Equity-Debt Imbalance Factor and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity-Debt Imbalance Factor (EDIF), 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 EDIF achieves an annualized gross (net) Sharpe ratio of 0.46 (0.34), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (17) bps/month with a t-statistic of 2.75 (2.38), 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, Inventory Growth, change in net operating assets) is 18 bps/month with a t-statistic of 2.64.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns. While the literature has extensively documented various return predictors, understanding how firms' financing decisions affect expected returns remains an important challenge. The interplay between equity and debt financing choices may contain valuable information about future firm performance and risk that is not fully incorporated into stock prices.

Prior research has examined equity issuance and debt levels separately, but their joint dynamics and relative changes have received limited attention. This gap is particularly notable given that managers actively choose between these financing sources based on their private information about future prospects and risks. The relative changes in equity versus debt financing may therefore serve as a powerful signal about managerial expectations that is not fully reflected in individual financing measures.

We hypothesize that the Equity-Debt Imbalance Factor (EDIF) captures valuable information about future returns through multiple economic channels. First, following Myers and Majluf (1984), managers time the market by issuing equity when they believe shares are overvalued and debt when shares are undervalued. The relative change between equity and debt financing may therefore signal management's private information about fundamental value.

Second, building on Baker and Wurgler (2002), firms' financing choices reflect both market timing and future investment opportunities. When managers anticipate strong growth prospects requiring flexibility, they may prefer equity over debt financing. Conversely, mature firms with stable cash flows tend to increase leverage. The EDIF measure can thus indicate management's assessment of the firm's growth trajectory and risk profile.

Third, consistent with Titman (1984), changes in capital structure affect stakeholder relationships and operating decisions. Firms increasing equity relative to debt signal a longer-term orientation and willingness to share upside with new shareholders, while debt increases suggest confidence in stable cash flows. Therefore, EDIF may capture information about management's strategic positioning and expected operational performance.

Our empirical analysis reveals that EDIF strongly predicts future stock returns. A value-weighted long-short strategy based on EDIF quintiles generates monthly abnormal returns of 19 basis points (t-statistic = 2.75) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.46, placing it in the top 11% of documented return predictors.

The predictive power of EDIF remains robust across various specifications. The signal maintains significance when controlling for size, with the long-short strategy earning a monthly alpha of 32 basis points (t-statistic = 3.66) among large-cap stocks. After accounting for transaction costs following Novy-Marx and Velikov (2016), the strategy delivers a net Sharpe ratio of 0.34.

Most importantly, EDIF's predictive ability persists after controlling for related anomalies. In spanning tests that include the six most closely related financing-based predictors and the Fama-French six factors, EDIF generates an alpha of 18 basis points per month (t-statistic = 2.64). This indicates that EDIF captures unique information not contained in existing factors.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures the joint dynamics of equity and debt financing decisions, extending work by Baker and Wurgler (2002) on market timing and Titman (1984) on capital structure. While prior research has examined equity issuance and leverage separately, EDIF provides a unified measure of firms' financing choices.

Second, we demonstrate robust return predictability that survives stringent controls for existing factors and related anomalies. Our results suggest that the market does not fully incorporate the information content of firms' relative financing decisions, contributing to the literature on market efficiency and limits to arbitrage documented in Shleifer and Vishny (1997).

Third, our findings have important implications for both academic research and investment practice. For researchers, we provide new evidence on how financing decisions reflect managerial information and affect expected returns. For practitioners, EDIF represents a novel signal that can enhance portfolio formation, particularly given its effectiveness among large, liquid stocks and resilience to transaction costs.

2 Data

Our study examines the predictive power of the Equity-Debt Imbalance Factor, a financial signal constructed from accounting data to analyze cross-sectional returns. We obtain accounting and financial data from COMPUSTAT, utilizing firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item DLTIS, which represents the long-term debt issuance, and CEQ, which represents the total common/ordinary equity. Long-term debt issuance (DLTIS) captures the amount of new long-term debt issued by the firm during the fiscal year, while common equity (CEQ) represents the shareholders' equity excluding preferred stock and minority interests. The construction of our signal follows a specific methodology where we first calculate the difference between the current period's DLTIS and its lagged value, effectively measuring the change in debt issuance. This difference is then scaled by the lagged value of common equity (CEQ) to normalize the measure across firms of different sizes. By scaling the change in debt issuance by lagged equity, our signal captures the relative magnitude of debt financing changes in relation to the firm's equity base. This construction allows us to measure the firm's evolving financing patterns and potential imbalances between debt and equity financing decisions. We compute this ratio 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 EDIF signal. Panel A plots the time-series of the mean, median, and interquartile range for EDIF. On average, the cross-sectional mean (median) EDIF is -0.28 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input EDIF data. The signal's interquartile range spans -0.17 to 0.16. Panel B of Figure 1 plots the time-series of the coverage of the EDIF signal for the CRSP universe. On average, the EDIF signal is available for 6.30% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does EDIF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EDIF 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 EDIF portfolio and sells the low EDIF 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 EDIF strategy earns an average return of 0.23% per month with a t-statistic of 3.25. The annualized

Sharpe ratio of the strategy is 0.46. The alphas range from 0.19% to 0.29% per month and have t-statistics exceeding 2.75 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 0.30, with a t-statistic of 6.54 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 558 stocks and an average market capitalization of at least $1,385 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 22 bps/month with a t-statistics of 4.76. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-one 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 -3-20bps/month. The lowest return, (-3 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.53. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EDIF 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 EDIF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EDIF, as well as average returns and alphas for long/short trading EDIF 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 EDIF strategy achieves an average return of 32 bps/month with a t-statistic of 3.66. Among these large cap stocks, the alphas for the EDIF strategy relative to the five most common factor models range from 24 to 37 bps/month with t-statistics between 2.76 and 4.29.

