Debt Issue Impact on EBIT and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Debt Issue Impact on EBIT (DIIE), 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 DIIE achieves an annualized gross (net) Sharpe ratio of 0.41 (0.30), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (18) bps/month with a t-statistic of 2.74 (2.26), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Change in financial liabilities, Change in net financial assets, Investment to revenue, Accruals, Sales growth over inventory growth) is 17 bps/month with a t-statistic of 2.19.

1 Introduction

The efficient market hypothesis suggests that stock 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 (Stambaugh and Yuan, 2017). While considerable research has examined how firms' financing decisions affect their stock returns (Bradshaw et al., 2006), the specific channel through which debt issuance impacts operating performance and subsequent stock returns remains understudied. This gap is particularly notable given the central role of operating performance in firm valuation.

Prior research has established that external financing activities often signal management's private information about future prospects (Myers and Majluf, 1984). However, existing studies have primarily focused on aggregate measures of external financing or broad categories of debt issuance, without examining how new debt specifically impacts firms' operating performance trajectory and the resulting stock price implications.

We propose that the impact of debt issuance on earnings before interest and taxes (EBIT) provides a novel signal about future stock returns. This hypothesis builds on three theoretical foundations. First, the trade-off theory of capital structure suggests that firms balance the tax benefits of debt against financial distress costs (Kraus and Litzenberger, 1973), implying that debt issuance decisions reflect management's assessment of future operating performance capacity.

Second, agency theory indicates that debt serves as a disciplining mechanism by committing future free cash flows to debt service (Jensen and Meckling, 1976). The magnitude of debt's impact on EBIT should therefore signal management's confidence in future operating performance improvements. Third, the pecking order theory suggests that firms prefer debt to equity financing when they are undervalued

(?), making debt issuance decisions particularly informative about future prospects.

Based on these theoretical frameworks, we hypothesize that firms whose EBIT shows positive sensitivity to debt issuance will outperform those showing negative sensitivity. This relationship should persist after controlling for known risk factors and related anomalies, as it captures management's private information about operating efficiency improvements that is not fully reflected in current stock prices.

Our empirical analysis reveals strong support for the predictive power of Debt Issue Impact on EBIT (DIIE). A value-weighted long-short portfolio strategy based on DIIE quintiles generates significant abnormal returns of 22 basis points per month (t-statistic = 2.92) and an annualized Sharpe ratio of 0.41. The strategy's performance remains robust after controlling for common risk factors, with monthly alphas ranging from 22 to 27 basis points across various factor models.

Importantly, the DIIE signal's predictive power persists among large-cap stocks, with the long-short strategy earning 25 basis points per month (t-statistic = 2.82) in the largest size quintile. This finding suggests that the anomaly is not driven by small, illiquid stocks. After accounting for transaction costs following (Novy-Marx and Velikov, 2016), the strategy maintains significant net returns of 16 basis points per month (t-statistic = 2.12).

The signal's economic value is further demonstrated by its performance relative to existing anomalies. DIIE's gross (net) Sharpe ratio of 0.41 (0.30) exceeds 84% (91%) of documented anomalies, and it maintains significant alpha when controlling for the six most closely related strategies, including net debt financing and change in financial liabilities.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures management's private information about operating performance improvements through the lens of debt issuance decisions. This extends the work of (Bradshaw et al., 2006) and (Lewellen and Resutek, 2016) by identifying a specific channel through which financing decisions signal future returns.

Second, we contribute to the growing literature on investment-based asset pricing (Hou et al., 2015) by showing how debt issuance decisions reflect management's expectations about future productivity improvements. Our findings suggest that the market does not fully incorporate this information, creating a profitable trading opportunity that survives transaction costs and is implementable even among large-cap stocks.

Third, our results have important implications for the broader literature on market efficiency and the real effects of financing decisions. The persistence of the DIIE anomaly, particularly among large stocks, suggests that sophisticated investors may not fully appreciate how debt issuance decisions reflect management's private information about operating performance improvements. This finding adds to our understanding of how financing decisions contain valuable information about future stock returns (Baker and Wurgler, 2002).

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the impact of debt issuance relative to operating earnings. 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 EBIT for earnings before interest and taxes. Long-term debt issuance (DLTIS) represents the cash proceeds from issuing long-term debt during the fiscal year, while EBIT provides a measure of core operating performance before financing costs and tax effects. The construction of the signal follows a change-based approach, where we calculate the year-over-year change in DLTIS and scale this difference by the previous year's EBIT. Specifically, we subtract the prior year's DLTIS from the current year's DLTIS and divide this difference by lagged EBIT. This ratio captures the relative magnitude of changes in debt financing against the firm's operational income base, offering insight into how significantly new debt issuance might impact the firm's earnings capacity. By focusing on this relationship, the signal aims to reflect aspects of capital structure decisions and their potential implications for firm performance in a manner that is both scalable and interpretable. We construct 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 DIIE signal. Panel A plots the time-series of the mean, median, and interquartile range for DIIE. On average, the cross-sectional mean (median) DIIE is -0.60 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DIIE data. The signal's interquartile range spans -0.59 to 0.74. Panel B of Figure 1 plots the time-series of the coverage of the DIIE signal for the CRSP universe. On average, the DIIE signal is available for 6.24% of CRSP names, which on average make up 7.37% of total market capitalization.

