# 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

The following automatically generated report tests the asset pricing implications of Capital Debt Depreciation Delta (CDDD), and its robustness in predicting returns in the cross-section of equities. It is produced using the methodology of Novy-Marx and Velikov (2023), from input data consisting of firm-month observations for the proposed predictor.[1]

# 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) reflects the systematic allocation of asset costs over their useful lives. 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 captures the relative change in debt issuance compared to the firm's depreciation base, potentially offering insights into the firm's capital structure dynamics and asset replacement patterns. By focusing on this relationship, the signal aims to reflect aspects of financing decisions and asset maintenance in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability

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[1]It used version v0.4.1 of the publicly available code repository at https://github.com/velikov-mihail/AssayingAnomalies. See more details at http://AssayingAnomalies.com.

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 fac-

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tors. 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 80th 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.[2] The vertical red line shows where the Sharpe

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[2]The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

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).[3] 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% (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.

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[3]The figure assumes an initial investment of $1 in T-bills and $1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

# 6 Does 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.[4] 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 $\beta_{CDDD}$ 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 $\alpha$ 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. 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

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[4]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.

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.[5] We

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

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.

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. The signal's ability to generate alpha even after controlling for related factors indicates that CDDD provides incremental information beyond existing known anomalies.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be

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

tested. Second, transaction costs and market impact could affect the strategy's real-world implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore several promising directions. First, investigating the underlying economic mechanisms driving the CDDD effect could provide valuable insights into market efficiency and asset pricing. Second, examining the signal's interaction with other established anomalies might reveal important complementarities or conditional relationships. Finally, testing the signal's robustness across different market regimes and international markets would help establish its broader applicability.

In conclusion, CDDD represents a valuable addition to the investment practitioner's toolkit, offering meaningful predictive power for stock returns while maintaining robustness to standard risk factors and related anomalies.
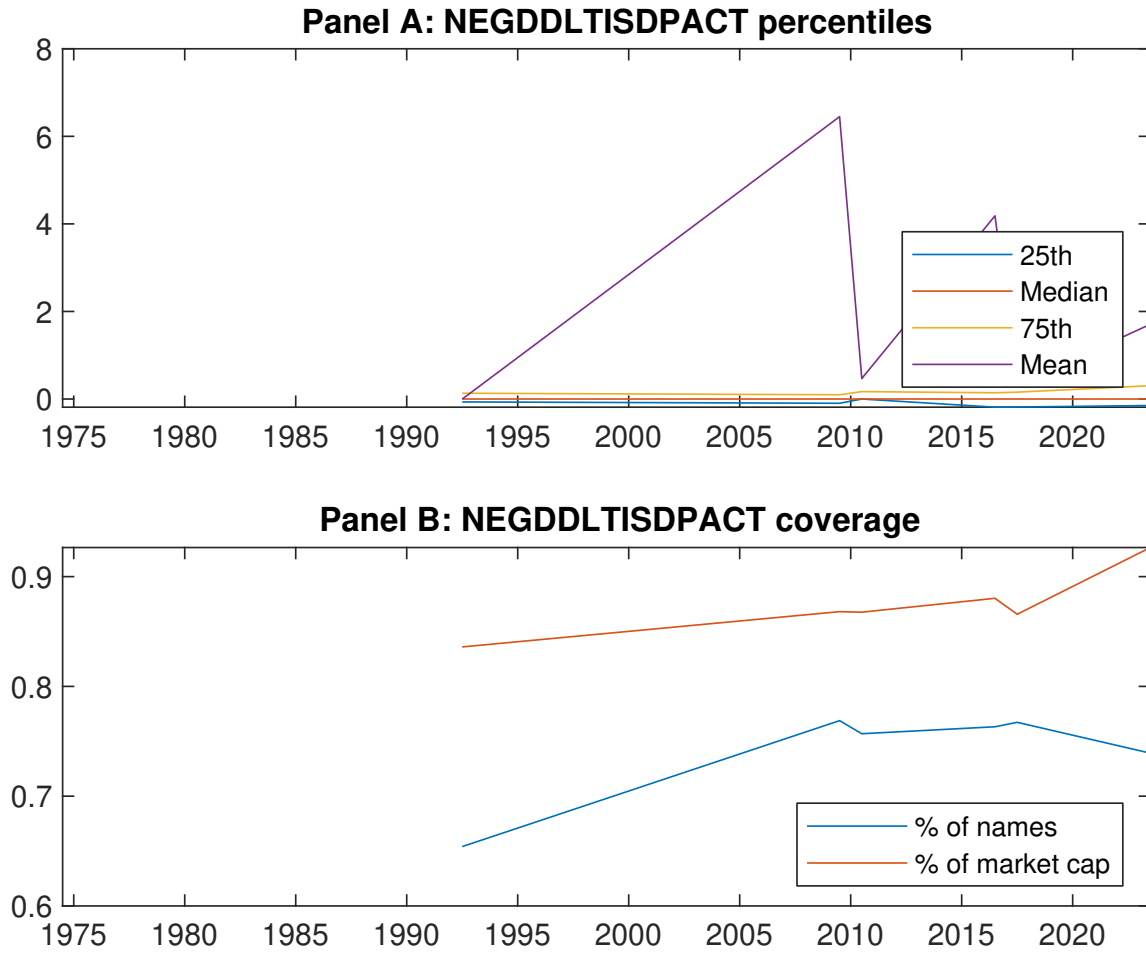
**Figure 1:** Times series of CDDD percentiles and coverage.
This figure plots descriptive statistics for CDDD. Panel A shows cross-sectional percentiles of CDDD over the sample. Panel B plots the monthly coverage of CDDD relative to the universe of CRSP stocks with available market capitalizations.

