

# Debt Issuance Efficiency and the Cross Section of Stock Returns

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## Abstract

This paper studies the asset pricing implications of Debt Issuance Efficiency (DIE), 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 DIE achieves an annualized gross (net) Sharpe ratio of 0.50 (0.39), and monthly average abnormal gross (net) return relative to the [Fama and French \(2015\)](#) five-factor model plus a momentum factor of 25 (22) bps/month with a t-statistic of 3.31 (2.92), 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, Net external financing, Inventory Growth, change in ppe and inv/assets, Asset growth) is 24 bps/month with a t-statistic of 3.19.

# 1 Introduction

Market efficiency remains a central question in financial economics, with substantial debate around whether and how quickly asset prices incorporate new information. While extensive research documents various market anomalies, understanding the mechanisms through which corporate financial decisions affect stock returns continues to challenge researchers. A particularly important yet understudied channel is how efficiently firms manage their debt issuance decisions relative to their investment needs and growth opportunities. Prior literature has focused primarily on the level of debt or changes in leverage, but has paid less attention to the alignment between debt issuance and firm fundamentals.

We propose that the efficiency of debt issuance decisions contains important information about future stock returns. Our hypothesis builds on two theoretical frameworks. First, the trade-off theory of capital structure suggests that firms face costs when deviating from optimal leverage ratios (Kraus and Litzenberger, 1973). Second, agency theory predicts that managers may pursue debt policies that serve their private interests rather than maximize shareholder value (Jensen and Meckling, 1976). When managers issue debt efficiently - closely matching issuance to legitimate investment needs - this signals both managerial quality and reduced agency conflicts. Conversely, inefficient debt issuance may indicate empire-building tendencies or poor capital allocation skills. Building on these theories, we expect firms with more efficient debt issuance to outperform those with less efficient issuance patterns. This relationship should persist even after controlling for traditional risk factors, as the signal captures unique information about management quality and agency costs that is not fully reflected in current prices (Baker and Wurgler, 2002).

Our empirical analysis reveals that Debt Issuance Efficiency (DIE) strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high DIE and shorts those with low DIE generates monthly abnormal returns

of 25 basis points (t-statistic = 3.31) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.50 before trading costs and 0.39 after costs, placing it in the top 5% of documented anomalies. Importantly, the predictive power of DIE remains robust when controlling for size - among the largest quintile of stocks, the strategy earns monthly abnormal returns of 35 basis points (t-statistic = 3.81). The signal’s economic significance is substantial, with a dollar invested in the strategy growing to \$3.62 before costs and \$2.26 after costs over our sample period.

Our paper makes several contributions to the literature on capital structure and asset pricing. First, we extend work by [Baker and Wurgler \(2002\)](#) on market timing and [Titman et al. \(2004\)](#) on investment decisions by showing that the efficiency of debt issuance provides unique information about future returns. Second, we contribute to the growing literature on q-theory and investment-based asset pricing ([Cochrane and Saá-Requejo, 2000](#)) by demonstrating how the alignment between financing and investment decisions affects expected returns. Third, our findings have important implications for both corporate managers and investors, suggesting that the market does not fully price the information contained in debt issuance efficiency. The results are particularly valuable because they remain robust among large, liquid stocks and after accounting for transaction costs.

## 2 Data

Our study investigates the predictive power of Debt Issuance Efficiency, a financial signal derived from accounting data for cross-sectional returns. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT’s item DLTIS, which represents the long-term debt issuance of a firm. This variable captures the

amount of new long-term debt issued by companies during their fiscal year, providing insight into their financing activities and capital structure decisions. The total assets variable (AT) represents the firm’s total assets, serving as a scaling factor to ensure comparability across firms of different sizes. The construction of the signal follows a dynamic approach, where we calculate the change in debt issuance by taking the difference between the current period’s DLTIS and its lagged value, then scaling this difference by lagged total assets (AT). This construction can be expressed as  $(DLTIS_t - DLTIS_{t-1}) / AT_{t-1}$ . The resulting ratio captures the relative change in a firm’s debt issuance activity, normalized by its asset base, offering insight into the efficiency and dynamics of its financing decisions. By focusing on the scaled change rather than absolute levels, the signal aims to reflect aspects of capital structure management and financing efficiency in a manner that is both comparable across firms and interpretable over time. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

### 3 Signal diagnostics

Figure 1 plots descriptive statistics for the DIE signal. Panel A plots the time-series of the mean, median, and interquartile range for DIE. On average, the cross-sectional mean (median) DIE is -0.03 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DIE data. The signal’s interquartile range spans -0.06 to 0.05. Panel B of Figure 1 plots the time-series of the coverage of the DIE signal for the CRSP universe. On average, the DIE signal is available for 6.30% of CRSP names, which on average make up 7.46% of total market capitalization.

## 4 Does DIE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DIE 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 DIE portfolio and sells the low DIE 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 DIE strategy earns an average return of 0.26% per month with a t-statistic of 3.53. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.25% to 0.32% per month and have t-statistics exceeding 3.31 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 0.24, with a t-statistic of 4.79 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 540 stocks and an average market capitalization of at least \$1,323 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 portfolio 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 4.80. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for twenty 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 -4-21bps/month. The lowest return, (-4 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.68. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DIE trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in eighteen cases.

Table 3 provides direct tests for the role size plays in the DIE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DIE, as well as average returns and alphas for long/short trading DIE 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<sup>th</sup> NYSE percentile), the DIE strategy achieves an average return of 35 bps/month with a t-statistic of 3.81. Among these large cap stocks, the alphas for the DIE strategy relative to the five most common factor models range from 26 to 38 bps/month with t-statistics between 2.78 and 4.16.