4 Does DIIE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DIIE 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 DIIE portfolio and sells the low DIIE 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 DIIE strategy earns an average return of 0.22% per month with a t-statistic of 2.92. The annualized Sharpe ratio of the strategy is 0.41. The alphas range from 0.22% to 0.27% per month and have t-statistics exceeding 2.74 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is -0.15, with a t-statistic of -4.44 on the HML factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 536 stocks and an average market capitalization of at least $1,161 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using NYSE breakpoints and equal-weighted portfolios, and equals 10 bps/month with a t-statistics of 2.41. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for ten exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between -15-18bps/month. The lowest return, (-15 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -2.55. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DIIE trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in fifteen cases.

Table 3 provides direct tests for the role size plays in the DIIE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DIIE, as well as average returns and alphas for long/short trading DIIE 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 DIIE strategy achieves an average return of 25 bps/month with a t-statistic of 2.82. Among these large cap stocks, the alphas for the DIIE strategy relative to the five most common factor models range from 21 to 29 bps/month with t-statistics between 2.29 and 3.31.

5 How does DIIE perform relative to the zoo?

Figure 2 puts the performance of DIIE 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 DIIE strategy falls in the distribution. The DIIE strategy's gross (net) Sharpe ratio of 0.41 (0.30) is greater than 84% (91%) 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 DIIE strategy (red line).[2] Ignoring trading costs, a \$1 invested in the DIIE strategy would have yielded \$2.65 which ranks the DIIE strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DIIE strategy would have yielded \$1.56 which ranks the DIIE strategy in the top 7% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the DIIE relative to those. Panel A shows that the DIIE strategy gross alphas fall between the 48 and 70 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction

[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.

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

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

[3]When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

stands for 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 DIIE. Stocks are finally grouped into five DIIE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIIE trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DIIE 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 DIIE signal in these Fama-MacBeth regressions exceed 0.08, with the minimum t-statistic occurring when controlling for Change in financial liabilities. Controlling for all six closely related anomalies, the t-statistic on DIIE is 0.46.

Similarly, Table 5 reports results from spanning tests that regress returns to the DIIE 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 DIIE strategy earns alphas that range from 17-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.21, which is achieved when controlling for Change in financial liabilities. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DIIE trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.19.

7 Does DIIE add relative to the whole zoo?

Finally, we can ask how much adding DIIE 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 DIIE 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 DIIE grows to $1027.62.

8 Conclusion

This study provides compelling evidence for the significance of Debt Issue Impact on EBIT (DIIE) 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 DIIE generates economically and statistically significant returns, even after accounting for transaction costs and controlling for well-established risk factors.

The signal's performance is particularly noteworthy, achieving an annualized net Sharpe ratio of 0.30 and maintaining significant abnormal returns of 18 basis points per month after costs when measured against the Fama-French five-factor model

[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 DIIE is available.

augmented with momentum. Moreover, the signal's predictive power persists even after controlling for six closely related strategies from the factor zoo, yielding a significant alpha of 17 basis points per month.

These results have important implications for both academic research and practical investment management. For academics, our findings contribute to the growing literature on return predictability and suggest that the relationship between debt issuance and operating performance contains valuable information for asset pricing. For practitioners, the DIIE signal represents a potentially valuable tool for portfolio construction and risk management, particularly given its robustness to transaction costs.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across all market conditions. Future research could explore the signal's performance in different geographical markets, investigate its interaction with other anomalies, and examine its effectiveness across different market regimes and economic cycles. Additionally, researchers might consider studying the underlying economic mechanisms driving the DIIE signal's predictive power and its potential variations across different industry sectors.

