Stock-PPE Scale Signal and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock-PPE Scale Signal (SPSS), 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 SPSS achieves an annualized gross (net) Sharpe ratio of 0.55 (0.49), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (21) bps/month with a t-statistic of 2.69 (2.71), 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), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth) is 17 bps/month with a t-statistic of 2.38.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional asset pricing theory suggests that systematic risk should be the primary driver of expected returns, a growing body of evidence documents various firm characteristics that predict future stock returns. Understanding these return predictors is crucial for both testing market efficiency and improving asset allocation decisions.

Despite extensive research on cross-sectional return predictability, the relationship between firms' physical capital investments and their stock returns remains incompletely understood. While prior work has examined various aspects of capital investment, including capital expenditures and asset growth, the scaling relationship between stock issuance and property, plant and equipment (PPE) has received limited attention.

The Stock-PPE Scale Signal (SPSS) captures a fundamental aspect of firms' capital structure and investment decisions. When firms issue equity to finance PPE investments, the relative scaling between new shares and physical capital provides information about management's assessment of investment opportunities and potential agency conflicts. Building on Myers (1984)'s pecking order theory, firms preferentially use internal funds and debt before equity financing, suggesting that substantial equity issuance relative to PPE investment may signal overvaluation or agency problems.

The theoretical link between SPSS and future returns operates through two primary channels. First, following Baker and Wurgler (2003), managers time the equity market by issuing shares when their stock is overvalued, implying that high SPSS values may predict lower future returns as prices revert to fundamental values. Second, as argued by Jensen (1986), agency problems are particularly severe when managers have access to substantial equity financing relative to their tangible investment opportunities, leading to value-destroying investments.

These mechanisms suggest that firms with high SPSS values - those issuing relatively more equity per unit of PPE investment - should underperform firms with low SPSS values. This relationship should be particularly pronounced after controlling for other known determinants of returns, including size, value, and momentum factors identified by Fama and French (2018).

Our empirical analysis reveals that SPSS strongly predicts future stock returns. A value-weighted long-short portfolio strategy that buys stocks with low SPSS values and sells stocks with high SPSS values generates significant abnormal returns. Specifically, this strategy earns a monthly alpha of 21 basis points (t-statistic = 2.69) relative to the Fama-French five-factor model augmented with momentum.

The predictive power of SPSS is robust across various methodological choices and subsamples. The signal maintains its significance among large-cap stocks, with the long-short strategy earning a monthly alpha of 23 basis points (t-statistic = 2.32) among stocks in the largest size quintile. This finding is particularly important as it suggests the anomaly is not driven by small, illiquid stocks.

Importantly, SPSS continues to predict returns even after controlling for related anomalies. When we simultaneously control for the six most closely related predictors - including share issuance, asset growth, and equity financing measures - SPSS generates a monthly alpha of 17 basis points (t-statistic = 2.38). This indicates that SPSS captures unique information about future returns not contained in previously documented predictors.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures the scaling relationship between equity issuance and physical capital investment. While prior work by Titman et al. (2004) and Cooper et al. (2008) examines investment-based anomalies, and Pontiff and

Woodgate (2008) studies equity issuance, we are the first to explicitly consider their interaction through a scaling relationship.

Second, we contribute to the growing literature on investment-based asset pricing, exemplified by Zhang (2005) and Hou et al. (2015). Our findings suggest that the manner in which firms finance their investments, not just the level of investment, contains important information about future returns. The robust predictive power of SPSS, even among large firms, provides new insights into the efficiency of corporate investment decisions.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of considering scaling relationships between firm characteristics rather than examining them in isolation. For practitioners, SPSS represents a novel signal that can be incorporated into quantitative investment strategies, particularly given its effectiveness among large, liquid stocks and its robustness to transaction costs.

2 Data

Our study examines the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the difference in common stock (CSTK) scaled by property, plant, and equipment (PPEGT). We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK for common stock and item PPEGT for property, plant, and equipment. Common stock (CSTK) represents the total par or stated value of common stock outstanding, while property, plant, and equipment (PPEGT) captures the gross value of long-term physical assets used in business operations. The construction of the Stock-PPE Scale Signal follows a specific methodology where we first calculate the difference between the current period's CSTK and its lagged value, then scale this difference by the lagged value of PPEGT. This scaling approach provides a standardized measure of changes in common stock relative to the firm's fixed asset base, potentially offering insights into capital structure decisions and asset utilization efficiency. We construct this measure using end-of-fiscal-year values for both CSTK and PPEGT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SPSS signal. Panel A plots the time-series of the mean, median, and interquartile range for SPSS. On average, the cross-sectional mean (median) SPSS is -0.04 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SPSS 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 SPSS signal for the CRSP universe. On average, the SPSS signal is available for 5.96% of CRSP names, which on average make up 7.35% of total market capitalization.

4 Does SPSS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SPSS 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 SPSS portfolio and sells the low SPSS 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 SPSS strategy earns an average return of 0.33% per month with a t-statistic of 4.16. The annualized Sharpe ratio of the strategy is 0.55. The alphas range from 0.21% to 0.38% per month and have t-statistics exceeding 2.69 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 0.36, with a t-statistic of 7.00 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 503 stocks and an average market capitalization of at least $1,349 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 name breakpoints and value-weighted portfolios, and equals 30 bps/month with a t-statistics of 3.76. Out of the twenty-five alphas reported in

Panel A, the t-statistics for twenty-five exceed two, and for seventeen 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 26-33bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using name breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.27. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SPSS 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 SPSS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SPSS, as well as average returns and alphas for long/short trading SPSS 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 SPSS strategy achieves an average return of 28 bps/month with a t-statistic of 2.97. Among these large cap stocks, the alphas for the SPSS strategy relative to the five most common factor models range from 23 to 31 bps/month with t-statistics between 2.32 and 3.19.

