Capital Expenditure to Long-term Debt Issuance Differential and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Capital Expenditure to Long-term Debt Issuance Differential (CEDIDTFDP), 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 CEDIDTFDP achieves an annualized gross (net) Sharpe ratio of 0.61 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (19) bps/month with a t-statistic of 3.12 (2.72), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in financial liabilities, Net debt financing, Net external financing, Asset growth, change in ppe and inv/assets, Employment growth) is 20 bps/month with a t-statistic of 2.85.

1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all available information, making it difficult to systematically earn excess returns. However, a growing body of literature documents various market anomalies that appear to contradict this notion (Schwert, 2003). While many of these anomalies are well-documented, the relationship between firms' real investment decisions and their financing choices remains an important yet underexplored area in asset pricing. Understanding this relationship is crucial as it reflects management's revealed preferences about capital allocation and expected returns (Baker and Wurgler, 2013).

Prior research has separately examined how capital expenditures and debt issuance predict returns, but their interaction and relative timing have received limited attention. This gap is particularly notable given that managers' joint decisions about investment and financing likely contain important information about future firm performance (Titman et al., 2004).

We propose that the differential between capital expenditures and long-term debt issuance (CEDIDTFDP) serves as an important signal of future stock returns. This hypothesis builds on two theoretical frameworks. First, the Q-theory of investment (Cochrane, 1991) suggests that firms invest more when their expected returns are lower. Second, the market timing theory of capital structure (Baker and Wurgler, 2002) predicts that firms issue more debt when their cost of debt is relatively low compared to their cost of equity.

When firms' capital expenditures exceed their debt issuance, it may indicate that managers are funding investments through internal cash flows or equity, suggesting high expected returns that make debt financing relatively expensive (?). Conversely, when debt issuance exceeds capital expenditures, it could signal that managers are taking advantage of temporarily low borrowing costs, potentially indicating lower future returns (Baker and Wurgler, 2013).

This mechanism is distinct from previously documented investment and financing effects. While asset growth (Cooper et al., 2008) and external financing (Bradshaw et al., 2006) are known return predictors, CEDIDTFDP captures the dynamic interaction between real investment and financing decisions, potentially providing incremental information about future returns.

Our empirical analysis reveals that CEDIDTFDP strongly predicts cross-sectional stock returns. A value-weighted long-short strategy based on CEDIDTFDP quintiles generates monthly abnormal returns of 21 basis points (t-statistic = 3.12) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized gross Sharpe ratio of 0.61, placing it in the 96th percentile among documented market anomalies.

Importantly, the predictive power of CEDIDTFDP persists after controlling for size. Among the largest quintile of stocks, the strategy earns monthly abnormal returns of 38 basis points (t-statistic = 4.36), demonstrating that the effect is not confined to small, illiquid stocks. After accounting for transaction costs following (Novy-Marx and Velikov, 2016), the strategy maintains a significant net alpha of 19 basis points per month (t-statistic = 2.72).

The signal's robustness is further confirmed through extensive controls for related anomalies. When we simultaneously control for six closely related strategies including asset growth and external financing, CEDIDTFDP continues to generate significant abnormal returns of 20 basis points per month (t-statistic = 2.85), indicating that it captures unique information about expected returns.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the joint dynamics of corporate investment and financing decisions, extending the work of (Titman et al., 2004) and (Bradshaw et al., 2006) who separately examined investment and financing effects.

Second, we demonstrate that CEDIDTFDP's predictive power is distinct from known anomalies. While prior research has documented return predictability based on investment (Cooper et al., 2008) and external financing (Baker and Wurgler, 2002), our findings suggest that the relative magnitude of these activities contains incremental information about expected returns. This adds to our understanding of how managers' joint capital allocation decisions reflect their private information.

Finally, our results have important implications for both academic research and investment practice. The robustness of CEDIDTFDP's predictive power among large stocks and after transaction costs suggests a meaningful violation of market efficiency that survives trading frictions. This finding contributes to the ongoing debate about market efficiency and the economic sources of cross-sectional return predictability (Schwert, 2003).

2 Data

Our study examines the predictive power of a financial signal that captures the relationship between changes in long-term debt issuance and capital expenditure. 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 CAPXV for capital expenditure. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while capital expenditure (CAPXV) reflects the funds used to acquire fixed assets.construction of our signal, the Capital Expenditure to Long-term Debt Issuance Differential, involves a two-step process. First, we calculate the change in long-term debt issuance by taking the difference between the current period's DLTIS and its value from the previous period. Second, we scale this difference by the previous period's capital expenditure (CAPXV). This scaling ensures comparability across firms of different sizes and provides a meaningful measure of how changes in debt financing relate to historical investment activities. The resulting signal captures the dynamic relationship between firms' financing decisions and their prior capital investments, potentially offering insights into their financial flexibility and investment efficiency. We use end-of-fiscal-year values for both DLTIS and CAPXV to maintain consistency in our calculations across firms and time periods.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CEDIDTFDP signal. Panel A plots the time-series of the mean, median, and interquartile range for CEDIDTFDP. On average, the cross-sectional mean (median) CEDIDTFDP is -4.37 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input CEDIDTFDP data. The signal's interquartile range spans -2.76 to 3.00. Panel B of Figure 1 plots the time-series of the coverage of the CEDIDTFDP signal for the CRSP universe. On average, the CEDIDTFDP signal is available for 5.86% of CRSP names, which on average make up 7.13% of total market capitalization.