5 How does EDIF perform relative to the zoo?

Figure 2 puts the performance of EDIF 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 EDIF strategy falls in the distribution. The EDIF strategy's gross (net) Sharpe ratio of 0.46 (0.34) is greater than 89% (93%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the EDIF strategy (red line).[2] Ignoring trading costs, a $1 invested in the EDIF strategy would have yielded $2.81 which ranks the EDIF strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EDIF strategy would have yielded $1.72 which ranks the EDIF strategy in the top 6% 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 EDIF relative to those. Panel A shows that the EDIF strategy gross alphas fall between the 57 and 69 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 EDIF strategy has a positive net generalized alpha for five out of the five factor models. In these cases EDIF ranks between the 77 and 86 percentiles in terms of

[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.

how much it could have expanded the achievable investment frontier.

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

[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.

five EDIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EDIF trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EDIF 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 EDIF signal in these Fama-MacBeth regressions exceed 1.61, 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 EDIF is 0.86.

Similarly, Table 5 reports results from spanning tests that regress returns to the EDIF 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 EDIF strategy earns alphas that range from 18-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.69, 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 EDIF trading strategy achieves an alpha of 18bps/month with a t-statistic of 2.64.

7 Does EDIF add relative to the whole zoo?

Finally, we can ask how much adding EDIF 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 EDIF 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 EDIF grows to $982.62.

8 Conclusion

This study provides compelling evidence for the significance of the Equity-Debt Imbalance Factor (EDIF) as a robust predictor of stock returns. Our findings demonstrate that EDIF-based trading strategies yield economically and statistically significant results, with a value-weighted long/short strategy achieving notable Sharpe ratios and consistent abnormal returns, even after accounting for transaction costs. The signal's predictive power persists when controlling for established factors, including the Fama-French five-factor model and momentum, as well as related anomalies from the factor zoo.

Particularly noteworthy is the signal's ability to generate significant alpha (18 bps/month) even after controlling for six closely related strategies, suggesting that EDIF captures unique information about future stock returns that is not subsumed by existing factors. The robust t-statistics across various specifications further validate the statistical significance of our findings.

[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 EDIF is available.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be explored. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could extend this work in several directions. Investigating the signal's performance in international markets would test its global applicability. Additionally, examining the interaction between EDIF and other market anomalies could provide insights into the underlying economic mechanisms. Finally, exploring the signal's effectiveness across different market conditions and its potential time variation would enhance our understanding of its reliability as a predictive tool.

In conclusion, our findings suggest that EDIF represents a valuable addition to the asset pricing literature and could be practically useful for investment professionals, though careful consideration should be given to implementation costs and market conditions.

