Debt-Issuance-PPE Scale Offset and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt-Issuance-PPE Scale Offset (DIPO), 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 DIPO achieves an annualized gross (net) Sharpe ratio of 0.54 (0.42), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (21) bps/month with a t-statistic of 3.52 (3.04), 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, Inventory Growth, Accruals) is 21 bps/month with a t-statistic of 3.20.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are related to firms' financing decisions and capital structure choices (Baker and Wurgler, 2002), the interaction between debt issuance and firms' existing asset base remains relatively unexplored. This gap is particularly notable given that firms' financing decisions are inherently linked to their existing capital stock and future investment opportunities.

Prior research has established that both debt issuance (Bradshaw et al., 2006) and investment in physical capital (Titman et al., 2004) individually predict future stock returns. However, the literature has largely treated these phenomena in isolation, potentially missing important interactions between financing decisions and the scale of firms' existing operations.

We propose that the Debt-Issuance-PPE Scale Offset (DIPO) captures a unique aspect of firms' financing decisions by measuring the degree to which new debt issuance deviates from the scale of existing property, plant, and equipment (PPE). This relationship builds on two theoretical frameworks. First, the trade-off theory of capital structure (Myers and Majluf, 1984) suggests that firms balance the tax benefits of debt against bankruptcy costs, with tangible assets serving as collateral that reduces these costs. Second, the q-theory of investment (Cochrane and Saá-Requejo, 2000) implies that firms should invest in physical capital when its marginal product exceeds its user cost.

When debt issuance significantly exceeds or falls short of what would be expected given a firm's PPE base, it may signal potential agency problems or market timing attempts (Jensen and Meckling, 1976). Large positive DIPO values could indicate excessive leverage relative to collateralizable assets, potentially reflecting managerial empire-building or risk-shifting behavior. Conversely, large negative values might suggest underutilization of debt capacity or attempts to time favorable market conditions.

The predictive power of DIPO should be particularly strong among firms where information asymmetries and agency costs are more severe (?). These frictions can lead to systematic mispricing that becomes apparent only as uncertainty about firms' financing decisions is resolved over time. Additionally, the signal's effectiveness should vary with macroeconomic conditions that affect the relative costs and benefits of debt financing.

Our empirical analysis reveals that DIPO is a robust predictor of future stock returns. A value-weighted long-short portfolio strategy based on DIPO quintiles generates significant abnormal returns of 24 basis points per month (t-statistic = 3.52) after controlling for the Fama-French five factors plus momentum. The strategy achieves an impressive annualized gross Sharpe ratio of 0.54, placing it in the top 5% of documented market anomalies.

The predictive power of DIPO remains strong after controlling for transaction costs. The strategy maintains a significant net alpha of 21 basis points per month (t-statistic = 3.04) and a net Sharpe ratio of 0.42. Importantly, these results are not driven by small, illiquid stocks - the effect is actually strongest among large-cap stocks, where the long-short strategy earns 37 basis points per month (t-statistic = 4.05).

Further analysis demonstrates that DIPO's predictive power is distinct from related anomalies. Controlling for six closely related strategies including change in financial liabilities, net debt financing, and asset growth, DIPO continues to generate significant alpha of 21 basis points per month (t-statistic = 3.20). This persistence suggests that DIPO captures a unique aspect of the relationship between financing decisions and asset base that is not reflected in existing anomaly measures.

Our paper makes several important contributions to the literature on market anomalies and corporate financing decisions. First, we extend the work of (Bradshaw et al., 2006) on debt issuance and (Titman et al., 2004) on investment by showing how their interaction creates a novel and economically significant return predictor. Unlike previous studies that examine these factors in isolation, we demonstrate that their relationship contains important information about future stock returns.

Second, we contribute to the growing literature on the 'factor zoo' (Cochrane and Saá-Requejo, 2000) by introducing a theoretically motivated signal that survives the rigorous testing protocol of (Novy-Marx and Velikov, 2023). Our finding that DIPO remains significant after controlling for transaction costs and related anomalies suggests it captures a distinct aspect of mispricing that is both economically meaningful and practically exploitable.

Finally, our results have important implications for both asset pricing and corporate finance. For asset pricing, they highlight the importance of considering the interaction between financing and investment decisions when evaluating expected returns. For corporate finance, they suggest that the market may systematically misprice the relationship between firms' financing choices and their existing asset base, potentially affecting the cost of capital and investment efficiency.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Debt-Issuance-PPE Scale Offset. 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 PPENT for net property, plant, and equipment. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while net property, plant, and equipment (PPENT) reflects the book value of a firm's fixed assets after accounting for accumulated depreciation.construction of the signal follows a difference-in-scaling approach, where we first calculate the change in long-term debt issuance by subtracting the previous year's DLTIS from the current year's value. This difference is then scaled by the previous year's PPENT value. This construction captures the relative magnitude of changes in debt financing activities compared to the firm's existing capital base, providing insight into the firm's financing decisions and capital structure dynamics. By scaling the debt issuance change by lagged fixed assets, the signal accounts for firm size and allows for meaningful cross-sectional comparison. 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 DIPO signal. Panel A plots the time-series of the mean, median, and interquartile range for DIPO. On average, the cross-sectional mean (median) DIPO is -0.98 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DIPO data. The signal's interquartile range spans -0.46 to 0.49. Panel B of Figure 1 plots the time-series of the coverage of the DIPO signal for the CRSP universe. On average, the DIPO signal is available for 6.21% of CRSP names, which on average make up 7.34% of total market capitalization.

