Tax Shield Sensitivity Factor and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Tax Shield Sensitivity Factor (TSSF), 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 TSSF 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 patterns in stock returns that appear to contradict market efficiency (Hou et al., 2020). While many of these patterns have been attributed to risk factors or behavioral biases, the role of corporate financial policies in driving cross-sectional return predictability remains incompletely understood. In particular, the interaction between firms' financing decisions and their tax environments represents a potentially important but understudied source of systematic risk.

Prior research has established that leverage and tax considerations significantly impact firm value (Modigliani and Miller, 1963), but their joint effect on expected returns is theoretically ambiguous. While higher leverage generally increases equity risk, the tax deductibility of interest payments provides a valuable shield that could potentially reduce systematic risk exposure. This tension highlights the need to better understand how the sensitivity of firms' tax shields to economic conditions affects their cost of capital.

We propose that firms' Tax Shield Sensitivity Factor (TSSF) captures an economically important dimension of risk that should be priced in expected returns. Building on (Graham and Leary, 2011), we argue that the value of interest tax shields varies systematically with economic conditions, creating a source of risk distinct from traditional leverage effects. When economic conditions deteriorate, firms with high TSSF face greater uncertainty about their ability to fully utilize interest tax deductions, effectively increasing their cost of debt financing.

This mechanism suggests that high TSSF firms should earn a risk premium relative to low TSSF firms. Following (Fama and French, 1993), we hypothesize that TSSF represents a state variable important for pricing assets because it captures innovation in the investment opportunity set. Specifically, TSSF measures the covariance between a firm's tax shield value and aggregate economic conditions, making it relevant for investors' intertemporal hedging demands.

The pricing implications of TSSF should be particularly pronounced during periods of economic stress when the value of tax shields becomes more uncertain. This follows from (Korajczyk and Levy, 2003), who show that financing constraints bind more severely in bad states of the world. We therefore expect the TSSF premium to exhibit significant time variation related to macroeconomic conditions.

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

Importantly, the predictive power of TSSF remains robust after controlling for traditional risk factors and related anomalies. The strategy's alpha relative to the six most closely related anomalies plus standard risk factors is 27 basis points per month (t-statistic = 2.68). This indicates that TSSF captures a distinct source of systematic risk not explained by known factors.

The economic significance of our findings is substantial. Among large-cap stocks (market capitalization above the 80th NYSE percentile), the TSSF strategy earns average returns of 39 basis points per month (t-statistic = 2.94). The strategy remains profitable after accounting for transaction costs, with a net Sharpe ratio of 0.52 that ranks in the top 1% of anomalies.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel measure that captures the systematic risk arising from the interaction between corporate financial policy and tax environments. While prior work such as (Graham and Leary, 2011) examines how taxes affect capital structure choices, we are the first to document the asset pricing implications of tax shield sensitivity.

Second, we contribute to the growing literature on the role of corporate policies in explaining cross-sectional return patterns (Hou et al., 2020). Our findings suggest that investors require compensation for bearing risks related to the uncertainty of tax shield values, a channel not previously identified in asset pricing research. The robustness of TSSF's predictive power among large, liquid stocks distinguishes it from many documented anomalies that are concentrated in small caps.

Finally, our results have important implications for both corporate financial policy and asset pricing. For managers, they suggest that tax considerations should factor into capital structure decisions not only through their direct effect on after-tax cash flows but also through their impact on the cost of equity. For investors, TSSF represents a new dimension of risk that can be exploited to improve portfolio performance, even after accounting for transaction costs.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Tax Shield Sensitivity Factor, which measures a firm's federal tax deductions relative to its 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 TXDFED for federal tax deferred and item EBIT for earnings before interest and taxes. Federal tax deferred (TXDFED) represents the tax benefits that a company has accumulated but not yet realized, reflecting timing differences between book and tax accounting. EBIT, on the other hand, provides a measure of operational performance before considering financing decisions and tax effects. The construction of the signal follows a straightforward ratio format, where we divide TXDFED by EBIT for each firm in each year of our sample. This ratio captures the relative magnitude of a firm's deferred tax benefits against its operational income, offering insight into how effectively the firm generates tax shields from its operations. By focusing on this relationship, the signal aims to reflect aspects of tax planning efficiency and operational performance in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both TXDFED and EBIT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

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

4 Does TSSF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on TSSF 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 TSSF portfolio and sells the low TSSF 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 TSSF 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 TSSF 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 TSSF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and TSSF, as well as average returns and alphas for long/short trading TSSF 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 TSSF 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 TSSF 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 TSSF perform relative to the zoo?