4 Does CEDIDTFDP predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CEDIDTFDP 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 CEDIDTFDP portfolio and sells the low CEDIDTFDP 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 CEDIDTFDP strategy earns an average return of 0.29% per month with a t-statistic of 4.26. The annualized Sharpe ratio of the strategy is 0.61. The alphas range from 0.21% to 0.34% per month and have t-statistics exceeding 3.12 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 0.28, with a t-statistic of 6.01 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 504 stocks and an average market capitalization of at least $1,414 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 23 bps/month with a t-statistics of 4.95. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-three 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 -3-24bps/month. The lowest return, (-3 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.49. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CEDIDTFDP trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in eighteen cases.

Table 3 provides direct tests for the role size plays in the CEDIDTFDP strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CEDIDTFDP, as well as average returns and alphas for long/short trading CEDIDTFDP 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 CEDIDTFDP strategy achieves an average return of 38 bps/month with a t-statistic of 4.36. Among these large cap stocks, the alphas for the CEDIDTFDP strategy relative to the five most common factor models range from 29 to 42 bps/month with t-statistics between 3.34 and 4.88.

5 How does CEDIDTFDP perform relative to the zoo?

Figure 2 puts the performance of CEDIDTFDP 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 CEDIDTFDP strategy falls in the distribution. The CEDIDTFDP strategy's gross (net) Sharpe ratio of 0.61 (0.48) is greater than 96% (99%) 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 CEDIDTFDP strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CEDIDTFDP strategy would have yielded \$4.29 which ranks the CEDIDTFDP strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CEDIDTFDP strategy would have yielded \$2.75 which ranks the CEDIDTFDP strategy in the top 3% 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 CEDIDTFDP relative to those. Panel A shows that the CEDIDTFDP strategy gross alphas fall between the 66 and 74 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

[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.

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 CEDIDTFDP strategy has a positive net generalized alpha for five out of the five factor models. In these cases CEDIDTFDP ranks between the 81 and 89 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does CEDIDTFDP 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 CEDIDTFDP 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 CEDIDTFDP or at least to weaken the power CEDIDTFDP has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CEDIDTFDP conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{CEDIDTFDP}$ from Fama-MacBeth regressions of the form

[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.

$r_{i,t} = \alpha + \beta_{CEDIDTFDP} CEDIDTFDP_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CEDIDTFDP,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CEDIDTFDP. Stocks are finally grouped into five CEDIDTFDP portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CEDIDTFDP trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CEDIDTFDP 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 CEDIDTFDP signal in these Fama-MacBeth regressions exceed 2.65, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on CEDIDTFDP is 1.58.

Similarly, Table 5 reports results from spanning tests that regress returns to the CEDIDTFDP 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 CEDIDTFDP strategy earns alphas that range from 21-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.01, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CEDIDTFDP trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.85.

7 Does CEDIDTFDP add relative to the whole zoo?

Finally, we can ask how much adding CEDIDTFDP 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 CEDIDTFDP 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 CEDIDTFDP grows to $951.45.

[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 CEDIDTFDP is available.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Capital Expenditure to Long-term Debt Issuance Differential (CEDIDTFDP) as a robust predictor of stock returns. The signal demonstrates significant predictive power, generating impressive risk-adjusted returns with an annualized gross Sharpe ratio of 0.61 (0.48 net) and maintaining statistical significance even after controlling for established risk factors and related anomalies.

Our findings reveal that a value-weighted long/short strategy based on CEDIDTFDP delivers economically meaningful abnormal returns of 21 basis points per month (19 bps net) relative to the Fama-French five-factor model augmented with momentum. Notably, the signal's predictive power persists even after accounting for six closely related investment and financing-based strategies, yielding a significant alpha of 20 bps per month.

These results have important implications for both academic research and investment practice. For academics, our findings contribute to the growing literature on the relationship between corporate investment decisions, financing choices, and stock returns. For practitioners, CEDIDTFDP represents a potentially valuable tool for portfolio management and security selection.

However, several limitations should be noted. First, the study's findings may be sensitive to the specific time period examined. Second, transaction costs and market impact could affect the real-world implementation of trading strategies based on this signal. Future research could explore the signal's performance in international markets, investigate its interaction with other established anomalies, and examine the underlying economic mechanisms driving its predictive power. Additionally, researchers might consider studying how the signal's effectiveness varies across different market conditions and business cycles.

