Profitable Liquidity Score and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Profitable Liquidity Score (PLS), 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 PLS achieves an annualized gross (net) Sharpe ratio of 0.40 (0.36), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 32 (24) bps/month with a t-statistic of 3.52 (2.64), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Price, Realized (Total) Volatility, net income / book equity, Analyst earnings per share) is 38 bps/month with a t-statistic of 3.97.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns (Harvey et al., 2016). While the literature has documented hundreds of return predictors, understanding which signals truly capture distinct economic mechanisms versus those that are merely repackaging known effects remains crucial (Cochrane and Pedersen, 2023).

Liquidity and profitability have emerged as two fundamental firm characteristics that drive expected returns, yet their interaction remains understudied. While Pastor and Stambaugh (2003) show that liquidity risk commands a premium and Novy-Marx (2013) demonstrates that profitable firms earn higher returns, the joint dynamics of these characteristics may contain additional information about future performance.

We propose that firms exhibiting both high profitability and high liquidity should command lower expected returns due to three economic mechanisms. First, following Amihud (2002), liquid stocks face lower transaction costs and therefore require smaller return premiums to compensate investors. Second, as argued by Fama and French (2015), highly profitable firms generate internal cash flows that reduce financial distress risk. Third, the combination of high liquidity and profitability likely indicates lower information asymmetry, as these characteristics attract greater analyst coverage and institutional ownership (Hong et al., 2000).

Moreover, the interaction between profitability and liquidity may capture firms' life cycle stages (**?**). Mature firms tend to be both more profitable and more liquid as they establish stable market positions and attract broader investor bases. In contrast, growing firms often exhibit either high profitability with low liquidity (due to rapid reinvestment) or high liquidity with low profitability (due to recent public offerings).

This reasoning suggests that examining profitability and liquidity jointly through our Profitable Liquidity Score (PLS) should provide incremental information about expected returns beyond examining either characteristic in isolation. The PLS specifically captures firms that deviate from the typical profitability-liquidity relationship observed over their life cycles.

Our empirical analysis reveals that PLS strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio formed on PLS quintiles generates a monthly alpha of 32 basis points (t-statistic = 3.52) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.40 before trading costs and 0.36 after accounting for transaction costs following Novy-Marx and Velikov (2016).

Importantly, the predictive power of PLS persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 39 basis points (t-statistic = 3.62) in the largest size quintile. This suggests that the effect is not merely a small-stock phenomenon and is likely exploitable by institutional investors.

The signal's robustness is further demonstrated by its performance relative to closely related anomalies. Controlling for the six most similar predictors identified through correlation and spanning tests, PLS continues to generate a significant monthly alpha of 38 basis points (t-statistic = 3.97). This indicates that PLS captures a distinct source of predictable variation in returns.

Our study makes several contributions to the asset pricing literature. First, we extend work on the interaction between firm characteristics, building on Asness et al. (2018) who show that combining value and momentum signals yields superior performance. Our findings demonstrate that considering profitability and liquidity jointly provides novel insights beyond their individual effects documented by Novy-Marx (2013) and Pastor and Stambaugh (2003).

Second, we contribute to the growing literature on characteristic screening and portfolio formation methodologies. While Green et al. (2013) show that many accounting-based anomalies are not robust to transaction costs, our PLS strategy remains profitable after accounting for trading frictions. The signal's effectiveness among large-cap stocks also addresses concerns about anomaly returns being concentrated in illiquid securities.

Finally, our results have implications for both academic research and investment practice. For academics, we demonstrate the importance of considering characteristic interactions when studying cross-sectional return prediction. For practitioners, we provide a novel signal that can be implemented in a cost-effective manner and remains robust across different market segments.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the ratio of cash holdings to earnings before interest, taxes, depreciation, and amortization (EBITDA). 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 CH for cash holdings and item EBITDA for earnings. Cash holdings (CH) represent the firm's cash and short-term investments, which are the most liquid assets on a company's balance sheet, including cash on hand and marketable securities. EBITDA, on the other hand, provides a measure of core operating performance by isolating operating income from non-operating expenses and tax effects. The construction of the signal follows a straightforward ratio format, where we divide CH by EBITDA for each firm in each year of our sample. This ratio captures the relative scale of a firm's most liquid assets against its operational income, offering insight into how effectively the firm generates earnings relative to its cash reserves. By focusing on this relationship, the signal aims to reflect aspects of liquidity management and operational efficiency in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both CH and EBITDA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the PLS signal. Panel A plots the time-series of the mean, median, and interquartile range for PLS. On average, the cross-sectional mean (median) PLS is 0.26 (0.29) over the 1971 to 2023 sample, where the starting date is determined by the availability of the input PLS data. The signal's interquartile range spans -0.97 to 1.43. Panel B of Figure 1 plots the time-series of the coverage of the PLS signal for the CRSP universe. On average, the PLS signal is available for 6.96% of CRSP names, which on average make up 7.44% of total market capitalization.

