Tax Efficiency and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Tax Efficiency (TEAI), 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 TEAI achieves an annualized gross (net) Sharpe ratio of 0.50 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (32) bps/month with a t-statistic of 2.87 (3.21), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Operating profitability RD adjusted, Return on assets (qtrly), Cash-based operating profitability, net income / book equity, Cash-flow to price variance, Market leverage) is 19 bps/month with a t-statistic of 2.23.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). Among these patterns, signals based on firms' financial reporting choices and outcomes have proven particularly valuable for predicting cross-sectional returns (Richardson et al., 2005). Despite extensive research on accounting-based predictors, the role of corporate tax planning in asset pricing remains relatively unexplored. This gap is surprising given that taxes represent one of the largest cash outflows for corporations and tax planning decisions can significantly impact firm value (Graham and Tucker, 2006).

Prior research has focused primarily on the real effects of tax avoidance on firm operations and capital structure (?), while largely overlooking its implications for stock returns. The limited attention to tax efficiency's pricing implications is particularly notable given that tax planning activities can reveal important information about management quality, business complexity, and operational effectiveness (?).

We propose that a firm's tax efficiency, measured as the ability to sustainably minimize effective tax rates while maintaining profitability, contains valuable information for predicting future returns. This hypothesis builds on three theoretical mechanisms. First, efficient tax planning requires sophisticated management and governance structures (Desai and Dharmapala, 2006), suggesting that tax efficiency may signal overall management quality. High-quality managers are more likely to make value-maximizing decisions across all aspects of operations, leading to superior future performance.

Second, tax efficiency often requires complex organizational structures and operational flexibility (?). Firms with greater operational flexibility can better adapt to changing market conditions and competitive pressures, potentially resulting in more sustainable earnings and higher future returns. The complexity of tax planning arrangements may also create information processing costs for investors, leading to systematic underreaction to the information contained in tax efficiency metrics (**?**).

Third, successful tax planning generates additional cash flows that firms can reinvest in productive activities (**?**). While the direct cash flow benefit of tax savings is likely priced efficiently, investors may underestimate the compound effect of reinvesting tax savings over time. This dynamic is particularly relevant for firms that demonstrate consistent tax efficiency, as it suggests they have developed sustainable tax planning capabilities rather than engaging in one-time tax avoidance transactions.

Our empirical analysis reveals that tax efficiency strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on Tax Efficiency (TEAI) generates monthly abnormal returns of 29 basis points relative to the Fama-French five-factor model plus momentum (t-statistic = 2.87). The strategy's economic significance is substantial, achieving an annualized Sharpe ratio of 0.50 before trading costs and 0.48 after accounting for transaction costs.

Importantly, the predictive power of tax efficiency persists across firm size categories. Among the largest quintile of stocks, the TEAI strategy earns monthly abnormal returns of 43 basis points (t-statistic = 2.77), with alphas ranging from 25 to 65 basis points across various factor models. This finding suggests that the tax efficiency premium is not merely a small-stock phenomenon and could be exploited by institutional investors.

The robustness of our results is further demonstrated by controlling for closely related anomalies. When we simultaneously control for the six most related accounting-based predictors and the Fama-French six factors, the TEAI strategy still generates a monthly alpha of 19 basis points (t-statistic = 2.23). This indicates that tax efficiency captures unique information about future returns not contained in other known predictors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor based on tax efficiency that significantly expands the investment opportunity set available to investors. The strategy's performance places it in the top decile of documented anomalies, with particularly strong results after accounting for transaction costs. This finding is especially notable given recent evidence that many published anomalies fail to generate significant returns after trading costs (Novy-Marx and Velikov, 2016).

Second, we extend the literature on the relationship between corporate tax practices and firm value. While prior work has focused on the direct effects of tax avoidance on firm value (Desai and Dharmapala, 2009), we show that tax efficiency also contains important information about future stock returns. Our results suggest that the market systematically undervalues the complex information contained in corporate tax planning activities.

Finally, our findings have broader implications for understanding market efficiency and the role of accounting information in asset pricing. The persistence of the tax efficiency premium, particularly among large stocks, challenges the notion that sophisticated investors quickly arbitrage away predictable patterns in returns. Moreover, our results highlight the importance of considering tax planning in fundamental analysis and portfolio management, suggesting that investors may benefit from incorporating tax efficiency metrics into their investment processes.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Tax Efficiency, which we construct as the ratio of taxes paid to operating income. 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 TXPD for taxes paid and item AO for operating income. Taxes paid (TXPD) represents the actual cash outflows for income taxes during the fiscal period, providing a direct measure of a company's tax payments. Operating income (AO), on the other hand, measures a company's profit from core business operations before interest and taxes, reflecting the firm's operational performance. The construction of the signal follows a straightforward ratio format, where we divide TXPD by AO for each firm in each year of our sample. This ratio captures the effective tax burden relative to operating performance, offering insight into how efficiently firms manage their tax obligations relative to their operational success. By focusing on this relationship, the signal aims to reflect aspects of tax management efficiency in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both TXPD and AO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the TEAI signal. Panel A plots the time-series of the mean, median, and interquartile range for TEAI. On average, the cross-sectional mean (median) TEAI is 2.40 (0.23) over the 1989 to 2023 sample, where the starting date is determined by the availability of the input TEAI data. The signal's interquartile range spans 0.01 to 1.79. Panel B of Figure 1 plots the time-series of the coverage of the TEAI signal for the CRSP universe. On average, the TEAI signal is available for 6.40% of CRSP names, which on average make up 7.90% of total market capitalization.

