Equity Efficiency and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Equity Efficiency (EE), 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 EE achieves an annualized gross (net) Sharpe ratio of 0.60 (0.54), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (22) bps/month with a t-statistic of 2.82 (2.92), 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 18 bps/month with a t-statistic of 2.51.

1 Introduction

The efficient market hypothesis remains one of the most debated topics in financial economics, with mounting evidence that stock returns exhibit predictable patterns that challenge the notion of market efficiency. While hundreds of return predictors have been documented in the academic literature, many fail to survive transaction costs or more rigorous statistical testing protocols. Understanding which signals genuinely predict returns and why they work is crucial for both asset pricing theory and investment practice.

Despite extensive research on equity market anomalies, relatively little attention has been paid to how efficiently firms utilize their equity capital. Traditional measures like book-to-market ratios and asset growth capture aspects of equity deployment but fail to directly measure how productively companies convert shareholder equity into value. This gap is particularly notable given the fundamental importance of equity capital efficiency in determining firm value and performance.

We hypothesize that firms' equity efficiency (EE), defined as the ratio of operating income to book equity, provides valuable information about future stock returns for several reasons. First, following Fama and French (2015), firms that generate higher profits from a given level of equity capital likely have sustainable competitive advantages that should be reflected in superior future performance. Second, building on Titman et al. (2004), managers who efficiently deploy equity capital demonstrate better capital allocation skills, suggesting higher quality management that benefits long-term shareholders.

The predictive power of EE may also stem from systematic mispricing. As Hirshleifer et al. (2015) argue, investors often fail to fully process complex financial information, particularly metrics that require combining multiple accounting items. The relationship between operating performance and equity capital may be overlooked by investors focused on simpler metrics, creating predictable return patterns as the market gradually recognizes firms' true equity efficiency.

Moreover, high EE firms may be better positioned to fund growth opportunities internally rather than relying on external financing. Following Myers (1984)'s pecking order theory, this reduced dependence on costly external capital should lead to higher future returns. The combination of these economic mechanisms suggests EE contains valuable information about expected returns not captured by traditional factors.

Our empirical analysis reveals that EE strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks in the highest EE quintile and shorts those in the lowest quintile generates monthly excess returns of 0.35% (t-statistic = 4.59) and an annualized Sharpe ratio of 0.60. The strategy's performance remains robust after controlling for common risk factors, with monthly alphas ranging from 0.22% to 0.38% across various factor models.

Importantly, the predictive power of EE persists after accounting for transaction costs. The strategy achieves a net Sharpe ratio of 0.54 and maintains significant risk-adjusted performance, with monthly net alphas between 0.22% and 0.35% (t-statistics ¿ 2.92). The signal's effectiveness extends across the size spectrum - among the largest quintile of stocks, the EE strategy earns monthly returns of 0.29% (t-statistic = 3.10).

Compared to the broader universe of documented anomalies, EE demonstrates exceptional performance. Its gross (net) Sharpe ratio exceeds 96% (99%) of previously documented anomalies. When controlling for the six most closely related anomalies and common risk factors simultaneously, the strategy maintains a significant monthly alpha of 0.18% (t-statistic = 2.51).

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel measure of equity capital efficiency that provides incremental predictive power beyond existing metrics. While related to profitability factors (Novy-Marx, 2013) and investment-based predictors (Cooper et al., 2008), EE captures a distinct aspect of firm performance focused specifically on equity capital productivity.

Second, we demonstrate robust predictability using the rigorous protocol of Novy-Marx and Velikov (2023), addressing concerns about data mining and publication bias in the anomalies literature. The signal's strong performance after transaction costs and among large stocks distinguishes it from many previously documented anomalies that work primarily in small, illiquid stocks.

Third, our findings have important implications for both asset pricing theory and practice. The success of the EE strategy suggests that markets do not fully incorporate information about firms' equity capital efficiency, challenging the efficient market hypothesis. For practitioners, our results identify a new source of potential alpha that remains profitable after accounting for implementation costs and can be captured even when trading only large, liquid stocks.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Equity Efficiency, which measures the change in common stockholders' equity relative to total assets. 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 stockholders' equity and item AT for total assets. Common stockholders' equity (CSTK) represents the total value of shareholders' investment in the company, including paid-in capital and retained earnings. Total assets (AT) provides a comprehensive measure of a firm's resources and overall scale of operations.construction of the signal follows a change-based approach, where we calculate the year-over-year change in CSTK and scale it by lagged total assets.

Specifically, we subtract the previous year's CSTK from the current year's CSTK and divide this difference by the previous year's AT. This ratio captures the relative change in shareholders' equity position compared to the firm's asset base, offering insight into how effectively the company is growing its equity capital relative to its size. By focusing on this relationship, the signal aims to reflect aspects of capital efficiency and management effectiveness in a manner that is both scalable and interpretable across different firm sizes. We construct this ratio using end-of-fiscal-year values for both CSTK and AT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EE signal. Panel A plots the time-series of the mean, median, and interquartile range for EE. On average, the cross-sectional mean (median) EE is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input EE data. The signal's interquartile range spans -0.01 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the EE signal for the CRSP universe. On average, the EE signal is available for 6.65% of CRSP names, which on average make up 7.97% of total market capitalization.