**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] |
| $\alpha_{CAPM}$ | -0.09 | 0.04 | 0.02 | 0.10 | 0.19 | 0.28 |
| | [-1.74] | [0.73] | [0.30] | [2.01] | [3.48] | [4.06] |
| $\alpha_{FF3}$ | -0.08 | 0.02 | 0.08 | 0.10 | 0.19 | 0.28 |
| | [-1.57] | [0.35] | [1.38] | [2.05] | [3.79] | [4.03] |
| $\alpha_{FF4}$ | -0.06 | 0.02 | 0.13 | 0.07 | 0.17 | 0.23 |
| | [-1.15] | [0.44] | [2.24] | [1.37] | [3.30] | [3.36] |
| $\alpha_{FF5}$ | -0.06 | -0.07 | 0.11 | 0.01 | 0.15 | 0.20 |
| | [-1.11] | [-1.38] | [1.91] | [0.20] | [2.79] | [2.95] |
| $\alpha_{FF6}$ | -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 | | | | | | |
| $\beta_{MKT}$ | 1.10 | 0.95 | 0.96 | 0.95 | 1.05 | -0.06 |
| | [89.71] | [85.27] | [71.46] | [82.46] | [87.15] | [-3.45] |
| $\beta_{SMB}$ | 0.10 | -0.13 | 0.01 | -0.06 | 0.14 | 0.04 |
| | [5.28] | [-7.27] | [0.27] | [-3.65] | [7.77] | [1.78] |
| $\beta_{HML}$ | -0.00 | 0.06 | -0.17 | -0.07 | -0.10 | -0.10 |
| | [-0.14] | [2.69] | [-6.62] | [-3.19] | [-4.53] | [-3.29] |
| $\beta_{RMW}$ | 0.05 | 0.14 | -0.02 | 0.08 | 0.07 | 0.02 |
| | [1.89] | [6.54] | [-0.58] | [3.48] | [2.79] | [0.64] |
| $\beta_{CMA}$ | -0.15 | 0.11 | -0.06 | 0.24 | 0.09 | 0.24 |
| | [-4.32] | [3.47] | [-1.52] | [7.11] | [2.51] | [5.21] |
| $\beta_{UMD}$ | -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 | |