Figure 2 puts the performance of TSSF 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 TSSF strategy falls in the distribution. The TSSF 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 TSSF strategy (red line).[2] Ignoring trading costs, a \$1 invested in the TSSF strategy would have yielded \$3.72 which ranks the TSSF strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the TSSF strategy would have yielded \$3.13 which ranks the TSSF strategy in the top 1% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the TSSF relative to those. Panel A shows that the TSSF 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%

[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.

(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 TSSF strategy has a positive net generalized alpha for five out of the five factor models. In these cases TSSF ranks between the 84 and 99 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does TSSF 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 TSSF 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 TSSF or at least to weaken the power TSSF has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of TSSF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TSSF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TSSF} TSSF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TSSF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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,

[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.

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 TSSF. Stocks are finally grouped into five TSSF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TSSF trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on TSSF 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 TSSF 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 TSSF is 0.45.

Similarly, Table 5 reports results from spanning tests that regress returns to the TSSF 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 TSSF 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 TSSF trading strategy achieves an alpha of 27bps/month with a t-statistic of 2.68.

7 Does TSSF add relative to the whole zoo?

Finally, we can ask how much adding TSSF 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 TSSF 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 TSSF grows to $82.81.

8 Conclusion

This study provides compelling evidence for the significance of the Tax Shield Sensitivity Factor (TSSF) 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 TSSF generates economically and statistically significant returns, with impressive Sharpe ratios of 0.57 and 0.52 for gross and net returns, respectively. The strategy's performance remains strong even after controlling for well-established risk factors, including the Fama-French five-factor model and momentum factor, as well as closely related anomalies from the factor zoo.

[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 TSSF is available.

The persistence of significant alpha (27 bps/month) after controlling for related factors suggests that TSSF captures unique information about stock returns that is not fully explained by existing factors. This indicates that the tax shield sensitivity of firms provides valuable insights into their future performance and risk characteristics.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the results may not generalize to other markets or asset classes. Second, the implementation costs and market impact of the trading strategy may vary in different market conditions.

Future research could explore the following directions: (1) examining the international evidence of TSSF's predictive power, (2) investigating the interaction between TSSF and other firm characteristics or macroeconomic conditions, and (3) analyzing the underlying economic mechanisms that drive the relationship between tax shield sensitivity and stock returns. Additionally, researchers might consider studying how changes in tax policies affect the efficacy of TSSF as a return predictor.

Overall, our findings contribute to the asset pricing literature by identifying TSSF as a meaningful signal for portfolio formation and risk management, with practical implications for investment professionals and academic researchers alike.