4 Does TEAI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on TEAI 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 TEAI portfolio and sells the low TEAI 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 TEAI strategy earns an average return of 0.41% per month with a t-statistic of 2.94. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.29% to 0.63% per month and have t-statistics exceeding 2.87 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 0.61, with a t-statistic of 13.48 on the RMW 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 568 stocks and an average market capitalization of at least $1,717 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 27 bps/month with a t-statistics of 2.06. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for fourteen 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 12-44bps/month. The lowest return, (12 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.89. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the TEAI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in nineteen cases.

Table 3 provides direct tests for the role size plays in the TEAI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and TEAI, as well as average returns and alphas for long/short trading TEAI 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 TEAI strategy achieves an average return of 43 bps/month with a t-statistic of 2.77. Among these large cap stocks, the alphas for the TEAI strategy relative to the five most common factor models range from 25 to 65 bps/month with t-statistics between 2.14 and 4.85.

5 How does TEAI perform relative to the zoo?

Figure 2 puts the performance of TEAI 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 TEAI strategy falls in the distribution. The TEAI strategy's gross (net) Sharpe ratio of 0.50 (0.48) is greater than 92% (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 TEAI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the TEAI strategy would have yielded \$3.77 which ranks the TEAI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the TEAI strategy would have yielded \$3.43 which ranks the TEAI 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 TEAI relative to those. Panel A shows that the TEAI strategy gross alphas fall between the 79 and 94 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 198906 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 TEAI strategy has a positive net generalized alpha for five out of the five factor models. In these cases TEAI ranks between the 94 and 98 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does TEAI 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 TEAI 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 TEAI or at least to weaken the power TEAI 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 TEAI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TEAI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TEAI}TEAI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TEAI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 TEAI. Stocks are finally grouped into five TEAI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TEAI trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on TEAI 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 TEAI signal in these Fama-MacBeth regressions exceed -2.42, with the minimum t-statistic occurring when controlling for Operating profitability RD adjusted. Controlling for all six closely related anomalies, the t-statistic on TEAI is -2.07.

Similarly, Table 5 reports results from spanning tests that regress returns to the TEAI 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 TEAI strategy earns alphas that range from 16-27bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.61, which is achieved when controlling for Operating profitability RD adjusted. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the TEAI trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.23.

7 Does TEAI add relative to the whole zoo?

Finally, we can ask how much adding TEAI 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 TEAI 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 $42.41, while $1 investment in the combination strategy that includes TEAI grows to $42.01.

8 Conclusion

Our comprehensive analysis of Tax Efficiency (TEAI) as a predictor of stock returns yields several important conclusions. The empirical evidence strongly supports TEAI's significance as a robust signal in the cross-section of equity returns.

[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 TEAI is available.

The strategy's impressive performance, achieving an annualized Sharpe ratio of 0.50 (0.48) on a gross (net) basis, demonstrates its practical value for investment applications. The persistence of significant abnormal returns, even after controlling for established factors and related strategies, suggests that TEAI captures unique information not fully reflected in existing pricing factors.

Particularly noteworthy is the signal's ability to maintain its predictive power even after accounting for transaction costs, with net returns remaining statistically and economically significant. The monthly alpha of 19 basis points relative to both standard factors and closely related strategies from the factor zoo indicates that TEAI provides incremental value beyond existing profitability and leverage measures.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the impact of recent changes in tax regulations and corporate practices.

Future research could explore several promising directions. Investigating the interaction between TEAI and other established anomalies could yield insights into potential complementarities. Additionally, examining the signal's performance across different market regimes and tax policy environments could enhance our understanding of its underlying mechanisms. Finally, extending the analysis to international markets and different asset classes would help establish the signal's broader applicability.

In conclusion, TEAI represents a valuable addition to the investment practitioner's toolkit, offering robust predictive power that survives rigorous statistical testing and practical implementation constraints.