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**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 | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| 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 | $r^e_{net}$ | $\alpha^*_{\text{CAPM}}$ | $\alpha^*_{\text{FF3}}$ | $\alpha^*_{\text{FF4}}$ | $\alpha^*_{\text{FF5}}$ | $\alpha^*_{\text{FF6}}$ |
| 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

|  |  | \multicolumn{5}{c}{CDDD Quintiles} | \multicolumn{6}{c}{CDDD Strategies} |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| | (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] |
| Size quintiles | (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

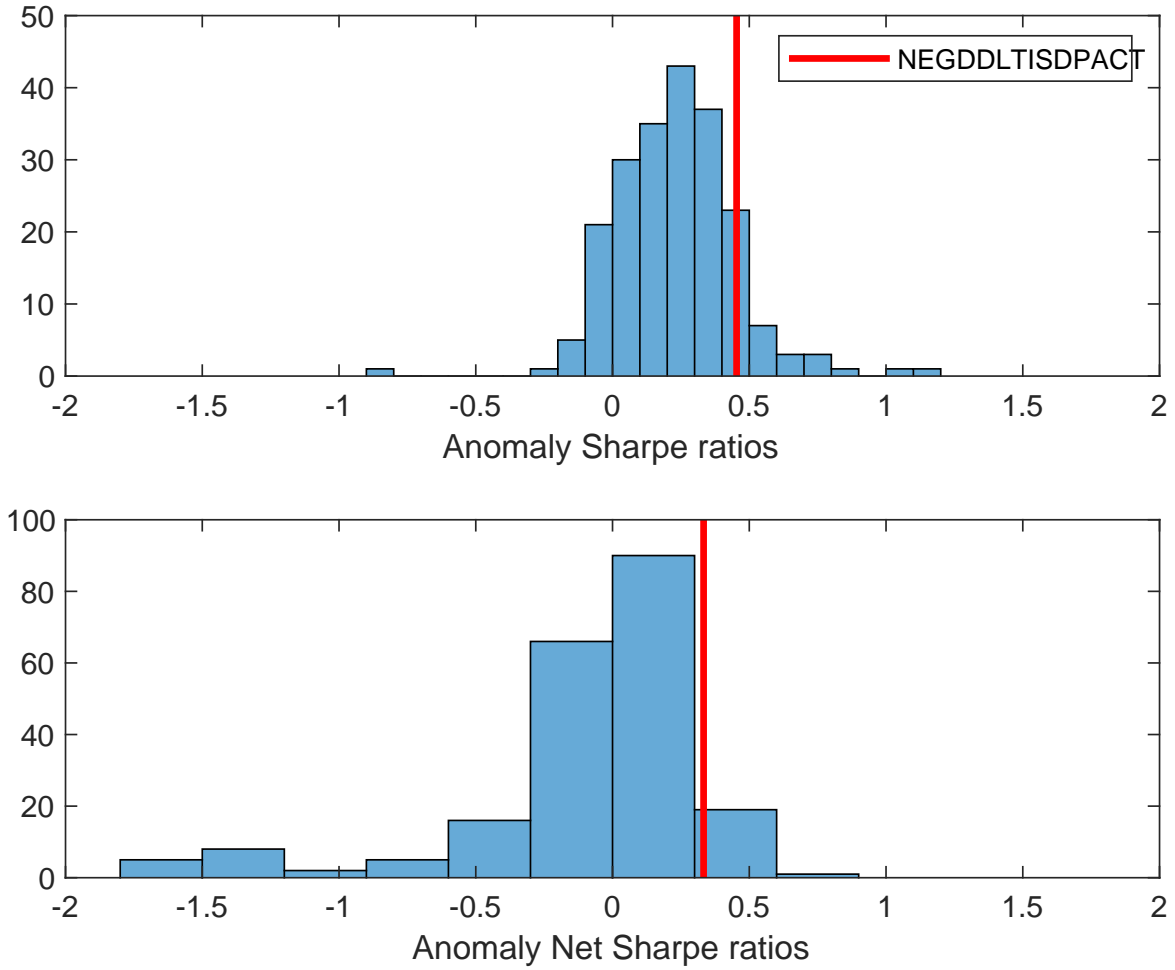|  |  | \multicolumn{5}{c}{CDDD Quintiles} | \multicolumn{5}{c}{CDDD Quintiles} |
|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | \multicolumn{5}{c}{Average $n$} | \multicolumn{5}{c}{Average market capitalization ($\$10^6$)} |
|  |  | (L) | (2) | (3) | (4) | (H) | (L) | (2) | (3) | (4) | (H) |
| | (1) | 373 | 375 | 375 | 374 | 370 | 34 | 30 | 29 | 30 | 32 |
| | (2) | 102 | 103 | 103 | 103 | 102 | 55 | 55 | 53 | 56 | 55 |
| Size quintiles | (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.
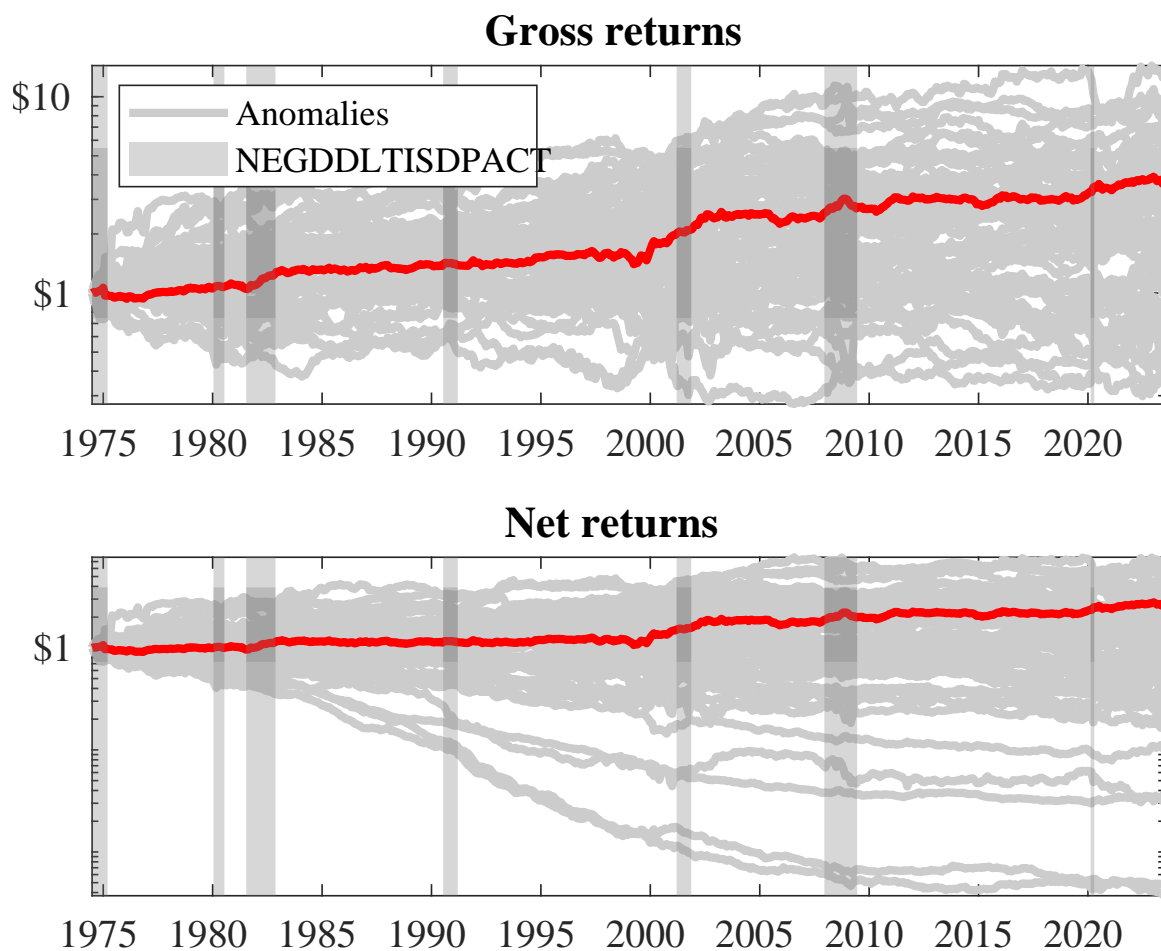
**Figure 3:** Dollar invested.

