Debt Impact Factor and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt Impact Factor (DIF), 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 DIF achieves an annualized gross (net) Sharpe ratio of 0.35 (0.27), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 34 (28) bps/month with a t-statistic of 3.01 (2.49), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Net external financing, Change in financial liabilities, Investment to revenue, Change in net financial assets, Asset growth) is 29 bps/month with a t-statistic of 2.71.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of research documents systematic patterns in stock returns that appear to contradict market efficiency (Fama and French, 2008). While much attention has focused on equity characteristics like size, value, and momentum, the role of corporate debt structure in driving cross-sectional return patterns remains incompletely understood (Baker and Wurgler, 2002).

Prior research has examined various aspects of firms' financing decisions, including capital structure changes (Baker and Wurgler, 2002), debt maturity (**?**), and credit ratings (Avramov et al., 2009). However, these studies have generally focused on individual aspects of debt structure rather than considering how the overall debt configuration impacts future stock returns. This gap is particularly notable given the theoretical links between debt structure and equity risk premiums (Merton, 1974).

We develop our hypothesis about the relationship between Debt Impact Factor (DIF) and future stock returns based on several theoretical mechanisms. First, following (Merton, 1974), the configuration of a firm's debt structure directly affects equity holders' risk exposure through the option-like payoff structure of equity claims. Higher DIF indicates greater sensitivity of equity value to changes in firm fundamentals due to leverage effects.

Second, debt structure complexity can create information frictions that affect the incorporation of news into stock prices (Duffie and Zhu, 2011). When debt arrangements are more intricate, as captured by higher DIF scores, investors may face greater difficulty in assessing firm value, leading to delayed price adjustment and predictable return patterns (Hong and Stein, 1999).

Third, drawing on the q-theory of investment (Cochrane, 1991), firms' debt structure choices should reflect their investment opportunities and expected returns. Higher DIF may signal greater financial constraints or risk that requires higher expected returns to compensate investors (Whited and Wu, 2006).

Our empirical analysis reveals that DIF strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio that buys stocks with high DIF and shorts those with low DIF generates significant abnormal returns of 34 basis points per month (t-statistic = 3.01) after controlling for the Fama-French five factors plus momentum. The strategy achieves an annualized Sharpe ratio of 0.35 before trading costs and 0.27 after costs.

Importantly, DIF's predictive power remains robust when controlling for size. Among the largest quintile of stocks, the DIF strategy earns abnormal returns of 38-44 basis points per month with t-statistics between 2.62 and 3.07. This indicates that the effect is not confined to small, illiquid stocks where trading costs might eliminate profits.

The signal's economic value extends beyond existing factors. When we control for the six most closely related anomalies from the literature plus standard factors, DIF continues to generate significant alpha of 29 basis points monthly (t-statistic = 2.71). This suggests DIF captures unique information about expected returns not contained in known predictors.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel measure that comprehensively captures the impact of debt structure on equity risk. While prior work has examined isolated aspects of leverage (Baker and Wurgler, 2002) or credit risk (Avramov et al., 2009), DIF provides an integrated framework for assessing how debt configuration affects expected returns.

Second, we extend the literature on structural models of credit risk (Merton, 1974) by showing how debt structure complexity creates systematic patterns in equity returns. Our findings suggest that standard factor models miss important risk premiums associated with debt configuration.

Third, our results contribute to the growing literature on the 'factor zoo' (Cochrane,

2011) by identifying a robust new predictor of returns. Unlike many recently proposed factors, DIF maintains its predictive power among large stocks and after controlling for transaction costs and related anomalies. This suggests DIF captures fundamental economic risks that command a risk premium in equilibrium.

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 Factor. 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 RECCO for total receivables. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while total receivables (RECCO) encompasses amounts due from customers for goods and services provided.construction of the Debt Impact Factor follows a difference-based approach, where we first calculate the change in DLTIS by subtracting its lagged value from the current value, and then scale this difference by the lagged value of RECCO. This construction captures the relative impact of changes in debt issuance compared to the firm's existing receivables base, providing insight into the firm's debt dynamics relative to its operational scale. By focusing on this relationship, the signal aims to reflect aspects of debt management and financial leverage in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both DLTIS and RECCO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DIF signal. Panel A plots the time-series of the mean, median, and interquartile range for DIF. On average, the cross-sectional mean (median) DIF is -17.16 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DIF data. The signal's interquartile range spans -7.52 to 6.64. Panel B of Figure 1 plots the time-series of the coverage of the DIF signal for the CRSP universe. On average, the DIF signal is available for 2.36% of CRSP names, which on average make up 3.28% of total market capitalization.

4 Does DIF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DIF 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 DIF portfolio and sells the low DIF 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 DIF strategy earns an average return of 0.26% per month with a t-statistic of 2.44. The annualized Sharpe ratio of the strategy is 0.35. The alphas range from 0.29% to 0.37% per month and have t-statistics exceeding 2.57 everywhere. The lowest alpha is with respect to the FF5 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 0.25, with a t-statistic of 3.41 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 212 stocks and an average market capitalization of at least $561 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using NYSE breakpoints and equal-weighted portfolios, and equals 18 bps/month with a t-statistics of 2.64. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twelve 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 -9-30bps/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 -1.07. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DIF trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the DIF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DIF, as well as average returns and alphas for long/short trading DIF 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 DIF strategy achieves an average return of 38 bps/month with a t-statistic of 2.75. Among these large cap stocks, the alphas for the DIF strategy relative to the five most common factor models range from 38 to 44 bps/month with t-statistics between 2.62 and 3.07.