4 Does DIPO predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DIPO 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 DIPO portfolio and sells the low DIPO 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 DIPO strategy earns an average return of 0.26% per month with a t-statistic of 3.78. The annualized Sharpe ratio of the strategy is 0.54. The alphas range from 0.24% to 0.34% per month and have t-statistics exceeding 3.52 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 0.33, with a t-statistic of 7.24 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 496 stocks and an average market capitalization of at least $1,698 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 17 bps/month with a t-statistics of 3.90. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three 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 -10-23bps/month. The lowest return, (-10 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.63. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DIPO 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 DIPO strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DIPO, as well as average returns and alphas for long/short trading DIPO 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 DIPO strategy achieves an average return of 37 bps/month with a t-statistic of 4.05. Among these large cap stocks, the alphas for the DIPO strategy relative to the five most common factor models range from 26 to 44 bps/month with t-statistics between 2.94 and 4.81.

5 How does DIPO perform relative to the zoo?

Figure 2 puts the performance of DIPO 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 DIPO strategy falls in the distribution. The DIPO strategy's gross (net) Sharpe ratio of 0.54 (0.42) is greater than 95% (98%) 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 DIPO strategy (red line).[2] Ignoring trading costs, a $1 invested in the DIPO strategy would have yielded $3.59 which ranks the DIPO strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DIPO strategy would have yielded $2.27 which ranks the DIPO strategy in the top 5% across the 212 anomalies.

[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.

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 DIPO relative to those. Panel A shows that the DIPO strategy gross alphas fall between the 62 and 75 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 197406 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The DIPO strategy has a positive net generalized alpha for five out of the five factor models. In these cases DIPO ranks between the 80 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does DIPO 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 DIPO with 210 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 DIPO or at least to weaken

[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.

the power DIPO has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DIPO conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIPO} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DIPO} DIPO_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DIPO,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on DIPO. Stocks are finally grouped into five DIPO portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIPO trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DIPO 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 DIPO signal in these Fama-MacBeth regressions exceed 2.06, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DIPO is 1.21.

Similarly, Table 5 reports results from spanning tests that regress returns to the DIPO 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 DIPO strategy earns alphas that range from 23-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.38, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DIPO trading strategy achieves an alpha of 21bps/month with a t-statistic of 3.20.

7 Does DIPO add relative to the whole zoo?

Finally, we can ask how much adding DIPO 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 DIPO 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 DIPO grows to $984.90.

8 Conclusion

This study provides compelling evidence for the significance of the Debt-Issuance-PPE Scale Offset (DIPO) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on DIPO gen-

[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 DIPO is available.

erates economically and statistically significant returns, with impressive Sharpe ratios of 0.54 and 0.42 on a gross and net basis, respectively. The signal's predictive power remains strong even after controlling for well-established factors and related anomalies, as evidenced by the significant alpha of 21 bps per month (t-statistic = 3.20) when controlling for the Fama-French five factors, momentum, and six closely related strategies.

The persistence of DIPO's predictive ability, even after accounting for transaction costs and controlling for various factors, suggests that this signal captures a distinct aspect of asset pricing that is not fully explained by existing factors. This has important implications for both academic research and practical investment management, as it provides a new tool for portfolio construction and risk management.

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 tested. Second, the study period may not capture all market conditions, and the signal's performance during extreme market events requires further investigation.

Future research could explore the underlying economic mechanisms driving the DIPO effect, its interaction with other market anomalies, and its performance in different asset classes and international markets. Additionally, investigating the signal's stability across different market regimes and its potential applications in factor investing strategies would be valuable extensions of this work.