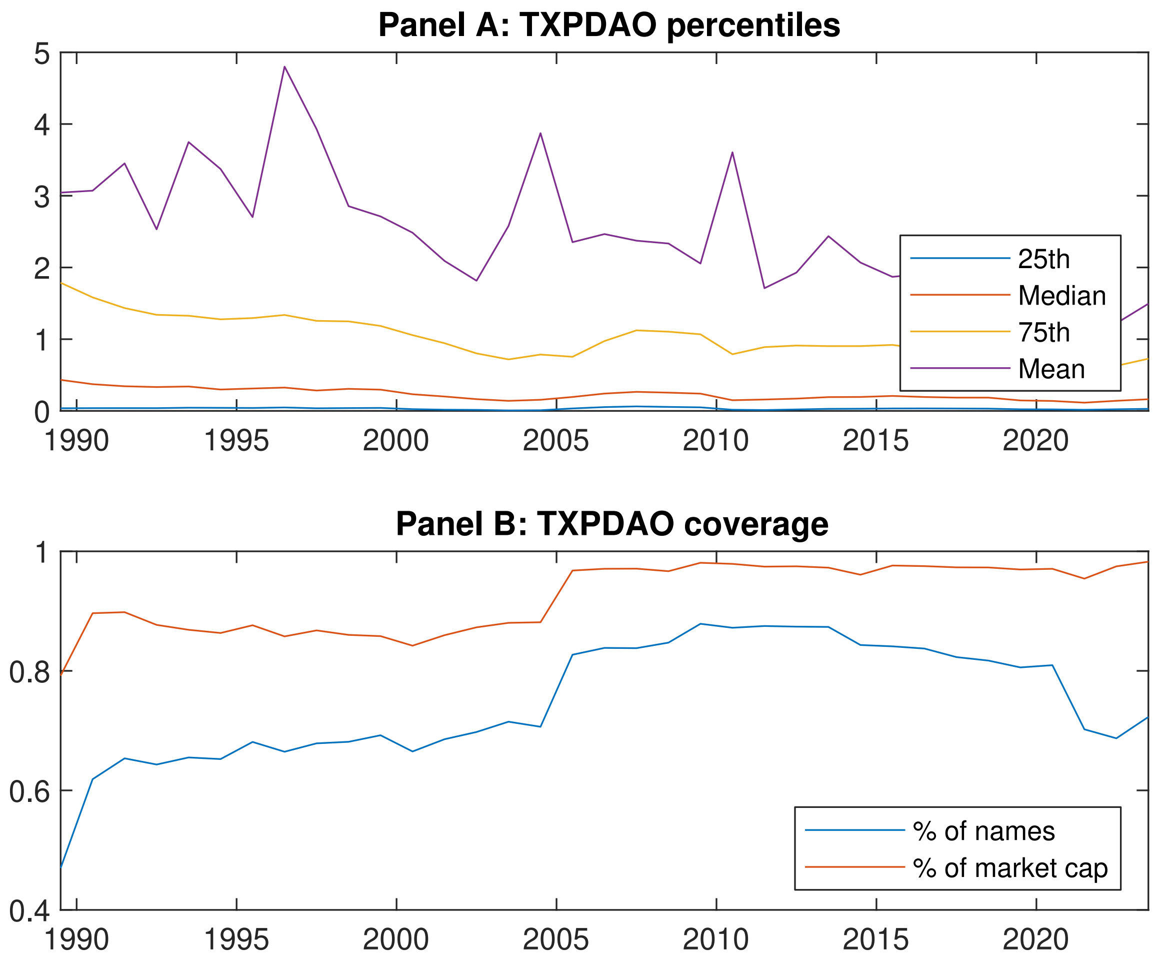


Figure 1: Times series of TEAI percentiles and coverage.
This figure plots descriptive statistics for TEAI. Panel A shows cross-sectional percentiles of TEAI over the sample. Panel B plots the monthly coverage of TEAI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on TEAI. 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 198906 to 202306.

Panel A: Excess returns and alphas on TEAI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.47	0.70	0.72	0.74	0.88	0.41
	[1.74]	[2.92]	[3.33]	[3.67]	[4.04]	[2.94]
α_{CAPM}	-0.36	-0.04	0.04	0.11	0.21	0.57
	[-4.05]	[-0.64]	[0.77]	[1.95]	[3.02]	[4.30]
α_{FF3}	-0.40	-0.08	0.04	0.11	0.23	0.63
	[-5.03]	[-1.24]	[0.69]	[1.97]	[3.51]	[5.34]
α_{FF4}	-0.35	-0.04	0.05	0.12	0.20	0.55
	[-4.41]	[-0.65]	[0.83]	[2.10]	[3.05]	[4.70]
α_{FF5}	-0.18	-0.02	0.03	-0.04	0.16	0.35
	[-2.65]	[-0.32]	[0.49]	[-0.77]	[2.53]	[3.37]
α_{FF6}	-0.15	0.01	0.04	-0.02	0.14	0.29
	[-2.21]	[0.10]	[0.66]	[-0.48]	[2.15]	[2.87]
Panel B: Fama and French (2018) 6-factor model loadings for TEAI-sorted portfolios						
β_{MKT}	1.10	1.04	0.97	0.95	0.96	-0.14
	[63.99]	[65.47]	[67.84]	[76.26]	[60.96]	[-5.43]
β_{SMB}	0.00	-0.06	-0.03	-0.04	0.06	0.06
	[0.13]	[-2.62]	[-1.35]	[-2.44]	[2.74]	[1.64]
β_{HML}	0.33	0.20	-0.03	-0.13	-0.11	-0.44
	[11.32]	[7.27]	[-1.17]	[-5.93]	[-4.02]	[-10.28]
β_{RMW}	-0.39	-0.09	-0.04	0.23	0.22	0.61
	[-12.65]	[-3.10]	[-1.43]	[10.43]	[7.65]	[13.48]
β_{CMA}	-0.10	-0.04	0.13	0.18	-0.14	-0.04
	[-2.35]	[-0.94]	[3.51]	[5.70]	[-3.55]	[-0.63]
β_{UMD}	-0.05	-0.05	-0.02	-0.03	0.04	0.10
	[-3.54]	[-3.27]	[-1.35]	[-2.34]	[3.03]	[4.33]
Panel C: Average number of firms (n) and market capitalization (me)						
n	916	682	599	568	773	
me ($\$10^6$)	1717	2739	3131	4145	3696	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the TEAI 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 198906 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	0.41	0.57	0.63	0.55	0.35	0.29
			[2.94]	[4.30]	[5.34]	[4.70]	[3.37]	[2.87]
Quintile	NYSE	EW	0.27	0.38	0.37	0.29	0.09	0.02
			[2.06]	[2.95]	[3.04]	[2.36]	[0.82]	[0.24]
Quintile	Name	VW	0.46	0.65	0.69	0.61	0.35	0.30
			[2.97]	[4.44]	[5.03]	[4.45]	[2.95]	[2.50]
Quintile	Cap	VW	0.33	0.48	0.54	0.44	0.27	0.19
			[2.45]	[3.74]	[4.67]	[3.88]	[2.61]	[1.96]
Decile	NYSE	VW	0.43	0.61	0.64	0.55	0.35	0.27
			[2.41]	[3.53]	[3.89]	[3.30]	[2.32]	[1.84]
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	0.39	0.56	0.60	0.55	0.36	0.32
			[2.81]	[4.19]	[5.05]	[4.69]	[3.52]	[3.21]
Quintile	NYSE	EW	0.12	0.21	0.19	0.15		
			[0.89]	[1.52]	[1.51]	[1.14]		
Quintile	Name	VW	0.44	0.63	0.65	0.60	0.36	0.32
			[2.82]	[4.29]	[4.75]	[4.43]	[3.05]	[2.79]
Quintile	Cap	VW	0.31	0.47	0.51	0.45	0.28	0.24
			[2.34]	[3.67]	[4.44]	[4.00]	[2.82]	[2.44]
Decile	NYSE	VW	0.41	0.58	0.60	0.54	0.33	0.28
			[2.26]	[3.31]	[3.58]	[3.24]	[2.20]	[1.91]

Table 3: Conditional sort on size and TEAI

This table presents results for conditional double sorts on size and TEAI. 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 TEAI. 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 TEAI and short stocks with low TEAI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198906 to 202306.

