Revenue Efficiency Factor and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Revenue Efficiency Factor (REF), and its robustness in predicting returns in the cross-section of equities using the protocol proposed by Novy-Marx and Velikov (2023a). A value-weighted long/short trading strategy based on REF achieves an annualized gross (net) Sharpe ratio of 0.50 (0.44), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (28) bps/month with a t-statistic of 3.30 (3.29), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 25 bps/month with a t-statistic of 3.08.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different market conditions and methodological specifications is frequently questioned (Hou et al., 2020).

In this paper, we introduce a novel predictor of cross-sectional stock returns - the Revenue Efficiency Factor (REF) - which captures how effectively firms convert their operational resources into revenue. This metric bridges an important gap in the literature by connecting firms' operational efficiency to their market performance, offering both theoretical grounding and practical investment implications.

The theoretical foundation for REF's predictive power rests on several established frameworks. First, the q-theory of investment (Cochrane and Saá-Requejo, 2000) suggests that firms' optimal investment decisions should reflect their marginal productivity of capital. REF directly measures this productivity through the lens of revenue generation efficiency, providing a forward-looking indicator of firm performance.

Second, the competitive advantage literature (**?**) argues that superior operational efficiency can create sustainable competitive advantages. Firms with higher REF scores demonstrate better resource utilization, which should translate into sustained profitability and higher stock returns. This relationship is particularly relevant in competitive markets where operational efficiency is crucial for survival and growth.

Third, the information processing theory (Hong and Stein, 1999) suggests that markets may underreact to complex information about firm fundamentals. The multidimensional nature of operational efficiency metrics makes REF potentially difficult for market participants to fully incorporate into their valuation models, creating a persistent source of mispricing.

Our empirical analysis reveals strong evidence that REF predicts cross-sectional stock returns. A value-weighted long-short portfolio strategy based on REF quintiles generates a monthly alpha of 29 basis points (t-statistic = 3.30) relative to the Fama-French six-factor model. This performance remains robust after accounting for transaction costs, with a net alpha of 28 basis points (t-statistic = 3.29).

Importantly, REF's predictive power persists across different size segments. Among the largest quintile of stocks, the strategy yields a monthly alpha of 25 basis points (t-statistic = 2.40), addressing concerns about implementability and economic significance. The signal's effectiveness among large-cap stocks distinguishes it from many other documented anomalies that work primarily in small caps.

Further analysis demonstrates REF's incremental value beyond existing factors. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the strategy maintains a significant alpha of 25 basis points per month (t-statistic = 3.08). This finding suggests that REF captures a distinct aspect of firm performance not reflected in existing metrics.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of (Novy-Marx and Velikov, 2023b) on return prediction by introducing a novel signal that combines operational and financial metrics in a theoretically motivated framework. Unlike traditional financial ratios studied in (Fama and French, 2015), REF provides a more comprehensive measure of firm efficiency.

Second, we contribute to the literature on quality investing (Asness et al., 2019) by demonstrating that operational efficiency metrics can generate significant risk-adjusted returns. Our findings suggest that markets systematically undervalue operational excellence, creating opportunities for informed investors.

Third, our work advances the understanding of market efficiency and information processing. Building on (Hong and Stein, 1999), we show that complex operational metrics contain valuable information that is not immediately reflected in stock prices. The persistence of REF's predictive power, particularly among large-cap stocks, challenges traditional efficient market assumptions and suggests practical implications for investment management.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Revenue Efficiency Factor. 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 CSTK for common stock and item XSGA for selling, general, and administrative expenses. Common stock (CSTK) represents the total value of common shares issued by the company, while XSGA captures the operational expenses associated with running the business, including marketing, administrative costs, and other overhead expenses.construction of the signal follows a difference-to-scale format, where we calculate the year-over-year change in CSTK and scale it by the previous year's XSGA for each firm in our sample. This construction method captures the relative change in equity capital against the firm's operational cost base, providing insight into how efficiently the firm is utilizing its administrative resources to support equity growth. By focusing on this relationship, the signal aims to reflect aspects of capital efficiency and operational scalability in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for both CSTK and XSGA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the REF signal. Panel A plots the time-series of the mean, median, and interquartile range for REF. On average, the cross-sectional mean (median) REF is -0.04 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input REF data. The signal's interquartile range spans -0.04 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the REF signal for the CRSP universe. On average, the REF signal is available for 5.65% of CRSP names, which on average make up 6.49% of total market capitalization.

4 Does REF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on REF 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 REF portfolio and sells the low REF 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 REF strategy earns an average return of 0.33% per month with a t-statistic of 3.79. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.29% to 0.39% per month and have t-statistics exceeding 3.30 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 0.22, with a t-statistic of 3.84 on the CMA factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 534 stocks and an average market capitalization of at least $1,200 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 cap breakpoints and value-weighted portfolios, and equals 29 bps/month with a t-statistics of 3.27. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-three exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between 25-34bps/month. The lowest return, (25 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.87. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the REF trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the REF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and REF, as well as average returns and alphas for long/short trading REF 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 REF strategy achieves an average return of 25 bps/month with a t-statistic of 2.40. Among these large cap stocks, the alphas for the REF strategy relative to the five most common factor models range from 23 to 29 bps/month with t-statistics between 2.15 and 2.80.

