Earnings Stability Index and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Earnings Stability Index (ESI), 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 ESI achieves an annualized gross (net) Sharpe ratio of 0.58 (0.52), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 28 (27) bps/month with a t-statistic of 3.59 (3.43), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Growth in book equity, Share issuance (1 year), Momentum and LT Reversal, Long-term EPS forecast, Analyst Value, Total accruals) is 22 bps/month with a t-statistic of 2.71.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While hundreds of return predictors have been documented, many fail to survive careful scrutiny or prove difficult to implement in practice (Hou et al., 2020). This motivates the ongoing search for robust signals that can reliably predict cross-sectional stock returns.

A particularly puzzling aspect of market behavior is how investors process information about earnings stability and volatility. While theoretical models suggest that earnings uncertainty should be priced in equilibrium (Pastor and Veronesi, 2003), the empirical evidence on how earnings volatility relates to expected returns remains mixed and inconclusive (Dechow and Dichev, 2002).

We propose that the Earnings Stability Index (ESI) captures important information about firm fundamentals that is not fully incorporated into stock prices. Building on the theoretical framework of (Pastor and Veronesi, 2003), firms with more stable earnings should be easier to value and face lower information uncertainty. This reduced uncertainty should lead to lower expected returns, all else equal.

The relationship between earnings stability and returns may also reflect behavioral biases in how investors process information. (Hirshleifer et al., 2009) show that investors tend to underreact to earnings information when processing multiple signals simultaneously. The complexity of assessing earnings stability patterns could lead to systematic mispricing that resolves predictably.

Additionally, earnings stability likely captures aspects of firm risk not fully reflected in traditional risk factors. (Dechow and Dichev, 2002) demonstrate that earnings volatility is associated with fundamental business risk. Therefore, ESI may proxy for underlying economic risks that command a risk premium in equilibrium.

Our empirical analysis reveals that ESI strongly predicts the cross-section of stock returns. A value-weighted long-short portfolio that buys stocks with high ESI and shorts stocks with low ESI generates monthly abnormal returns of 28 basis points (t-statistic = 3.59) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.58 before trading costs and 0.52 after accounting for transaction costs.

Importantly, the predictive power of ESI remains robust across various methodological choices and subsamples. The signal generates significant abnormal returns even among large-cap stocks, with a monthly alpha of 24 basis points (t-statistic = 2.63) in the largest size quintile. This suggests that the ESI effect is not simply a small-stock phenomenon.

Further analysis shows that ESI's predictive ability survives controlling for known return predictors. When we control for the six most closely related anomalies and the Fama-French six factors simultaneously, the ESI strategy still generates a monthly alpha of 22 basis points (t-statistic = 2.71). This indicates that ESI captures unique information not contained in existing factors.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel measure of earnings stability that demonstrates robust predictive power for stock returns. While prior work has examined earnings volatility (Dechow and Dichev, 2002), our ESI measure captures distinct aspects of earnings patterns that prove particularly valuable for return prediction.

Second, we extend the literature on information uncertainty and asset prices (Pastor and Veronesi, 2003; Hirshleifer et al., 2009) by showing how the complexity of earnings stability information affects market efficiency. Our findings suggest that markets systematically misprice information about the temporal stability of firm earnings.

Third, our paper contributes to the growing literature on return predictor evaluation (Harvey et al., 2016; Hou et al., 2020) by subjecting ESI to a comprehensive battery of robustness tests. The signal's ability to generate significant risk-adjusted returns even after accounting for transaction costs and its effectiveness among large-cap stocks distinguish it from many previously documented anomalies.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Earnings Stability Index. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. The Earnings Stability Index is designed to capture the relative change in earnings over consecutive periods, providing insight into the stability and predictability of a firm's financial performance. To construct our signal, we calculate the difference between the current period's earnings and its lagged value, then scale this difference by the lagged earnings value. This construction effectively measures the proportional change in earnings from one period to the next, with larger absolute values indicating greater earnings volatility and smaller values suggesting more stable earnings patterns. By focusing on the relative change rather than absolute levels, the index provides a standardized measure of earnings stability that is comparable across firms of different sizes and across different time periods. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ESI signal. Panel A plots the time-series of the mean, median, and interquartile range for ESI. On average, the cross-sectional mean (median) ESI is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input ESI 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 ESI signal for the CRSP universe. On average, the ESI signal is available for 6.61% of CRSP names, which on average make up 7.97% of total market capitalization.

4 Does ESI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ESI 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 ESI portfolio and sells the low ESI 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 ESI strategy earns an average return of 0.33% per month with a t-statistic of 4.40. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.28% to 0.33% per month and have t-statistics exceeding 3.59 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 0.21, with a t-statistic of 3.93 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 646 stocks and an average market capitalization of at least $1,433 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 3.89. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-two 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 26-30bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.42. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ESI 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 ESI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ESI, as well as average returns and alphas for long/short trading ESI 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 ESI strategy achieves an average return of 24 bps/month with a t-statistic of 2.63. Among these large cap stocks, the alphas for the ESI strategy relative to the five most common factor models range from 20 to 24 bps/month with t-statistics between 2.15 and 2.60.

