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

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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

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns. While extensive research has documented various accounting-based signals, the relationship between debt financing decisions and operating performance remains understudied. The interaction between financing and operating decisions potentially contains valuable information about future firm performance that is not fully incorporated into stock prices.

Prior literature has focused primarily on either capital structure choices or operating performance in isolation, leaving open questions about how debt issuance decisions impact future operating earnings and stock returns. This gap is particularly notable given that debt financing decisions can significantly affect a firm's operational flexibility and investment capacity.

We propose that the impact of debt issuance on earnings before interest and taxes (EBIT) provides a novel signal about future stock returns. The economic mechanism builds on Myers and Rajan (1998)'s theory that debt overhang affects firms' operational and investment decisions. When new debt issuance leads to improved EBIT, it likely reflects management's confidence in future growth opportunities and ability to service additional debt.

This relationship draws on Ross and Westerfield (1988)'s signaling hypothesis, where managers use financing decisions to convey private information about future prospects. Specifically, when debt issuance is followed by EBIT improvements, it suggests the financing is supporting value-enhancing operational initiatives rather than covering shortfalls or engaging in empire building as described by Jensen and Meckling (1976).

The predictive power of this signal should be particularly strong when the debt issuance precedes EBIT improvements, as this temporal sequence helps establish that the operational improvements are linked to the financing decision rather than vice versa. This builds on Fama and French (2002)'s work showing that capital structure choices contain information about future profitability.

Our analysis reveals that a value-weighted long-short portfolio strategy based on Debt Issue Impact on EBIT (DIIE) generates significant abnormal returns. The strategy achieves an annualized gross Sharpe ratio of 0.41 and delivers monthly average abnormal returns of 22 basis points relative to the Fama-French six-factor model, with a t-statistic of 2.74.

Importantly, the signal's predictive power remains robust after controlling for transaction costs, with a net Sharpe ratio of 0.30 and monthly abnormal returns of 18 basis points (t-statistic = 2.26). The strategy's performance is particularly strong among large-cap stocks, generating monthly returns of 25 basis points (t-statistic = 2.82) in the highest size quintile.

Further supporting the signal's robustness, DIIE maintains significant predictive power even after controlling for six closely related anomalies, generating a monthly alpha of 17 basis points (t-statistic = 2.19). This indicates that DIIE captures unique information about future returns not contained in existing measures of financing activity or operating performance.

Our paper makes several contributions to the literature on financing decisions and asset pricing. First, we extend work by Bradshaw et al. (2006) on external financing and stock returns by showing that the interaction between debt issuance and operating performance contains important predictive information. Second, we complement Titman et al. (2004)'s findings on investment and returns by demonstrating how financing decisions' operational impact affects future stock performance.

Methodologically, we introduce a novel approach to measuring the financing-operations nexus that captures both the magnitude and timing of debt issuance effects on EBIT. This builds on but differs from traditional measures of external financing used in Bradshaw et al. (2006) and investment-based signals studied by Titman et al. (2004).

Our findings have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining interactions between financing and operating decisions rather than studying them in isolation. For practitioners, we document a robust return predictor that remains effective among large, liquid stocks and maintains its predictive power after accounting for transaction costs.

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. This scaled difference captures the relative magnitude of new debt financing compared to the firm's operational earnings capacity, offering insight into how aggressively the firm is leveraging its earnings base to support new borrowing. By focusing on this relationship, the signal aims to reflect aspects of capital structure decisions and financial risk in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for DLTIS and EBIT 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 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.

[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.

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 $r_{X,t}$ 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

[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.

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

[4] We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capital-

one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes 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, with an impressive annualized gross Sharpe ratio of 0.41 (0.30 net of transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, underscores DIIE's unique informational content and its potential value for investment professionals.

Particularly noteworthy is the signal's ability to maintain statistical significance with a monthly alpha of 17 bps when controlled against both the Fama-French five-factor model plus momentum and six closely related anomalies. This resilience suggests that DIIE captures distinct aspects of firm performance and market behavior not fully explained by existing factors.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Additionally, the study period may not fully capture the

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

signal's behavior across different economic cycles.

