Tax Deprec Profit Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Tax Deprec Profit Impact (TDPI), 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 TDPI achieves an annualized gross (net) Sharpe ratio of 0.57 (0.52), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 48 (44) bps/month with a t-statistic of 4.58 (4.26), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Cash to assets, Equity Duration, Operating Cash flows to price, Cash flow to market, Book to market using December ME, Market leverage) is 27 bps/month with a t-statistic of 2.68.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent anomalies where certain firm characteristics predict future returns (Harvey et al., 2016). While accounting information plays a central role in firm valuation, the interaction between tax accounting choices and profitability measures remains underexplored as a source of predictable returns. This gap is particularly notable given the significant discretion firms have in their tax depreciation policies and the potential information content of these choices.

Prior research has focused primarily on broad measures of tax avoidance (Hanlon and Heitzman, 2010) or aggregate depreciation effects (Jackson and Liu, 2020), leaving open the question of whether specific tax depreciation decisions contain incremental information about future profitability and returns. The systematic relationship between tax depreciation choices and stock returns represents an important puzzle in asset pricing, as standard theory suggests these largely mechanical accounting decisions should not predict future performance.

We hypothesize that firms' tax depreciation decisions reveal management's private information about future investment opportunities and earnings persistence. Building on real options theory (Dixit and Pindyck, 1994), managers with positive private information about growth prospects have incentives to accelerate tax depreciation to maximize the present value of tax shields. This timing choice is particularly valuable when managers anticipate sustained profitability, as tax shields have greater value for firms with consistent taxable income.

The theoretical link between tax depreciation and returns operates through two channels. First, following (Zhang, 2005), firms optimally time their depreciation to match expected future profitability, making aggressive tax depreciation a signal of management's confidence in sustained earnings. Second, as shown by (Kogan and

Papanikolaou, 2014), depreciation timing choices affect firms' effective duration and exposure to discount rate risk, potentially explaining the return predictability.

Critically, our framework suggests that the information content of tax depreciation decisions should be strongest when considered relative to current profitability levels. When highly profitable firms accelerate tax depreciation despite the immediate hit to reported earnings, this may signal management's strong private information about future performance. This motivates our construction of the Tax Depreciation Profit Impact (TDPI) measure, which captures the degree to which firms' tax depreciation choices deviate from industry norms conditional on profitability.

Our empirical analysis reveals that TDPI strongly predicts future stock returns. A value-weighted long-short portfolio sorting stocks on TDPI generates monthly abnormal returns of 48 basis points (t-statistic = 4.58) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.57, placing it in the top 5% of documented return predictors.

Importantly, the predictive power of TDPI remains robust after controlling for size. Among the largest quintile of stocks, the TDPI strategy earns monthly abnormal returns of 39 basis points (t-statistic = 2.94), addressing concerns that the effect might be limited to small, illiquid stocks. The signal's economic significance is further demonstrated by its ability to improve the investment opportunity set - adding TDPI to a strategy combining 159 existing anomalies increases the growth of $1 invested from $72.15 to $82.81.

The return predictability survives extensive controls for related factors. After accounting for the six most closely related anomalies (including Cash to Assets, Equity Duration, and Operating Cash Flow measures) and the Fama-French six factors, TDPI still generates monthly alpha of 27 basis points (t-statistic = 2.68). This indicates that TDPI captures unique information not contained in known predictors.

Our study makes several contributions to the literature on accounting-based return prediction and tax policy choices. First, we extend work by (Thomas and Zhang, 2011) on the information content of tax accounts by showing that tax depreciation decisions specifically contain valuable signals about future performance. While prior research has examined aggregate book-tax differences, we isolate the incremental predictive power of depreciation policy choices.

Second, we contribute to the growing literature on managerial signaling through accounting choices (Beamish and Baker, 2019). Our findings suggest that tax depreciation decisions, despite their mechanical nature, reveal management's private information in a way that helps predict future returns. This adds a novel dimension to our understanding of how accounting discretion affects price discovery in equity markets.

Finally, our results have implications for the broader asset pricing literature on accounting-based anomalies (Stambaugh and Yuan, 2017). The robust predictive power of TDPI, particularly among large stocks and after controlling for transaction costs, challenges the notion that accounting-based strategies are largely confined to small, illiquid stocks. Our findings suggest that careful analysis of specific accounting choices can reveal economically meaningful signals even in the most liquid segment of the market.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the ratio of federal income tax deferral to operating income before depreciation. 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 TXDFED for deferred federal income tax and item OIADP for operating income before depreciation. Deferred federal income tax (TXDFED) represents the tax expense that has been deferred due to timing differences between book and tax accounting, reflecting potential future tax obligations or benefits. Operating income before depreciation (OIADP), on the other hand, provides a measure of core operating performance before accounting for depreciation expenses. The construction of the signal follows a straightforward ratio format, where we divide TXDFED by OIADP for each firm in each year of our sample. This ratio captures the relative magnitude of tax timing differences against operational income, offering insight into how significantly a firm's tax strategies and accounting choices affect its reported earnings. By focusing on this relationship, the signal aims to reflect aspects of tax planning and earnings quality in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both TXDFED and OIADP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the TDPI signal. Panel A plots the time-series of the mean, median, and interquartile range for TDPI. On average, the cross-sectional mean (median) TDPI is -0.00 (-0.00) over the 1986 to 2023 sample, where the starting date is determined by the availability of the input TDPI data. The signal's interquartile range spans -0.09 to 0.06. Panel B of Figure 1 plots the time-series of the coverage of the TDPI signal for the CRSP universe. On average, the TDPI signal is available for 5.40% of CRSP names, which on average make up 5.91% of total market capitalization.