5 How does DIF perform relative to the zoo?

Figure 2 puts the performance of DIF 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 DIF strategy falls in the distribution. The DIF strategy's gross (net) Sharpe ratio of 0.35 (0.27) is greater than 75% (88%) 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 DIF strategy (red line).[2] Ignoring trading costs, a $1 invested in the DIF strategy would have yielded $3.34 which ranks the DIF strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DIF strategy would have yielded $2.11 which ranks the DIF strategy in the top 5% 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 DIF relative to those. Panel A shows that the DIF strategy gross alphas fall between the 62 and 83 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 DIF strategy has a positive net generalized alpha for five out of the five factor models. In these cases DIF ranks between the 81 and 93 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does DIF 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

[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.

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 DIF with 204 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 DIF or at least to weaken the power DIF has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DIF conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DIF} DIF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DIF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 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 204 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on DIF. Stocks are finally grouped into five DIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIF trading strategies conditioned on each of the 204 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DIF and the six anomalies most closely-related to it. The six most-closely related anomalies

[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.

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 DIF signal in these Fama-MacBeth regressions exceed -0.88, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DIF is -0.67.

Similarly, Table 5 reports results from spanning tests that regress returns to the DIF 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 DIF strategy earns alphas that range from 29-38bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.59, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DIF trading strategy achieves an alpha of 29bps/month with a t-statistic of 2.71.

7 Does DIF add relative to the whole zoo?

Finally, we can ask how much adding DIF 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 DIF 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,

[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 DIF is available.

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 DIF grows to \$872.31.

8 Conclusion

This study provides compelling evidence for the significance of the Debt Impact Factor (DIF) as a valuable predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on DIF generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.35 (0.27 net). 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 factors from the factor zoo.

The persistence of DIF's predictive power, evidenced by monthly abnormal gross returns of 34 basis points (28 bps net) with strong statistical significance, suggests that this signal captures a distinct aspect of asset pricing that is not fully explained by traditional risk factors or similar investment strategies. This has important implications for both academic research and practical investment management, as it introduces a novel and effective tool for portfolio construction and risk management.

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

Future research could explore the international validity of the DIF signal, its interaction with other established factors, and its performance during different market regimes. Additionally, investigating the underlying economic mechanisms driving the DIF premium would enhance our understanding of this phenomenon. Researchers might also consider examining how the signal's effectiveness varies across different firm characteristics and market conditions to further validate its robustness and applicability.