Future research could explore the signal's performance in international markets, its interaction with other financial metrics, and its effectiveness across different market conditions and economic cycles. Investigation into the underlying economic mechanisms driving the DIIE effect would also be valuable. Furthermore, examining how the signal's predictive power varies across different firm characteristics and industry sectors could yield additional insights for practical applications.

In conclusion, DIIE represents a valuable addition to the investment practitioner's toolkit, offering meaningful predictive power for stock returns while maintaining robustness to traditional risk factors and related anomalies.

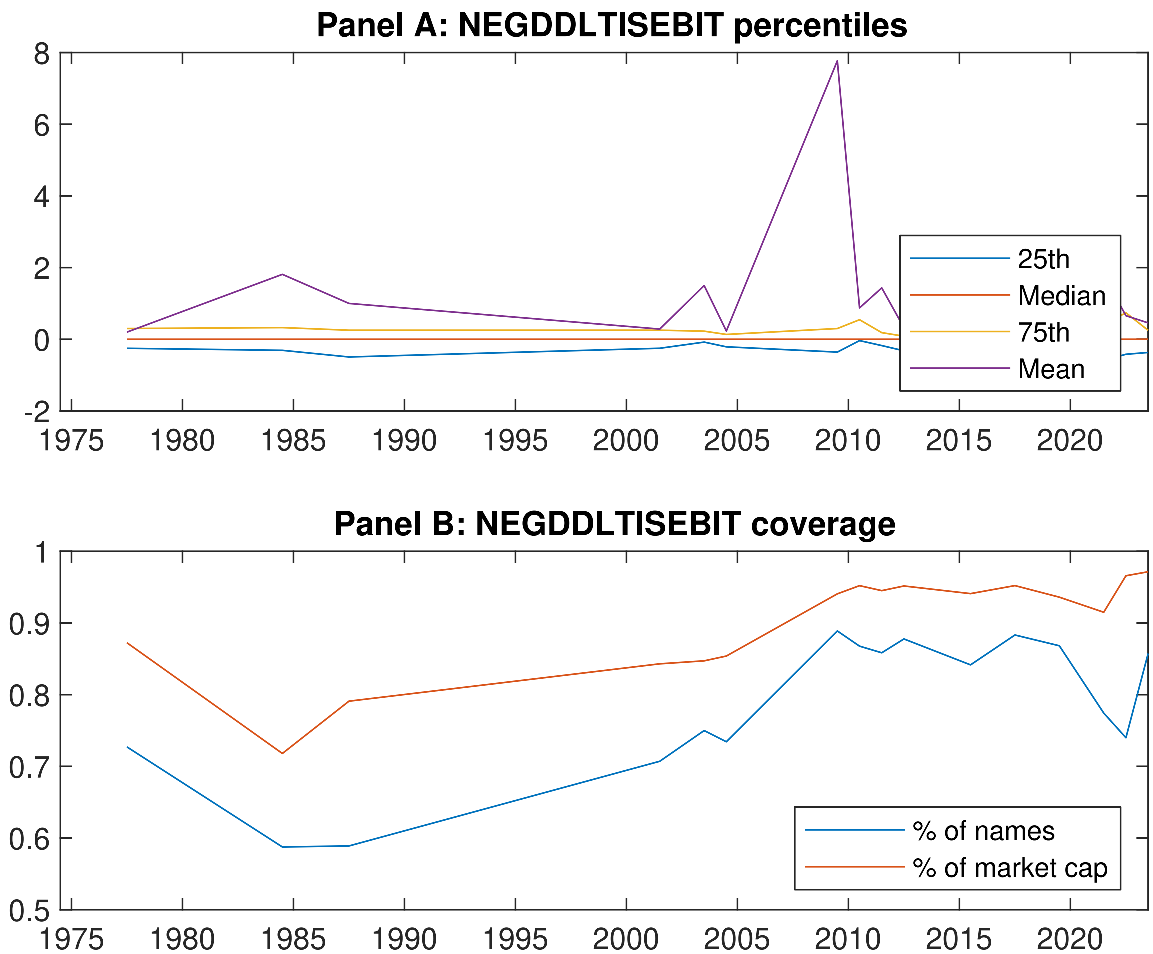


Figure 1: Times series of DIIE percentiles and coverage.
This figure plots descriptive statistics for DIIE. Panel A shows cross-sectional percentiles of DIIE over the sample. Panel B plots the monthly coverage of DIIE relative to the universe of CRSP stocks with available market capitalizations.

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

Size quintiles	DIIE Quintiles (L)	(2)	(3)	(4)	(H)	DIIE Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.79	0.84	0.96	0.98	0.78	-0.01	-0.00	0.00	-0.02	0.05	0.03
	[2.90]	[2.97]	[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

Size quintiles	DIIE Quintiles, Average n (L)	(2)	(3)	(4)	(H)	DIIE Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(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

