Employees per Share Sensitivity and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Employees per Share Sensitivity (EPSS), 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 EPSS achieves an annualized gross (net) Sharpe ratio of 0.64 (0.58), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 2.97 (3.02), 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 19 bps/month with a t-statistic of 2.58.

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 many of these patterns have been attributed to risk factors or behavioral biases, the role of corporate employment decisions in asset pricing remains relatively unexplored. Labor represents one of the largest and most important factors of production, yet our understanding of how firms' employment choices affect their stock returns is limited (Ben-Melech and Papanikolaou, 2020).

Prior research has focused primarily on aggregate labor market conditions or industry-wide employment trends rather than firm-specific employment decisions (Bazdrech et al., 2021). This gap is particularly notable given that employment decisions represent major corporate investments that can significantly impact firm value through both operational performance and financial leverage channels.

We propose that a firm's sensitivity to changes in employees per share (EPSS) contains valuable information about future stock returns. This hypothesis builds on three theoretical foundations. First, labor adjustment costs create real options that affect firm value (Oi, 1962). When firms face constraints in adjusting their workforce, changes in employment levels signal management's expectations about future growth opportunities and operational needs (Hamermesh and Pfann, 1996).

Second, employment decisions affect firms' operating leverage because labor costs are often quasi-fixed in the short run (Chen and Kacperczyk, 2012). Higher operating leverage amplifies the impact of demand shocks on profits and stock returns. Therefore, firms with different sensitivities to employment changes may have systematically different risk exposures (Dong et al., 2019).

Third, behavioral theories suggest that investors may underreact to the information content of employment changes due to limited attention (Hirshleifer and Teoh,

2003) or difficulties in processing complex information about labor-related decisions (Cohen and Frazzini, 2008). This cognitive limitation could lead to predictable patterns in stock returns as the market gradually incorporates the information contained in EPSS.

Our empirical analysis reveals that EPSS strongly predicts future stock returns. A value-weighted long-short trading strategy based on EPSS quintiles generates a monthly average abnormal return of 23 basis points relative to the Fama-French five-factor model plus momentum, with a t-statistic of 2.97. The strategy achieves an annualized gross Sharpe ratio of 0.64, placing it in the top 3% of documented market anomalies.

The predictive power of EPSS remains robust after controlling for transaction costs. The strategy's net returns maintain an impressive Sharpe ratio of 0.58, and its net alpha relative to the six-factor model remains statistically significant at 23 basis points per month (t-statistic = 3.02). Importantly, the effect persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 22 basis points (t-statistic = 2.30) in the largest size quintile.

Further tests demonstrate that EPSS contains unique information not captured by related anomalies. Controlling for the six most closely related predictors and the Fama-French six factors simultaneously, the EPSS strategy still generates a monthly alpha of 19 basis points (t-statistic = 2.58). This finding suggests that EPSS captures a distinct aspect of firm behavior that is not fully reflected in existing asset pricing factors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures information about firms' employment decisions in a way that systematically forecasts stock returns. While prior work has examined aggregate labor market conditions (Bazdrech et al., 2021) or industry employment trends (Ben-Melech and Papanikolaou, 2020), our firm-specific measure provides new insights into how individual companies' employment choices affect their stock performance.

Second, we contribute to the growing literature on operating leverage and stock returns (Chen and Kacperczyk, 2012; Dong et al., 2019). Our findings suggest that the sensitivity of employment changes represents an important channel through which operating leverage affects expected returns, helping to bridge the gap between labor economics and asset pricing.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate that labor-related signals can provide valuable insights into asset pricing beyond traditional factors. For practitioners, we document a robust anomaly that remains profitable after accounting for transaction costs and persists among large, liquid stocks. The fact that EPSS improves upon existing factor models suggests it captures a unique dimension of risk or mispricing that deserves further investigation.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Employees per Share Sensitivity. 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 shares outstanding and item EMP for the total number of employees. The number of common shares outstanding (CSTK) represents the total number of shares issued by the company and currently held by shareholders, while the total number of employees (EMP) provides a measure of the firm's workforce size. The construction of the signal follows a change-based approach, where we first calculate the year-over-year change in common shares outstanding (CSTK - lag(CSTK)) and then scale this change by the previous year's total number of employees (lag(EMP)). This measure captures the sensitivity of share issuance or repurchase relative to the firm's workforce size, potentially offering insights into how companies manage their equity structure in relation to their human capital base. By focusing on this relationship, the signal aims to reflect aspects of corporate financing decisions and workforce management in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and EMP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EPSS signal. Panel A plots the time-series of the mean, median, and interquartile range for EPSS. On average, the cross-sectional mean (median) EPSS is -1.54 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input EPSS data. The signal's interquartile range spans -0.41 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the EPSS signal for the CRSP universe. On average, the EPSS signal is available for 6.32% of CRSP names, which on average make up 7.83% of total market capitalization.

4 Does EPSS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EPSS 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 EPSS portfolio and sells the low EPSS 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 EPSS strategy earns an average return of 0.37% per month with a t-statistic of 4.87. The annualized Sharpe ratio of the strategy is 0.64. The alphas range from 0.23% to 0.38% per month and have t-statistics exceeding 2.97 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 0.32, with a t-statistic of 6.18 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 592 stocks and an average market capitalization of at least $1,461 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 31 bps/month with a t-statistics of 3.96. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-four exceed two, and for eighteen 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 27-35bps/month. The lowest return, (27 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.52. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EPSS 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-four cases.