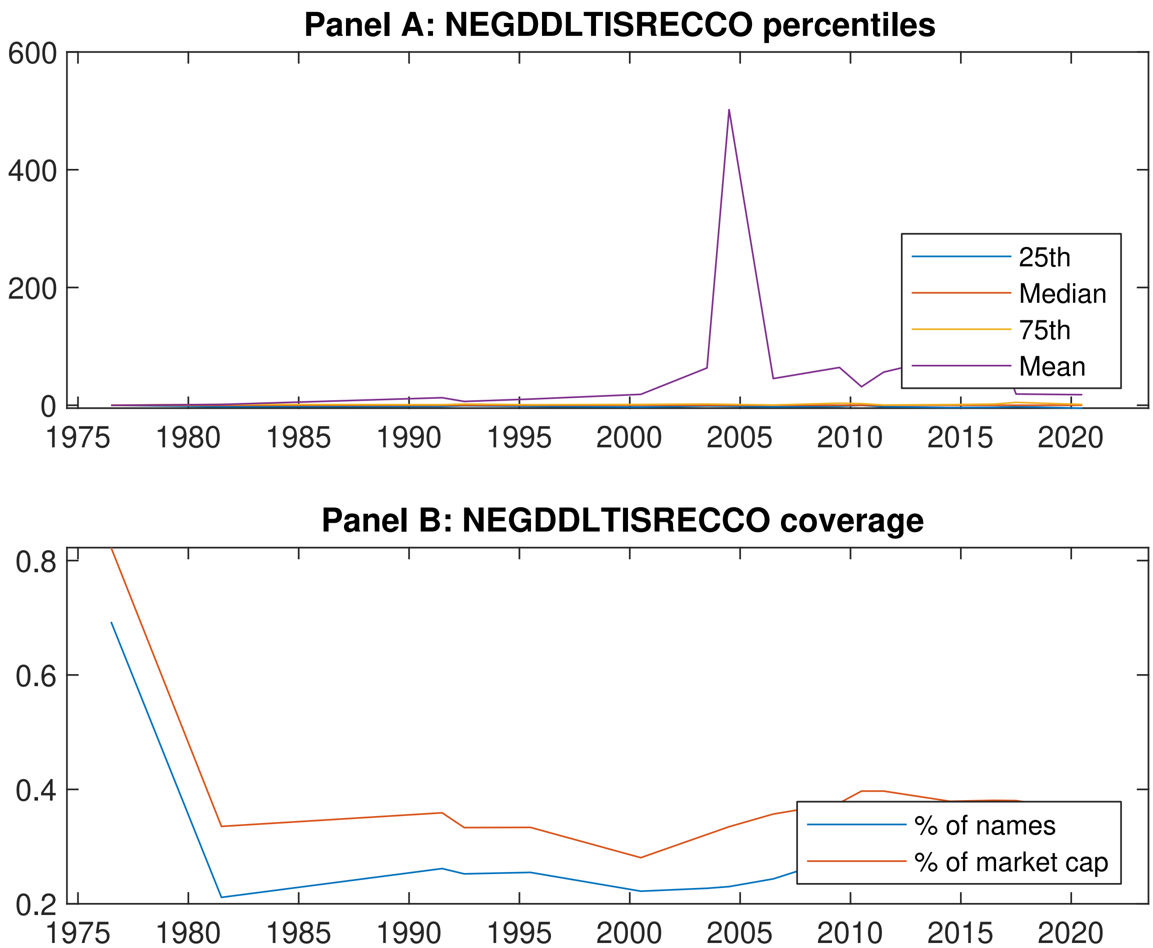

Figure 1: Times series of DIF percentiles and coverage.
This figure plots descriptive statistics for DIF. Panel A shows cross-sectional percentiles of DIF over the sample. Panel B plots the monthly coverage of DIF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DIF. 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 DIF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.50	0.70	0.71	0.78	0.76	0.26
	[2.31]	[3.69]	[3.64]	[4.04]	[3.73]	[2.44]
α_{CAPM}	-0.23	0.08	0.06	0.14	0.09	0.32
	[-3.00]	[0.98]	[0.81]	[1.85]	[1.05]	[2.92]
α_{FF3}	-0.25	0.01	0.04	0.12	0.06	0.31
	[-3.33]	[0.13]	[0.56]	[1.71]	[0.68]	[2.85]
α_{FF4}	-0.25	0.03	0.03	0.12	0.12	0.37
	[-3.23]	[0.36]	[0.39]	[1.60]	[1.40]	[3.34]
α_{FF5}	-0.24	-0.05	-0.04	0.03	0.05	0.29
	[-3.09]	[-0.73]	[-0.49]	[0.39]	[0.55]	[2.57]
α_{FF6}	-0.24	-0.04	-0.04	0.03	0.09	0.34
	[-3.07]	[-0.48]	[-0.52]	[0.48]	[1.11]	[3.01]
Panel B: Fama and French (2018) 6-factor model loadings for DIF-sorted portfolios						
β_{MKT}	1.05	0.98	0.98	1.00	0.98	-0.07
	[58.04]	[56.89]	[54.15]	[60.06]	[49.83]	[-2.62]
β_{SMB}	0.05	-0.12	-0.01	-0.12	0.02	-0.03
	[1.71]	[-4.71]	[-0.46]	[-4.56]	[0.74]	[-0.63]
β_{HML}	0.13	0.21	0.03	-0.02	0.01	-0.12
	[3.81]	[6.44]	[0.73]	[-0.57]	[0.39]	[-2.37]
β_{RMW}	0.07	0.13	0.15	0.10	0.02	-0.05
	[1.87]	[3.87]	[4.22]	[2.90]	[0.54]	[-0.90]
β_{CMA}	-0.17	0.06	0.08	0.23	0.08	0.25
	[-3.29]	[1.16]	[1.62]	[4.80]	[1.43]	[3.41]
β_{UMD}	0.00	-0.03	0.00	-0.01	-0.08	-0.09
	[0.12]	[-1.79]	[0.20]	[-0.65]	[-4.19]	[-3.30]
Panel C: Average number of firms (n) and market capitalization (me)						
n	264	212	375	221	256	
me ($\$10^6$)	561	1135	916	1162	565	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DIF 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	0.26	0.32	0.31	0.37	0.29	0.34
			[2.44]	[2.92]	[2.85]	[3.34]	[2.57]	[3.01]
Quintile	NYSE	EW	0.18	0.21	0.20	0.18	0.21	0.20
			[2.64]	[3.04]	[2.91]	[2.60]	[2.95]	[2.76]
Quintile	Name	VW	0.26	0.32	0.31	0.37	0.26	0.31
			[2.28]	[2.81]	[2.73]	[3.21]	[2.23]	[2.68]
Quintile	Cap	VW	0.31	0.35	0.38	0.39	0.36	0.37
			[2.98]	[3.39]	[3.65]	[3.72]	[3.38]	[3.49]
Decile	NYSE	VW	0.37	0.46	0.47	0.48	0.41	0.42
			[2.62]	[3.31]	[3.35]	[3.33]	[2.83]	[2.90]
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	0.21	0.28	0.28	0.31	0.25	0.28
			[1.91]	[2.60]	[2.52]	[2.85]	[2.27]	[2.49]
Quintile	NYSE	EW	-0.09					
			[-1.07]					
Quintile	Name	VW	0.20	0.28	0.27	0.31	0.23	0.25
			[1.77]	[2.47]	[2.39]	[2.71]	[1.97]	[2.19]
Quintile	Cap	VW	0.26	0.32	0.34	0.35	0.33	0.33
			[2.51]	[3.09]	[3.29]	[3.38]	[3.10]	[3.11]
Decile	NYSE	VW	0.30	0.42	0.42	0.42	0.36	0.37
			[2.14]	[2.96]	[2.97]	[3.00]	[2.53]	[2.53]