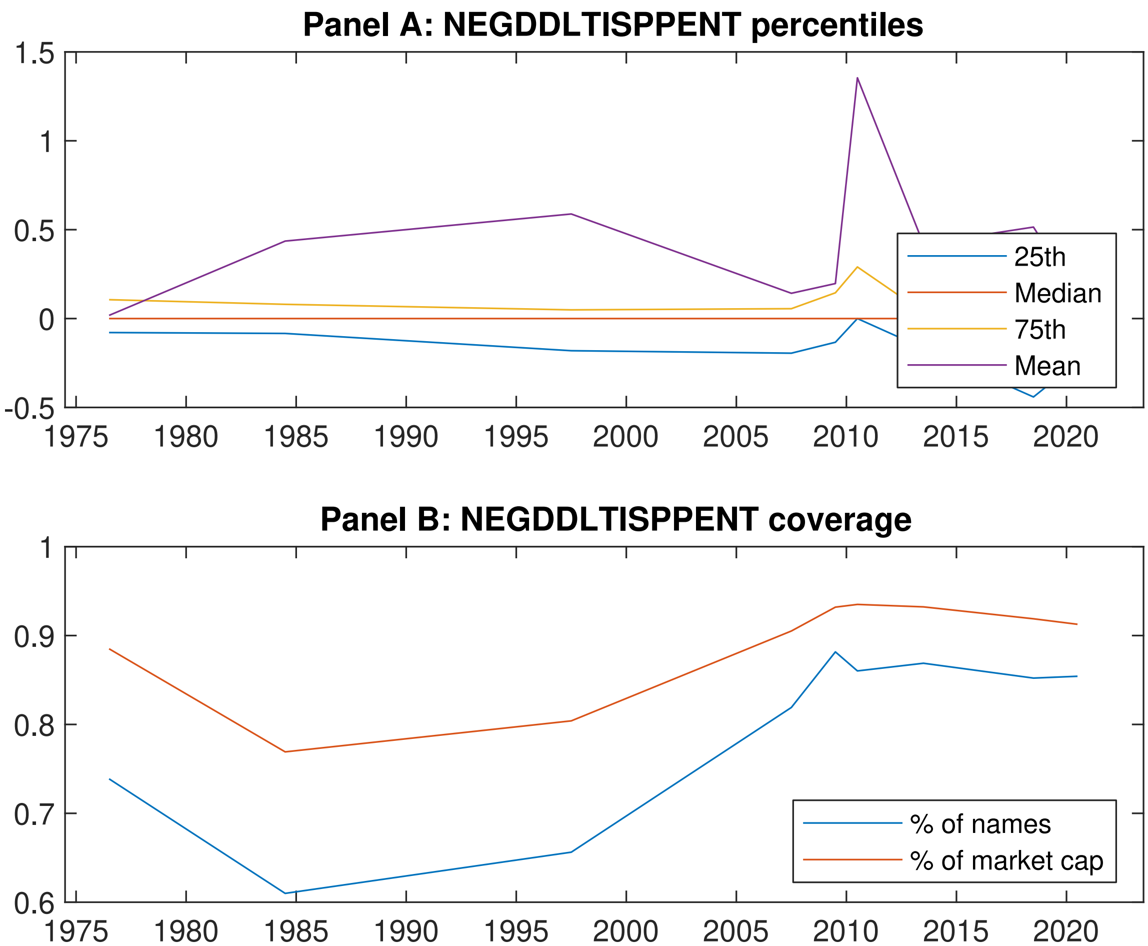


Figure 1: Times series of DIPO percentiles and coverage.
This figure plots descriptive statistics for DIPO. Panel A shows cross-sectional percentiles of DIPO over the sample. Panel B plots the monthly coverage of DIPO relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DIPO. 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 DIPO-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.61	0.69	0.71	0.72	0.87	0.26
	[2.74]	[3.80]	[3.58]	[4.03]	[4.19]	[3.78]
α_{CAPM}	-0.17	0.06	0.03	0.10	0.15	0.31
	[-2.96]	[1.19]	[0.45]	[1.97]	[2.73]	[4.55]
α_{FF3}	-0.21	0.04	0.08	0.10	0.13	0.34
	[-3.73]	[0.86]	[1.48]	[1.90]	[2.57]	[4.96]
α_{FF4}	-0.17	0.04	0.12	0.06	0.13	0.30
	[-3.04]	[0.99]	[2.27]	[1.09]	[2.38]	[4.27]
α_{FF5}	-0.17	-0.04	0.13	-0.00	0.09	0.26
	[-3.15]	[-0.90]	[2.41]	[-0.07]	[1.74]	[3.88]
α_{FF6}	-0.15	-0.03	0.16	-0.02	0.09	0.24
	[-2.74]	[-0.62]	[2.89]	[-0.47]	[1.70]	[3.52]
Panel B: Fama and French (2018) 6-factor model loadings for DIPO-sorted portfolios						
β_{MKT}	1.10	0.98	0.95	0.95	1.05	-0.05
	[88.79]	[94.89]	[73.93]	[80.54]	[85.24]	[-3.15]
β_{SMB}	0.13	-0.12	-0.00	-0.04	0.14	0.02
	[6.52]	[-7.55]	[-0.13]	[-2.43]	[7.57]	[0.81]
β_{HML}	0.15	0.04	-0.12	-0.06	-0.05	-0.21
	[6.38]	[2.08]	[-4.96]	[-2.54]	[-2.29]	[-6.88]
β_{RMW}	0.07	0.12	-0.03	0.10	0.05	-0.02
	[2.85]	[5.87]	[-1.34]	[4.24]	[2.16]	[-0.56]
β_{CMA}	-0.23	0.14	-0.12	0.24	0.10	0.33
	[-6.43]	[4.54]	[-3.31]	[6.86]	[2.69]	[7.24]
β_{UMD}	-0.04	-0.02	-0.05	0.04	0.00	0.04
	[-3.04]	[-2.09]	[-3.63]	[3.02]	[0.18]	[2.56]
Panel C: Average number of firms (n) and market capitalization (me)						
n	721	496	1040	537	696	
me (\$$10^6$)	1710	2612	2100	2455	1698	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DIPO 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	0.26	0.31	0.34	0.30	0.26	0.24
			[3.78]	[4.55]	[4.96]	[4.27]	[3.88]	[3.52]
Quintile	NYSE	EW	0.17	0.19	0.18	0.18	0.17	0.17
			[3.90]	[4.37]	[4.23]	[4.05]	[3.88]	[3.84]
Quintile	Name	VW	0.27	0.33	0.34	0.29	0.25	0.23
			[3.68]	[4.57]	[4.75]	[4.03]	[3.57]	[3.20]
Quintile	Cap	VW	0.27	0.32	0.35	0.29	0.24	0.21
			[4.01]	[4.89]	[5.25]	[4.42]	[3.76]	[3.31]
Decile	NYSE	VW	0.29	0.35	0.34	0.28	0.18	0.15
			[3.07]	[3.71]	[3.54]	[2.87]	[1.92]	[1.62]
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	0.21	0.27	0.29	0.27	0.23	0.21
			[2.92]	[3.83]	[4.17]	[3.83]	[3.30]	[3.04]
Quintile	NYSE	EW	-0.10					
			[-1.63]					
Quintile	Name	VW	0.21	0.28	0.29	0.26	0.22	0.20
			[2.83]	[3.82]	[3.97]	[3.62]	[3.02]	[2.75]
Quintile	Cap	VW	0.22	0.29	0.31	0.28	0.22	0.20
			[3.23]	[4.29]	[4.58]	[4.18]	[3.33]	[3.05]
Decile	NYSE	VW	0.23	0.29	0.28	0.24	0.15	0.12
			[2.33]	[2.97]	[2.83]	[2.48]	[1.54]	[1.30]