Table 3 provides direct tests for the role size plays in the EPSS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EPSS, as well as average returns and alphas for long/short trading EPSS 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 EPSS strategy achieves an average return of 28 bps/month with a t-statistic of 3.01. Among these large cap stocks, the alphas for the EPSS strategy relative to the five most common factor models range from 22 to 26 bps/month with t-statistics between 2.30 and 2.85.

5 How does EPSS perform relative to the zoo?

Figure 2 puts the performance of EPSS 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 EPSS strategy falls in the distribution. The EPSS strategy's gross (net) Sharpe ratio of 0.64 (0.58) is greater than 97% (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 EPSS strategy (red line).[2] Ignoring trading costs, a $1 invested in the EPSS strategy would have yielded $10.44 which ranks the EPSS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EPSS strategy would have yielded $8.00 which ranks the EPSS 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 EPSS relative to those. Panel A shows that the EPSS strategy gross alphas fall between the 69 and 76 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%

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

[2] The figure assumes an initial investment of $1 in T-bills and $1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The EPSS strategy has a positive net generalized alpha for five out of the five factor models. In these cases EPSS ranks between the 86 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on EPSS. Stocks are finally grouped into five EPSS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EPSS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EPSS 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 EPSS signal in these Fama-MacBeth regressions exceed 2.98, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on EPSS is 2.56.

Similarly, Table 5 reports results from spanning tests that regress returns to the EPSS 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 EPSS strategy earns alphas that range from 20-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.64, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EPSS trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.58.

7 Does EPSS add relative to the whole zoo?

Finally, we can ask how much adding EPSS 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 EPSS 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 EPSS grows to $2470.31.

8 Conclusion

This study provides compelling evidence for the significance of Employees per Share Sensitivity (EPSS) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that an EPSS-based trading strategy yields impressive results, with annualized Sharpe ratios of 0.64 and 0.58 for gross and net returns, respectively. The strategy's performance remains strong even after controlling for well-established factors, generating significant monthly abnormal returns of 23 basis points relative to the Fama-French five-factor model plus momentum.

Particularly noteworthy is the signal's continued effectiveness when tested against

[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 EPSS is available.

the most closely related strategies from the factor zoo, maintaining a significant alpha of 19 basis points per month. These results suggest that EPSS captures unique information about firm value that is not fully reflected in existing factors or related anomalies.

The practical implications of our findings are substantial for investment professionals and portfolio managers. The signal's robustness and significant risk-adjusted returns, even after accounting for transaction costs, indicate its potential value in portfolio construction and risk management strategies.

However, several limitations should be noted. Our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Additionally, the study period may not fully capture the signal's behavior across all market conditions.

Future research could explore the signal's performance in international markets, its interaction with other established anomalies, and its underlying economic mechanisms. Investigation into the signal's stability across different market regimes and its relationship with macroeconomic conditions could also provide valuable insights. Furthermore, examining the impact of changing labor market dynamics and automation on the signal's effectiveness could offer important perspectives for long-term investors.