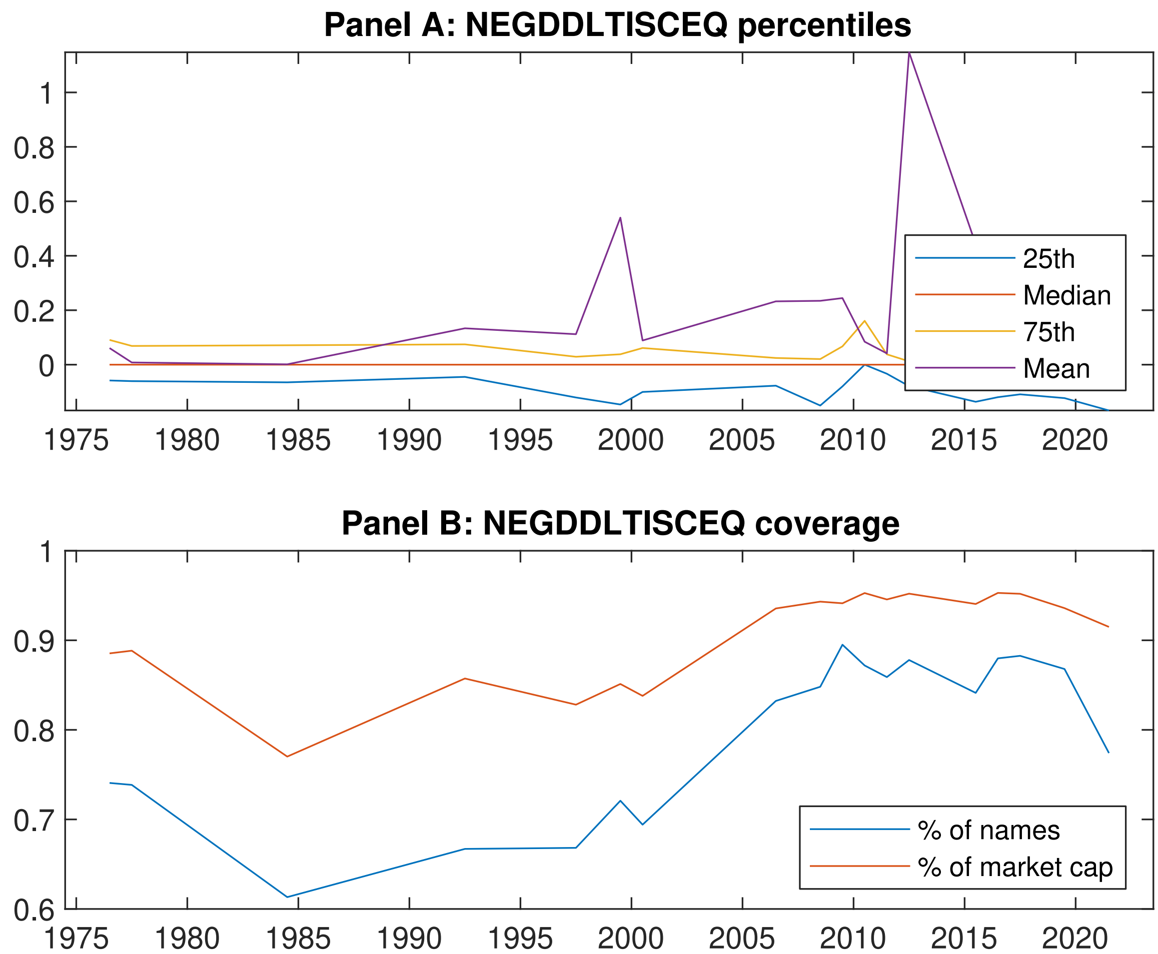


Figure 1: Times series of EDIF percentiles and coverage.
This figure plots descriptive statistics for EDIF. Panel A shows cross-sectional percentiles of EDIF over the sample. Panel B plots the monthly coverage of EDIF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EDIF. 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 EDIF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.60	0.67	0.69	0.78	0.83	0.23
	[2.74]	[3.64]	[3.42]	[4.29]	[4.14]	[3.25]
α_{CAPM}	-0.16	0.03	-0.01	0.15	0.13	0.29
	[-2.91]	[0.62]	[-0.10]	[3.08]	[2.55]	[4.26]
α_{FF3}	-0.19	-0.01	0.05	0.14	0.11	0.29
	[-3.36]	[-0.33]	[0.97]	[2.91]	[2.15]	[4.25]
α_{FF4}	-0.16	0.01	0.09	0.10	0.10	0.26
	[-2.82]	[0.20]	[1.66]	[2.09]	[1.90]	[3.65]
α_{FF5}	-0.18	-0.06	0.10	0.07	0.02	0.21
	[-3.34]	[-1.41]	[1.76]	[1.42]	[0.49]	[3.03]
α_{FF6}	-0.17	-0.04	0.12	0.05	0.03	0.19
	[-2.99]	[-0.93]	[2.19]	[0.96]	[0.50]	[2.75]
Panel B: Fama and French (2018) 6-factor model loadings for EDIF-sorted portfolios						
β_{MKT}	1.09	0.98	0.97	0.97	1.03	-0.06
	[85.61]	[96.69]	[75.44]	[87.47]	[89.20]	[-3.60]
β_{SMB}	0.12	-0.11	-0.01	-0.03	0.13	0.01
	[5.92]	[-7.25]	[-0.52]	[-1.71]	[7.18]	[0.49]
β_{HML}	0.08	0.14	-0.14	-0.02	-0.05	-0.13
	[3.27]	[7.29]	[-5.83]	[-0.76]	[-2.09]	[-4.13]
β_{RMW}	0.11	0.11	-0.04	0.07	0.13	0.02
	[4.23]	[5.25]	[-1.61]	[3.11]	[5.54]	[0.65]
β_{CMA}	-0.15	0.05	-0.08	0.15	0.15	0.30
	[-4.12]	[1.55]	[-2.25]	[4.75]	[4.48]	[6.54]
β_{UMD}	-0.03	-0.04	-0.04	0.04	-0.00	0.03
	[-2.53]	[-3.62]	[-3.24]	[3.46]	[-0.06]	[1.97]
Panel C: Average number of firms (n) and market capitalization (me)						
n	654	558	1087	611	627	
me ($\$10^6$)	1457	2846	2158	2929	1385	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EDIF 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	0.23	0.29	0.29	0.26	0.21	0.19
			[3.25]	[4.26]	[4.25]	[3.65]	[3.03]	[2.75]
Quintile	NYSE	EW	0.22	0.25	0.24	0.22	0.20	0.19
			[4.76]	[5.37]	[5.11]	[4.54]	[4.23]	[3.93]
Quintile	Name	VW	0.23	0.31	0.31	0.26	0.24	0.21
			[3.34]	[4.58]	[4.54]	[3.76]	[3.53]	[3.08]
Quintile	Cap	VW	0.24	0.29	0.29	0.24	0.20	0.16
			[3.77]	[4.51]	[4.52]	[3.63]	[3.04]	[2.55]
Decile	NYSE	VW	0.27	0.36	0.37	0.31	0.29	0.26
			[2.76]	[3.75]	[3.77]	[3.18]	[2.97]	[2.64]
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	0.17	0.25	0.25	0.23	0.18	0.17
			[2.42]	[3.57]	[3.54]	[3.25]	[2.58]	[2.38]
Quintile	NYSE	EW	-0.03					
			[-0.53]					
Quintile	Name	VW	0.18	0.27	0.26	0.23	0.21	0.19
			[2.51]	[3.90]	[3.84]	[3.45]	[3.04]	[2.78]
Quintile	Cap	VW	0.20	0.26	0.26	0.23	0.18	0.16
			[2.98]	[3.97]	[3.93]	[3.50]	[2.73]	[2.43]
Decile	NYSE	VW	0.20	0.31	0.31	0.28	0.25	0.23
			[2.05]	[3.12]	[3.12]	[2.83]	[2.50]	[2.29]