5 How does REF perform relative to the zoo?

Figure 2 puts the performance of REF 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 REF strategy falls in the distribution. The REF strategy's gross (net)

[1] The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

Sharpe ratio of 0.50 (0.44) 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 REF strategy (red line).[2] Ignoring trading costs, a $1 invested in the REF strategy would have yielded $7.26 which ranks the REF strategy in the top 2% across the 212 anomalies. Accounting for trading costs, a $1 invested in the REF strategy would have yielded $5.42 which ranks the REF 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 REF relative to those. Panel A shows that the REF strategy gross alphas fall between the 72 and 79 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 196606 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 REF strategy has a positive net generalized alpha for five out of the five factor models. In these cases REF ranks between the 88 and 93 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does REF 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 REF 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 REF or at least to weaken the power REF has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of REF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{REF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{REF} REF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{REF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 REF. Stocks are finally grouped into five REF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[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.

REF trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on REF 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 REF signal in these Fama-MacBeth regressions exceed 1.94, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on REF is 0.65.

Similarly, Table 5 reports results from spanning tests that regress returns to the REF 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 REF strategy earns alphas that range from 26-31bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.99, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the REF trading strategy achieves an alpha of 25bps/month with a t-statistic of 3.08.

7 Does REF add relative to the whole zoo?

Finally, we can ask how much adding REF 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 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the REF signal.[4] We consider one different methods for combining signals.

[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 REF is available.

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 155-anomaly combination strategy grows to \$2333.55, while \$1 investment in the combination strategy that includes REF grows to \$2366.46.

8 Conclusion

This study provides compelling evidence for the significance of the Revenue Efficiency Factor (REF) 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 REF generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.50 (0.44 after transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that REF captures unique information content not fully reflected in existing pricing factors.

Particularly noteworthy is the strategy's ability to maintain significant alpha (25 bps/month) when controlling for both the Fama-French five factors plus momentum, and the six most closely related anomalies from the factor zoo. This robustness strengthens the case for REF as a meaningful addition to the asset pricing literature and suggests practical value for investment professionals.

However, several limitations warrant consideration. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we account for transaction costs, implementation challenges such as short-selling constraints and market impact costs may affect real-world performance.

Future research could explore the interaction between REF and other emerging factors, investigate its performance in different market regimes, and examine its applicability across different asset classes. Additionally, studying the underlying economic mechanisms driving the REF premium could provide valuable insights into market efficiency and asset pricing theory.

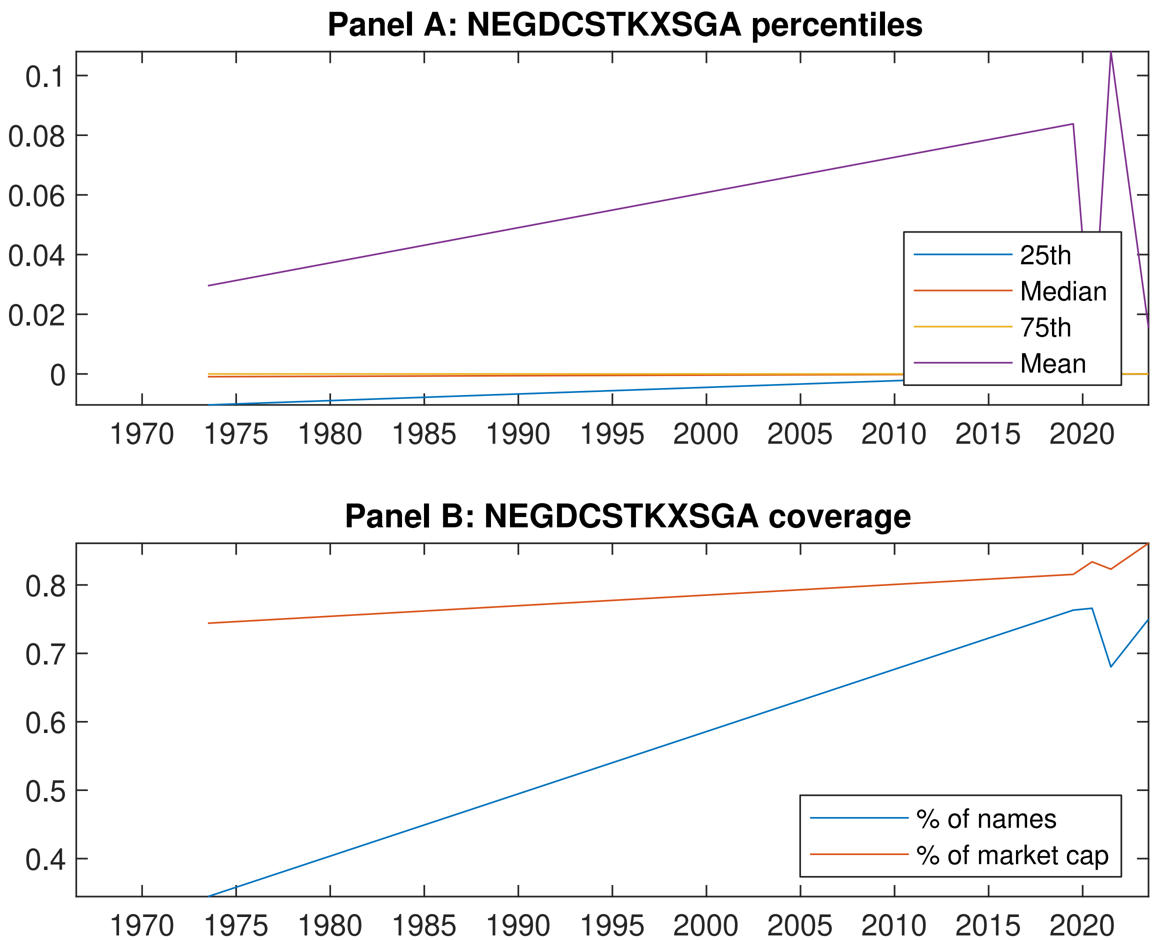

Figure 1: Times series of REF percentiles and coverage.
This figure plots descriptive statistics for REF. Panel A shows cross-sectional percentiles of REF over the sample. Panel B plots the monthly coverage of REF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on REF. 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 196606 to 202306.