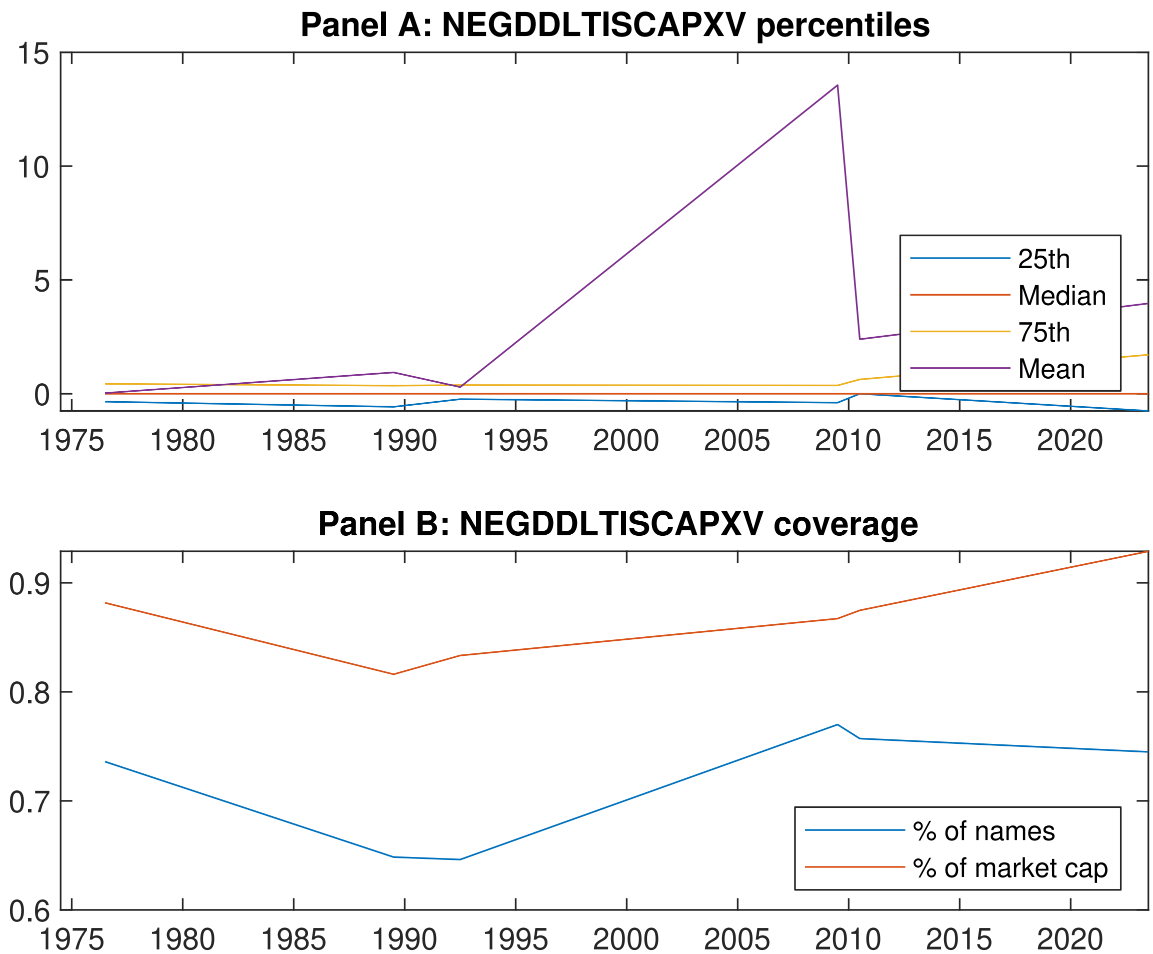


Figure 1: Times series of CEDIDTFDP percentiles and coverage.
This figure plots descriptive statistics for CEDIDTFDP. Panel A shows cross-sectional percentiles of CEDIDTFDP over the sample. Panel B plots the monthly coverage of CEDIDTFDP relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CEDIDTFDP. 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 CEDIDTFDP-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.60	0.70	0.71	0.76	0.89	0.29
	[2.76]	[3.80]	[3.51]	[4.19]	[4.40]	[4.26]
α_{CAPM}	-0.16	0.06	0.02	0.13	0.18	0.34
	[-3.04]	[1.22]	[0.25]	[2.55]	[3.54]	[5.06]
α_{FF3}	-0.16	0.04	0.09	0.14	0.17	0.34
	[-3.13]	[0.95]	[1.49]	[2.62]	[3.32]	[4.90]
α_{FF4}	-0.13	0.04	0.14	0.09	0.16	0.29
	[-2.51]	[0.90]	[2.48]	[1.76]	[3.02]	[4.23]
α_{FF5}	-0.14	-0.04	0.15	0.03	0.10	0.24
	[-2.67]	[-0.89]	[2.60]	[0.66]	[1.83]	[3.45]
α_{FF6}	-0.12	-0.03	0.19	0.01	0.09	0.21
	[-2.28]	[-0.74]	[3.23]	[0.22]	[1.78]	[3.12]
Panel B: Fama and French (2018) 6-factor model loadings for CEDIDTFDP-sorted portfolios						
β_{MKT}	1.07	0.98	0.96	0.97	1.04	-0.03
	[88.45]	[96.60]	[72.19]	[82.28]	[86.35]	[-1.87]
β_{SMB}	0.10	-0.12	0.00	-0.03	0.11	0.01
	[5.53]	[-7.33]	[0.08]	[-1.39]	[5.86]	[0.23]
β_{HML}	0.02	0.05	-0.17	-0.10	-0.06	-0.08
	[0.75]	[2.40]	[-6.52]	[-4.25]	[-2.70]	[-2.64]
β_{RMW}	0.04	0.14	-0.05	0.09	0.11	0.07
	[1.78]	[6.69]	[-1.94]	[3.83]	[4.66]	[2.20]
β_{CMA}	-0.13	0.11	-0.13	0.26	0.15	0.28
	[-3.70]	[3.75]	[-3.50]	[7.46]	[4.14]	[6.01]
β_{UMD}	-0.03	-0.01	-0.06	0.04	0.00	0.04
	[-2.84]	[-1.08]	[-4.55]	[3.28]	[0.21]	[2.34]
Panel C: Average number of firms (n) and market capitalization (me)						
n	642	504	1012	557	607	
me ($\$10^6$)	1414	2599	2109	2546	1423	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CEDIDTFDP 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	0.29	0.34	0.34	0.29	0.24	0.21
			[4.26]	[5.06]	[4.90]	[4.23]	[3.45]	[3.12]
Quintile	NYSE	EW	0.23	0.25	0.24	0.23	0.23	0.23
			[4.95]	[5.40]	[5.12]	[4.85]	[4.87]	[4.75]
Quintile	Name	VW	0.25	0.30	0.31	0.28	0.25	0.23
			[3.52]	[4.17]	[4.30]	[3.78]	[3.47]	[3.21]
Quintile	Cap	VW	0.29	0.33	0.34	0.29	0.25	0.23
			[4.58]	[5.25]	[5.36]	[4.58]	[4.01]	[3.59]
Decile	NYSE	VW	0.28	0.32	0.32	0.30	0.19	0.19
			[3.14]	[3.56]	[3.55]	[3.29]	[2.17]	[2.16]
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	0.23	0.29	0.29	0.26	0.20	0.19
			[3.38]	[4.24]	[4.12]	[3.78]	[2.93]	[2.72]
Quintile	NYSE	EW	-0.03					
			[-0.49]					
Quintile	Name	VW	0.19	0.25	0.26	0.24	0.21	0.19
			[2.67]	[3.38]	[3.50]	[3.24]	[2.85]	[2.64]
Quintile	Cap	VW	0.24	0.29	0.30	0.27	0.22	0.20
			[3.75]	[4.48]	[4.57]	[4.19]	[3.45]	[3.18]
Decile	NYSE	VW	0.21	0.25	0.25	0.24	0.14	0.14
			[2.30]	[2.72]	[2.72]	[2.59]	[1.61]	[1.52]

