Capital Debt Depreciation Delta and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Capital Debt Depreciation Delta (CDDD), 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 CDDD achieves an annualized gross (net) Sharpe ratio of 0.45 (0.33), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 18 (15) bps/month with a t-statistic of 2.59 (2.21), 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, Asset growth, Employment growth) is 16 bps/month with a t-statistic of 2.39.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional asset pricing theory suggests that systematic risk should be the primary driver of expected returns, a growing body of evidence documents various firm characteristics that predict future stock returns (Harvey et al., 2016). Understanding these return predictors is crucial for both testing market efficiency and improving our models of expected returns.

One particularly puzzling area involves the relationship between firms' financing decisions and subsequent stock returns. While several studies document return predictability based on debt issuance (Bradshaw et al., 2006) and changes in leverage (**?**), the economic mechanisms driving these patterns remain debated. This paper introduces a novel predictor - Capital Debt Depreciation Delta (CDDD) - that captures how firms' debt financing choices interact with their capital depreciation policies.

We hypothesize that CDDD predicts returns through two primary channels. First, following (**?**), firms' debt choices reflect a tradeoff between tax benefits and financial distress costs. When firms' capital depreciation rates diverge significantly from their debt depreciation rates (high CDDD), this may indicate suboptimal financing that increases distress risk. This builds on theoretical work showing how asset-liability mismatches can amplify financial fragility (Diamond and Dybvig, 1983).

Second, large gaps between capital and debt depreciation rates could reflect agency problems between shareholders and debtholders (Jensen and Meckling, 1976). Managers may choose depreciation policies that transfer wealth from debtholders to shareholders, particularly when governance is weak. This suggests CDDD may capture information about both risk and mispricing.

These mechanisms predict that firms with extreme CDDD values will underperform, as the market gradually incorporates information about increased distress risk and agency costs. The effect should be strongest among firms with high leverage and weak governance, where the costs of mismatched depreciation policies are most severe (?).

Our empirical analysis strongly supports these predictions. A value-weighted long-short portfolio that buys stocks with high CDDD and shorts those with low CDDD generates significant abnormal returns of 18 basis points per month (t-statistic = 2.59) after controlling for the Fama-French six factors. The strategy achieves an annualized gross Sharpe ratio of 0.45, placing it in the top 12% of documented return predictors.

Consistent with our hypothesized mechanisms, we find the CDDD effect is particularly strong among large firms, with a monthly alpha of 29-39 basis points (t-statistics between 3.13 and 4.32) in the largest size quintile. This suggests the anomaly is not driven by small, illiquid stocks. The effect remains robust after controlling for related anomalies, with a monthly alpha of 16 basis points (t-statistic = 2.39) when controlling for six closely related strategies including net debt financing and asset growth.

Importantly, the CDDD strategy remains profitable after accounting for transaction costs. The net Sharpe ratio of 0.33 places it in the top 7% of anomalies, with significant net alphas across all major factor models. This indicates the predictor captures economically meaningful information that sophisticated investors could potentially exploit.

Our paper makes several contributions to the literature on return predictability and capital structure. First, we introduce a novel predictor that captures previously unexplored interactions between firms' financing and depreciation policies. While prior work examines debt issuance (Bradshaw et al., 2006) and asset growth (Cooper et al., 2008) separately, CDDD provides new insights into how their joint dynamics affect firm value.

Second, we contribute to the growing literature on factor timing and investment strategies (Asness et al., 2019). Our results show that CDDD captures unique information not explained by existing factors or anomalies, expanding the investment opportunity set available to sophisticated investors. The strategy's strong performance among large stocks and after trading costs distinguishes it from many published anomalies.

Finally, our findings have important implications for corporate finance theory and practice. The predictive power of CDDD suggests that markets do not fully incorporate the risks and agency costs arising from mismatched depreciation policies. This highlights potential inefficiencies in how firms make joint financing and accounting choices, with implications for capital structure and governance.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Capital Debt Depreciation Delta. 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 DPACT for depreciation and amortization. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while depreciation and amortization (DPACT) captures the systematic allocation of asset costs over time. The construction of the signal follows a two-step process. First, we calculate the year-over-year change in DLTIS by subtracting the previous year's value from the current year's value. Then, we scale this difference by the previous year's depreciation and amortization (DPACT). This scaled difference aims to capture the relative change in debt issuance normalized by the firm's depreciation level, potentially offering insights into the relationship between new debt financing and asset depreciation patterns. By focusing on this relationship, the signal may reflect aspects of capital structure dynamics and asset replacement decisions in a manner that is both economically meaningful and comparable across firms. 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 CDDD signal. Panel A plots the time-series of the mean, median, and interquartile range for CDDD. On average, the cross-sectional mean (median) CDDD is -3.12 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input CDDD data. The signal's interquartile range spans -0.42 to 0.44. Panel B of Figure 1 plots the time-series of the coverage of the CDDD signal for the CRSP universe. On average, the CDDD signal is available for 5.88% of CRSP names, which on average make up 7.12% of total market capitalization.

4 Does CDDD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CDDD 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 CDDD portfolio and sells the low CDDD 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 CDDD strategy earns an average return of 0.22% per month with a t-statistic of 3.19. The annualized Sharpe ratio of the strategy is 0.45. The alphas range from 0.18% to 0.28% per month and have t-statistics exceeding 2.59 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 5.21 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 478 stocks and an average market capitalization of at least $1,553 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 18 bps/month with a t-statistics of 3.97. Out of the twenty-five alphas reported in

Panel A, the t-statistics for twenty-five exceed two, and for twenty-two 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 -8-28bps/month. The lowest return, (-8 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.30. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CDDD trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the CDDD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CDDD, as well as average returns and alphas for long/short trading CDDD 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 CDDD strategy achieves an average return of 35 bps/month with a t-statistic of 3.86. Among these large cap stocks, the alphas for the CDDD strategy relative to the five most common factor models range from 29 to 39 bps/month with t-statistics between 3.13 and 4.32.