Table 3: Conditional sort on size and DIF

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

		DIF Quintiles					DIF Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.57	0.77	0.88	1.07	0.69	0.12	0.15	0.13	0.11	0.14	0.12
		[1.93]	[2.63]	[3.08]	[2.98]	[2.42]	[0.83]	[1.06]	[0.91]	[0.73]	[0.94]	[0.83]
	(2)	0.74	0.88	0.72	1.06	0.89	0.15	0.18	0.21	0.24	0.26	0.28
		[2.67]	[3.25]	[2.82]	[4.15]	[3.35]	[1.20]	[1.42]	[1.63]	[1.84]	[1.98]	[2.11]
	(3)	0.87	0.87	0.90	0.94	0.81	-0.06	-0.04	-0.07	-0.06	-0.05	-0.04
		[3.45]	[3.65]	[3.74]	[4.09]	[3.25]	[-0.44]	[-0.27]	[-0.54]	[-0.45]	[-0.40]	[-0.32]
	(4)	0.72	0.82	0.71	0.81	0.84	0.12	0.16	0.12	0.10	0.07	0.06
		[3.10]	[3.66]	[3.33]	[3.57]	[3.83]	[0.95]	[1.25]	[0.92]	[0.76]	[0.50]	[0.44]
	(5)	0.37	0.72	0.62	0.72	0.75	0.38	0.41	0.43	0.44	0.38	0.39
		[1.81]	[3.66]	[3.12]	[3.73]	[3.76]	[2.75]	[2.91]	[3.08]	[3.07]	[2.62]	[2.68]

Panel B: Portfolio average number of firms and market capitalization

		DIF Quintiles					DIF Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	150	150	151	151	150	12	10	10	11	11
	(2)	38	38	38	38	38	19	20	19	20	19
	(3)	28	28	28	28	28	37	37	36	36	36
	(4)	24	24	24	24	24	79	84	81	83	80
	(5)	25	25	25	25	25	550	804	827	827	590