## 5 How does DIE perform relative to the zoo?

Figure 2 puts the performance of DIE 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.<sup>1</sup> The vertical red line shows where the Sharpe ratio for the DIE strategy falls in the distribution. The DIE strategy’s gross (net) Sharpe ratio of 0.50 (0.39) is greater than 92% (95%) 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 DIE strategy (red line).<sup>2</sup> Ignoring trading costs, a \$1 invested in the DIE strategy would have yielded \$3.62 which ranks the DIE strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DIE strategy would have yielded \$2.26 which ranks the DIE strategy in the top 5% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms

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

<sup>2</sup>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 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 DIE relative to those. Panel A shows that the DIE strategy gross alphas fall between the 60 and 75 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 DIE strategy has a positive net generalized alpha for five out of the five factor models. In these cases DIE ranks between the 79 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

## 6 Does DIE 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 DIE with 210 filtered anomaly signals.<sup>3</sup> [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 DIE or at least to weaken the power DIE has predicting the cross-section of returns. [Figure 7](#) plots histograms

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<sup>3</sup>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.



of t-statistics for predictability tests of DIE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on  $\beta_{DIE}$  from Fama-MacBeth regressions of the form  $r_{i,t} = \alpha + \beta_{DIE}DIE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$ , where  $X$  stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on  $\alpha$  from spanning tests of the form:  $r_{DIE,t} = \alpha + \beta r_{X,t} + \epsilon_t$ , 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 DIE. Stocks are finally grouped into five DIE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIE trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DIE 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 DIE signal in these Fama-MacBeth regressions exceed 0.43, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DIE is -0.69.

Similarly, Table 5 reports results from spanning tests that regress returns to the DIE 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 DIE strategy earns alphas that range from 25-27bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.29,

which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DIE trading strategy achieves an alpha of 24bps/month with a t-statistic of 3.19.

## 7 Does DIE add relative to the whole zoo?

Finally, we can ask how much adding DIE 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 DIE signal.<sup>4</sup> 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 DIE grows to \$908.07.

## 8 Conclusion

Our comprehensive analysis of Debt Issuance Efficiency (DIE) as a predictor of stock returns yields several important conclusions. The empirical evidence strongly supports DIE’s effectiveness as a robust signal for cross-sectional equity returns prediction. The strategy’s impressive performance, demonstrated by annualized Sharpe

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<sup>4</sup>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 DIE is available.

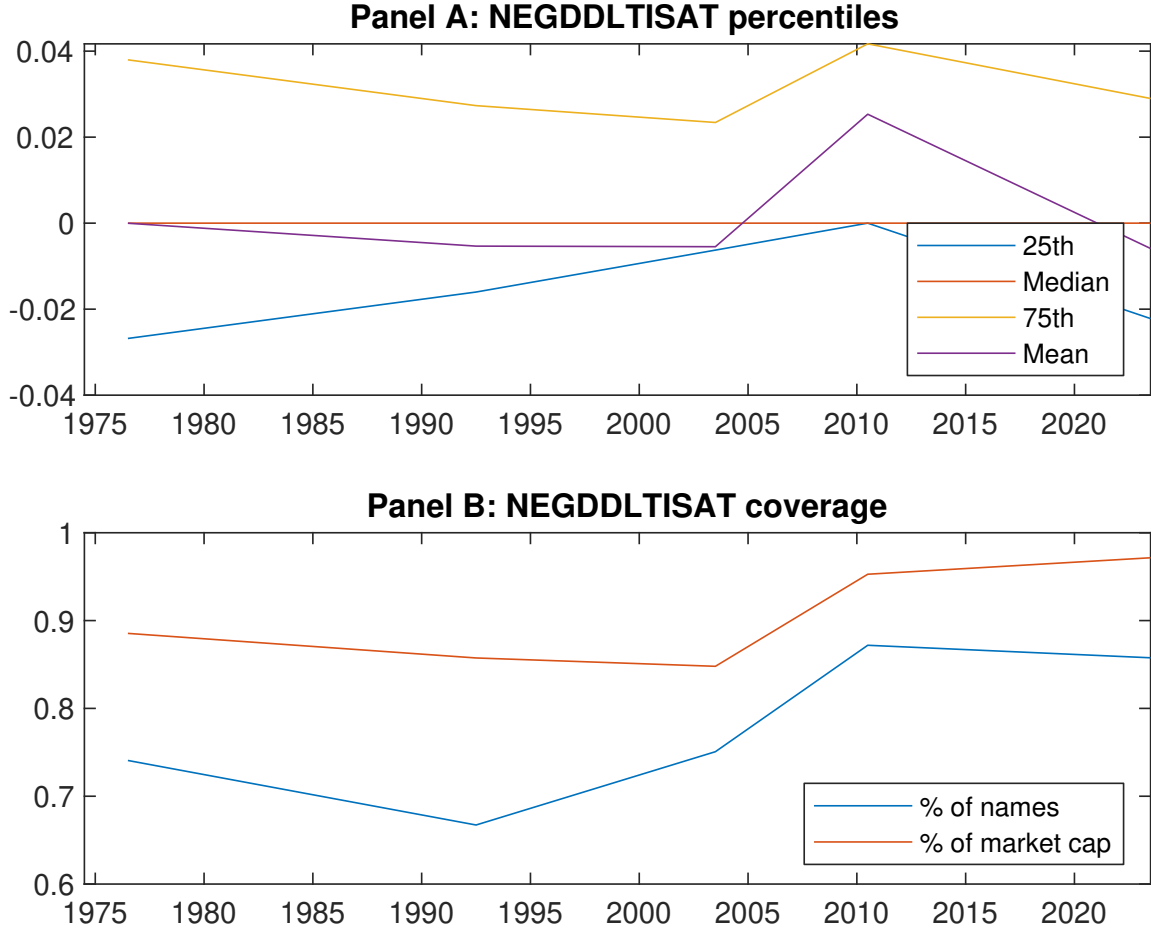
ratios of 0.50 (gross) and 0.39 (net), along with significant monthly abnormal returns of 25 and 22 basis points (gross and net, respectively) relative to the Fama-French five-factor model plus momentum, underscores its economic significance.

