFE) contains valuable information about future stock returns through several economic channels. First, following (Myers, 1984)'s pecking order theory, firms with higher DFE likely face lower information asymmetry costs when accessing debt markets, signaling superior management quality and future performance prospects.

Second, building on (Jensen and Meckling, 1976)'s agency theory framework, efficient debt funding may indicate better alignment between managers' and debtholders' interests, reducing agency costs and improving overall firm value. This suggests that firms with higher DFE should command a premium in the market.

Third, consistent with (Modigliani and Miller, 1958)'s capital structure irrelevance proposition, in perfect markets, DFE should not matter for stock returns. However, in the presence of market frictions such as information asymmetry and agency costs, DFE may serve as an important signal of firm quality that is not fully incorporated into prices, creating predictable return patterns.

Our empirical analysis reveals that DFE strongly predicts future stock returns. A value-weighted long-short trading strategy that buys stocks with high DFE and shorts those with low DFE generates significant abnormal returns of 20 basis points per month (t-statistic = 2.92) after controlling for the Fama-French six factors. The strategy achieves an impressive annualized Sharpe ratio of 0.57 before trading costs and 0.45 after costs.

Importantly, the predictive power of DFE remains robust across various methodological specifications. The signal performs particularly well among large-cap stocks, with the long-short strategy earning 39 basis points per month (t-statistic = 4.29) in the largest size quintile. This suggests that the DFE effect is not merely a small-stock phenomenon.

Further analysis shows that DFE's predictive power persists even after controlling for six closely related anomalies, including changes in financial liabilities, net debt financing, and asset growth. The strategy generates an alpha of 20 basis points per month (t-statistic = 2.91) in spanning tests that control for these related anomalies and the Fama-French six factors simultaneously.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the efficiency dimension of corporate debt financing, extending beyond the quantity-focused measures in (Bradshaw et al., 2006) and (Spiess and Affleck-Graves, 1999). This adds to our understanding of how financing decisions affect stock returns.

Second, we demonstrate that DFE's predictive power is distinct from known anomalies and robust to comprehensive controls. Unlike many anomalies that work primarily in small stocks (Hou et al., 2020), DFE generates significant abnormal returns even among large-cap stocks, suggesting greater practical relevance for institutional investors.

Third, our findings have important implications for both academic research and practice. For researchers, we provide new evidence on the role of financing efficiency in asset pricing. For practitioners, our results suggest that incorporating DFE into investment strategies could potentially improve portfolio performance, as evidenced by the signal's strong performance in combination strategies with other anomalies.

2 Data

Our study investigates the predictive power of Debt Funding Efficiency, a financial signal derived from accounting data for cross-sectional returns. 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 CAPX for capital expenditures. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while capital expenditures (CAPX) reflect the firm's investments in long-term assets such as property, plant, and equipment. The construction of the Debt Funding Efficiency signal follows a specific methodology where we first calculate the change in DLTIS by subtracting its lagged value from the current value, and then scale this difference by lagged capital expenditures (CAPX). This ratio captures the relative change in debt financing relative to the firm's prior investment activities, offering insight into how efficiently the firm utilizes debt to fund its growth opportunities. By focusing on this relationship, the signal aims to reflect aspects of capital structure decisions and financing 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 DFE signal. Panel A plots the time-series of the mean, median, and interquartile range for DFE. On average, the cross-sectional mean (median) DFE is -3.48 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DFE data. The signal's interquartile range spans -3.29 to 4.29. Panel B of Figure 1 plots the time-series of the coverage of the DFE signal for the CRSP universe. On average, the DFE signal is available for 6.12% of CRSP names, which on average make up 7.21% of total market capitalization.

4 Does DFE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DFE 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 DFE portfolio and sells the low DFE 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 DFE strategy earns an average return of 0.28% per month with a t-statistic of 4.04. The annualized Sharpe ratio of the strategy is 0.57. The alphas range from 0.20% to 0.33% per month and have t-statistics exceeding 2.92 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.29, with a t-statistic of 6.38 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 511 stocks and an average market capitalization of at least $1,452 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 20 bps/month with a t-statistics of 4.37. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five 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 -7-26bps/month. The lowest return, (-7 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.17. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DFE 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 DFE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DFE, as well as average returns and alphas for long/short trading DFE 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 DFE strategy achieves an average return of 39 bps/month with a t-statistic of 4.29. Among these large cap stocks, the alphas for the DFE strategy relative to the five most common factor models range from 30 to 45 bps/month with t-statistics between 3.33 and 4.94.

5 How does DFE perform relative to the zoo?

Figure 2 puts the performance of DFE 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 DFE strategy falls in the distribution. The DFE strategy's gross (net) Sharpe ratio of 0.57 (0.45) is greater than 95% (99%) of anomaly Sharpe ratios,

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

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 DFE strategy (red line).[2] Ignoring trading costs, a \$1 invested in the DFE strategy would have yielded \$3.98 which ranks the DFE strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DFE strategy would have yielded \$2.51 which ranks the DFE strategy in the top 4% 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 DFE relative to those. Panel A shows that the DFE strategy gross alphas fall between the 63 and 74 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 DFE strategy has a positive net generalized alpha for five out of the five factor models. In these cases DFE ranks between the 81 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

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

[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.