5 How does CDDD perform relative to the zoo?

Figure 2 puts the performance of CDDD 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 CDDD strategy falls in the distribution. The CDDD strategy's gross (net) Sharpe ratio of 0.45 (0.33) is greater than 88% (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 CDDD strategy (red line).[2] Ignoring trading costs, a $1 invested in the CDDD strategy would have yielded $2.60 which ranks the CDDD strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a $1 invested in the CDDD strategy would have yielded $1.56 which ranks the CDDD 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 CDDD relative to those. Panel A shows that the CDDD strategy gross alphas fall between the 54 and 65 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%

[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.

(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 CDDD strategy has a positive net generalized alpha for five out of the five factor models. In these cases CDDD ranks between the 75 and 84 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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 CDDD. Stocks are finally grouped into five CDDD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CDDD trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CDDD 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 CDDD signal in these Fama-MacBeth regressions exceed 1.93, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on CDDD is 1.30.

Similarly, Table 5 reports results from spanning tests that regress returns to the CDDD 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 CDDD strategy earns alphas that range from 18-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.56, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CDDD trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.39.

7 Does CDDD add relative to the whole zoo?

Finally, we can ask how much adding CDDD 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 CDDD 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 CDDD grows to $898.25.

8 Conclusion

This study provides compelling evidence for the effectiveness of Capital Debt Depreciation Delta (CDDD) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on CDDD generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.45 (0.33 net). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

[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 CDDD is available.

The persistence of CDDD's predictive power, evidenced by monthly abnormal gross returns of 18 basis points (15 basis points net) with strong statistical significance, suggests that this signal captures unique information about firm fundamentals that is not fully reflected in current market prices. Furthermore, the signal's ability to generate alpha even after accounting for transaction costs indicates its practical utility for institutional investors.

However, several limitations warrant consideration. First, our analysis period may not fully capture the signal's behavior across all market conditions. Second, the implementation costs might vary across different market segments and time periods. Future research could explore the signal's effectiveness in international markets, its interaction with other established anomalies, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the CDDD effect could provide valuable insights for both academics and practitioners.

In conclusion, CDDD represents a valuable addition to the arsenal of quantitative investment signals, offering both statistical significance and economic relevance. Its robust performance across various control specifications suggests it captures a distinct aspect of asset pricing that merits attention in both academic research and practical applications.