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.
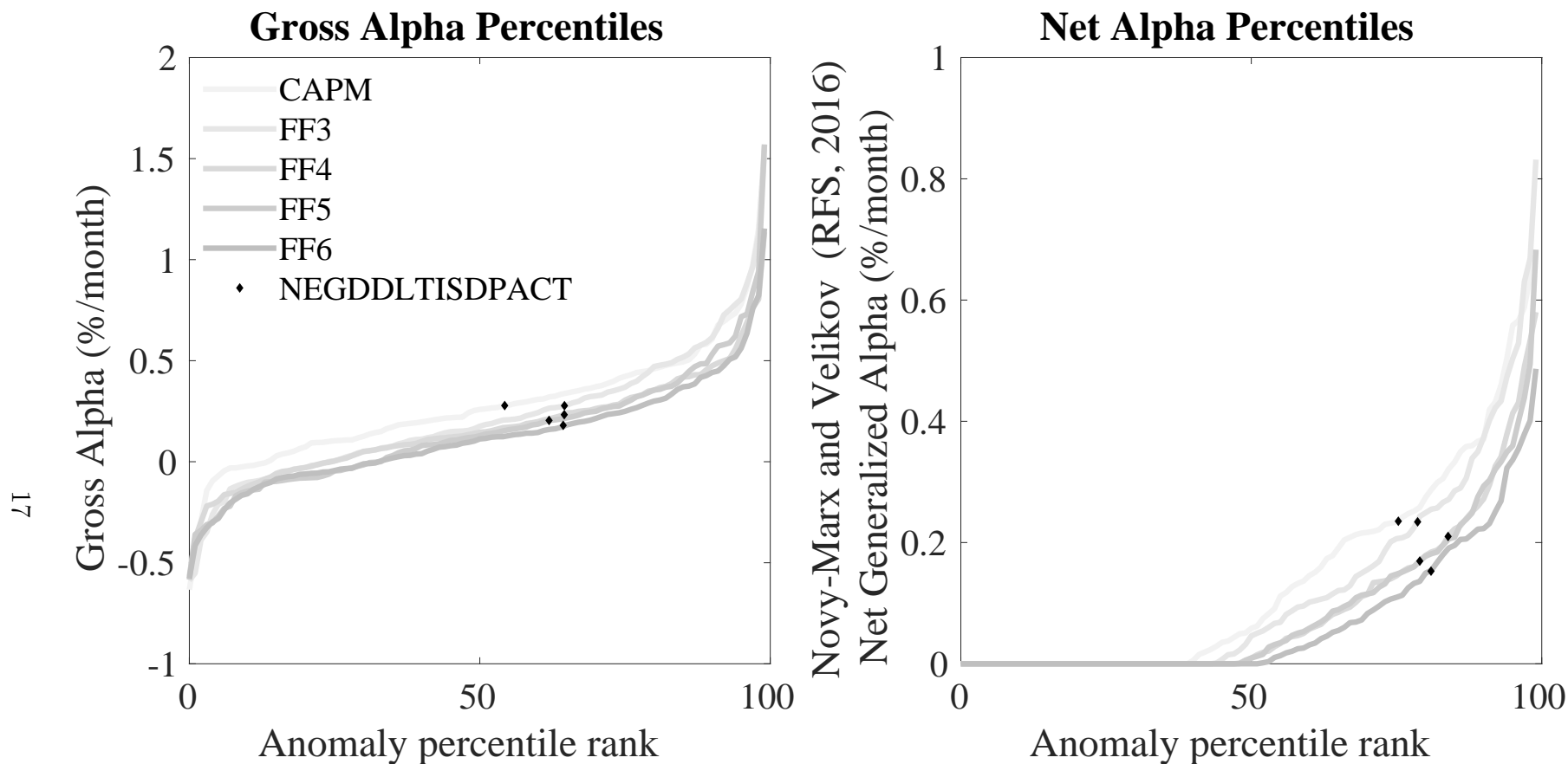
## Gross Alpha Percentiles