5 How does SPSS perform relative to the zoo?

Figure 2 puts the performance of SPSS 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 SPSS strategy falls in the distribution. The SPSS strategy's gross (net) Sharpe ratio of 0.55 (0.49) 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 SPSS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the SPSS strategy would have yielded \$7.83 which ranks the SPSS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SPSS strategy would have yielded \$5.80 which ranks the SPSS 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 SPSS relative to those. Panel A shows that the SPSS strategy gross alphas fall between the 65 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%

[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 SPSS strategy has a positive net generalized alpha for five out of the five factor models. In these cases SPSS ranks between the 85 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SPSS 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 SPSS 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 SPSS or at least to weaken the power SPSS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SPSS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SPSS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SPSS} SPSS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SPSS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SPSS. Stocks are finally grouped into five SPSS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SPSS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SPSS 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 SPSS signal in these Fama-MacBeth regressions exceed 2.11, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SPSS is 1.40.

Similarly, Table 5 reports results from spanning tests that regress returns to the SPSS 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 SPSS strategy earns alphas that range from 18-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.32, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SPSS trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.38.

7 Does SPSS add relative to the whole zoo?

Finally, we can ask how much adding SPSS 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 SPSS 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 SPSS grows to $2106.54.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock-PPE Scale Signal (SPSS) as a valuable predictor of cross-sectional stock returns. Our analysis demonstrates that SPSS-based trading strategies yield economically and statistically significant results, with impressive Sharpe ratios and consistent abnormal returns even after accounting for transaction costs. The signal's robustness is particularly noteworthy, maintaining its predictive power even when controlling for established factors and related anomalies from the factor zoo.

The findings have important implications for both academic research and prac-

[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 SPSS is available.

tical investment management. For academics, our results contribute to the growing literature on return predictability and asset pricing anomalies, suggesting that the relationship between physical capital scaling and stock returns deserves further attention. For practitioners, the SPSS signal represents a potentially valuable tool for portfolio management, given its ability to generate significant risk-adjusted returns even after accounting for transaction costs.

However, several limitations should be noted. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market conditions. Second, while we control for various related factors, there might be other unexplored interactions or mechanisms driving our results.

Future research could explore several promising directions. First, investigating the economic mechanisms underlying the SPSS signal's predictive power could provide valuable insights. Second, examining the signal's performance in international markets would test its global applicability. Finally, studying how the signal interacts with other established anomalies could lead to more refined trading strategies and a better understanding of cross-sectional return predictability.