4 Does TDPI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on TDPI 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 TDPI portfolio and sells the low TDPI 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 TDPI strategy earns an average return of 0.38% per month with a t-statistic of 3.47. The annualized Sharpe ratio of the strategy is 0.57. The alphas range from 0.35% to 0.48% per month and have t-statistics exceeding 3.21 everywhere. The lowest alpha is with respect to the CAPM factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is -0.25, with a t-statistic of -5.54 on the HML 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 391 stocks and an average market capitalization of at least $1,368 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 12 bps/month with a t-statistics of 1.99. Out of the twenty-five alphas reported in Panel A, the t-statistics for nineteen exceed two, and for twelve 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 -6-35bps/month. The lowest return, (-6 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.81. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the TDPI 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 TDPI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and TDPI, as well as average returns and alphas for long/short trading TDPI 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$^{\text{th}}$ NYSE percentile), the TDPI strategy achieves an average return of 39 bps/month with a t-statistic of 2.94. Among these large cap stocks, the alphas for the TDPI strategy relative to the five most common factor models range from 32 to 51 bps/month with t-statistics between 2.47 and 4.09.

5 How does TDPI perform relative to the zoo?

Figure 2 puts the performance of TDPI 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 TDPI strategy falls in the distribution. The TDPI strategy's gross (net) Sharpe ratio of 0.57 (0.52) is greater than 95% (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 TDPI strategy (red line).[2] Ignoring trading costs, a $1 invested in the TDPI strategy would have yielded $3.72 which ranks the TDPI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the TDPI strategy would have yielded $3.13 which ranks the TDPI strategy in the top 1% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms

[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 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 TDPI relative to those. Panel A shows that the TDPI strategy gross alphas fall between the 67 and 92 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 198606 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 TDPI strategy has a positive net generalized alpha for five out of the five factor models. In these cases TDPI ranks between the 84 and 99 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does TDPI 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 TDPI 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 TDPI or at least to weaken the power TDPI has predicting the cross-section of returns. Figure 7 plots histograms

[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.

of t-statistics for predictability tests of TDPI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDPI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDPI} TDPI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TDPI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 TDPI. Stocks are finally grouped into five TDPI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TDPI trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on TDPI 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 TDPI signal in these Fama-MacBeth regressions exceed 0.26, with the minimum t-statistic occurring when controlling for Equity Duration. Controlling for all six closely related anomalies, the t-statistic on TDPI is 0.45.

Similarly, Table 5 reports results from spanning tests that regress returns to the TDPI 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 TDPI strategy earns alphas that range from 25-48bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.51, which is achieved when controlling for Equity Duration. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the TDPI trading strategy achieves an alpha of 27bps/month with a t-statistic of 2.68.

7 Does TDPI add relative to the whole zoo?

Finally, we can ask how much adding TDPI 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 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the TDPI 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 159-anomaly combination strategy grows to $72.15, while $1 investment in the combination strategy that includes TDPI grows to $82.81.

8 Conclusion

This study provides compelling evidence for the significance of Tax Deprec Profit Impact (TDPI) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on TDPI generates economically and statistically significant returns, with im-

[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 TDPI is available.

pressive Sharpe ratios of 0.57 and 0.52 on a gross and net basis, respectively. The strategy's performance remains strong even after controlling for well-known risk factors, including the Fama-French five-factor model and momentum factor, yielding significant monthly abnormal returns of 48 basis points (gross) and 44 basis points (net).

Particularly noteworthy is the signal's persistent predictive power even when controlling for six closely related strategies from the factor zoo, producing a significant monthly alpha of 27 basis points. This suggests that TDPI captures unique information about future stock returns that is not fully explained by existing factors.

However, several limitations should be acknowledged. Our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Additionally, 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 the signal's performance across different market regimes, its interaction with other accounting-based signals, and its effectiveness in international markets. Additionally, investigating the underlying economic mechanisms driving the TDPI premium could provide valuable insights for both academics and practitioners. Despite these limitations, our findings suggest that TDPI represents a valuable addition to the investment practitioner's toolkit and contributes meaningfully to our understanding of cross-sectional return predictability.