Panel A: Excess returns and alphas on REF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.49	0.65	0.71	0.78	0.33
	[2.36]	[2.48]	[3.35]	[4.12]	[4.60]	[3.79]
α_{CAPM}	-0.14	-0.13	0.05	0.18	0.25	0.39
	[-2.40]	[-2.27]	[0.80]	[3.17]	[4.93]	[4.63]
α_{FF3}	-0.14	-0.09	0.09	0.15	0.22	0.36
	[-2.35]	[-1.69]	[1.67]	[2.73]	[4.32]	[4.18]
α_{FF4}	-0.12	-0.07	0.13	0.10	0.20	0.32
	[-1.98]	[-1.25]	[2.37]	[1.78]	[3.89]	[3.68]
α_{FF5}	-0.19	-0.02	0.14	0.04	0.12	0.31
	[-3.25]	[-0.35]	[2.37]	[0.71]	[2.43]	[3.62]
α_{FF6}	-0.17	-0.01	0.16	0.01	0.11	0.29
	[-2.90]	[-0.12]	[2.87]	[0.10]	[2.28]	[3.30]
Panel B: Fama and French (2018) 6-factor model loadings for REF-sorted portfolios						
β_{MKT}	1.05	1.04	1.00	0.99	0.98	-0.07
	[74.19]	[79.89]	[74.30]	[77.16]	[83.11]	[-3.30]
β_{SMB}	0.02	0.05	0.06	-0.00	0.01	-0.02
	[1.11]	[2.58]	[2.93]	[-0.24]	[0.41]	[-0.53]
β_{HML}	-0.01	-0.08	-0.11	0.02	0.02	0.02
	[-0.23]	[-3.29]	[-4.41]	[0.80]	[0.75]	[0.59]
β_{RMW}	0.17	-0.12	-0.03	0.17	0.14	-0.04
	[6.29]	[-4.90]	[-0.95]	[7.01]	[5.90]	[-0.93]
β_{CMA}	-0.02	-0.10	-0.11	0.18	0.20	0.22
	[-0.50]	[-2.73]	[-2.87]	[5.03]	[6.10]	[3.84]
β_{UMD}	-0.03	-0.02	-0.05	0.05	0.01	0.04
	[-2.15]	[-1.52]	[-3.38]	[4.07]	[0.78]	[1.92]
Panel C: Average number of firms (n) and market capitalization (me)						
n	654	608	534	604	652	
me ($\$10^6$)	1451	1200	1708	1762	2074	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the REF 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 196606 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	0.33	0.39	0.36	0.32	0.31	0.29
			[3.79]	[4.63]	[4.18]	[3.68]	[3.62]	[3.30]
Quintile	NYSE	EW	0.55	0.62	0.57	0.50	0.48	0.43
			[8.76]	[10.74]	[10.15]	[9.07]	[8.56]	[7.84]
Quintile	Name	VW	0.33	0.39	0.36	0.33	0.32	0.31
			[3.75]	[4.55]	[4.12]	[3.74]	[3.67]	[3.43]
Quintile	Cap	VW	0.29	0.34	0.31	0.28	0.30	0.28
			[3.27]	[3.88]	[3.50]	[3.11]	[3.36]	[3.10]
Decile	NYSE	VW	0.35	0.39	0.35	0.29	0.36	0.32
			[3.30]	[3.63]	[3.23]	[2.68]	[3.33]	[2.90]
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	0.29	0.36	0.33	0.31	0.29	0.28
			[3.37]	[4.24]	[3.86]	[3.61]	[3.44]	[3.29]
Quintile	NYSE	EW	0.34	0.42	0.36	0.33	0.26	0.24
			[4.93]	[6.27]	[5.68]	[5.25]	[4.15]	[3.90]
Quintile	Name	VW	0.29	0.36	0.33	0.32	0.30	0.30
			[3.34]	[4.17]	[3.80]	[3.62]	[3.47]	[3.36]
Quintile	Cap	VW	0.25	0.31	0.28	0.26	0.28	0.27
			[2.87]	[3.53]	[3.21]	[3.02]	[3.15]	[3.03]
Decile	NYSE	VW	0.31	0.35	0.31	0.28	0.32	0.30
			[2.91]	[3.22]	[2.89]	[2.62]	[2.97]	[2.79]

Table 3: Conditional sort on size and REF

This table presents results for conditional double sorts on size and REF. 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 REF. 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 REF and short stocks with low REF .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