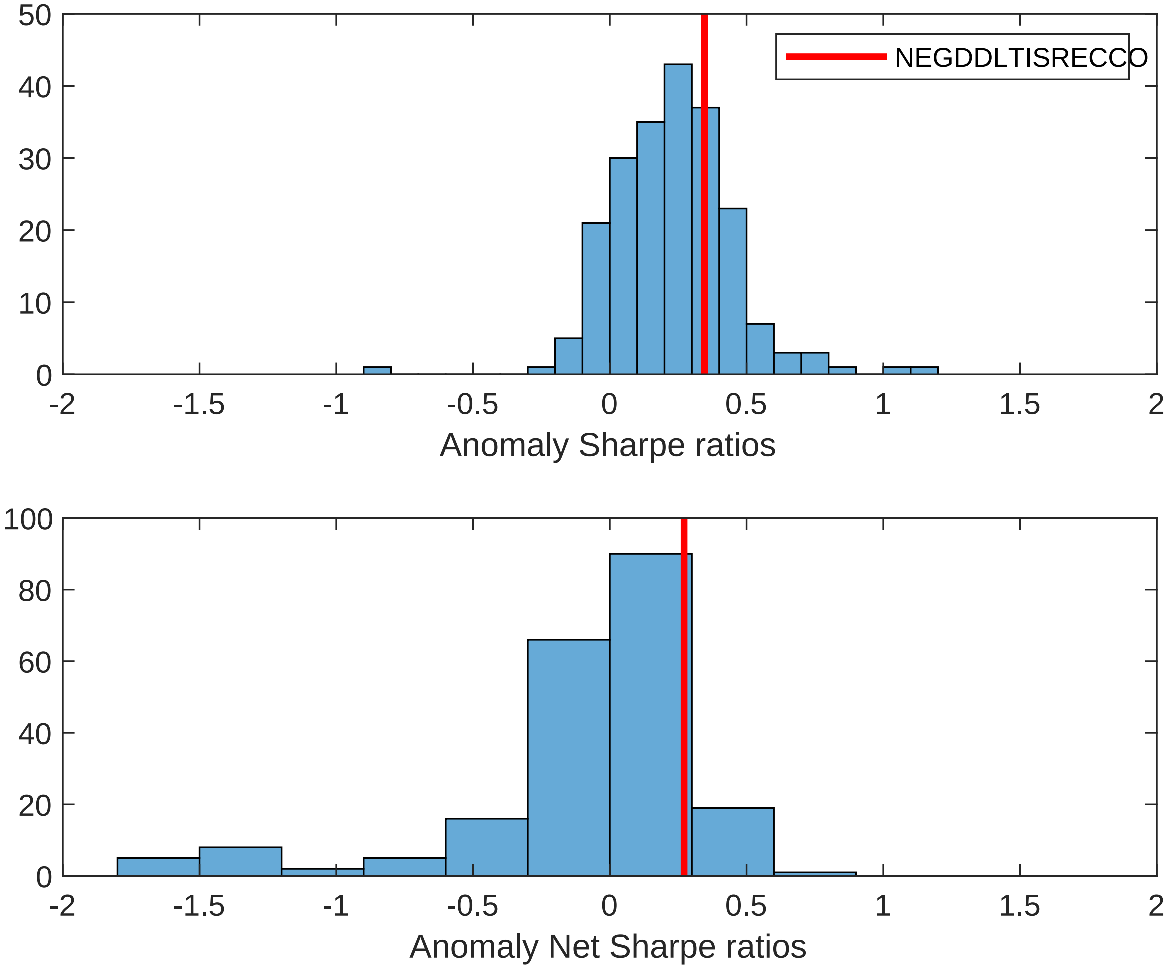

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

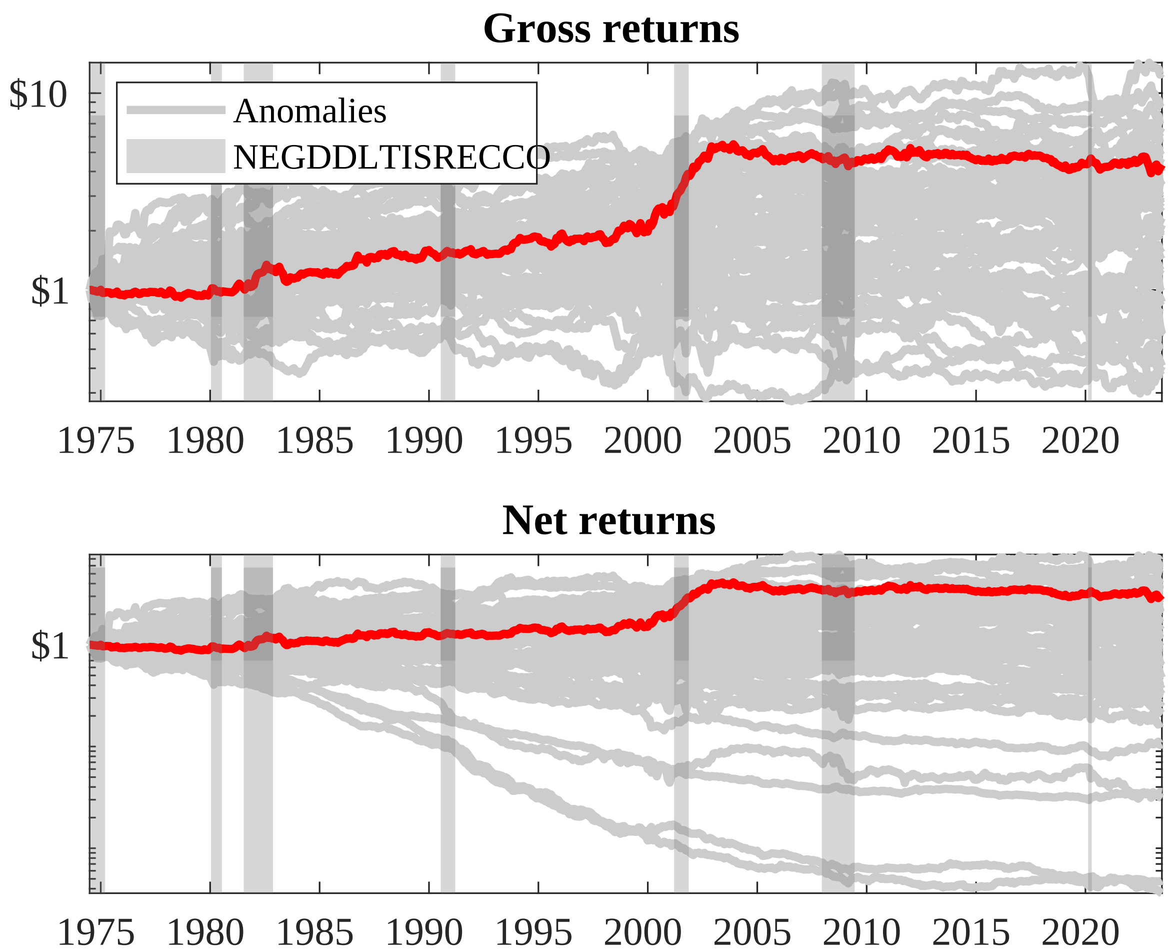

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

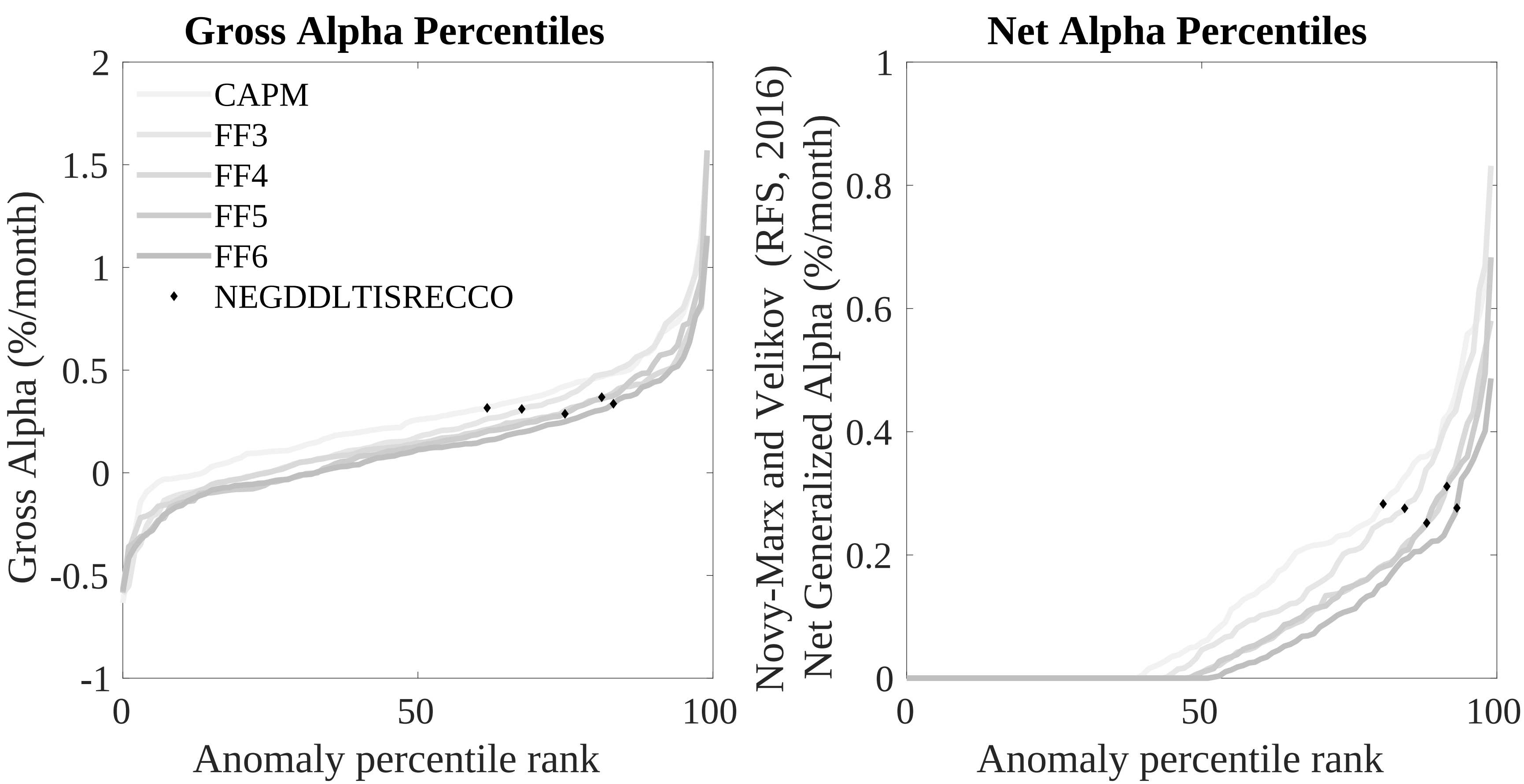

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DIF trading