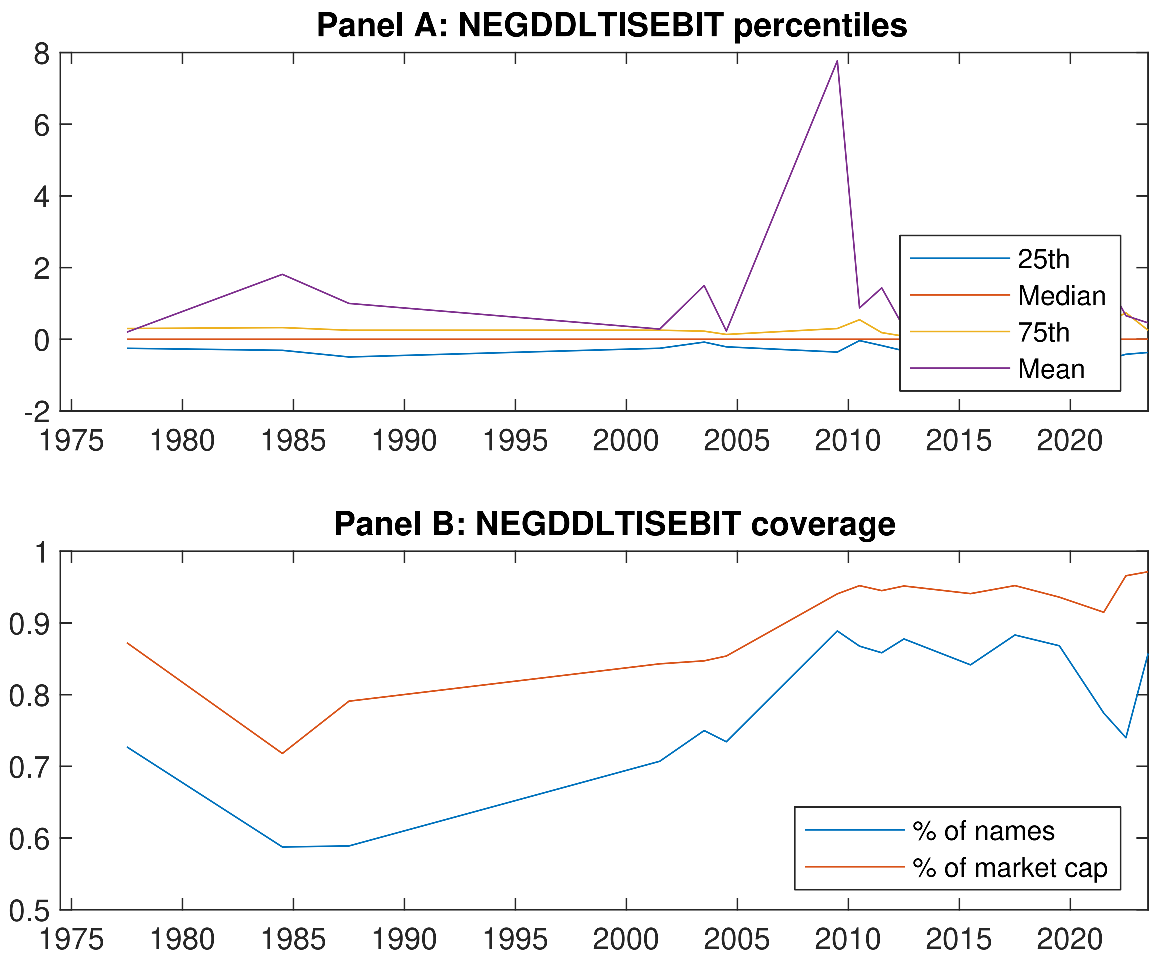


Figure 1: Times series of DIIE percentiles and coverage.
This figure plots descriptive statistics for DIIE. Panel A shows cross-sectional percentiles of DIIE over the sample. Panel B plots the monthly coverage of DIIE relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DIIE. 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 DIIE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.58	0.65	0.72	0.81	0.80	0.22
	[2.62]	[3.54]	[3.58]	[4.49]	[3.69]	[2.92]
α_{CAPM}	-0.19	0.01	0.02	0.18	0.05	0.24
	[-3.06]	[0.24]	[0.39]	[4.01]	[0.82]	[3.08]
α_{FF3}	-0.23	-0.03	0.07	0.18	0.04	0.27
	[-3.96]	[-0.60]	[1.42]	[4.03]	[0.60]	[3.47]
α_{FF4}	-0.20	-0.00	0.11	0.15	0.03	0.23
	[-3.45]	[-0.04]	[2.11]	[3.33]	[0.47]	[2.98]
α_{FF5}	-0.22	-0.08	0.10	0.09	0.02	0.24
	[-3.73]	[-1.89]	[1.81]	[2.10]	[0.26]	[3.02]
α_{FF6}	-0.20	-0.06	0.12	0.08	0.01	0.22
	[-3.41]	[-1.37]	[2.27]	[1.78]	[0.23]	[2.74]
Panel B: Fama and French (2018) 6-factor model loadings for DIIE-sorted portfolios						
β_{MKT}	1.09	0.99	0.98	0.96	1.08	-0.01
	[80.33]	[99.37]	[79.08]	[95.20]	[76.22]	[-0.56]
β_{SMB}	0.17	-0.11	-0.01	-0.04	0.16	-0.01
	[7.94]	[-7.39]	[-0.43]	[-2.37]	[7.23]	[-0.30]
β_{HML}	0.10	0.11	-0.14	-0.05	-0.05	-0.15
	[4.02]	[5.78]	[-5.81]	[-2.57]	[-1.80]	[-4.44]
β_{RMW}	0.06	0.12	0.00	0.10	0.00	-0.06
	[2.30]	[5.94]	[0.07]	[5.04]	[0.06]	[-1.68]
β_{CMA}	-0.11	0.06	-0.06	0.18	0.09	0.20
	[-2.84]	[2.15]	[-1.66]	[6.00]	[2.16]	[3.83]
β_{UMD}	-0.03	-0.04	-0.04	0.02	0.00	0.04
	[-2.32]	[-3.96]	[-3.47]	[2.29]	[0.27]	[1.96]
Panel C: Average number of firms (n) and market capitalization (me)						
n	655	536	1073	592	643	
me ($\$10^6$)	1161	2996	2357	3044	1191	

Table 2: Robustness to sorting methodology & trading costs

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

Panel A: Gross Returns and Alphas

Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.22	0.24	0.27	0.23	0.24	0.22
			[2.92]	[3.08]	[3.47]	[2.98]	[3.02]	[2.74]
Quintile	NYSE	EW	0.10	0.11	0.11	0.11	0.12	0.12
			[2.41]	[2.55]	[2.59]	[2.50]	[2.75]	[2.71]
Quintile	Name	VW	0.21	0.24	0.26	0.23	0.21	0.20
			[2.96]	[3.39]	[3.70]	[3.20]	[2.99]	[2.73]
Quintile	Cap	VW	0.22	0.25	0.27	0.23	0.19	0.18
			[3.55]	[4.01]	[4.29]	[3.69]	[3.04]	[2.76]
Decile	NYSE	VW	0.26	0.25	0.25	0.25	0.20	0.21
			[2.50]	[2.43]	[2.38]	[2.38]	[1.90]	[1.97]

Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas

Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.16	0.19	0.21	0.20	0.20	0.18
			[2.12]	[2.46]	[2.77]	[2.53]	[2.47]	[2.26]
Quintile	NYSE	EW	-0.15					
			[-2.55]					
Quintile	Name	VW	0.15	0.19	0.21	0.19	0.18	0.16
			[2.12]	[2.70]	[2.94]	[2.69]	[2.44]	[2.23]
Quintile	Cap	VW	0.17	0.21	0.23	0.21	0.17	0.15
			[2.75]	[3.35]	[3.56]	[3.27]	[2.57]	[2.35]
Decile	NYSE	VW	0.18	0.19	0.18	0.19	0.14	0.14
			[1.75]	[1.81]	[1.74]	[1.77]	[1.30]	[1.32]