## Net Alpha Percentiles



**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.
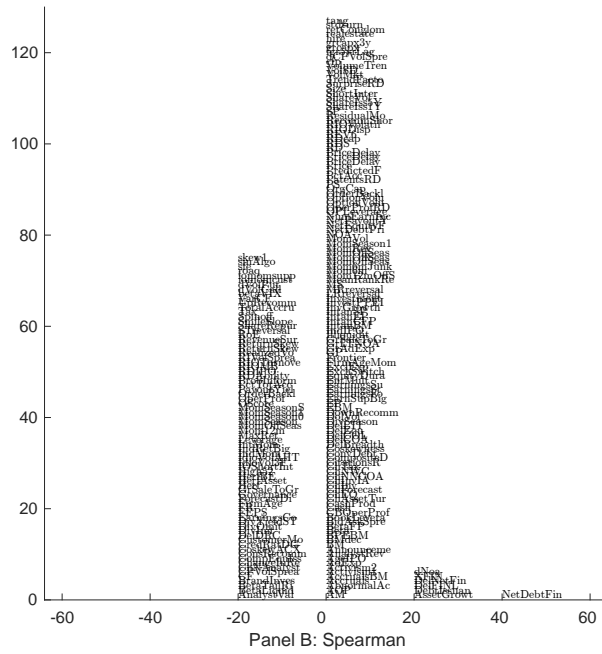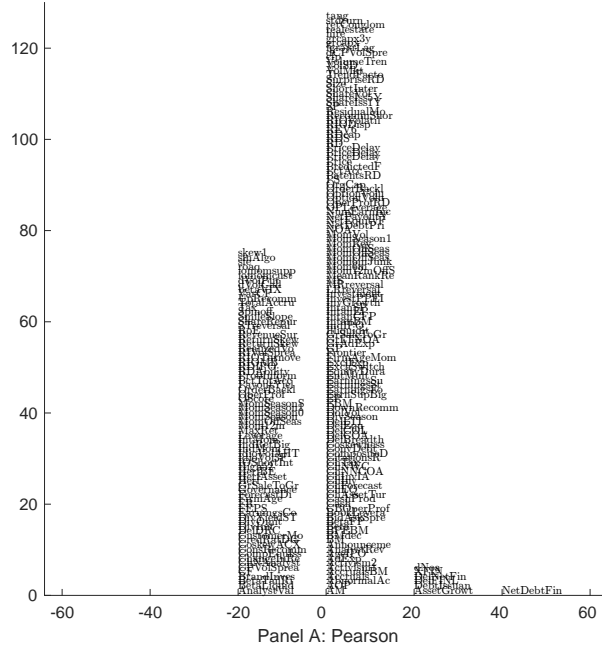
**Figure 5:** Distribution of correlations.

