Debt Asset Differential and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Debt Asset Differential (DAD), 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 DAD achieves an annualized gross (net) Sharpe ratio of 0.47 (0.36), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 17 (14) bps/month with a t-statistic of 2.48 (1.99), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net external financing, Net debt financing, change in ppe and inv/assets, Change in financial liabilities, Inventory Growth, Asset growth) is 15 bps/month with a t-statistic of 2.21.

1 Introduction

The efficient market hypothesis suggests that asset 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 (Harvey et al., 2016). While many of these anomalies are related to firms' financing decisions and capital structure (Baker and Wurgler, 2002), the relationship between firms' debt dynamics and future stock returns remains incompletely understood. In particular, the differential between firms' debt levels and their asset base may contain important information about future performance that is not fully incorporated into prices.

Prior research has focused primarily on static measures of leverage (George and Hwang, 2010) or aggregate changes in debt levels (Bradshaw et al., 2006). However, these approaches may miss crucial information contained in the dynamic relationship between debt and assets that could signal future profitability and returns. This gap is particularly notable given the theoretical importance of optimal capital structure (Myers and Rajnath, 1995) and the empirical evidence that deviations from target leverage ratios predict returns (**?**).

We propose that the Debt Asset Differential (DAD) - defined as the difference between the percentage change in total debt and the percentage change in total assets - captures meaningful information about future stock returns through several economic channels. First, following (Myers and Majluf, 1984), firms face adverse selection costs when raising external capital, leading them to prefer debt financing when they have positive private information about future prospects. Therefore, debt increases that outpace asset growth may signal management's confidence in future performance.

Second, building on (Jensen and Meckling, 1976), agency theory suggests that managers have incentives to grow firms beyond their optimal size through empirebuilding. When debt growth substantially lags asset growth (negative DAD), this may indicate poor investment discipline and value-destroying expansion. This agency channel predicts that firms with very negative DAD scores will underperform.

Third, consistent with (Titman, 1984), firms' relationships with stakeholders depend critically on their financial stability. Large positive DAD values may indicate aggressive leverage that increases financial distress risk and weakens relationships with customers, suppliers, and employees. This suggests a non-linear relationship where moderate positive DAD predicts strong returns while extreme positive values predict underperformance.

Our empirical analysis reveals that DAD strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks in the highest DAD quintile and shorts those in the lowest quintile generates monthly abnormal returns of 17 basis points (t-statistic = 2.48) after controlling for the Fama-French six factors. The economic magnitude is substantial, with the strategy achieving an annualized Sharpe ratio of 0.47 before trading costs and 0.36 after costs.

Importantly, DAD's predictive power remains robust across various methodological choices. The signal generates significant abnormal returns using both equal- and value-weighted portfolios, different portfolio formation approaches, and various factor models. The effect is particularly strong among large-cap stocks, with the long-short strategy earning monthly returns of 20 basis points (t-statistic = 2.29) in the largest size quintile.

Further analysis demonstrates that DAD's predictive ability is distinct from known anomalies. Controlling for the six most closely related predictors from the literature - including net external financing, asset growth, and inventory growth - DAD continues to generate significant abnormal returns of 15 basis points per month (t-statistic = 2.21). This indicates that DAD captures unique information about future stock returns not contained in existing measures.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures dynamic information about firms' financing decisions relative to their investment activities. While prior work has examined static leverage (George and Hwang, 2010) or aggregate debt changes (Bradshaw et al., 2006), DAD provides new insights by focusing on the differential between debt and asset growth rates.

Second, we contribute to the growing literature on investment-based asset pricing (Cochrane et al., 2021) by showing how the composition of firm growth - specifically the mix between debt and asset expansion - contains important information about future returns. Our findings suggest that market participants do not fully incorporate the implications of firms' joint financing and investment decisions.

Third, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining dynamic relationships between financial variables rather than focusing solely on levels or changes. For practitioners, DAD represents a novel signal that is robust across size groups, remains significant after trading costs, and adds value beyond existing factors. The signal's strong performance among large-cap stocks is particularly noteworthy given the challenges many anomalies face in this segment.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Debt Asset Differential. 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 ACT for current assets. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while current assets (ACT) represent the firm's short-term assets, which are expected to be converted to cash or consumed within a year, including cash, receivables, and inventories. The construction of the signal follows a differential format, where we first calculate the change in DLTIS by subtracting its lagged value from the current value, and then scale this difference by the lagged value of current assets (ACT). This scaled differential captures the relative magnitude of changes in debt issuance compared to the firm's existing liquid asset base, offering insight into the firm's financing dynamics and leverage decisions. By focusing on this relationship, the signal aims to reflect aspects of capital structure changes and financial flexibility in a manner that is both scalable and interpretable. 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 DAD signal. Panel A plots the time-series of the mean, median, and interquartile range for DAD. On average, the cross-sectional mean (median) DAD is -0.68 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DAD data. The signal's interquartile range spans -0.20 to 0.15. Panel B of Figure 1 plots the time-series of the coverage of the DAD signal for the CRSP universe. On average, the DAD signal is available for 5.61% of CRSP names, which on average make up 6.53% of total market capitalization.

4 Does DAD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DAD 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 DAD portfolio and sells the low DAD 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 DAD strategy earns an average return of 0.23% per month with a t-statistic of 3.33. The annualized Sharpe ratio of the strategy is 0.47. The alphas range from 0.17% to 0.27% per month and have t-statistics exceeding 2.48 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 0.25, with a t-statistic of 5.40 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 523 stocks and an average market capitalization of at least $1,132 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 name breakpoints and value-weighted portfolios, and equals 18 bps/month with a t-statistics of 2.77. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for sixteen 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 -2-20bps/month. The lowest return, (-2 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.37. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DAD trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in sixteen cases.