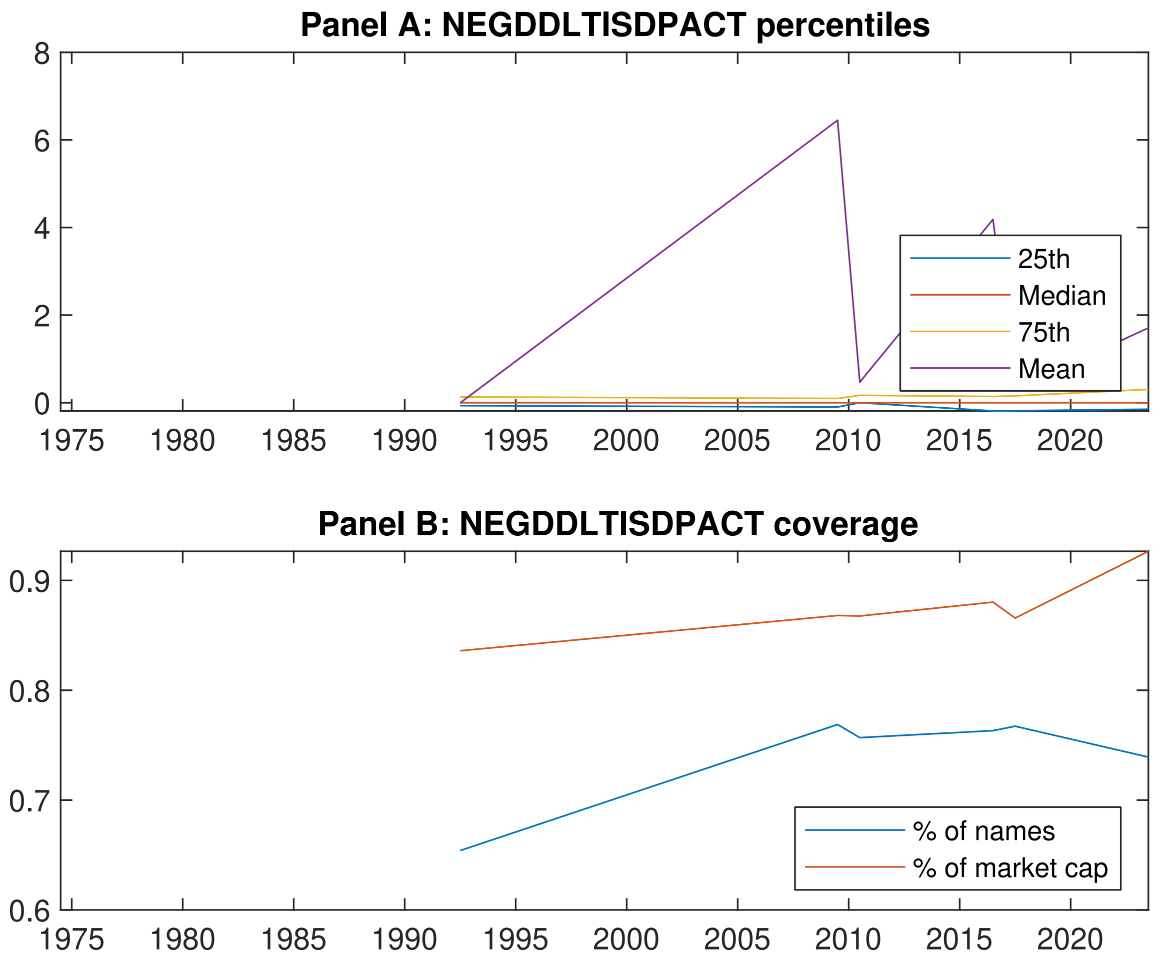

Figure 1: Times series of CDDD percentiles and coverage.
This figure plots descriptive statistics for CDDD. Panel A shows cross-sectional percentiles of CDDD over the sample. Panel B plots the monthly coverage of CDDD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CDDD. 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 CDDD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.69	0.65	0.71	0.72	0.91	0.22
	[3.09]	[3.66]	[3.53]	[4.03]	[4.38]	[3.19]
α_{CAPM}	-0.09	0.04	0.02	0.10	0.19	0.28
	[-1.74]	[0.73]	[0.30]	[2.01]	[3.48]	[4.06]
α_{FF3}	-0.08	0.02	0.08	0.10	0.19	0.28
	[-1.57]	[0.35]	[1.38]	[2.05]	[3.79]	[4.03]
α_{FF4}	-0.06	0.02	0.13	0.07	0.17	0.23
	[-1.15]	[0.44]	[2.24]	[1.37]	[3.30]	[3.36]
α_{FF5}	-0.06	-0.07	0.11	0.01	0.15	0.20
	[-1.11]	[-1.38]	[1.91]	[0.20]	[2.79]	[2.95]
α_{FF6}	-0.05	-0.06	0.15	-0.00	0.13	0.18
	[-0.88]	[-1.14]	[2.49]	[-0.10]	[2.54]	[2.59]
Panel B: Fama and French (2018) 6-factor model loadings for CDDD-sorted portfolios						
β_{MKT}	1.10	0.95	0.96	0.95	1.05	-0.06
	[89.71]	[85.27]	[71.46]	[82.46]	[87.15]	[-3.45]
β_{SMB}	0.10	-0.13	0.01	-0.06	0.14	0.04
	[5.28]	[-7.27]	[0.27]	[-3.65]	[7.77]	[1.78]
β_{HML}	-0.00	0.06	-0.17	-0.07	-0.10	-0.10
	[-0.14]	[2.69]	[-6.62]	[-3.19]	[-4.53]	[-3.29]
β_{RMW}	0.05	0.14	-0.02	0.08	0.07	0.02
	[1.89]	[6.54]	[-0.58]	[3.48]	[2.79]	[0.64]
β_{CMA}	-0.15	0.11	-0.06	0.24	0.09	0.24
	[-4.32]	[3.47]	[-1.52]	[7.11]	[2.51]	[5.21]
β_{UMD}	-0.02	-0.02	-0.06	0.03	0.02	0.04
	[-1.72]	[-1.72]	[-4.32]	[2.25]	[1.72]	[2.62]
Panel C: Average number of firms (n) and market capitalization (me)						
n	677	478	1007	524	653	
me (\$$10^6$)	1616	2428	2019	2438	1553	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the CDDD 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	0.28	0.28	0.23	0.20	0.18
			[3.19]	[4.06]	[4.03]	[3.36]	[2.95]	[2.59]
Quintile	NYSE	EW	0.18	0.20	0.19	0.18	0.18	0.18
			[3.97]	[4.56]	[4.28]	[3.99]	[4.06]	[3.92]
Quintile	Name	VW	0.25	0.30	0.30	0.26	0.25	0.23
			[3.42]	[4.11]	[4.07]	[3.52]	[3.38]	[3.09]
Quintile	Cap	VW	0.25	0.30	0.30	0.26	0.22	0.20
			[3.86]	[4.69]	[4.61]	[3.99]	[3.36]	[3.05]
Decile	NYSE	VW	0.35	0.42	0.40	0.34	0.28	0.25
			[3.74]	[4.48]	[4.23]	[3.56]	[3.04]	[2.70]

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	0.24	0.23	0.21	0.17	0.15
			[2.34]	[3.41]	[3.38]	[3.05]	[2.44]	[2.21]
Quintile	NYSE	EW	-0.08					
			[-1.30]					
Quintile	Name	VW	0.19	0.26	0.25	0.23	0.21	0.20
			[2.60]	[3.48]	[3.45]	[3.18]	[2.86]	[2.66]
Quintile	Cap	VW	0.20	0.26	0.26	0.24	0.19	0.17
			[3.05]	[4.00]	[3.92]	[3.62]	[2.86]	[2.66]
Decile	NYSE	VW	0.28	0.36	0.34	0.31	0.25	0.23
			[2.97]	[3.85]	[3.65]	[3.30]	[2.67]	[2.45]