Table 3: Conditional sort on size and DIIE

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

		DIIE Quintiles					DIIE Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.79	0.84	0.96	0.98	0.78	-0.01	-0.00	0.00	-0.02	0.05	0.03
		[2.90]	[2.97]	[3.47]	[3.32]	[2.85]	[-0.14]	[-0.00]	[0.00]	[-0.31]	[0.64]	[0.37]
	(2)	0.81	0.92	0.81	0.95	0.90	0.09	0.12	0.10	0.10	0.11	0.11
		[3.04]	[3.62]	[3.17]	[3.71]	[3.48]	[1.17]	[1.55]	[1.28]	[1.28]	[1.35]	[1.34]
	(3)	0.87	0.87	0.87	0.84	0.90	0.03	0.06	0.07	0.07	0.11	0.10
		[3.44]	[3.85]	[3.56]	[3.70]	[3.70]	[0.40]	[0.74]	[0.90]	[0.81]	[1.29]	[1.19]
	(4)	0.67	0.88	0.89	0.81	0.93	0.26	0.28	0.30	0.26	0.34	0.30
		[2.84]	[4.13]	[3.95]	[3.82]	[4.11]	[3.23]	[3.50]	[3.70]	[3.17]	[4.02]	[3.62]
	(5)	0.52	0.65	0.63	0.74	0.77	0.25	0.26	0.29	0.27	0.21	0.21
		[2.56]	[3.53]	[3.11]	[4.01]	[3.84]	[2.82]	[2.93]	[3.31]	[2.99]	[2.40]	[2.29]

Panel B: Portfolio average number of firms and market capitalization

		DIIE Quintiles					DIIE Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	396	396	397	397	395	37	33	33	34	36
	(2)	107	107	107	107	107	60	61	58	60	60
	(3)	75	75	75	75	75	105	106	102	103	104
	(4)	63	63	63	63	62	220	231	220	231	218
	(5)	58	58	59	58	58	1273	2050	1870	2128	1318

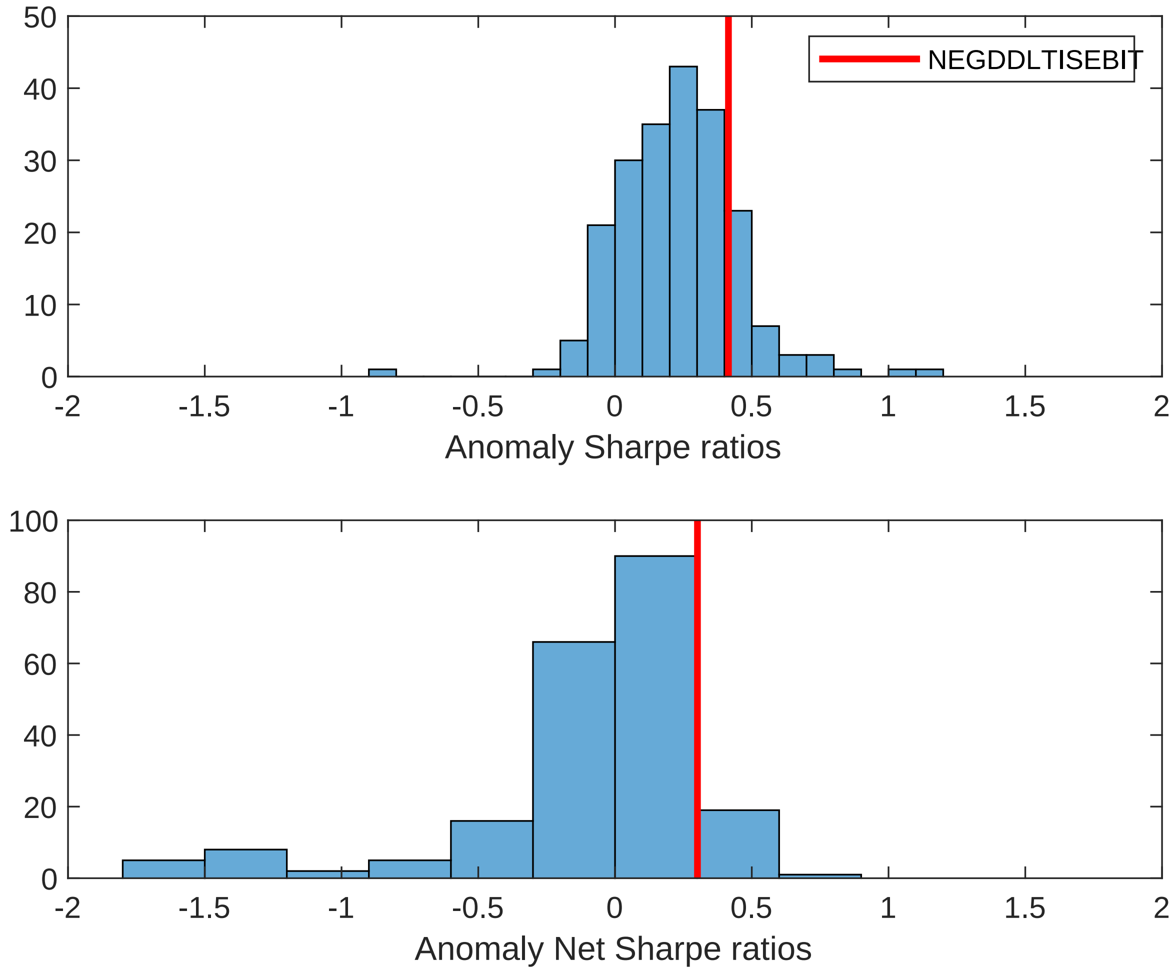


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIIE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