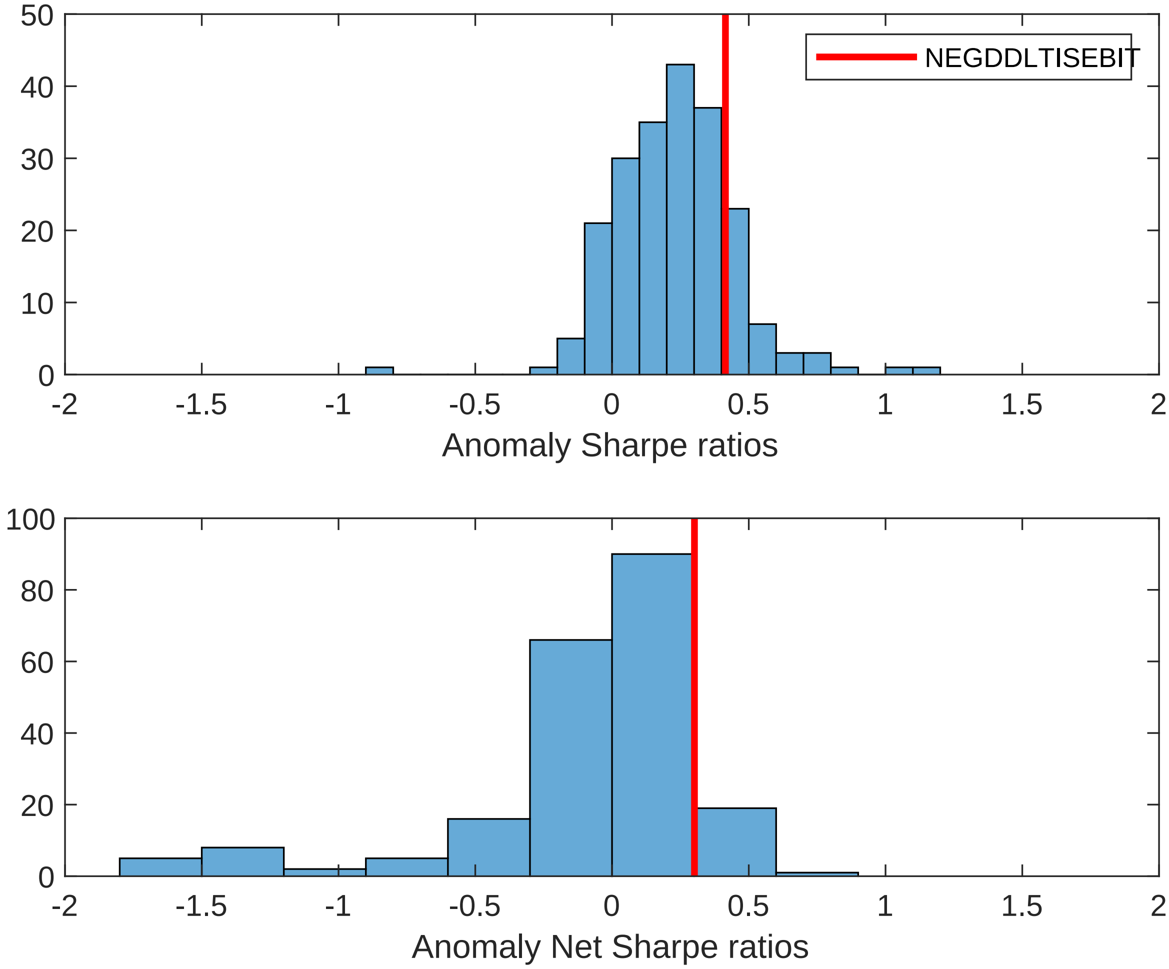


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIIE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