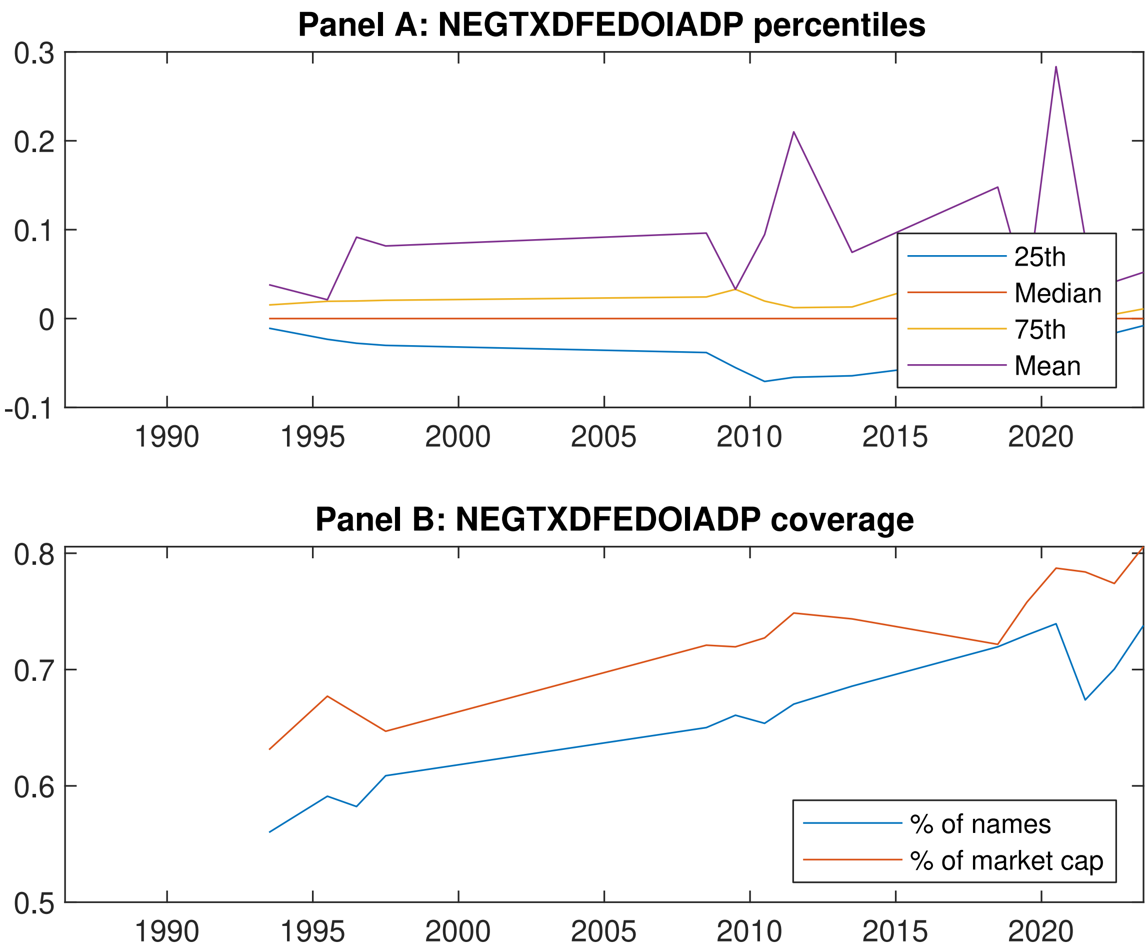

Figure 1: Times series of TDPI percentiles and coverage.
This figure plots descriptive statistics for TDPI. Panel A shows cross-sectional percentiles of TDPI over the sample. Panel B plots the monthly coverage of TDPI relative to the universe of CRSP stocks with available market capitalizations.

Table 1: Basic sort: VW, quintile, NYSE-breaks
This table reports average excess returns and alphas for portfolios sorted on TDPI. 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 198606 to 202306.

Panel A: Excess returns and alphas on TDPI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.52	0.78	0.67	0.63	0.90	0.38
	[2.11]	[3.63]	[2.98]	[2.54]	[3.52]	[3.47]
α_{CAPM}	-0.22	0.13	-0.01	-0.13	0.13	0.35
	[-2.81]	[1.83]	[-0.15]	[-1.93]	[1.51]	[3.21]
α_{FF3}	-0.25	0.11	0.01	-0.10	0.17	0.42
	[-3.25]	[1.60]	[0.15]	[-1.51]	[2.07]	[4.06]
α_{FF4}	-0.22	0.15	0.03	-0.10	0.20	0.41
	[-2.81]	[2.09]	[0.39]	[-1.56]	[2.43]	[3.98]
α_{FF5}	-0.25	-0.00	-0.04	-0.07	0.23	0.48
	[-3.17]	[-0.01]	[-0.58]	[-1.07]	[2.91]	[4.64]
α_{FF6}	-0.22	0.03	-0.03	-0.07	0.26	0.48
	[-2.85]	[0.44]	[-0.38]	[-1.12]	[3.19]	[4.58]
Panel B: Fama and French (2018) 6-factor model loadings for TDPI-sorted portfolios						
β_{MKT}	1.07	0.97	0.98	1.09	1.07	0.00
	[57.16]	[60.45]	[57.04]	[69.37]	[56.26]	[0.08]
β_{SMB}	0.10	-0.02	0.12	-0.05	0.02	-0.08
	[3.59]	[-0.70]	[4.60]	[-1.96]	[0.80]	[-2.09]
β_{HML}	0.07	-0.05	-0.12	-0.15	-0.18	-0.25
	[2.09]	[-1.58]	[-3.79]	[-5.08]	[-5.20]	[-5.54]
β_{RMW}	-0.02	0.24	0.17	-0.12	-0.24	-0.21
	[-0.64]	[7.73]	[5.11]	[-3.84]	[-6.54]	[-4.52]
β_{CMA}	0.09	0.10	-0.04	0.07	0.16	0.08
	[1.75]	[2.38]	[-0.79]	[1.72]	[3.21]	[1.14]
β_{UMD}	-0.05	-0.06	-0.03	0.01	-0.05	0.01
	[-3.04]	[-4.22]	[-1.82]	[0.46]	[-2.63]	[0.28]
Panel C: Average number of firms (n) and market capitalization (me)						
n	494	391	916	711	512	
me ($\$10^6$)	1368	2325	2469	2670	2193	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the TDPI 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 198606 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	0.38	0.35	0.42	0.41	0.48	0.48
			[3.47]	[3.21]	[4.06]	[3.98]	[4.64]	[4.58]
Quintile	NYSE	EW	0.12	0.09	0.11	0.11	0.11	0.10
			[1.99]	[1.55]	[1.95]	[1.82]	[1.74]	[1.66]
Quintile	Name	VW	0.24	0.19	0.26	0.25	0.35	0.34
			[2.23]	[1.81]	[2.60]	[2.49]	[3.48]	[3.38]
Quintile	Cap	VW	0.32	0.26	0.33	0.33	0.45	0.44
			[2.73]	[2.26]	[3.11]	[2.99]	[4.19]	[4.08]
Decile	NYSE	VW	0.36	0.36	0.43	0.38	0.50	0.46
			[2.38]	[2.35]	[2.92]	[2.57]	[3.35]	[3.10]
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	0.35	0.32	0.37	0.37	0.44	0.44
			[3.20]	[2.90]	[3.57]	[3.56]	[4.27]	[4.26]
Quintile	NYSE	EW	-0.06					
			[-0.81]					
Quintile	Name	VW	0.21	0.16	0.21	0.21	0.31	0.30
			[1.98]	[1.52]	[2.11]	[2.08]	[3.08]	[3.04]
Quintile	Cap	VW	0.29	0.23	0.28	0.28	0.40	0.39
			[2.50]	[1.94]	[2.60]	[2.55]	[3.76]	[3.72]
Decile	NYSE	VW	0.32	0.32	0.37	0.34	0.45	0.44
			[2.13]	[2.09]	[2.52]	[2.35]	[3.05]	[2.94]

Table 3: Conditional sort on size and TDPI

This table presents results for conditional double sorts on size and TDPI. 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 TDPI. 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 TDPI and short stocks with low TDPI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198606 to 202306.