Table 3: Conditional sort on size and EDIF

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

		EDIF Quintiles					EDIF Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.71	0.92	0.98	0.91	0.81	0.10	0.14	0.13	0.07	0.05	0.02
		[2.56]	[3.37]	[3.56]	[3.22]	[2.91]	[1.07]	[1.50]	[1.37]	[0.79]	[0.55]	[0.25]
	(2)	0.76	0.98	0.81	0.91	0.92	0.16	0.19	0.16	0.16	0.10	0.11
		[2.84]	[3.87]	[3.22]	[3.69]	[3.58]	[1.98]	[2.37]	[2.02]	[2.02]	[1.23]	[1.33]
	(3)	0.83	0.85	0.85	0.87	0.94	0.11	0.17	0.17	0.13	0.15	0.12
		[3.26]	[3.86]	[3.46]	[3.86]	[3.99]	[1.47]	[2.23]	[2.17]	[1.61]	[1.90]	[1.55]
	(4)	0.73	0.82	0.93	0.74	0.93	0.20	0.25	0.24	0.21	0.21	0.19
		[3.11]	[3.97]	[4.11]	[3.54]	[4.26]	[2.63]	[3.30]	[3.12]	[2.66]	[2.62]	[2.33]
	(5)	0.48	0.67	0.61	0.71	0.80	0.32	0.36	0.37	0.30	0.28	0.24
		[2.34]	[3.73]	[3.00]	[3.84]	[4.09]	[3.66]	[4.14]	[4.29]	[3.47]	[3.24]	[2.76]

Panel B: Portfolio average number of firms and market capitalization

		EDIF Quintiles					EDIF Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	397	400	400	400	396	37	34	33	33	36
	(2)	108	108	108	108	108	60	60	59	60	60
	(3)	77	77	77	77	77	105	106	102	103	106
	(4)	64	65	65	65	64	225	230	224	227	224
	(5)	59	59	59	59	59	1347	2016	1862	2003	1422

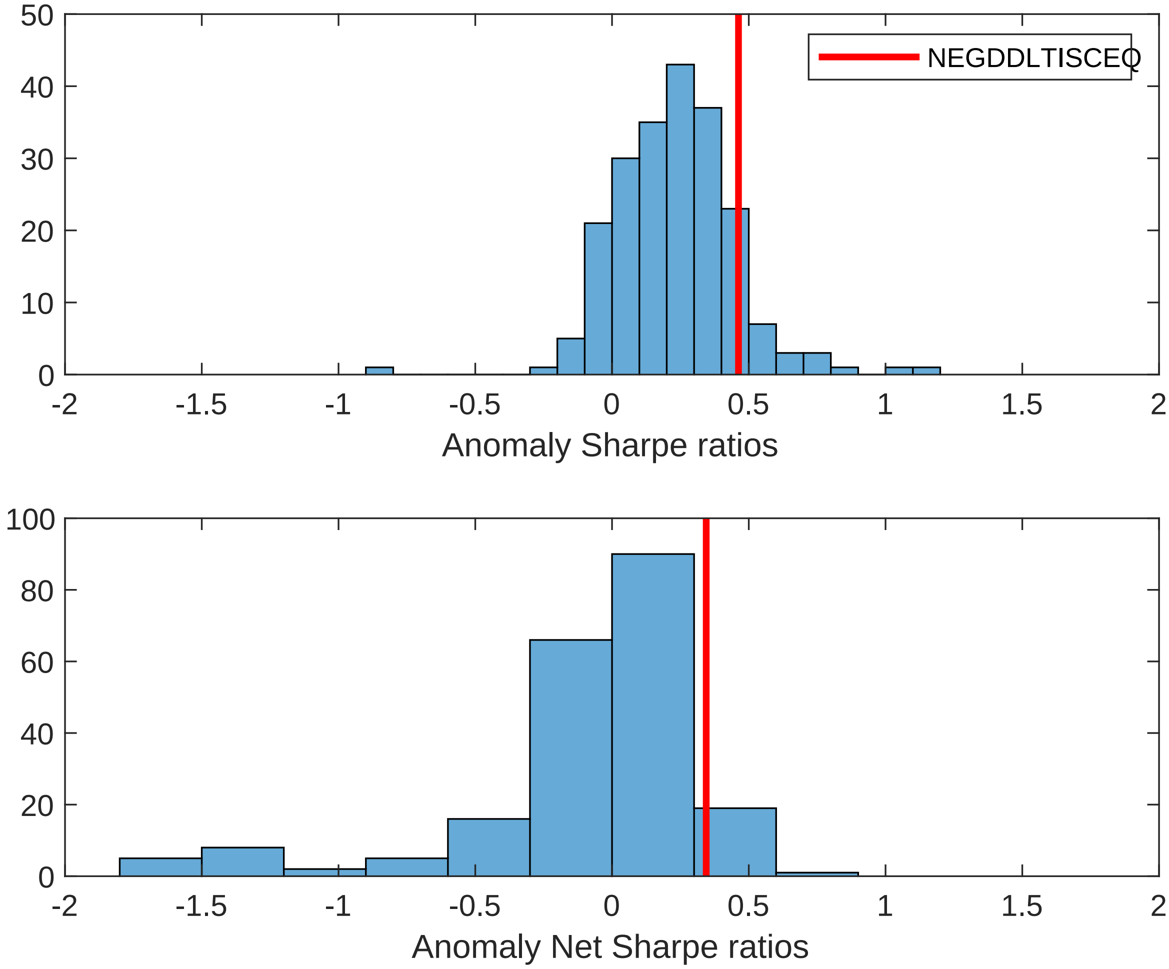


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EDIF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