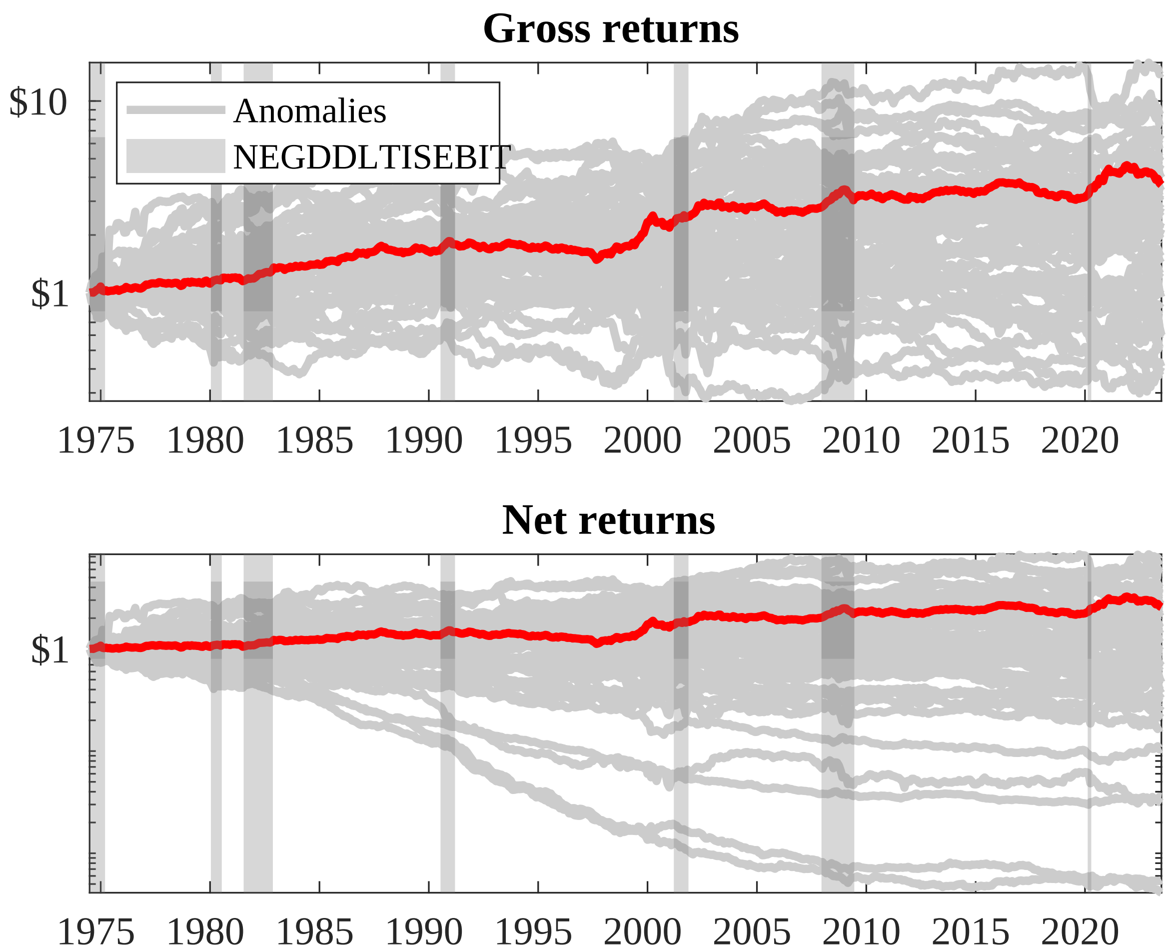


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIIE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