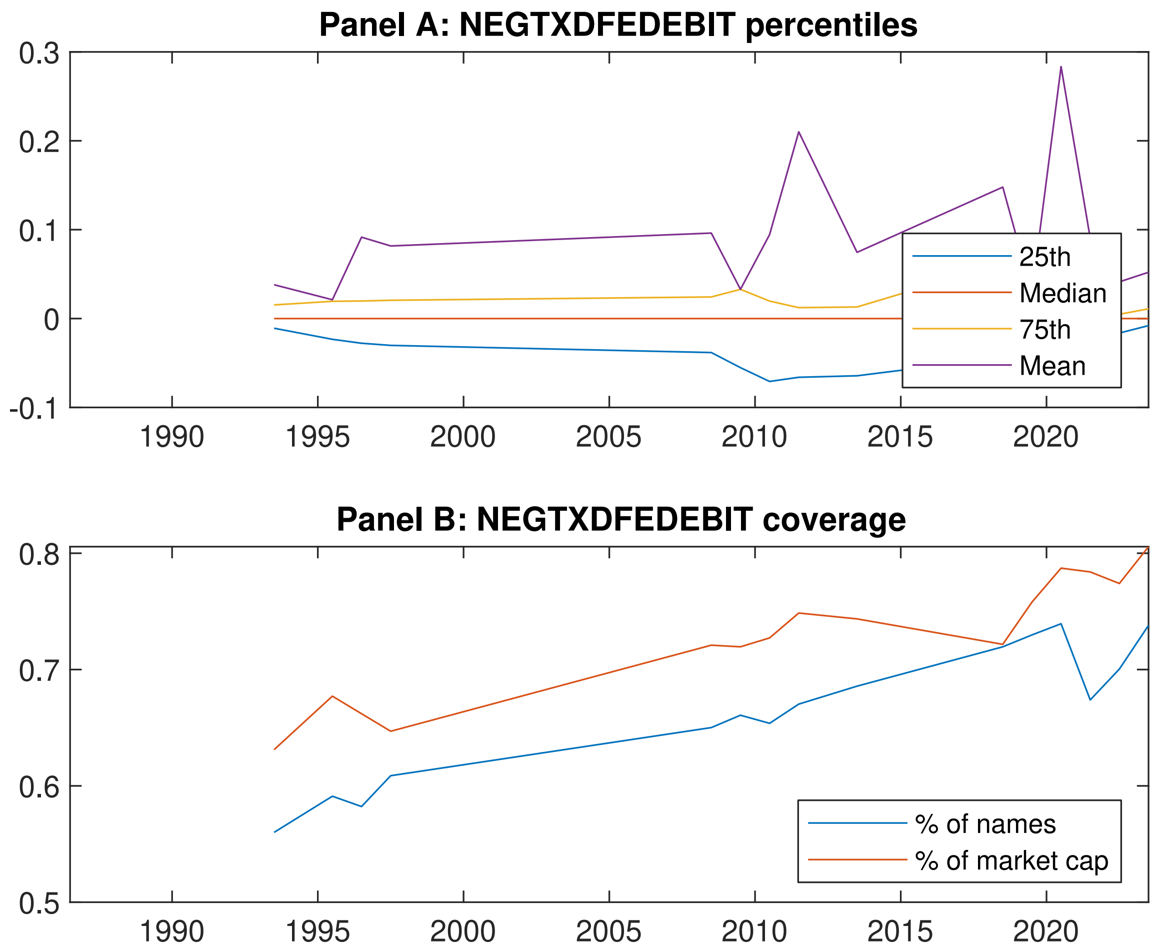


Figure 1: Times series of TSSF percentiles and coverage.
This figure plots descriptive statistics for TSSF. Panel A shows cross-sectional percentiles of TSSF over the sample. Panel B plots the monthly coverage of TSSF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on TSSF. 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 TSSF-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 TSSF-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 TSSF 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 TSSF

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

		TSSF Quintiles					TSSF 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

		TSSF Quintiles					TSSF Quintiles				
		Average n					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