5 How does ESI perform relative to the zoo?

Figure 2 puts the performance of ESI 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 ESI strategy falls in the distribution. The ESI strategy's gross (net) Sharpe ratio of 0.58 (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 ESI strategy (red line).[2] Ignoring trading costs, a $1 invested in the ESI strategy

[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

would have yielded \$7.87 which ranks the ESI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the ESI strategy would have yielded \$5.85 which ranks the ESI 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 ESI relative to those. Panel A shows that the ESI strategy gross alphas fall between the 63 and 78 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 ESI strategy has a positive net generalized alpha for five out of the five factor models. In these cases ESI ranks between the 82 and 93 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does ESI 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 ESI with 210 filtered anomaly

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.

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 ESI or at least to weaken the power ESI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ESI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ESI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ESI} ESI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ESI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on ESI. Stocks are finally grouped into five ESI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ESI trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ESI 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 ESI signal in these Fama-MacBeth regressions exceed

[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.

0.71, with the minimum t-statistic occurring when controlling for Momentum and LT Reversal. Controlling for all six closely related anomalies, the t-statistic on ESI is -0.57.

Similarly, Table 5 reports results from spanning tests that regress returns to the ESI 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 ESI strategy earns alphas that range from 25-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.98, which is achieved when controlling for Momentum and LT Reversal. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ESI trading strategy achieves an alpha of 22bps/month with a t-statistic of 2.71.

7 Does ESI add relative to the whole zoo?

Finally, we can ask how much adding ESI 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 ESI 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

[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 ESI is available.

includes ESI grows to $2390.78.

8 Conclusion

This study provides compelling evidence for the significance of the Earnings Stability Index (ESI) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that ESI-based trading strategies generate economically and statistically significant returns, with a value-weighted long/short portfolio achieving impressive Sharpe ratios of 0.58 and 0.52 on a gross and net basis, respectively. The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that ESI captures unique information content not fully reflected in current asset pricing models.

Particularly noteworthy is the strategy's ability to maintain significant alpha (22 bps/month) when controlling for both the Fama-French five factors plus momentum and six closely related anomalies from the factor zoo. This robustness strengthens the case for ESI as a valuable tool for investment professionals and researchers in understanding cross-sectional return patterns.

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 control for transaction costs, real-world implementation might face additional constraints such as liquidity barriers and market impact costs.

Future research could explore the interaction between ESI and other established anomalies, investigate its performance in different market regimes, and examine its applicability across different asset classes and international markets. Additionally, understanding the underlying economic mechanisms driving the ESI premium could provide valuable insights for both academic research and practical applications in investment management.