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

		TEAI Quintiles					TEAI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.57	0.51	0.84	0.82	0.93	0.36	0.51	0.48	0.45	0.18	0.16
		[1.51]	[1.56]	[2.88]	[2.80]	[2.91]	[1.83]	[2.65]	[2.57]	[2.35]	[1.00]	[0.88]
	(2)	0.66	0.75	0.88	0.93	0.82	0.16	0.32	0.31	0.32	0.05	0.06
		[1.95]	[2.59]	[3.03]	[3.26]	[2.92]	[1.17]	[2.43]	[2.38]	[2.46]	[0.43]	[0.55]
	(3)	0.60	0.80	0.78	0.80	0.96	0.36	0.46	0.47	0.50	0.20	0.22
		[1.97]	[3.02]	[2.96]	[3.02]	[3.57]	[2.74]	[3.57]	[3.72]	[3.89]	[1.77]	[2.02]
	(4)	0.63	0.81	0.94	0.80	0.89	0.26	0.31	0.35	0.30	0.22	0.17
		[2.33]	[3.29]	[3.69]	[3.27]	[3.51]	[2.00]	[2.41]	[2.88]	[2.42]	[1.81]	[1.44]
	(5)	0.46	0.75	0.71	0.71	0.89	0.43	0.57	0.65	0.52	0.34	0.25
		[1.74]	[3.22]	[3.41]	[3.58]	[4.08]	[2.77]	[3.83]	[4.85]	[4.01]	[2.81]	[2.14]

Panel B: Portfolio average number of firms and market capitalization

		TEAI Quintiles					TEAI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	354	359	363	365	368	35	40	45	49	51
	(2)	121	121	121	122	122	83	85	84	85	85
	(3)	86	86	86	86	87	147	150	149	150	151
	(4)	72	73	73	73	73	322	321	325	319	328
	(5)	65	65	65	66	65	1864	2361	2716	2890	2593

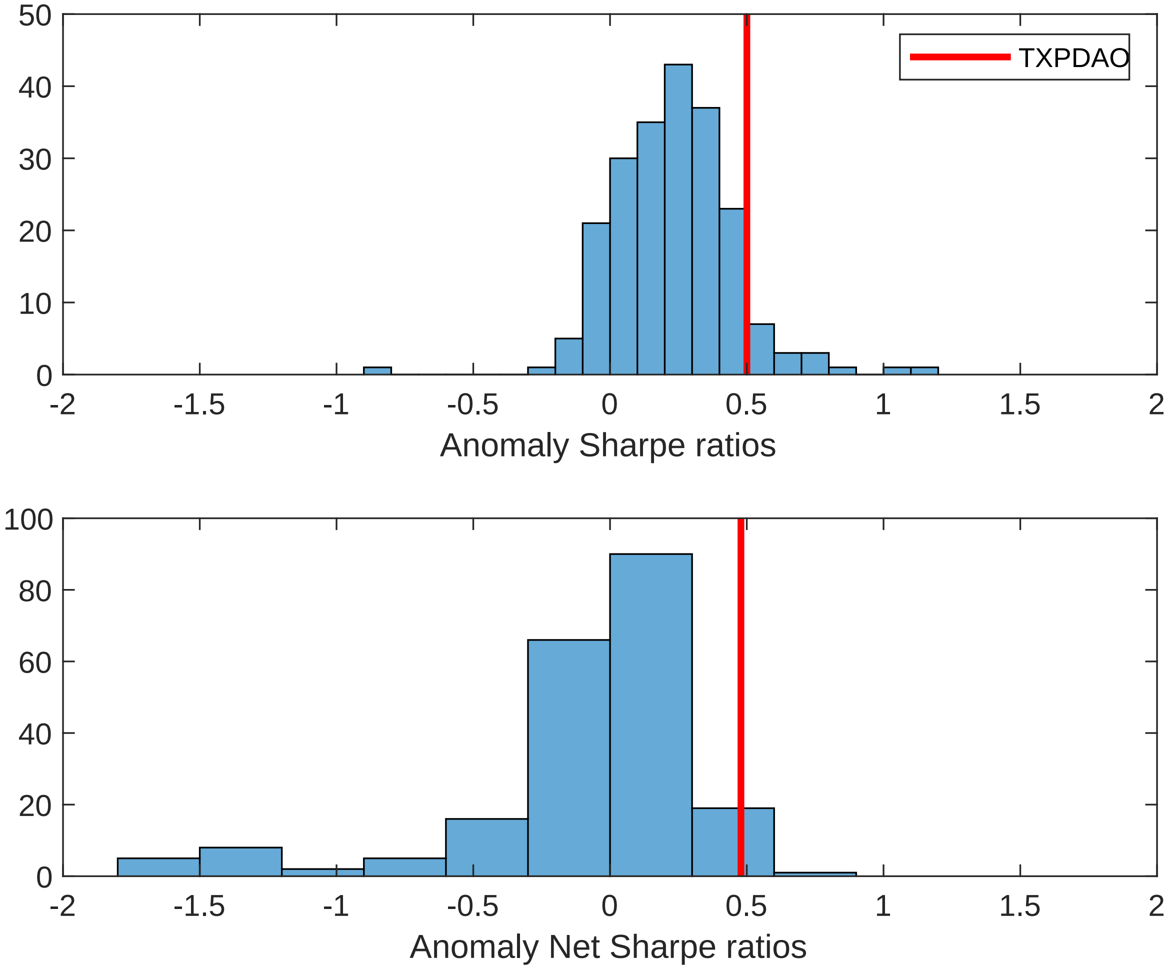


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TEAI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