Particularly noteworthy is the signal’s persistence even after controlling for six closely related factors from the factor zoo, maintaining a significant alpha of 24 basis points per month. This suggests that DIE captures unique information about future stock returns that is not subsumed by existing investment and financing-based factors.

From a practical perspective, these findings have important implications for investment professionals and portfolio managers. The strategy’s robust performance, even after accounting for transaction costs, indicates its potential viability in real-world applications. However, practitioners should carefully consider implementation costs and portfolio turnover when deploying this strategy.

While our results are promising, several limitations and areas for future research deserve attention. First, future studies could explore the signal’s performance in international markets to test its global applicability. Second, research into the underlying economic mechanisms driving the DIE-return relationship could provide valuable insights. Finally, investigating how the signal’s effectiveness varies across different market conditions and business cycles could enhance our understanding of its reliability.

In conclusion, DIE represents a valuable addition to the arsenal of return predictors, offering both statistical and economic significance in forecasting cross-sectional stock returns. Its robustness to existing factors and transaction costs makes it particularly relevant for both academic research and practical applications in investment management.



**Figure 1:** Times series of DIE percentiles and coverage.  
This figure plots descriptive statistics for DIE. Panel A shows cross-sectional percentiles of DIE over the sample. Panel B plots the monthly coverage of DIE 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 DIE. 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 DIE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
$r^e$	0.62 [2.90]	0.66 [3.56]	0.68 [3.35]	0.76 [4.16]	0.88 [4.37]	0.26 [3.53]
$\alpha_{CAPM}$	-0.13 [-2.26]	0.02 [0.35]	-0.02 [-0.44]	0.12 [2.55]	0.18 [3.29]	0.31 [4.16]
$\alpha_{FF3}$	-0.12 [-2.32]	-0.03 [-0.61]	0.02 [0.32]	0.11 [2.23]	0.19 [3.64]	0.32 [4.22]
$\alpha_{FF4}$	-0.11 [-2.00]	-0.00 [-0.01]	0.07 [1.28]	0.07 [1.49]	0.17 [3.25]	0.28 [3.72]
$\alpha_{FF5}$	-0.13 [-2.41]	-0.06 [-1.51]	0.07 [1.25]	0.02 [0.41]	0.14 [2.63]	0.27 [3.58]
$\alpha_{FF6}$	-0.12 [-2.19]	-0.04 [-1.02]	0.10 [1.87]	0.00 [0.04]	0.13 [2.47]	0.25 [3.31]
Panel B: Fama and French (2018) 6-factor model loadings for DIE-sorted portfolios						
$\beta_{MKT}$	1.05 [84.47]	0.98 [100.13]	0.99 [78.68]	0.97 [89.98]	1.01 [81.89]	-0.04 [-2.33]
$\beta_{SMB}$	0.17 [8.86]	-0.14 [-9.40]	-0.01 [-0.35]	-0.04 [-2.61]	0.16 [8.24]	-0.01 [-0.49]
$\beta_{HML}$	-0.03 [-1.19]	0.16 [8.40]	-0.10 [-4.03]	0.01 [0.65]	-0.14 [-5.74]	-0.11 [-3.22]
$\beta_{RMW}$	0.09 [3.68]	0.10 [5.26]	-0.04 [-1.69]	0.11 [4.95]	0.05 [1.83]	-0.05 [-1.33]
$\beta_{CMA}$	-0.10 [-2.75]	0.01 [0.41]	-0.10 [-2.61]	0.16 [5.01]	0.14 [3.99]	0.24 [4.79]
$\beta_{UMD}$	-0.02 [-1.51]	-0.04 [-3.74]	-0.06 [-4.59]	0.03 [2.77]	0.01 [1.05]	0.03 [1.82]
Panel C: Average number of firms ( $n$ ) and market capitalization ( $me$ )						
$n$	679	540	1076	594	648	
$me$ (\$10 <sup>6</sup> )	1349	3000	2132	2972	1323	