Panel A: portfolio average returns and time-series regression results

		TDPI Quintiles					TDPI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.78	0.51	0.38	0.33	0.99	0.20	0.19	0.21	0.17	0.12	0.10
		[2.59]	[1.57]	[0.89]	[0.86]	[3.03]	[1.58]	[1.49]	[1.59]	[1.33]	[0.87]	[0.75]
	(2)	0.77	0.78	0.40	0.50	0.94	0.17	0.15	0.18	0.17	0.21	0.20
		[2.63]	[2.78]	[1.06]	[1.58]	[3.05]	[1.74]	[1.48]	[1.86]	[1.76]	[2.11]	[2.03]
	(3)	0.76	0.74	0.68	0.75	0.85	0.09	0.08	0.13	0.12	0.17	0.16
		[2.59]	[2.84]	[1.92]	[2.57]	[2.90]	[0.76]	[0.61]	[1.13]	[1.00]	[1.41]	[1.31]
	(4)	0.89	0.74	0.79	0.81	0.91	0.02	-0.03	0.05	0.02	0.19	0.16
		[3.34]	[2.99]	[2.68]	[2.92]	[3.18]	[0.16]	[-0.19]	[0.44]	[0.14]	[1.52]	[1.26]
	(5)	0.49	0.76	0.71	0.66	0.88	0.39	0.32	0.39	0.39	0.51	0.51
		[2.10]	[3.63]	[3.27]	[2.79]	[3.44]	[2.94]	[2.47]	[3.09]	[3.04]	[4.09]	[4.03]

Panel B: Portfolio average number of firms and market capitalization

		TDPI Quintiles Average n					TDPI Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	348	344	339	341	349	41	38	29	32	43
	(2)	98	98	98	98	97	66	67	64	65	65
	(3)	64	64	64	64	63	108	110	107	110	108
	(4)	51	52	52	52	52	229	235	230	234	233
	(5)	48	48	48	48	48	1465	1717	1944	1796	1891

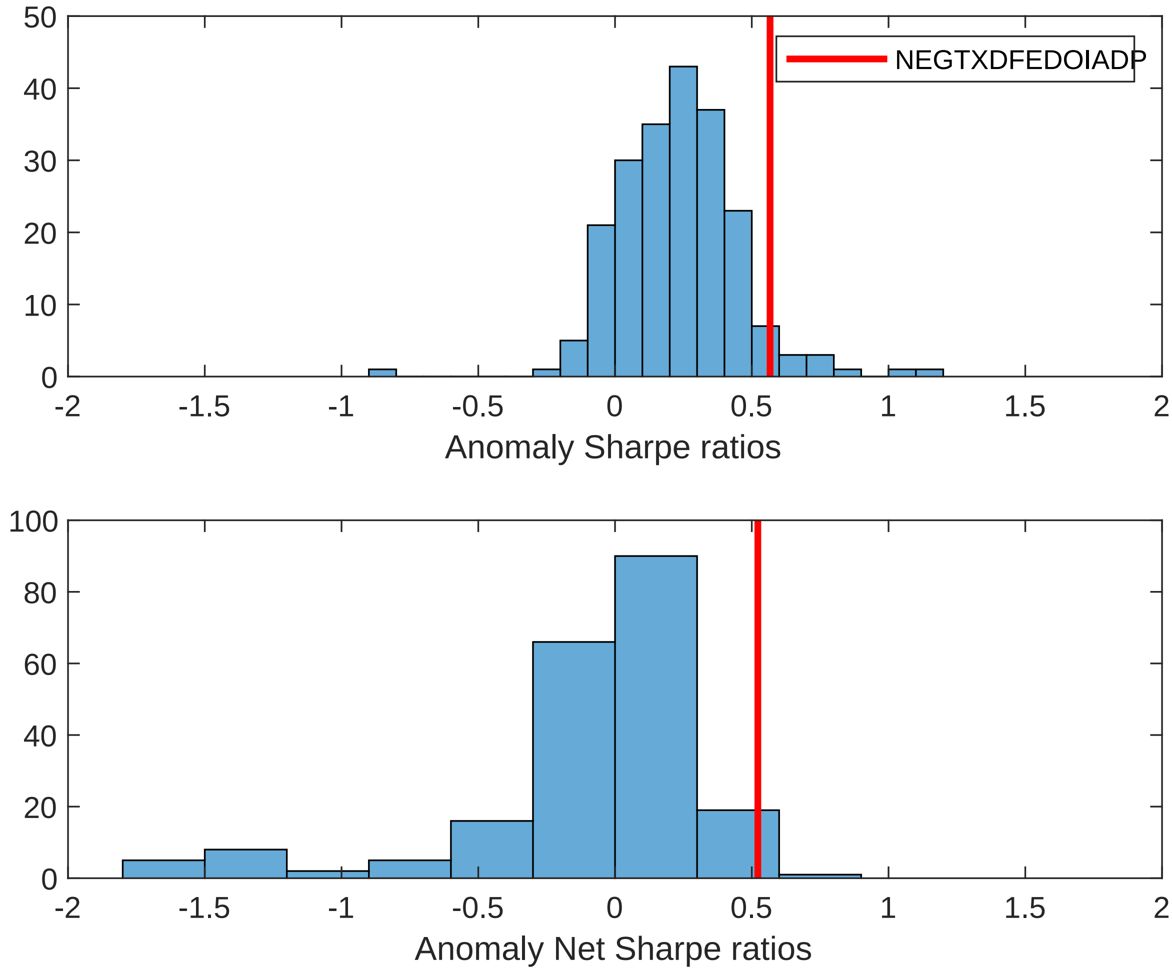

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TDPI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