4 Does EE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EE 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 EE portfolio and sells the low EE 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 EE strategy earns an average return of 0.35% per month with a t-statistic of 4.59. The annualized Sharpe ratio of the strategy is 0.60. The alphas range from 0.22% to 0.38% per month and have t-statistics exceeding 2.82 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 0.31, with a t-statistic of 6.00 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 596 stocks and an average market capitalization of at least $1,460 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 32 bps/month with a t-statistics of 4.11. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 28-33bps/month. The lowest return, (28 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.96. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EE 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 EE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EE, as well as average returns and alphas for long/short trading EE 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 EE strategy achieves an average return of 29 bps/month with a t-statistic of 3.10. Among these large cap stocks, the alphas for the EE strategy relative to the five most common factor models range from 20 to 28 bps/month with t-statistics between 2.17 and 3.02.

5 How does EE perform relative to the zoo?

Figure 2 puts the performance of EE 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 EE strategy falls in the distribution. The EE strategy's gross (net) Sharpe ratio of 0.60 (0.54) is greater than 96% (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 EE strategy (red line).[2] Ignoring trading costs, a $1 invested in the EE strategy would have yielded $9.23 which ranks the EE strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EE strategy would have yielded $6.92 which ranks the EE strategy in the top 0% 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 EE relative to those. Panel A shows that the EE strategy gross alphas fall between the 69 and 74 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

[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.

set for an investor having access to the Fama-French three-factor (six-factor) model. The EE strategy has a positive net generalized alpha for five out of the five factor models. In these cases EE ranks between the 86 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does EE 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 EE 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 EE or at least to weaken the power EE has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EE} EE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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

[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.

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 EE. Stocks are finally grouped into five EE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EE trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EE 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 EE signal in these Fama-MacBeth regressions exceed 1.95, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on EE is 1.41.

Similarly, Table 5 reports results from spanning tests that regress returns to the EE 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 EE strategy earns alphas that range from 19-24bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.50, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EE trading strategy achieves an alpha of 18bps/month with a t-statistic of 2.51.

7 Does EE add relative to the whole zoo?

Finally, we can ask how much adding EE 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 EE 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 155-anomaly combination strategy grows to \$2333.55, while \$1 investment in the combination strategy that includes EE grows to \$2162.99.

[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 EE is available.