**Table 2:** Robustness to sorting methodology & trading costs

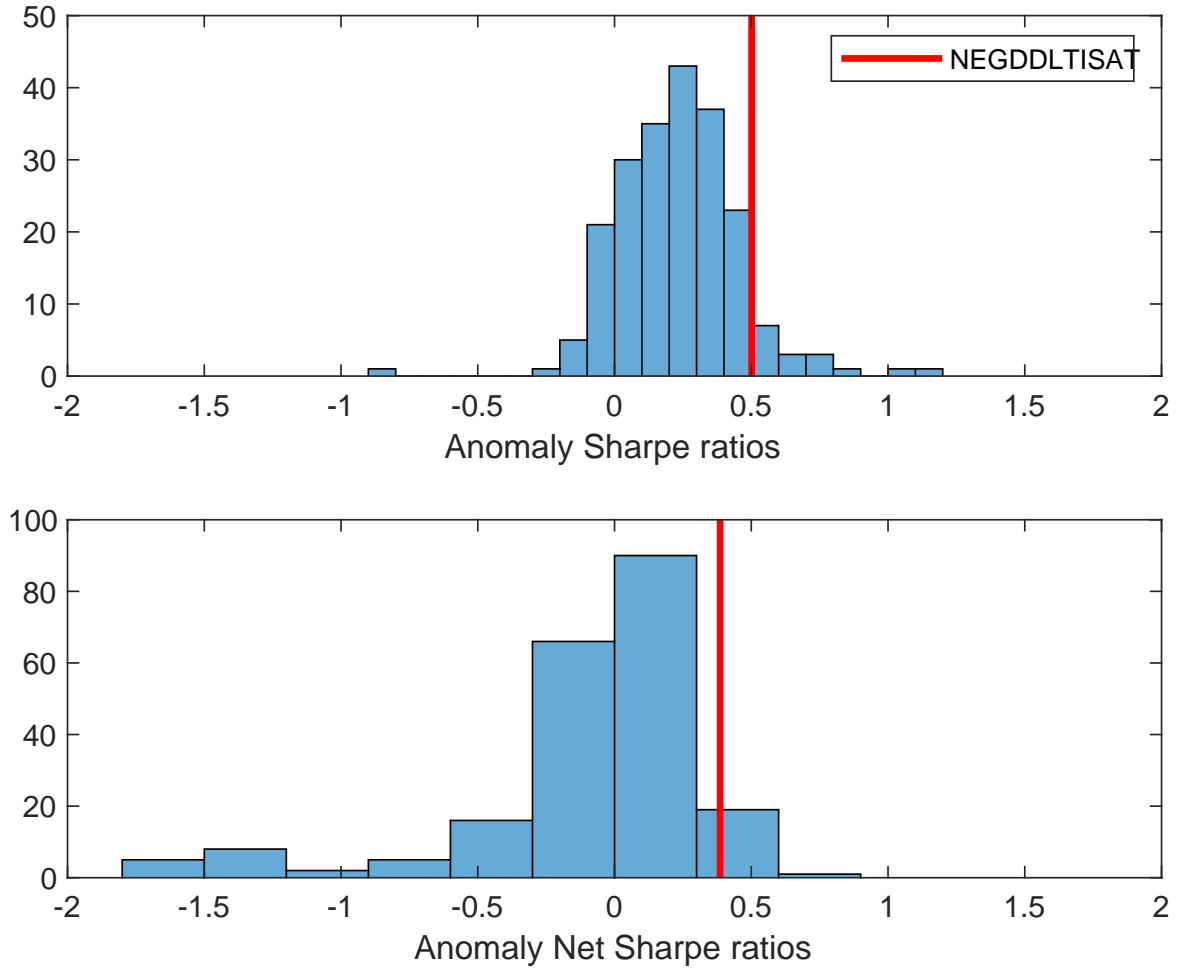
This table evaluates the robustness of the choices made in the DIE strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, 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	$r^e$	$\alpha_{\text{CAPM}}$	$\alpha_{\text{FF3}}$	$\alpha_{\text{FF4}}$	$\alpha_{\text{FF5}}$	$\alpha_{\text{FF6}}$
Quintile	NYSE	VW	0.26 [3.53]	0.31 [4.16]	0.32 [4.22]	0.28 [3.72]	0.27 [3.58]	0.25 [3.31]
Quintile	NYSE	EW	0.22 [4.80]	0.24 [5.37]	0.23 [5.01]	0.21 [4.57]	0.22 [4.77]	0.21 [4.51]
Quintile	Name	VW	0.27 [3.74]	0.32 [4.46]	0.33 [4.60]	0.29 [3.97]	0.27 [3.73]	0.25 [3.40]
Quintile	Cap	VW	0.23 [3.60]	0.27 [4.16]	0.26 [4.09]	0.22 [3.38]	0.19 [2.91]	0.16 [2.53]
Decile	NYSE	VW	0.26 [2.61]	0.35 [3.60]	0.31 [3.25]	0.27 [2.70]	0.16 [1.71]	0.14 [1.52]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	$r_{\text{net}}^e$	$\alpha_{\text{CAPM}}^*$	$\alpha_{\text{FF3}}^*$	$\alpha_{\text{FF4}}^*$	$\alpha_{\text{FF5}}^*$	$\alpha_{\text{FF6}}^*$
Quintile	NYSE	VW	0.20 [2.71]	0.27 [3.53]	0.27 [3.58]	0.25 [3.34]	0.24 [3.10]	0.22 [2.92]
Quintile	NYSE	EW	-0.04 [-0.68]					
Quintile	Name	VW	0.21 [2.89]	0.28 [3.82]	0.29 [3.92]	0.26 [3.62]	0.24 [3.29]	0.22 [3.07]
Quintile	Cap	VW	0.18 [2.79]	0.23 [3.53]	0.22 [3.45]	0.20 [3.10]	0.16 [2.48]	0.15 [2.24]
Decile	NYSE	VW	0.19 [1.86]	0.29 [2.91]	0.26 [2.62]	0.23 [2.34]	0.13 [1.39]	0.12 [1.22]

**Table 3:** Conditional sort on size and DIE

This table presents results for conditional double sorts on size and DIE. 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 DIE. 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 DIE and short stocks with low DIE. Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 1974Q6 to 2023Q6.