4 Does PLS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on PLS 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 PLS portfolio and sells the low PLS 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 PLS strategy earns an average return of 0.30% per month with a t-statistic of 2.90. The annualized Sharpe ratio of the strategy is 0.40. The alphas range from 0.14% to 0.32% per month and have t-statistics exceeding 1.54 everywhere. The lowest alpha is with respect to the

FF3 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 0.17, with a t-statistic of 8.12 on the MKT 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 494 stocks and an average market capitalization of at least $1,360 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 27 bps/month with a t-statistics of 2.77. Out of the twenty-five alphas reported in Panel A, the t-statistics for eleven exceed two, and for six 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 16-33bps/month. The lowest return, (16 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.30. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the PLS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-one cases, and significantly expands the achievable frontier in six cases.

Table 3 provides direct tests for the role size plays in the PLS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and PLS, as well as average returns and alphas for long/short trading PLS 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 PLS strategy achieves an average return of 26 bps/month with a t-statistic of 2.17. Among these large cap stocks, the alphas for the PLS strategy relative to the five most common factor models range from 9 to 39 bps/month with t-statistics between 0.81 and 3.62.

5 How does PLS perform relative to the zoo?

Figure 2 puts the performance of PLS 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 PLS strategy falls in the distribution. The PLS strategy's gross (net) Sharpe ratio of 0.40 (0.36) is greater than 82% (94%) 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 PLS strategy (red line).[2] Ignoring trading costs, a $1 invested in the PLS strategy would have yielded $4.06 which ranks the PLS strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a $1 invested in the PLS strategy would have yielded $3.29 which ranks the PLS strategy in the top 2% 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 PLS relative to those. Panel A shows that the PLS strategy gross alphas fall between the 32 and 82 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 197106 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 PLS strategy has a positive net generalized alpha for five out of the five factor models. In these cases PLS ranks between the 56 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

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

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

PLS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on PLS 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 PLS signal in these Fama-MacBeth regressions exceed -0.40, with the minimum t-statistic occurring when controlling for Realized (Total) Volatility. Controlling for all six closely related anomalies, the t-statistic on PLS is -0.40.

Similarly, Table 5 reports results from spanning tests that regress returns to the PLS 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 PLS strategy earns alphas that range from 32-37bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.52, which is achieved when controlling for Realized (Total) Volatility. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the PLS trading strategy achieves an alpha of 38bps/month with a t-statistic of 3.97.

7 Does PLS add relative to the whole zoo?

Finally, we can ask how much adding PLS 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 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the PLS signal.[4] We consider

[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 capital-

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 156-anomaly combination strategy grows to $1203.74, while $1 investment in the combination strategy that includes PLS grows to $1438.99.

8 Conclusion

Our comprehensive analysis of the Profitable Liquidity Score (PLS) demonstrates its significant value as a robust predictor of cross-sectional stock returns. The empirical results reveal that a value-weighted long/short strategy based on PLS generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.40 (0.36 after transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that PLS captures unique information content not explained by traditional pricing factors or known anomalies.

Particularly noteworthy is the signal's ability to maintain its predictive power when accounting for transaction costs, yielding a net monthly alpha of 24 basis points relative to the Fama-French five-factor model plus momentum. The signal's robustness is further emphasized by its significant alpha of 38 basis points per month when controlling for six closely related anomalies, indicating that PLS provides incremental information beyond existing measures of idiosyncratic risk, price levels, volatility, and profitability metrics.

However, several limitations warrant consideration. First, our analysis focuses

ization on CRSP in the period for which PLS is available.

primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across different market regimes. Future research could explore the signal's performance in international markets, its interaction with other anomalies, and its effectiveness during specific market conditions or economic cycles. Additionally, investigating the underlying economic mechanisms driving the PLS premium could provide valuable insights into market efficiency and asset pricing theory.

In conclusion, our findings suggest that PLS represents a valuable addition to the quantitative investor's toolkit, offering meaningful economic gains even after accounting for transaction costs and existing factors. The results contribute to our understanding of market efficiency and the ongoing debate about the proliferation of return predictors in asset pricing research.