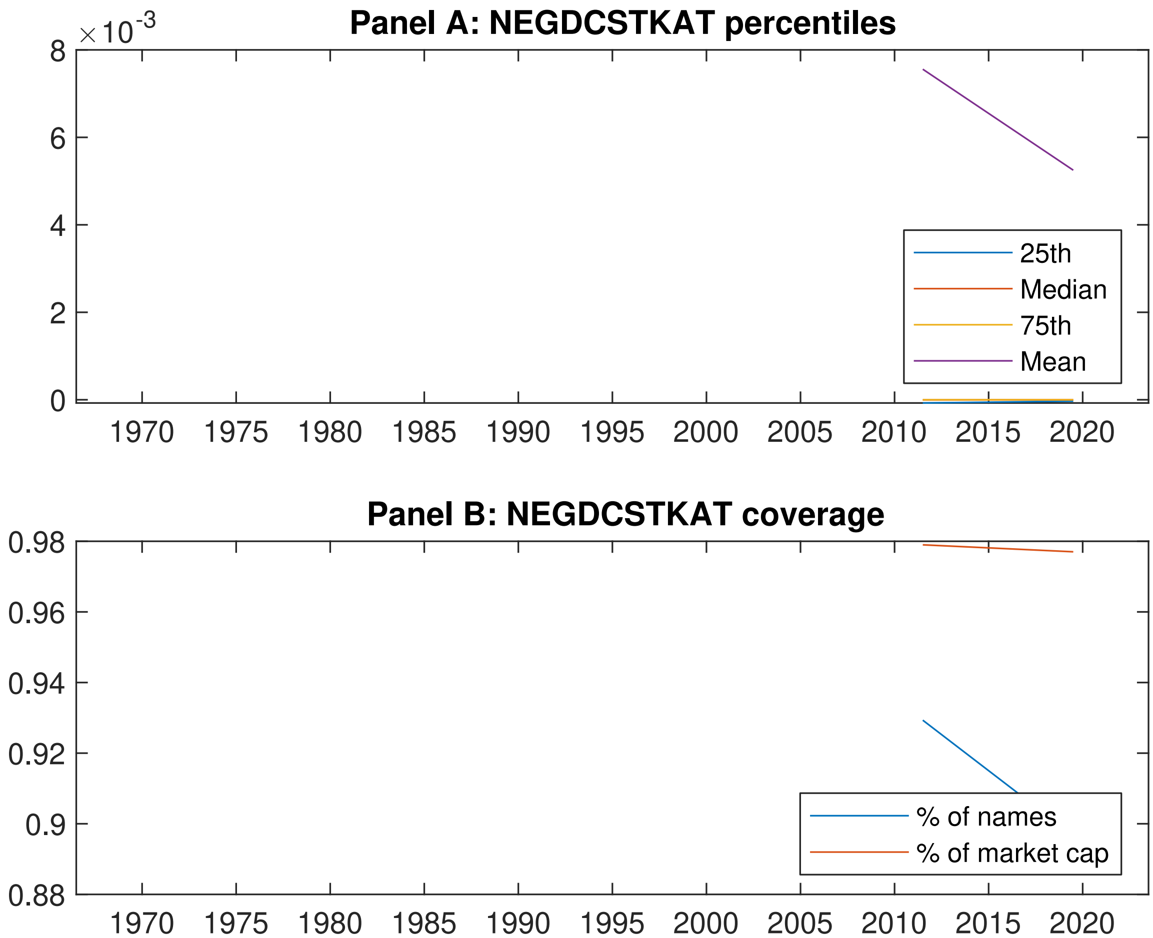


Figure 1: Times series of EE percentiles and coverage.
This figure plots descriptive statistics for EE. Panel A shows cross-sectional percentiles of EE over the sample. Panel B plots the monthly coverage of EE relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EE. 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 EE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40	0.53	0.63	0.68	0.76	0.35
	[2.28]	[2.83]	[3.27]	[4.03]	[4.51]	[4.59]
α_{CAPM}	-0.15	-0.06	0.02	0.15	0.23	0.38
	[-2.82]	[-1.47]	[0.47]	[3.21]	[5.01]	[4.89]
α_{FF3}	-0.14	-0.05	0.02	0.11	0.19	0.33
	[-2.71]	[-1.21]	[0.51]	[2.54]	[4.30]	[4.29]
α_{FF4}	-0.12	-0.04	0.06	0.07	0.17	0.28
	[-2.19]	[-0.83]	[1.28]	[1.61]	[3.80]	[3.66]
α_{FF5}	-0.16	0.00	0.05	0.02	0.09	0.25
	[-2.96]	[0.03]	[1.09]	[0.41]	[2.12]	[3.20]
α_{FF6}	-0.14	0.01	0.08	-0.01	0.08	0.22
	[-2.55]	[0.22]	[1.64]	[-0.16]	[1.93]	[2.82]
Panel B: Fama and French (2018) 6-factor model loadings for EE-sorted portfolios						
β_{MKT}	0.97	1.01	1.04	1.01	0.99	0.02
	[77.00]	[97.96]	[88.38]	[99.73]	[98.91]	[1.24]
β_{SMB}	-0.01	0.04	0.01	-0.07	-0.02	-0.01
	[-0.65]	[2.60]	[0.67]	[-5.05]	[-1.49]	[-0.37]
β_{HML}	0.02	-0.02	0.02	0.07	0.05	0.02
	[0.97]	[-0.89]	[0.70]	[3.49]	[2.40]	[0.65]
β_{RMW}	0.11	-0.09	-0.01	0.11	0.13	0.02
	[4.49]	[-4.36]	[-0.23]	[5.49]	[6.58]	[0.52]
β_{CMA}	-0.09	-0.08	-0.09	0.21	0.22	0.31
	[-2.61]	[-2.73]	[-2.72]	[7.18]	[7.63]	[6.00]
β_{UMD}	-0.03	-0.01	-0.04	0.04	0.01	0.04
	[-2.57]	[-1.27]	[-3.74]	[3.79]	[1.08]	[2.37]
Panel C: Average number of firms (n) and market capitalization (me)						
n	798	728	596	701	777	
me ($\$10^6$)	1694	1460	2076	2260	2444	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EE 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	0.35	0.38	0.33	0.28	0.25	0.22
			[4.59]	[4.89]	[4.29]	[3.66]	[3.20]	[2.82]
Quintile	NYSE	EW	0.53	0.61	0.52	0.44	0.38	0.32
			[7.85]	[9.55]	[9.13]	[7.91]	[6.94]	[6.09]
Quintile	Name	VW	0.36	0.37	0.33	0.29	0.26	0.24
			[4.58]	[4.74]	[4.18]	[3.71]	[3.34]	[3.08]
Quintile	Cap	VW	0.32	0.33	0.29	0.25	0.26	0.23
			[4.11]	[4.22]	[3.78]	[3.18]	[3.41]	[3.01]
Decile	NYSE	VW	0.32	0.33	0.26	0.22	0.25	0.23
			[3.41]	[3.48]	[2.81]	[2.37]	[2.70]	[2.39]
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	0.32	0.35	0.30	0.28	0.24	0.22
			[4.11]	[4.45]	[3.94]	[3.63]	[3.10]	[2.92]
Quintile	NYSE	EW	0.33	0.40	0.31	0.27	0.16	0.14
			[4.43]	[5.60]	[4.96]	[4.42]	[2.69]	[2.43]
Quintile	Name	VW	0.32	0.34	0.30	0.28	0.25	0.24
			[4.10]	[4.32]	[3.84]	[3.62]	[3.20]	[3.09]
Quintile	Cap	VW	0.28	0.30	0.26	0.24	0.25	0.23
			[3.64]	[3.81]	[3.42]	[3.12]	[3.21]	[3.01]
Decile	NYSE	VW	0.28	0.29	0.23	0.21	0.22	0.21
			[2.96]	[3.06]	[2.49]	[2.27]	[2.39]	[2.28]