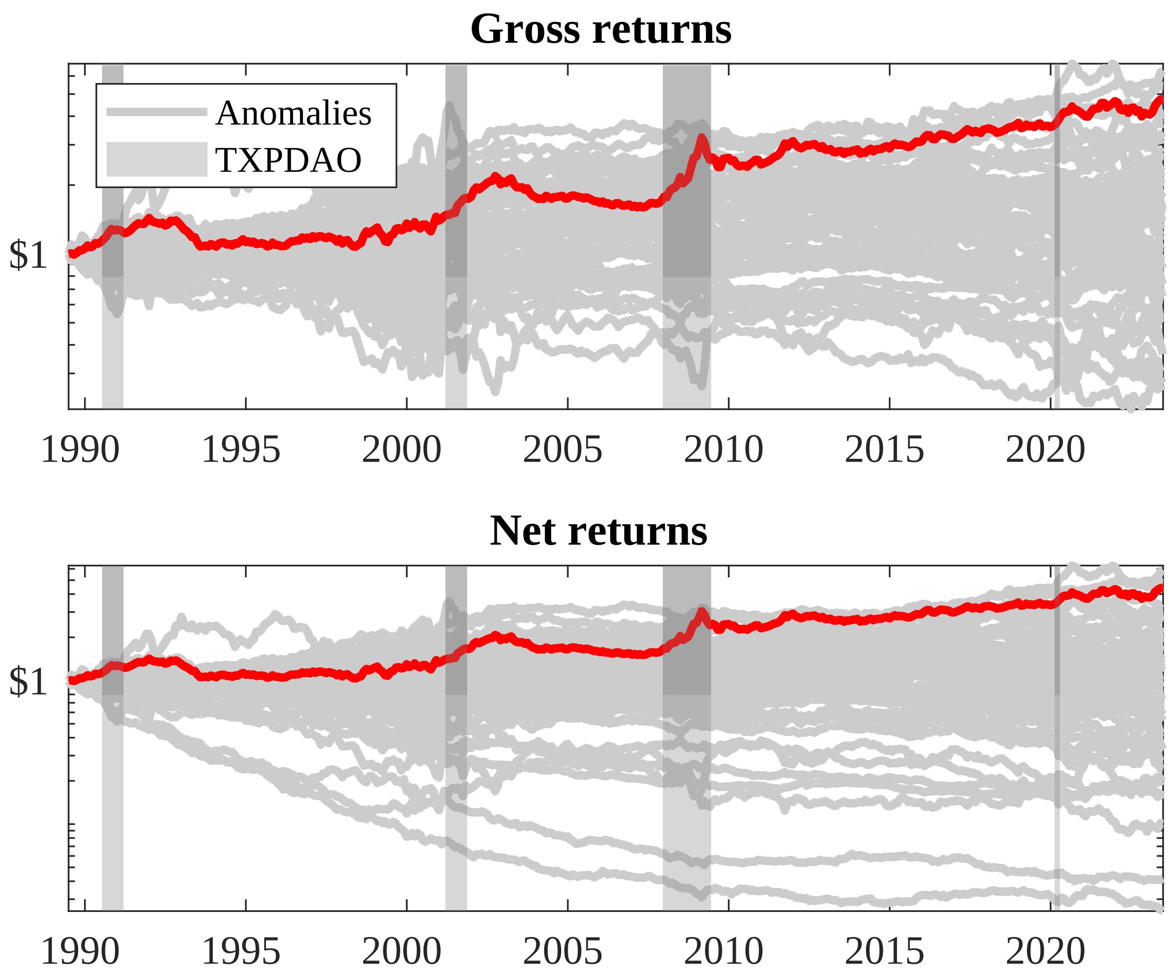


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TEAI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