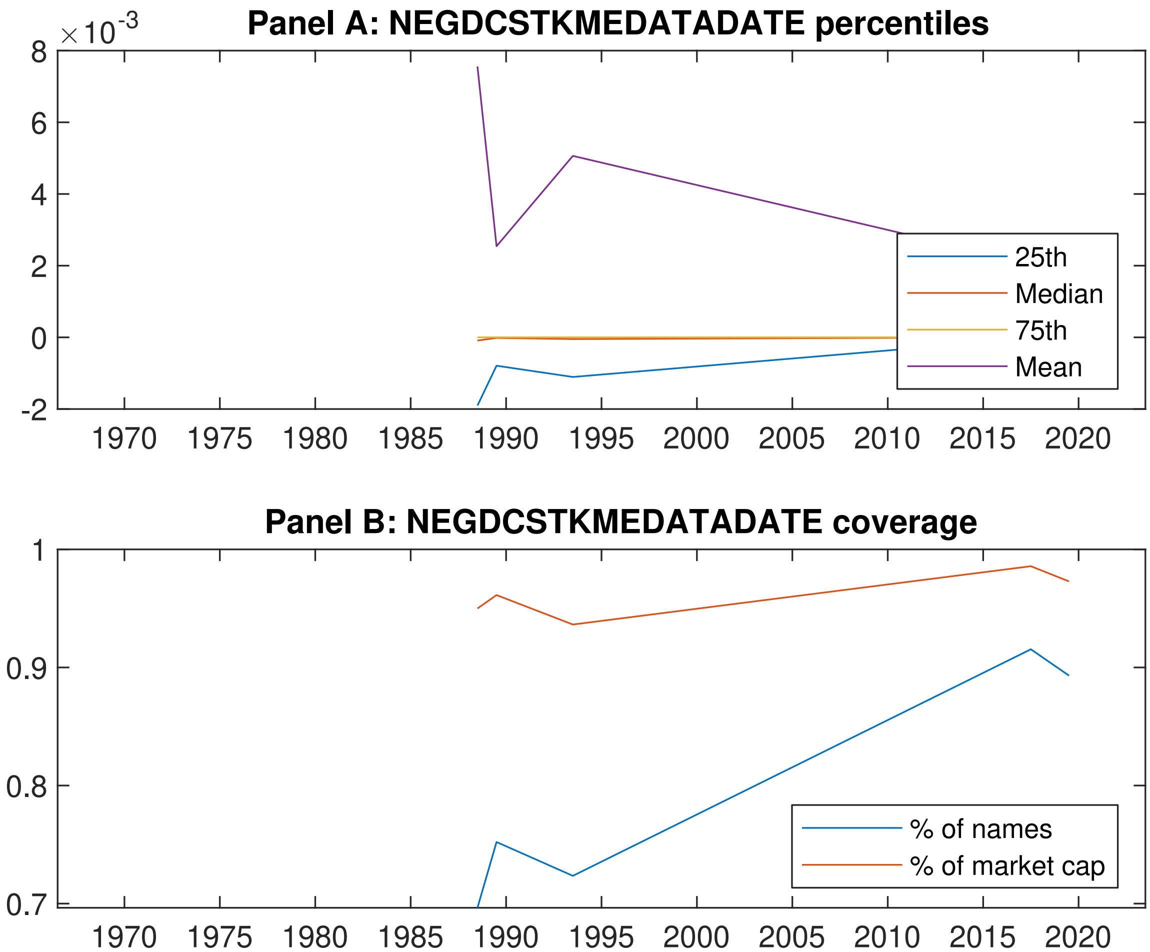


Figure 1: Times series of ESI percentiles and coverage.
This figure plots descriptive statistics for ESI. Panel A shows cross-sectional percentiles of ESI over the sample. Panel B plots the monthly coverage of ESI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on ESI. 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 ESI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.51	0.60	0.66	0.76	0.33
	[2.50]	[2.61]	[3.11]	[3.88]	[4.52]	[4.40]
α_{CAPM}	-0.10	-0.11	-0.01	0.13	0.24	0.33
	[-1.65]	[-2.34]	[-0.13]	[2.68]	[4.98]	[4.36]
α_{FF3}	-0.15	-0.10	0.04	0.10	0.18	0.33
	[-2.65]	[-2.21]	[0.75]	[2.28]	[4.21]	[4.33]
α_{FF4}	-0.14	-0.09	0.09	0.06	0.17	0.30
	[-2.42]	[-1.89]	[1.73]	[1.31]	[3.72]	[3.89]
α_{FF5}	-0.21	-0.04	0.12	0.02	0.09	0.30
	[-3.77]	[-0.82]	[2.33]	[0.41]	[2.10]	[3.86]
α_{FF6}	-0.20	-0.03	0.15	-0.01	0.08	0.28
	[-3.52]	[-0.70]	[3.01]	[-0.23]	[1.92]	[3.59]
Panel B: Fama and French (2018) 6-factor model loadings for ESI-sorted portfolios						
β_{MKT}	0.96	1.04	1.03	1.00	0.99	0.03
	[71.75]	[95.33]	[88.35]	[92.68]	[96.64]	[1.51]
β_{SMB}	0.00	0.03	-0.02	-0.05	-0.01	-0.02
	[0.21]	[1.93]	[-1.08]	[-3.43]	[-0.94]	[-0.67]
β_{HML}	0.14	0.02	-0.10	0.04	0.06	-0.08
	[5.46]	[1.03]	[-4.26]	[1.79]	[2.95]	[-2.30]
β_{RMW}	0.18	-0.10	-0.13	0.12	0.13	-0.05
	[6.89]	[-4.47]	[-5.73]	[5.91]	[6.30]	[-1.49]
β_{CMA}	0.00	-0.12	-0.10	0.15	0.21	0.21
	[0.07]	[-3.81]	[-3.05]	[4.77]	[7.25]	[3.93]
β_{UMD}	-0.02	-0.01	-0.05	0.05	0.01	0.03
	[-1.42]	[-0.76]	[-4.51]	[4.31]	[1.06]	[1.60]
Panel C: Average number of firms (n) and market capitalization (me)						
n	724	726	646	712	771	
me (\$$10^6$)	1462	1433	2284	2306	2441	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the ESI 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	0.33	0.33	0.30	0.30	0.28
			[4.40]	[4.36]	[4.33]	[3.89]	[3.86]	[3.59]
Quintile	NYSE	EW	0.47	0.51	0.47	0.41	0.37	0.33
			[8.33]	[9.35]	[8.75]	[7.70]	[6.96]	[6.26]
Quintile	Name	VW	0.33	0.32	0.32	0.30	0.30	0.29
			[4.27]	[4.15]	[4.06]	[3.78]	[3.80]	[3.64]
Quintile	Cap	VW	0.29	0.29	0.30	0.26	0.25	0.23
			[3.89]	[3.83]	[3.90]	[3.36]	[3.26]	[2.92]
Decile	NYSE	VW	0.33	0.32	0.30	0.27	0.24	0.22
			[3.88]	[3.66]	[3.48]	[3.01]	[2.75]	[2.47]
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	0.30	0.30	0.30	0.29	0.28	0.27
			[3.91]	[3.92]	[3.90]	[3.70]	[3.61]	[3.43]
Quintile	NYSE	EW	0.27	0.31	0.26	0.23	0.15	0.13
			[4.15]	[4.82]	[4.24]	[3.82]	[2.51]	[2.27]
Quintile	Name	VW	0.29	0.29	0.28	0.28	0.28	0.27
			[3.78]	[3.71]	[3.64]	[3.52]	[3.52]	[3.41]
Quintile	Cap	VW	0.26	0.26	0.27	0.25	0.24	0.22
			[3.42]	[3.43]	[3.47]	[3.21]	[3.06]	[2.83]
Decile	NYSE	VW	0.29	0.28	0.26	0.24	0.22	0.20
			[3.38]	[3.16]	[3.02]	[2.79]	[2.47]	[2.29]