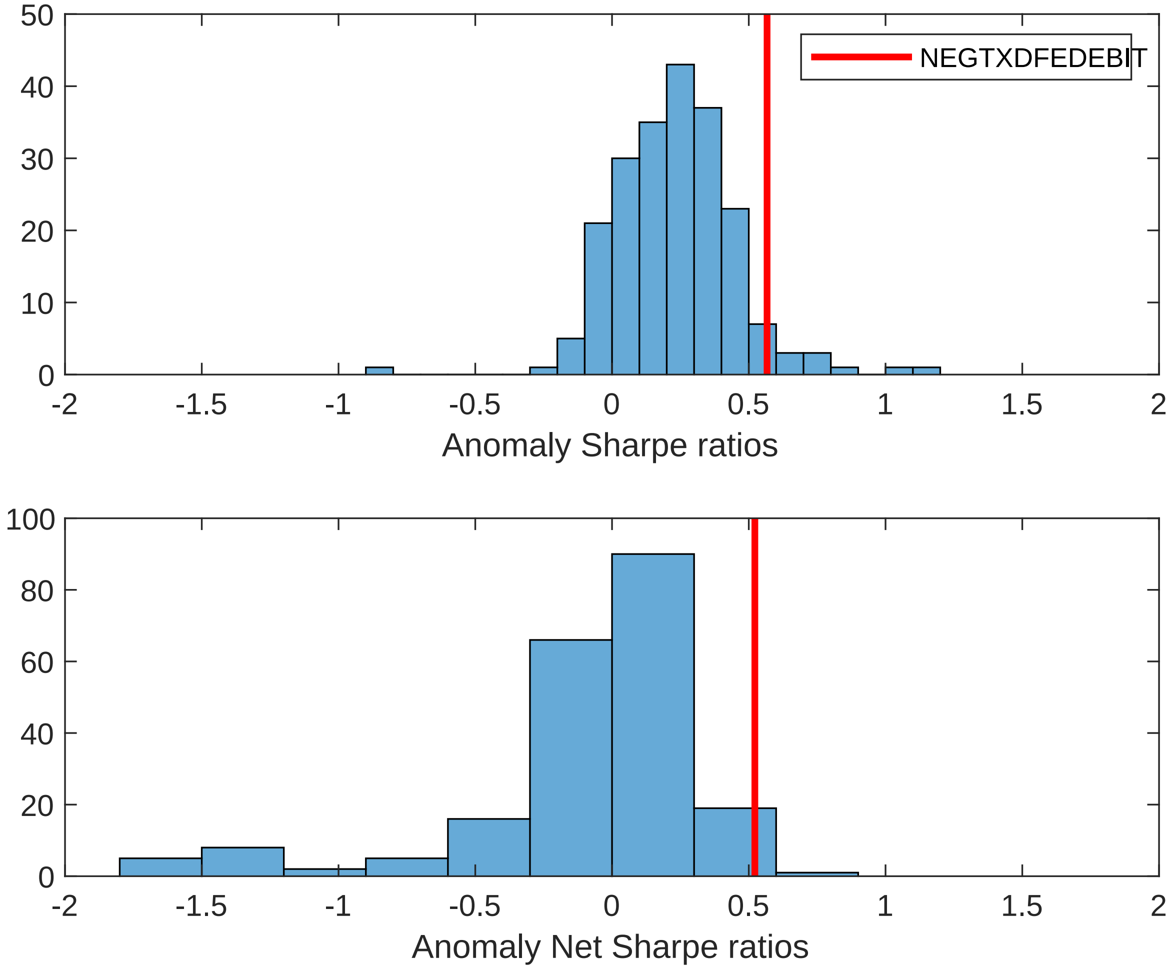


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TSSF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