		REF Quintiles					REF Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.41	0.60	0.92	0.96	0.95	0.54	0.59	0.57	0.50	0.49	0.44
		[1.61]	[2.24]	[3.48]	[3.69]	[4.02]	[7.36]	[8.18]	[7.85]	[6.85]	[6.69]	[6.01]
	(2)	0.53	0.61	0.88	0.92	0.89	0.36	0.41	0.35	0.33	0.30	0.29
		[2.23]	[2.44]	[3.49]	[3.89]	[3.93]	[4.18]	[4.87]	[4.20]	[3.88]	[3.47]	[3.30]
	(3)	0.53	0.62	0.82	0.84	0.92	0.39	0.45	0.41	0.42	0.36	0.37
		[2.32]	[2.60]	[3.52]	[3.73]	[4.35]	[4.68]	[5.48]	[5.09]	[5.09]	[4.32]	[4.41]
	(4)	0.50	0.61	0.75	0.83	0.80	0.31	0.40	0.34	0.33	0.24	0.24
		[2.18]	[2.73]	[3.31]	[3.94]	[4.10]	[3.42]	[4.73]	[4.15]	[3.93]	[2.85]	[2.83]
	(5)	0.51	0.51	0.49	0.53	0.76	0.25	0.29	0.26	0.23	0.28	0.26
		[2.76]	[2.65]	[2.62]	[3.03]	[4.50]	[2.40]	[2.80]	[2.49]	[2.15]	[2.66]	[2.41]

Panel B: Portfolio average number of firms and market capitalization

		REF Quintiles					REF Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	350	349	348	347	348	29	29	35	25	26
	(2)	96	96	95	95	95	49	49	49	49	49
	(3)	67	66	66	66	67	82	80	83	83	84
	(4)	53	52	53	53	53	165	166	169	171	175
	(5)	47	47	47	47	47	1183	1197	1404	1268	1496

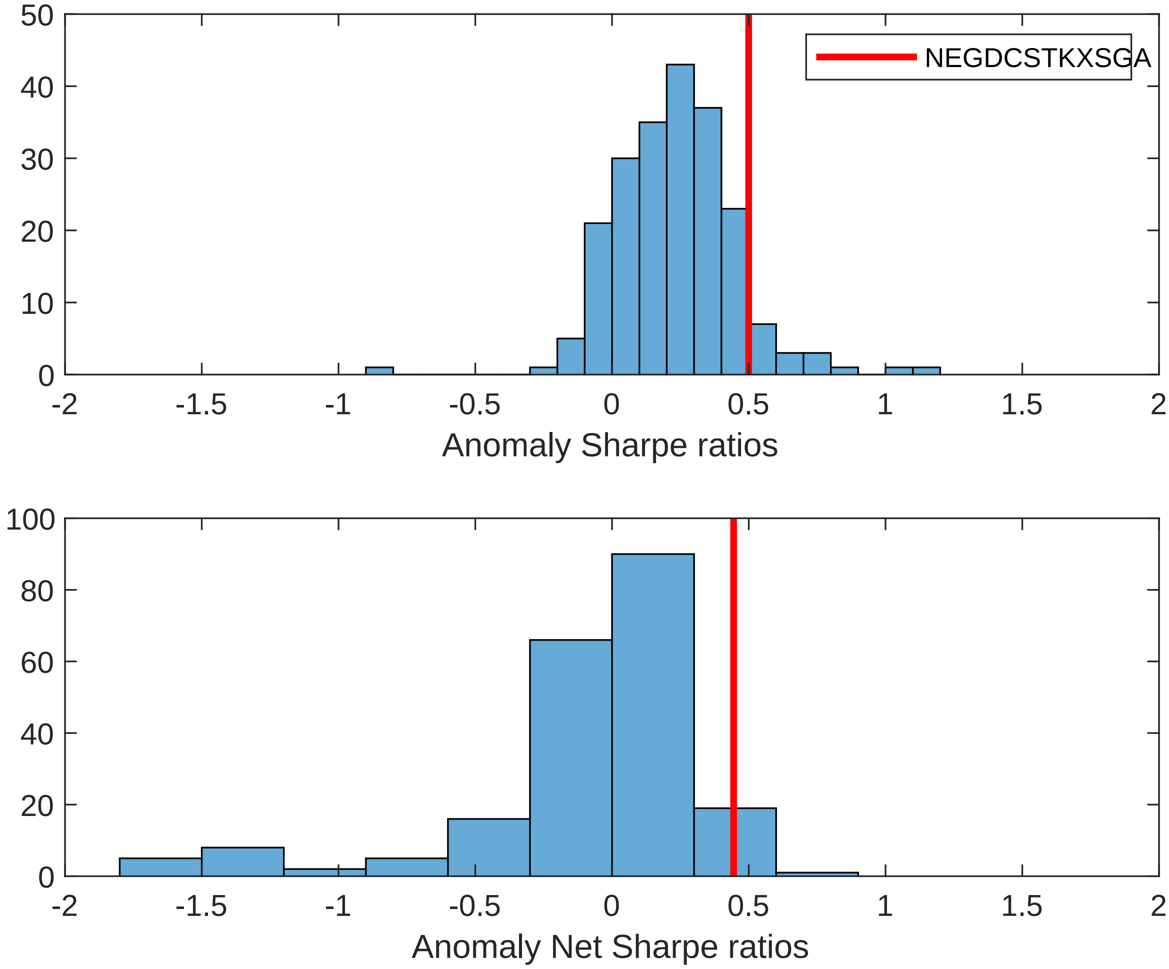

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the REF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