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.
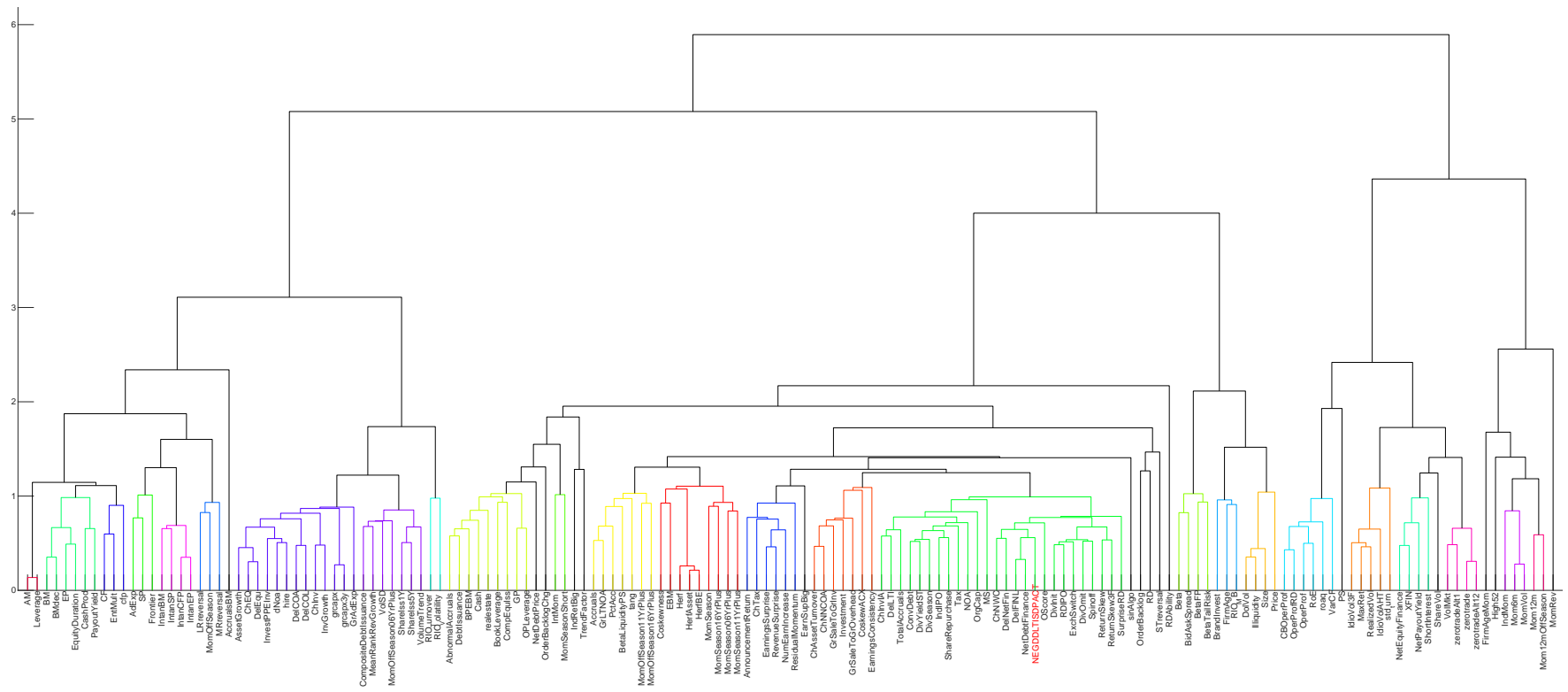
**Figure 6:** Agglomerative hierarchical cluster plot