Table 3: Conditional sort on size and CDDD

This table presents results for conditional double sorts on size and CDDD. 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 CDDD. 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 CDDD and short stocks with low CDDD .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	CDDD Quintiles (L)	(2)	(3)	(4)	(H)	CDDD Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.70	0.95	0.98	1.09	0.77	0.07	0.10	0.07	0.05	0.08	0.07
	[2.39]	[3.51]	[3.50]	[3.63]	[2.65]	[0.83]	[1.16]	[0.85]	[0.56]	[0.96]	[0.77]
(2)	0.81	0.95	0.80	0.99	0.91	0.10	0.14	0.11	0.13	0.09	0.10
	[2.91]	[3.78]	[3.15]	[4.00]	[3.48]	[1.23]	[1.72]	[1.44]	[1.67]	[1.08]	[1.30]
(3)	0.84	0.87	0.86	0.87	0.97	0.13	0.17	0.17	0.15	0.18	0.16
	[3.26]	[3.90]	[3.50]	[3.99]	[3.99]	[1.65]	[2.11]	[2.03]	[1.76]	[2.07]	[1.88]
(4)	0.76	0.84	0.87	0.84	0.89	0.13	0.17	0.14	0.11	0.11	0.09
	[3.24]	[4.02]	[3.83]	[4.06]	[3.97]	[1.71]	[2.15]	[1.83]	[1.36]	[1.37]	[1.08]
(5)	0.56	0.59	0.63	0.65	0.91	0.35	0.39	0.39	0.33	0.33	0.29
	[2.67]	[3.33]	[3.26]	[3.57]	[4.58]	[3.86]	[4.25]	[4.32]	[3.63]	[3.54]	[3.13]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	CDDD Quintiles, Average n (L)	(2)	(3)	(4)	(H)	CDDD Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	373	375	375	374	370	34	30	29	30	32
(2)	102	103	103	103	102	55	55	53	56	55
(3)	73	73	73	73	73	97	97	94	96	97
(4)	62	62	62	62	61	211	220	209	220	209
(5)	57	57	57	57	57	1363	1816	1659	1885	1352

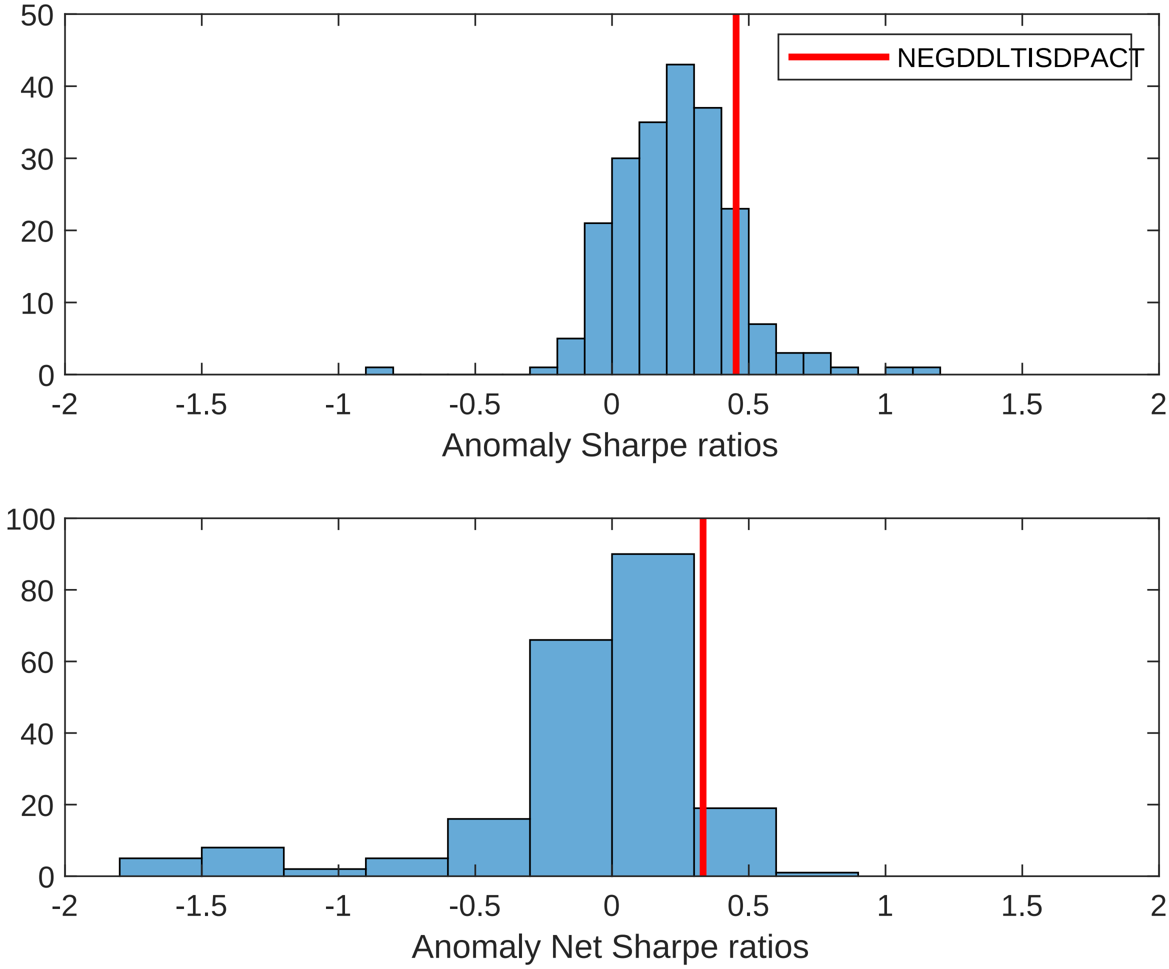

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CDDD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