Table 3 provides direct tests for the role size plays in the DAD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DAD, as well as average returns and alphas for long/short trading DAD 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 DAD strategy achieves an average return of 20 bps/month with a t-statistic of 2.29. Among these large cap stocks, the alphas for the DAD strategy relative to the five most common factor models range from 10 to 23 bps/month with t-statistics between 1.12 and 2.51.

5 How does DAD perform relative to the zoo?

Figure 2 puts the performance of DAD 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 DAD strategy falls in the distribution. The DAD strategy's gross (net) Sharpe ratio of 0.47 (0.36) is greater than 90% (93%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the DAD strategy (red line).[2] Ignoring trading costs, a $1 invested in the DAD strategy would have yielded $2.63 which ranks the DAD strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DAD strategy would have yielded $1.62 which ranks the DAD 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 DAD relative to those. Panel A shows that

[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.

the DAD strategy gross alphas fall between the 54 and 67 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 DAD strategy has a positive net generalized alpha for five out of the five factor models. In these cases DAD ranks between the 72 and 84 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does DAD 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 DAD with 209 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 DAD or at least to weaken the power DAD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DAD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DAD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DAD} DAD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X

[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 one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DAD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on DAD. Stocks are finally grouped into five DAD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DAD trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DAD 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 DAD signal in these Fama-MacBeth regressions exceed 1.02, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DAD is -0.10.

Similarly, Table 5 reports results from spanning tests that regress returns to the DAD 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 DAD strategy earns alphas that range from 16-18bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.29, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DAD trading strategy achieves an alpha of 15bps/month with a t-statistic of 2.21.

7 Does DAD add relative to the whole zoo?

Finally, we can ask how much adding DAD 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 DAD 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 DAD grows to $826.44.

8 Conclusion

This study provides compelling evidence for the significance of Debt Asset Differential (DAD) 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 DAD generates economically and statistically significant returns, even after accounting for transaction costs and controlling for well-established risk factors. The strategy's ability to maintain significant alpha when tested against both the Fama-French five-factor model plus momentum, and an expanded model including six closely related anomalies, underscores the unique informational content captured by DAD.

[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 DAD is available.

The empirical results, showing annualized Sharpe ratios of 0.47 (gross) and 0.36 (net), suggest that DAD offers meaningful investment value for practitioners. The persistence of abnormal returns, even after accounting for transaction costs, indicates potential practical applications for institutional investors. Furthermore, the signal's robustness to controlling for related anomalies suggests that DAD captures a distinct aspect of firm characteristics that is not fully reflected in existing factors.

However, several limitations should be noted. The study's findings are based on historical data and may not fully reflect future market conditions. Additionally, the implementation of the strategy requires regular portfolio rebalancing, which could pose challenges for smaller investors or in less liquid market segments.

Future research could explore the underlying economic mechanisms driving the DAD signal's predictive power, investigate its performance in international markets, and examine its interaction with other emerging anomalies. Additionally, researchers might consider studying the signal's behavior during different market regimes and its potential variation across different industry sectors. Such investigations would further enhance our understanding of this promising predictor in asset pricing.