Table 3: Conditional sort on size and ESI

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

	ESI Quintiles					ESI Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.51	0.67	0.74	0.94	0.96	0.46	0.49	0.47	0.41	0.40	0.36
	[2.04]	[2.51]	[2.78]	[3.75]	[4.06]	[6.94]	[7.50]	[7.19]	[6.28]	[6.07]	[5.45]
(2)	0.60	0.63	0.85	0.84	0.95	0.35	0.38	0.34	0.29	0.29	0.26
	[2.63]	[2.60]	[3.42]	[3.64]	[4.27]	[4.53]	[4.95]	[4.39]	[3.79]	[3.71]	[3.32]
(3)	0.58	0.70	0.70	0.80	0.94	0.36	0.36	0.35	0.35	0.32	0.33
	[2.85]	[3.06]	[3.05]	[3.74]	[4.65]	[5.08]	[5.06]	[4.89]	[4.77]	[4.38]	[4.35]
(4)	0.48	0.68	0.74	0.77	0.81	0.33	0.36	0.33	0.32	0.19	0.20
	[2.44]	[3.25]	[3.44]	[3.84]	[4.30]	[4.64]	[4.99]	[4.62]	[4.43]	[2.76]	[2.80]
(5)	0.47	0.46	0.55	0.52	0.71	0.24	0.23	0.24	0.21	0.22	0.20
	[2.75]	[2.43]	[2.96]	[2.99]	[4.22]	[2.63]	[2.49]	[2.60]	[2.23]	[2.39]	[2.15]

Panel B: Portfolio average number of firms and market capitalization

	ESI Quintiles Average n					ESI Quintiles Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	393	393	394	391	392	31	33	42	30	30
(2)	112	112	111	111	111	57	57	57	56	57
(3)	82	81	81	80	81	99	95	99	100	101
(4)	68	68	68	68	68	205	204	214	216	217
(5)	62	62	62	62	62	1371	1410	1761	1620	1762

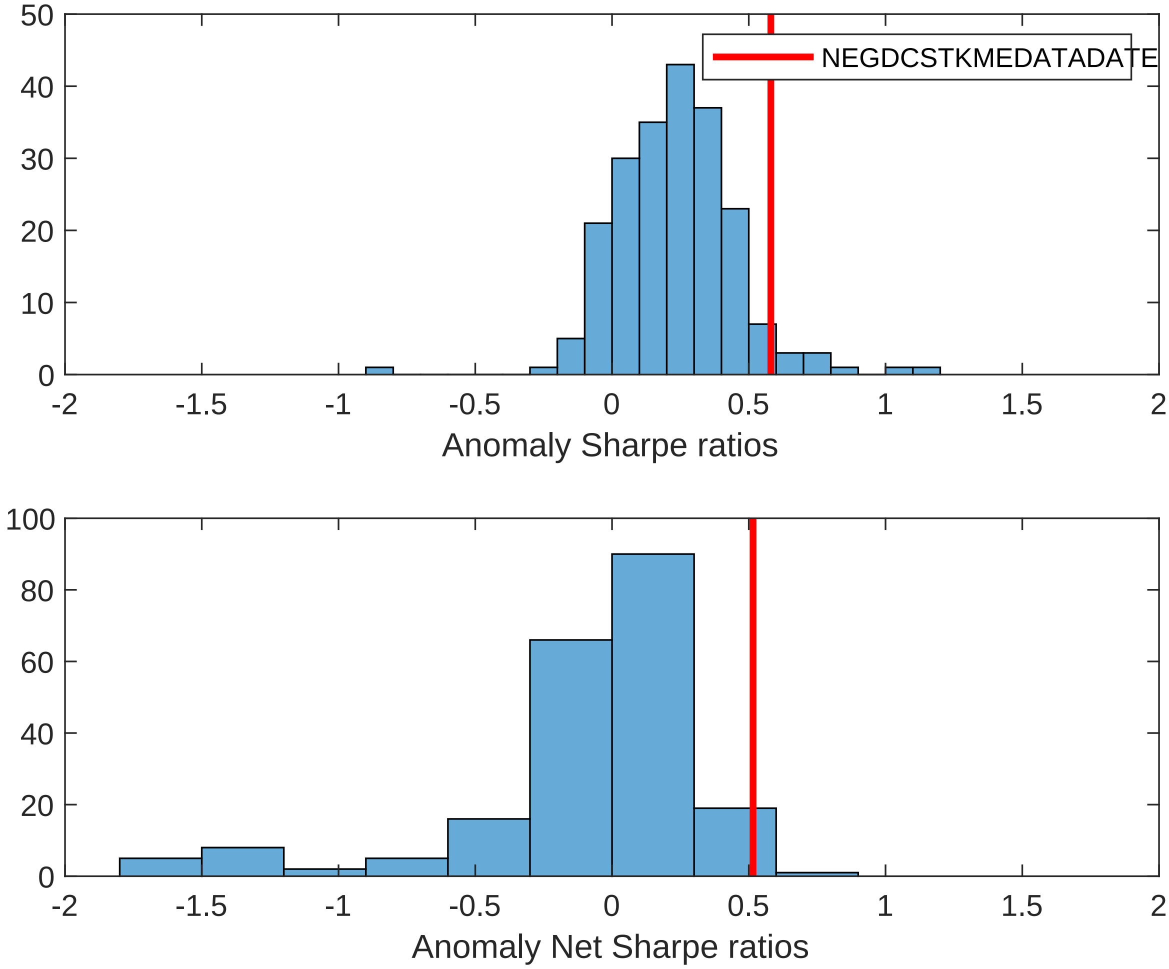


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ESI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