Table 3: Conditional sort on size and CEDIDTFDP

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

		CEDIDTFDP Quintiles					CEDIDTFDP Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.79	0.86	1.01	0.91	0.92	0.13	0.16	0.13	0.10	0.11	0.09
		[2.77]	[3.07]	[3.59]	[3.17]	[3.08]	[1.19]	[1.46]	[1.22]	[0.90]	[1.02]	[0.85]
	(2)	0.85	0.89	0.84	0.98	0.90	0.06	0.10	0.07	0.08	0.04	0.04
		[3.12]	[3.44]	[3.27]	[3.89]	[3.54]	[0.73]	[1.19]	[0.90]	[0.96]	[0.45]	[0.53]
	(3)	0.84	0.84	0.87	0.87	0.98	0.14	0.19	0.19	0.14	0.17	0.15
		[3.34]	[3.70]	[3.53]	[3.85]	[4.16]	[1.87]	[2.51]	[2.41]	[1.84]	[2.21]	[1.84]
	(4)	0.75	0.85	0.88	0.79	0.93	0.18	0.20	0.17	0.16	0.12	0.12
		[3.34]	[3.94]	[3.86]	[3.71]	[4.24]	[2.42]	[2.60]	[2.30]	[2.09]	[1.59]	[1.53]
	(5)	0.50	0.64	0.65	0.66	0.88	0.38	0.41	0.42	0.36	0.33	0.29
		[2.44]	[3.51]	[3.34]	[3.56]	[4.47]	[4.36]	[4.71]	[4.88]	[4.09]	[3.79]	[3.34]

Panel B: Portfolio average number of firms and market capitalization

		CEDIDTFDP Quintiles					CEDIDTFDP Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	371	373	372	372	367	33	31	29	30	32
	(2)	102	102	102	102	102	55	55	54	55	55
	(3)	73	73	73	73	73	97	97	95	95	98
	(4)	62	62	62	62	61	213	220	210	218	211
	(5)	56	56	56	56	56	1275	1888	1686	1916	1345

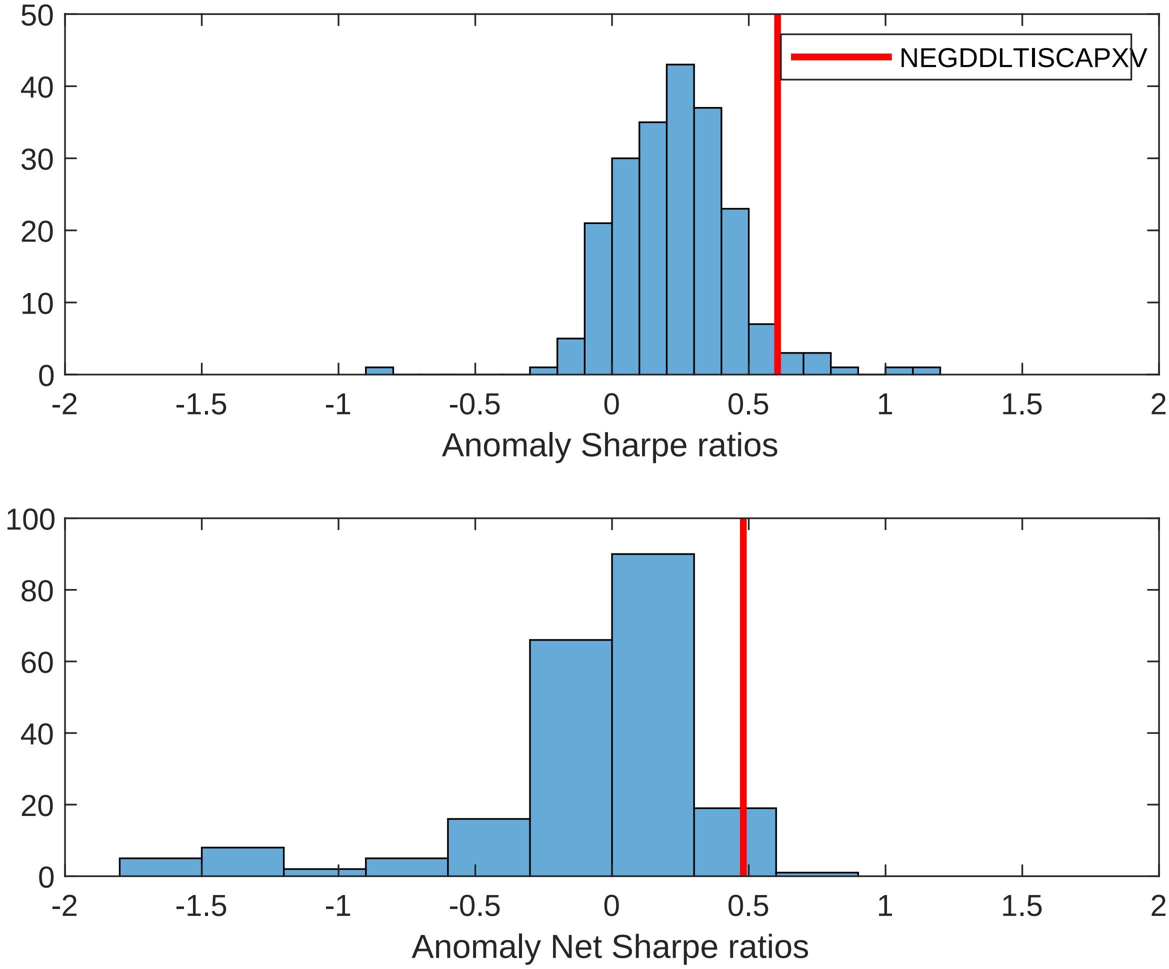


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CEDIDTFDP with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