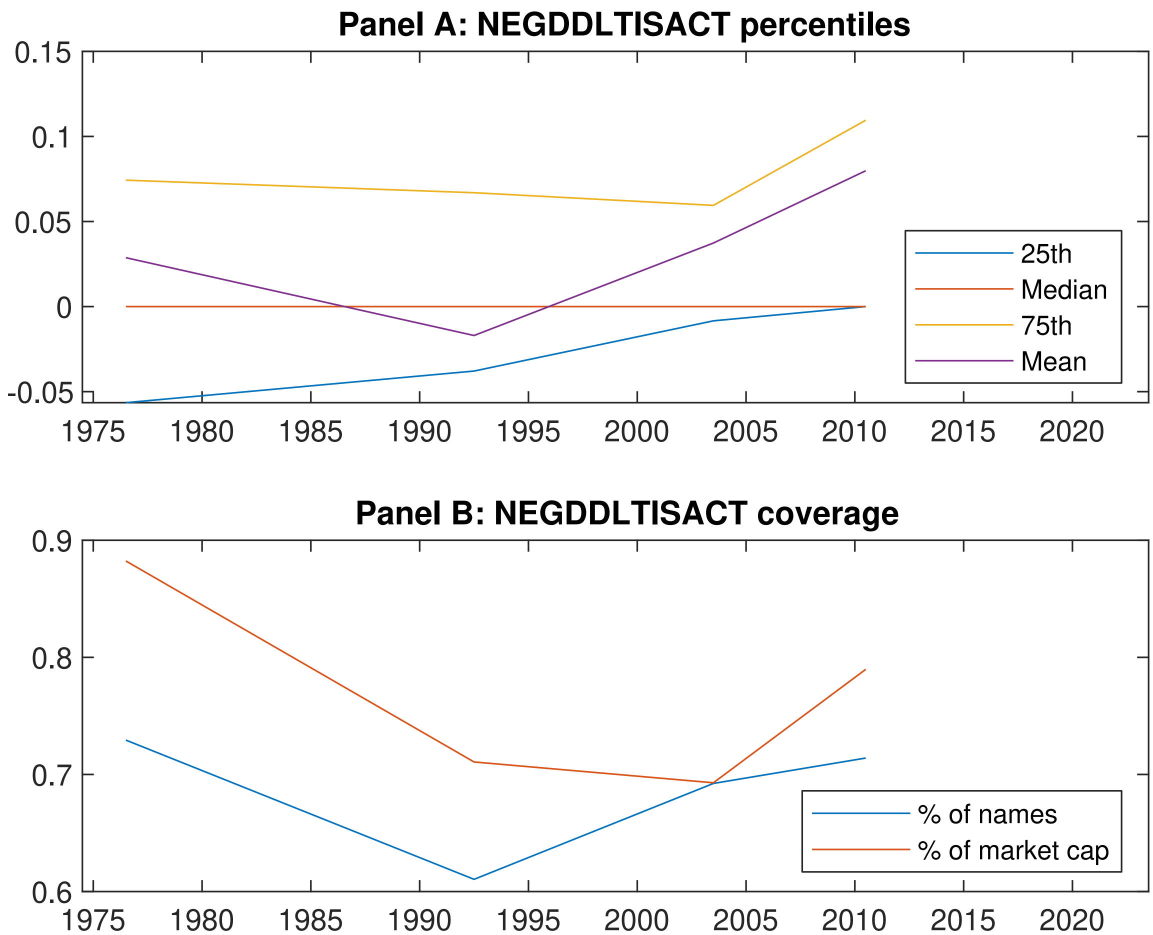


Figure 1: Times series of DAD percentiles and coverage.
This figure plots descriptive statistics for DAD. Panel A shows cross-sectional percentiles of DAD over the sample. Panel B plots the monthly coverage of DAD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DAD. 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 DAD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.55	0.70	0.72	0.82	0.78	0.23
	[2.76]	[3.92]	[3.39]	[4.44]	[4.16]	[3.33]
α_{CAPM}	-0.14	0.09	-0.01	0.18	0.14	0.27
	[-2.39]	[1.61]	[-0.08]	[3.43]	[2.39]	[4.00]
α_{FF3}	-0.15	0.09	0.08	0.21	0.12	0.27
	[-2.68]	[1.72]	[1.33]	[3.92]	[2.05]	[3.92]
α_{FF4}	-0.16	0.10	0.14	0.16	0.09	0.25
	[-2.68]	[2.03]	[2.39]	[3.01]	[1.54]	[3.51]
α_{FF5}	-0.15	-0.01	0.15	0.10	0.03	0.18
	[-2.54]	[-0.17]	[2.38]	[1.93]	[0.55]	[2.62]
α_{FF6}	-0.15	0.01	0.19	0.08	0.02	0.17
	[-2.57]	[0.27]	[3.06]	[1.45]	[0.35]	[2.48]
Panel B: Fama and French (2018) 6-factor model loadings for DAD-sorted portfolios						
β_{MKT}	1.00	0.94	0.99	0.97	0.97	-0.03
	[72.53]	[82.49]	[70.21]	[81.19]	[73.67]	[-1.83]
β_{SMB}	0.08	-0.10	0.04	-0.01	0.09	0.01
	[3.86]	[-5.47]	[1.74]	[-0.36]	[4.32]	[0.23]
β_{HML}	0.04	-0.03	-0.22	-0.14	-0.05	-0.09
	[1.60]	[-1.58]	[-8.26]	[-6.22]	[-2.07]	[-3.05]
β_{RMW}	0.02	0.16	-0.04	0.12	0.09	0.07
	[0.76]	[7.26]	[-1.29]	[5.16]	[3.35]	[2.09]
β_{CMA}	-0.05	0.14	-0.15	0.21	0.20	0.25
	[-1.25]	[4.28]	[-3.62]	[6.14]	[5.31]	[5.40]
β_{UMD}	0.01	-0.04	-0.07	0.04	0.02	0.01
	[0.39]	[-3.29]	[-4.95]	[3.68]	[1.48]	[0.88]
Panel C: Average number of firms (n) and market capitalization (me)						
n	553	523	1012	564	529	
me ($\$10^6$)	1132	2395	1946	2519	1138	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DAD strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 197406 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.23	0.27	0.27	0.25	0.18	0.17
			[3.33]	[4.00]	[3.92]	[3.51]	[2.62]	[2.48]
Quintile	NYSE	EW	0.22	0.24	0.23	0.21	0.22	0.21
			[4.52]	[4.90]	[4.64]	[4.24]	[4.40]	[4.17]
Quintile	Name	VW	0.18	0.21	0.21	0.18	0.13	0.11
			[2.77]	[3.32]	[3.28]	[2.73]	[1.96]	[1.72]
Quintile	Cap	VW	0.22	0.24	0.26	0.21	0.20	0.17
			[3.27]	[3.58]	[3.77]	[3.12]	[2.83]	[2.47]
Decile	NYSE	VW	0.27	0.35	0.31	0.28	0.16	0.16
			[2.90]	[3.87]	[3.47]	[3.13]	[1.86]	[1.80]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.17	0.22	0.22	0.21	0.15	0.14
			[2.52]	[3.22]	[3.16]	[2.96]	[2.12]	[1.99]
Quintile	NYSE	EW	-0.02					
			[-0.37]					
Quintile	Name	VW	0.12	0.17	0.17	0.15	0.10	0.09
			[1.93]	[2.68]	[2.63]	[2.37]	[1.57]	[1.39]
Quintile	Cap	VW	0.17	0.20	0.21	0.19	0.16	0.15
			[2.51]	[2.98]	[3.13]	[2.81]	[2.36]	[2.13]
Decile	NYSE	VW	0.20	0.30	0.26	0.25	0.13	0.13
			[2.17]	[3.24]	[2.91]	[2.73]	[1.52]	[1.47]