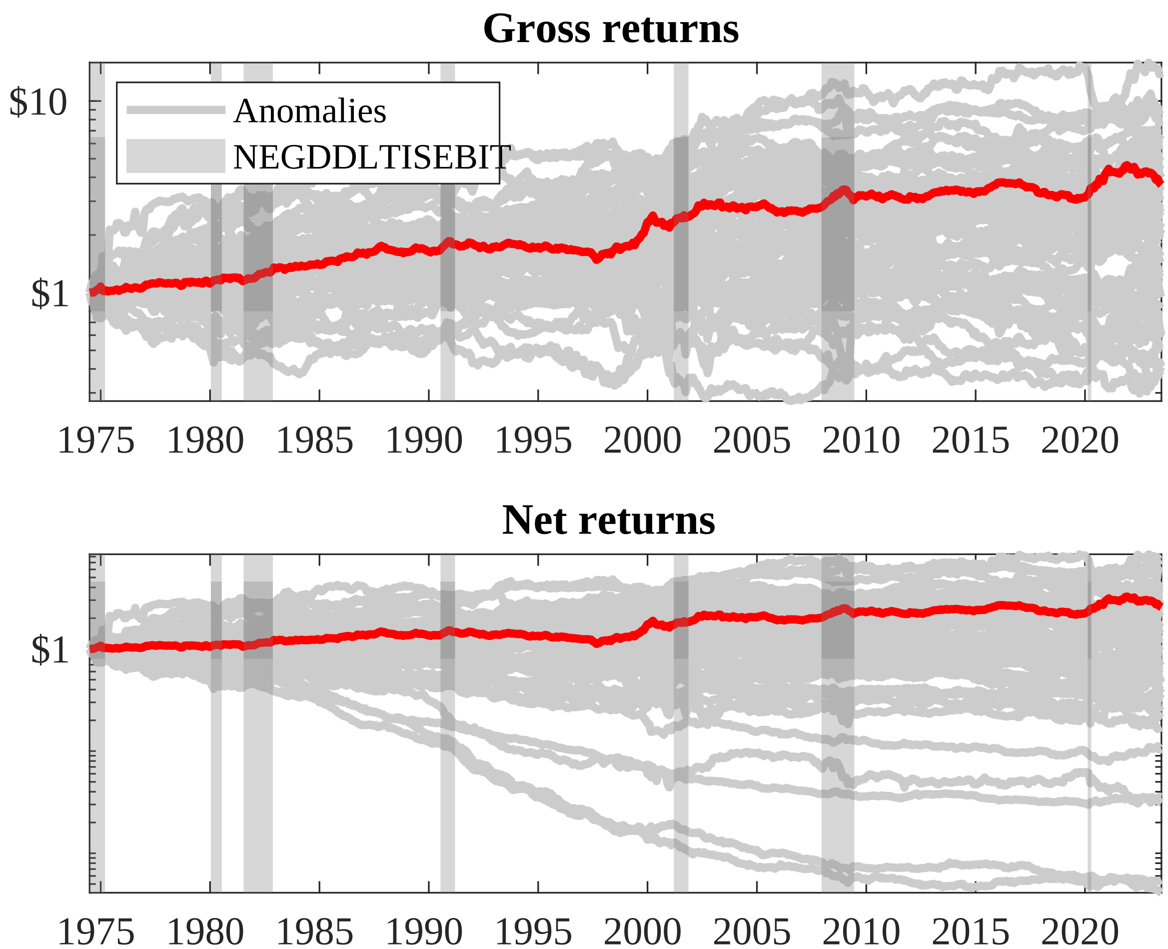


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIIE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