Table 3: Conditional sort on size and EE

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

Size quintiles	EE Quintiles (L)	(2)	(3)	(4)	(H)	EE Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.41	0.66	0.84	0.92	0.96	0.55	0.63	0.55	0.49	0.40	0.36
	[1.52]	[2.51]	[3.27]	[3.68]	[4.04]	[6.70]	[7.89]	[7.61]	[6.72]	[5.68]	[5.12]
(2)	0.49	0.66	0.88	0.87	0.95	0.46	0.53	0.42	0.38	0.34	0.31
	[2.04]	[2.75]	[3.62]	[3.85]	[4.27]	[5.16]	[6.15]	[5.28]	[4.66]	[4.17]	[3.79]
(3)	0.59	0.59	0.79	0.80	0.94	0.35	0.39	0.33	0.31	0.28	0.27
	[2.74]	[2.67]	[3.45]	[3.82]	[4.65]	[4.58]	[5.15]	[4.47]	[4.10]	[3.72]	[3.51]
(4)	0.48	0.59	0.79	0.81	0.81	0.33	0.37	0.29	0.26	0.13	0.12
	[2.40]	[2.85]	[3.71]	[4.08]	[4.29]	[4.07]	[4.61]	[3.92]	[3.51]	[1.82]	[1.70]
(5)	0.43	0.48	0.50	0.56	0.72	0.29	0.28	0.25	0.20	0.25	0.22
	[2.51]	[2.52]	[2.77]	[3.23]	[4.27]	[3.10]	[3.02]	[2.67]	[2.17]	[2.65]	[2.28]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EE Quintiles, Average n (L)	(2)	(3)	(4)	(H)	EE Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	398	397	397	394	396	32	34	41	30	30
(2)	113	112	112	111	112	57	57	58	56	57
(3)	82	81	81	81	81	99	96	99	100	101
(4)	68	68	68	68	68	204	206	213	216	217
(5)	63	62	62	62	62	1412	1411	1735	1607	1766