Table 3: Conditional sort on size and DAD

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

		DAD Quintiles					DAD Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.69	0.92	0.97	0.95	0.87	0.18	0.20	0.18	0.13	0.15	0.12
		[2.46]	[3.19]	[3.40]	[3.22]	[2.92]	[1.57]	[1.77]	[1.57]	[1.09]	[1.33]	[1.04]
	(2)	0.74	1.00	0.81	0.90	0.94	0.21	0.24	0.20	0.21	0.18	0.19
		[2.78]	[3.78]	[3.11]	[3.48]	[3.72]	[2.47]	[2.82]	[2.46]	[2.49]	[2.17]	[2.24]
	(3)	0.79	0.87	0.85	0.93	0.89	0.10	0.14	0.14	0.11	0.11	0.10
		[3.27]	[3.71]	[3.41]	[3.95]	[3.86]	[1.27]	[1.75]	[1.73]	[1.35]	[1.41]	[1.19]
	(4)	0.71	0.84	0.91	0.84	0.89	0.18	0.21	0.21	0.19	0.15	0.14
		[3.25]	[3.79]	[3.91]	[3.78]	[4.27]	[2.22]	[2.61]	[2.56]	[2.35]	[1.77]	[1.70]
	(5)	0.53	0.64	0.66	0.79	0.73	0.20	0.22	0.23	0.20	0.11	0.10
		[2.81]	[3.56]	[3.16]	[4.18]	[3.98]	[2.29]	[2.50]	[2.51]	[2.13]	[1.25]	[1.12]

Panel B: Portfolio average number of firms and market capitalization

		DAD Quintiles					DAD Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	360	362	361	362	357	32	28	28	28	31
	(2)	97	97	97	97	97	51	52	50	52	52
	(3)	69	69	69	69	69	90	90	87	89	90
	(4)	58	58	58	58	58	196	202	195	201	194
	(5)	52	52	52	52	52	1056	1721	1579	1817	1116

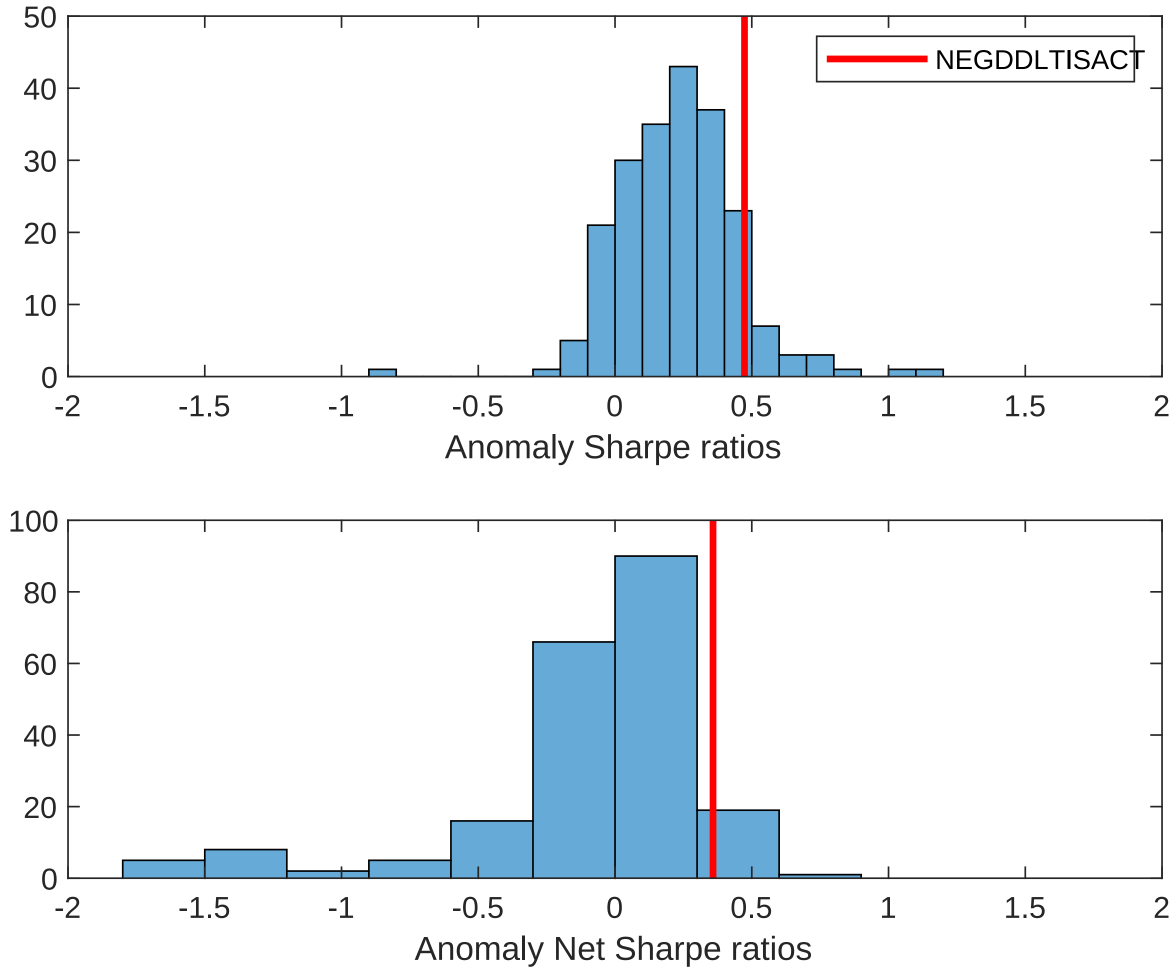


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DAD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