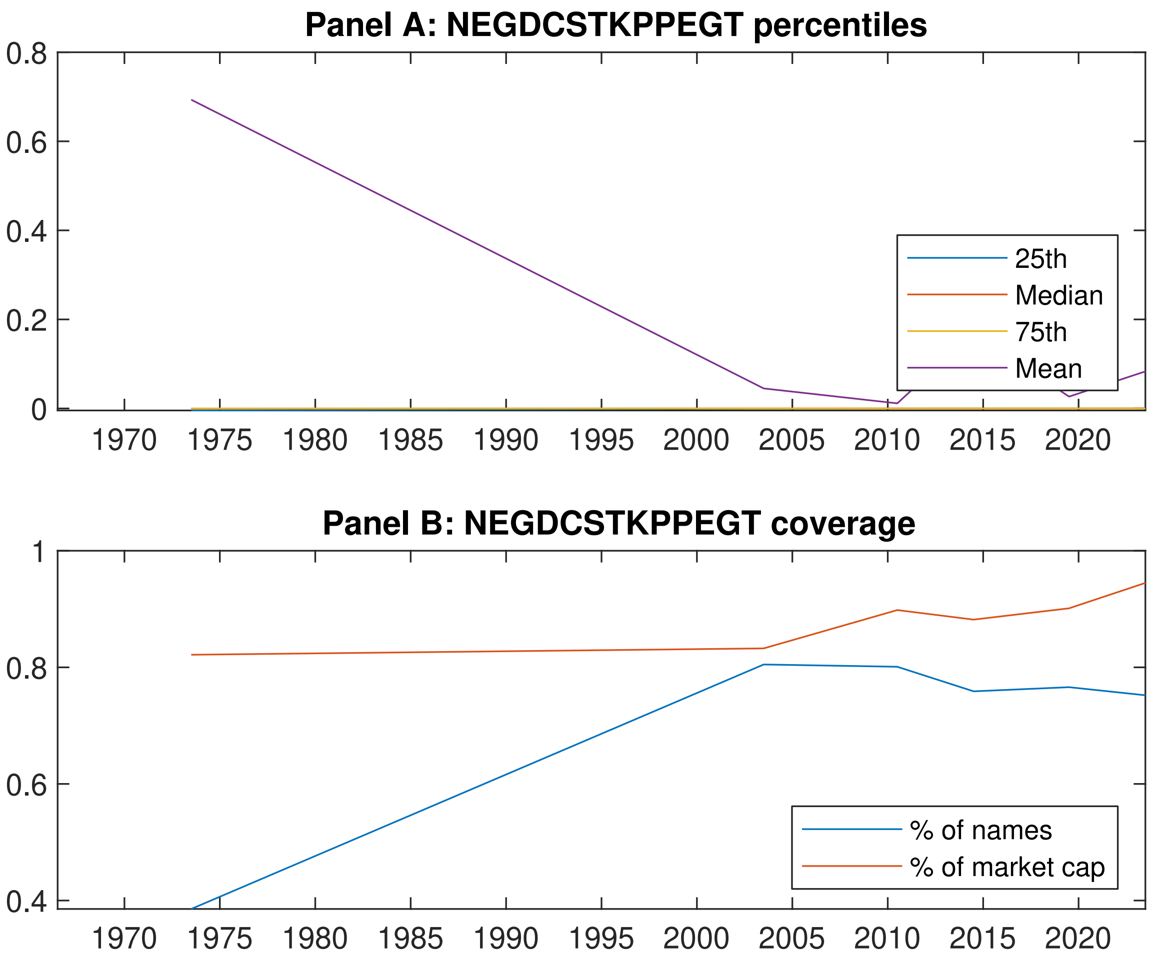

Figure 1: Times series of SPSS percentiles and coverage.
This figure plots descriptive statistics for SPSS. Panel A shows cross-sectional percentiles of SPSS over the sample. Panel B plots the monthly coverage of SPSS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SPSS. 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 SPSS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.52	0.65	0.70	0.76	0.33
	[2.34]	[2.77]	[3.49]	[4.17]	[4.52]	[4.16]
α_{CAPM}	-0.15	-0.07	0.07	0.18	0.24	0.38
	[-2.84]	[-1.53]	[1.30]	[3.57]	[4.87]	[4.78]
α_{FF3}	-0.11	-0.04	0.09	0.15	0.21	0.31
	[-2.12]	[-0.97]	[1.79]	[3.30]	[4.39]	[4.08]
α_{FF4}	-0.09	-0.01	0.11	0.10	0.19	0.29
	[-1.85]	[-0.25]	[2.08]	[2.25]	[4.06]	[3.70]
α_{FF5}	-0.12	0.02	0.09	0.05	0.10	0.22
	[-2.29]	[0.42]	[1.72]	[1.08]	[2.22]	[2.84]
α_{FF6}	-0.11	0.04	0.11	0.02	0.10	0.21
	[-2.09]	[0.90]	[1.96]	[0.42]	[2.20]	[2.69]
Panel B: Fama and French (2018) 6-factor model loadings for SPSS-sorted portfolios						
β_{MKT}	0.98	1.00	1.01	0.99	0.98	-0.00
	[81.51]	[91.69]	[78.25]	[94.10]	[90.31]	[-0.12]
β_{SMB}	0.02	0.04	0.02	-0.09	-0.01	-0.04
	[1.31]	[2.37]	[1.27]	[-5.76]	[-0.93]	[-1.42]
β_{HML}	-0.08	-0.08	-0.07	-0.01	-0.04	0.04
	[-3.26]	[-3.86]	[-2.75]	[-0.47]	[-1.76]	[1.11]
β_{RMW}	0.09	-0.12	0.04	0.10	0.12	0.03
	[3.82]	[-5.82]	[1.45]	[4.79]	[5.88]	[0.98]
β_{CMA}	-0.09	-0.06	-0.04	0.27	0.27	0.36
	[-2.64]	[-1.82]	[-0.99]	[8.88]	[8.82]	[7.00]
β_{UMD}	-0.01	-0.03	-0.02	0.05	-0.00	0.01
	[-1.19]	[-3.23]	[-1.70]	[4.48]	[-0.05]	[0.76]
Panel C: Average number of firms (n) and market capitalization (me)						
n	766	636	503	621	697	
me ($\$10^6$)	1598	1349	1845	2017	2257	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SPSS 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	0.38	0.31	0.29	0.22	0.21
			[4.16]	[4.78]	[4.08]	[3.70]	[2.84]	[2.69]
Quintile	NYSE	EW	0.54	0.64	0.53	0.44	0.34	0.28
			[6.71]	[8.53]	[8.27]	[6.99]	[5.81]	[4.90]
Quintile	Name	VW	0.30	0.34	0.27	0.24	0.17	0.16
			[3.76]	[4.24]	[3.50]	[3.03]	[2.26]	[2.05]
Quintile	Cap	VW	0.31	0.34	0.30	0.26	0.24	0.21
			[3.87]	[4.30]	[3.78]	[3.20]	[3.05]	[2.69]
Decile	NYSE	VW	0.34	0.39	0.30	0.25	0.28	0.25
			[3.47]	[3.98]	[3.13]	[2.62]	[2.92]	[2.57]
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	0.35	0.29	0.28	0.21	0.21
			[3.69]	[4.34]	[3.75]	[3.56]	[2.75]	[2.71]
Quintile	NYSE	EW	0.33	0.42	0.32	0.28	0.13	0.11
			[3.87]	[5.20]	[4.62]	[4.04]	[2.05]	[1.77]
Quintile	Name	VW	0.26	0.31	0.25	0.23	0.17	0.16
			[3.27]	[3.83]	[3.20]	[2.97]	[2.22]	[2.13]
Quintile	Cap	VW	0.27	0.31	0.27	0.25	0.23	0.22
			[3.42]	[3.91]	[3.45]	[3.16]	[2.94]	[2.76]
Decile	NYSE	VW	0.30	0.35	0.27	0.25	0.25	0.24
			[3.03]	[3.56]	[2.85]	[2.59]	[2.64]	[2.54]