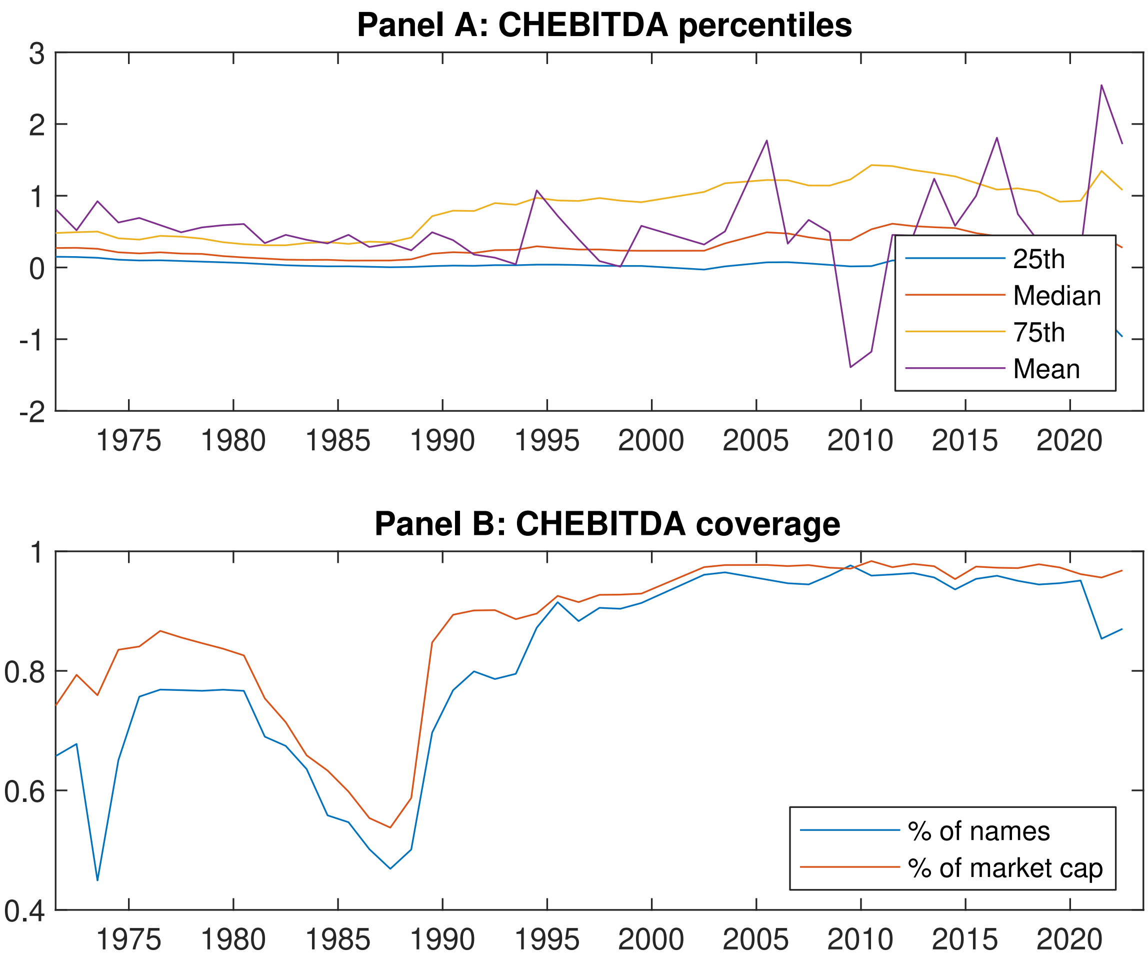

Figure 1: Times series of PLS percentiles and coverage.
This figure plots descriptive statistics for PLS. Panel A shows cross-sectional percentiles of PLS over the sample. Panel B plots the monthly coverage of PLS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on PLS. 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 197106 to 202306.