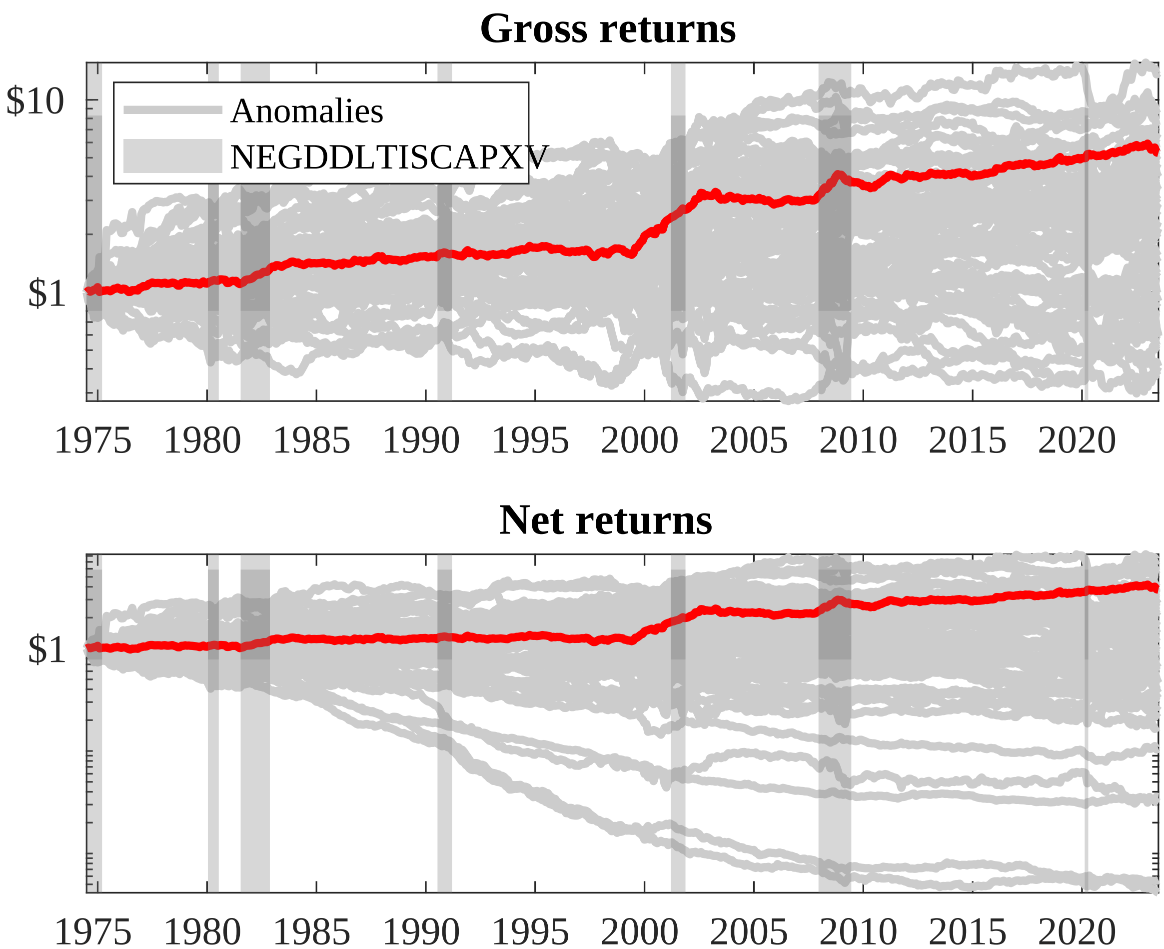


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CEDIDTFDP trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results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