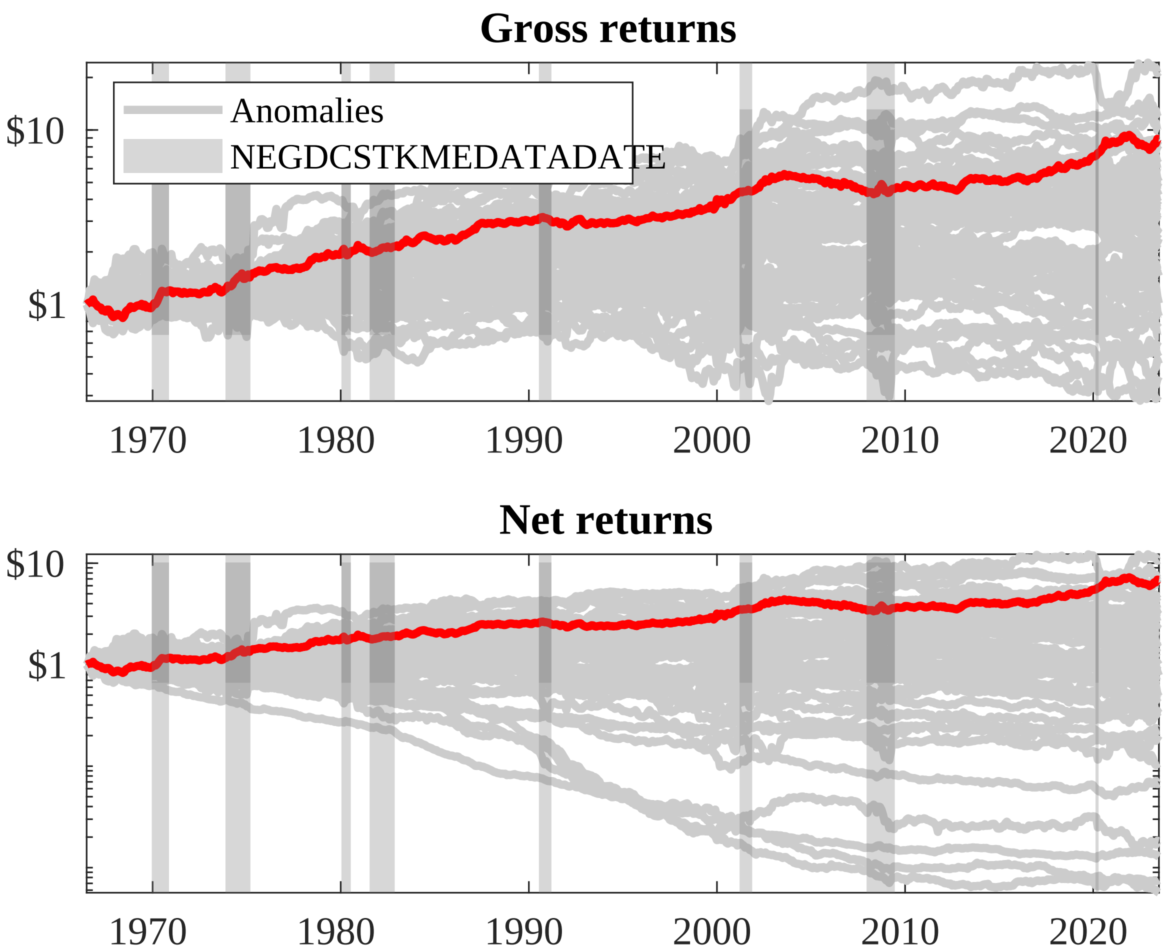


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ESI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