DFE trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DFE 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 DFE signal in these Fama-MacBeth regressions exceed 1.98, with the minimum t-statistic occurring when controlling for change in net operating assets. Controlling for all six closely related anomalies, the t-statistic on DFE is 0.87.

Similarly, Table 5 reports results from spanning tests that regress returns to the DFE 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 DFE strategy earns alphas that range from 19-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.79, which is achieved when controlling for change in net operating assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DFE trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.91.

7 Does DFE add relative to the whole zoo?

Finally, we can ask how much adding DFE 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 DFE signal.[4] We consider

[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 capital-

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 DFE grows to \$958.06.

8 Conclusion

This study provides compelling evidence for the significance of Debt Funding Efficiency (DFE) 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 DFE generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.57 (0.45 net of transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that DFE captures unique information about firm fundamentals that is not fully incorporated into stock prices.

Particularly noteworthy is the signal's ability to maintain its predictive power when tested against the Fama-French five-factor model plus momentum, as well as six closely related strategies from the factor zoo. The consistent alpha of 20 basis points per month (t-statistic of 2.91) in the presence of these controls underscores the distinctive nature of the DFE signal and its potential value for investment professionals.

However, several limitations should be considered. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains

ization on CRSP in the period for which DFE is available.

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

Future research could explore the interaction between DFE and other established market anomalies, investigate its performance in international markets, and examine the underlying economic mechanisms driving the signal's predictive power. Additionally, researchers might consider studying how the signal's effectiveness varies across different market conditions and whether its predictive power has diminished over time due to increased market efficiency or changes in the institutional environment.