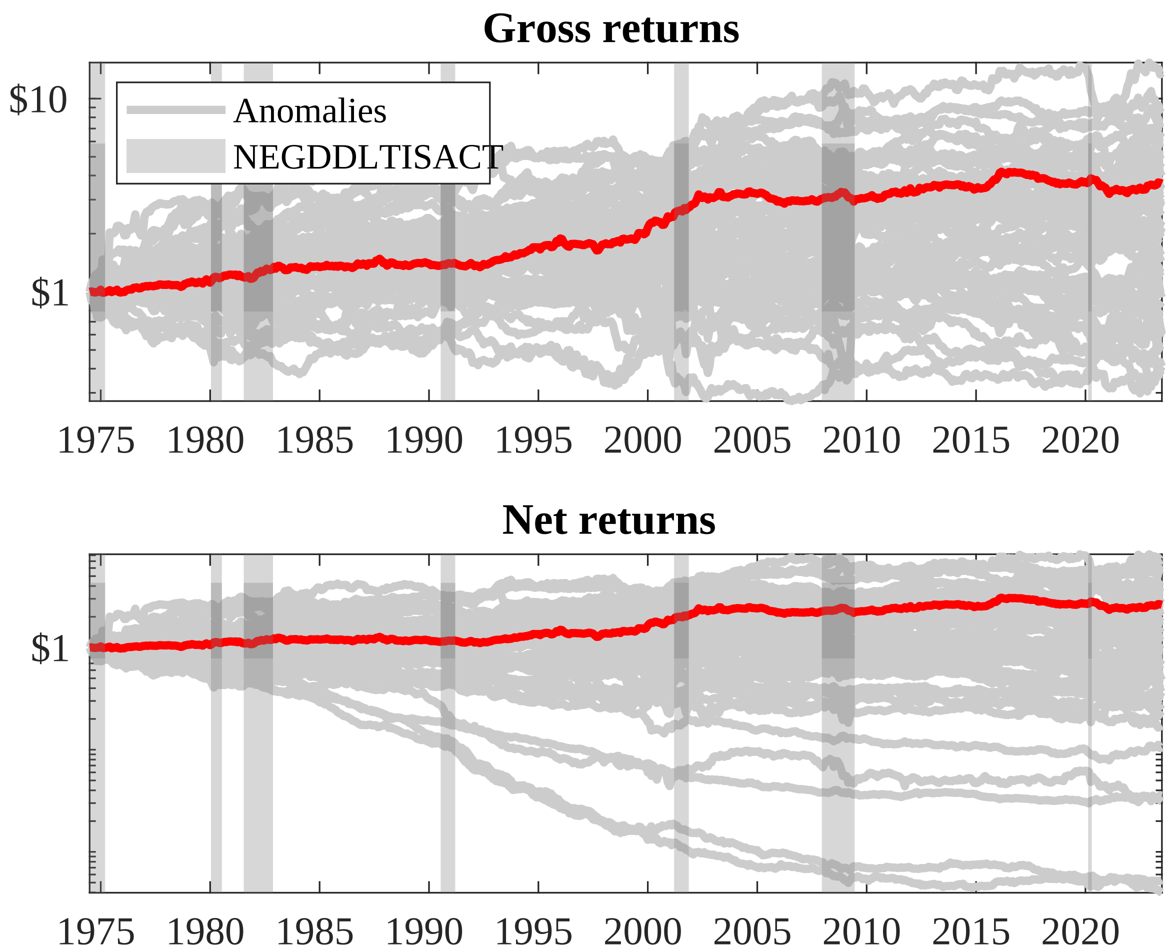


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DAD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