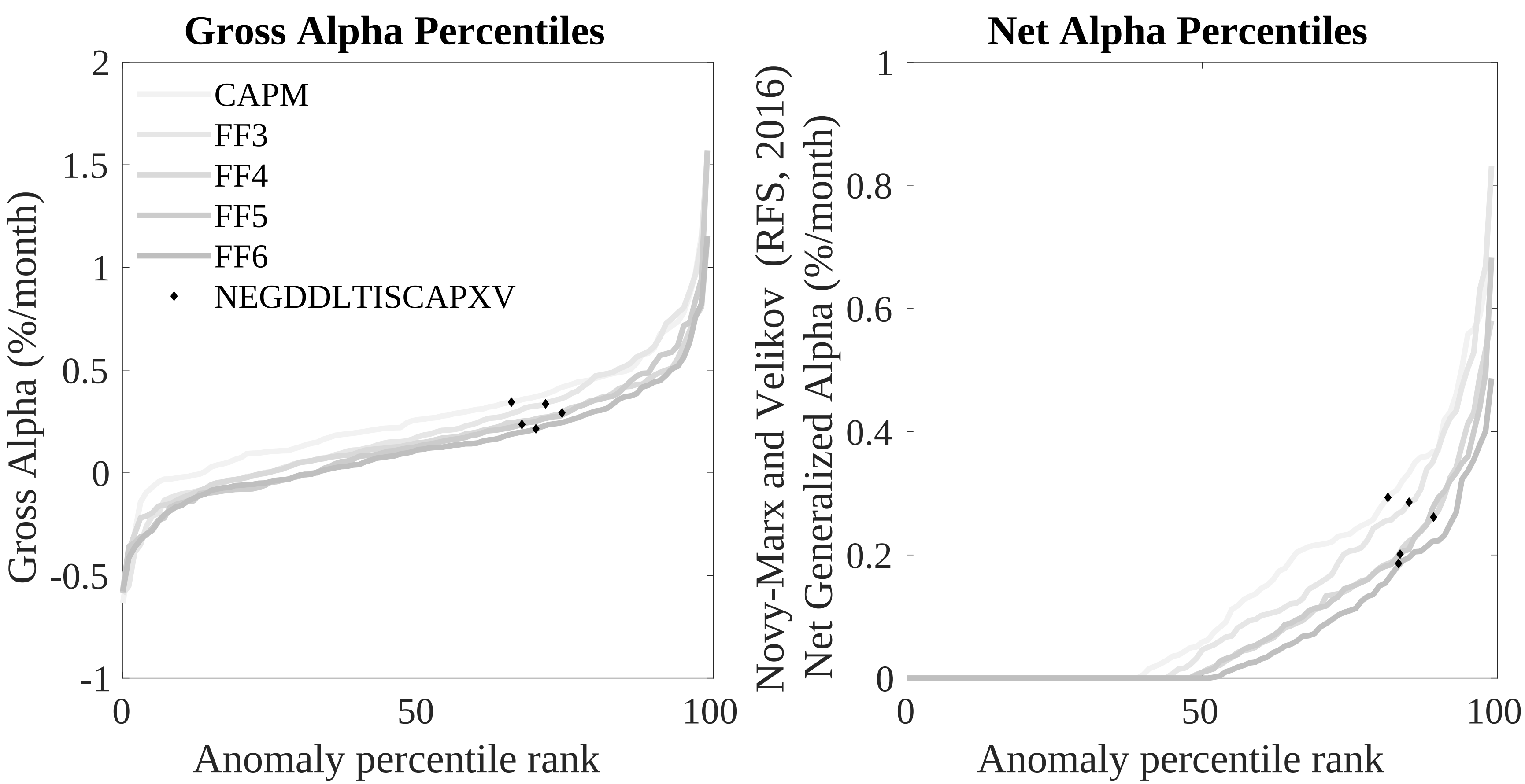
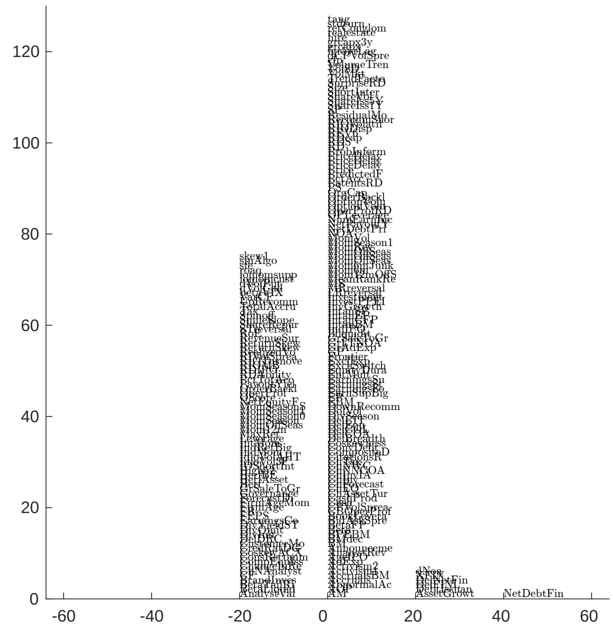
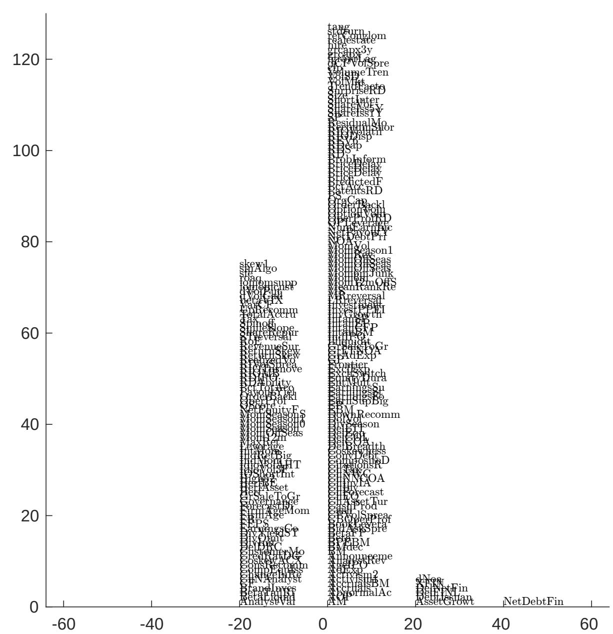


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CEDIDTFDP trading strategy alphas (diamonds). The strategies are constructed 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 CEDIDTFDP. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