Table 3: Conditional sort on size and SPSS

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

		SPSS Quintiles					SPSS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.37	0.68	0.85	0.99	0.99	0.62	0.72	0.61	0.53	0.41	0.36
		[1.26]	[2.48]	[3.23]	[3.73]	[3.98]	[6.08]	[7.18]	[6.87]	[5.99]	[4.91]	[4.34]
	(2)	0.44	0.71	0.88	0.89	0.94	0.49	0.59	0.44	0.38	0.31	0.27
		[1.72]	[2.88]	[3.53]	[3.79]	[4.10]	[4.66]	[5.77]	[4.89]	[4.18]	[3.40]	[2.97]
	(3)	0.66	0.56	0.81	0.80	0.93	0.27	0.35	0.24	0.22	0.15	0.14
		[2.87]	[2.52]	[3.48]	[3.79]	[4.51]	[2.98]	[3.91]	[2.92]	[2.70]	[1.77]	[1.72]
	(4)	0.51	0.59	0.81	0.79	0.80	0.29	0.35	0.24	0.21	0.06	0.05
		[2.44]	[2.79]	[3.85]	[3.99]	[4.20]	[3.25]	[4.03]	[3.12]	[2.66]	[0.79]	[0.65]
	(5)	0.45	0.53	0.48	0.55	0.73	0.28	0.31	0.26	0.23	0.24	0.23
		[2.53]	[2.83]	[2.69]	[3.18]	[4.38]	[2.97]	[3.19]	[2.75]	[2.40]	[2.55]	[2.32]

Panel B: Portfolio average number of firms and market capitalization

		SPSS Quintiles					SPSS Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	355	355	355	353	354	26	30	34	26	25
	(2)	99	99	98	99	99	50	50	51	50	50
	(3)	72	72	72	72	72	87	85	87	89	89
	(4)	62	62	62	62	62	189	188	196	197	200
	(5)	57	57	57	57	57	1276	1330	1595	1448	1620

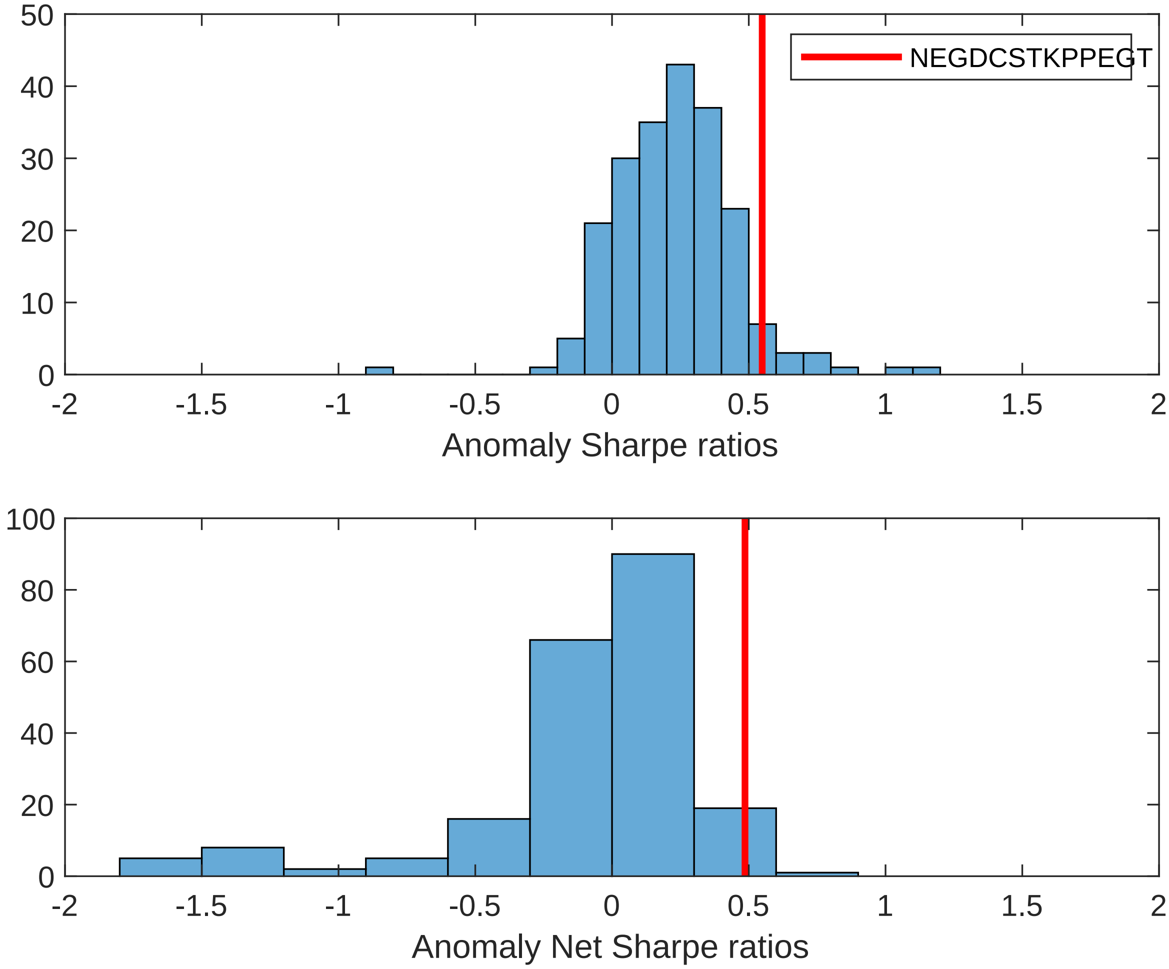

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SPSS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