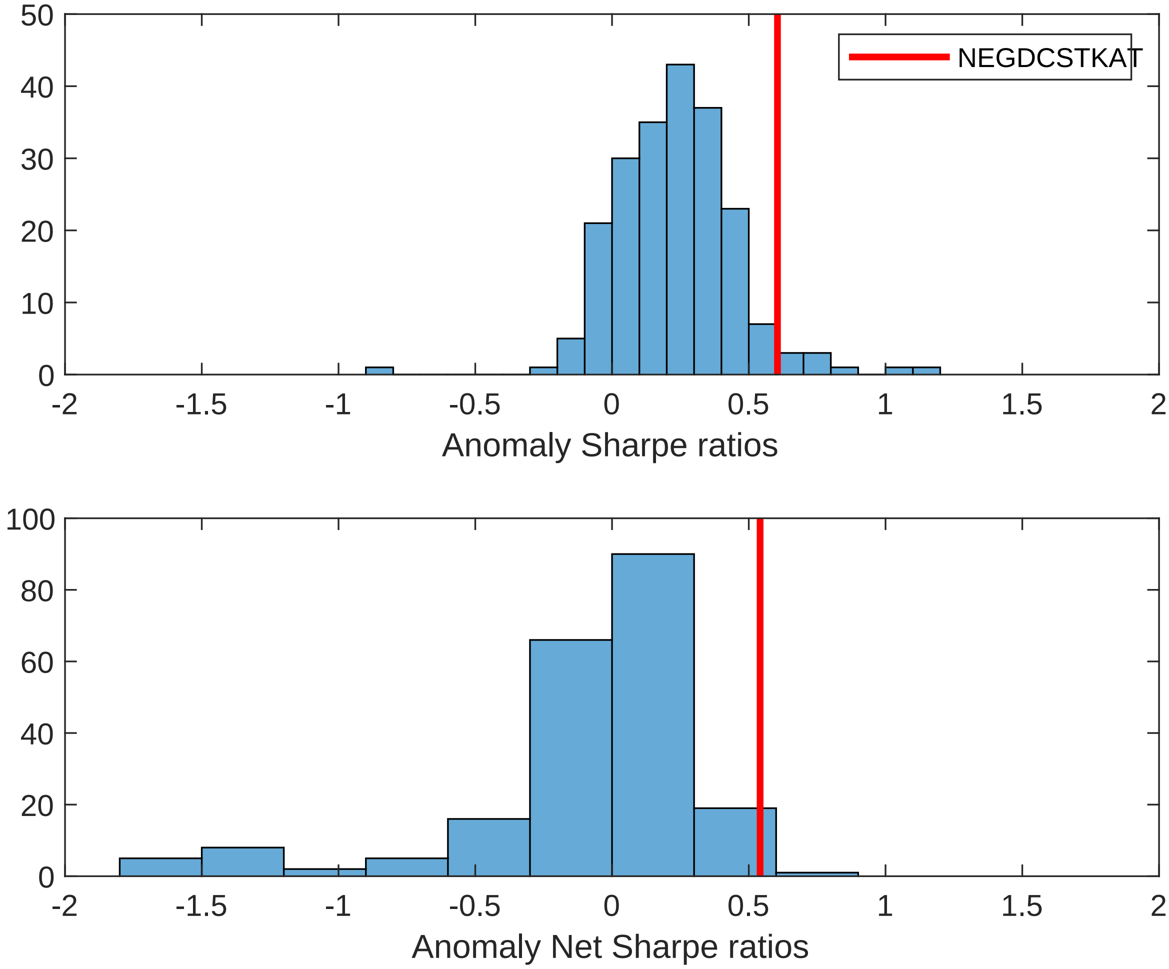


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

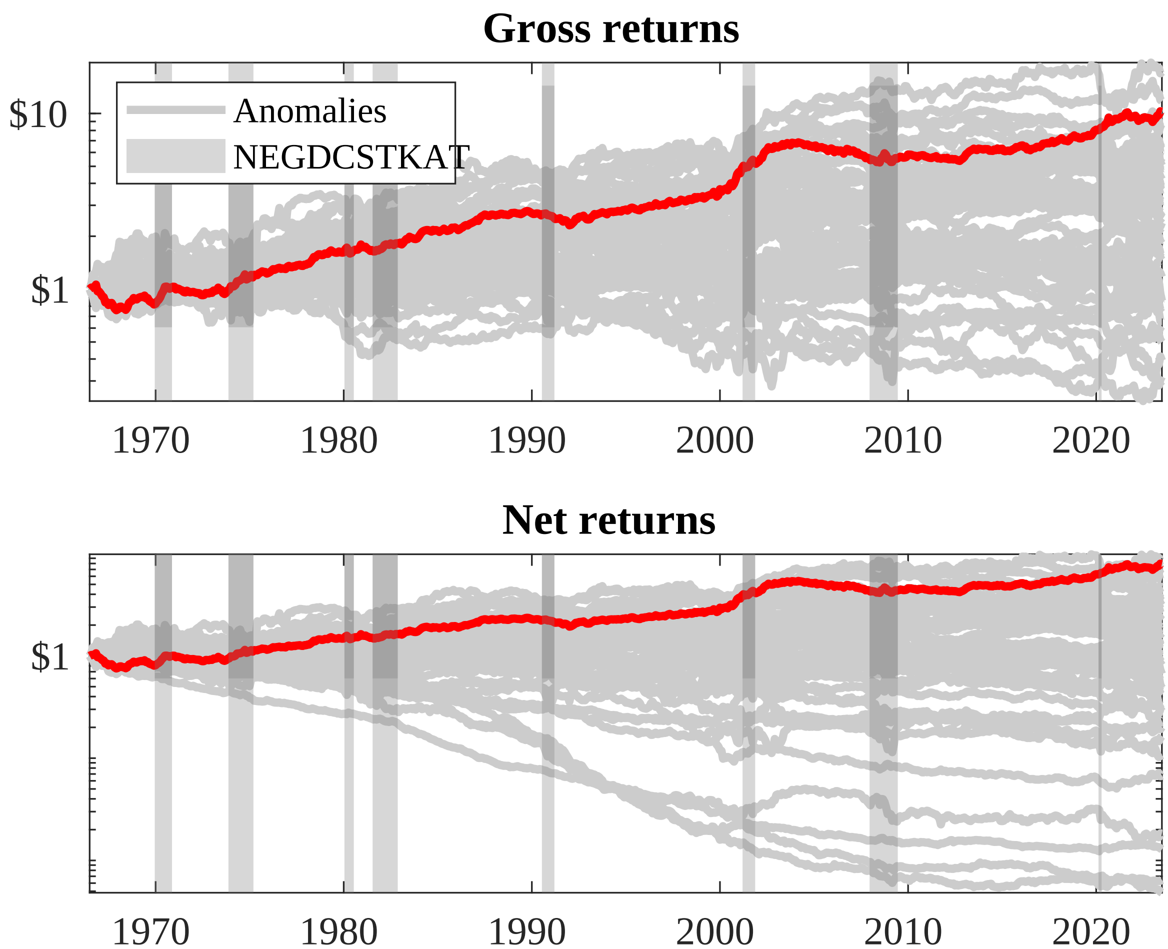


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

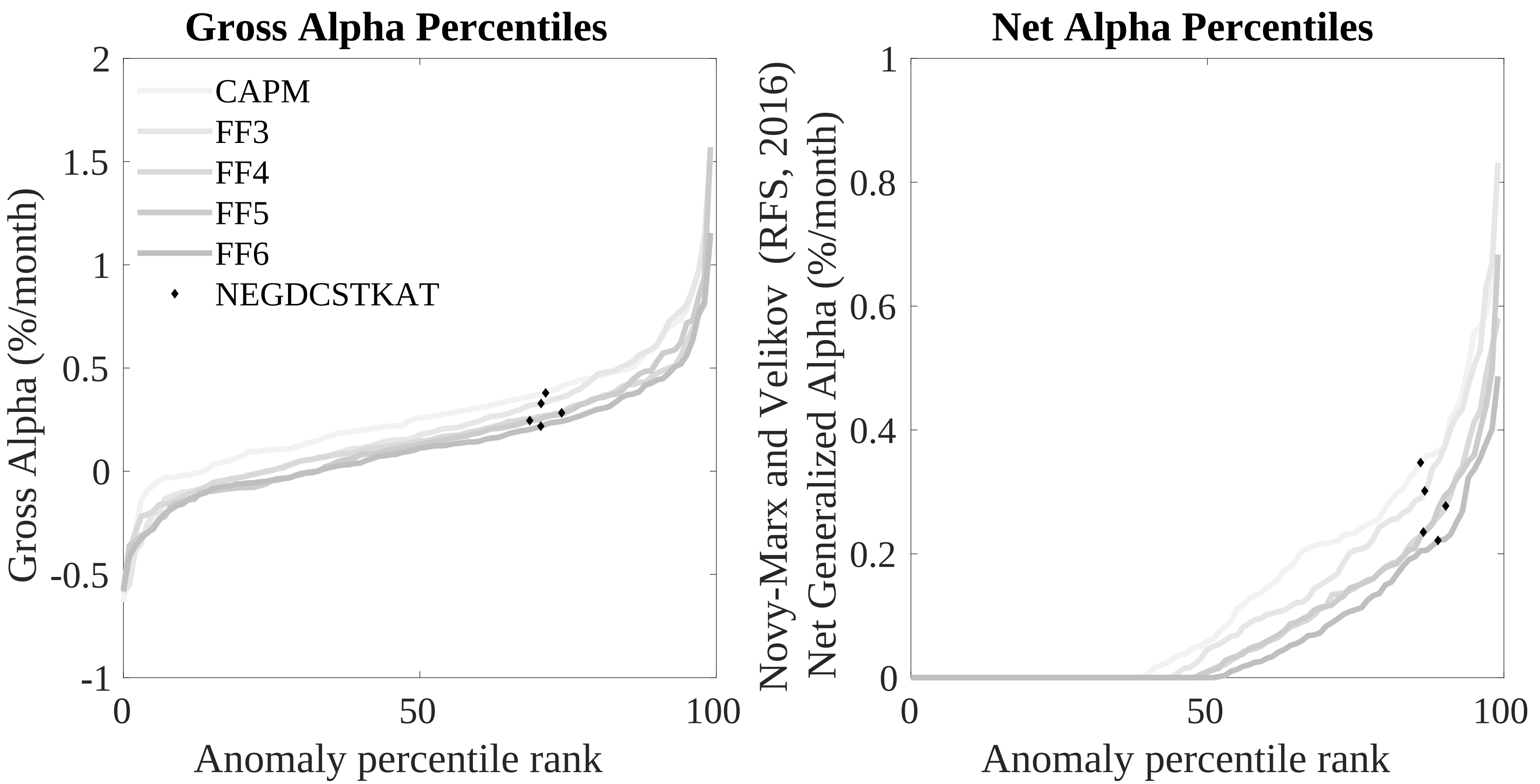