Table 3: Conditional sort on size and DIPO

This table presents results for conditional double sorts on size and DIPO. 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 DIPO. 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 DIPO and short stocks with low DIPO .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	DIPO Quintiles					DIPO Strategies					
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.74	0.89	1.01	0.95	0.81	0.06	0.09	0.06	0.05	0.02	0.01
	[2.60]	[3.34]	[3.64]	[3.46]	[2.77]	[0.69]	[0.92]	[0.63]	[0.48]	[0.16]	[0.14]
(2)	0.79	0.94	0.84	0.98	0.86	0.07	0.10	0.07	0.07	0.03	0.04
	[2.90]	[3.75]	[3.31]	[3.99]	[3.33]	[0.83]	[1.24]	[0.86]	[0.93]	[0.42]	[0.53]
(3)	0.84	0.86	0.84	0.87	0.95	0.11	0.16	0.16	0.12	0.17	0.14
	[3.25]	[3.86]	[3.45]	[4.00]	[3.92]	[1.44]	[2.10]	[2.07]	[1.53]	[2.16]	[1.79]
(4)	0.77	0.83	0.86	0.81	0.89	0.12	0.14	0.13	0.10	0.10	0.08
	[3.32]	[3.90]	[3.89]	[3.95]	[3.95]	[1.51]	[1.83]	[1.63]	[1.23]	[1.20]	[0.98]
(5)	0.53	0.64	0.65	0.61	0.90	0.37	0.42	0.44	0.36	0.31	0.26
	[2.46]	[3.58]	[3.44]	[3.32]	[4.47]	[4.05]	[4.60]	[4.81]	[3.93]	[3.43]	[2.94]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	DIPO Quintiles Average n					DIPO Quintiles Average market capitalization ($\$10^6$)				
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	393	395	395	395	390	36	34	32	33	35
(2)	107	107	107	107	107	59	60	58	60	59
(3)	76	76	76	76	76	104	104	100	103	103
(4)	63	64	64	64	63	221	228	218	228	219
(5)	58	58	58	58	58	1395	2024	1630	1956	1475

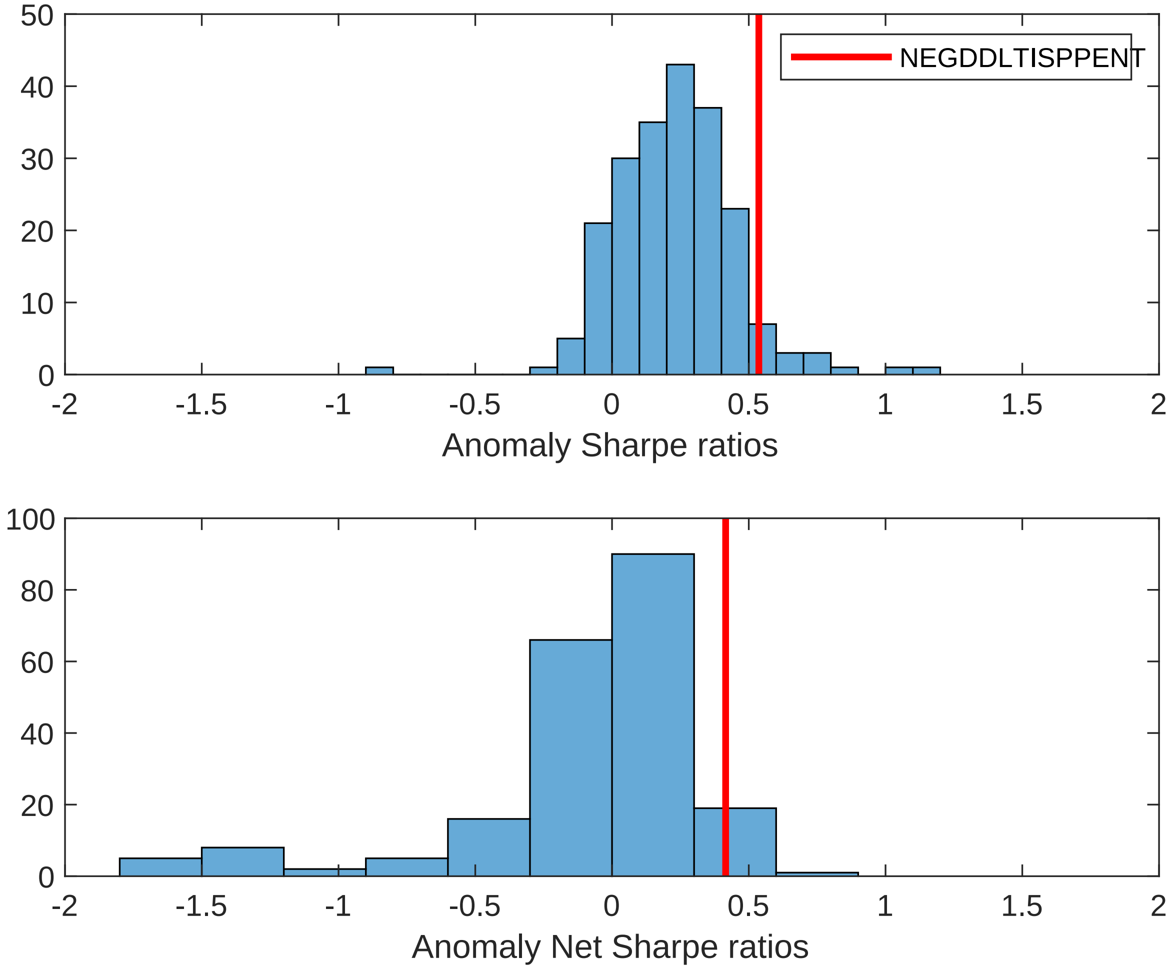


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DIPO with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