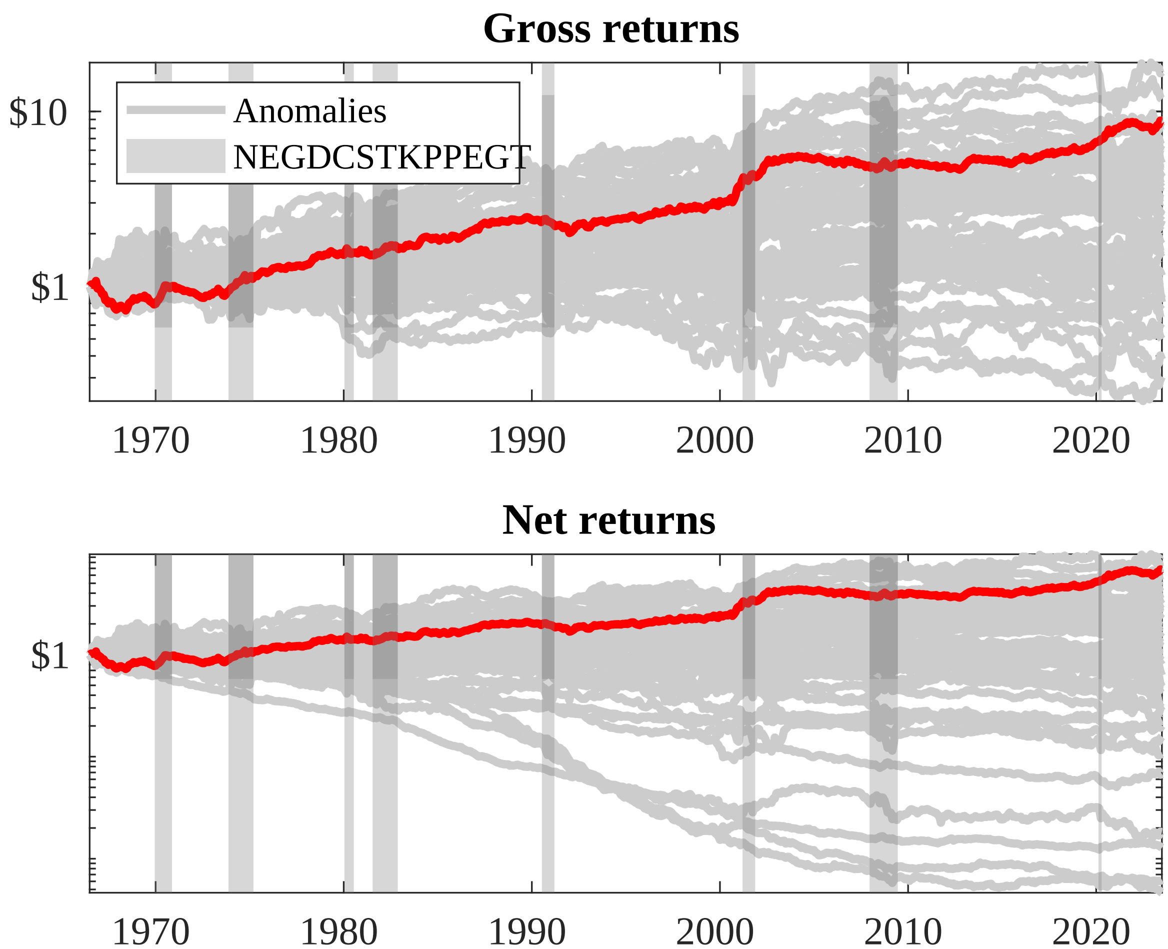

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SPSS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