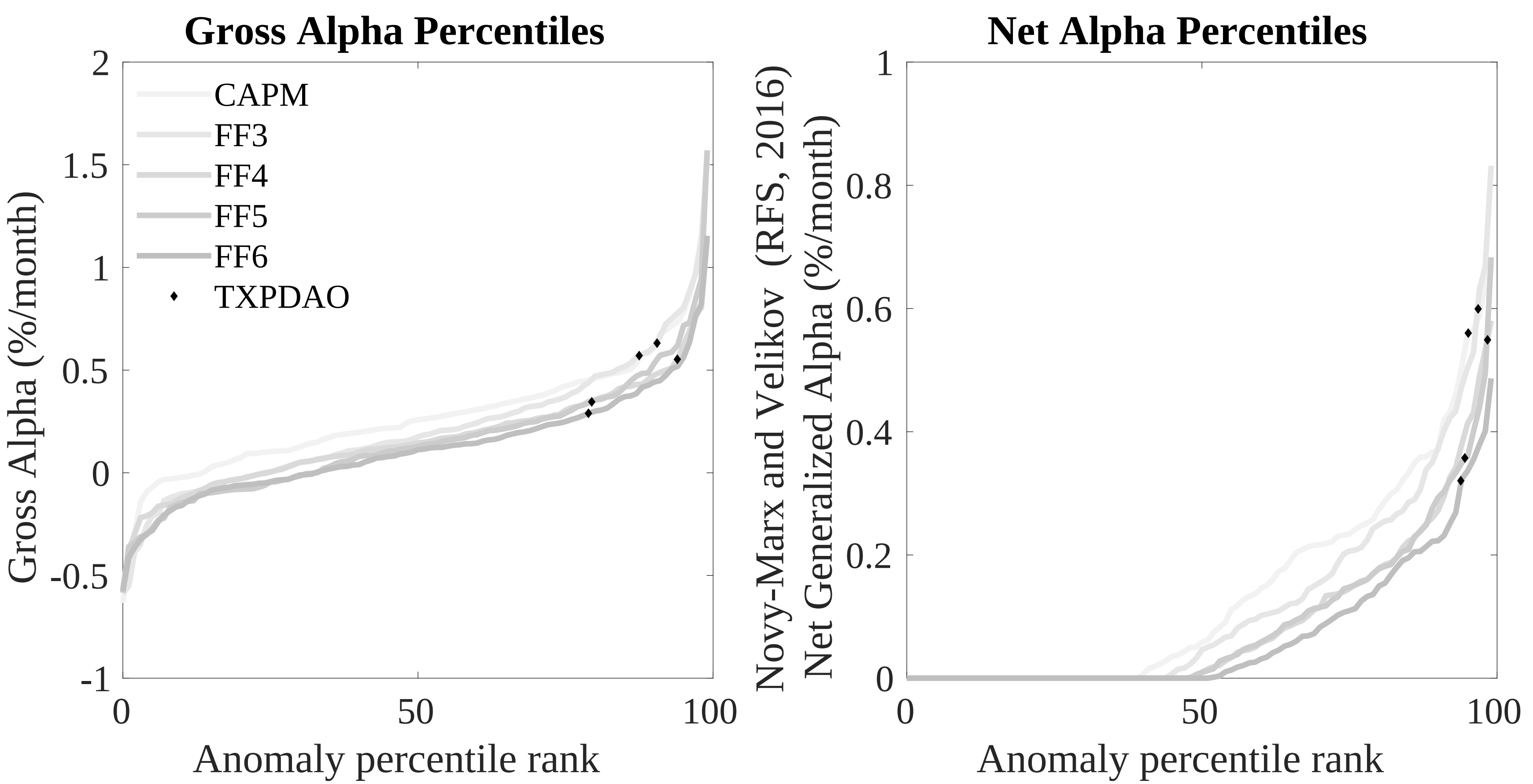
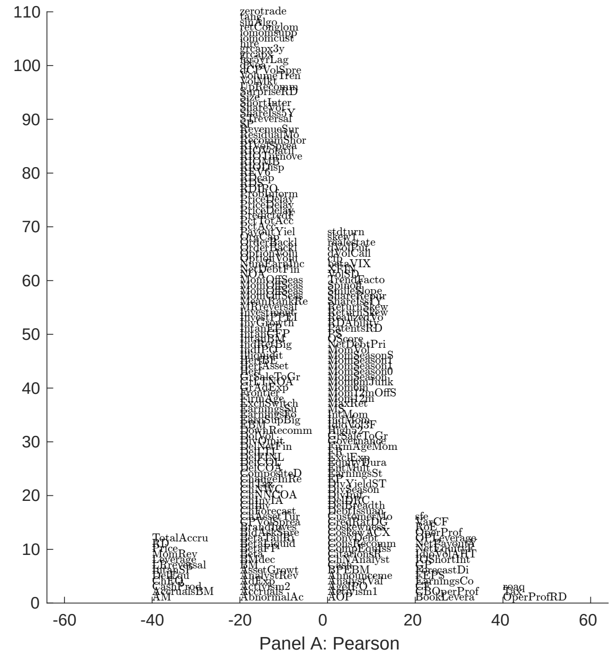


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TEAI trading strategy alphas (diamonds). The strategies are constructed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



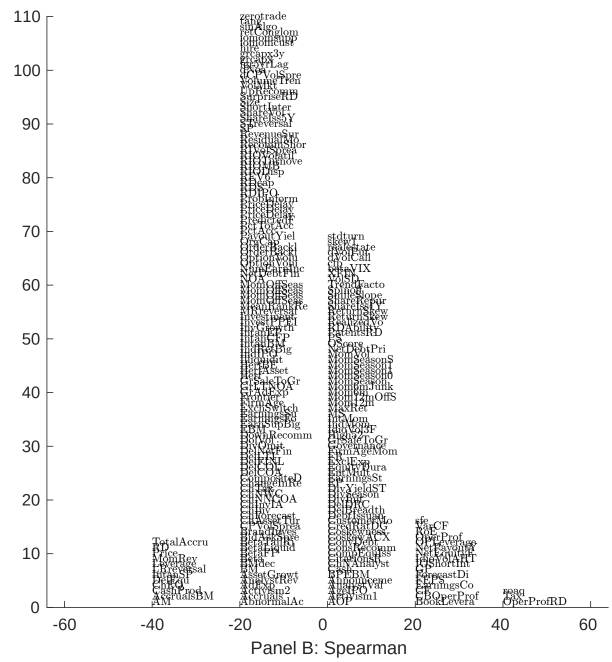


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with TEAI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