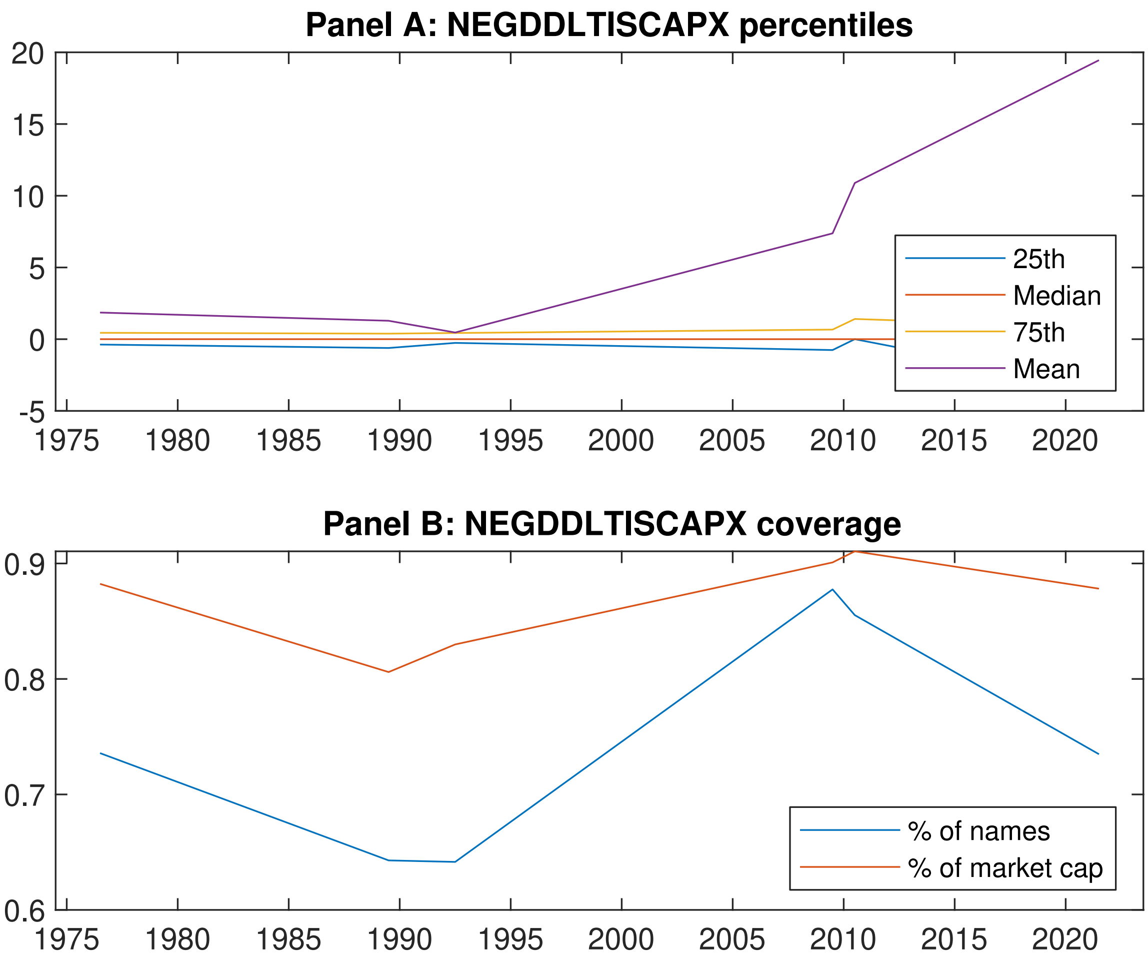

Figure 1: Times series of DFE percentiles and coverage.
This figure plots descriptive statistics for DFE. Panel A shows cross-sectional percentiles of DFE over the sample. Panel B plots the monthly coverage of DFE relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DFE. 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 DFE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.58	0.69	0.71	0.76	0.86	0.28
	[2.66]	[3.79]	[3.47]	[4.22]	[4.22]	[4.04]
α_{CAPM}	-0.18	0.06	0.01	0.14	0.15	0.33
	[-3.45]	[1.18]	[0.09]	[2.66]	[2.80]	[4.85]
α_{FF3}	-0.20	0.04	0.07	0.14	0.12	0.33
	[-3.91]	[0.87]	[1.31]	[2.68]	[2.35]	[4.74]
α_{FF4}	-0.17	0.04	0.12	0.10	0.12	0.29
	[-3.21]	[0.83]	[2.20]	[1.84]	[2.17]	[4.09]
α_{FF5}	-0.16	-0.04	0.13	0.04	0.06	0.22
	[-3.06]	[-0.91]	[2.34]	[0.73]	[1.14]	[3.22]
α_{FF6}	-0.14	-0.03	0.16	0.02	0.06	0.20
	[-2.65]	[-0.76]	[2.89]	[0.31]	[1.16]	[2.92]
Panel B: Fama and French (2018) 6-factor model loadings for DFE-sorted portfolios						
β_{MKT}	1.08	0.98	0.97	0.96	1.05	-0.03
	[89.44]	[97.89]	[74.11]	[82.42]	[84.41]	[-2.00]
β_{SMB}	0.11	-0.12	0.01	-0.02	0.12	0.01
	[5.78]	[-7.79]	[0.25]	[-1.24]	[6.18]	[0.44]
β_{HML}	0.08	0.06	-0.16	-0.09	-0.02	-0.10
	[3.52]	[3.00]	[-6.42]	[-3.96]	[-0.86]	[-3.34]
β_{RMW}	0.01	0.13	-0.04	0.09	0.09	0.08
	[0.58]	[6.51]	[-1.63]	[3.81]	[3.66]	[2.42]
β_{CMA}	-0.17	0.10	-0.13	0.25	0.13	0.29
	[-4.80]	[3.51]	[-3.46]	[7.43]	[3.51]	[6.38]
β_{UMD}	-0.04	-0.01	-0.05	0.04	-0.00	0.03
	[-3.05]	[-1.09]	[-4.08]	[3.18]	[-0.19]	[2.16]
Panel C: Average number of firms (n) and market capitalization (me)						
n	681	511	1037	565	644	
me (10^6)	1452	2657	2178	2558	1472	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DFE strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 197406 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.28	0.33	0.33	0.29	0.22	0.20
			[4.04]	[4.85]	[4.74]	[4.09]	[3.22]	[2.92]
Quintile	NYSE	EW	0.20	0.22	0.21	0.20	0.19	0.19
			[4.37]	[4.84]	[4.56]	[4.30]	[4.24]	[4.14]
Quintile	Name	VW	0.25	0.30	0.32	0.28	0.25	0.23
			[3.33]	[4.06]	[4.26]	[3.67]	[3.38]	[3.08]
Quintile	Cap	VW	0.31	0.36	0.37	0.31	0.27	0.24
			[4.70]	[5.49]	[5.69]	[4.84]	[4.28]	[3.81]
Decile	NYSE	VW	0.29	0.35	0.36	0.34	0.22	0.23
			[3.27]	[3.86]	[3.97]	[3.74]	[2.48]	[2.52]
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	0.22	0.28	0.28	0.25	0.19	0.17
			[3.16]	[4.03]	[3.94]	[3.61]	[2.70]	[2.49]
Quintile	NYSE	EW	-0.07					
			[-1.17]					
Quintile	Name	VW	0.19	0.25	0.26	0.24	0.21	0.19
			[2.51]	[3.30]	[3.47]	[3.17]	[2.80]	[2.56]
Quintile	Cap	VW	0.26	0.32	0.33	0.30	0.25	0.22
			[3.90]	[4.79]	[4.96]	[4.54]	[3.77]	[3.49]
Decile	NYSE	VW	0.22	0.28	0.29	0.28	0.18	0.17
			[2.45]	[3.06]	[3.14]	[3.04]	[1.95]	[1.87]

Table 3: Conditional sort on size and DFE

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

	DFE Quintiles					DFE Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.77	0.87	1.02	0.97	0.80	0.03	0.04	0.03	0.03	0.05	0.05
	[2.83]	[3.11]	[3.67]	[3.27]	[2.93]	[0.37]	[0.56]	[0.37]	[0.36]	[0.68]	[0.68]
(2)	0.83	0.90	0.83	0.99	0.86	0.03	0.07	0.03	0.04	-0.00	0.00
	[3.10]	[3.51]	[3.27]	[3.93]	[3.39]	[0.35]	[0.82]	[0.42]	[0.46]	[-0.04]	[0.03]
(3)	0.79	0.87	0.85	0.86	0.95	0.17	0.22	0.21	0.16	0.20	0.17
	[3.18]	[3.84]	[3.46]	[3.80]	[4.10]	[2.26]	[2.93]	[2.81]	[2.17]	[2.63]	[2.20]
(4)	0.76	0.83	0.88	0.80	0.91	0.15	0.18	0.16	0.14	0.11	0.10
	[3.38]	[3.86]	[3.87]	[3.75]	[4.18]	[2.06]	[2.36]	[2.11]	[1.81]	[1.43]	[1.30]
(5)	0.47	0.65	0.63	0.67	0.86	0.39	0.43	0.45	0.37	0.35	0.30
	[2.28]	[3.60]	[3.23]	[3.59]	[4.37]	[4.29]	[4.70]	[4.94]	[4.11]	[3.81]	[3.33]