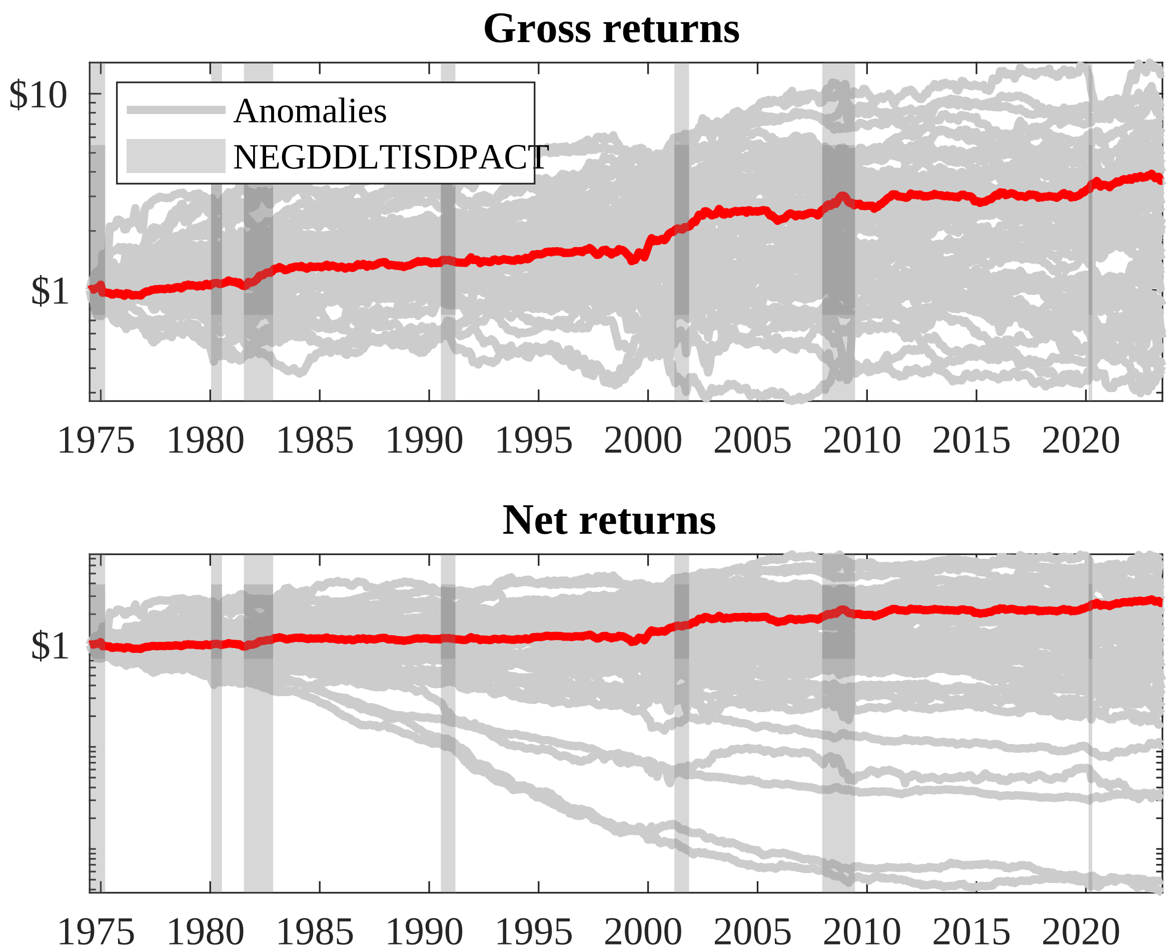

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CDDD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