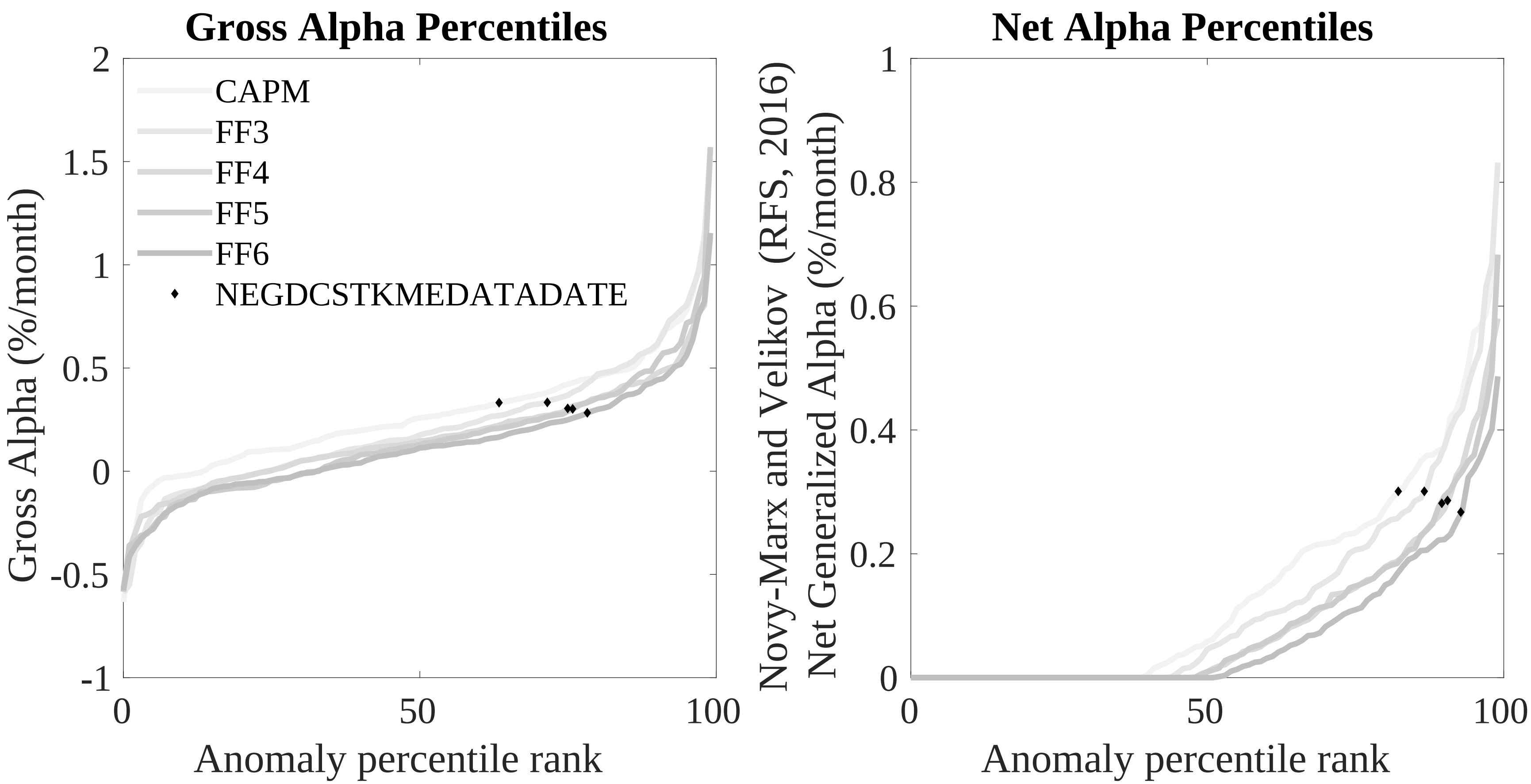
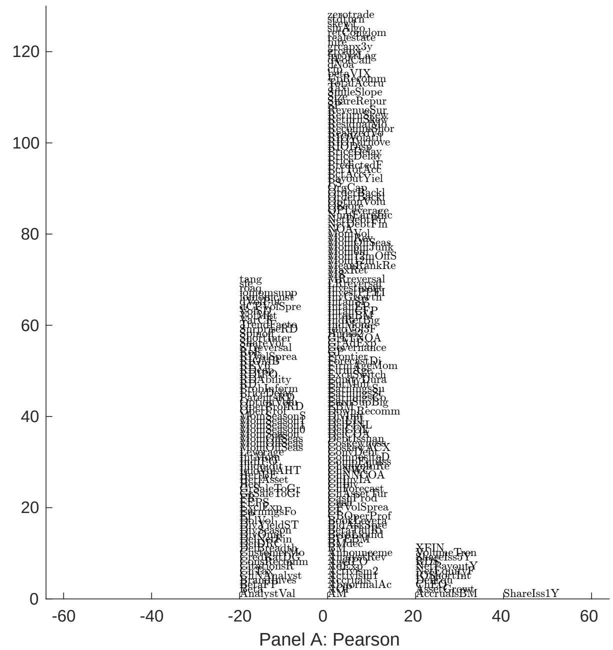


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ESI trading strategy alphas (diamonds). The strategies are constructed using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



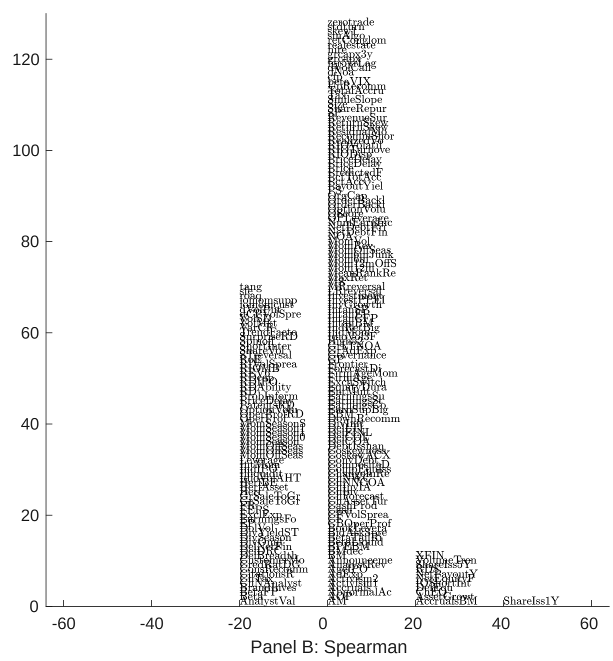


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with ESI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