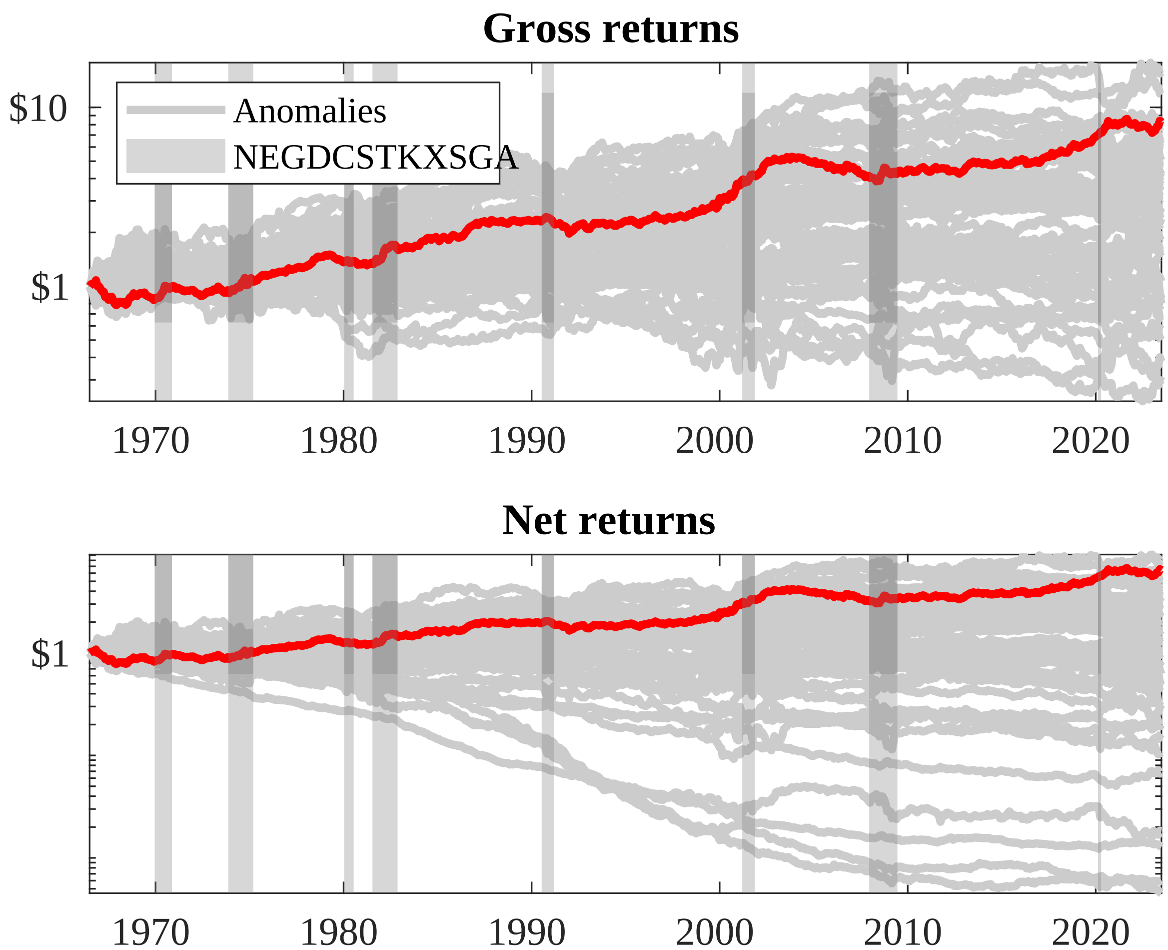

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the REF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