Panel A: Excess returns and alphas on PLS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.55	0.63	0.66	0.74	0.30
	[2.50]	[3.16]	[3.42]	[3.29]	[3.30]	[2.90]
α_{CAPM}	-0.11	0.01	0.05	0.02	0.04	0.15
	[-1.99]	[0.15]	[0.99]	[0.47]	[0.55]	[1.59]
α_{FF3}	-0.11	-0.02	0.02	0.03	0.03	0.14
	[-1.96]	[-0.30]	[0.51]	[0.57]	[0.48]	[1.54]
α_{FF4}	-0.14	-0.00	-0.00	0.06	0.07	0.21
	[-2.46]	[-0.09]	[-0.08]	[1.10]	[1.09]	[2.27]
α_{FF5}	-0.09	-0.16	-0.08	-0.00	0.19	0.28
	[-1.54]	[-3.41]	[-1.72]	[-0.05]	[3.35]	[3.07]
α_{FF6}	-0.11	-0.14	-0.09	0.02	0.21	0.32
	[-1.97]	[-2.97]	[-2.03]	[0.44]	[3.62]	[3.52]
Panel B: Fama and French (2018) 6-factor model loadings for PLS-sorted portfolios						
β_{MKT}	0.93	0.96	1.02	1.05	1.10	0.17
	[69.84]	[88.48]	[96.34]	[88.92]	[82.64]	[8.12]
β_{SMB}	-0.00	-0.06	0.02	0.09	0.12	0.12
	[-0.10]	[-3.40]	[1.19]	[5.19]	[5.97]	[3.82]
β_{HML}	0.00	-0.00	0.01	-0.06	0.09	0.08
	[0.07]	[-0.04]	[0.74]	[-2.55]	[3.42]	[2.11]
β_{RMW}	-0.09	0.31	0.20	0.09	-0.29	-0.19
	[-3.57]	[14.92]	[9.77]	[3.77]	[-11.02]	[-4.70]
β_{CMA}	0.03	0.13	0.11	0.03	-0.22	-0.25
	[0.73]	[4.24]	[3.54]	[0.81]	[-5.69]	[-4.05]
β_{UMD}	0.04	-0.03	0.02	-0.04	-0.03	-0.06
	[2.82]	[-2.63]	[2.12]	[-3.14]	[-1.96]	[-3.01]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1075	494	558	681	1079	
me ($\$10^6$)	1360	2431	2649	2304	1881	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the PLS 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 197106 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	0.30	0.15	0.14	0.21	0.28	0.32
			[2.90]	[1.59]	[1.54]	[2.27]	[3.07]	[3.52]
Quintile	NYSE	EW	0.36	0.43	0.33	0.21	0.09	0.01
			[3.01]	[3.65]	[3.02]	[1.99]	[0.92]	[0.09]
Quintile	Name	VW	0.38	0.45	0.26	0.27	-0.07	-0.05
			[2.24]	[2.65]	[1.79]	[1.78]	[-0.56]	[-0.38]
Quintile	Cap	VW	0.27	0.12	0.13	0.18	0.30	0.33
			[2.77]	[1.37]	[1.60]	[2.13]	[3.70]	[3.95]
Decile	NYSE	VW	0.36	0.29	0.19	0.24	0.14	0.18
			[2.92]	[2.36]	[1.58]	[2.04]	[1.12]	[1.52]
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	0.27	0.12	0.11	0.15	0.20	0.24
			[2.64]	[1.25]	[1.20]	[1.65]	[2.25]	[2.64]
Quintile	NYSE	EW	0.16	0.21	0.11	0.04		
			[1.30]	[1.69]	[0.95]	[0.40]		
Quintile	Name	VW	0.33	0.41	0.24	0.24		
			[1.98]	[2.39]	[1.62]	[1.63]		
Quintile	Cap	VW	0.25	0.09	0.11	0.14	0.23	0.25
			[2.51]	[1.06]	[1.26]	[1.60]	[2.82]	[3.06]
Decile	NYSE	VW	0.33	0.26	0.16	0.20	0.10	0.14
			[2.63]	[2.07]	[1.38]	[1.66]	[0.79]	[1.16]

Table 3: Conditional sort on size and PLS

This table presents results for conditional double sorts on size and PLS. 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 PLS. 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 PLS and short stocks with low PLS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197106 to 202306.

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

	PLS Quintiles					PLS Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.21	0.49	0.73	0.82	0.87	0.66	0.81	0.62	0.55	0.24	0.21
	[0.63]	[1.74]	[2.90]	[3.33]	[3.37]	[3.84]	[4.83]	[4.25]	[3.69]	[1.86]	[1.57]
(2)	0.48	0.71	0.80	0.76	0.84	0.36	0.49	0.33	0.32	0.12	0.12
	[1.62]	[2.99]	[3.32]	[3.07]	[3.53]	[2.61]	[3.60]	[2.74]	[2.62]	[1.04]	[1.07]
(3)	0.55	0.68	0.78	0.88	0.65	0.10	0.11	0.02	-0.07	-0.13	-0.19
	[2.20]	[3.19]	[3.33]	[3.72]	[2.72]	[0.79]	[0.91]	[0.14]	[-0.53]	[-1.08]	[-1.53]
(4)	0.59	0.65	0.65	0.78	0.80	0.21	0.09	0.10	0.12	0.21	0.22
	[2.93]	[3.26]	[3.07]	[3.45]	[3.24]	[1.86]	[0.82]	[1.01]	[1.11]	[2.06]	[2.07]
(5)	0.44	0.53	0.56	0.59	0.70	0.26	0.09	0.11	0.18	0.35	0.39
	[2.54]	[3.17]	[3.09]	[2.93]	[3.14]	[2.17]	[0.81]	[1.04]	[1.65]	[3.32]	[3.62]