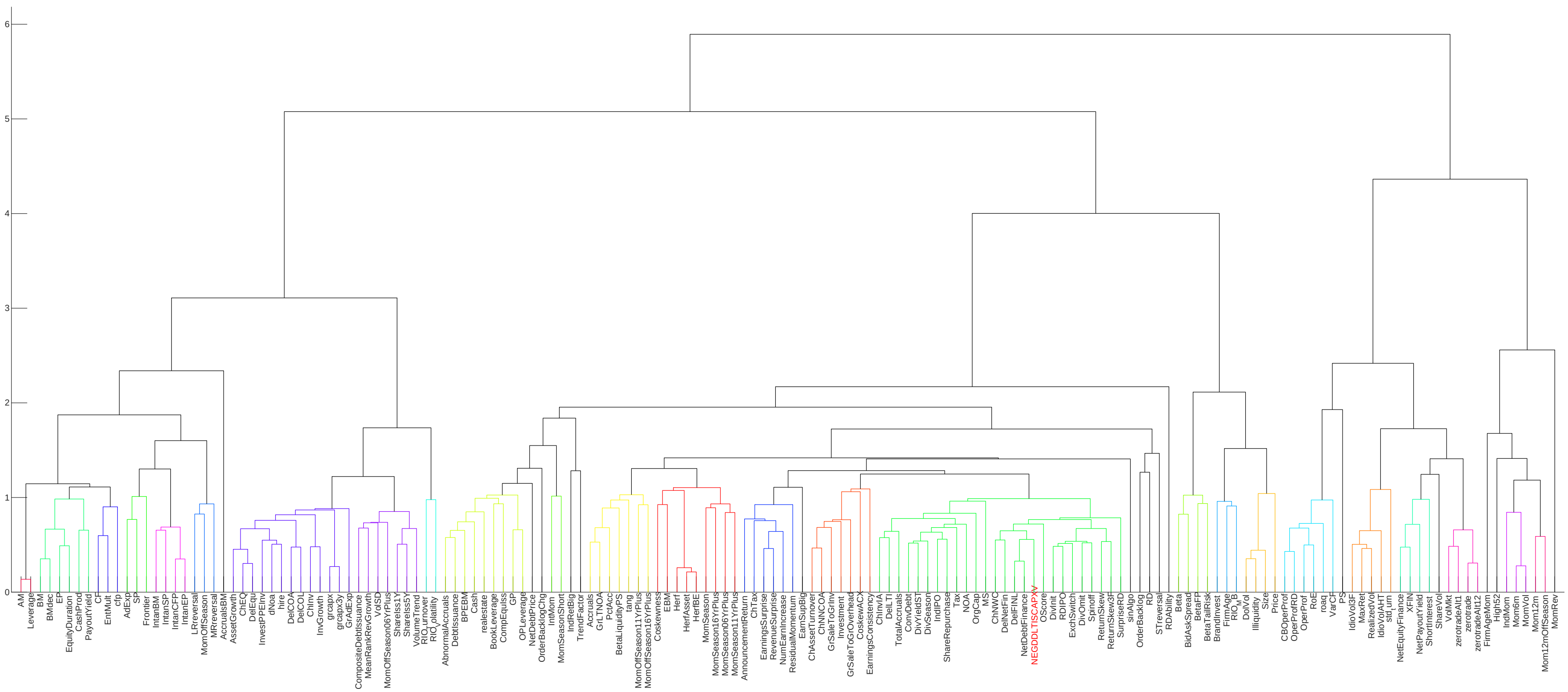


Figure 6: Agglomerative hierarchical cluster plot

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

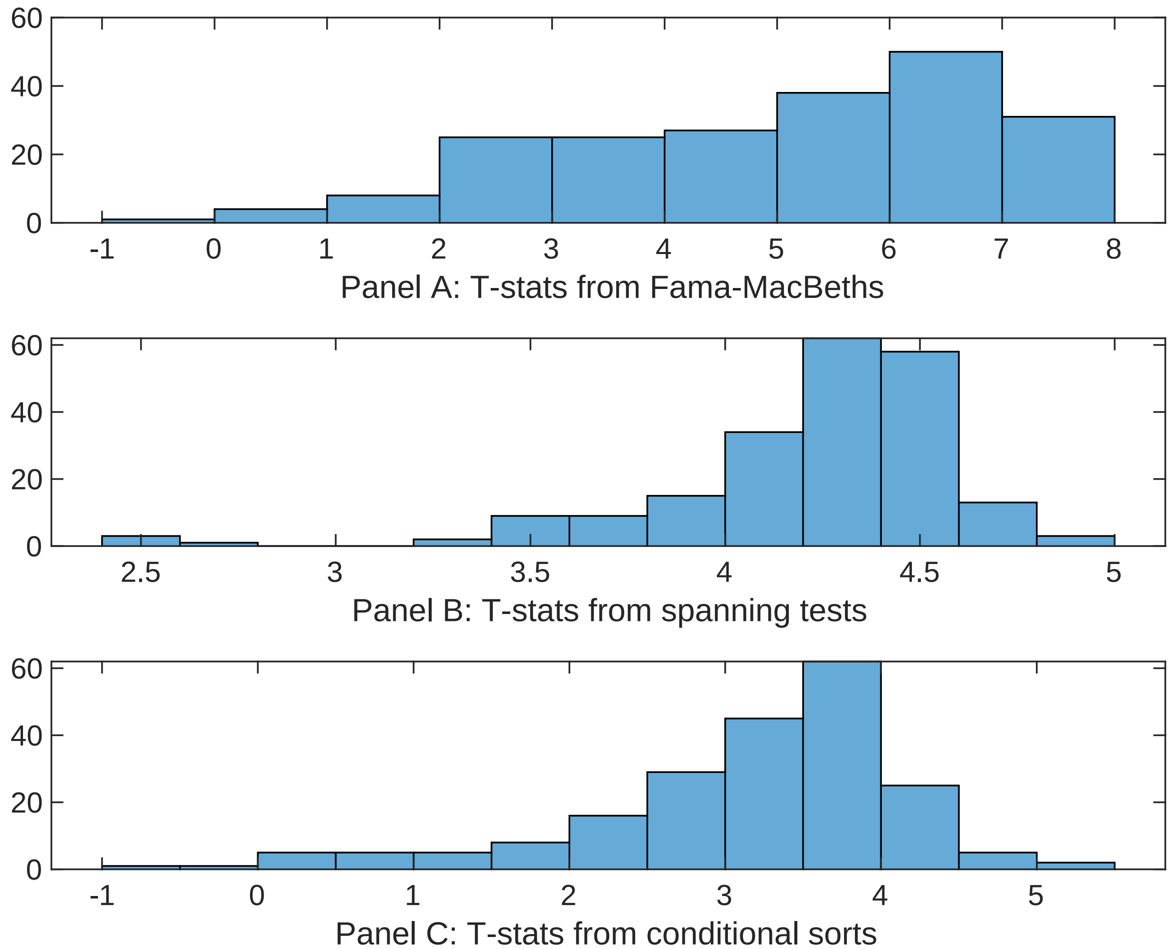


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CEDIDTFDP conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{CEDIDTFDP}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CEDIDTFDP} CEDIDTFDP_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CEDIDTFDP,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CEDIDTFDP. Stocks are finally grouped into five CEDIDTFDP portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CEDIDTFDP 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 CEDIDTFDP. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CEDIDTFDP} CEDIDTFDP_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, change in ppe and inv/assets, 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	0.15	0.15	0.14	0.15
	[5.52]	[5.49]	[5.86]	[5.94]	[5.89]	[5.49]	[6.15]
CEDIDTFDP	0.69	0.80	0.98	0.70	0.99	0.14	0.44
	[2.73]	[2.94]	[3.65]	[2.65]	[3.81]	[5.73]	[1.58]
Anomaly 1	0.17						-0.42
	[8.87]						[-1.07]
Anomaly 2		0.20					0.66
		[8.83]					[1.21]
Anomaly 3			0.19				0.85
			[6.23]				[1.69]
Anomaly 4				0.11			0.51
				[9.04]			[2.97]
Anomaly 5					0.16		0.77
					[7.42]		[3.19]
Anomaly 6						0.91	0.61
						[5.89]	[0.45]