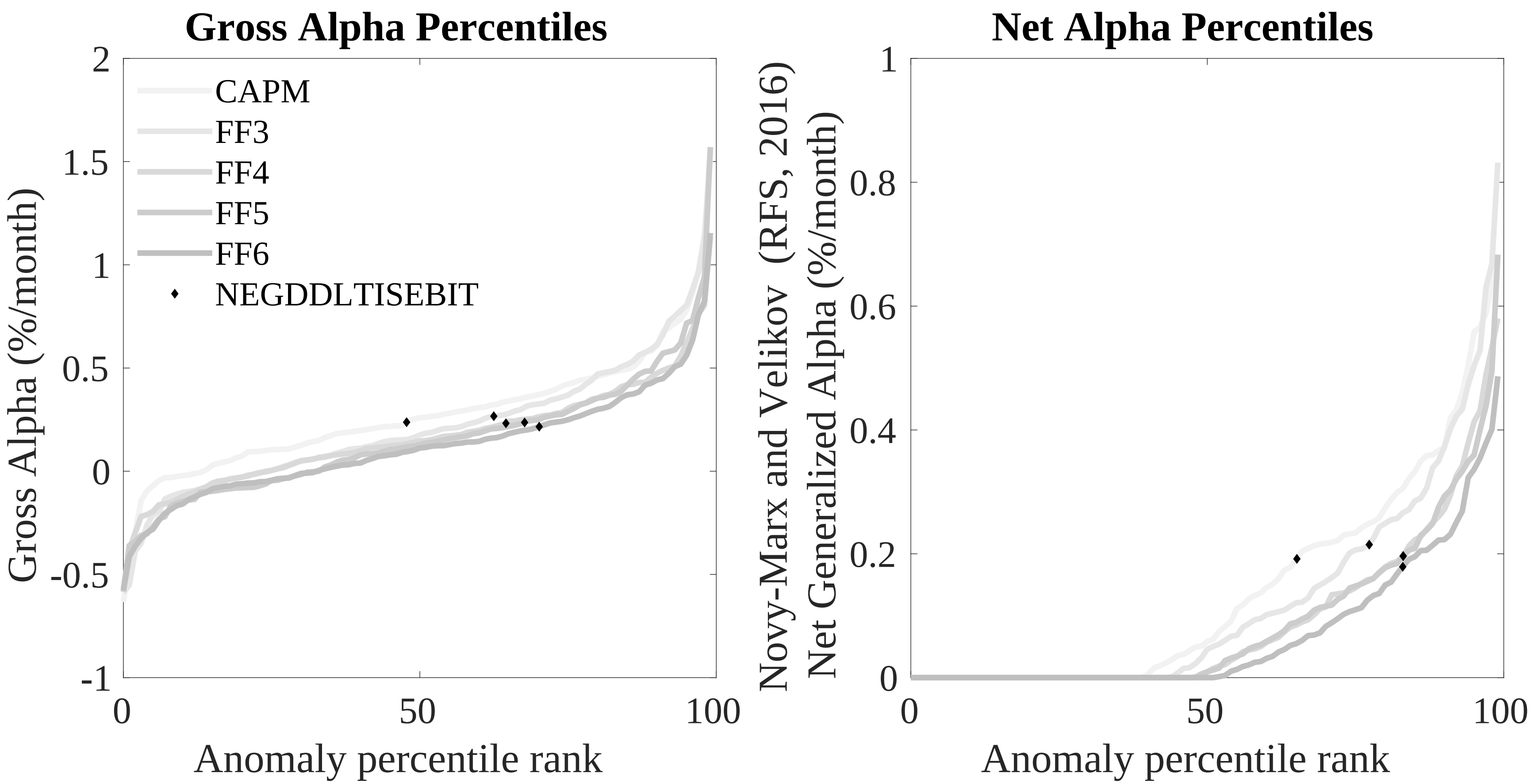
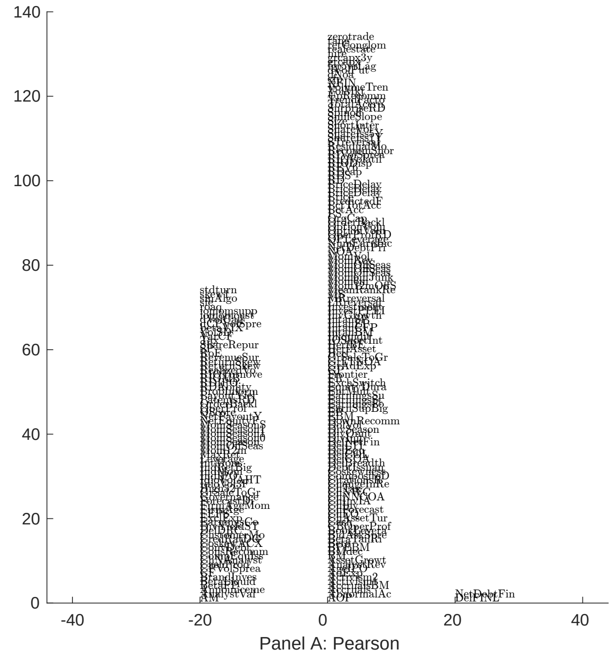