Panel B: Portfolio average number of firms and market capitalization

	PLS Quintiles Average n					PLS Quintiles Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	442	439	451	453	453	33	34	44	44	41
(2)	120	120	120	121	121	63	65	66	67	65
(3)	83	83	83	83	83	107	110	112	110	108
(4)	67	67	67	68	67	223	230	229	232	232
(5)	59	59	59	59	59	1284	1923	2021	1710	1471

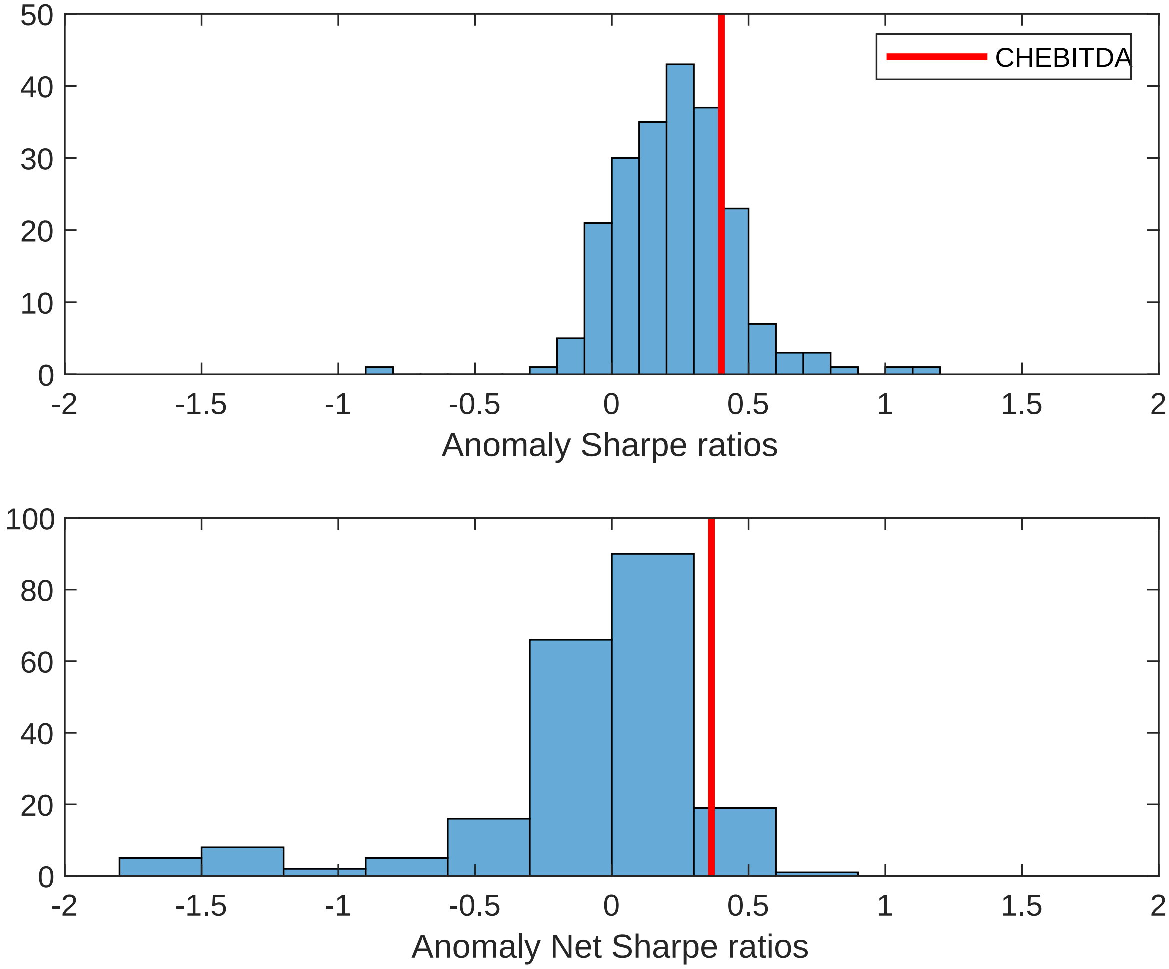

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the PLS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