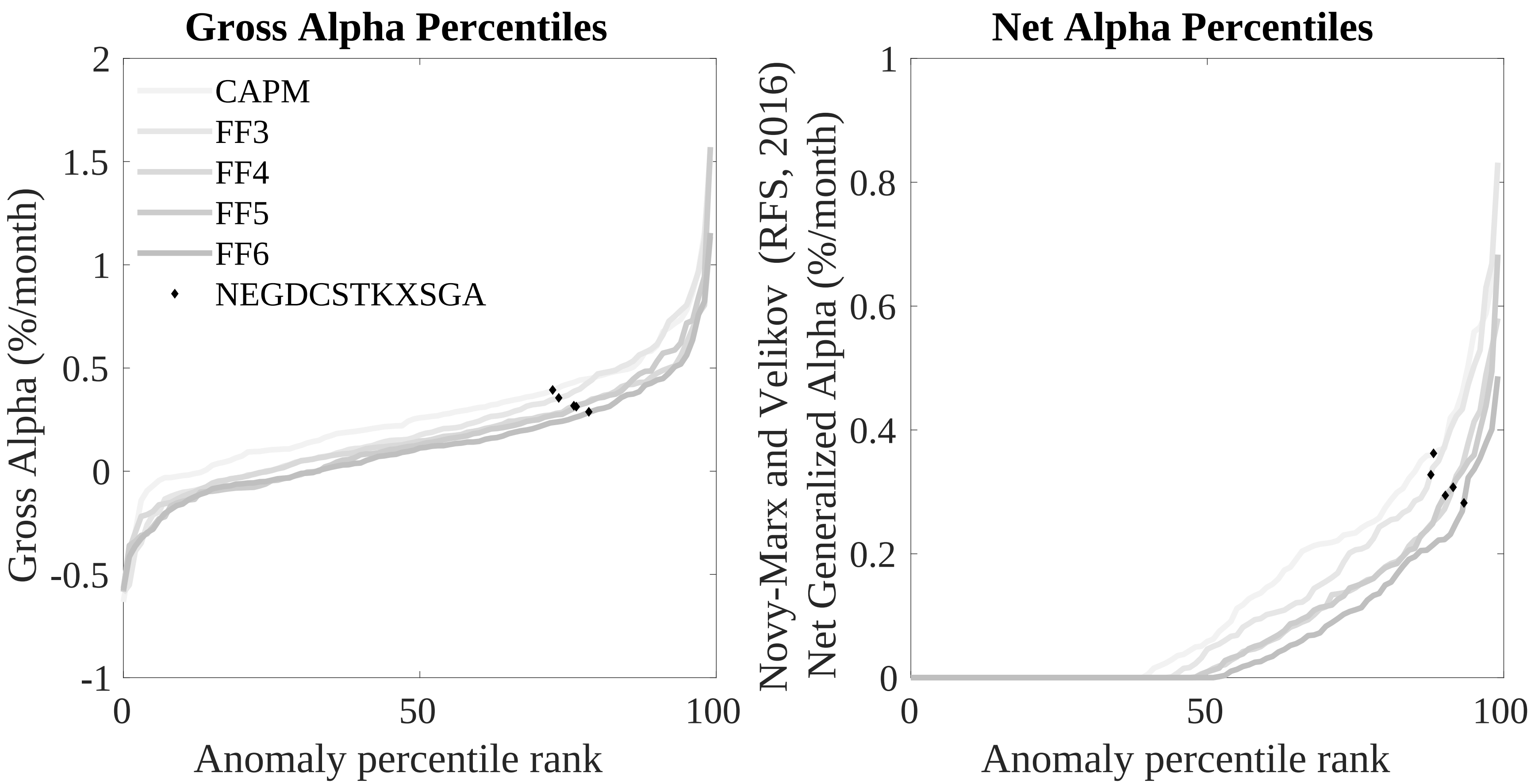

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the REF trading strategy alphas (diamonds). The strategies are constructed using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

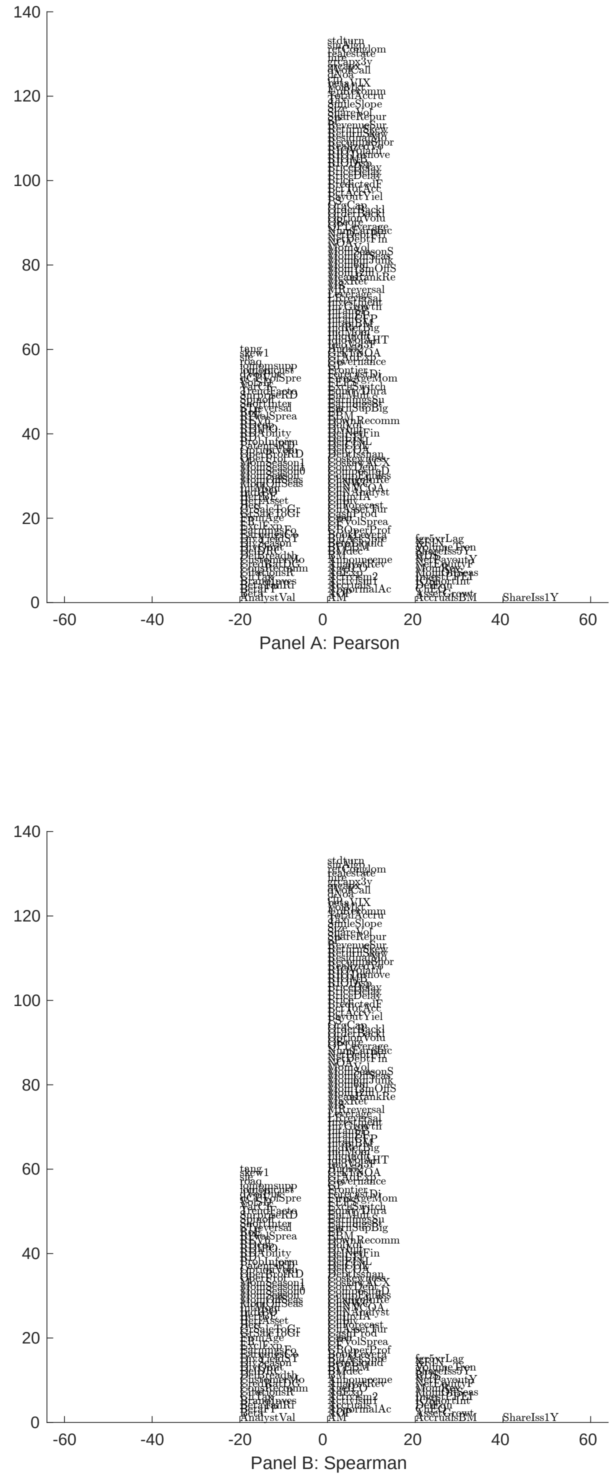

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with REF. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