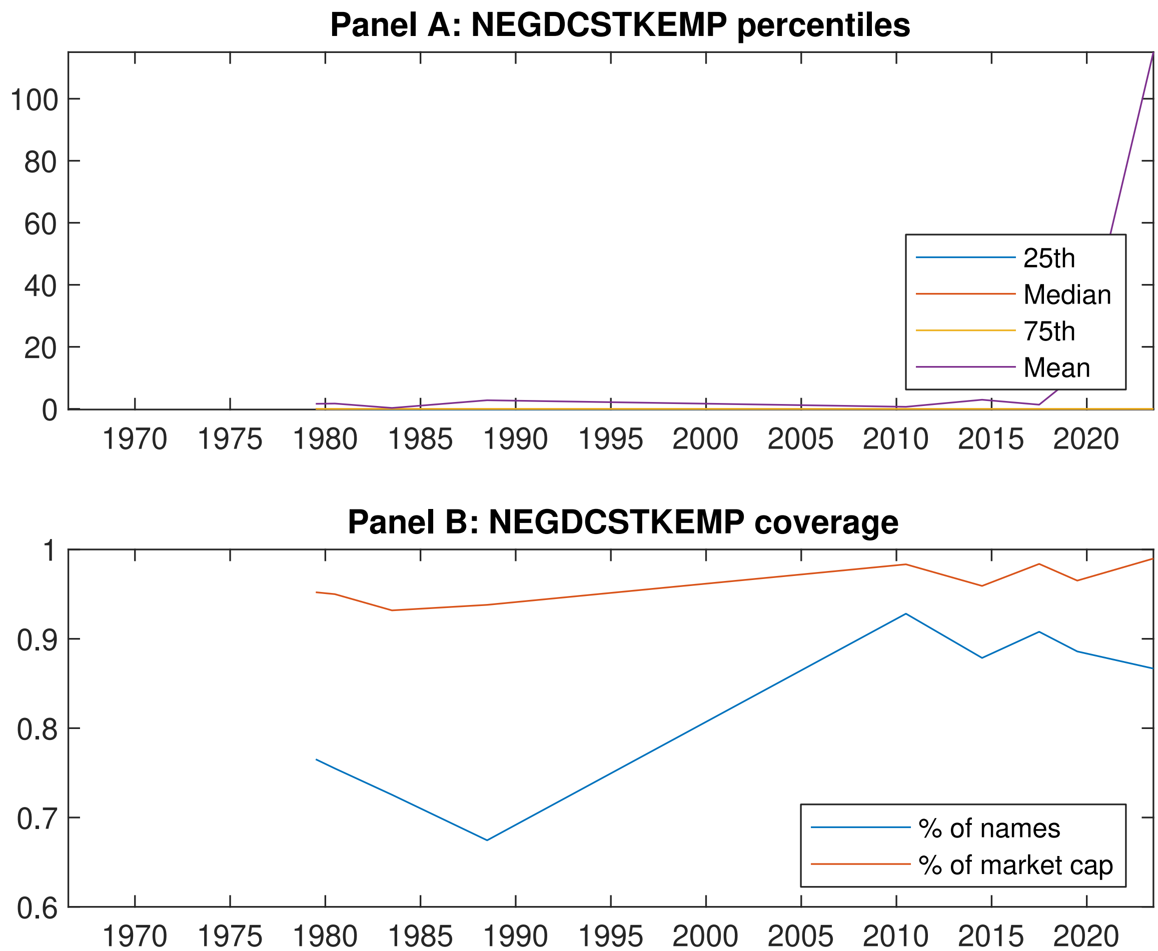


Figure 1: Times series of EPSS percentiles and coverage.
This figure plots descriptive statistics for EPSS. Panel A shows cross-sectional percentiles of EPSS over the sample. Panel B plots the monthly coverage of EPSS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EPSS. 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 EPSS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.39	0.56	0.66	0.68	0.76	0.37
	[2.27]	[2.93]	[3.42]	[3.97]	[4.54]	[4.87]
α_{CAPM}	-0.15	-0.05	0.06	0.15	0.24	0.38
	[-2.78]	[-1.07]	[1.05]	[2.93]	[5.03]	[4.99]
α_{FF3}	-0.16	-0.03	0.08	0.11	0.19	0.35
	[-3.03]	[-0.74]	[1.42]	[2.27]	[4.36]	[4.56]
α_{FF4}	-0.14	-0.00	0.10	0.08	0.18	0.32
	[-2.66]	[-0.02]	[1.81]	[1.60]	[3.92]	[4.05]
α_{FF5}	-0.15	0.03	0.10	0.01	0.10	0.25
	[-2.82]	[0.66]	[1.79]	[0.26]	[2.27]	[3.22]
α_{FF6}	-0.14	0.05	0.12	-0.01	0.09	0.23
	[-2.57]	[1.12]	[2.06]	[-0.11]	[2.14]	[2.97]
Panel B: Fama and French (2018) 6-factor model loadings for EPSS-sorted portfolios						
β_{MKT}	0.96	1.04	1.03	1.00	0.99	0.03
	[77.02]	[99.63]	[74.80]	[91.04]	[95.72]	[1.42]
β_{SMB}	-0.08	0.02	0.07	-0.05	-0.03	0.05
	[-4.38]	[1.17]	[3.36]	[-3.09]	[-1.74]	[2.01]
β_{HML}	0.09	-0.02	-0.04	0.07	0.03	-0.05
	[3.63]	[-0.89]	[-1.69]	[3.25]	[1.76]	[-1.49]
β_{RMW}	0.04	-0.09	0.01	0.14	0.12	0.08
	[1.71]	[-4.61]	[0.29]	[6.72]	[5.87]	[2.15]
β_{CMA}	-0.09	-0.10	-0.09	0.16	0.23	0.32
	[-2.64]	[-3.28]	[-2.35]	[5.23]	[7.73]	[6.18]
β_{UMD}	-0.02	-0.03	-0.03	0.03	0.01	0.03
	[-1.50]	[-3.10]	[-1.90]	[2.45]	[0.69]	[1.41]
Panel C: Average number of firms (n) and market capitalization (me)						
n	725	704	592	670	740	
me ($\$10^6$)	1831	1461	1910	2221	2414	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the EPSS 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	0.37	0.38	0.35	0.32	0.25	0.23
			[4.87]	[4.99]	[4.56]	[4.05]	[3.22]	[2.97]
Quintile	NYSE	EW	0.55	0.61	0.52	0.45	0.34	0.30
			[7.77]	[8.77]	[8.09]	[6.99]	[5.69]	[4.96]
Quintile	Name	VW	0.35	0.36	0.33	0.32	0.26	0.25
			[4.65]	[4.67]	[4.37]	[4.06]	[3.33]	[3.21]
Quintile	Cap	VW	0.31	0.31	0.29	0.25	0.22	0.20
			[3.96]	[3.91]	[3.65]	[3.17]	[2.76]	[2.49]
Decile	NYSE	VW	0.33	0.29	0.27	0.23	0.21	0.19
			[3.43]	[3.07]	[2.79]	[2.39]	[2.21]	[1.98]
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	0.34	0.35	0.32	0.31	0.24	0.23
			[4.41]	[4.59]	[4.21]	[3.97]	[3.17]	[3.02]
Quintile	NYSE	EW	0.35	0.41	0.33	0.29	0.14	0.13
			[4.66]	[5.39]	[4.69]	[4.21]	[2.26]	[2.02]
Quintile	Name	VW	0.32	0.33	0.31	0.30	0.25	0.24
			[4.18]	[4.29]	[4.03]	[3.90]	[3.23]	[3.15]
Quintile	Cap	VW	0.27	0.28	0.26	0.24	0.21	0.20
			[3.52]	[3.53]	[3.30]	[3.07]	[2.65]	[2.48]
Decile	NYSE	VW	0.29	0.26	0.24	0.22	0.20	0.18
			[3.02]	[2.74]	[2.49]	[2.30]	[2.05]	[1.91]