strategy alphas (diamonds). The strategies are constructed using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

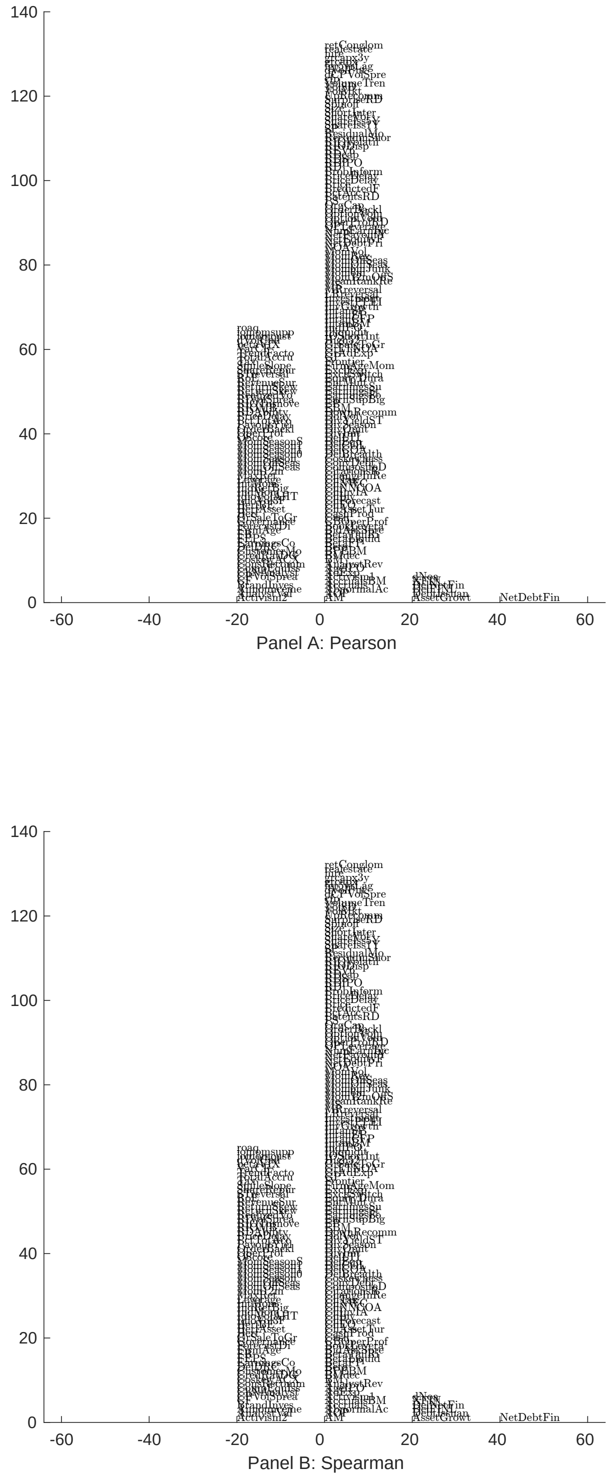

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 204 filtered anomaly signals with DIF. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