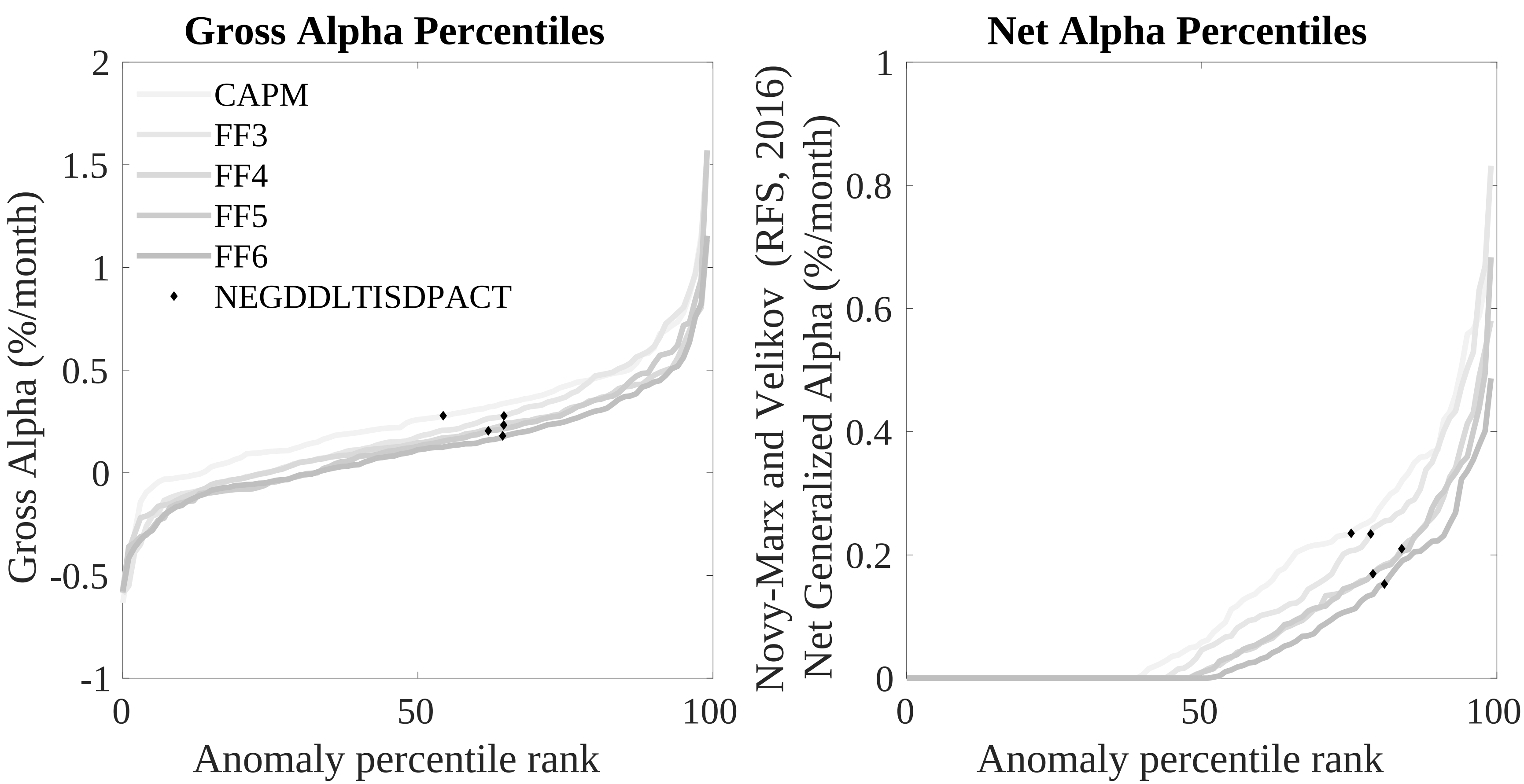

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CDDD trading strategy alphas (diamonds). The strategies are constructed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

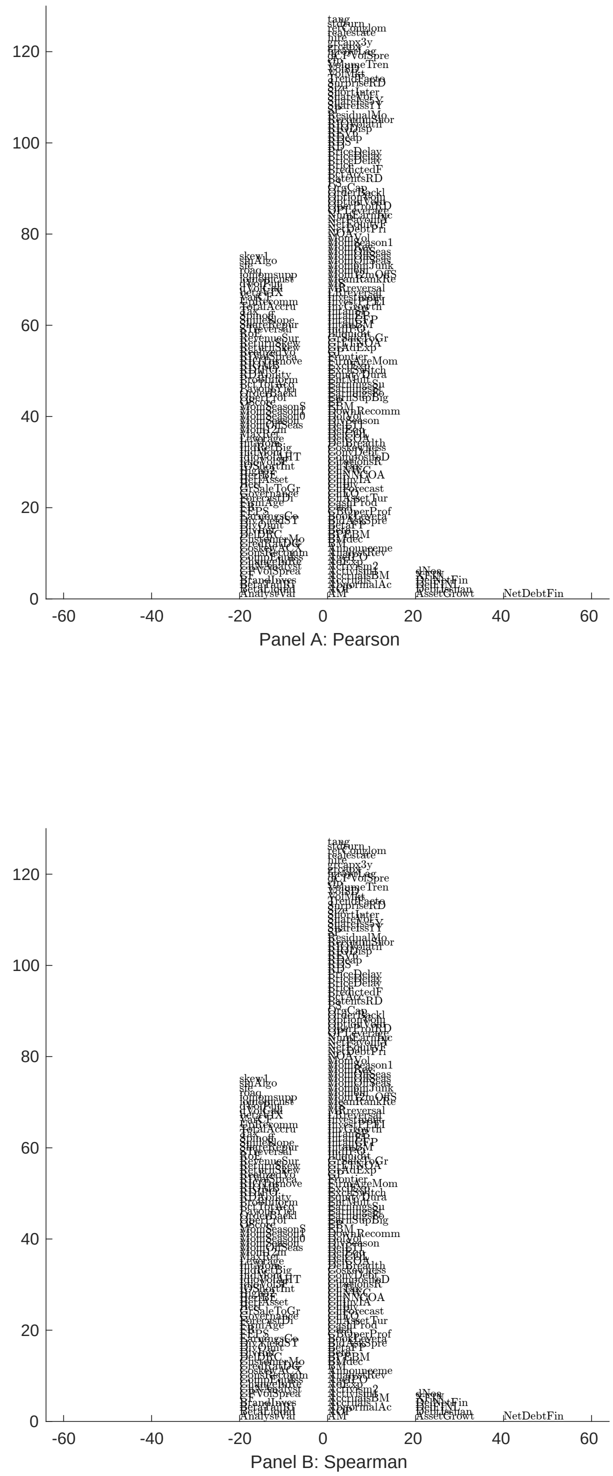

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with CDDD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