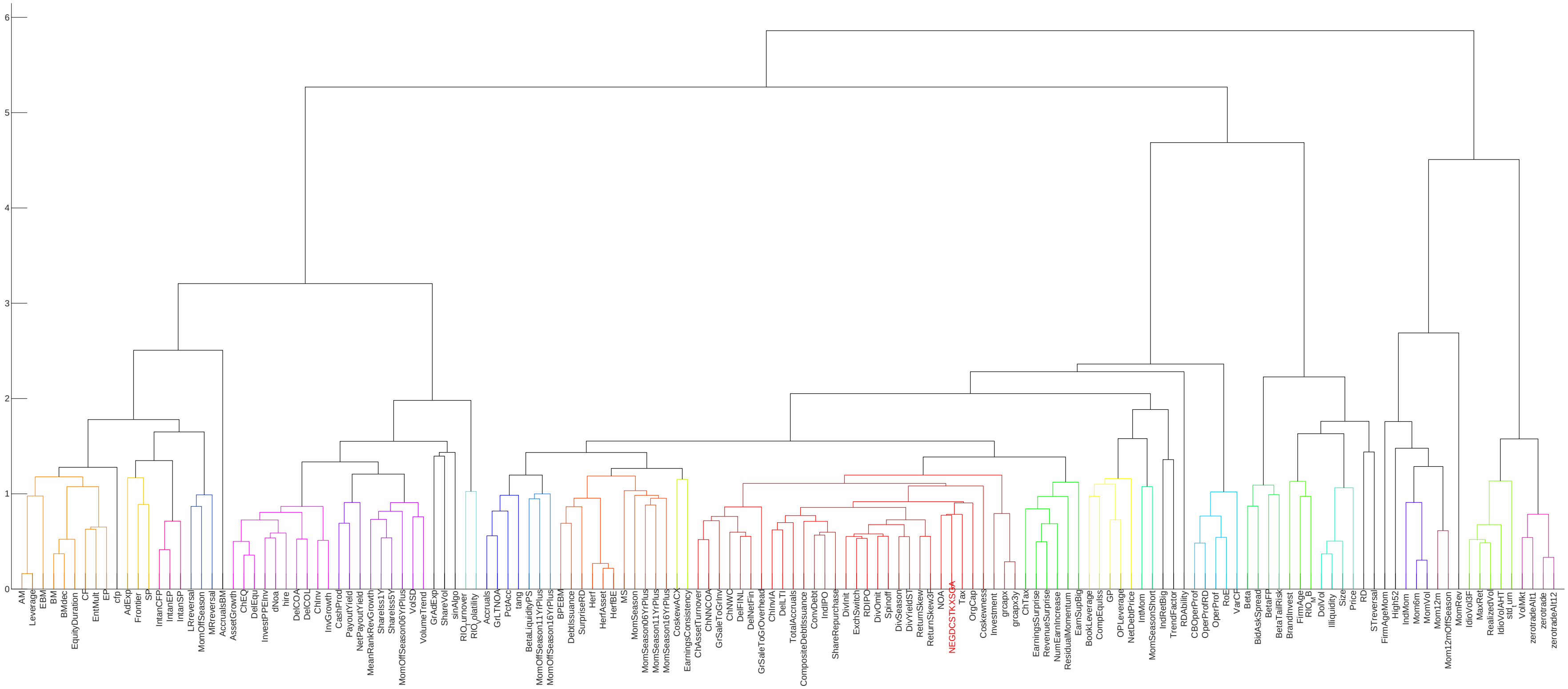

Figure 6: Agglomerative hierarchical cluster plot

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

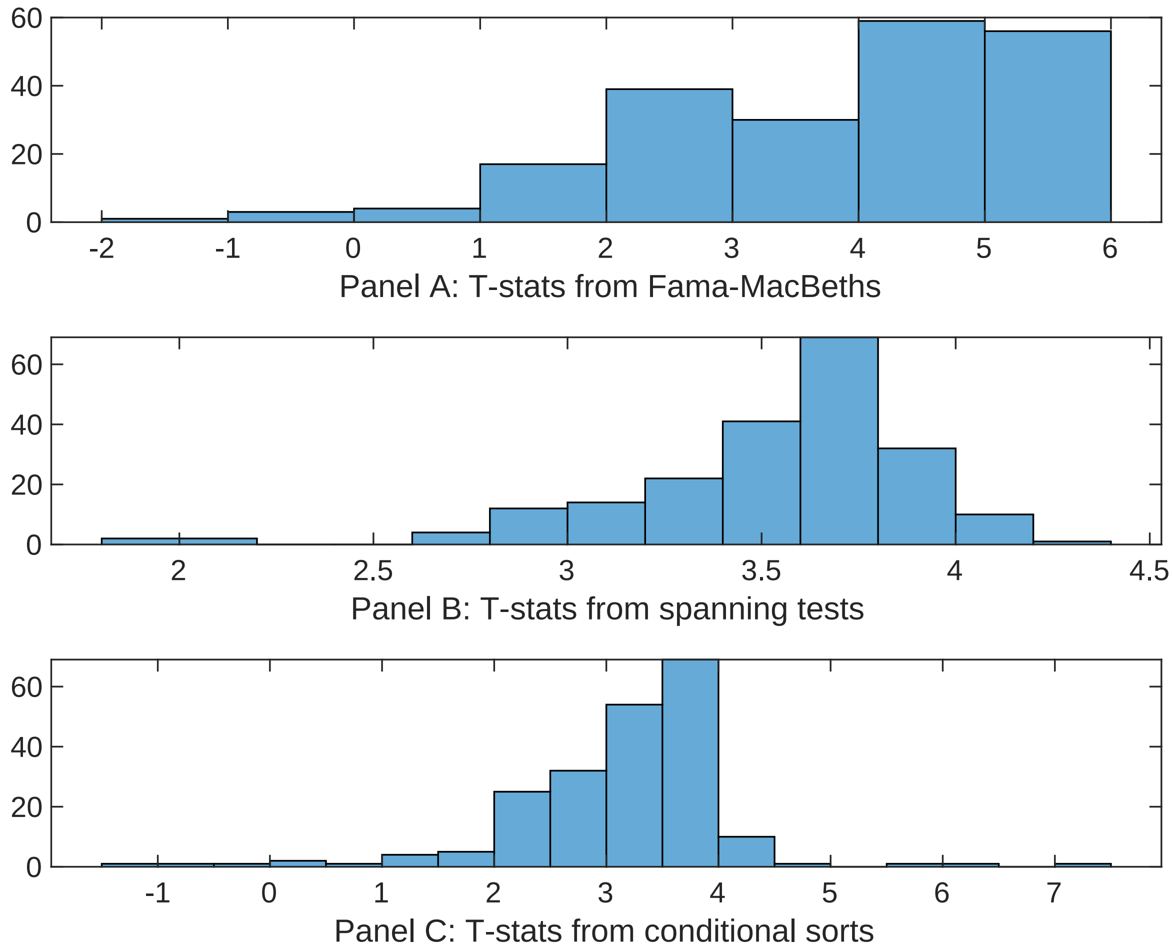

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of REF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{REF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{REF} REF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{REF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 REF. Stocks are finally grouped into five REF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted REF 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 REF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{REF} REF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.13	0.18	0.12	0.13	0.13	0.14	0.12
	[5.54]	[7.24]	[5.07]	[5.87]	[5.46]	[5.90]	[5.02]
REF	0.79	0.75	0.49	0.69	0.74	0.53	0.16
	[4.31]	[4.23]	[1.94]	[3.69]	[4.09]	[2.94]	[0.65]
Anomaly 1	0.28						0.78
	[6.09]						[1.99]
Anomaly 2		0.51					-0.71
		[4.81]					[-0.40]
Anomaly 3			0.35				0.29
			[3.43]				[2.87]
Anomaly 4				0.40			0.89
				[4.49]			[0.97]
Anomaly 5					0.16		-0.17
					[4.47]		[-0.03]
Anomaly 6						0.11	0.70
						[9.07]	[6.96]
# months	679	684	679	679	684	684	679
$\bar{R}^2$(%)	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the REF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{REF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.26	0.29	0.28	0.26	0.31	0.30	0.25
	[3.11]	[3.45]	[3.33]	[2.99]	[3.67]	[3.37]	[3.08]
Anomaly 1	30.79						17.75
	[7.13]						[3.58]
Anomaly 2		40.84					36.21
		[8.83]					[5.39]
Anomaly 3			18.75				3.33
			[5.66]				[0.89]
Anomaly 4				20.96			6.05
				[4.68]			[1.27]
Anomaly 5					28.28		0.30