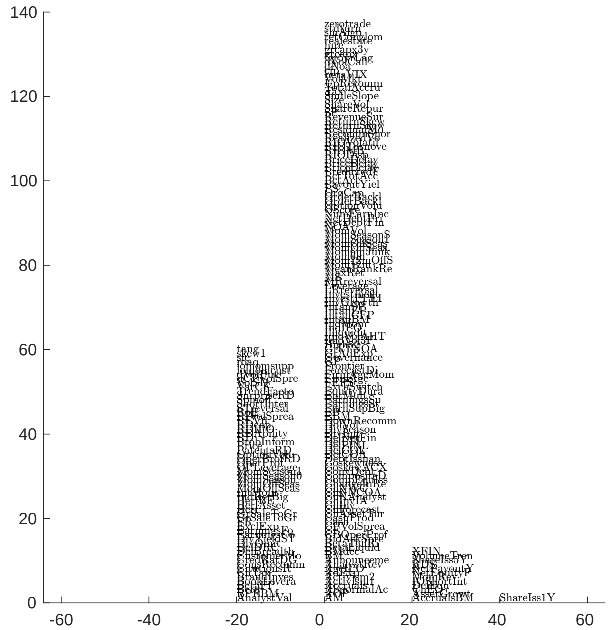
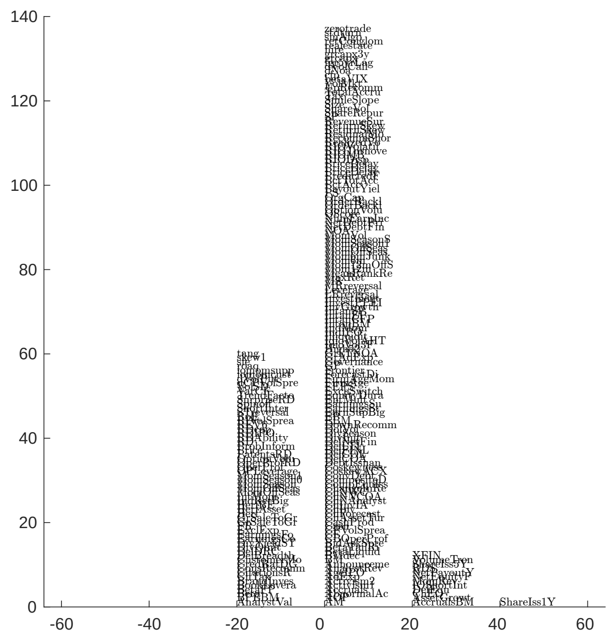


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EE trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