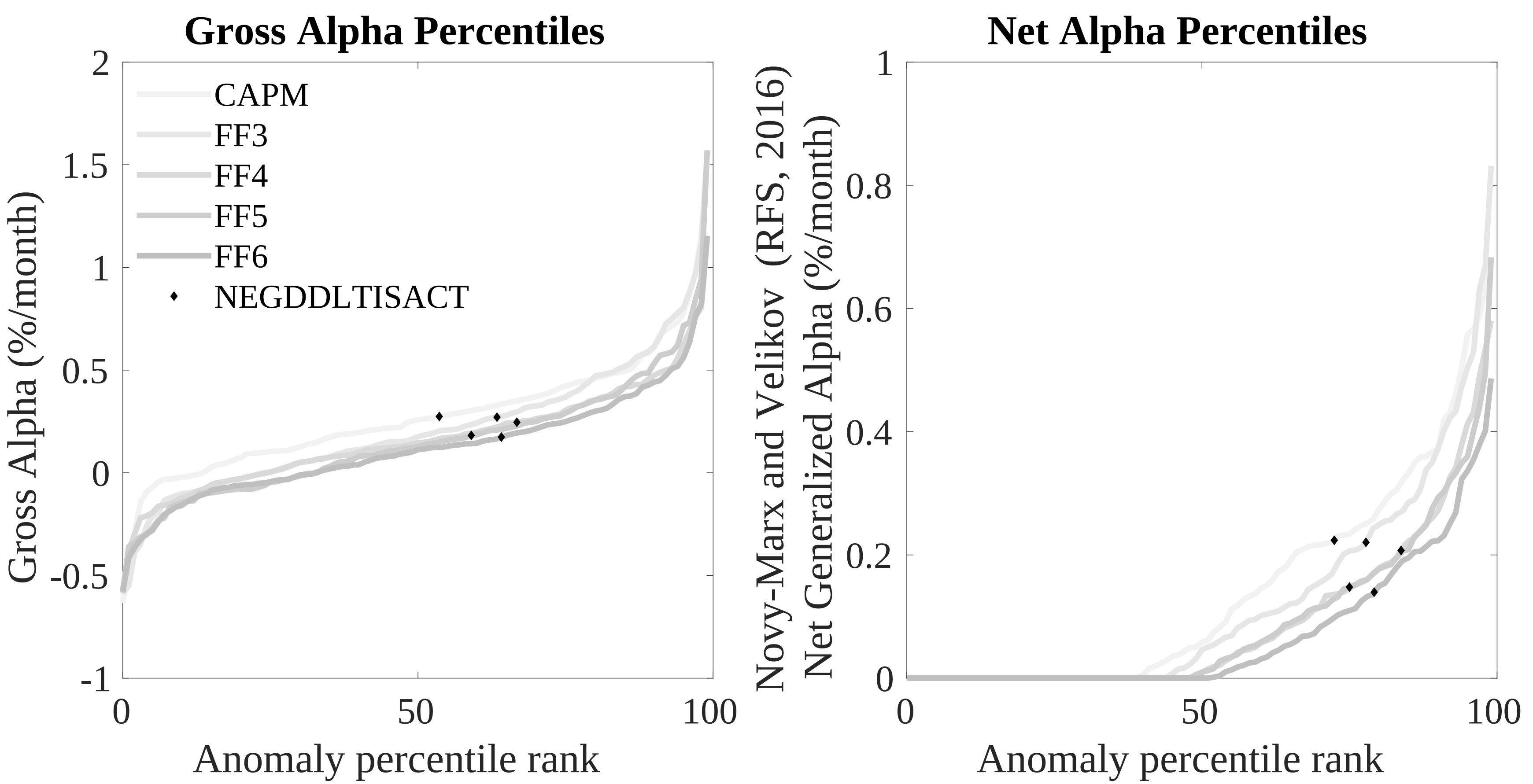
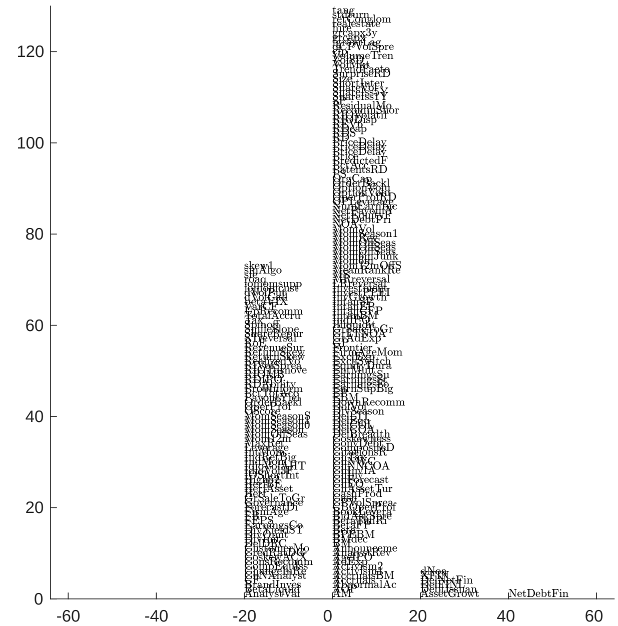
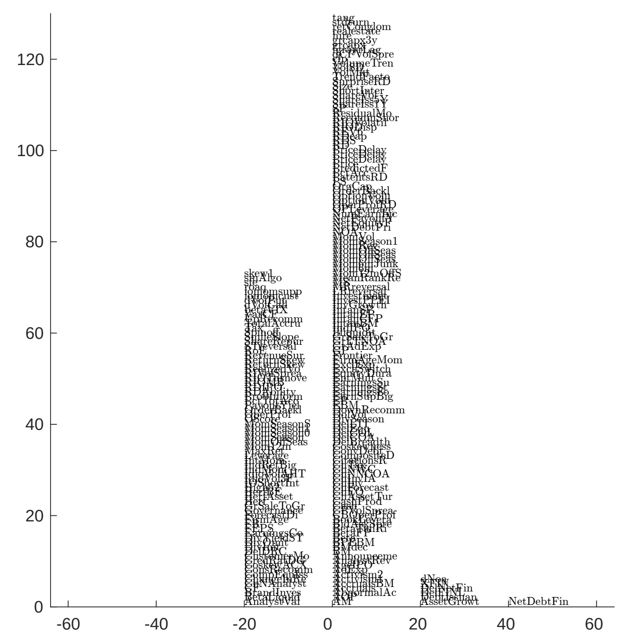


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DAD trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with DAD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