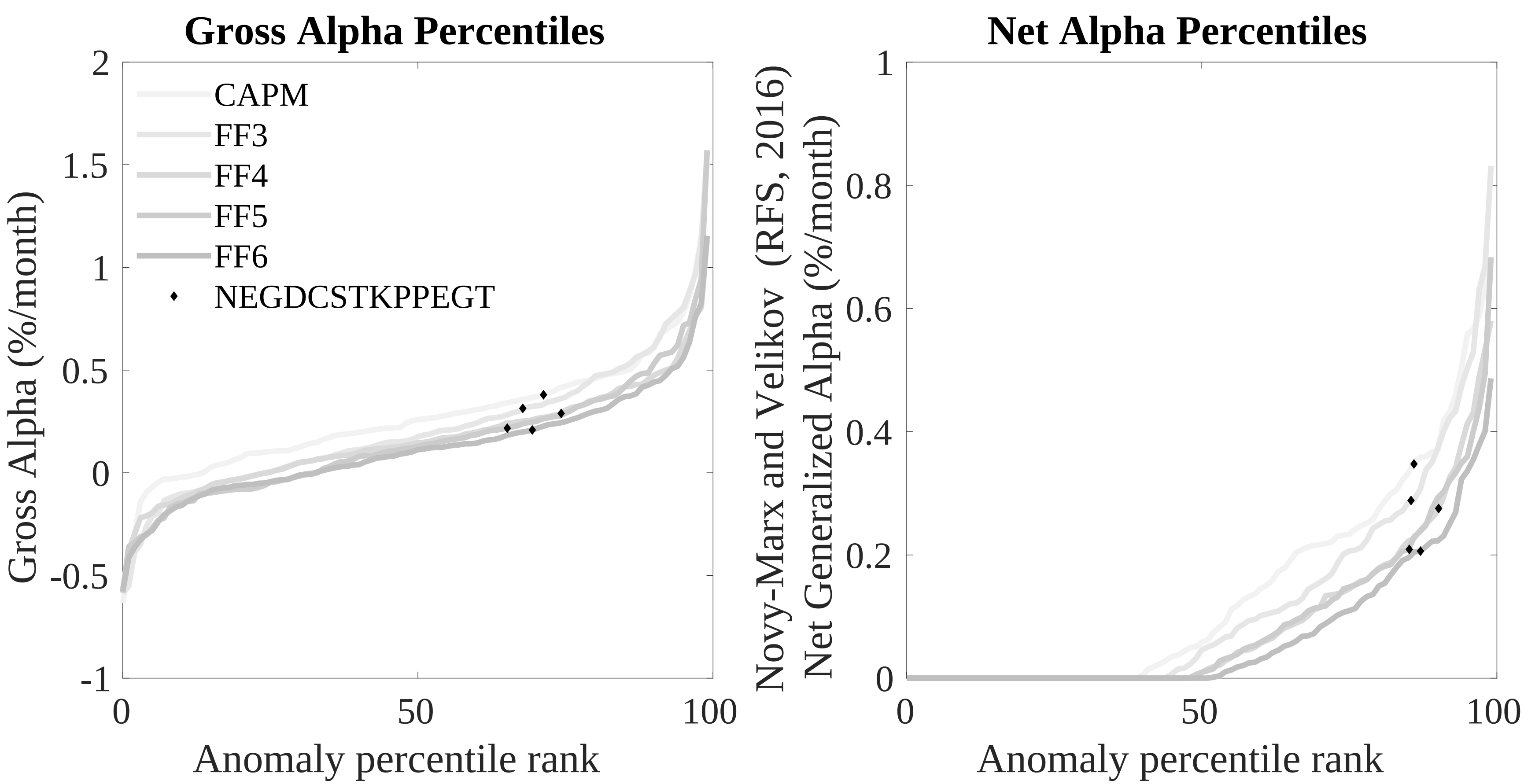

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SPSS trading strategy alphas (diamonds). The strategies are constructed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

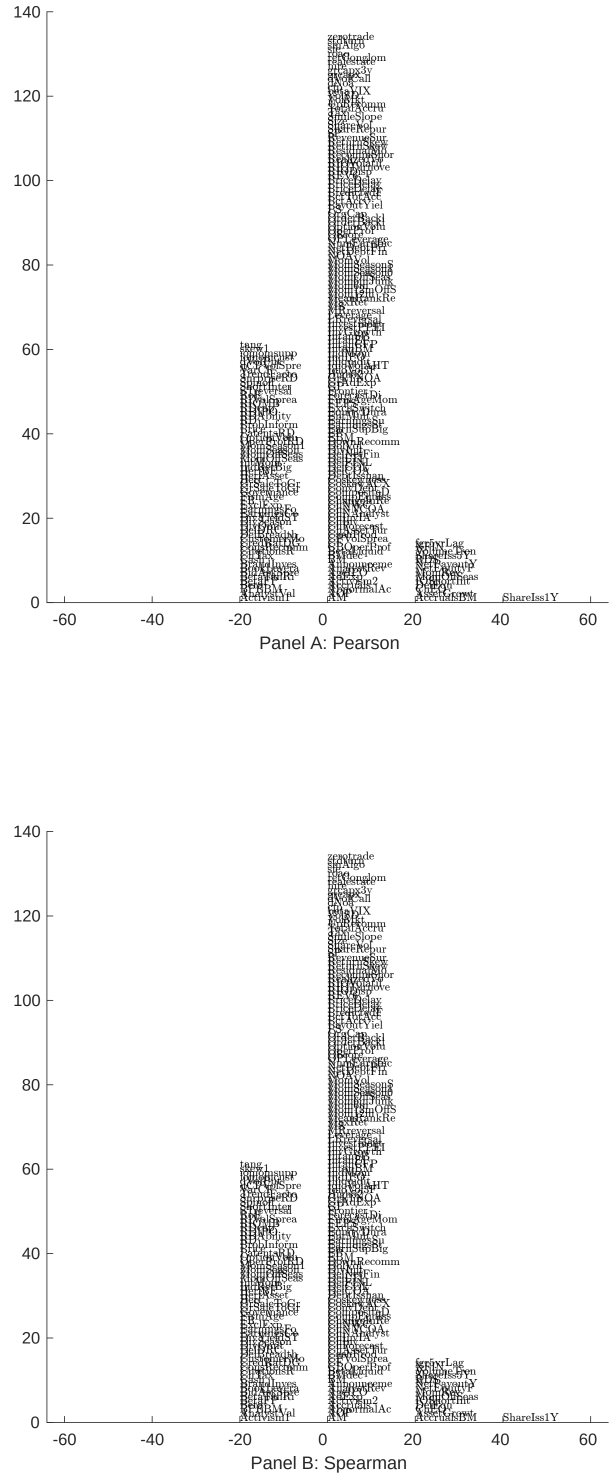

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SPSS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