# 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 CEDIDTFDP trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CEDIDTFDP} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Change in financial liabilities, Net debt financing, Net external financing, Asset growth, change in ppe and inv/assets, 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	0.21	0.21	0.21	0.22	0.22	0.23	0.20
	[3.01]	[3.02]	[3.01]	[3.18]	[3.15]	[3.23]	[2.85]
Anomaly 1	14.44						8.45
	[3.59]						[1.55]
Anomaly 2		14.53					6.47
		[3.77]					[1.20]
Anomaly 3			10.79				5.84
			[3.09]				[1.49]
Anomaly 4				9.36			4.41
				[2.09]			[0.91]
Anomaly 5					7.23		4.30
					[2.28]		[1.25]
Anomaly 6						3.01	-1.19
						[0.78]	[-0.29]
mkt	-3.04	-3.22	-1.76	-3.18	-3.39	-3.16	-2.44
	[-1.94]	[-2.05]	[-1.07]	[-2.01]	[-2.14]	[-1.99]	[-1.46]
smb	-1.17	-0.85	3.59	-0.82	0.25	0.25	0.39
	[-0.48]	[-0.35]	[1.34]	[-0.33]	[0.10]	[0.10]	[0.14]
hml	-7.47	-7.99	-6.99	-8.55	-9.05	-8.70	-7.55
	[-2.47]	[-2.65]	[-2.29]	[-2.81]	[-2.96]	[-2.78]	[-2.41]
rmw	6.18	6.10	0.83	7.34	7.54	7.39	2.77
	[1.97]	[1.94]	[0.22]	[2.33]	[2.40]	[2.34]	[0.72]
cma	22.31	23.40	19.89	15.45	21.48	24.35	10.98
	[4.69]	[5.02]	[3.87]	[2.14]	[4.12]	[4.19]	[1.46]
umd	2.46	2.66	3.82	4.24	3.78	3.70	2.69
	[1.51]	[1.65]	[2.40]	[2.63]	[2.37]	[2.29]	[1.63]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	13	14	13	12	12	12	14

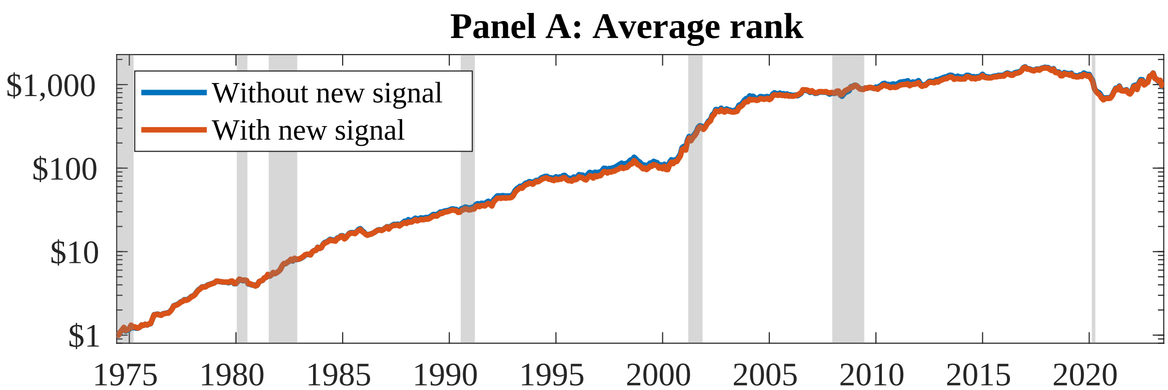


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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