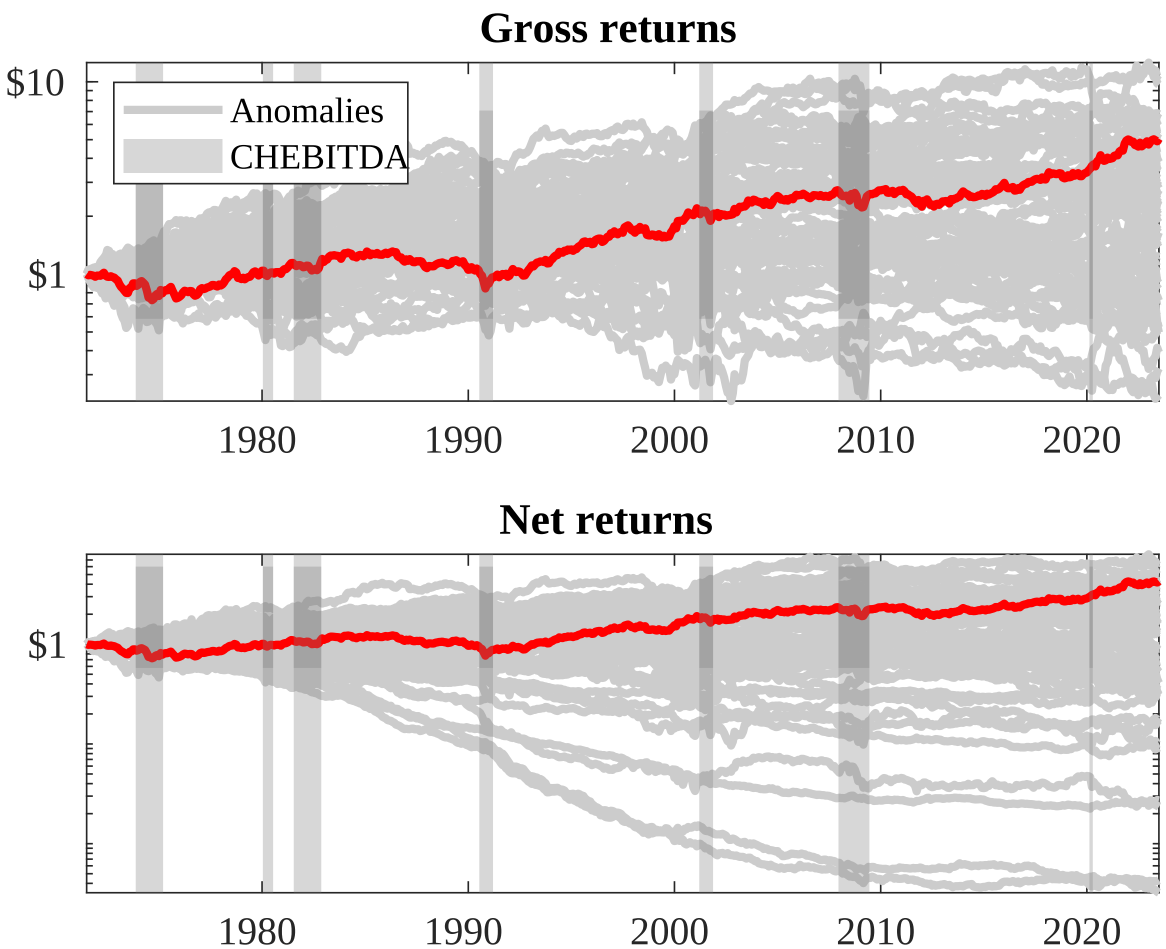

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the PLS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