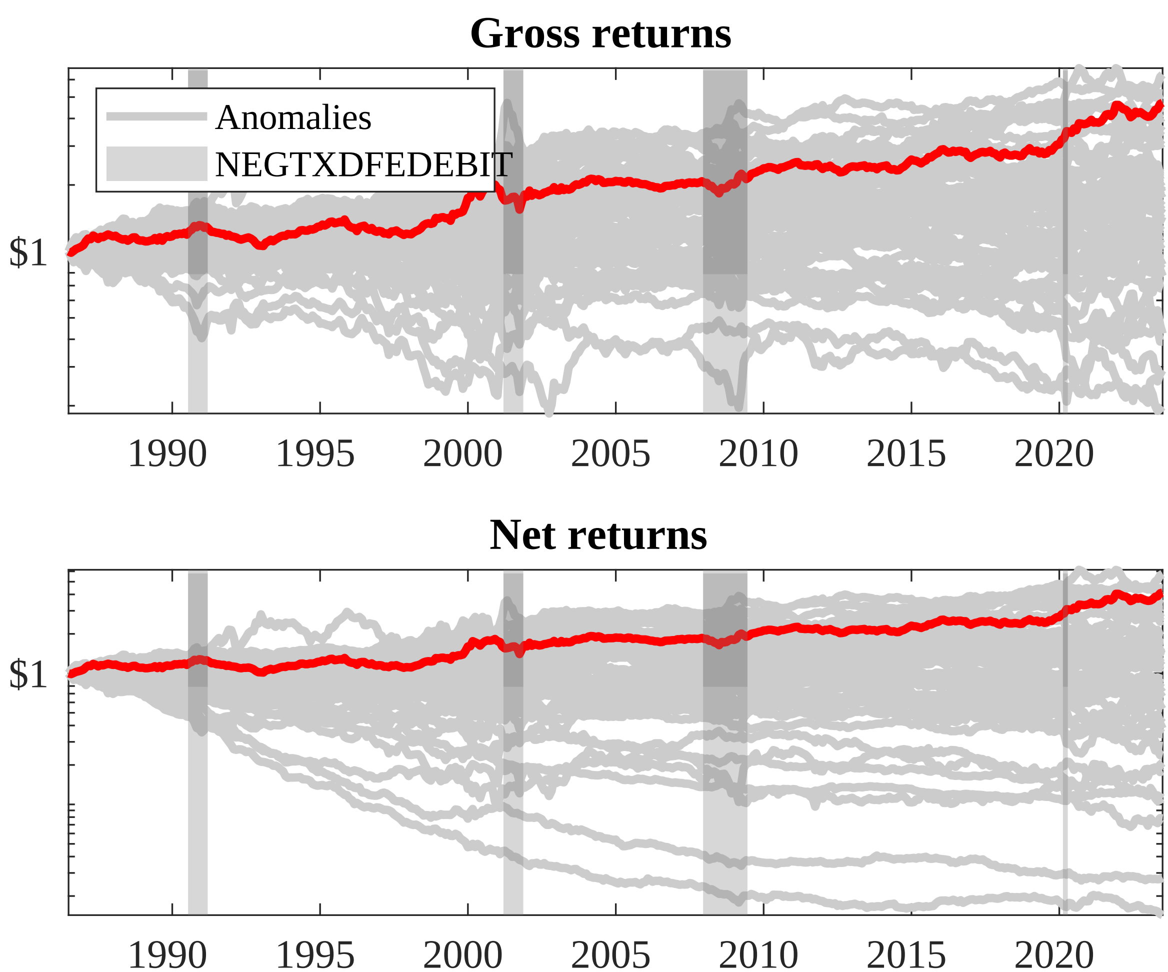


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TSSF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