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

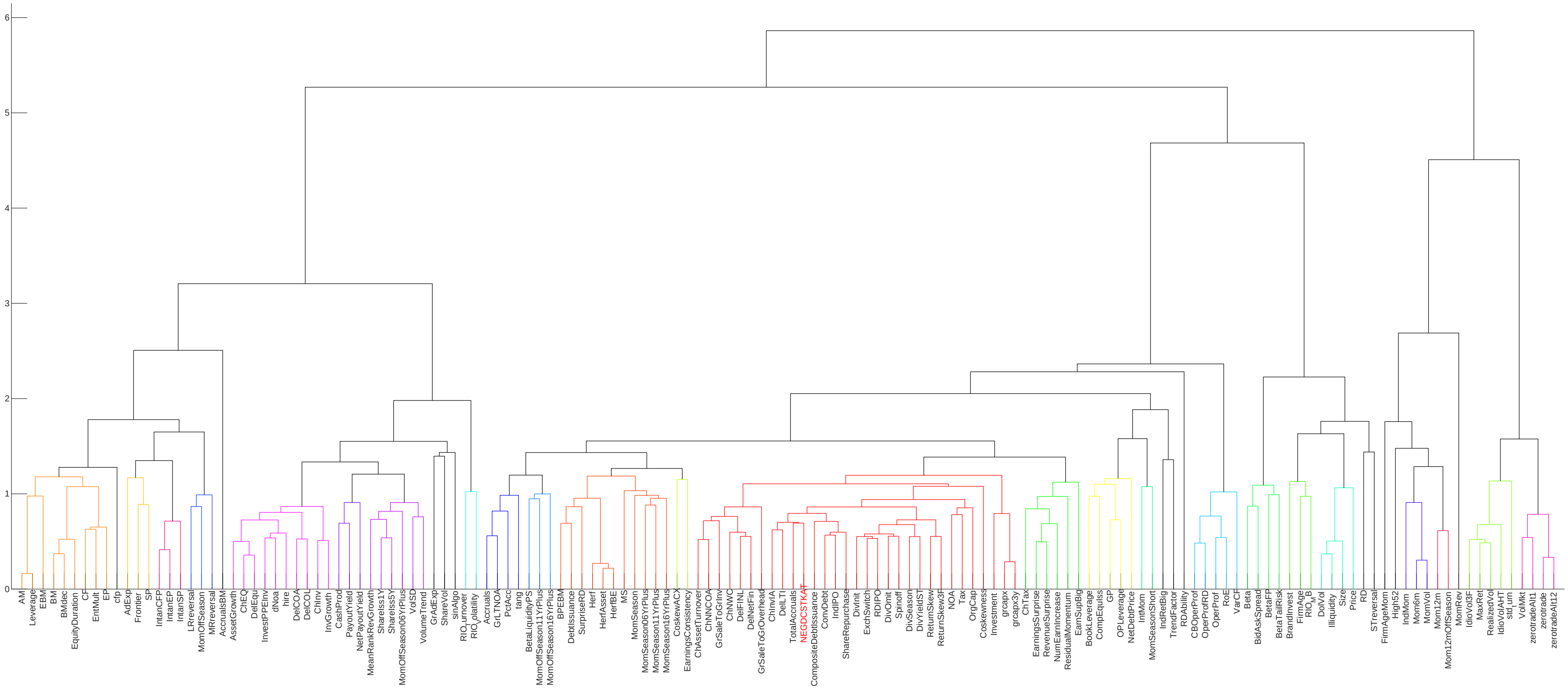


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

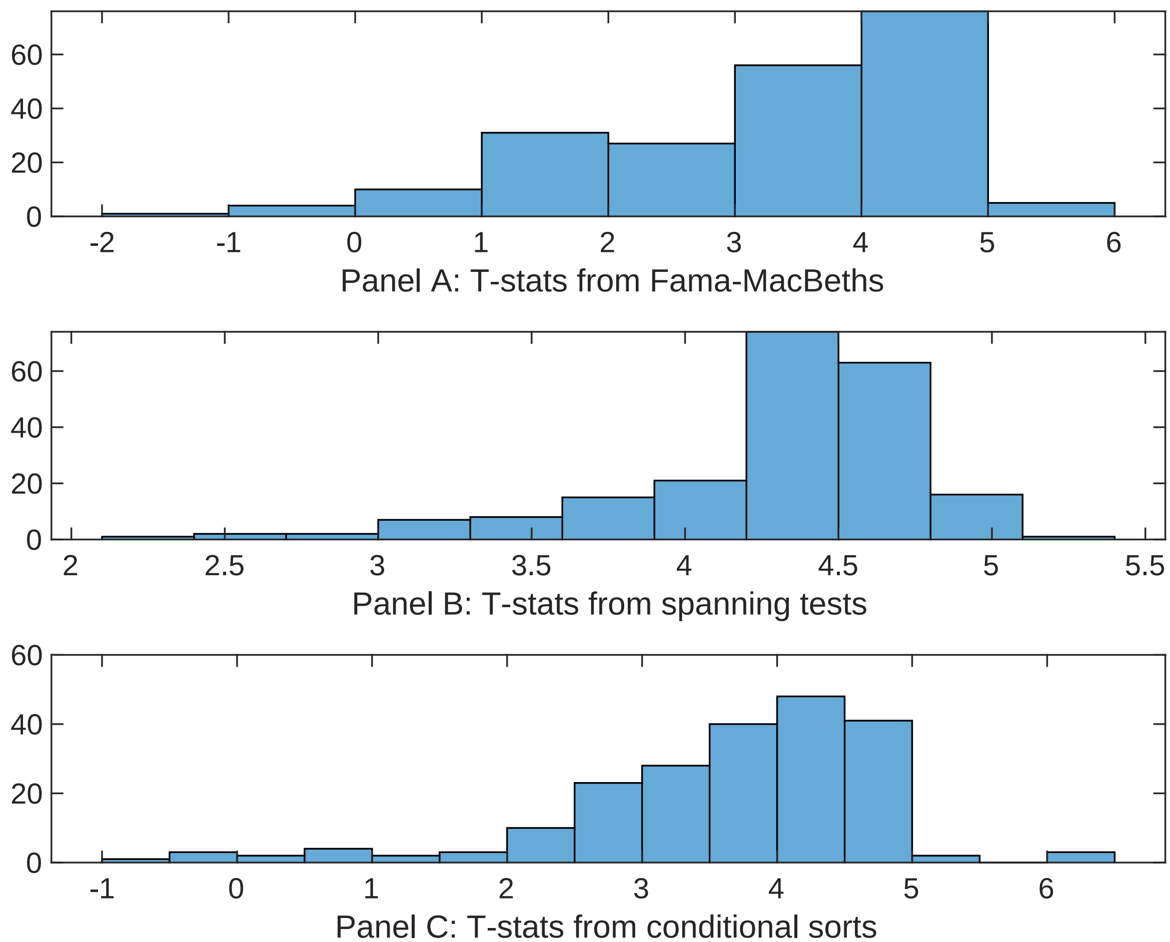


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EE} EE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EE. Stocks are finally grouped into five EE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EE 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 EE. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EE} EE_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.12	0.13	0.13
	[5.66]	[7.26]	[5.24]	[6.03]	[5.56]	[6.03]	[5.18]
EE	0.58	0.43	0.33	0.61	0.51	0.38	0.23
	[3.58]	[2.83]	[1.95]	[3.75]	[3.10]	[2.37]	[1.41]
Anomaly 1	0.26						0.98
	[5.90]						[2.45]
Anomaly 2		0.48					0.13
		[4.42]					[0.00]
Anomaly 3			0.28				0.23
			[2.48]				[2.14]
Anomaly 4				0.38			0.41
				[4.35]			[0.46]
Anomaly 5					0.14		-0.19
					[4.07]		[-0.35]
Anomaly 6						0.10	0.68
						[8.88]	[6.49]
# 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 EE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EE} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.20	0.22	0.21	0.19	0.24	0.22	0.18
	[2.64]	[2.94]	[2.82]	[2.50]	[3.12]	[2.89]	[2.51]
Anomaly 1	27.41						19.17
	[7.16]						[4.33]
Anomaly 2		34.58					35.09
		[8.41]					[5.86]
Anomaly 3			14.87				2.60
			[5.03]				[0.78]
Anomaly 4				13.64			-0.24
				[3.41]			[-0.06]