Table 3: Conditional sort on size and EPSS

This table presents results for conditional double sorts on size and EPSS. 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 EPSS. 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 EPSS and short stocks with low EPSS .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	EPSS Quintiles (L)	(2)	(3)	(4)	(H)	EPSS Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.40	0.66	0.87	0.95	0.97	0.57	0.63	0.57	0.51	0.38	0.35
	[1.50]	[2.39]	[3.36]	[3.74]	[4.06]	[6.68]	[7.58]	[7.20]	[6.42]	[5.12]	[4.66]
(2)	0.53	0.66	0.89	0.85	0.93	0.40	0.44	0.35	0.32	0.21	0.20
	[2.26]	[2.68]	[3.61]	[3.66]	[4.14]	[4.43]	[4.93]	[4.11]	[3.68]	[2.46]	[2.28]
(3)	0.54	0.61	0.82	0.79	0.91	0.38	0.39	0.36	0.35	0.24	0.25
	[2.60]	[2.66]	[3.58]	[3.69]	[4.52]	[4.79]	[4.95]	[4.54]	[4.33]	[3.08]	[3.07]
(4)	0.49	0.63	0.77	0.78	0.80	0.30	0.30	0.25	0.24	0.06	0.07
	[2.60]	[2.94]	[3.56]	[3.88]	[4.21]	[3.68]	[3.65]	[3.06]	[2.95]	[0.74]	[0.90]
(5)	0.44	0.47	0.55	0.52	0.71	0.28	0.26	0.25	0.23	0.23	0.22
	[2.58]	[2.46]	[2.99]	[2.98]	[4.25]	[3.01]	[2.85]	[2.75]	[2.49]	[2.45]	[2.30]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EPSS Quintiles, Average n (L)	(2)	(3)	(4)	(H)	EPSS Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	374	373	373	371	372	32	33	38	29	29
(2)	108	108	107	107	107	56	56	56	55	56
(3)	80	79	78	78	79	97	95	96	98	99
(4)	66	66	66	66	67	201	206	208	213	214
(5)	61	61	61	61	61	1379	1463	1683	1586	1757

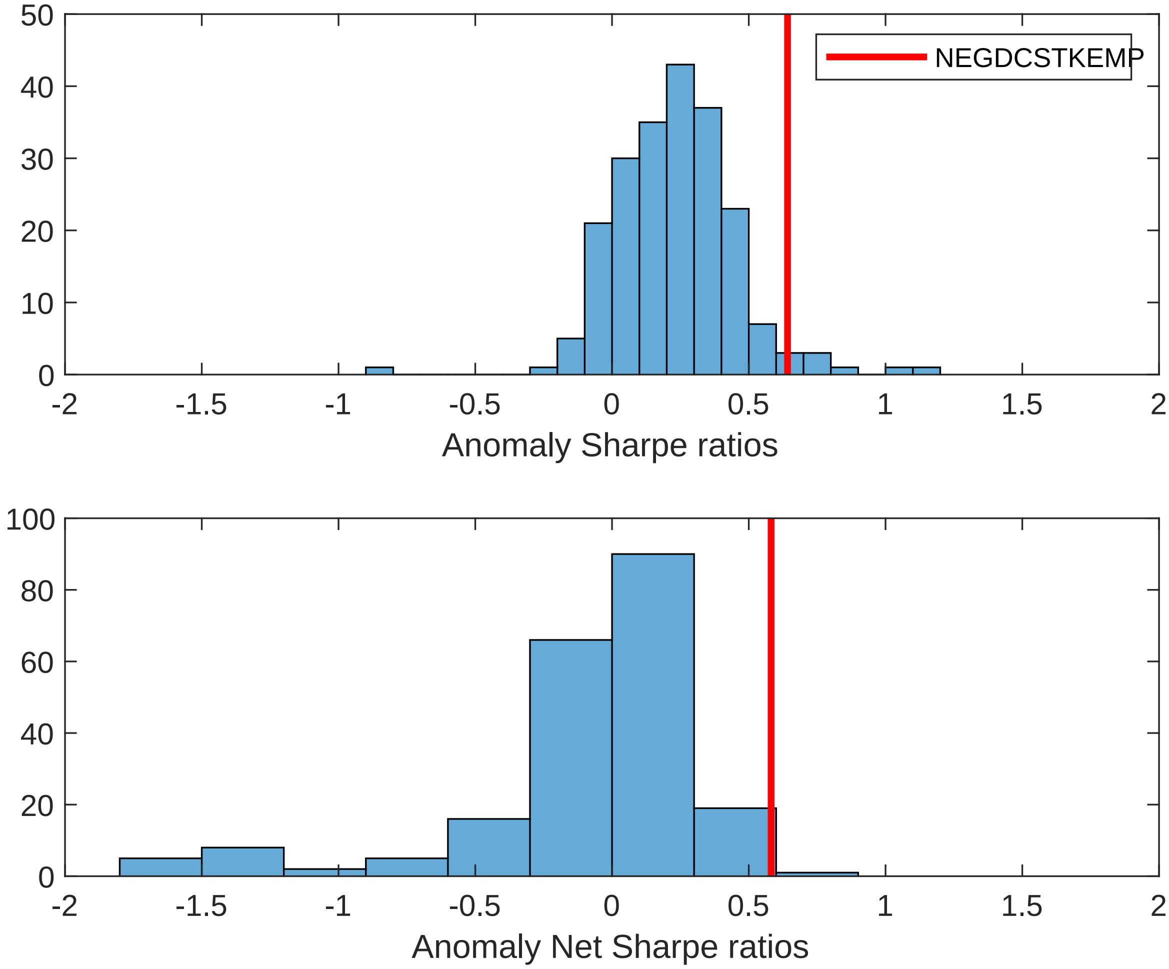


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EPSS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