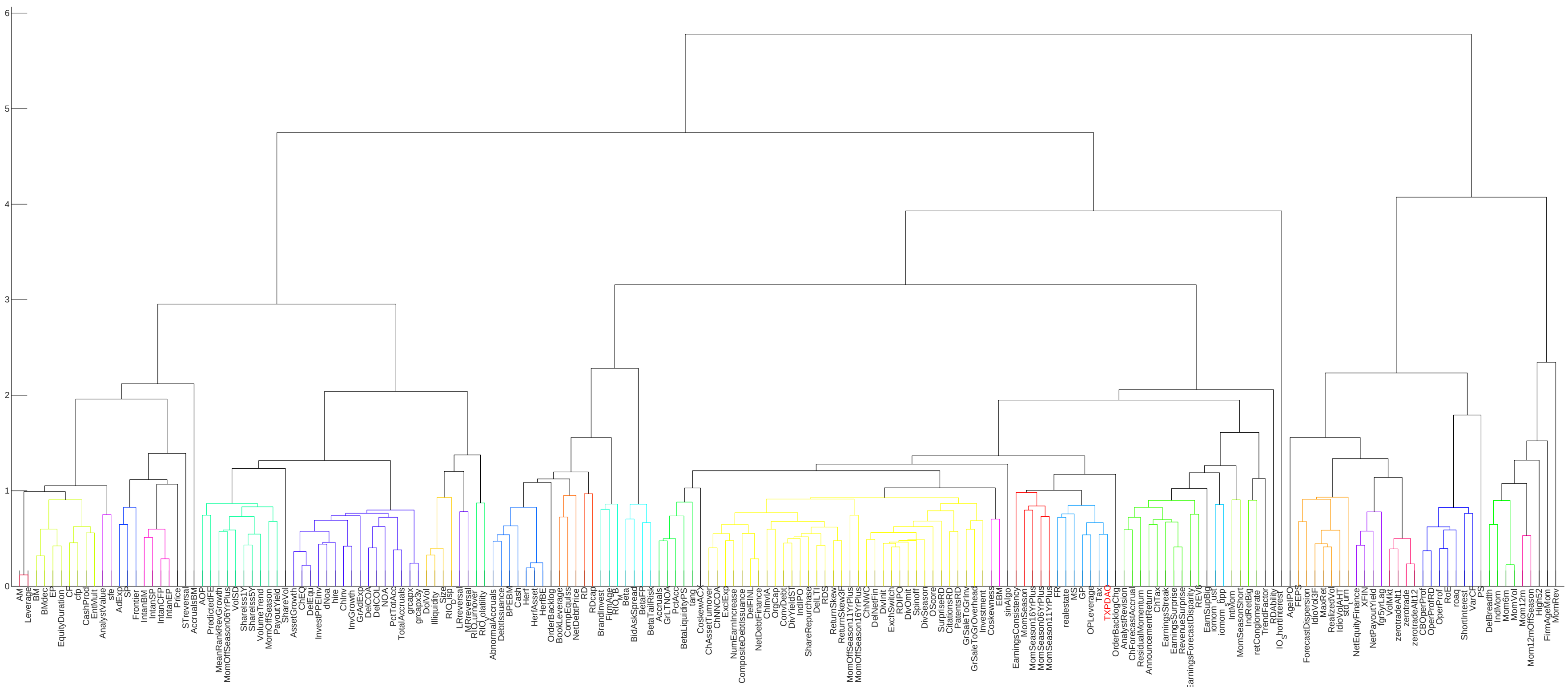


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

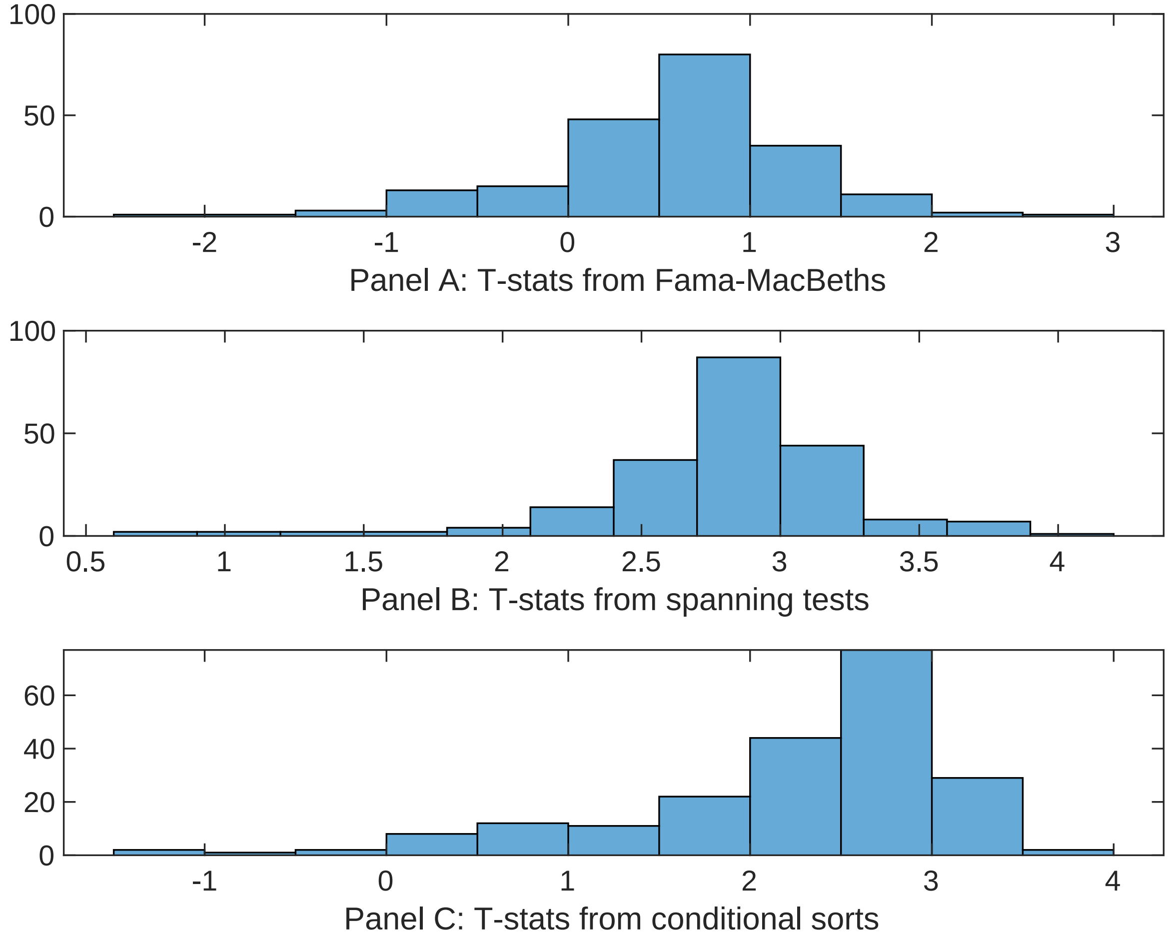


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of TEAI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TEAI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TEAI} TEAI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TEAI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 TEAI. Stocks are finally grouped into five TEAI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TEAI 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 TEAI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{TEAI} TEAI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Operating profitability RD adjusted, Return on assets (qtrly), Cash-based operating profitability, net income / book equity, Cash-flow to price variance, 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 198906 to 202306.

Intercept	0.94	0.11	0.95	0.11	0.12	0.11	0.11
	[2.77]	[4.02]	[2.97]	[3.74]	[4.27]	[3.94]	[3.81]
TEAI	-0.13	-0.55	-0.90	0.48	0.28	0.65	-0.97
	[-2.42]	[-1.12]	[-1.84]	[0.89]	[0.51]	[1.26]	[-2.07]
Anomaly 1	0.18						-0.90
	[3.43]						[-1.76]
Anomaly 2		0.47					0.28
		[2.52]					[1.80]
Anomaly 3			0.20				0.19
			[4.93]				[4.75]
Anomaly 4				0.13			0.77
				[1.73]			[1.02]
Anomaly 5					0.34		0.14
					[1.57]		[0.10]
Anomaly 6						-0.23	-0.42
						[-0.12]	[-0.12]