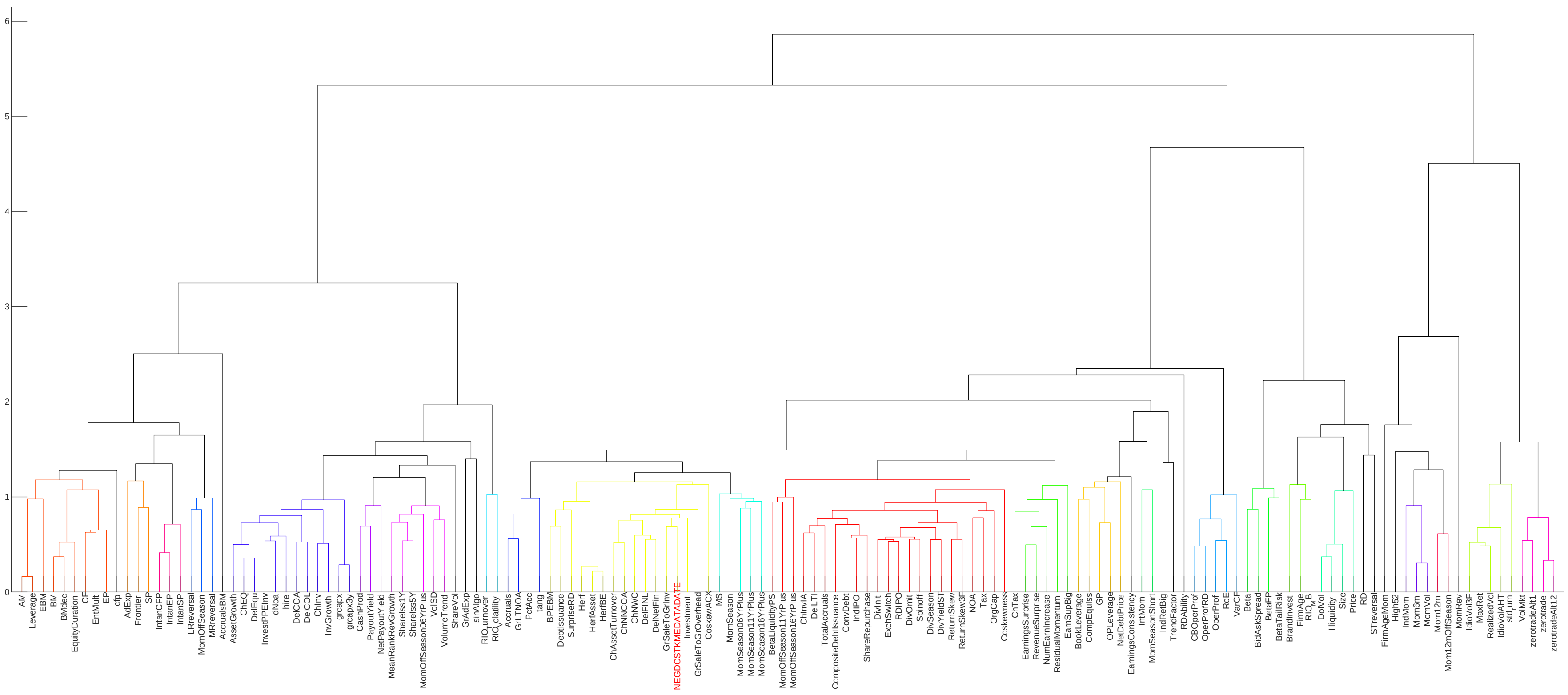


Figure 6: Agglomerative hierarchical cluster plot

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

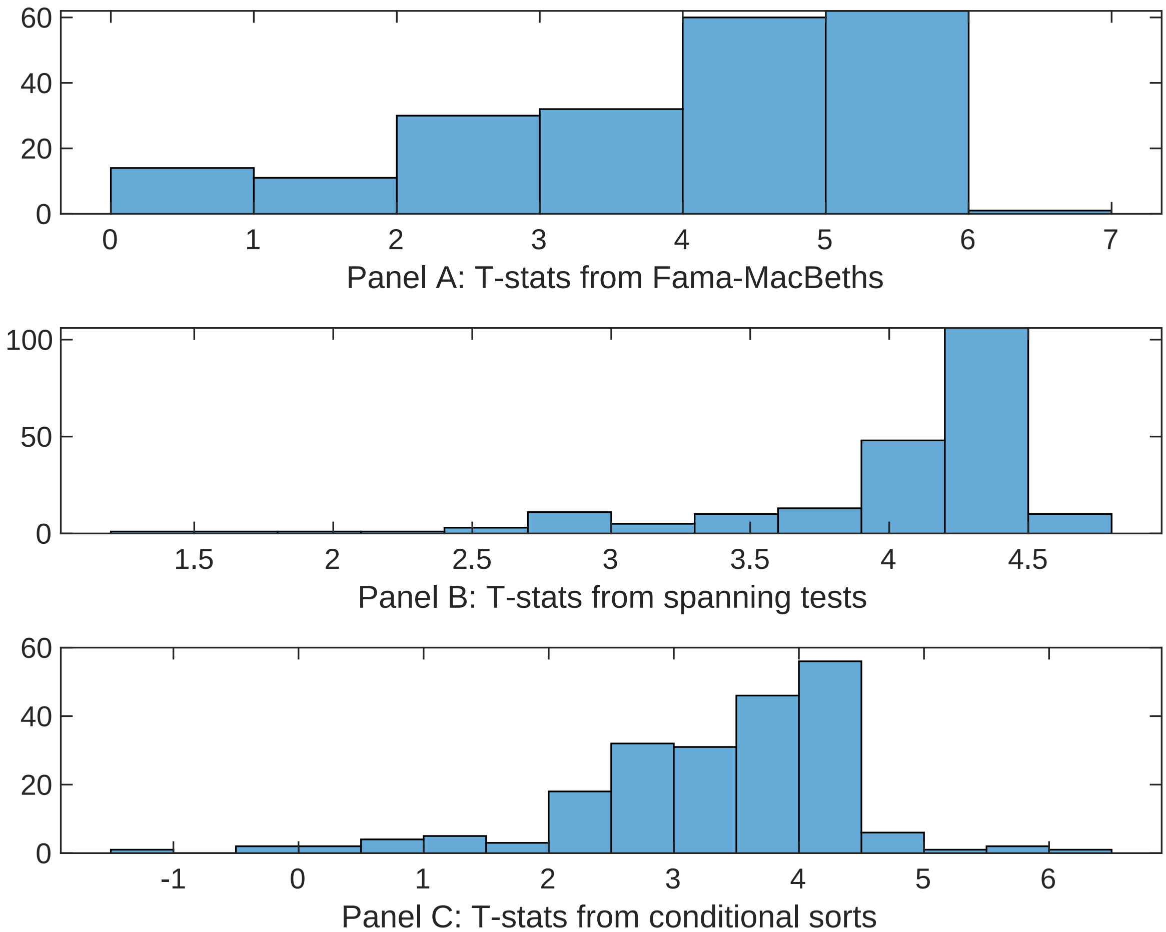


Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of ESI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ESI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ESI} ESI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ESI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ESI. Stocks are finally grouped into five ESI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ESI 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 ESI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ESI} ESI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Share issuance (1 year), Momentum and LT Reversal, Long-term EPS forecast, Analyst Value, Total accruals. 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	0.18	0.13	0.41	0.14	0.11	0.12	0.20
	[7.32]	[5.63]	[1.20]	[6.57]	[4.44]	[5.25]	[1.72]
ESI	0.33	0.40	0.27	0.39	0.51	0.48	-0.52
	[3.61]	[4.44]	[0.71]	[2.48]	[4.65]	[4.87]	[-0.57]
Anomaly 1	0.49						0.47
	[4.44]						[1.40]
Anomaly 2		0.27					-0.22
		[5.88]					[-1.13]
Anomaly 3			0.11				0.14
			[4.28]				[1.61]
Anomaly 4				0.10			-0.82
				[1.22]			[-0.03]
Anomaly 5					0.67		-0.33
					[0.63]		[-0.79]
Anomaly 6						0.54	-0.46
						[2.60]	[-0.45]