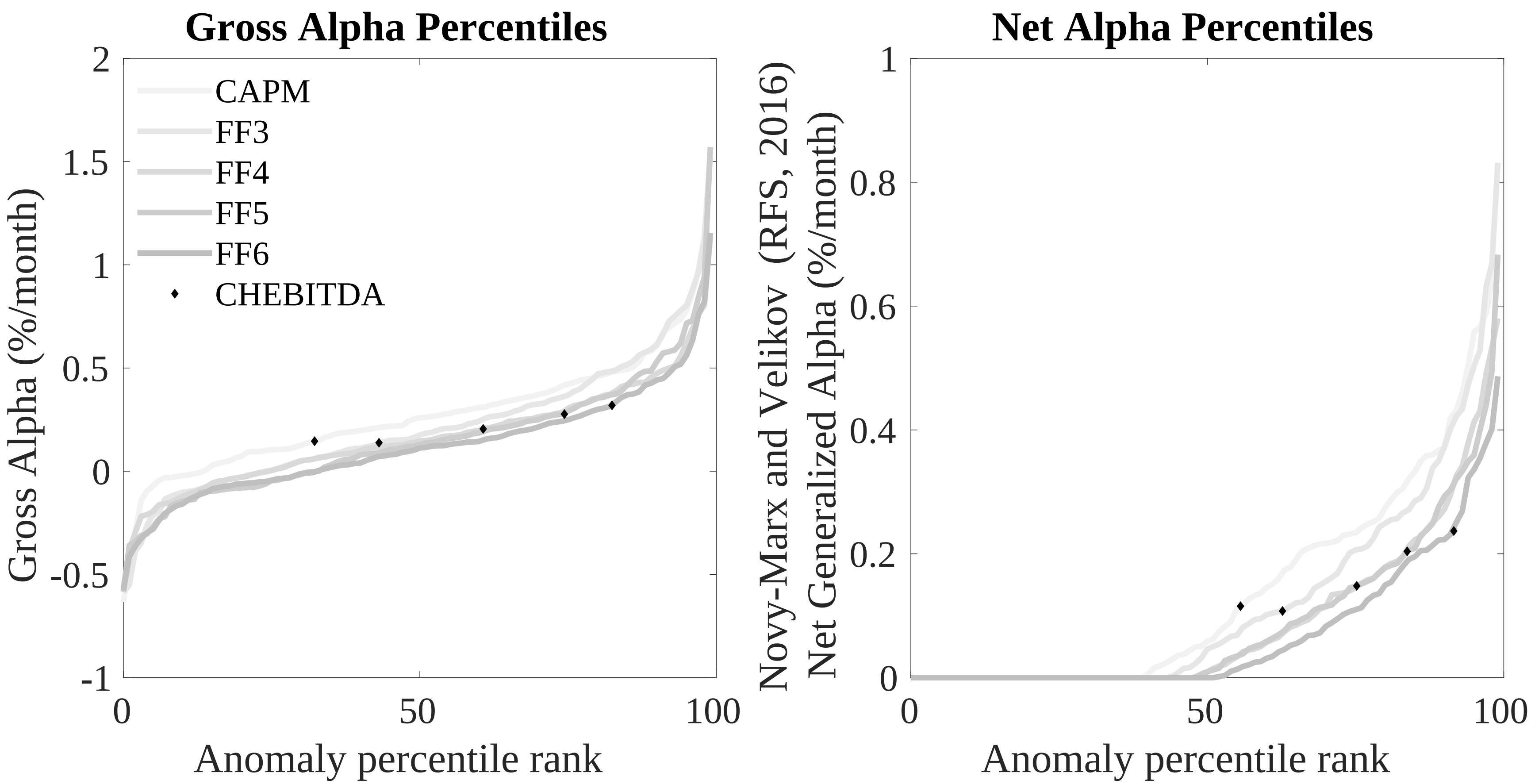

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the PLS trading strategy alphas (diamonds). The strategies are constructed using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