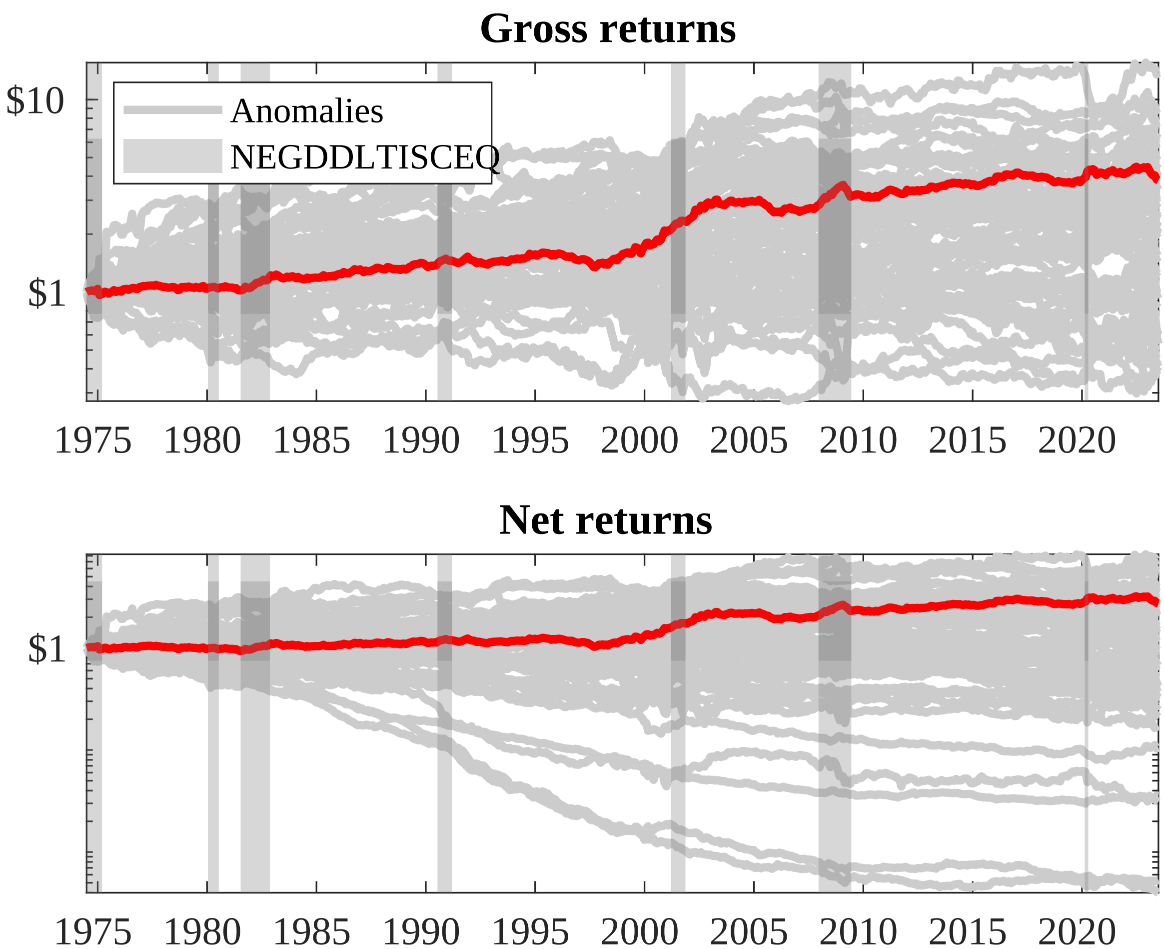


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EDIF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