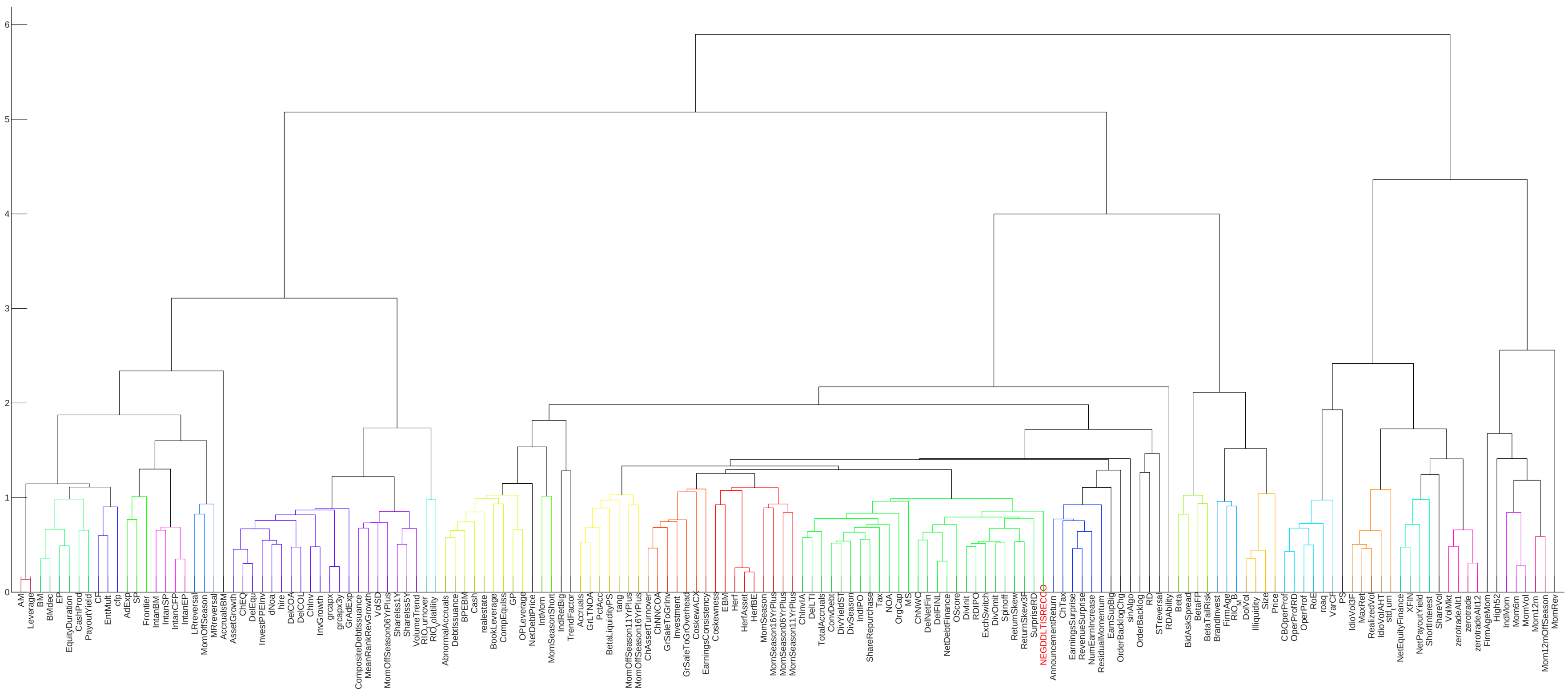

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

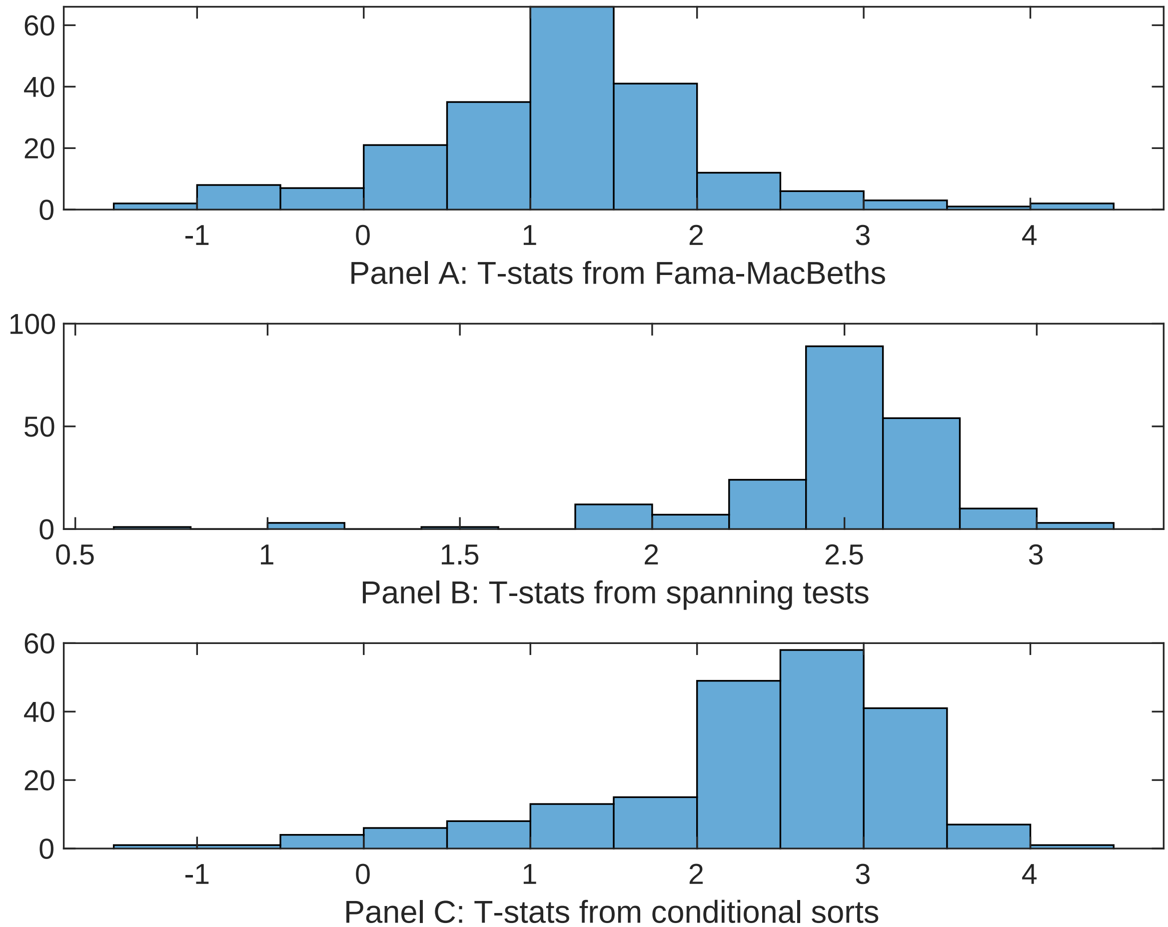

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DIF conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DIF} DIF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DIF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 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 204 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on DIF. Stocks are finally grouped into five DIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIF trading strategies conditioned on each of the 204 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies

This table presents Fama-MacBeth results of returns on DIF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DIF} DIF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net debt financing, Net external financing, Change in financial liabilities, Investment to revenue, Change in net financial assets, 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	0.13	0.14	0.13	0.15	0.13	0.14	0.15
	[5.28]	[5.66]	[5.34]	[5.91]	[5.22]	[5.77]	[5.84]
DIF	-0.18	0.73	-0.19	0.17	-0.37	-0.29	-0.24
	[-0.73]	[0.03]	[-0.82]	[0.59]	[-0.17]	[-0.88]	[-0.67]
Anomaly 1	0.24						0.98
	[7.36]						[1.25]
Anomaly 2		0.20					0.93
		[5.76]					[1.33]
Anomaly 3			0.20				-0.11
			[7.51]				[-1.45]
Anomaly 4				0.20			0.77
				[3.37]			[1.40]
Anomaly 5					0.10		0.36
					[5.06]		[0.86]
Anomaly 6						0.12	0.97