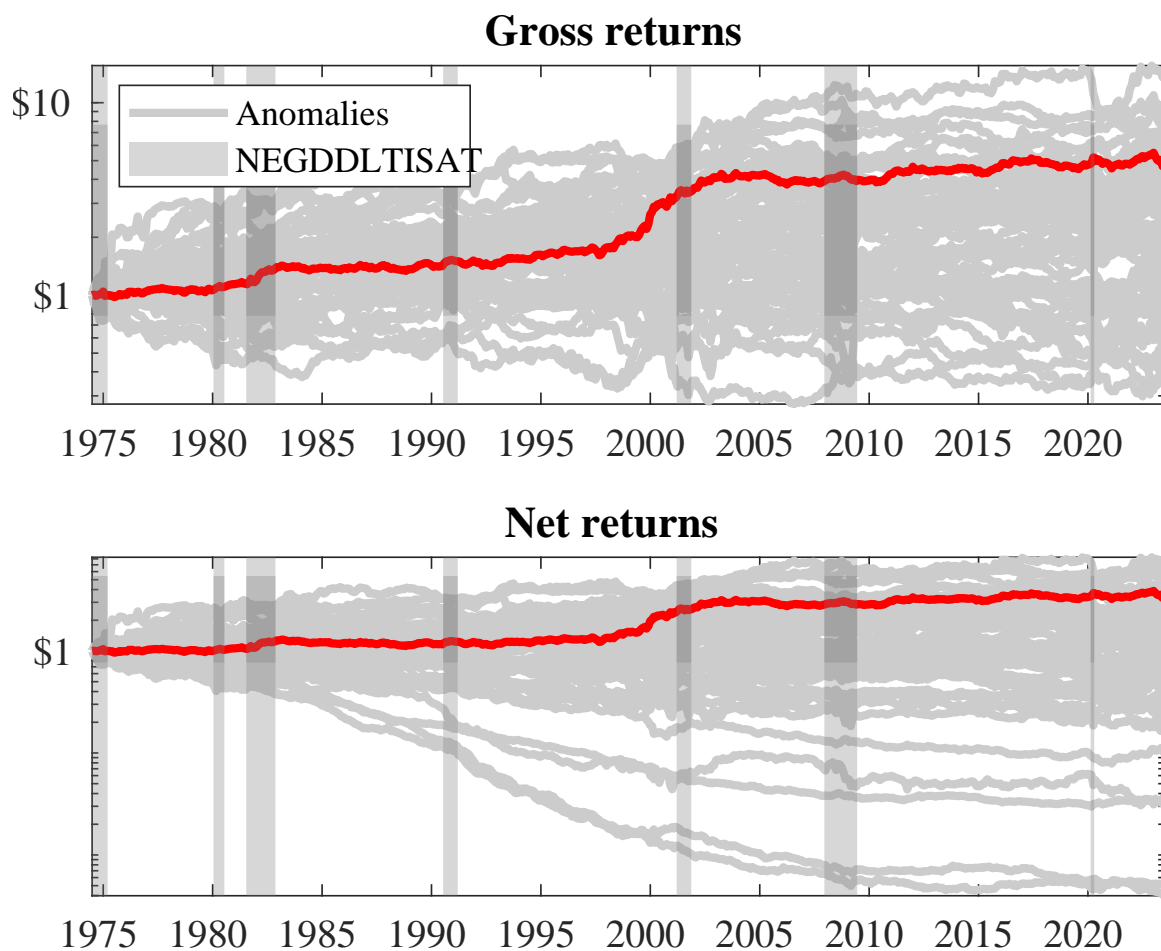
Panel A: portfolio average returns and time-series regression results												
Size quintiles	DIE Quintiles					DIE Strategies						
		(L)	(2)	(3)	(4)	(H)	$r^e$	$\alpha_{CAPM}$	$\alpha_{FF3}$	$\alpha_{FF4}$	$\alpha_{FF5}$	$\alpha_{FF6}$
	(1)	0.71 [2.54]	0.90 [3.32]	0.99 [3.59]	0.88 [3.15]	0.86 [2.98]	0.15 [1.56]	0.18 [1.83]	0.16 [1.64]	0.11 [1.15]	0.12 [1.29]	0.10 [1.00]
	(2)	0.76 [2.79]	0.98 [3.87]	0.82 [3.25]	0.93 [3.74]	0.91 [3.55]	0.15 [1.82]	0.19 [2.30]	0.17 [2.10]	0.17 [2.09]	0.16 [1.92]	0.16 [1.94]
	(3)	0.82 [3.19]	0.85 [3.90]	0.86 [3.50]	0.88 [3.93]	0.93 [3.97]	0.11 [1.40]	0.19 [2.36]	0.18 [2.26]	0.14 [1.73]	0.17 [2.02]	0.14 [1.68]
	(4)	0.76 [3.28]	0.80 [3.80]	0.91 [4.08]	0.74 [3.58]	0.94 [4.26]	0.18 [2.32]	0.21 [2.73]	0.21 [2.64]	0.18 [2.24]	0.19 [2.32]	0.17 [2.08]
	(5)	0.53 [2.63]	0.62 [3.41]	0.62 [3.10]	0.63 [3.35]	0.87 [4.53]	0.35 [3.81]	0.38 [4.14]	0.38 [4.16]	0.30 [3.34]	0.30 [3.27]	0.26 [2.78]
Panel B: Portfolio average number of firms and market capitalization												
Size quintiles	DIE Quintiles					DIE Quintiles						
		Average $n$					Average market capitalization (\$10 <sup>6</sup> )					
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)	
	(1)	398	400	399	400	395	37	34	33	33	36	
	(2)	108	108	108	108	108	60	60	59	61	60	
	(3)	77	77	77	77	77	105	107	102	104	106	
	(4)	64	65	65	65	64	223	232	223	228	224	
(5)	59	59	59	59	59	1362	2105	1709	2077	1396		