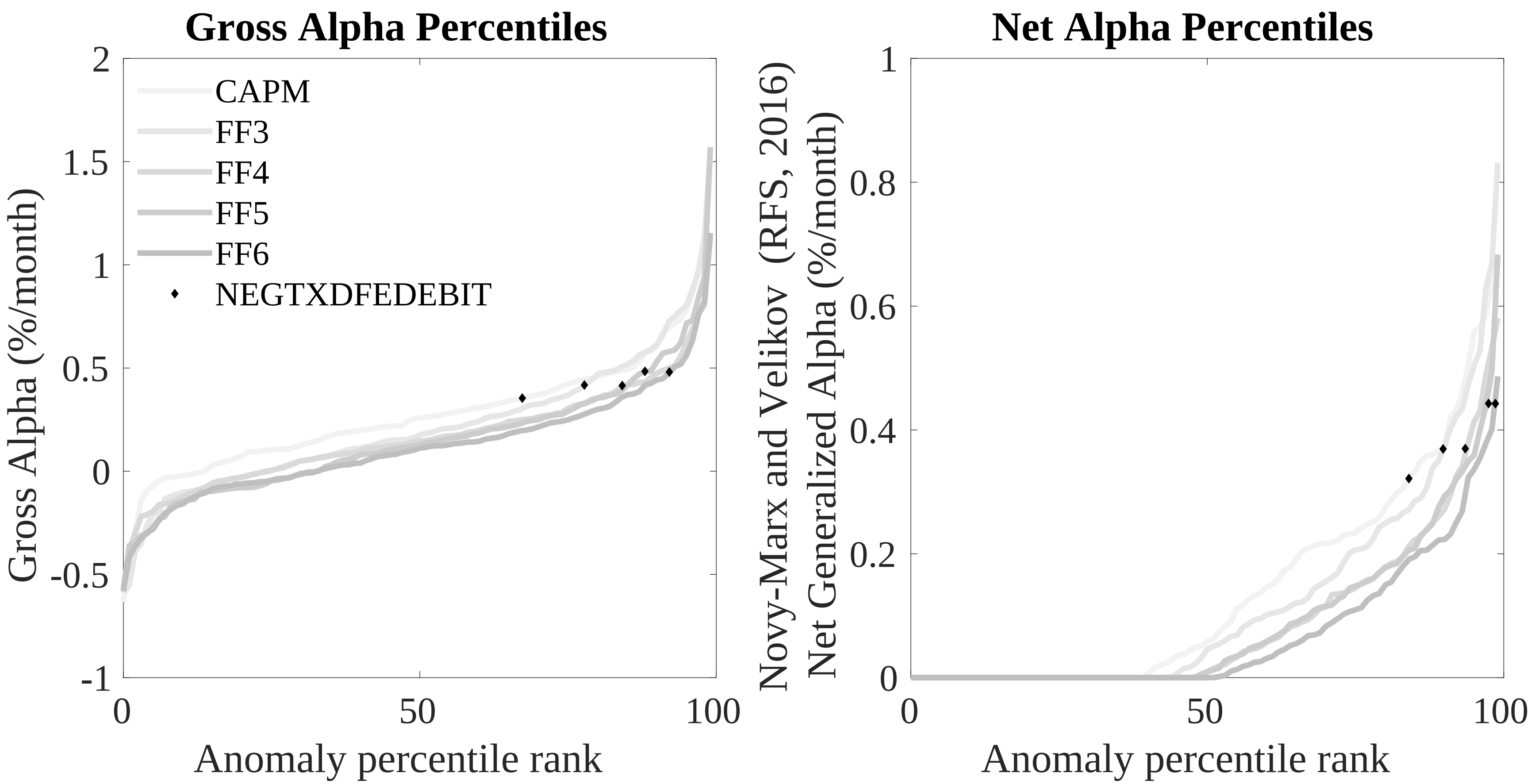
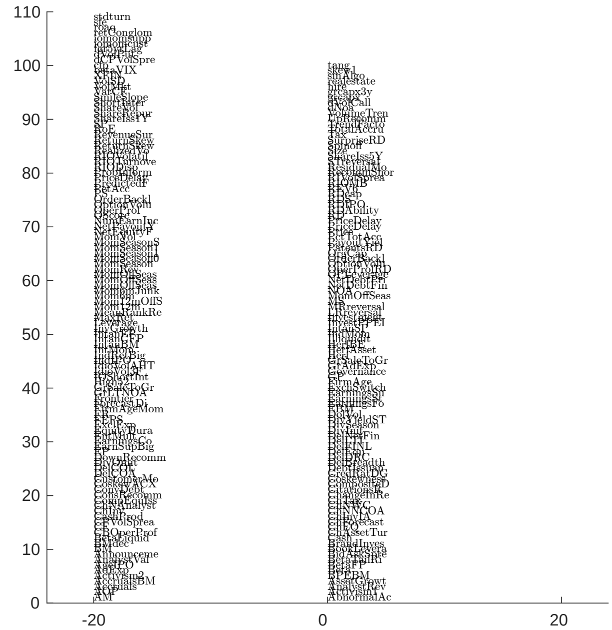
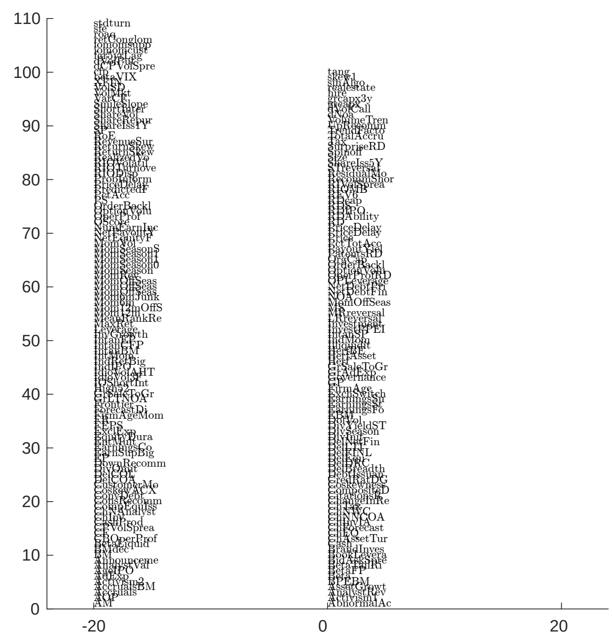


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TSSF trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.