Anomaly 5					21.08		-5.72
					[5.23]		[-1.02]
Anomaly 6						4.74	-16.90
						[0.93]	[-3.20]
mkt	4.55	3.53	4.90	4.37	2.06	2.41	5.53
	[2.58]	[2.02]	[2.68]	[2.35]	[1.15]	[1.32]	[3.08]
smb	0.66	-1.89	2.40	-1.15	-1.06	-1.15	1.32
	[0.26]	[-0.75]	[0.92]	[-0.44]	[-0.41]	[-0.43]	[0.51]
hml	-0.59	-1.38	-2.71	-0.71	0.00	2.53	-3.36
	[-0.17]	[-0.41]	[-0.74]	[-0.19]	[0.00]	[0.72]	[-0.93]
rmw	-7.26	3.39	-6.58	-0.75	3.67	1.49	-4.42
	[-1.99]	[1.00]	[-1.70]	[-0.21]	[1.04]	[0.42]	[-1.10]
cma	17.73	-3.69	20.26	27.13	8.69	24.88	11.97
	[3.29]	[-0.58]	[3.60]	[5.06]	[1.32]	[3.08]	[1.54]
umd	4.08	3.94	5.70	4.56	4.95	4.42	3.22
	[2.36]	[2.28]	[3.21]	[2.56]	[2.78]	[2.43]	[1.87]
# months	680	684	680	680	684	684	680
$\bar{R}^2$(%)	19	19	16	14	14	11	24

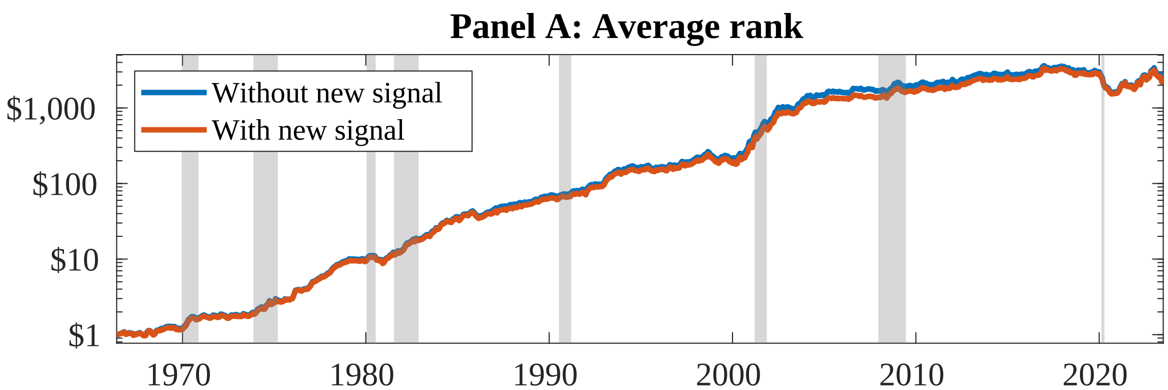


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines indicate combination trading strategies that utilize the 155 anomalies as well as EE. 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.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63(4):1609–1651.

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.

Hirshleifer, D., Li, J., and Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics*, 76:87–106.

Myers, S. C. (1984). The capital structure puzzle. *Journal of Finance*, 39(3):574–592.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

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*.

Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.