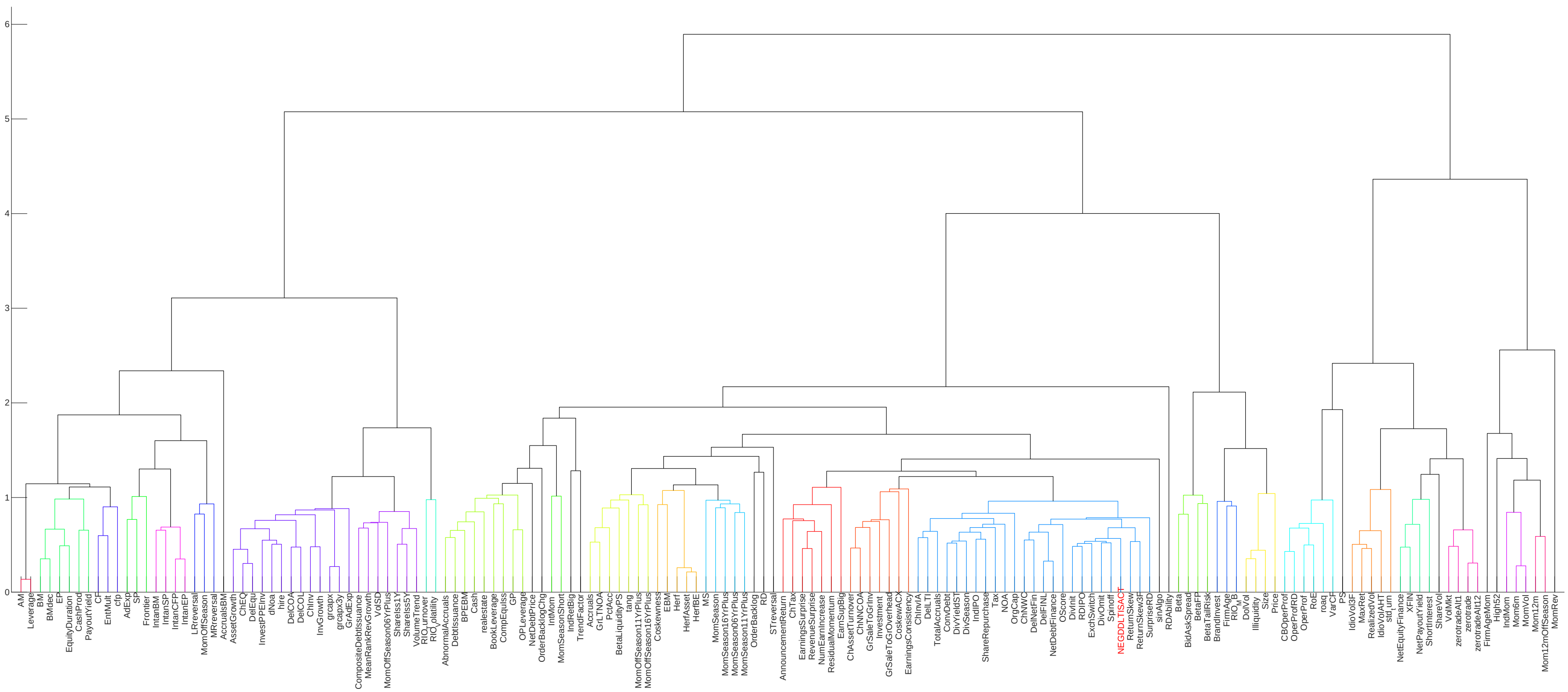


Figure 6: Agglomerative hierarchical cluster plot

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

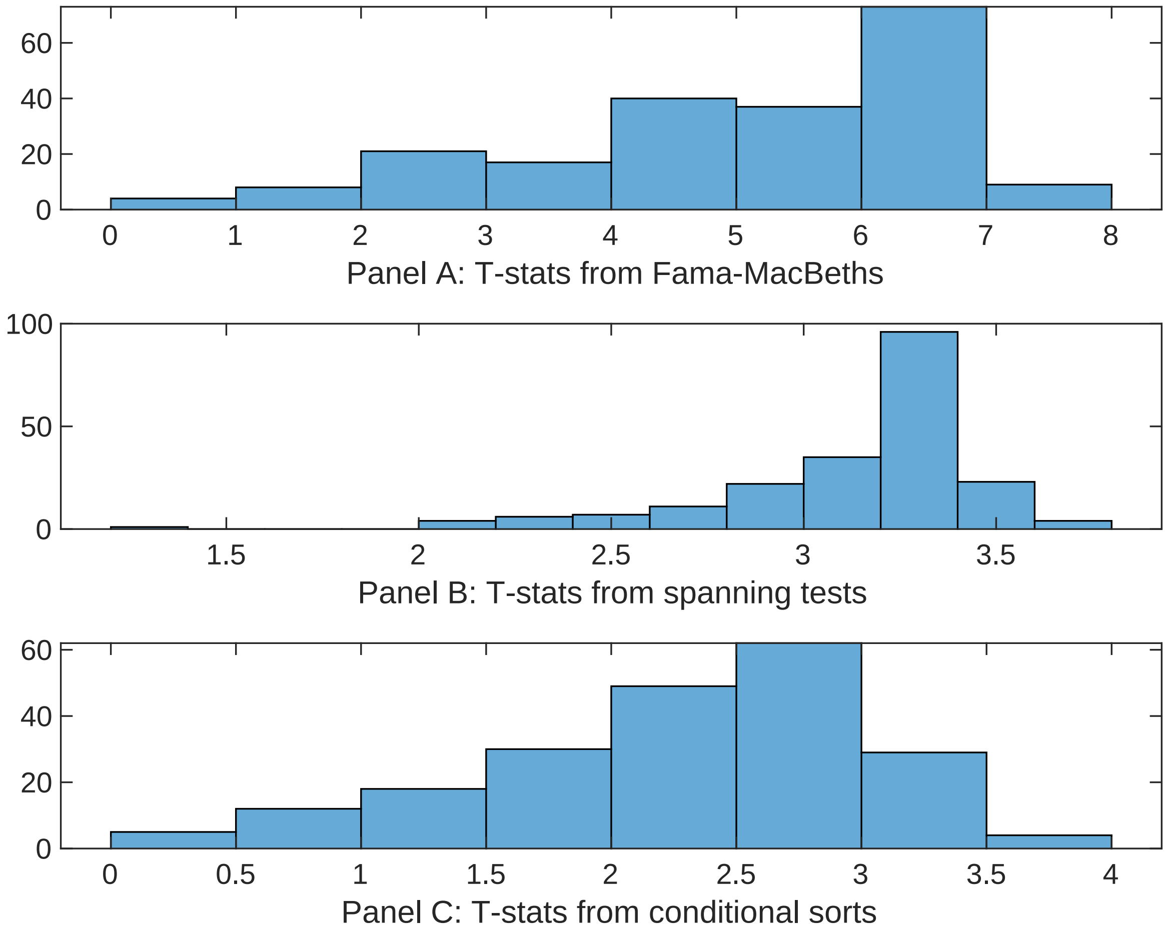


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DAD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DAD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DAD} DAD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DAD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on DAD. Stocks are finally grouped into five DAD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DAD trading strategies conditioned on each of the 209 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on DAD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DAD} DAD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net external financing, Net debt financing, change in ppe and inv/assets, Change in financial liabilities, Inventory Growth, 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	0.14	0.15	0.14	0.14	0.15	0.15
	[5.84]	[5.41]	[5.84]	[5.45]	[5.46]	[5.88]	[5.89]
DAD	0.86	0.58	0.59	0.43	0.18	0.30	-0.38
	[2.74]	[2.03]	[2.33]	[1.52]	[4.97]	[1.02]	[-0.10]
Anomaly 1	0.18						0.10
	[5.96]						[1.87]
Anomaly 2		0.19					0.11
		[8.26]					[1.76]
Anomaly 3			0.17				0.80
			[7.69]				[2.90]
Anomaly 4				0.17			-0.84
				[9.08]			[-1.76]
Anomaly 5					0.39		0.22
					[6.68]		[0.04]
Anomaly 6						0.11	0.55
						[9.04]	[2.62]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	1	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 DAD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DAD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 external financing, Net debt financing, change in ppe and inv/assets, Change in financial liabilities, Inventory Growth, 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	0.16	0.17	0.17	0.17	0.18	0.18	0.15