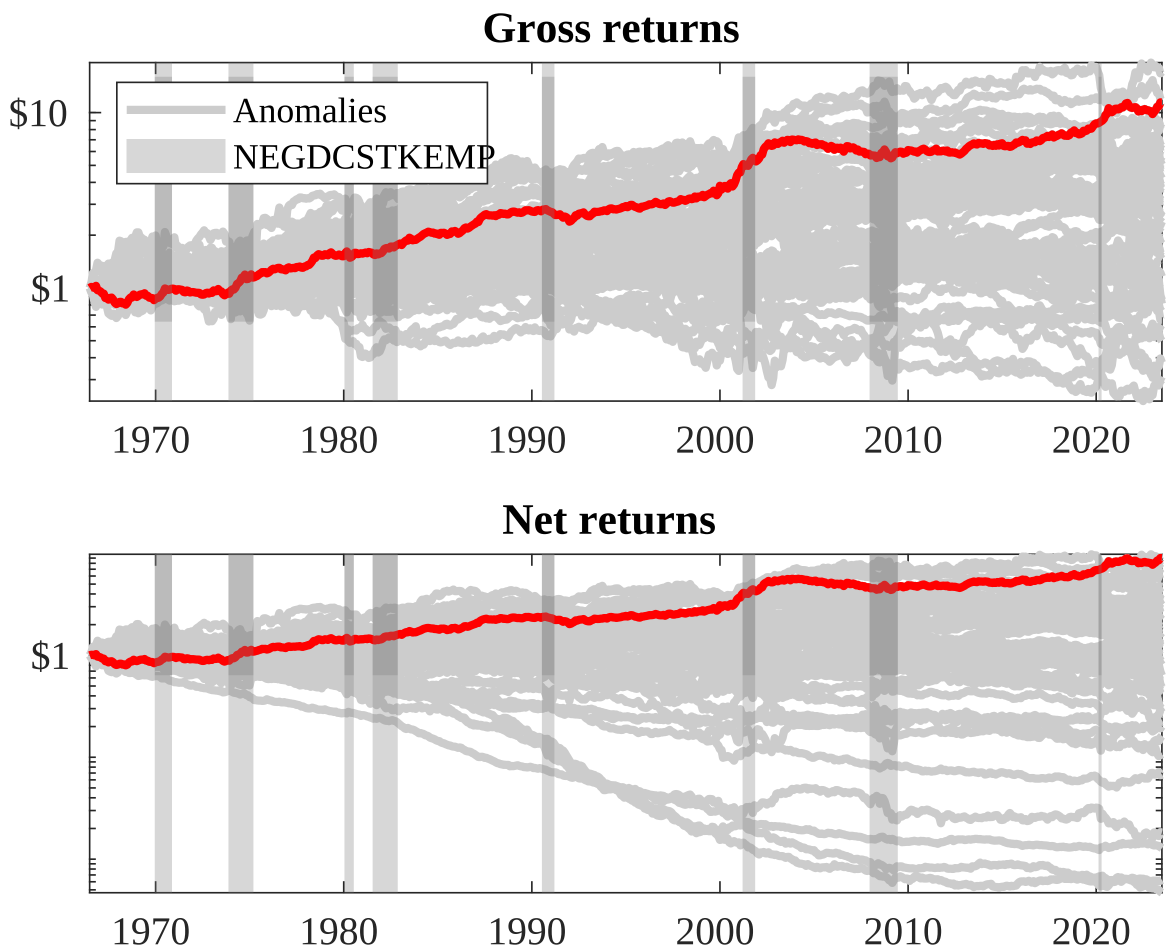


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EPSS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