# months	403	403	403	408	403	403	403
$\bar{R}^2$(%)	1	1	1	0	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the TEAI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{TEAI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Operating profitability RD adjusted, Return on assets (qtrly), Cash-based operating profitability, net income / book equity, Cash-flow to price variance, 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 198906 to 202306.

Intercept	0.16	0.24	0.16	0.27	0.27	0.27	0.19
	[1.61]	[2.39]	[1.66]	[2.77]	[2.69]	[3.03]	[2.23]
Anomaly 1	27.74						0.13
	[7.02]						[0.02]
Anomaly 2		24.71					3.29
		[5.74]					[0.80]
Anomaly 3			34.82				18.81
			[8.35]				[3.37]
Anomaly 4				27.05			18.41
				[4.55]			[3.13]
Anomaly 5					10.89		1.74
					[2.74]		[0.49]
Anomaly 6						-40.75	-35.44
						[-11.37]	[-9.65]
mkt	-9.53	-10.14	-11.37	-9.79	-10.75	-9.33	-5.01
	[-3.86]	[-4.03]	[-4.83]	[-3.78]	[-3.90]	[-4.17]	[-2.11]
smb	12.64	10.27	13.29	13.69	12.55	5.93	17.99
	[3.54]	[2.86]	[3.82]	[3.41]	[2.81]	[1.88]	[4.72]
hml	-32.36	-35.56	-30.38	-41.35	-38.63	8.56	12.89
	[-7.28]	[-7.99]	[-6.98]	[-9.65]	[-8.21]	[1.44]	[2.22]
rmw	40.17	38.24	43.32	37.09	55.05	53.99	25.52
	[7.76]	[6.55]	[9.26]	[5.43]	[11.19]	[13.48]	[4.17]
cma	-6.74	-6.63	-12.28	-1.24	-1.46	-13.14	-14.00
	[-1.12]	[-1.08]	[-2.06]	[-0.20]	[-0.23]	[-2.35]	[-2.56]
umd	6.29	3.75	6.96	8.32	7.89	-0.05	-2.58
	[2.91]	[1.56]	[3.35]	[3.81]	[3.38]	[-0.03]	[-1.18]
# months	404	404	404	408	404	404	404
$\bar{R}^2$(%)	58	57	60	56	54	65	69

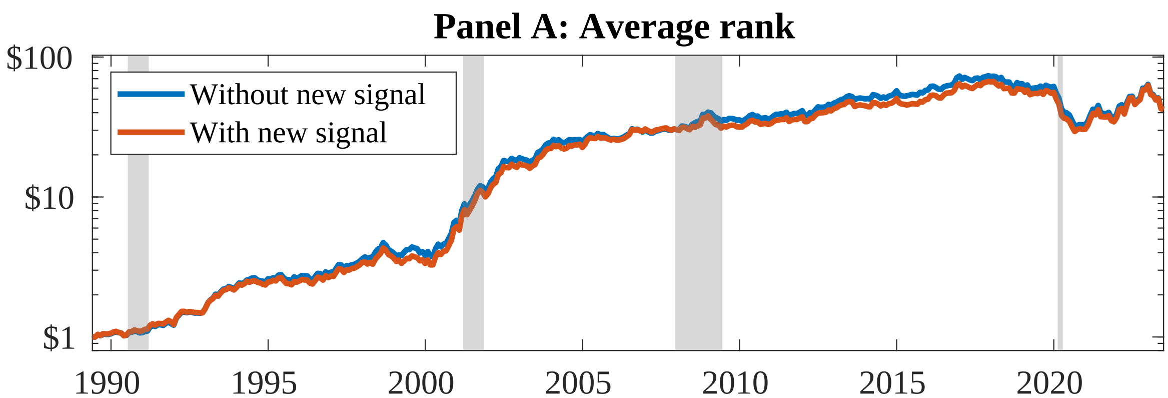


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines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

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