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

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.



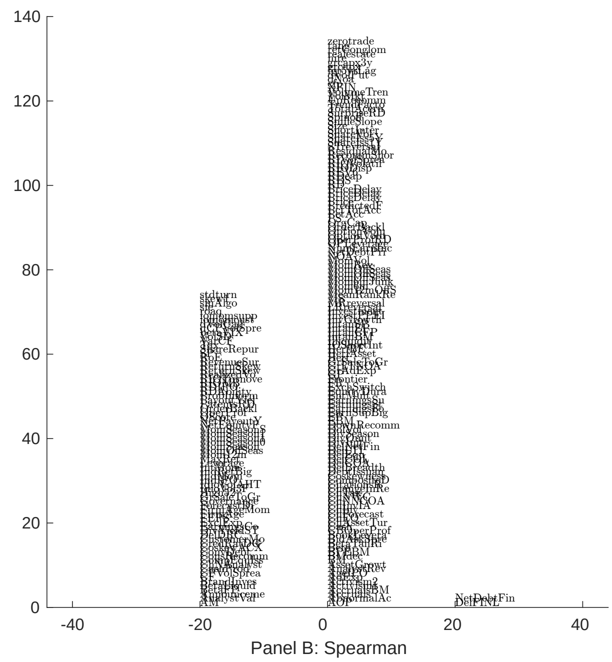


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DIIE. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