					[6.26]		[0.05]
Anomaly 6						5.88	-19.57
						[1.02]	[-3.30]
mkt	-4.27	-5.34	-3.58	-3.81	-7.13	-6.67	-2.82
	[-2.15]	[-2.72]	[-1.75]	[-1.84]	[-3.55]	[-3.23]	[-1.40]
smb	0.42	-2.68	2.71	-2.11	-1.76	-1.84	0.65
	[0.15]	[-0.94]	[0.92]	[-0.72]	[-0.60]	[-0.60]	[0.22]
hml	-0.59	-2.06	-3.85	-2.55	-0.87	2.54	-5.77
	[-0.15]	[-0.54]	[-0.93]	[-0.61]	[-0.22]	[0.64]	[-1.43]
rmw	-13.86	-1.77	-14.30	-7.73	-1.09	-4.02	-10.42
	[-3.37]	[-0.46]	[-3.29]	[-1.92]	[-0.28]	[-1.00]	[-2.32]
cma	7.22	-18.55	8.39	15.59	-7.45	14.84	-3.13
	[1.19]	[-2.57]	[1.33]	[2.60]	[-1.01]	[1.63]	[-0.36]
umd	3.76	3.52	5.72	4.25	4.82	4.10	3.10
	[1.92]	[1.81]	[2.87]	[2.13]	[2.41]	[1.99]	[1.60]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	17	19	15	14	14	10	23

Panel A: Average rank

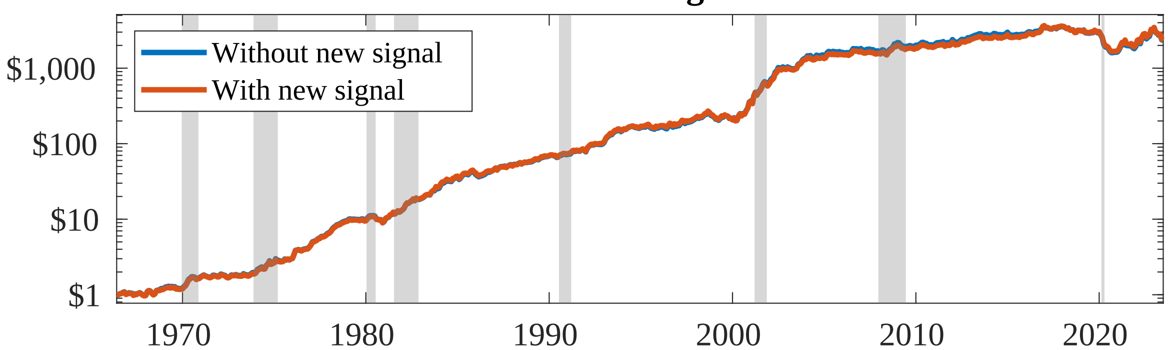

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines indicate combination trading strategies that utilize the 155 anomalies as well as REF. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

References

Asness, C. S., Frazzini, A., and Pedersen, L. H. (2019). Quality minus junk. *Review of Accounting Studies*, 24(1):34–112.

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.

Cochrane, J. H. and Saá-Requejo, J. (2000). Beyond arbitrage: Good-deal asset price bounds in incomplete markets. *Journal of Political Economy*, 108(1):79–119.

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.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184.

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

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. (2023a). Assaying anomalies. *Working paper*.

Novy-Marx, R. and Velikov, M. (2023b). Assaying anomalies. *Journal of Finance*, 78(4):1873–1918.