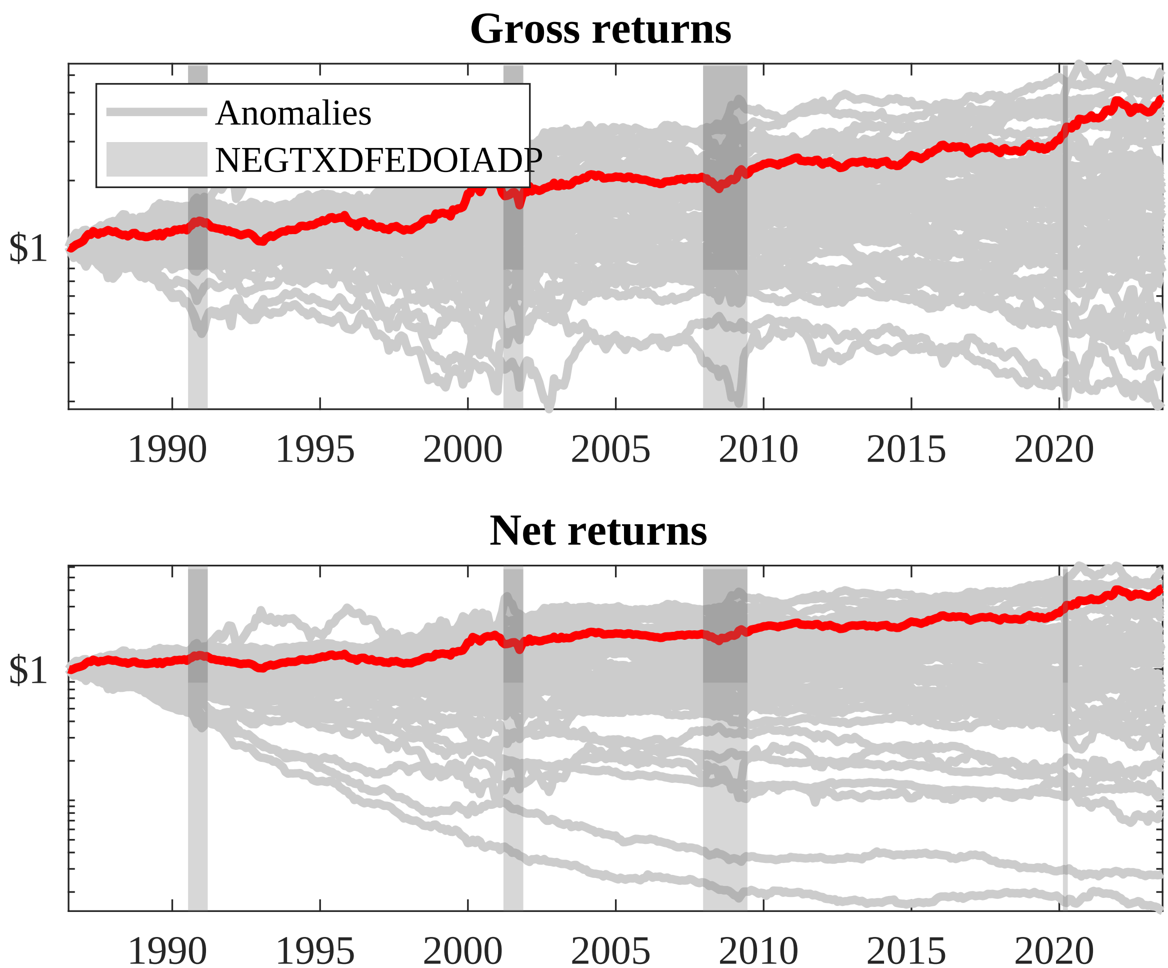

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TDPI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