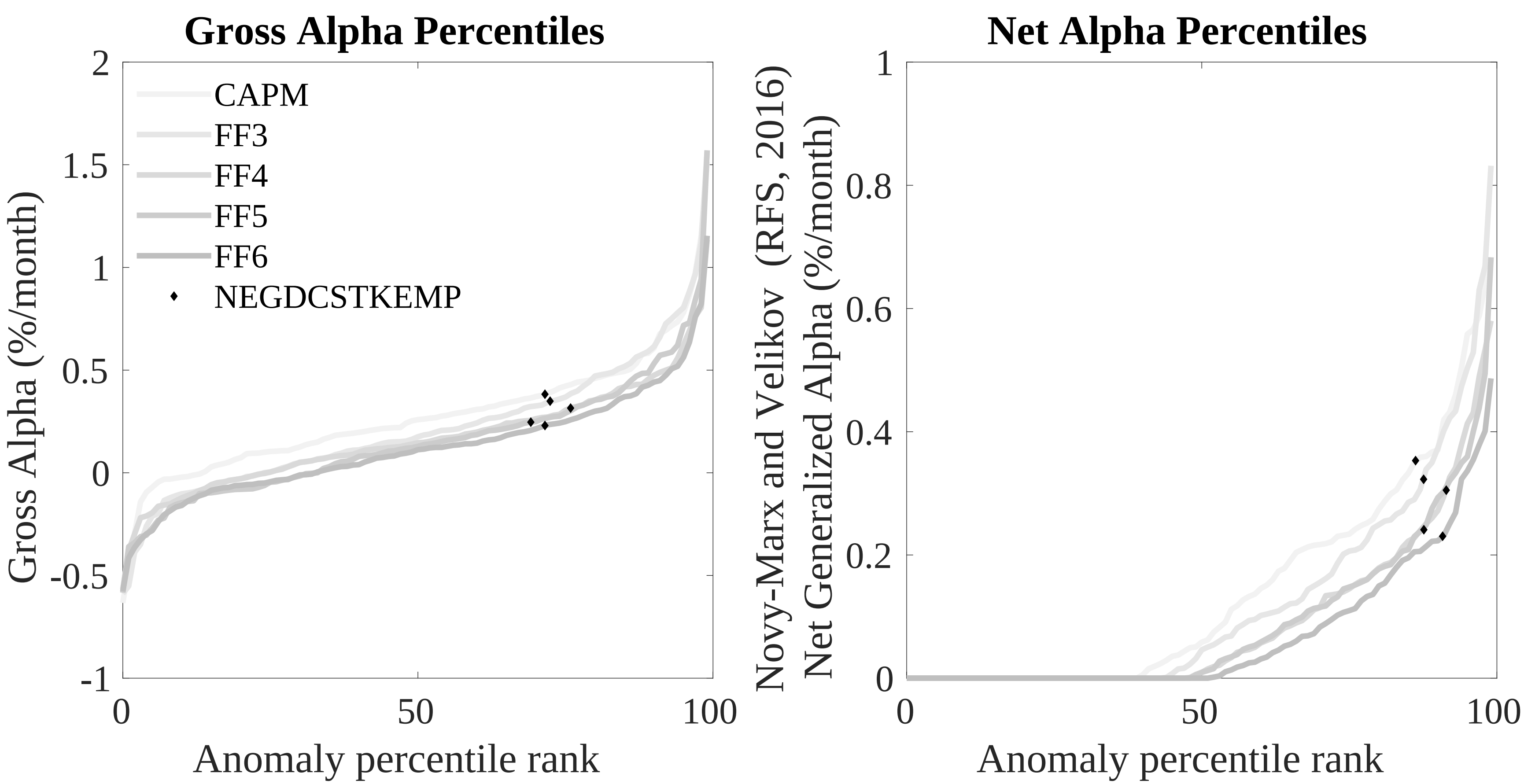
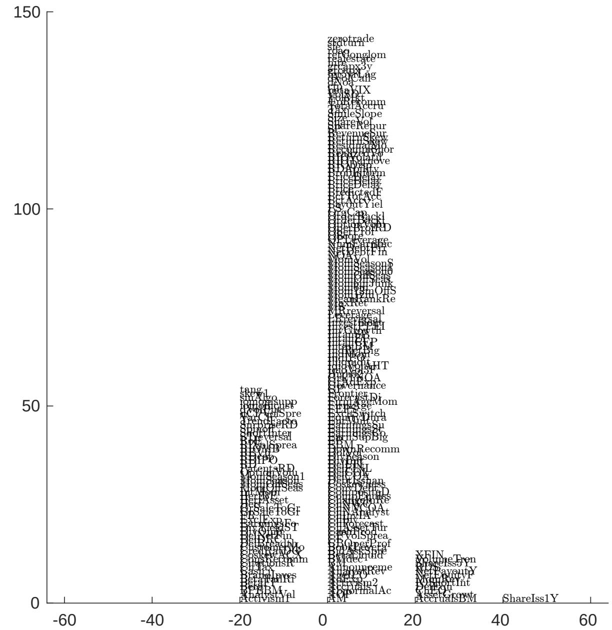
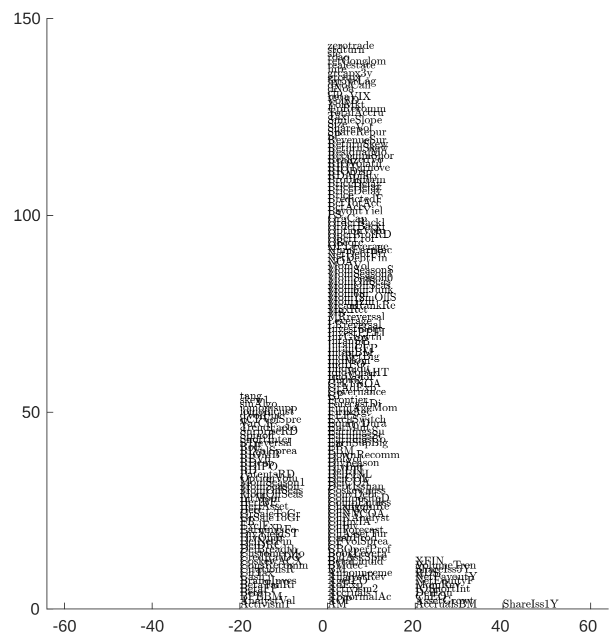


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EPSS trading strategy alphas (diamonds). The strategies are constructed 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 EPSS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