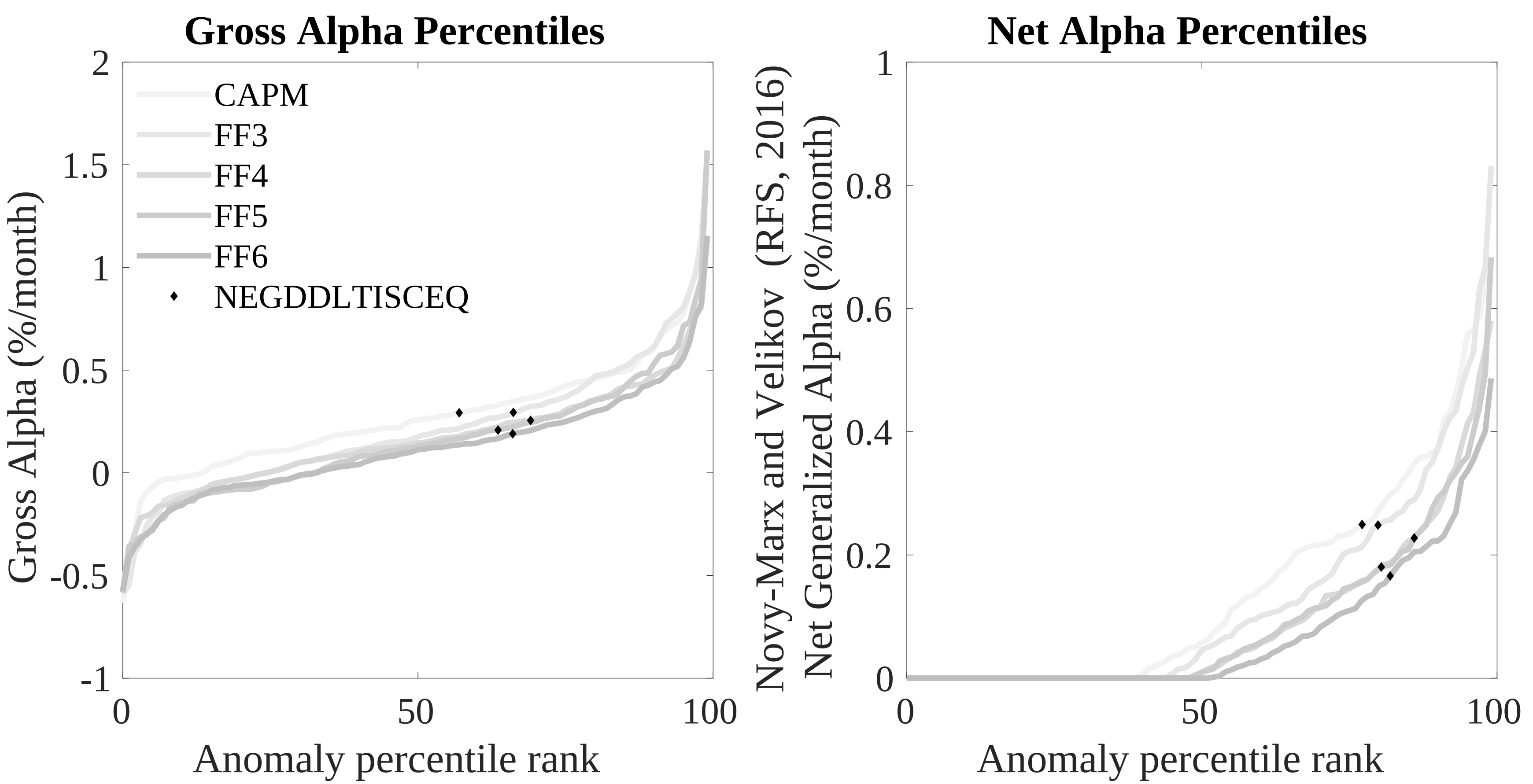
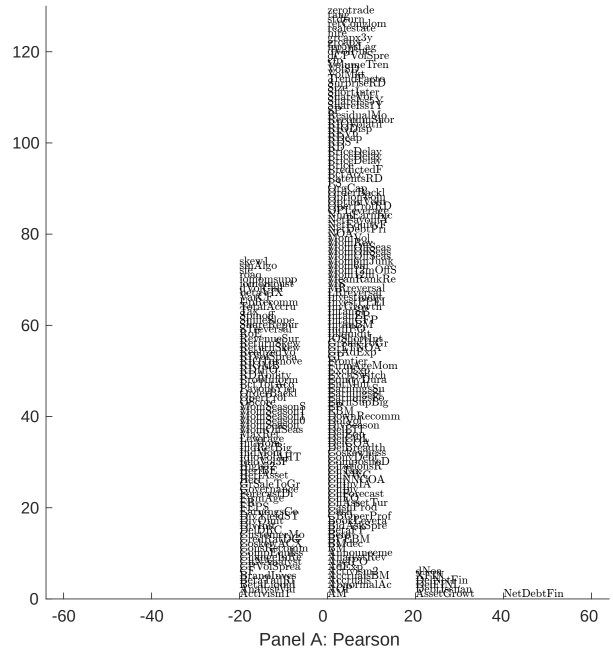


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EDIF trading strategy alphas (diamonds). The strategies are constructed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



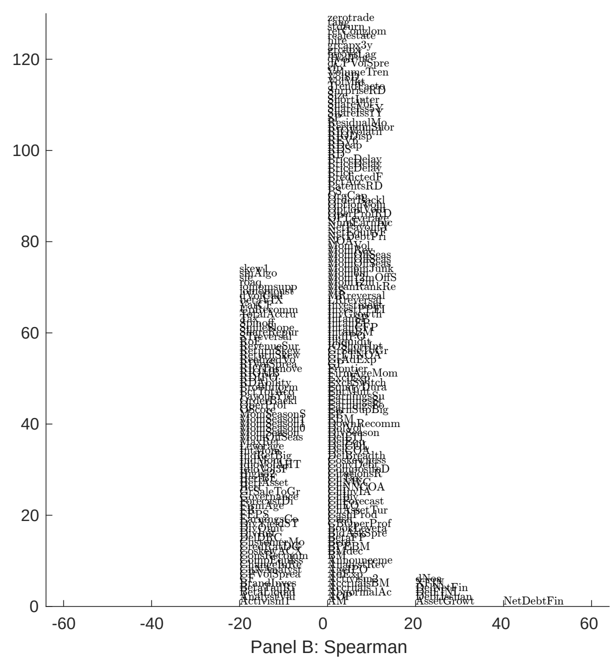


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with EDIF. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