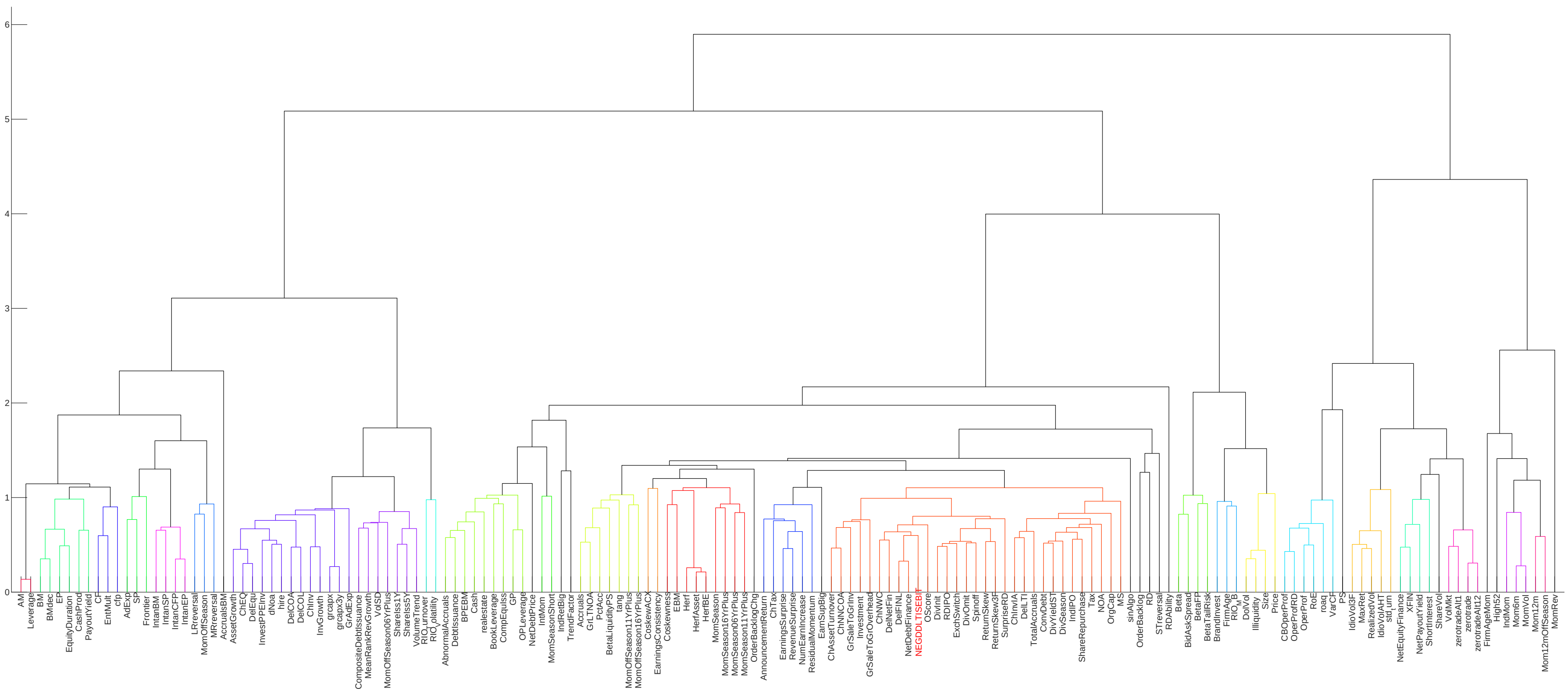


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

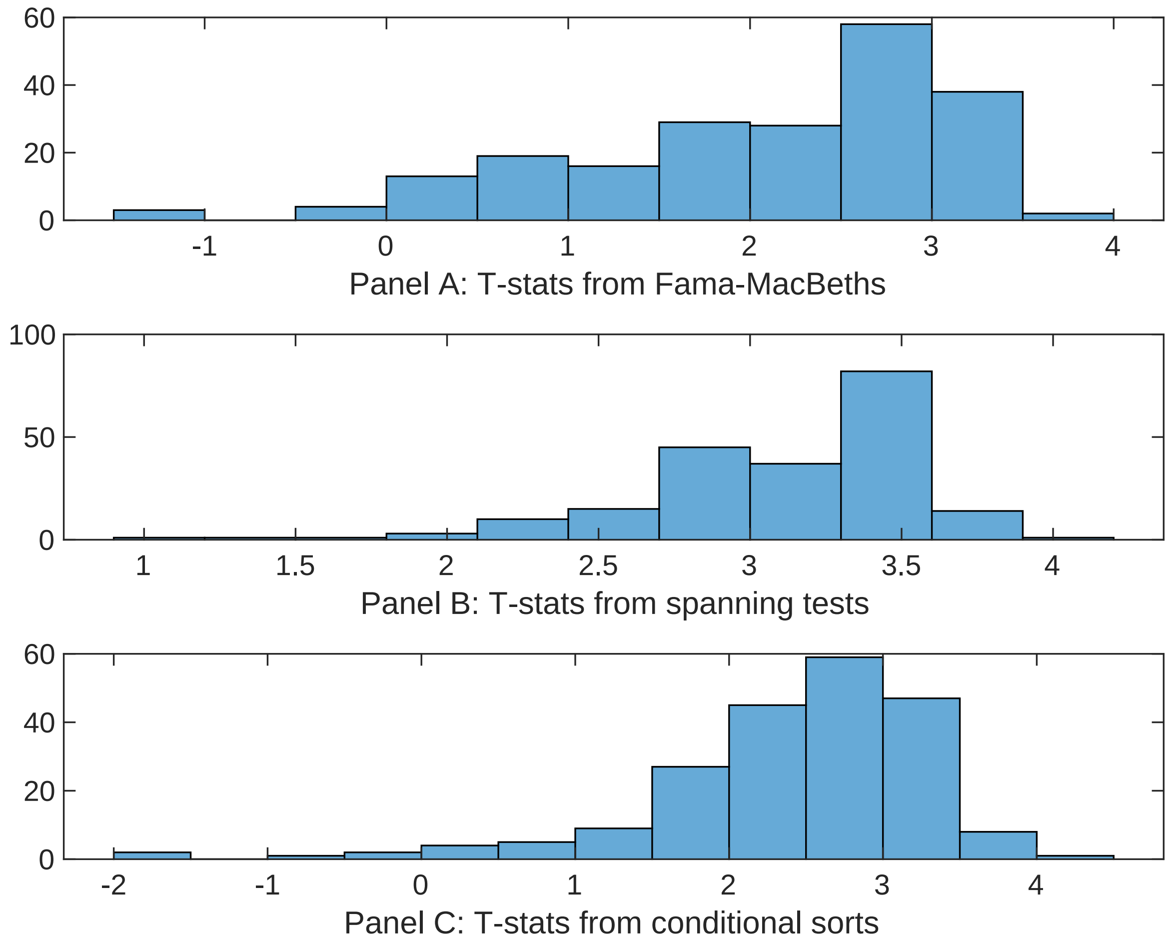


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DIIE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIIE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