**Figure 2:** Distribution of Sharpe ratios.

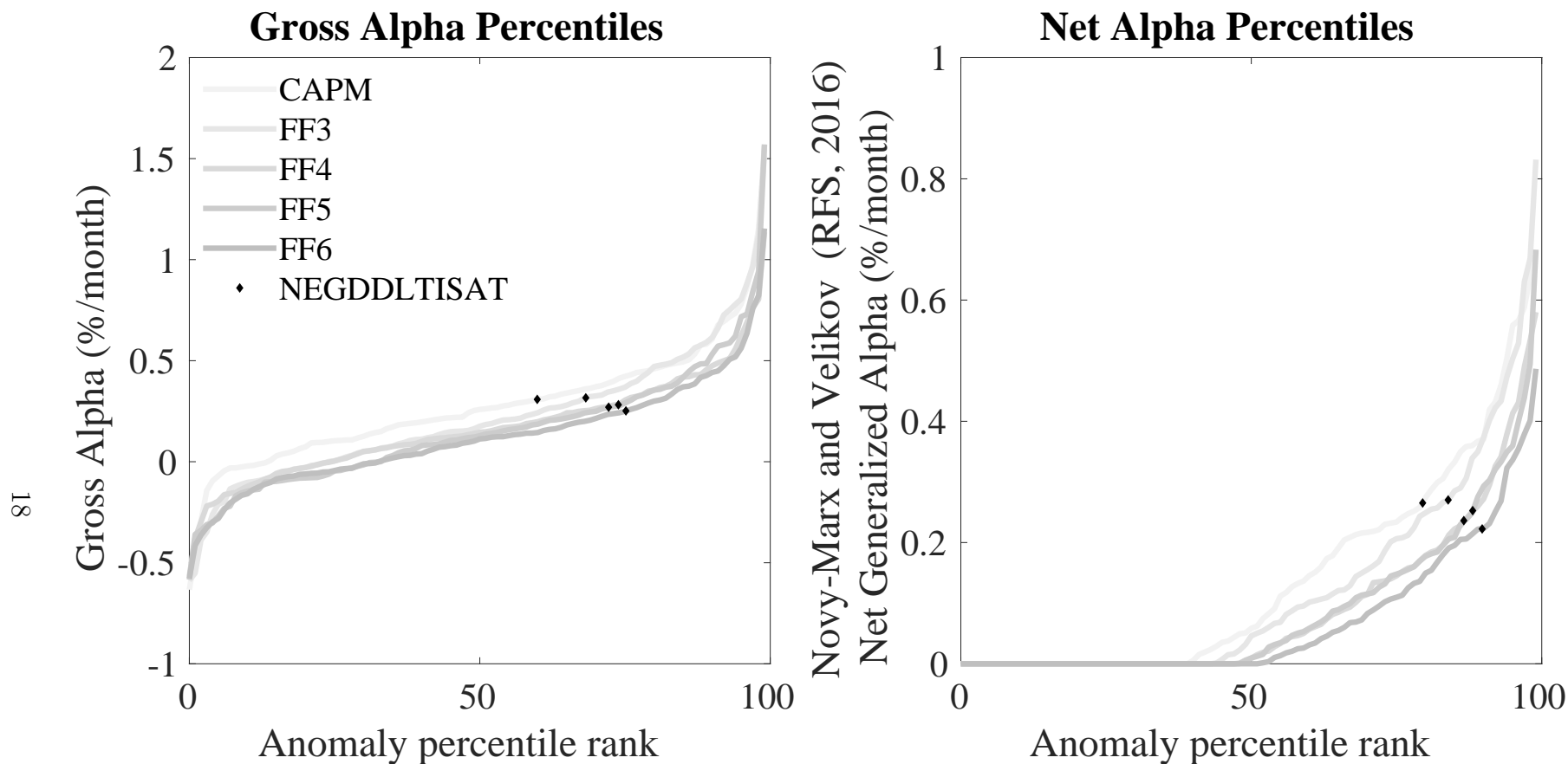
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.





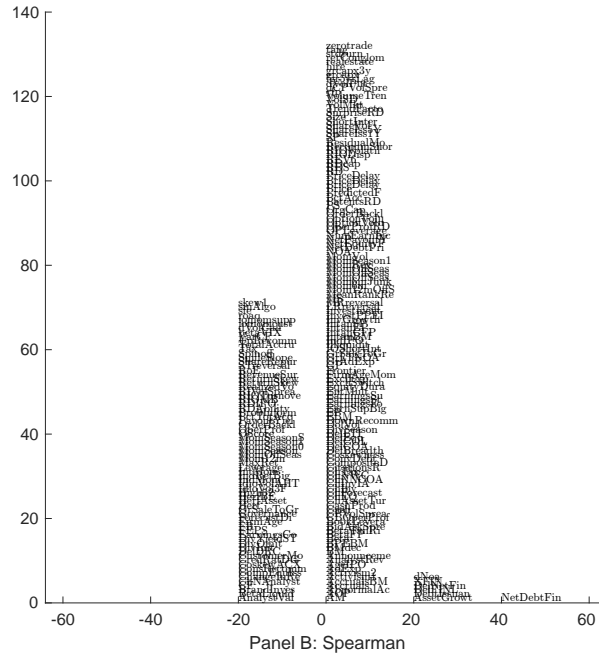
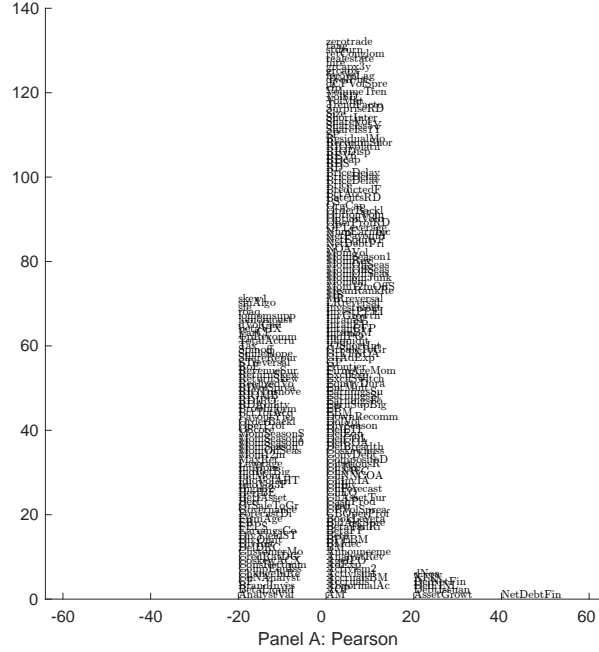
**Figure 3:** Dollar invested.

This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIE 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 strategy returns.