Panel B: Portfolio average number of firms and market capitalization

	DFE Quintiles Average n					DFE Quintiles Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	387	388	388	388	384	35	34	32	33	34
(2)	106	106	106	106	106	58	59	57	60	59
(3)	75	75	75	75	75	103	103	100	101	103
(4)	63	63	63	63	63	220	227	218	225	218
(5)	57	57	57	57	57	1269	1940	1716	1953	1357

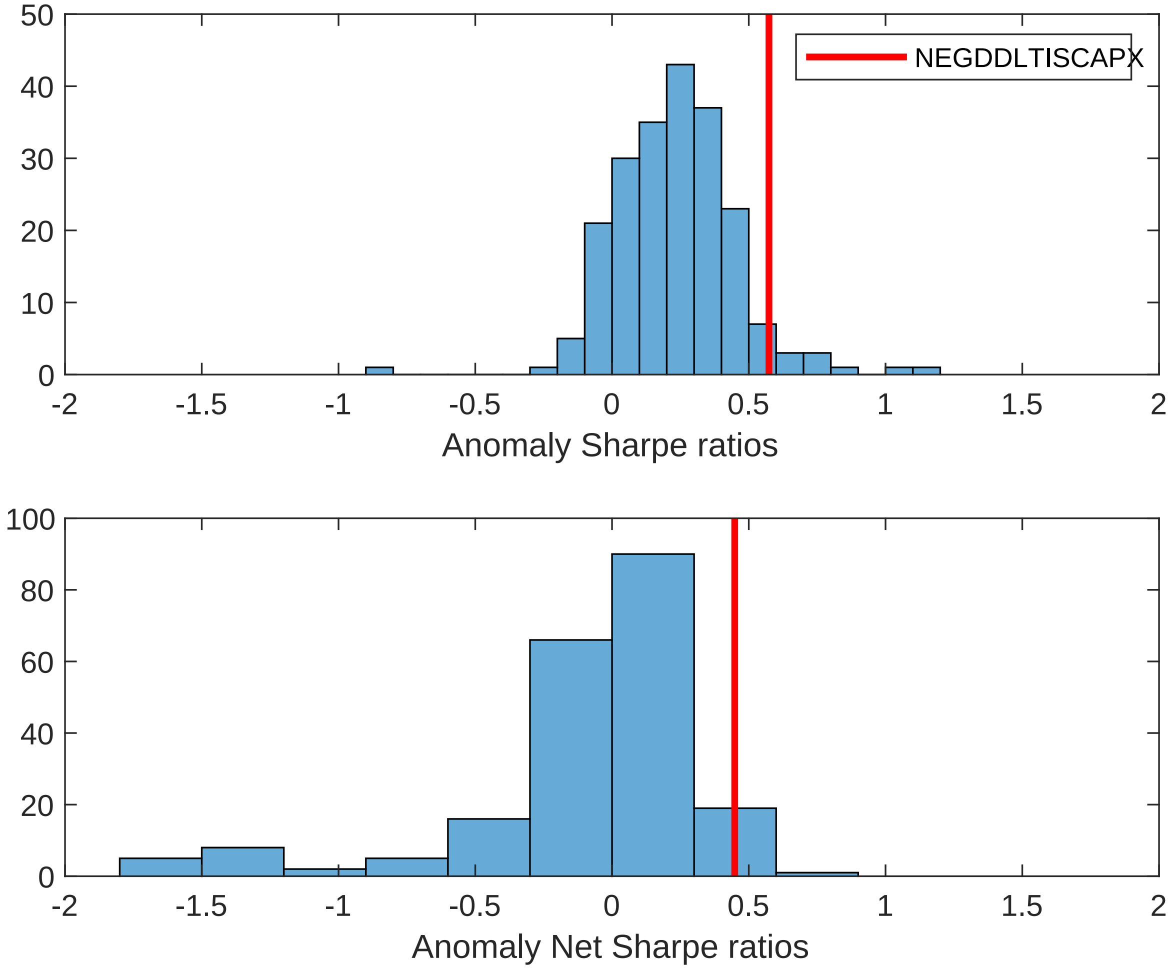

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DFE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