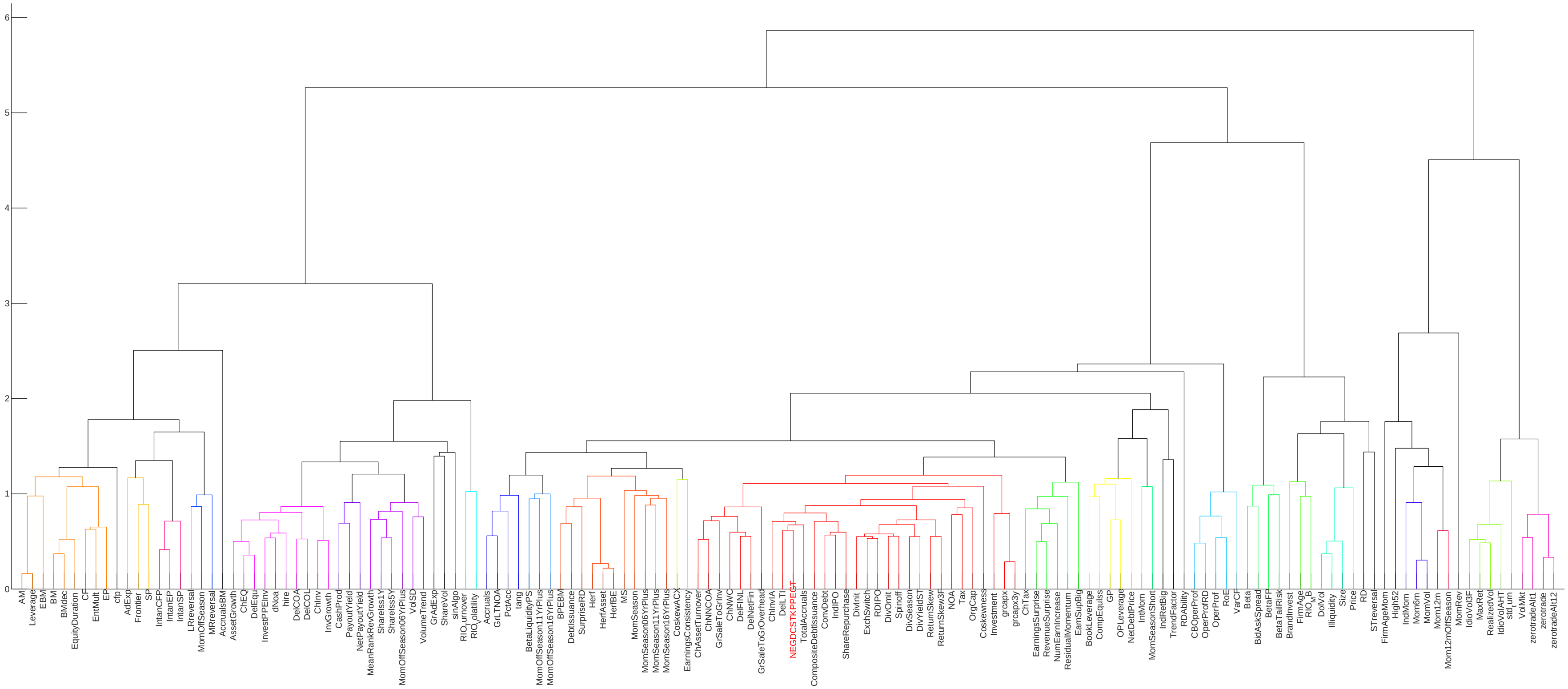

Figure 6: Agglomerative hierarchical cluster plot

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

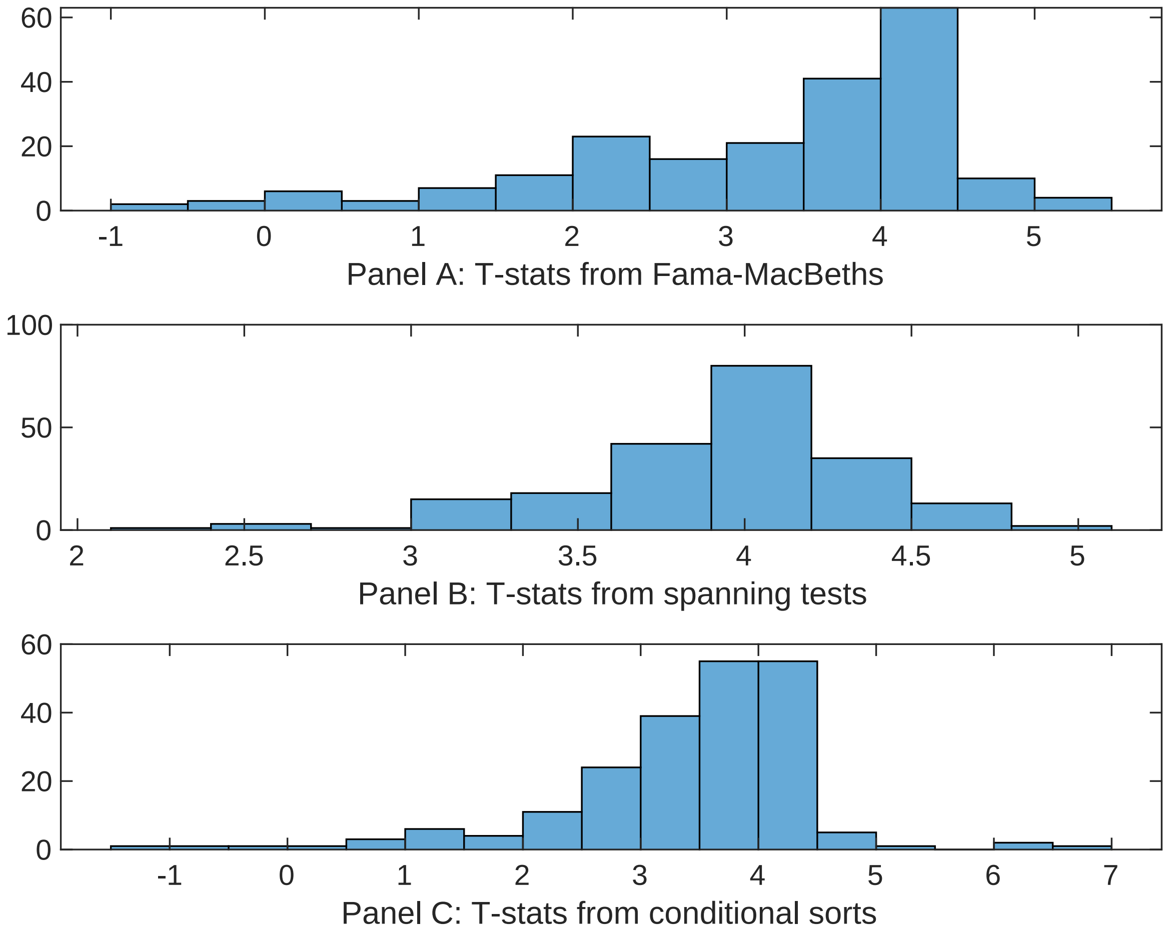

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SPSS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SPSS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SPSS} SPSS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SPSS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SPSS. Stocks are finally grouped into five SPSS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SPSS 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 SPSS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SPSS} SPSS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Net Payout Yield, Growth in book equity, 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	0.12	0.18	0.13	0.13	0.14	0.13
	[5.53]	[5.25]	[7.09]	[5.92]	[5.46]	[5.90]	[5.11]
SPSS	0.17	0.96	0.14	0.18	0.16	0.11	0.59
	[3.70]	[2.11]	[3.17]	[3.94]	[3.36]	[2.51]	[1.40]
Anomaly 1	0.27						0.11
	[5.88]						[2.67]
Anomaly 2		0.28					0.23
		[2.55]					[2.18]
Anomaly 3			0.49				0.40
			[4.54]				[0.00]
Anomaly 4				0.34			0.41
				[3.61]			[0.45]
Anomaly 5					0.15		-0.19
					[4.21]		[-0.33]
Anomaly 6						0.10	0.68
						[8.93]	[6.47]