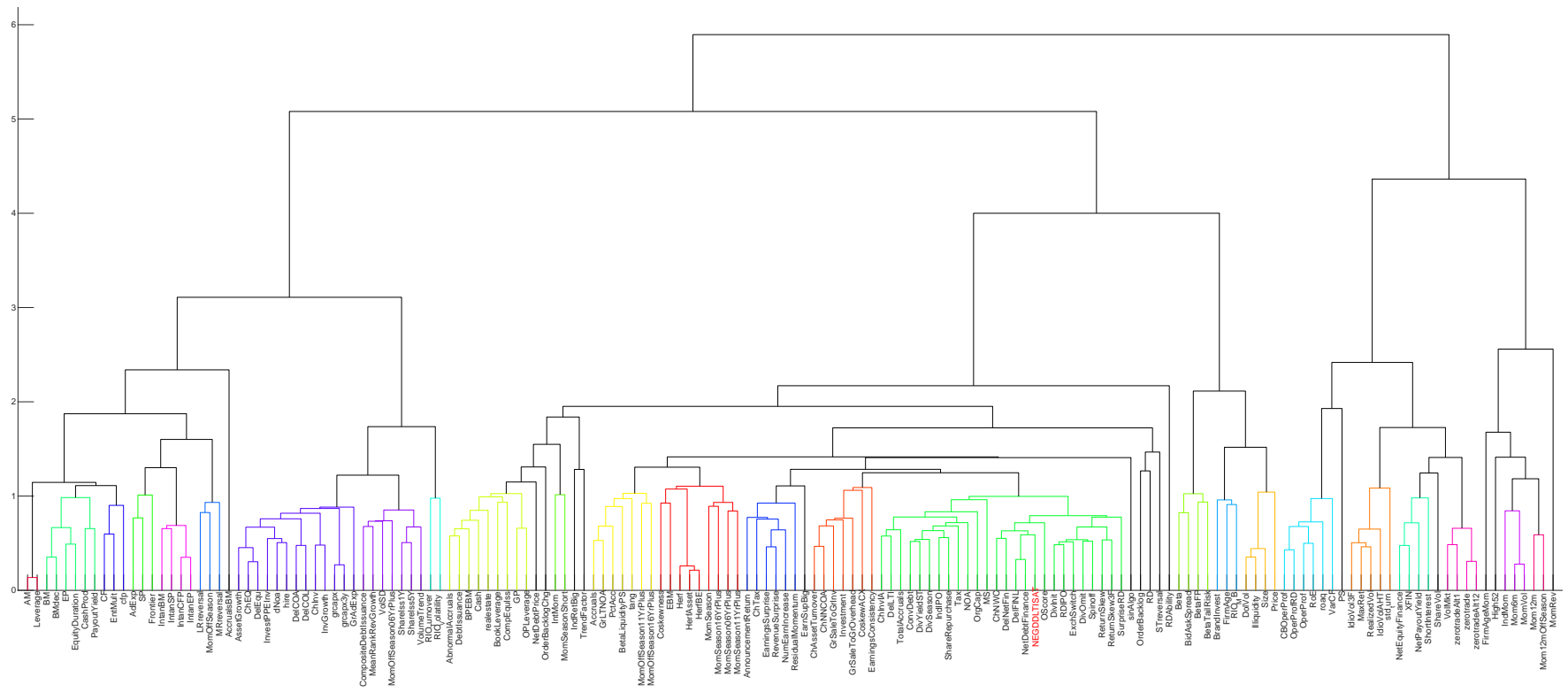
**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models

This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DIE 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.



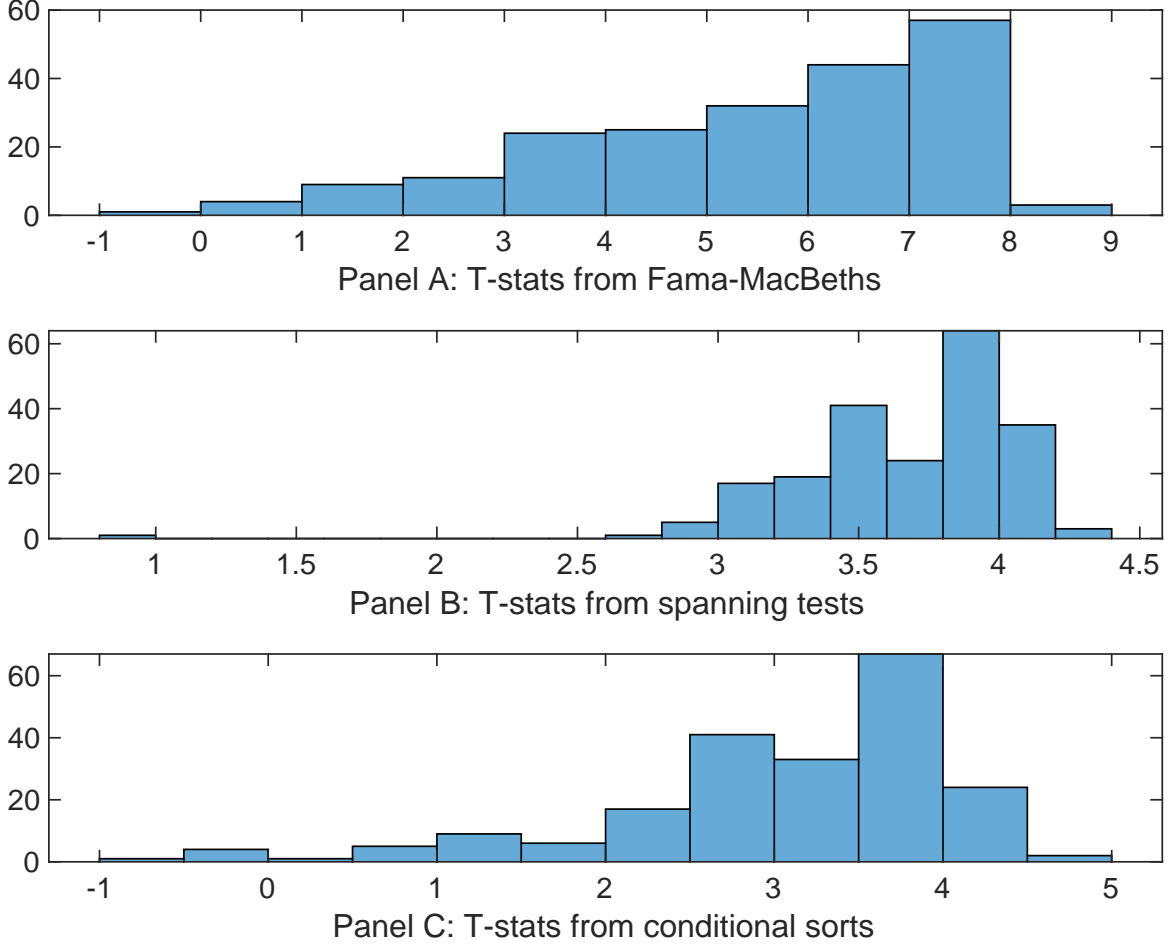
**Figure 5:** Distribution of correlations.