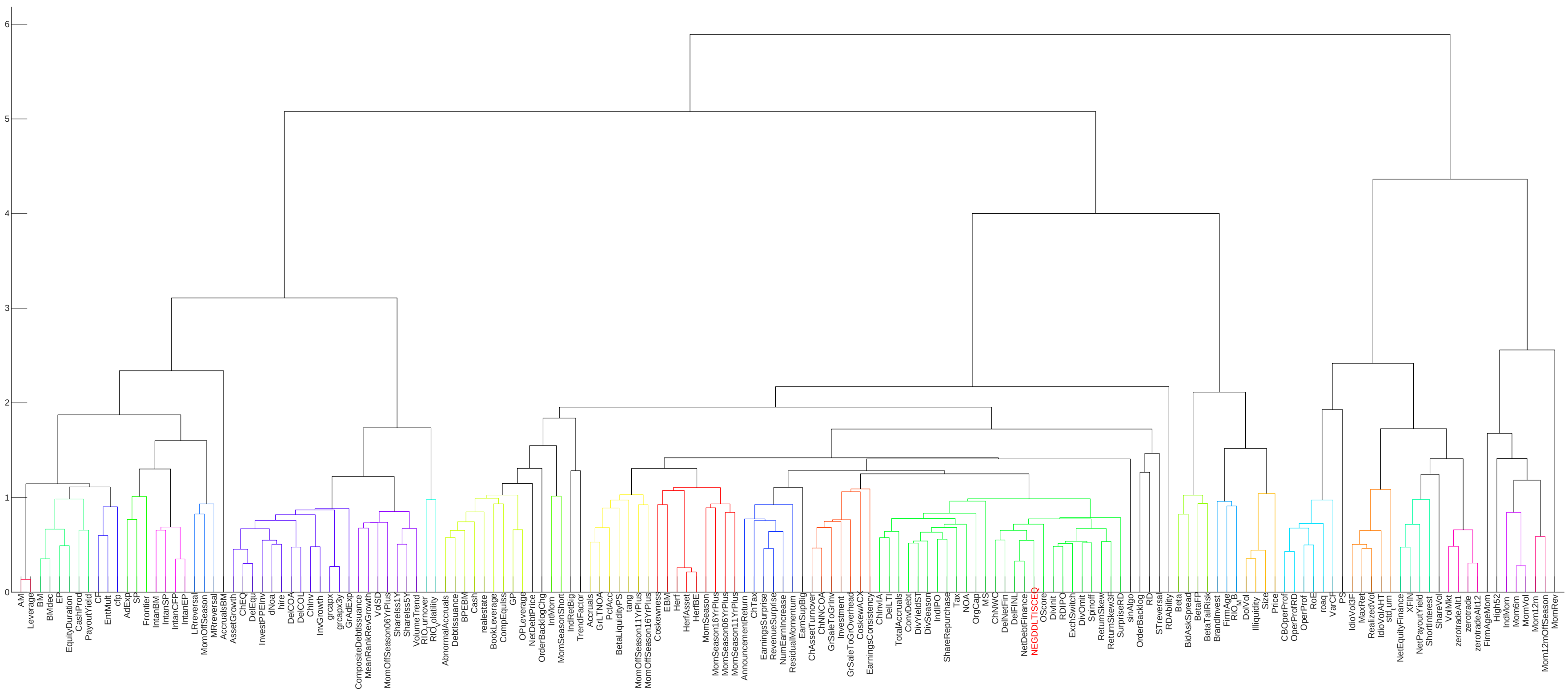


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

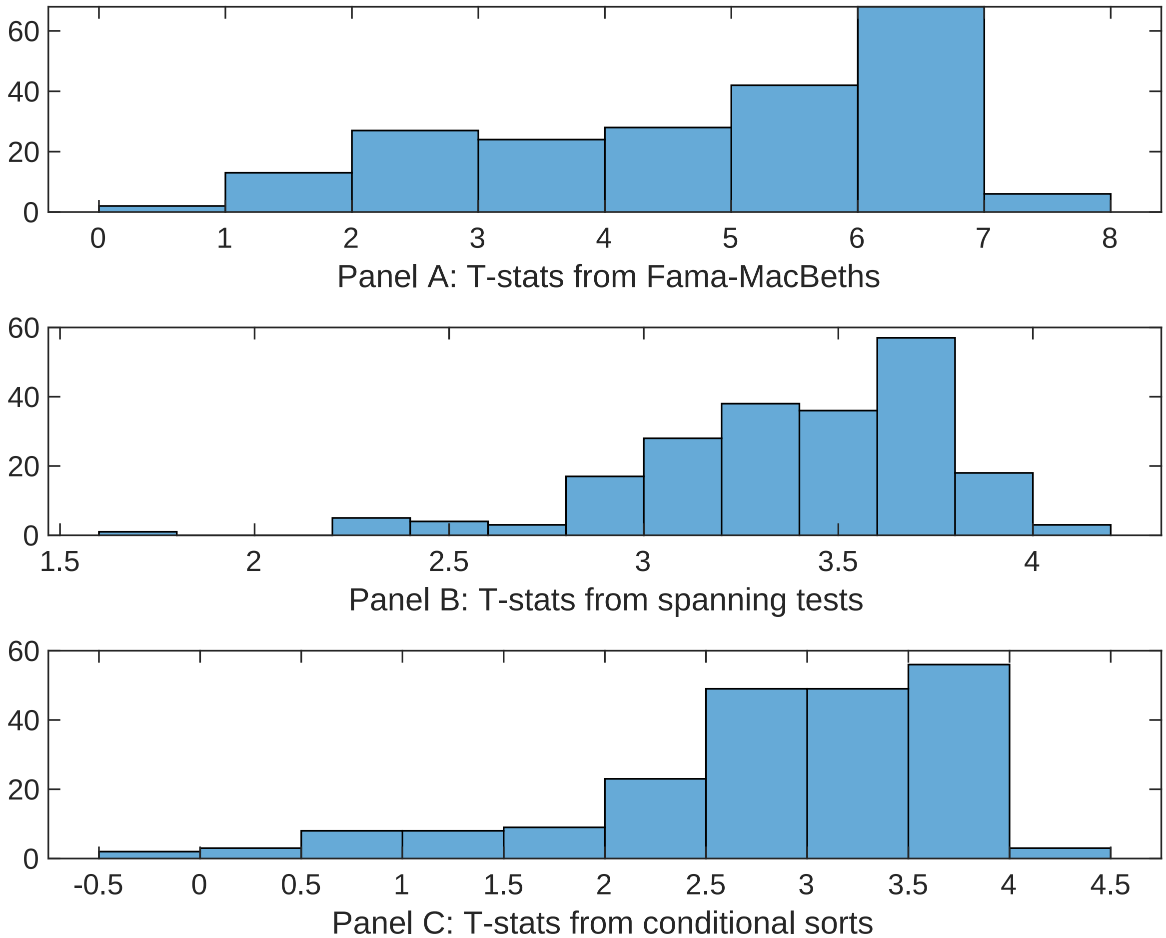


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EDIF conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EDIF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EDIF} EDIF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EDIF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EDIF. Stocks are finally grouped into five EDIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EDIF 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 EDIF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EDIF} EDIF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, Inventory 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
	[5.51]	[5.48]	[5.85]	[5.95]	[5.46]	[5.80]	[5.83]
EDIF	0.48	0.59	0.83	0.41	0.13	0.38	0.25
	[1.96]	[2.38]	[3.16]	[1.65]	[4.65]	[1.61]	[0.86]
Anomaly 1	0.17						-0.11
	[9.15]						[-2.33]
Anomaly 2		0.19					0.11
		[8.49]					[1.66]
Anomaly 3			0.18				0.96
			[6.05]				[1.72]
Anomaly 4				0.11			0.44
				[9.16]			[2.05]
Anomaly 5					0.40		0.28
					[6.94]		[0.51]
Anomaly 6						0.14	0.87
						[10.04]	[4.94]