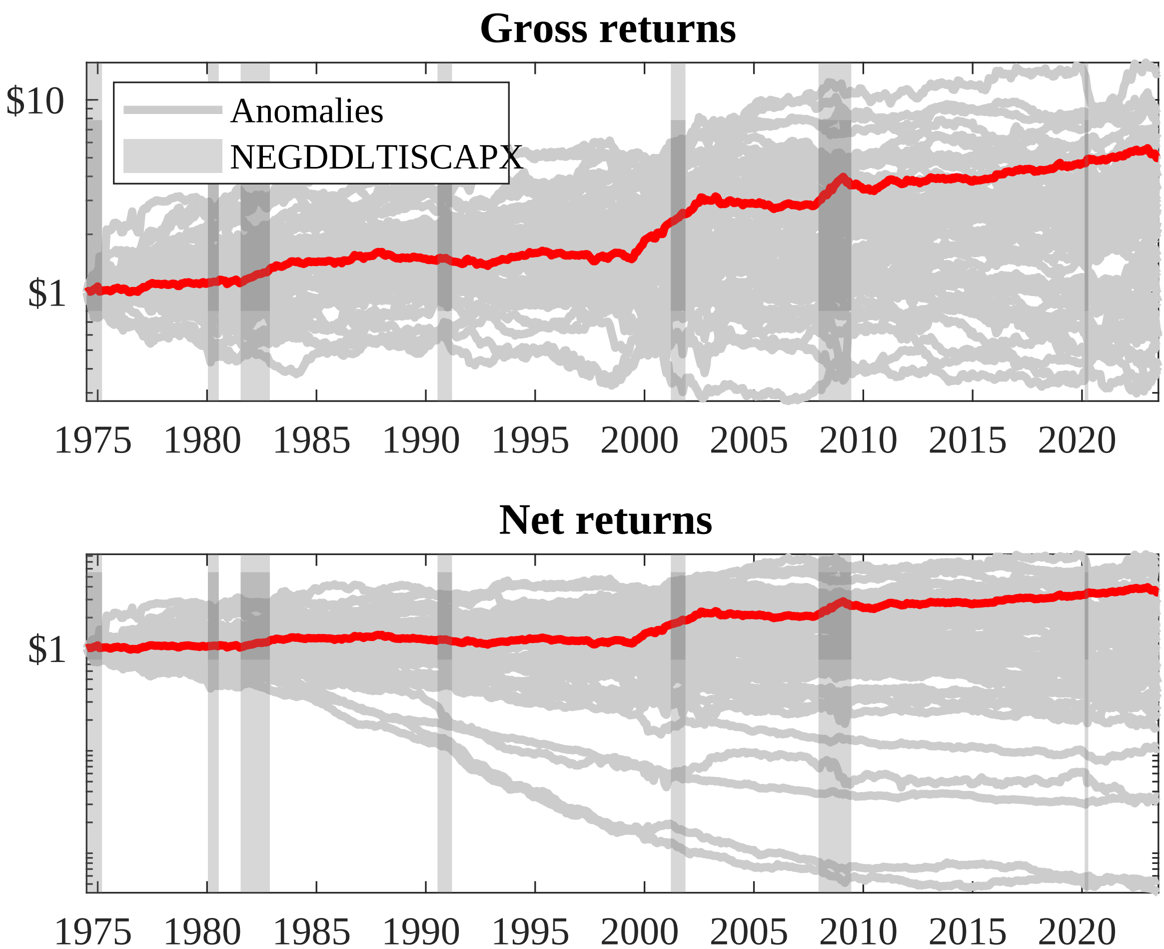

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DFE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