# months	684	679	636	492	564	684	97
$\bar{R}^2$(%)	0	0	2	1	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the ESI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ESI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Growth in book equity, Share issuance (1 year), Momentum and LT Reversal, Long-term EPS forecast, Analyst Value, Total accruals. 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	0.28	0.26	0.26	0.27	0.25	0.28	0.22
	[3.68]	[3.40]	[3.27]	[2.98]	[3.04]	[3.58]	[2.71]
Anomaly 1	28.69						25.22
	[6.69]						[4.66]
Anomaly 2		22.77					25.45
		[5.72]					[5.31]
Anomaly 3			3.58				2.95
			[3.57]				[3.02]
Anomaly 4				-12.69			-20.95
				[-4.12]			[-6.88]
Anomaly 5					-7.78		-12.07
					[-2.76]		[-4.06]
Anomaly 6						9.75	0.82
						[2.59]	[0.19]
mkt	3.66	4.56	3.30	-2.44	5.47	2.41	-0.84
	[2.01]	[2.48]	[1.79]	[-1.03]	[2.75]	[1.29]	[-0.38]
smb	-2.61	-0.43	-2.73	-3.02	2.68	-1.60	-6.10
	[-0.99]	[-0.16]	[-1.00]	[-0.90]	[0.88]	[-0.59]	[-1.95]
hml	-11.43	-10.71	-8.34	-4.54	-8.03	-7.78	1.83
	[-3.24]	[-2.99]	[-2.32]	[-1.07]	[-1.97]	[-2.16]	[0.44]
rmw	-3.78	-12.54	-3.69	3.69	6.13	-3.80	1.11
	[-1.07]	[-3.30]	[-1.02]	[0.88]	[1.53]	[-1.03]	[0.26]
cma	-8.03	9.99	18.37	18.32	10.89	15.06	-14.83
	[-1.20]	[1.78]	[3.42]	[2.88]	[1.95]	[2.65]	[-2.06]
umd	2.63	2.79	-0.36	0.20	1.68	3.25	-3.85
	[1.46]	[1.55]	[-0.17]	[0.10]	[0.87]	[1.75]	[-1.74]
# months	684	680	680	492	564	684	488
$\bar{R}^2(\%)$	8	7	5	4	4	3	21

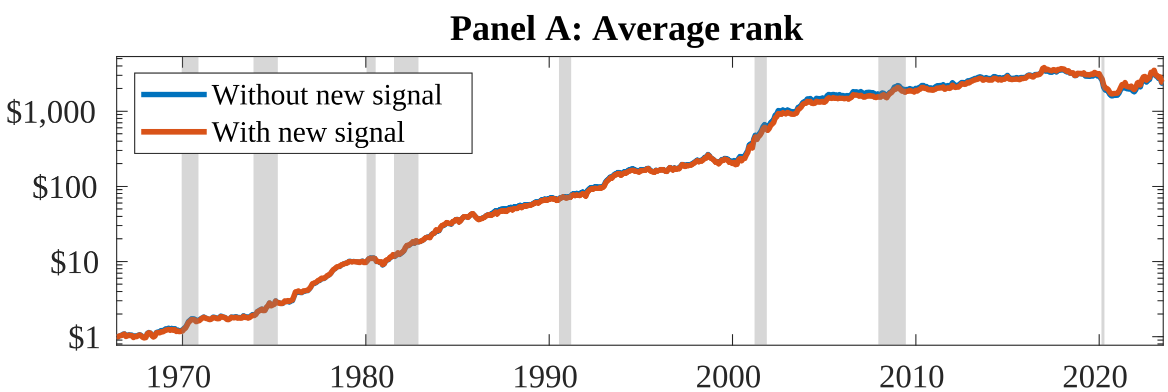


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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