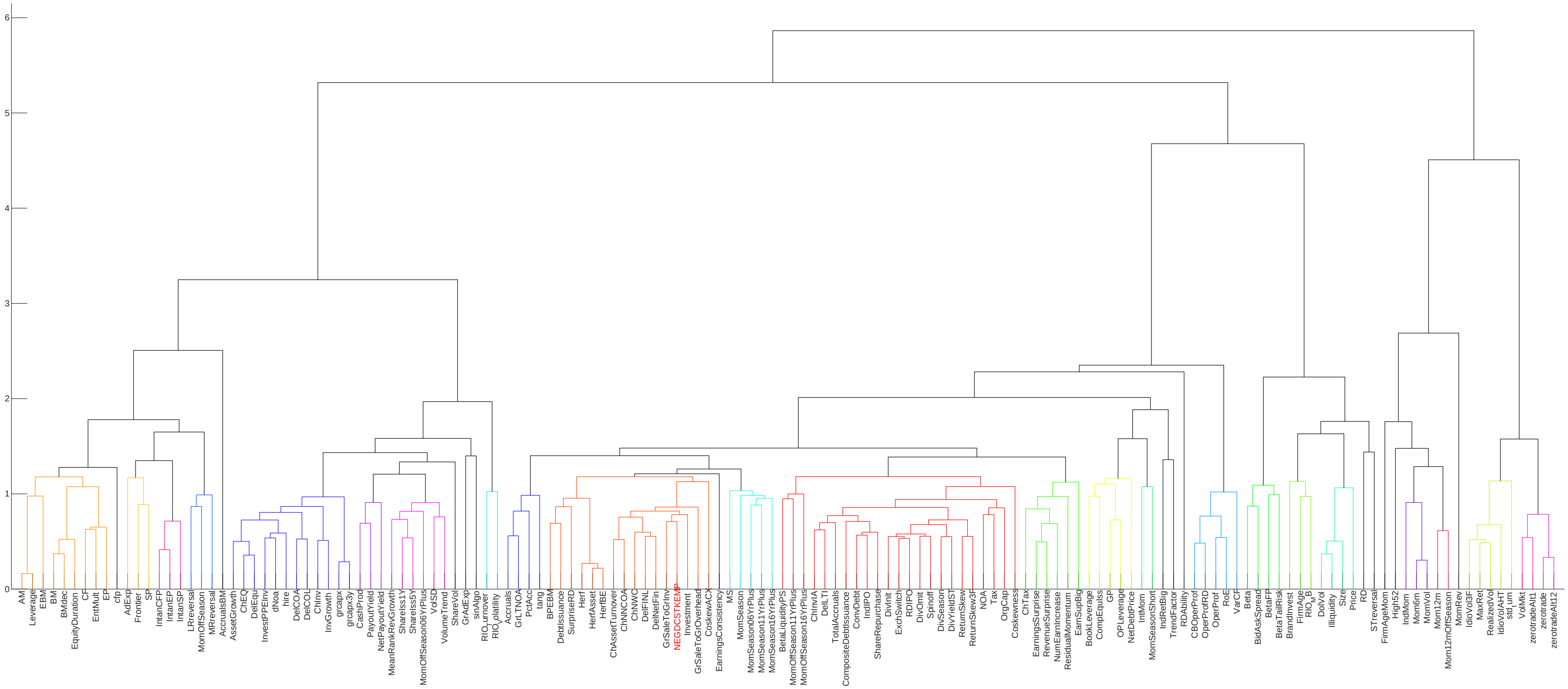


Figure 6: Agglomerative hierarchical cluster plot

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

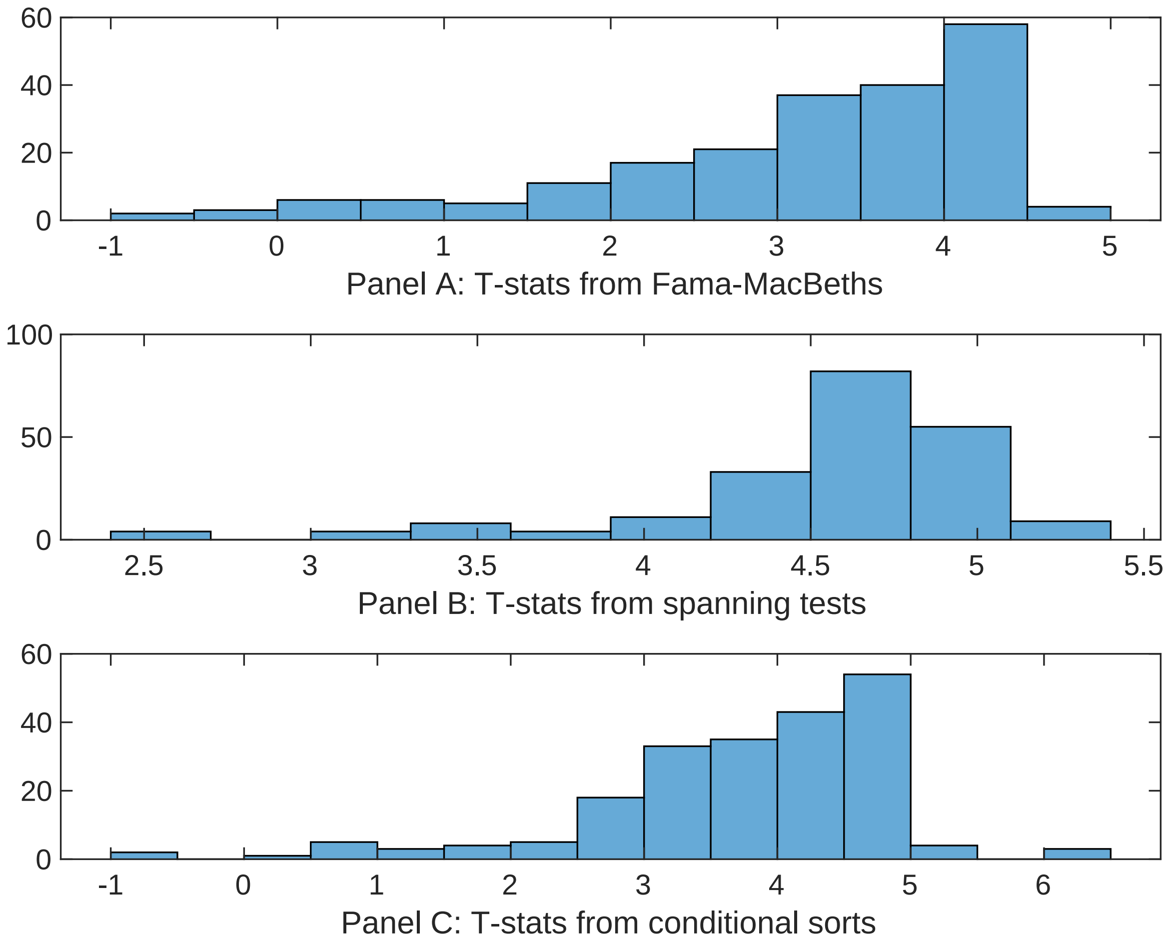


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EPSS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EPSS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EPSS} EPSS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EPSS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EPSS. Stocks are finally grouped into five EPSS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EPSS 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 EPSS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EPSS} EPSS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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
	[5.59]	[7.20]	[5.21]	[5.98]	[5.52]	[5.99]	[5.30]
EPSS	0.52	0.47	0.42	0.49	0.48	0.41	0.37
	[3.89]	[3.47]	[2.98]	[3.45]	[3.61]	[3.11]	[2.56]
Anomaly 1	0.25						0.92
	[5.65]						[2.27]
Anomaly 2		0.49					-0.36
		[4.12]					[-0.02]
Anomaly 3			0.28				0.25
			[2.46]				[2.26]
Anomaly 4				0.37			0.39
				[4.29]			[0.44]
Anomaly 5					0.15		-0.21
					[3.99]		[-0.36]
Anomaly 6						0.11	0.69
						[8.58]	[6.43]