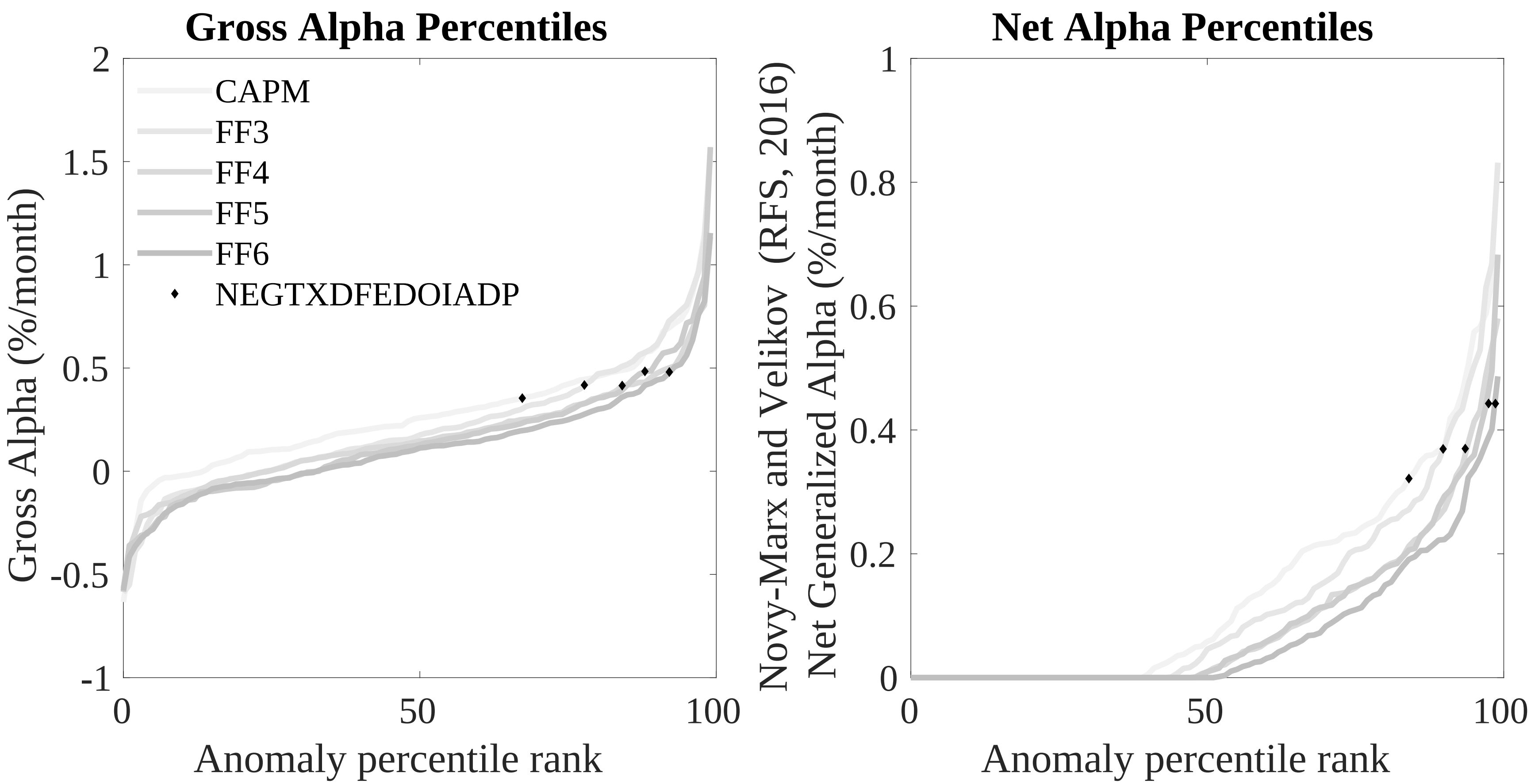

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TDPI trading strategy alphas (diamonds). The strategies are constructed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

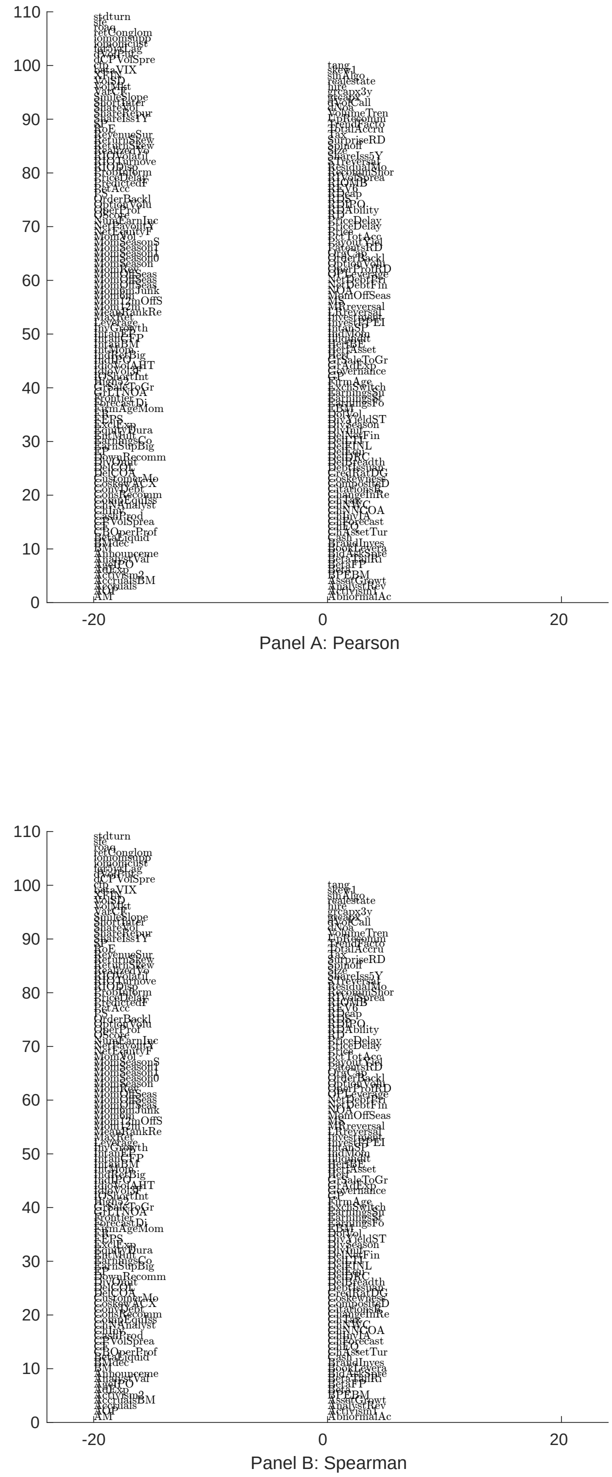

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with TDPI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