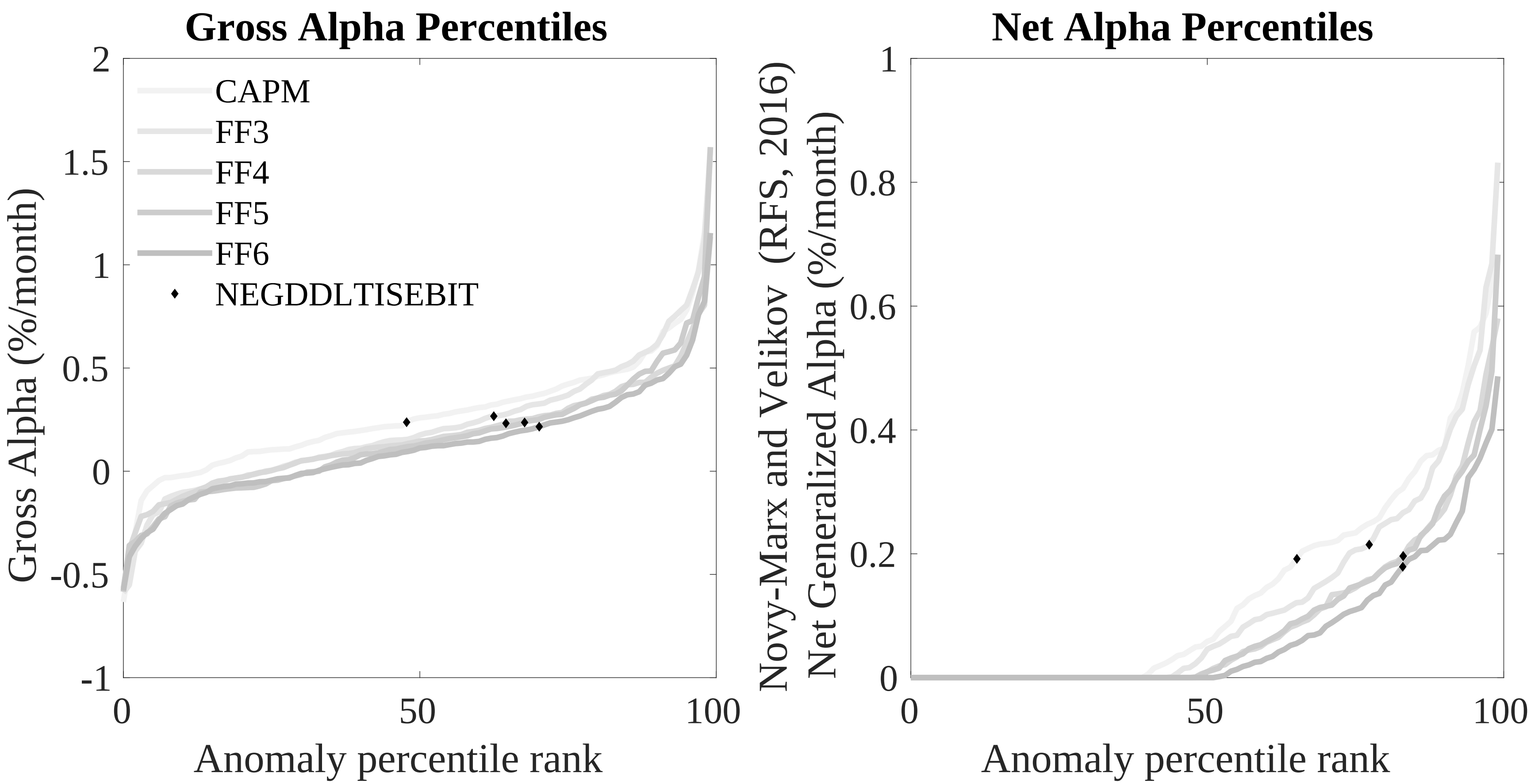
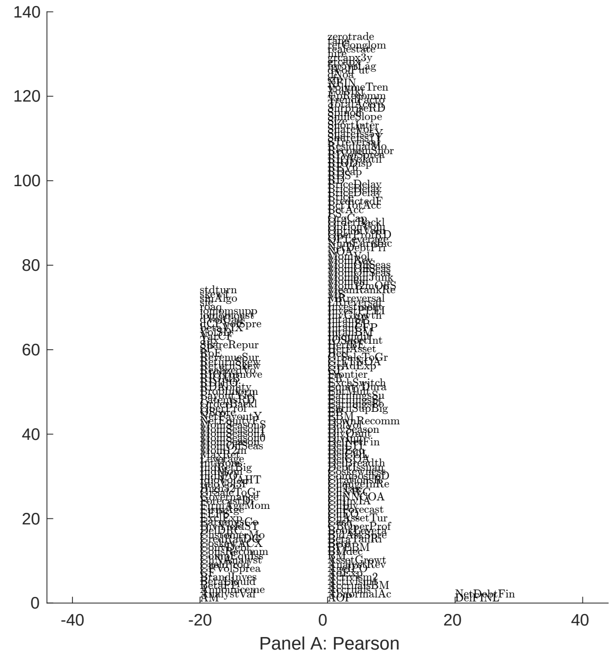


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DIIE trading strategy alphas (diamonds). The strategies are constructed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



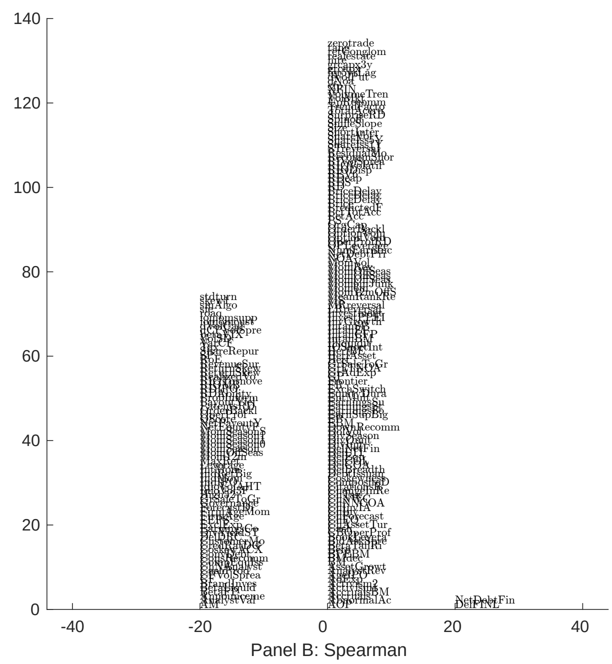


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DIIE. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