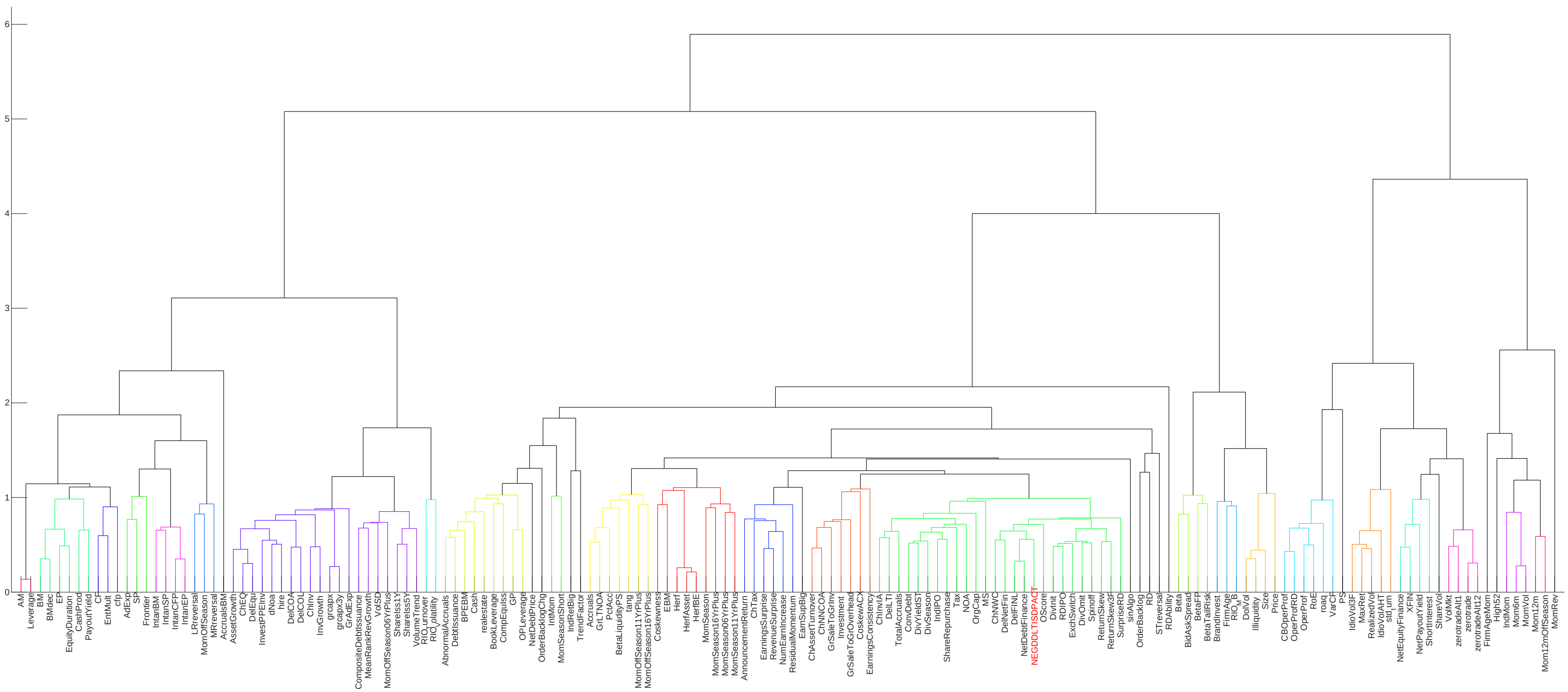

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

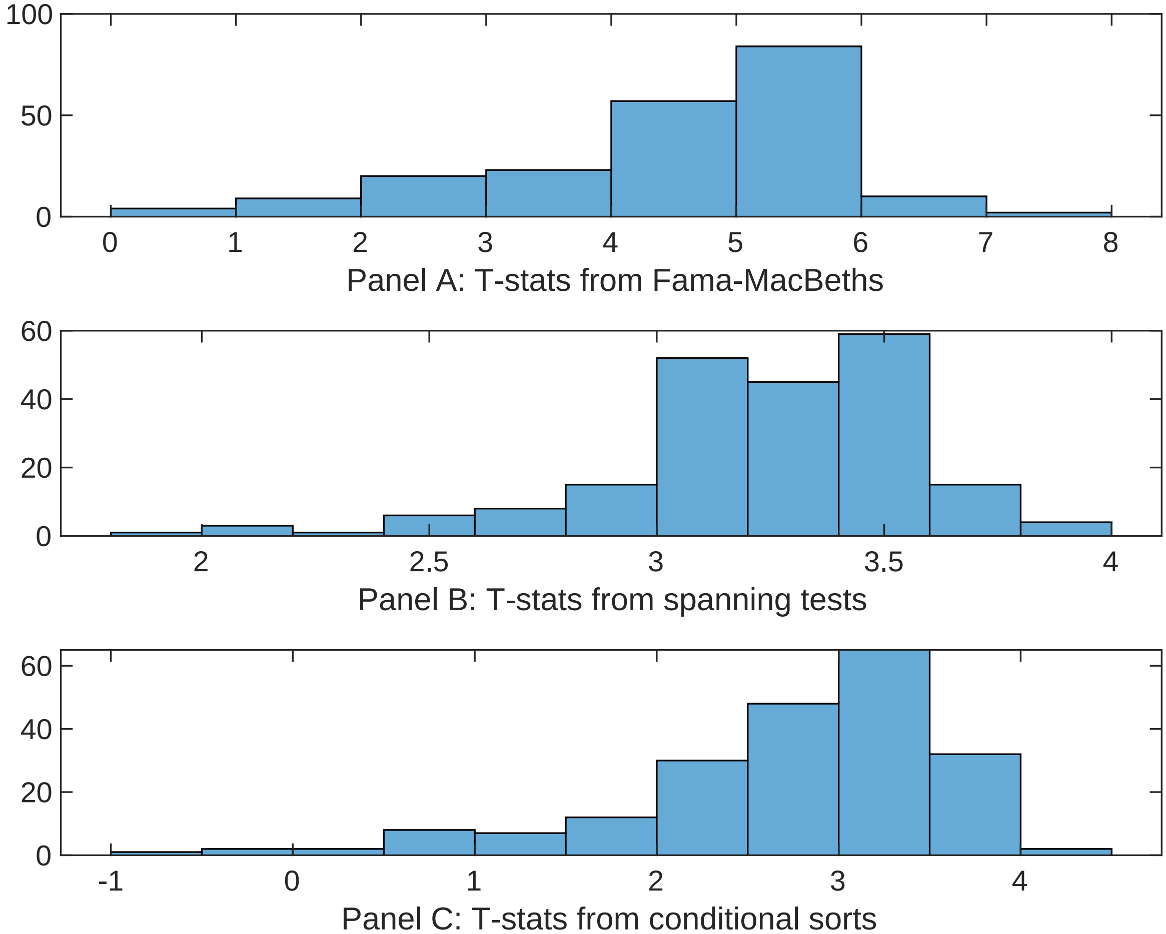

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CDDD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CDDD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CDDD}CDDD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CDDD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CDDD. Stocks are finally grouped into five CDDD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CDDD 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 CDDD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CDDD} CDDD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net debt financing, Change in financial liabilities, Net external financing, Inventory Growth, Asset growth, Employment 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	0.14	0.14	0.15	0.14	0.15
	[5.51]	[5.53]	[5.89]	[5.46]	[5.95]	[5.51]	[5.79]
CDDD	0.19	0.18	0.21	0.37	0.14	0.31	0.11
	[2.67]	[2.64]	[3.26]	[4.45]	[1.93]	[4.46]	[1.30]
Anomaly 1	0.19						0.98
	[8.63]						[1.51]
Anomaly 2		0.16					-0.62
		[9.09]					[-1.35]
Anomaly 3			0.18				0.99
			[6.16]				[1.80]
Anomaly 4				0.39			0.82
				[6.75]			[1.46]
Anomaly 5					0.10		0.72
					[8.81]		[3.71]
Anomaly 6						0.90	0.56
						[5.83]	[0.40]