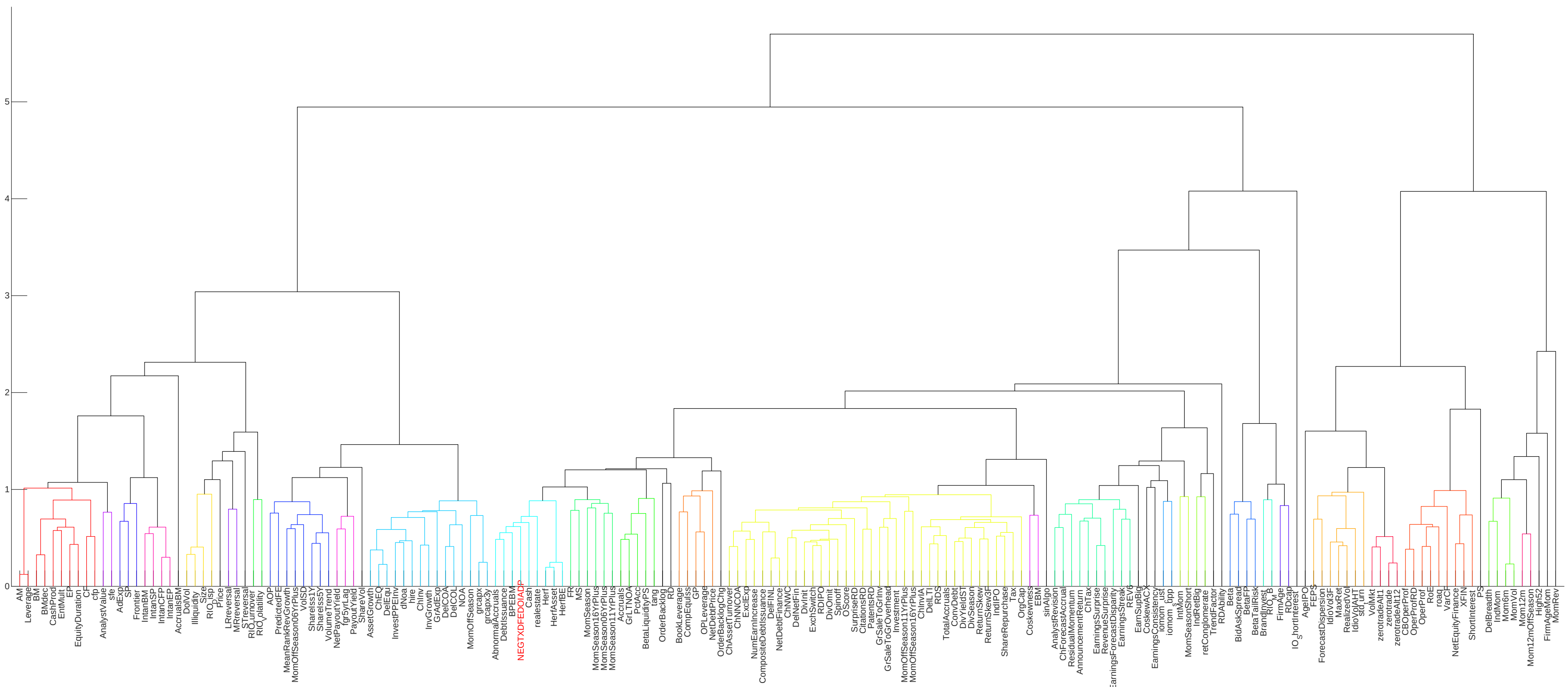

Figure 6: Agglomerative hierarchical cluster plot

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

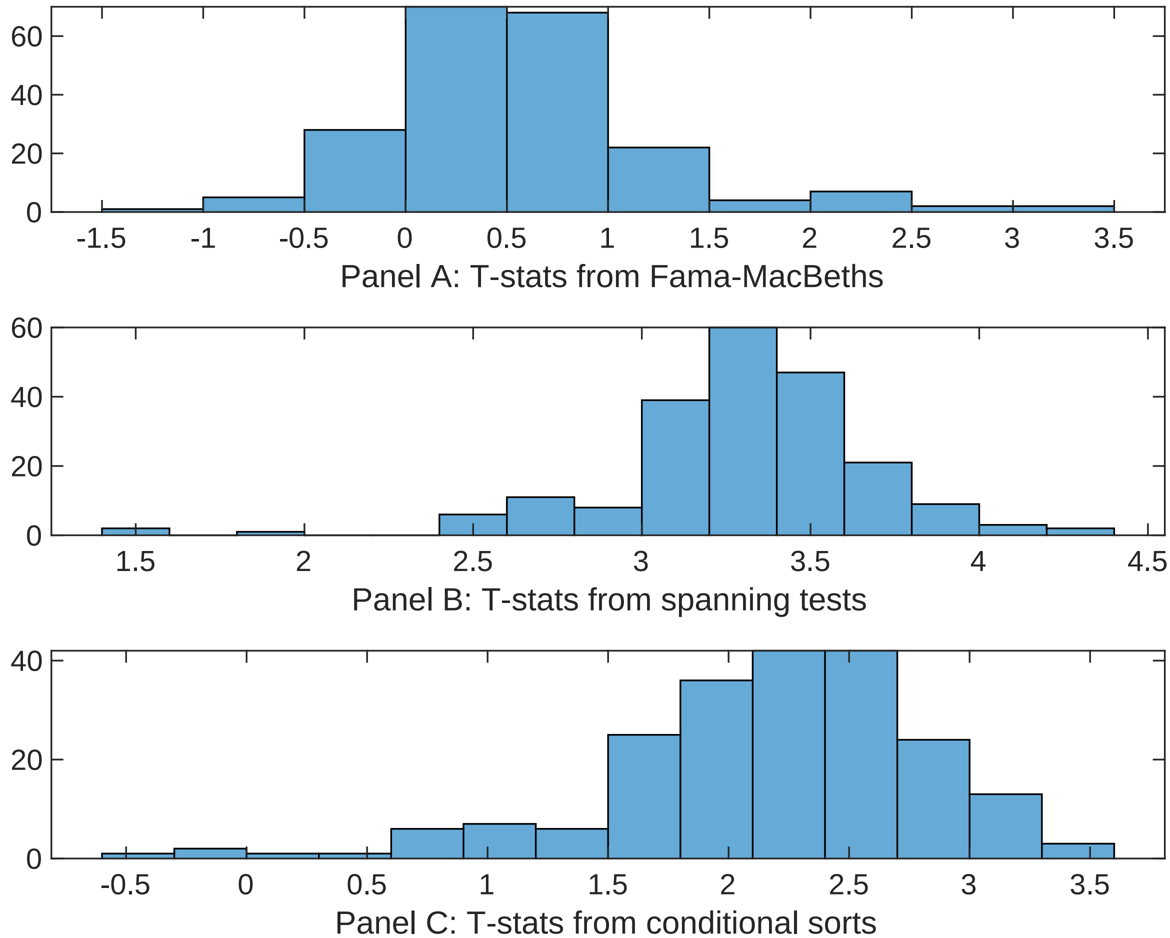

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of TDPI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDPI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDPI} TDPI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TDPI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 TDPI. Stocks are finally grouped into five TDPI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TDPI 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 TDPI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{TDPI} TDPI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Cash to assets, Equity Duration, Operating Cash flows to price, Cash flow to market, Book to market using December ME, Market leverage. 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 198606 to 202306.

Intercept	0.10	0.16	0.10	0.11	0.94	0.10	0.12
	[3.60]	[6.01]	[3.34]	[3.41]	[2.96]	[3.42]	[4.44]
TDPI	0.68	0.15	0.30	0.22	0.28	0.36	0.26
	[1.14]	[0.26]	[0.51]	[0.39]	[0.49]	[0.62]	[0.45]
Anomaly 1	0.60						0.10
	[1.46]						[2.98]
Anomaly 2		0.23					0.20
		[2.37]					[2.95]
Anomaly 3			0.85				0.78
			[2.78]				[4.12]
Anomaly 4				0.15			-0.23
				[0.44]			[-0.96]
Anomaly 5					0.28		0.21
					[3.27]		[2.92]
Anomaly 6						0.19	-0.26
						[0.83]	[-1.34]