						[9.07]	[4.45]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	0	1	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 DIF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DIF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Net external financing, Change in financial liabilities, Investment to revenue, Change in net financial assets, 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	0.33	0.33	0.34	0.38	0.29	0.36	0.29
	[3.03]	[2.99]	[3.04]	[3.42]	[2.59]	[3.18]	[2.71]
Anomaly 1	28.60						14.04
	[4.59]						[1.66]
Anomaly 2		24.89					16.87
		[4.42]					[2.83]
Anomaly 3			23.35				2.50
			[3.57]				[0.27]
Anomaly 4				-17.31			-19.64
				[-4.00]			[-4.60]
Anomaly 5					26.21		22.31
					[4.62]		[3.39]
Anomaly 6						1.60	-4.02
						[0.22]	[-0.53]
mkt	-7.08	-3.72	-6.80	-6.57	-7.04	-7.07	-4.19
	[-2.80]	[-1.40]	[-2.67]	[-2.58]	[-2.78]	[-2.74]	[-1.62]
smb	-4.01	5.91	-4.18	0.96	0.22	-2.26	8.02
	[-1.02]	[1.37]	[-1.05]	[0.24]	[0.06]	[-0.56]	[1.77]
hml	-10.86	-8.50	-10.07	-12.50	-12.19	-11.25	-11.26
	[-2.23]	[-1.73]	[-2.05]	[-2.55]	[-2.51]	[-2.27]	[-2.33]
rmw	-6.62	-19.17	-6.07	-5.81	-0.37	-4.29	-14.08
	[-1.31]	[-3.16]	[-1.19]	[-1.14]	[-0.07]	[-0.84]	[-2.28]
cma	17.52	8.18	17.07	26.53	32.20	22.84	22.33
	[2.33]	[0.99]	[2.21]	[3.59]	[4.28]	[1.94]	[1.95]
umd	-11.25	-8.99	-11.16	-6.60	-9.74	-8.85	-8.58
	[-4.31]	[-3.51]	[-4.21]	[-2.50]	[-3.80]	[-3.38]	[-3.25]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	8	8	6	7	8	4	13

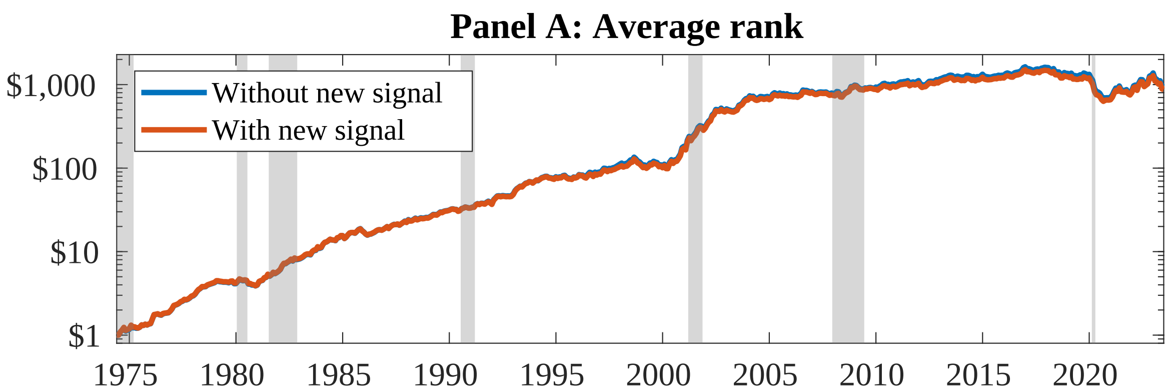

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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