Panel A: Pearson



Panel B: Spearman

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

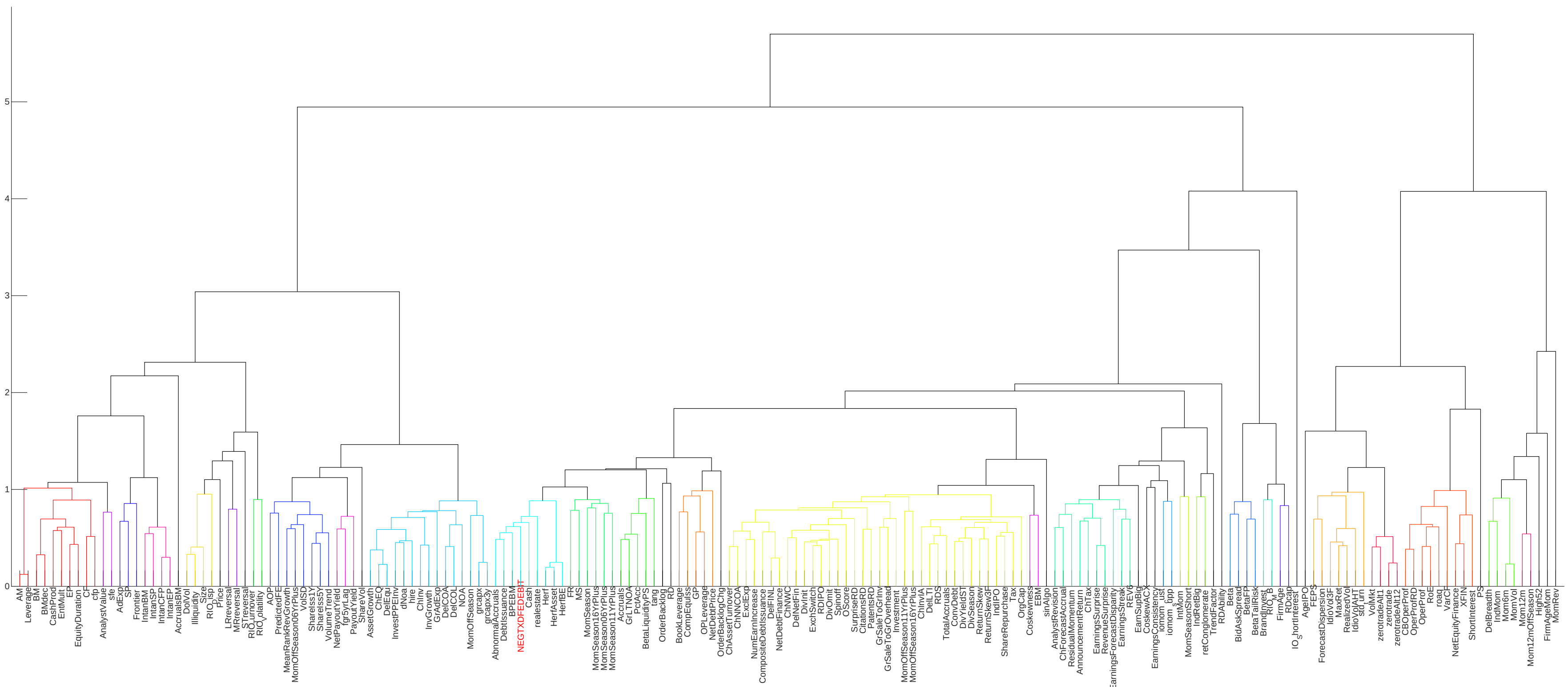


Figure 6: Agglomerative hierarchical cluster plot

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

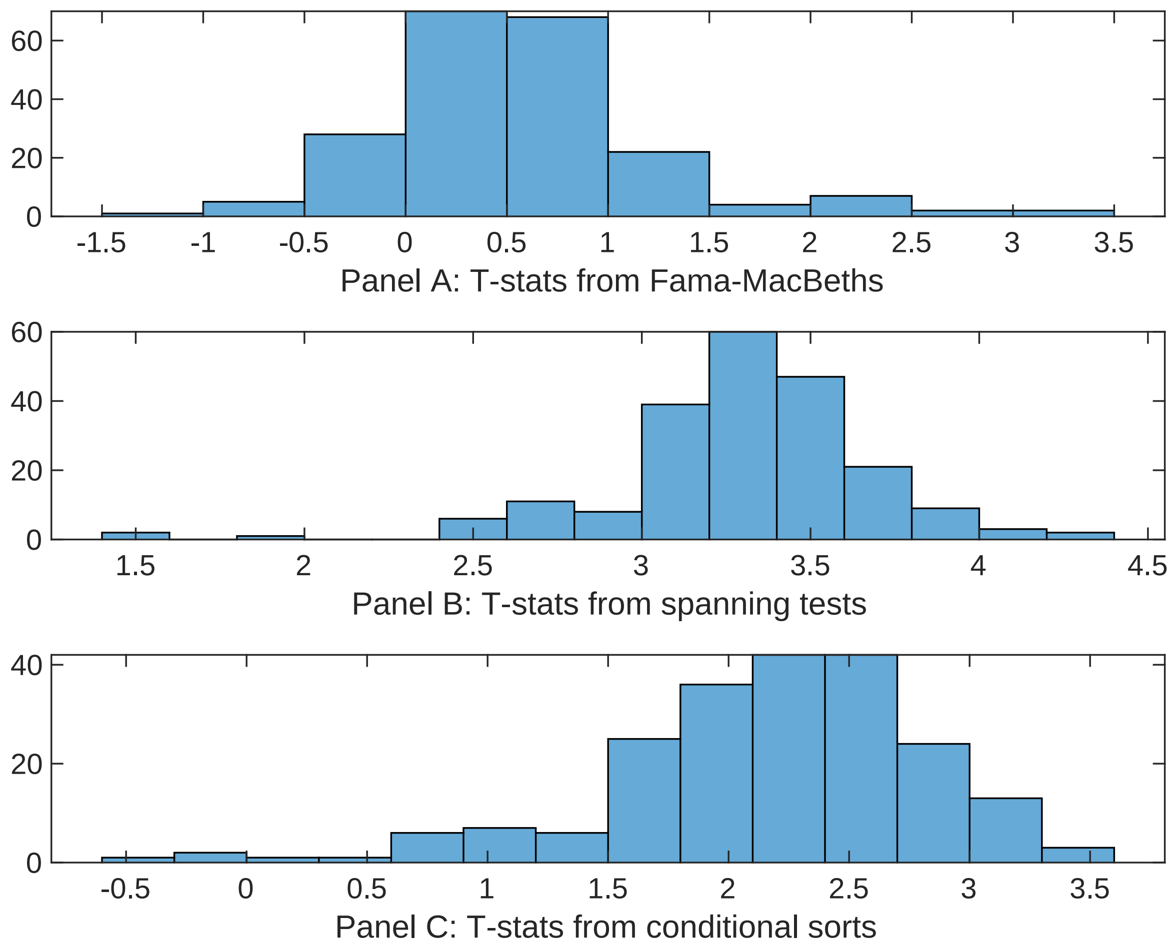


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of TSSF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TSSF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TSSF} TSSF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{TSSF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 TSSF. Stocks are finally grouped into five TSSF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TSSF 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 TSSF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{TSSF} TSSF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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]
TSSF	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 TSSF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{TSSF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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

Panel A: Average rank