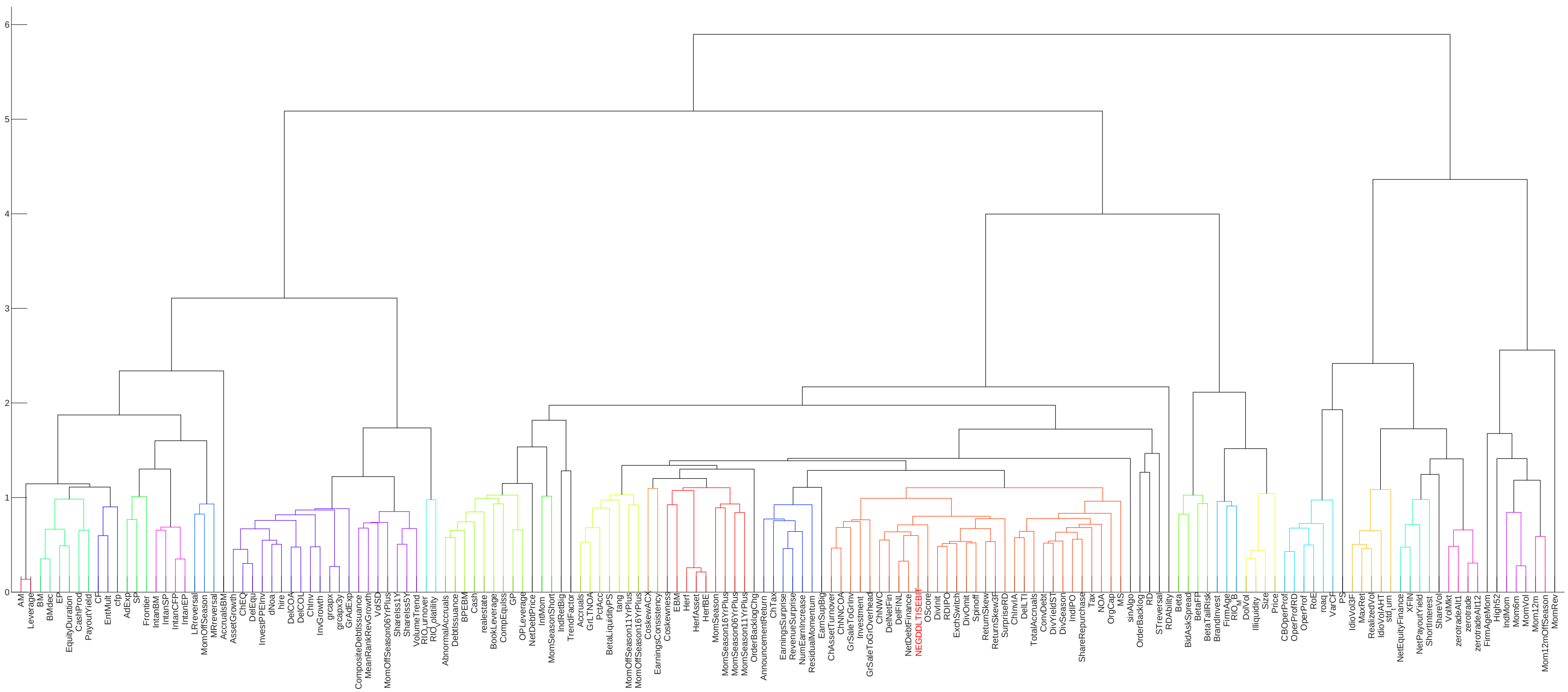


Figure 6: Agglomerative hierarchical cluster plot

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

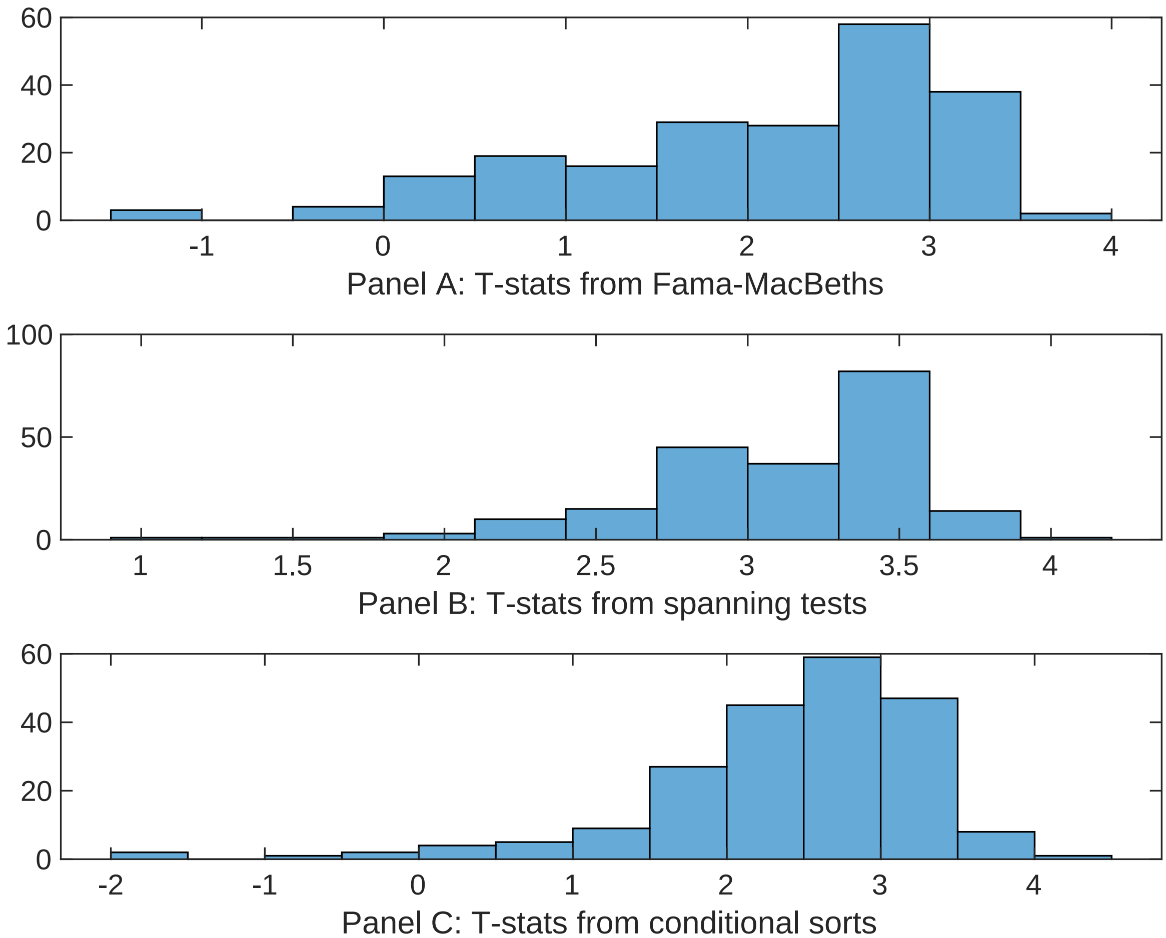


Figure 7: Distribution of t-stats on conditioning strategies

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

Intercept	0.14	0.14	0.13	0.16	0.13	0.13	0.15
	[5.46]	[5.50]	[5.36]	[6.32]	[5.13]	[5.33]	[6.09]
DIIE	0.17	0.30	0.49	0.12	0.88	0.12	0.21
	[0.42]	[0.08]	[1.24]	[2.64]	[2.22]	[2.69]	[0.46]
Anomaly 1	0.21						0.93
	[9.24]						[2.17]
Anomaly 2		0.18					0.15
		[9.65]					[2.97]
Anomaly 3			0.76				-0.85
			[5.00]				[-2.73]
Anomaly 4				0.24			0.18
				[5.50]			[3.83]
Anomaly 5					0.14		0.11
					[4.61]		[2.91]
Anomaly 6						0.14	0.90
						[4.79]	[2.80]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	0	0	0	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the DIIE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DIIE} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Net debt financing, Change in financial liabilities, Change in net financial assets, Investment to revenue, Accruals, Sales growth over inventory growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.21	0.21	0.17	0.21	0.21	0.22	0.17
	[2.70]	[2.68]	[2.21]	[2.73]	[2.62]	[2.81]	[2.19]
Anomaly 1	24.72						14.63
	[5.68]						[2.53]
Anomaly 2		23.63					5.22
		[5.18]					[0.82]
Anomaly 3			20.93				11.39
			[5.26]				[2.51]
Anomaly 4				9.95			6.33
				[3.25]			[2.07]
Anomaly 5					6.03		0.21