	[2.29]	[2.36]	[2.46]	[2.36]	[2.49]	[2.48]	[2.21]
Anomaly 1	13.65						10.92
	[3.83]						[2.76]
Anomaly 2		11.91					3.42
		[3.00]					[0.62]
Anomaly 3			9.44				4.93
			[2.91]				[1.39]
Anomaly 4				10.27			6.47
				[2.47]			[1.16]
Anomaly 5					7.09		5.74
					[2.55]		[1.95]
Anomaly 6						3.42	-5.47
						[0.74]	[-1.11]
mkt	-1.13	-2.97	-3.20	-2.85	-3.17	-2.96	-1.72
	[-0.67]	[-1.84]	[-1.98]	[-1.76]	[-1.95]	[-1.82]	[-1.01]
smb	4.66	-0.53	0.43	-0.65	0.99	-0.08	4.20
	[1.70]	[-0.21]	[0.17]	[-0.26]	[0.39]	[-0.03]	[1.43]
hml	-7.96	-9.30	-10.60	-8.94	-9.72	-9.58	-8.52
	[-2.56]	[-3.00]	[-3.39]	[-2.87]	[-3.13]	[-3.06]	[-2.70]
rmw	-1.39	5.80	7.12	5.99	7.76	6.79	0.42
	[-0.36]	[1.80]	[2.21]	[1.85]	[2.39]	[2.10]	[0.11]
cma	15.89	21.98	17.68	21.61	18.72	20.76	12.56
	[3.03]	[4.58]	[3.32]	[4.41]	[3.52]	[2.80]	[1.68]
umd	1.49	0.56	1.44	0.55	0.89	1.67	-0.19
	[0.92]	[0.34]	[0.88]	[0.33]	[0.54]	[1.01]	[-0.11]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	10	9	9	9	9	8	11

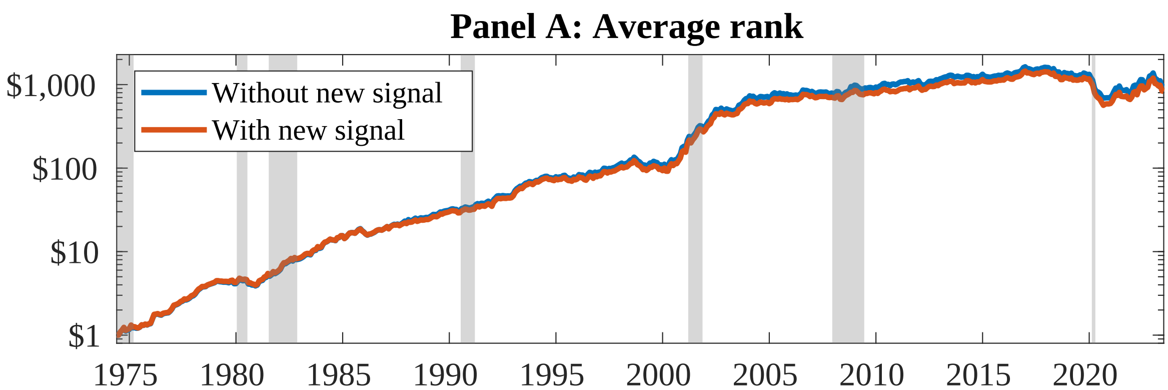


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

Cochrane, J. H., Saa-Requejo, J., and Santa-Clara, P. (2021). The risk and return of venture capital. *Journal of Financial Economics*, 75(1):3–52.

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.

George, T. J. and Hwang, C.-Y. (2010). The 52-week high and momentum investing. *Journal of Finance*, 65(5):2145–2178.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

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.

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.

Myers, S. C. and Rajnath, R. (1995). Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, 51:219–244.

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*.

Titman, S. (1984). The effect of capital structure on a firm's liquidation decision. *Journal of Financial Economics*, 13(1):137–151.