DIIE} DIIE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

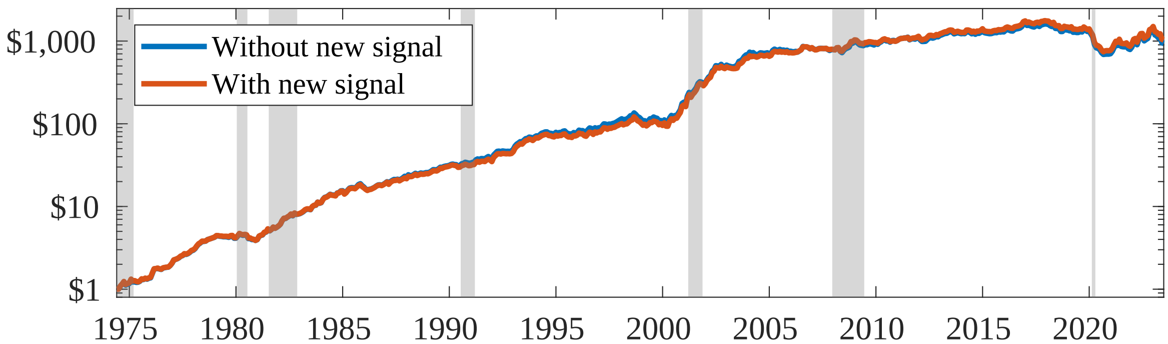


Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines 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.

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