					[1.90]		[0.06]
Anomaly 6						11.35	6.97
						[3.31]	[2.03]
mkt	-0.92	-0.64	-0.89	-1.21	-0.48	-1.23	-1.21
	[-0.52]	[-0.36]	[-0.50]	[-0.67]	[-0.27]	[-0.68]	[-0.68]
smb	-2.72	-3.18	0.78	-2.83	-0.10	-1.40	-2.79
	[-0.99]	[-1.15]	[0.28]	[-1.00]	[-0.04]	[-0.50]	[-0.96]
hml	-14.65	-13.80	-15.73	-14.17	-13.33	-14.64	-14.24
	[-4.31]	[-4.03]	[-4.61]	[-4.09]	[-3.72]	[-4.23]	[-4.10]
rmw	-8.35	-8.13	-3.20	-5.49	-4.46	-7.53	-6.33
	[-2.36]	[-2.29]	[-0.89]	[-1.53]	[-1.19]	[-2.09]	[-1.68]
cma	13.26	11.72	25.46	18.60	17.56	19.11	16.32
	[2.52]	[2.18]	[4.82]	[3.55]	[3.27]	[3.65]	[2.83]
umd	1.67	1.42	3.03	2.35	3.34	2.31	-0.07
	[0.92]	[0.77]	[1.68]	[1.26]	[1.81]	[1.24]	[-0.04]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	10	10	10	7	6	7	13

Panel A: Average rank

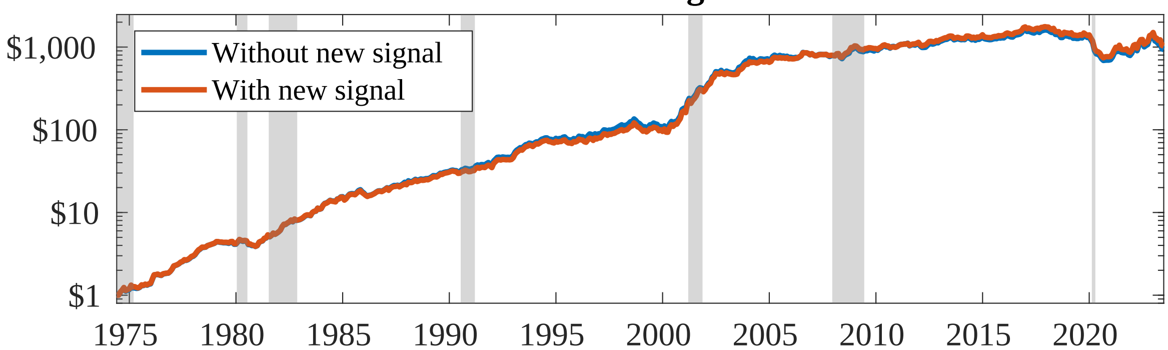


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

References

Baker, M. and Wurgler, J. (2002). Market timing and capital structure. *Journal of Finance*, 57(1):1–32.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, 42(1-2):53–85.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Kraus, A. and Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance*, 28(4):911–922.

Lewellen, J. and Resutek, R. J. (2016). The predictive power of investment and accruals. *Review of Financial Studies*, 29(10):2687–2723.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.

Stambaugh, R. F. and Yuan, Y. (2017). Mispricing factors. *Review of Financial Studies*, 30(4):1270–1315.