This figure plots a name histogram of correlations of 210 filtered anomaly signals with DIE. 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 DIE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on  $\beta_{DIE}$  from Fama-MacBeth regressions of the form  $r_{i,t} = \alpha + \beta_{DIE}DIE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$ , where  $X$  stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on  $\alpha$  from spanning tests of the form:  $r_{DIE,t} = \alpha + \beta r_{X,t} + \epsilon_t$ , 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 DIE. Stocks are finally grouped into five DIE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIE trading strategies conditioned on each of the 210 filtered anomalies.

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

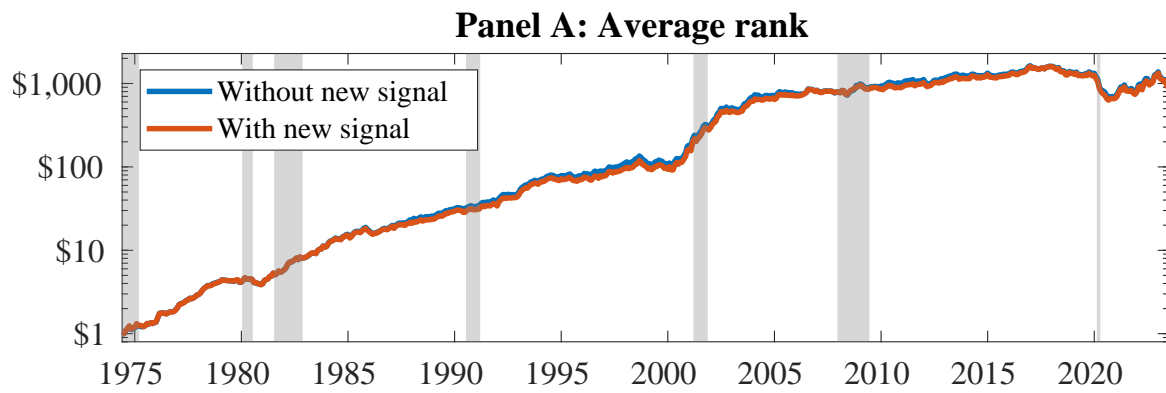
This table presents Fama-MacBeth results of returns on DIE. and the six most closely related anomalies. The regressions take the following form:  $r_{i,t} = \alpha + \beta_{DIE}DIE_{i,t} + \sum_{k=1}^s \beta_{X_k}X_{i,t}^k + \epsilon_{i,t}$ . The six most closely related anomalies,  $X$ , are Net debt financing, Change in financial liabilities, Net external financing, Inventory Growth, change in ppe and inv/assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the  $R^2$  from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.14 [5.49]	0.14 [5.52]	0.14 [5.86]	0.14 [5.47]	0.15 [5.88]	0.15 [5.95]	0.15 [5.89]
DIE	0.15 [1.58]	0.13 [1.40]	0.24 [2.24]	0.54 [5.35]	0.24 [2.68]	0.43 [0.43]	-0.77 [-0.69]
Anomaly 1	0.20 [8.25]						0.12 [1.87]
Anomaly 2		0.17 [8.92]					-0.84 [-1.76]
Anomaly 3			0.18 [5.81]				0.10 [1.82]
Anomaly 4				0.38 [6.67]			0.11 [0.18]
Anomaly 5					0.17 [7.60]		0.76 [2.76]
Anomaly 6						0.11 [8.97]	0.57 [2.72]
# 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 DIE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form:  $r_t^{DIE} = \alpha + \sum_{k=1}^6 \beta_{X_k} r_t^{X_k} + \sum_{j=1}^6 \beta_{f_j} r_t^{f_j} + \epsilon_t$ , 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, Net external financing, Inventory Growth, change in ppe and inv/assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the  $R^2$  from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.25 [3.31]	0.25 [3.30]	0.25 [3.29]	0.26 [3.48]	0.26 [3.45]	0.27 [3.47]	0.24 [3.19]
Anomaly 1	20.21 [4.76]						9.68 [1.65]
Anomaly 2		18.42 [4.14]					10.43 [1.75]
Anomaly 3			13.99 [3.62]				8.72 [2.06]
Anomaly 4				9.55 [3.18]			7.83 [2.49]
Anomaly 5					10.64 [3.04]		5.14 [1.36]
Anomaly 6						5.63 [1.13]	-4.71 [-0.90]
mkt	-4.28 [-2.48]	-4.06 [-2.34]	-2.39 [-1.31]	-4.54 [-2.60]	-4.53 [-2.59]	-4.25 [-2.42]	-3.33 [-1.84]
smb	-2.78 [-1.03]	-3.07 [-1.13]	3.07 [1.04]	-0.45 [-0.17]	-1.24 [-0.46]	-1.99 [-0.72]	1.17 [0.37]
hml	-10.22 [-3.08]	-9.57 [-2.87]	-8.94 [-2.65]	-10.84 [-3.23]	-11.77 [-3.48]	-10.69 [-3.16]	-9.65 [-2.86]
rmw	-5.98 [-1.73]	-5.74 [-1.65]	-12.70 [-3.05]	-3.01 [-0.86]	-3.95 [-1.14]	-4.31 [-1.23]	-9.87 [-2.33]
cma	18.32 [3.57]	17.37 [3.31]	14.13 [2.49]	15.00 [2.62]	15.20 [2.64]	16.48 [2.05]	6.62 [0.83]
umd	1.57 [0.88]	1.45 [0.80]	3.17 [1.81]	2.35 [1.32]	3.12 [1.77]	3.45 [1.93]	0.45 [0.25]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	11	10	9	9	8	7	13



**Figure 8:** Combination strategy performance

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



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