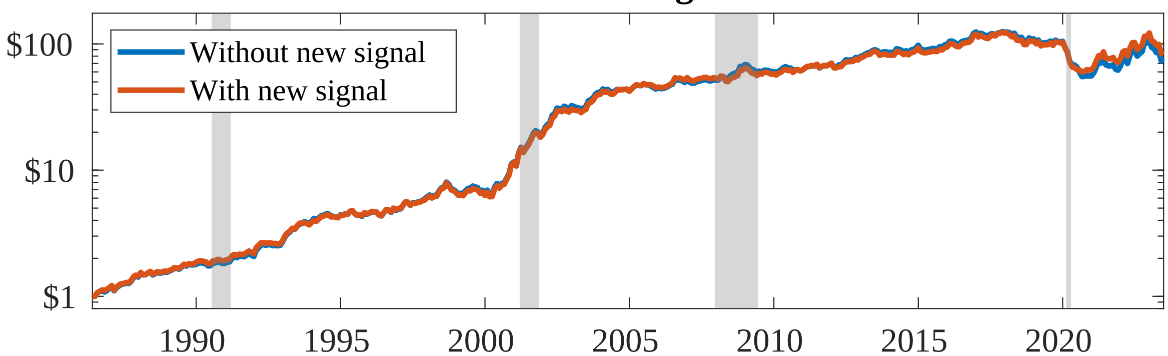


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines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

References

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

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

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

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

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

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

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

Graham, J. R. and Leary, M. T. (2011). A review of empirical capital structure research and directions for the future. *Annual Review of Financial Economics*, 3(1):309–345.

Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, 33(5):2019–2133.

Korajczyk, R. A. and Levy, A. (2003). Capital structure choice: macroeconomic conditions and financial constraints. *Journal of Financial Economics*, 68(1):75–109.

Modigliani, F. and Miller, M. H. (1963). Corporate income taxes and the cost of capital: a correction. *American Economic Review*, 53(3):433–443.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.