# 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 EDIF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EDIF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Inventory 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	0.18	0.18	0.19	0.20	0.20	0.19	0.18
	[2.69]	[2.70]	[2.69]	[2.89]	[2.89]	[2.73]	[2.64]
Anomaly 1	19.45						12.39
	[4.82]						[2.23]
Anomaly 2		20.40					9.83
		[5.29]					[1.84]
Anomaly 3			13.56				9.36
			[3.85]				[2.50]
Anomaly 4				6.98			0.09
				[1.54]			[0.02]
Anomaly 5					7.05		6.55
					[2.57]		[2.33]
Anomaly 6						5.74	-4.36
						[1.40]	[-0.96]
mkt	-5.48	-5.71	-3.88	-5.68	-5.90	-5.71	-4.48
	[-3.48]	[-3.64]	[-2.34]	[-3.55]	[-3.69]	[-3.56]	[-2.73]
smb	-0.49	-0.12	5.61	0.55	1.97	1.32	3.10
	[-0.20]	[-0.05]	[2.08]	[0.22]	[0.79]	[0.53]	[1.09]
hml	-11.13	-11.83	-10.60	-12.35	-12.35	-12.61	-10.20
	[-3.67]	[-3.93]	[-3.45]	[-4.01]	[-4.03]	[-4.06]	[-3.33]
rmw	0.32	0.14	-6.31	1.84	2.78	1.97	-4.75
	[0.10]	[0.05]	[-1.66]	[0.58]	[0.87]	[0.62]	[-1.24]
cma	23.17	24.42	20.57	20.95	23.37	25.37	14.03
	[4.86]	[5.24]	[3.98]	[2.86]	[4.46]	[4.56]	[1.92]
umd	1.32	1.52	3.14	3.47	2.55	3.00	0.72
	[0.81]	[0.94]	[1.96]	[2.13]	[1.56]	[1.85]	[0.43]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	16	17	15	13	14	13	18

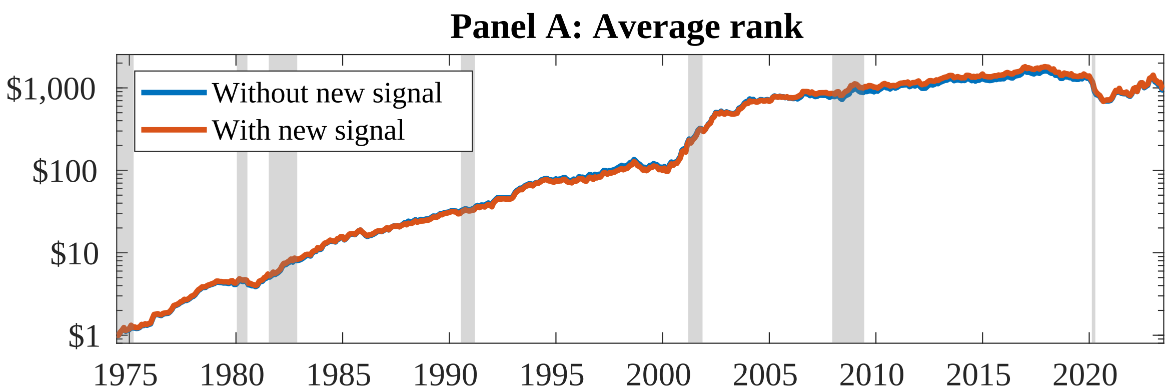


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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