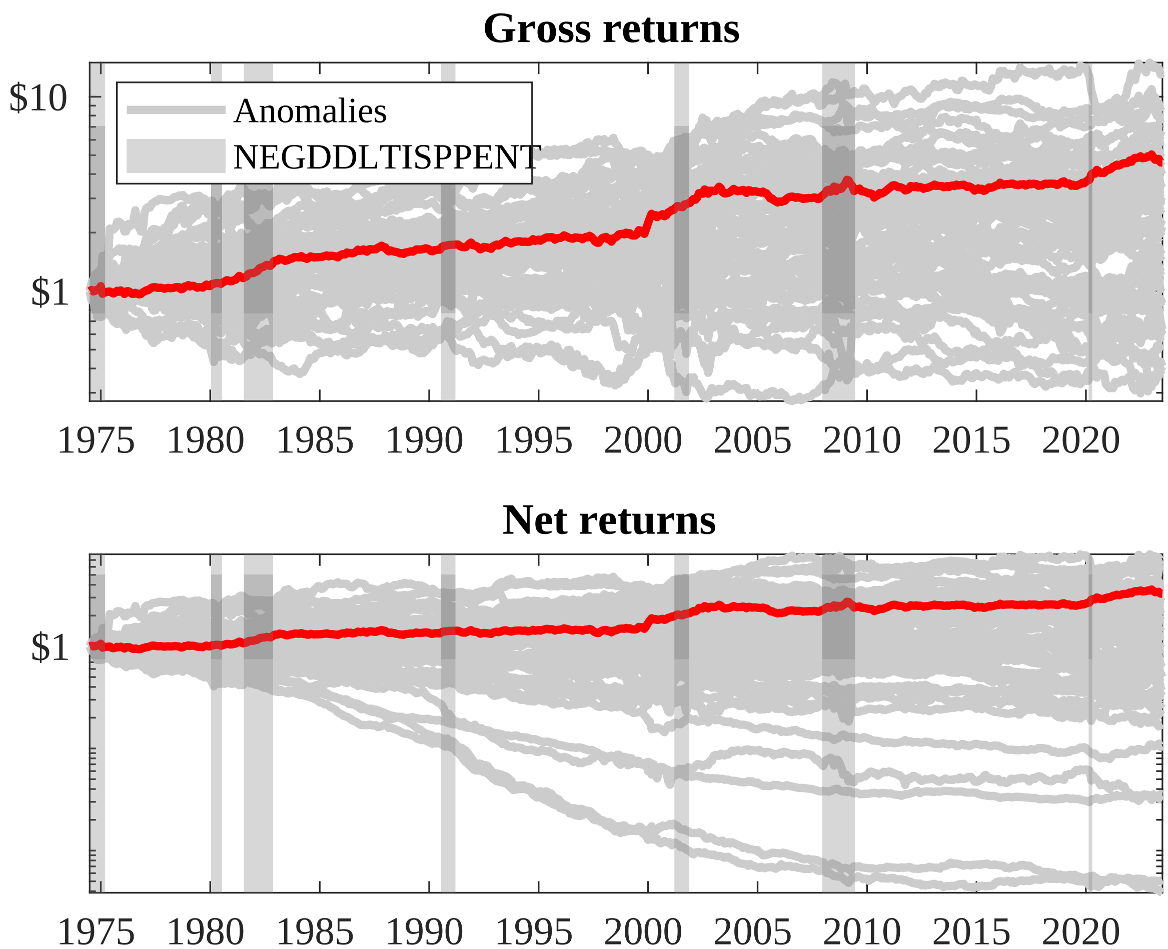


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DIPO trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