# months	679	684	679	679	684	684	679
$\bar{R}^2$(%)	0	0	1	0	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the EPSS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EPSS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.21	0.23	0.22	0.20	0.25	0.24	0.19
	[2.77]	[3.08]	[2.89]	[2.64]	[3.23]	[3.07]	[2.58]
Anomaly 1	27.34						17.62
	[7.12]						[3.97]
Anomaly 2		35.52					38.57
		[8.63]					[6.43]
Anomaly 3			13.11				0.10
			[4.40]				[0.03]
Anomaly 4				17.35			5.26
				[4.34]			[1.24]
Anomaly 5					19.17		-10.92
					[4.72]		[-1.95]
Anomaly 6						9.22	-11.24
						[1.81]	[-2.12]
mkt	4.83	3.88	4.94	5.08	2.41	2.75	6.23
	[2.73]	[2.22]	[2.68]	[2.75]	[1.33]	[1.50]	[3.46]
smb	7.02	4.40	8.49	4.89	5.29	4.72	6.16
	[2.76]	[1.74]	[3.22]	[1.87]	[2.02]	[1.74]	[2.36]
hml	-8.03	-9.07	-9.40	-9.36	-7.32	-5.24	-11.29
	[-2.33]	[-2.67]	[-2.54]	[-2.53]	[-2.08]	[-1.48]	[-3.13]
rmw	-1.41	9.33	0.28	4.30	9.37	7.34	1.86
	[-0.38]	[2.74]	[0.07]	[1.20]	[2.64]	[2.05]	[0.46]
cma	18.75	-3.53	22.69	26.68	11.77	20.52	8.80
	[3.46]	[-0.55]	[4.00]	[4.99]	[1.77]	[2.54]	[1.13]
umd	2.39	2.21	3.88	2.84	3.16	2.86	1.35
	[1.37]	[1.28]	[2.17]	[1.60]	[1.76]	[1.57]	[0.78]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	15	16	11	11	10	8	21

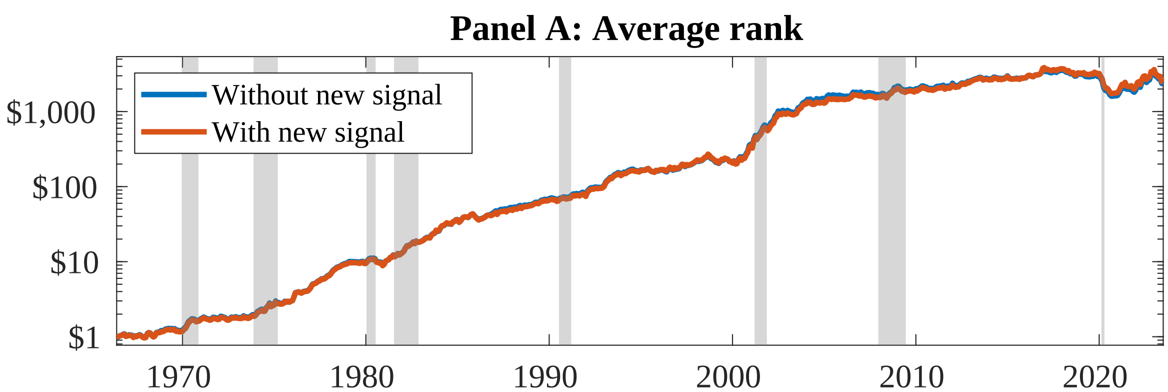


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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