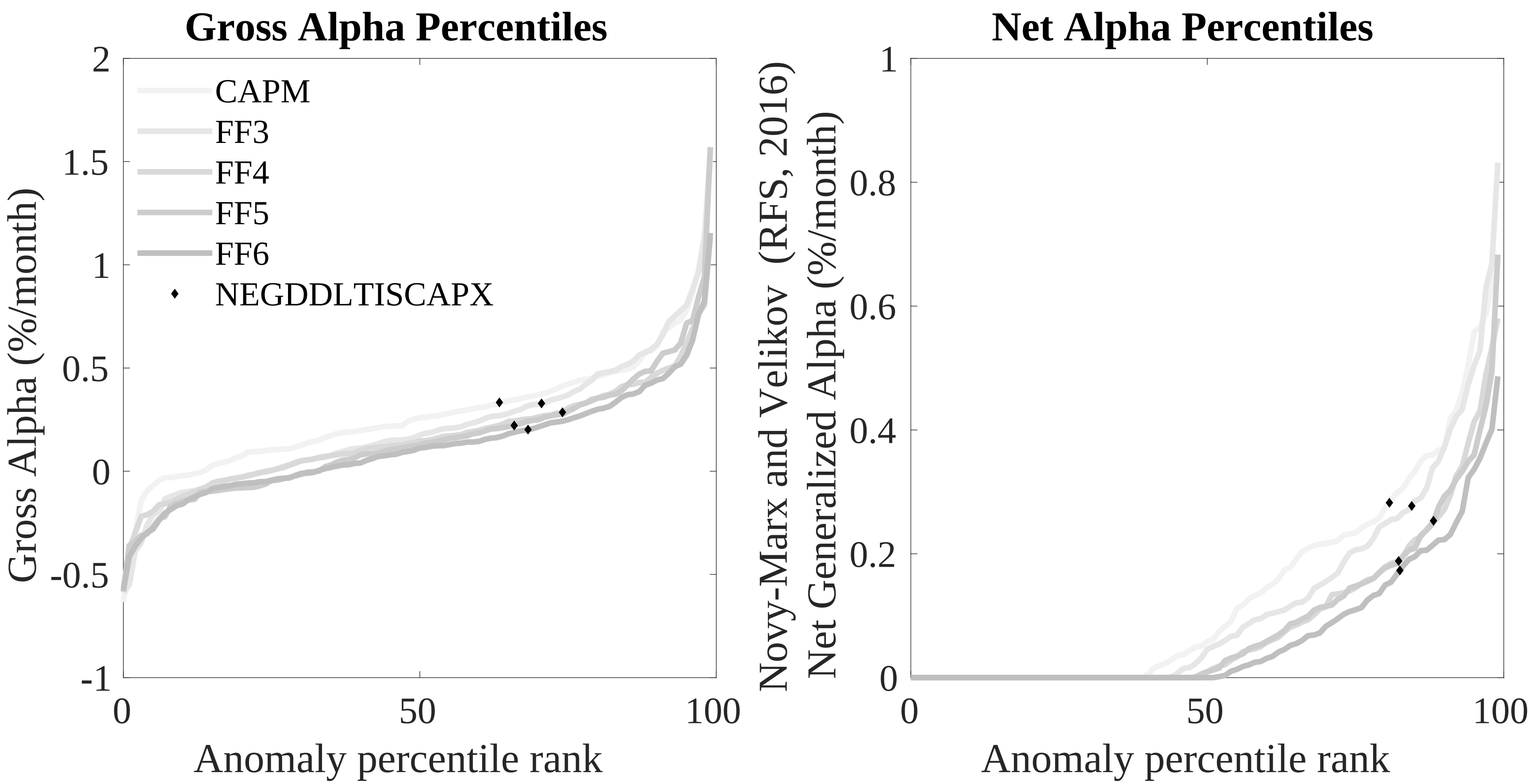

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DFE trading strategy alphas (diamonds). The strategies are constructed using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

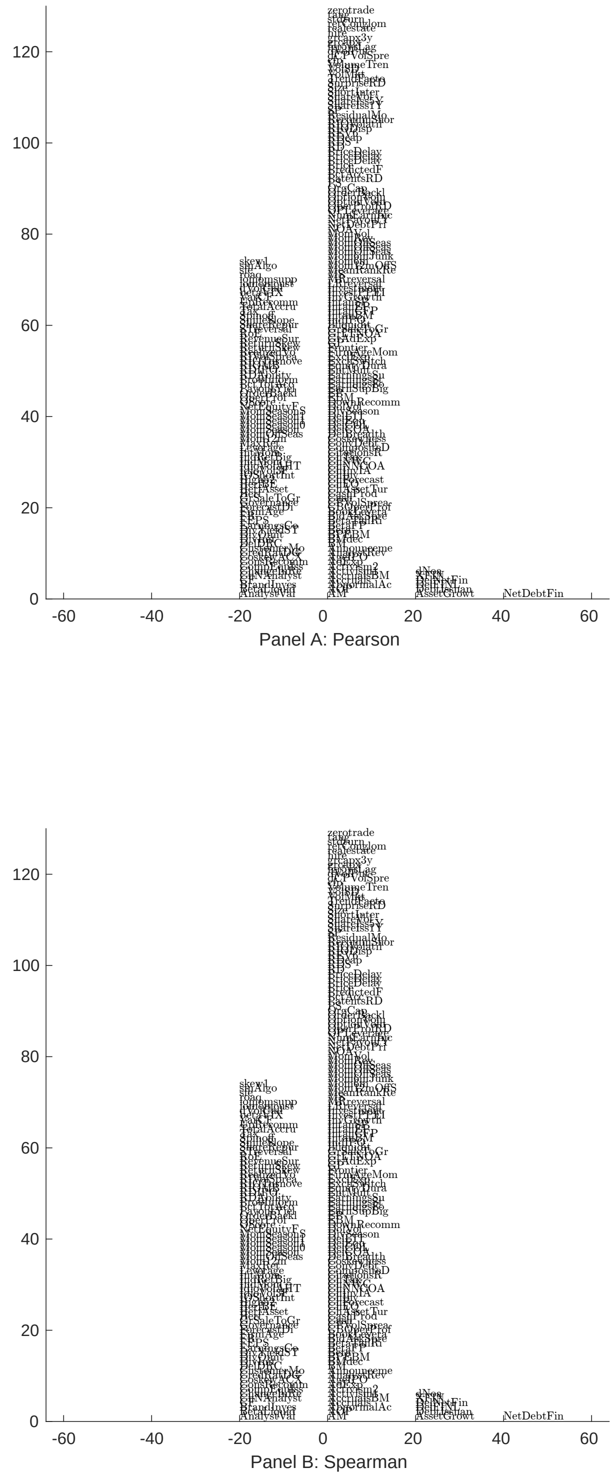

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DFE. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