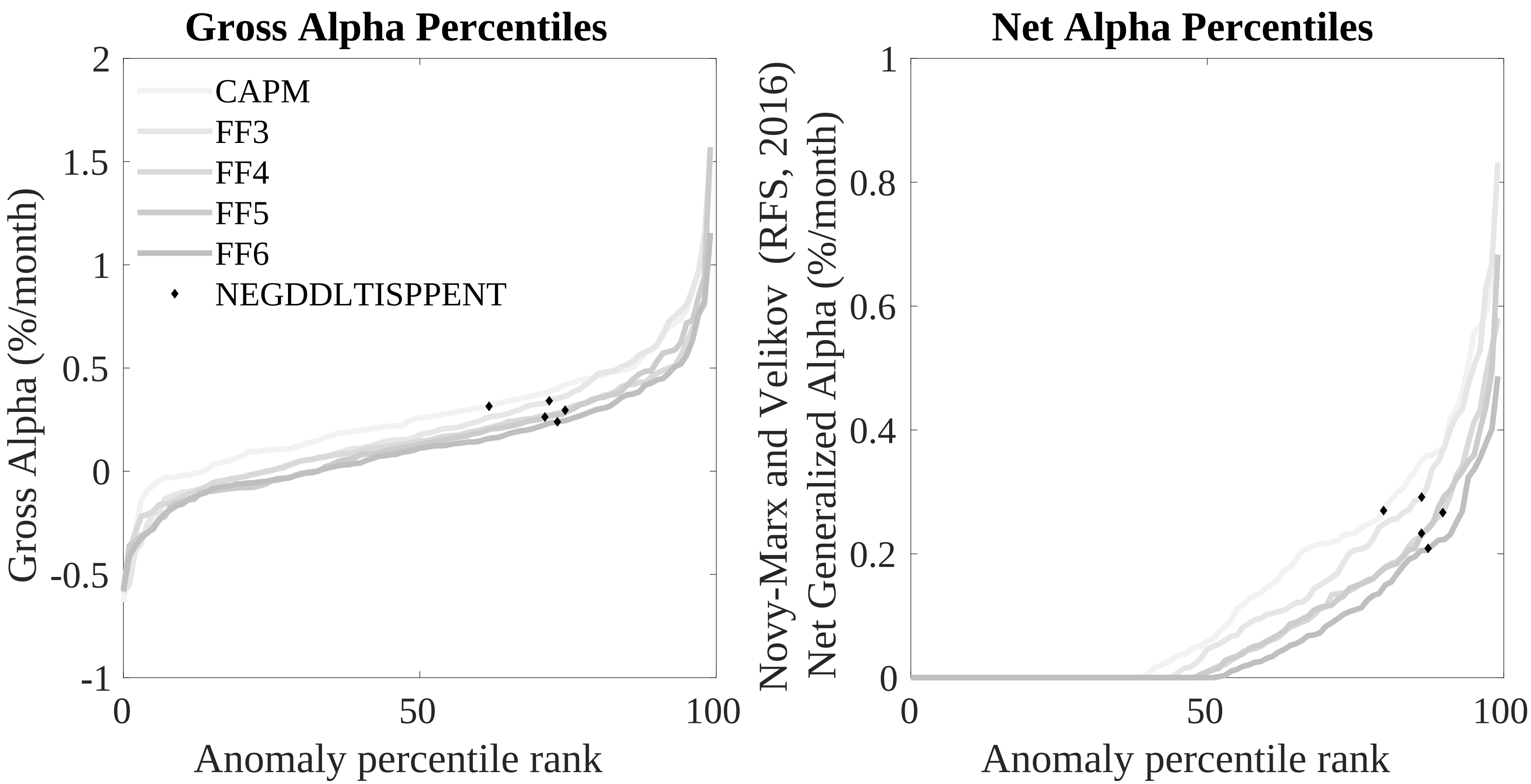
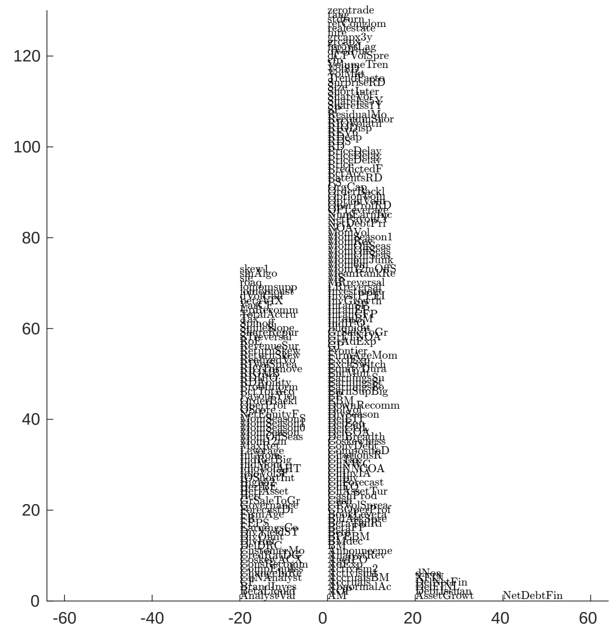
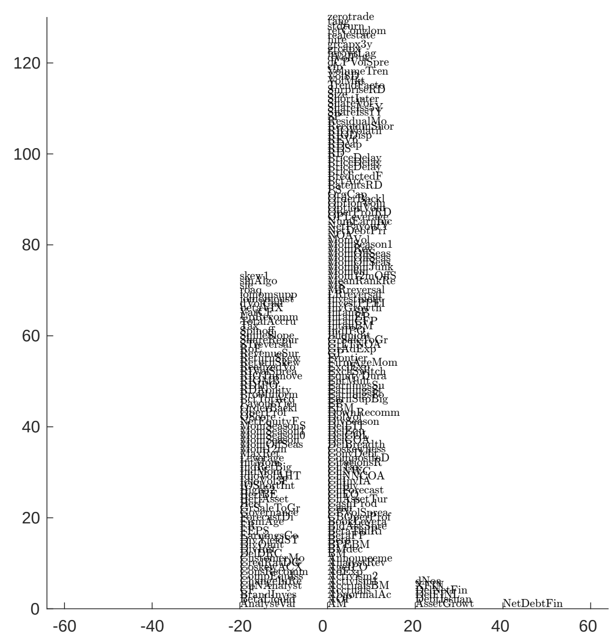


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DIPO trading strategy alphas (diamonds). The strategies are constructed 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 210 filtered anomaly signals with DIPO. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