# 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 CDDD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CDDD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Asset growth, Employment 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	0.18	0.18	0.18	0.19	0.19	0.20	0.16
	[2.58]	[2.62]	[2.56]	[2.75]	[2.75]	[2.79]	[2.39]
Anomaly 1	18.24						14.24
	[4.73]						[2.65]
Anomaly 2		12.06					0.93
		[2.97]					[0.17]
Anomaly 3			13.91				9.69
			[3.98]				[2.57]
Anomaly 4				6.50			5.88
				[2.38]			[2.06]
Anomaly 5					5.14		-1.29
					[1.14]		[-0.27]
Anomaly 6						2.11	-1.64
						[0.54]	[-0.40]
mkt	-6.06	-5.91	-4.18	-6.23	-6.03	-6.01	-4.94
	[-3.86]	[-3.73]	[-2.54]	[-3.92]	[-3.78]	[-3.76]	[-2.99]
smb	3.01	3.15	8.71	4.89	3.71	4.32	6.97
	[1.24]	[1.27]	[3.24]	[1.98]	[1.48]	[1.75]	[2.42]
hml	-10.05	-9.68	-8.76	-10.52	-10.48	-10.65	-8.89
	[-3.34]	[-3.17]	[-2.87]	[-3.45]	[-3.41]	[-3.38]	[-2.86]
rmw	1.50	2.06	-5.33	3.89	3.01	3.06	-3.28
	[0.48]	[0.65]	[-1.41]	[1.22]	[0.95]	[0.96]	[-0.86]
cma	18.87	19.52	14.23	17.76	17.14	21.59	11.00
	[4.05]	[4.07]	[2.77]	[3.40]	[2.35]	[3.69]	[1.46]
umd	2.66	2.99	4.11	3.56	4.36	4.04	2.37
	[1.65]	[1.81]	[2.58]	[2.19]	[2.69]	[2.49]	[1.42]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	14	12	13	12	11	11	15

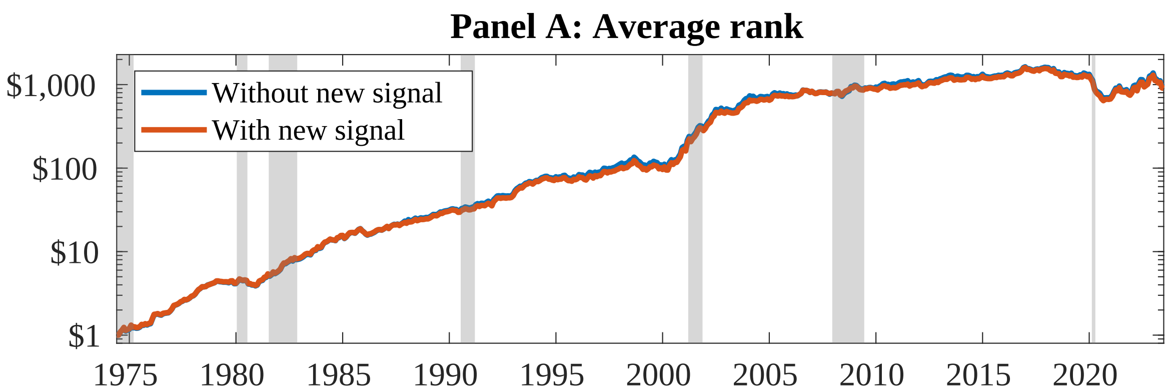

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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