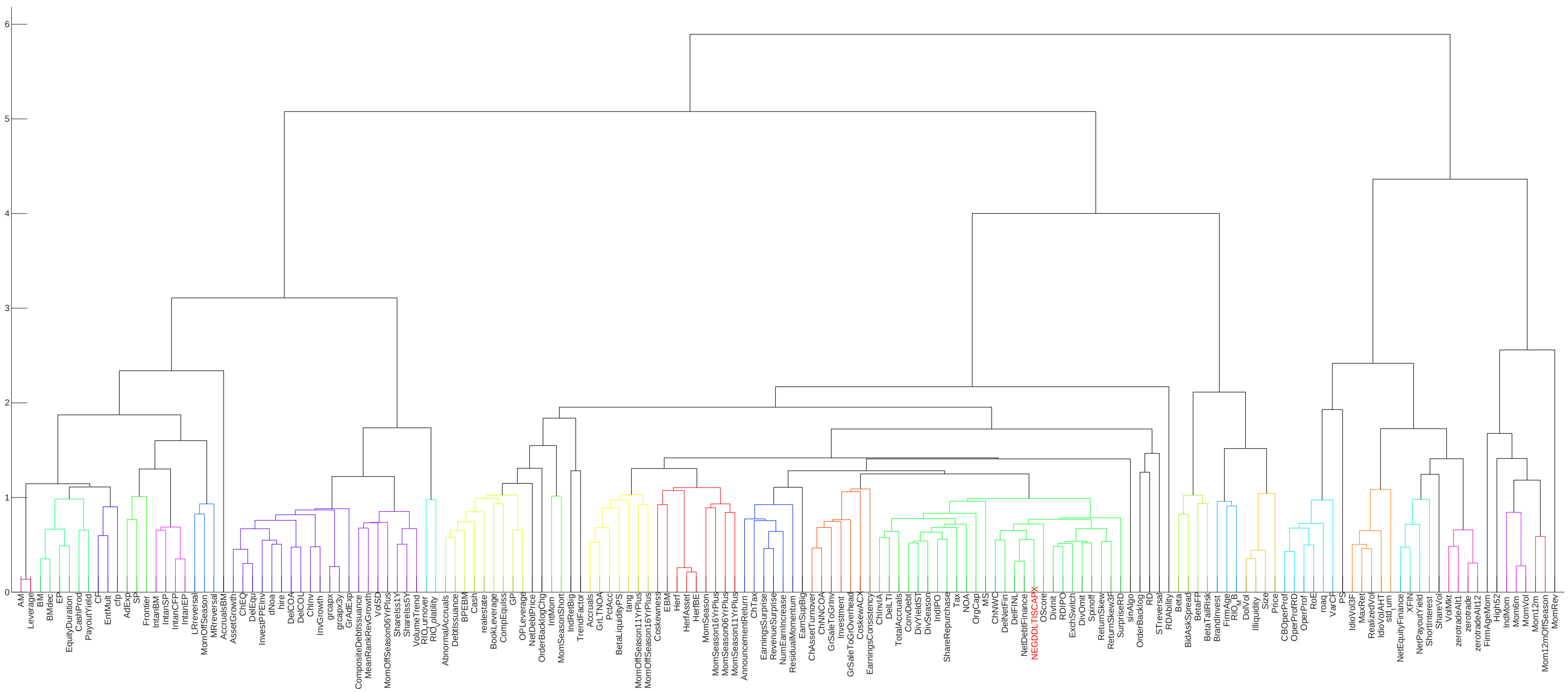

Figure 6: Agglomerative hierarchical cluster plot

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

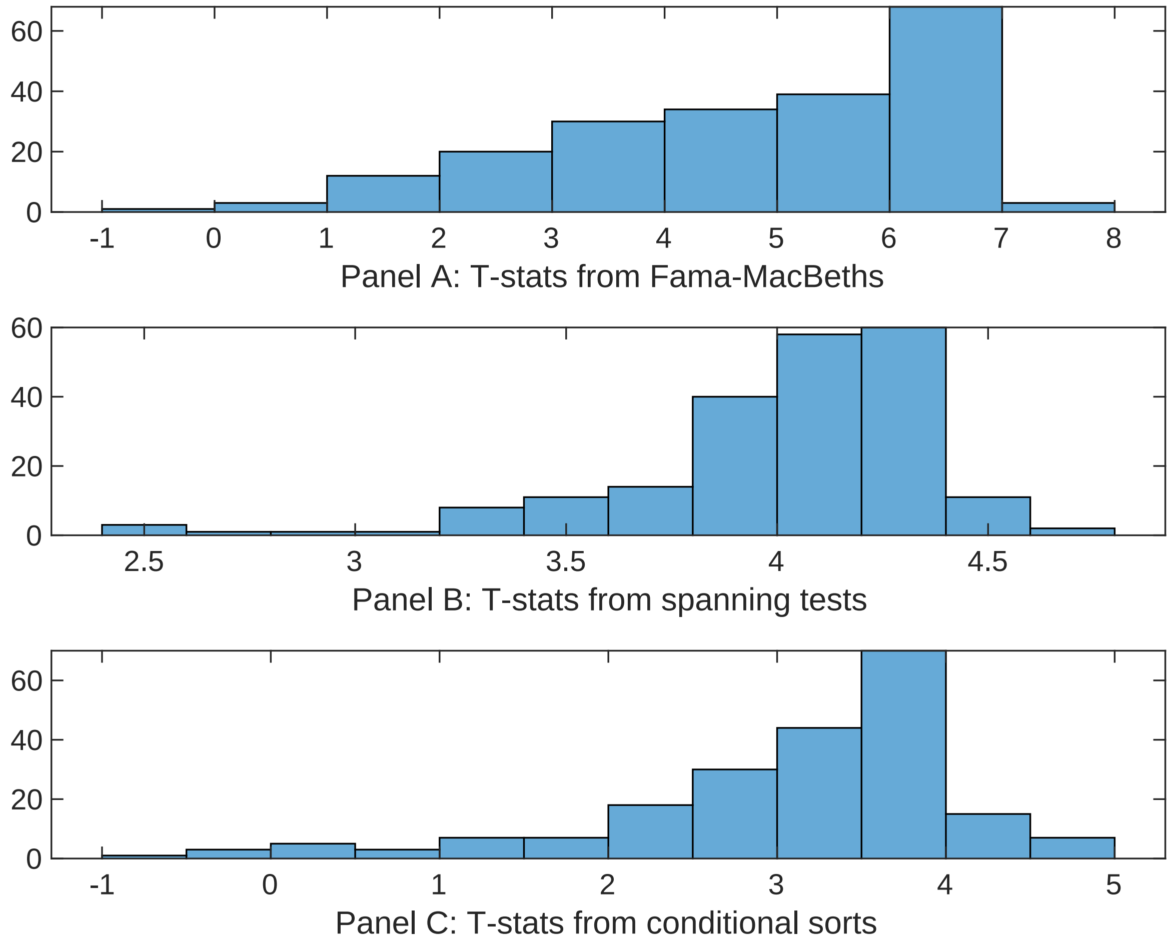

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DFE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DFE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DFE} DFE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DFE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DFE. Stocks are finally grouped into five DFE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DFE 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 DFE. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DFE} DFE_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, Employment growth, change in net operating assets. 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
	[5.53]	[5.50]	[5.86]	[5.96]	[5.50]	[5.82]	[6.08]
DFE	0.53	0.65	0.83	0.58	0.13	0.49	0.23
	[2.22]	[2.50]	[3.27]	[2.28]	[5.32]	[1.98]	[0.87]
Anomaly 1	0.17						-0.49
	[9.04]						[-1.22]
Anomaly 2		0.20					0.62
		[8.93]					[1.12]
Anomaly 3			0.19				0.80
			[6.20]				[1.56]
Anomaly 4				0.11			0.51
				[9.12]			[2.92]
Anomaly 5					0.93		0.10
					[6.07]		[0.82]
Anomaly 6						0.14	0.63
						[9.89]	[4.04]