This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.
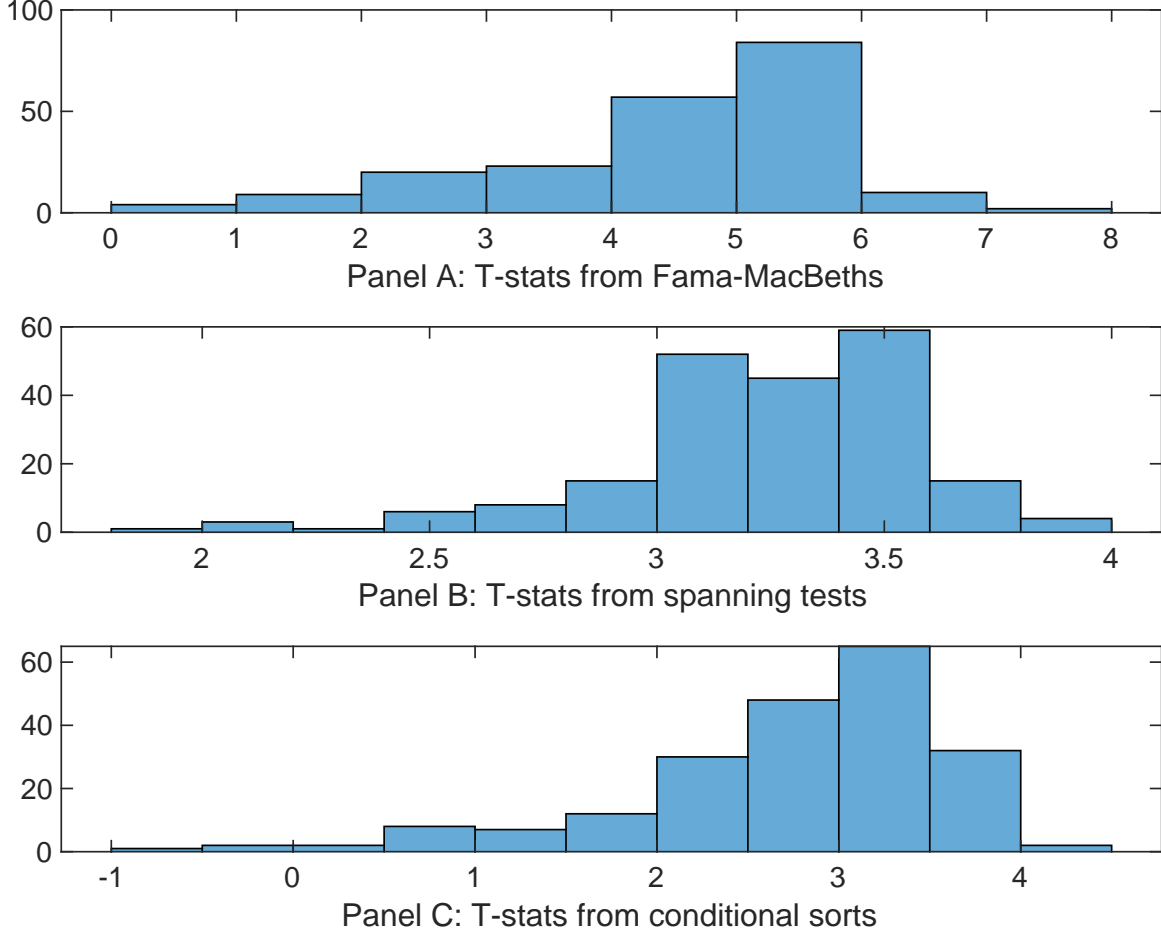
**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CDDD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{CDDD}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CDDD}CDDD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ 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 |

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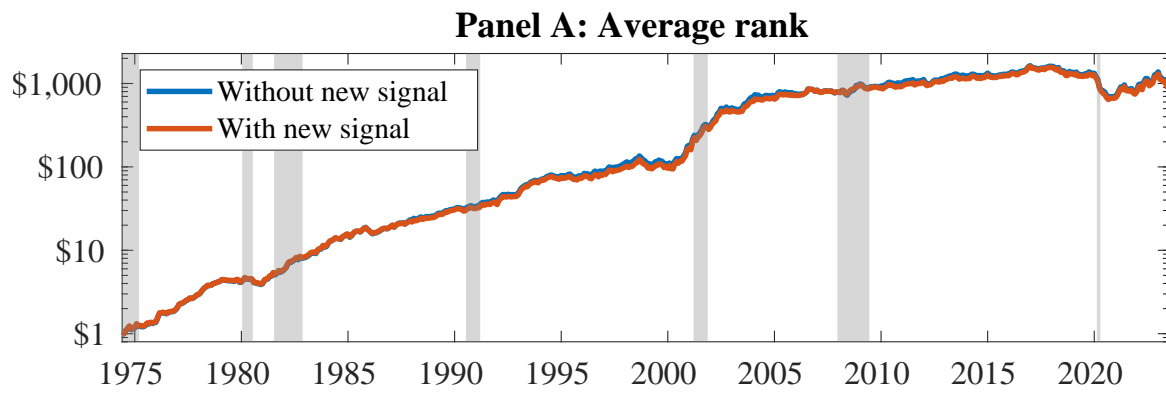
**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

# References

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

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

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

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

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

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

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

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.*