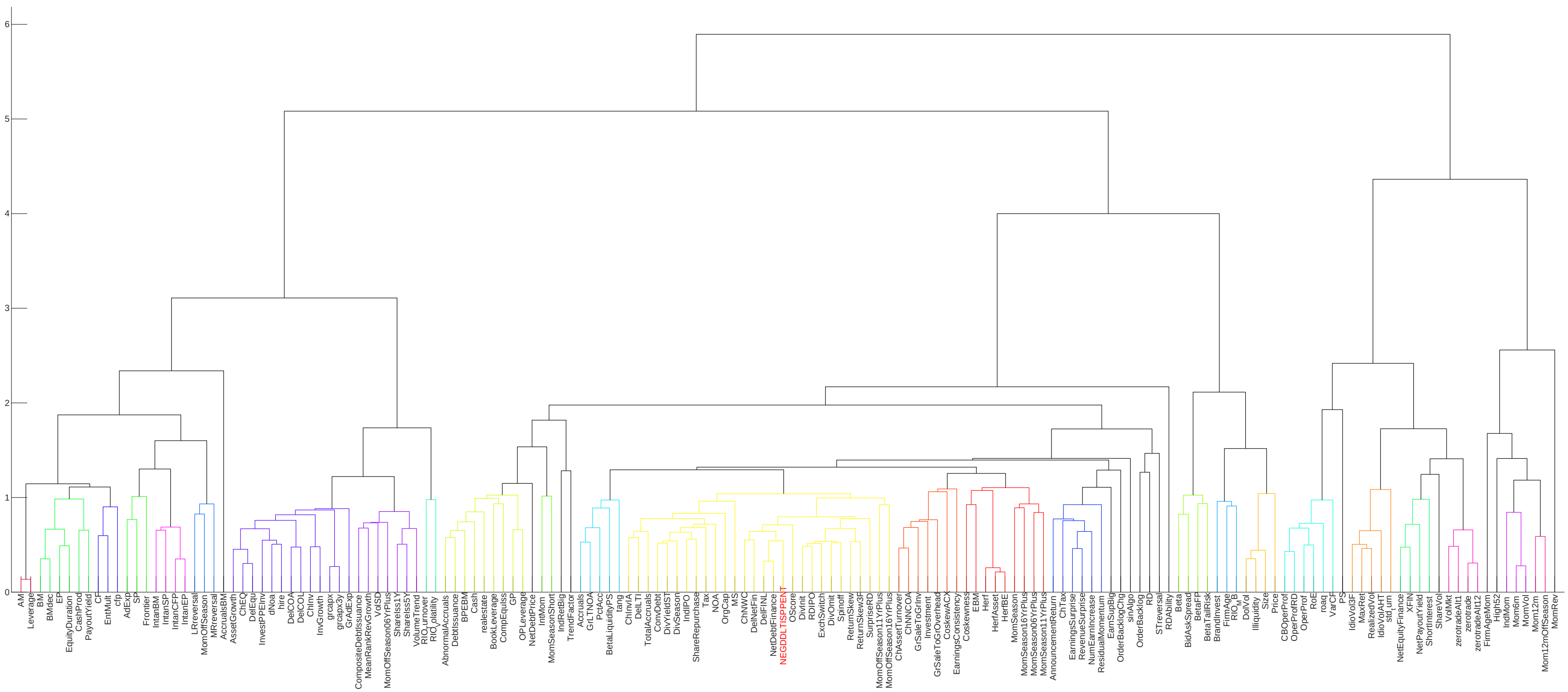


Figure 6: Agglomerative hierarchical cluster plot

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

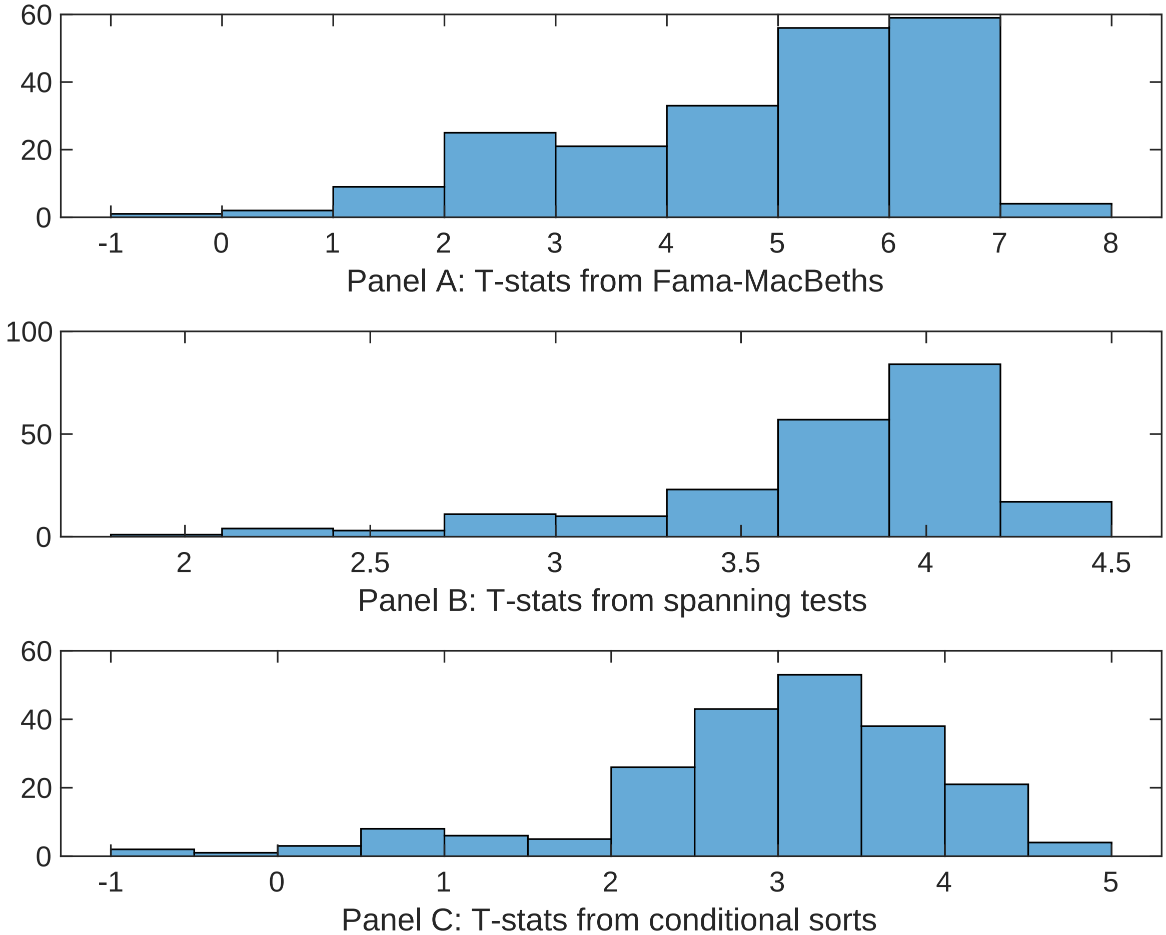


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DIPO conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DIPO} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DIPO} DIPO_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DIPO,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on DIPO. Stocks are finally grouped into five DIPO portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DIPO trading strategies conditioned on each of the 210 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on DIPO. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DIPO} DIPO_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, Inventory Growth, Accruals. 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	0.14	0.13	0.15
	[5.54]	[5.51]	[5.87]	[5.97]	[5.47]	[5.22]	[5.78]
DIPO	0.30	0.40	0.47	0.31	0.82	0.82	0.21
	[2.24]	[2.77]	[3.55]	[2.06]	[5.24]	[5.65]	[1.21]
Anomaly 1	0.17						-0.71
	[9.05]						[-1.55]
Anomaly 2		0.20					0.10
		[8.52]					[1.58]
Anomaly 3			0.18				0.99
			[6.09]				[1.80]
Anomaly 4				0.11			0.72
				[9.08]			[3.47]
Anomaly 5					0.38		0.43
					[6.68]		[0.76]
Anomaly 6						0.14	0.49
						[4.42]	[1.46]