# 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 DFE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DFE} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Employment growth, change in net operating assets. 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	0.19	0.19	0.19	0.21	0.22	0.20	0.20
	[2.79]	[2.80]	[2.80]	[2.98]	[3.06]	[2.90]	[2.91]
Anomaly 1	16.05						10.36
	[3.95]						[1.85]
Anomaly 2		16.51					8.66
		[4.24]					[1.60]
Anomaly 3			11.00				6.80
			[3.11]				[1.78]
Anomaly 4				10.42			8.31
				[2.31]			[1.66]
Anomaly 5					4.15		2.15
					[1.06]		[0.53]
Anomaly 6						1.44	-8.23
						[0.35]	[-1.80]
mkt	-3.09	-3.28	-1.79	-3.24	-3.19	-3.28	-2.16
	[-1.95]	[-2.07]	[-1.08]	[-2.02]	[-1.99]	[-2.04]	[-1.30]
smb	-0.63	-0.30	4.34	-0.25	0.99	0.82	0.64
	[-0.25]	[-0.12]	[1.60]	[-0.10]	[0.40]	[0.33]	[0.22]
hml	-9.39	-9.98	-8.97	-10.60	-10.92	-10.30	-8.79
	[-3.08]	[-3.28]	[-2.91]	[-3.45]	[-3.45]	[-3.31]	[-2.79]
rmw	6.52	6.39	1.16	7.80	7.89	7.77	2.08
	[2.06]	[2.02]	[0.30]	[2.45]	[2.47]	[2.43]	[0.54]
cma	23.77	24.88	21.75	16.12	25.30	28.03	12.69
	[4.95]	[5.29]	[4.18]	[2.21]	[4.30]	[5.03]	[1.67]
umd	2.05	2.24	3.55	4.02	3.38	3.54	2.37
	[1.24]	[1.38]	[2.21]	[2.47]	[2.07]	[2.18]	[1.42]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	14	14	13	13	12	12	15

Panel A: Average rank

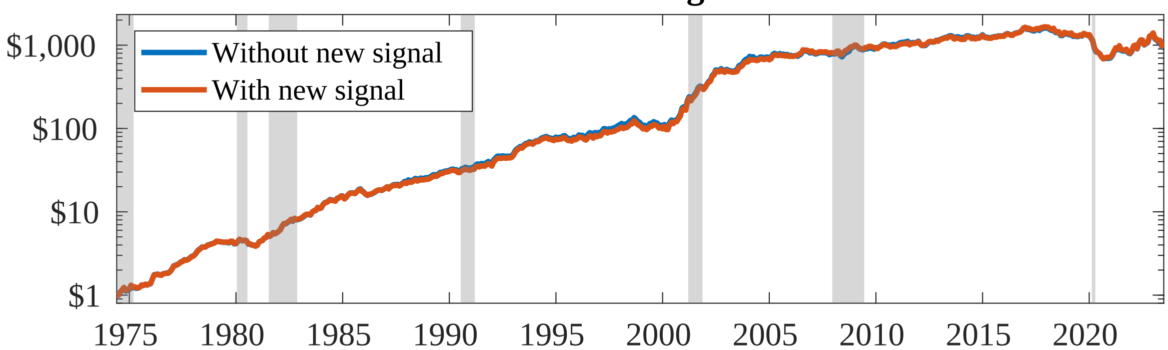

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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