# months	679	679	684	679	684	684	679
$\bar{R}^2$(%)	0	1	0	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 SPSS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SPSS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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), Net Payout Yield, Growth in book equity, 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	0.18	0.20	0.21	0.18	0.23	0.22	0.17
	[2.45]	[2.69]	[2.81]	[2.32]	[2.98]	[2.78]	[2.38]
Anomaly 1	26.22						17.05
	[6.85]						[3.85]
Anomaly 2		16.64					5.91
		[5.67]					[1.77]
Anomaly 3			34.21				34.67
			[8.29]				[5.79]
Anomaly 4				13.05			-1.00
				[3.27]			[-0.24]
Anomaly 5					20.12		-8.24
					[4.97]		[-1.47]
Anomaly 6						5.93	-14.45
						[1.16]	[-2.73]
mkt	2.09	2.77	1.11	1.92	-0.33	0.01	3.44
	[1.19]	[1.53]	[0.63]	[1.04]	[-0.19]	[0.00]	[1.91]
smb	-2.09	-0.03	-4.69	-3.81	-3.86	-4.09	-1.04
	[-0.82]	[-0.01]	[-1.85]	[-1.45]	[-1.48]	[-1.51]	[-0.40]
hml	1.43	-1.63	0.35	1.31	1.81	4.16	-2.10
	[0.42]	[-0.45]	[0.10]	[0.35]	[0.52]	[1.18]	[-0.58]
rmw	-5.29	-6.05	4.90	0.94	5.11	3.01	-4.20
	[-1.45]	[-1.57]	[1.44]	[0.26]	[1.44]	[0.84]	[-1.05]
cma	23.84	24.28	1.93	32.83	14.93	28.68	16.22
	[4.41]	[4.34]	[0.30]	[6.13]	[2.25]	[3.54]	[2.08]
umd	1.30	3.02	1.07	1.75	2.04	1.59	0.71
	[0.75]	[1.71]	[0.62]	[0.99]	[1.14]	[0.87]	[0.41]
# months	680	680	684	680	684	684	680
$\bar{R}^2$(%)	24	23	24	20	20	17	29

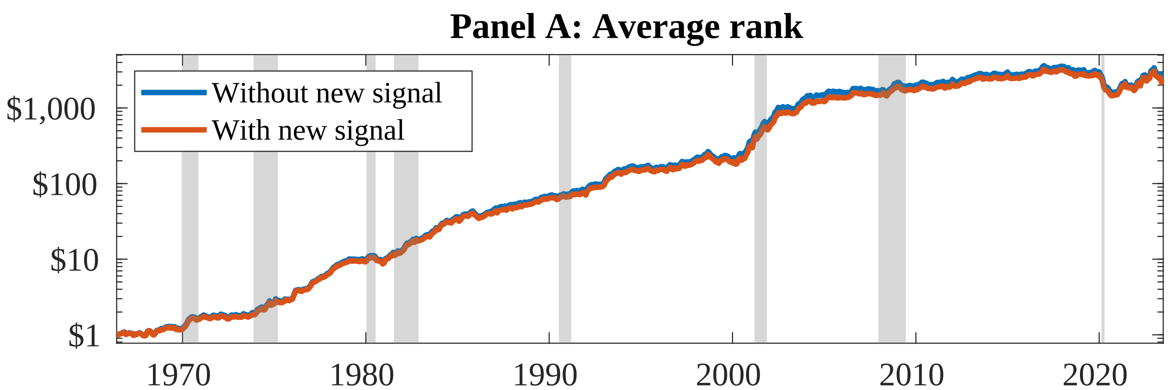

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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