# 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 DIPO trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DIPO} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Inventory Growth, Accruals. 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	0.23	0.23	0.23	0.25	0.25	0.23	0.21
	[3.42]	[3.44]	[3.42]	[3.62]	[3.60]	[3.38]	[3.20]
Anomaly 1	21.86						12.82
	[5.56]						[2.39]
Anomaly 2		21.76					10.02
		[5.78]					[1.91]
Anomaly 3			13.68				9.32
			[3.97]				[2.54]
Anomaly 4				7.20			0.88
				[1.62]			[0.19]
Anomaly 5					2.79		1.51
					[1.03]		[0.56]
Anomaly 6						4.23	1.63
						[1.54]	[0.59]
mkt	-4.87	-5.13	-3.28	-5.10	-5.20	-4.82	-3.64
	[-3.17]	[-3.35]	[-2.02]	[-3.25]	[-3.30]	[-3.05]	[-2.25]
smb	-0.45	0.05	5.90	0.77	1.78	2.18	3.01
	[-0.19]	[0.02]	[2.23]	[0.31]	[0.73]	[0.88]	[1.06]
hml	-19.51	-20.31	-19.07	-20.86	-20.67	-19.43	-18.49
	[-6.61]	[-6.91]	[-6.35]	[-6.90]	[-6.84]	[-6.26]	[-6.07]
rmw	-3.19	-3.30	-9.71	-1.49	-1.15	-0.21	-8.16
	[-1.04]	[-1.08]	[-2.61]	[-0.48]	[-0.37]	[-0.07]	[-2.13]
cma	24.94	26.65	23.06	23.25	29.73	30.80	16.16
	[5.37]	[5.86]	[4.55]	[3.24]	[5.76]	[6.62]	[2.24]
umd	2.10	2.42	4.16	4.49	3.94	3.96	1.93
	[1.32]	[1.54]	[2.65]	[2.81]	[2.45]	[2.48]	[1.19]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	20	20	18	16	16	16	21

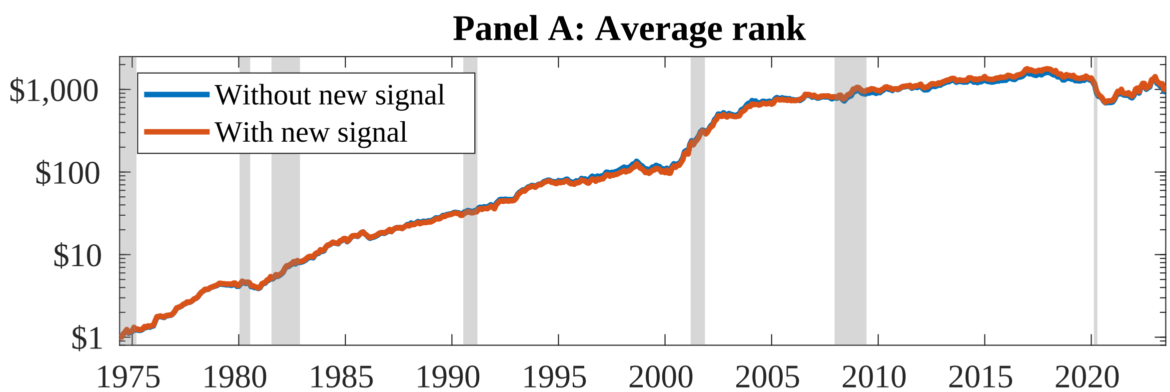


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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