# months	439	444	439	439	439	439	439
$\bar{R}^2(\%)$	1	0	1	1	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the TDPI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{TDPI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Cash to assets, Equity Duration, Operating Cash flows to price, Cash flow to market, Book to market using December ME, Market leverage. 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 198606 to 202306.

Intercept	0.25	0.47	0.48	0.46	0.44	0.44	0.27
	[2.51]	[4.44]	[4.58]	[4.35]	[4.20]	[4.19]	[2.68]
Anomaly 1	35.55						31.85
	[8.76]						[7.20]
Anomaly 2		-12.48					-2.71
		[-2.22]					[-0.41]
Anomaly 3			-17.33				-6.78
			[-4.25]				[-1.39]
Anomaly 4				-8.88			3.58
				[-2.35]			[0.76]
Anomaly 5					-25.78		-8.71
					[-3.72]		[-1.23]
Anomaly 6						-11.85	-5.73
						[-2.73]	[-1.28]
mkt	-6.83	-0.09	0.90	0.25	-0.92	1.65	-5.55
	[-2.79]	[-0.03]	[0.37]	[0.10]	[-0.37]	[0.65]	[-2.17]
smb	-6.10	-4.63	-3.81	-6.14	0.08	-6.35	-2.19
	[-1.75]	[-1.18]	[-1.01]	[-1.63]	[0.02]	[-1.69]	[-0.55]
hml	-11.95	-11.49	-11.65	-19.33	1.34	-9.55	8.70
	[-2.64]	[-1.48]	[-2.13]	[-3.77]	[0.16]	[-1.33]	[0.91]
rmw	-4.28	-21.39	-16.24	-18.57	-28.41	-23.14	-8.32
	[-0.88]	[-4.51]	[-3.34]	[-3.77]	[-5.61]	[-4.84]	[-1.50]
cma	21.26	3.91	13.03	11.09	10.05	6.46	19.01
	[3.33]	[0.57]	[1.95]	[1.64]	[1.51]	[0.96]	[2.76]
umd	-0.03	0.13	-6.57	-3.29	1.28	-2.16	-2.44
	[-0.01]	[0.05]	[-2.28]	[-1.14]	[0.55]	[-0.84]	[-0.78]
# months	440	444	440	440	440	440	440
$\bar{R}^2$(%)	29	18	19	17	19	17	29

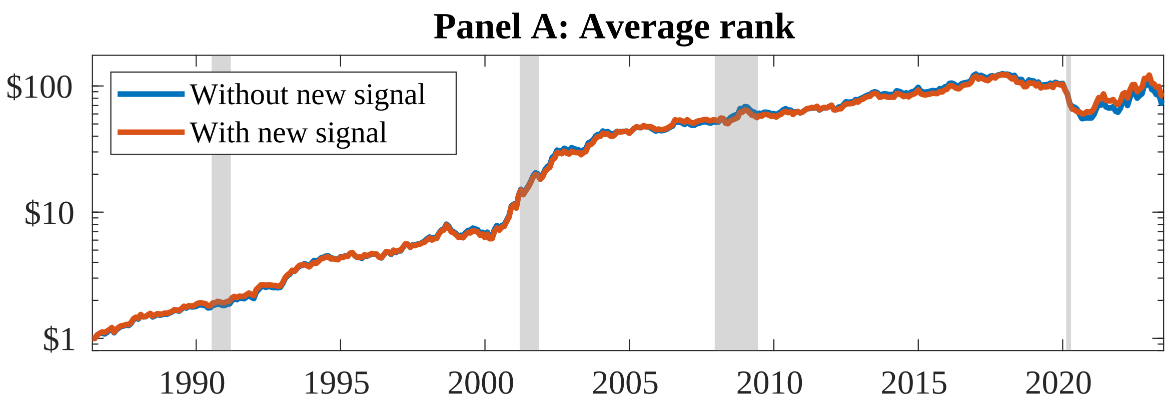

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as TDPI. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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