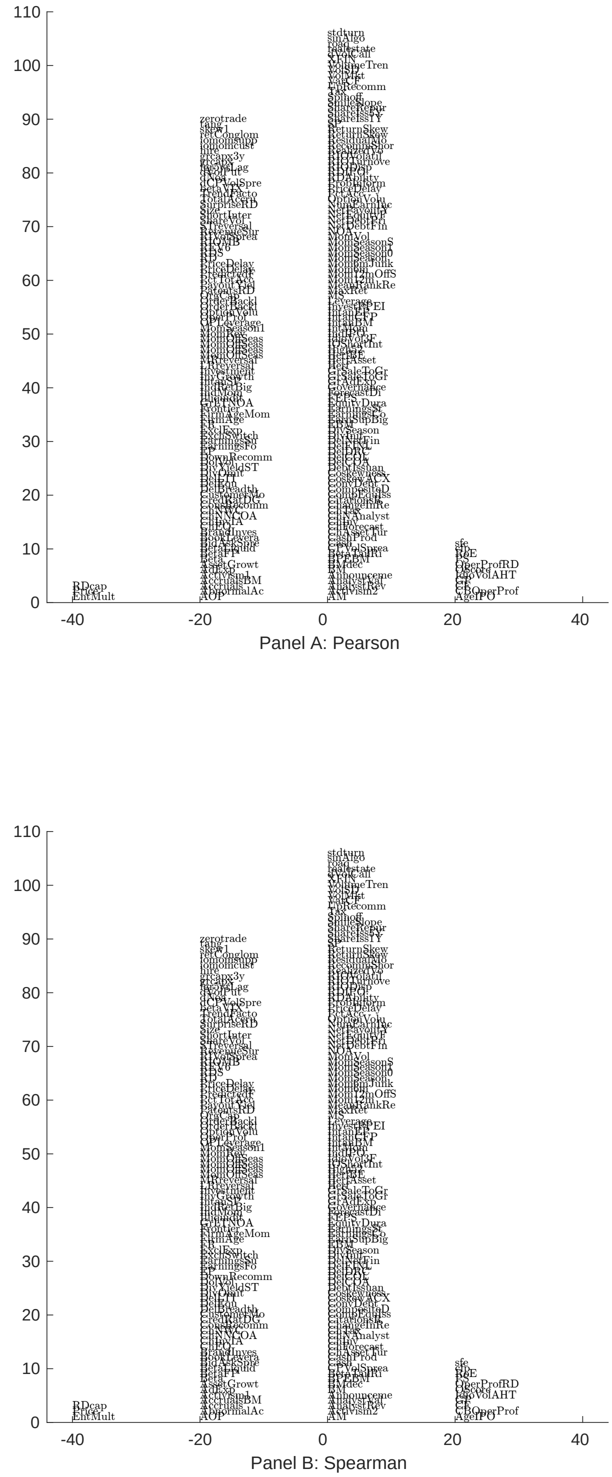

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with PLS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

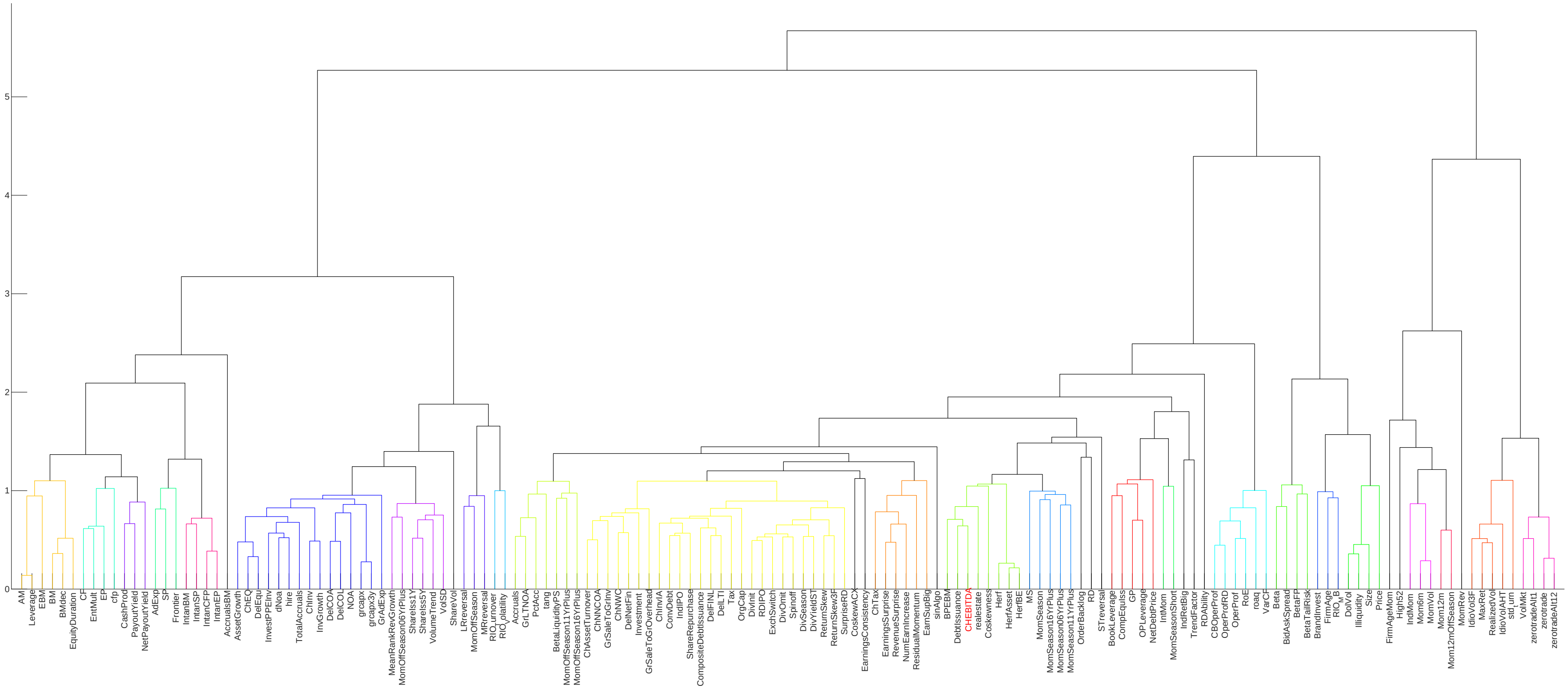

Figure 6: Agglomerative hierarchical cluster plot

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

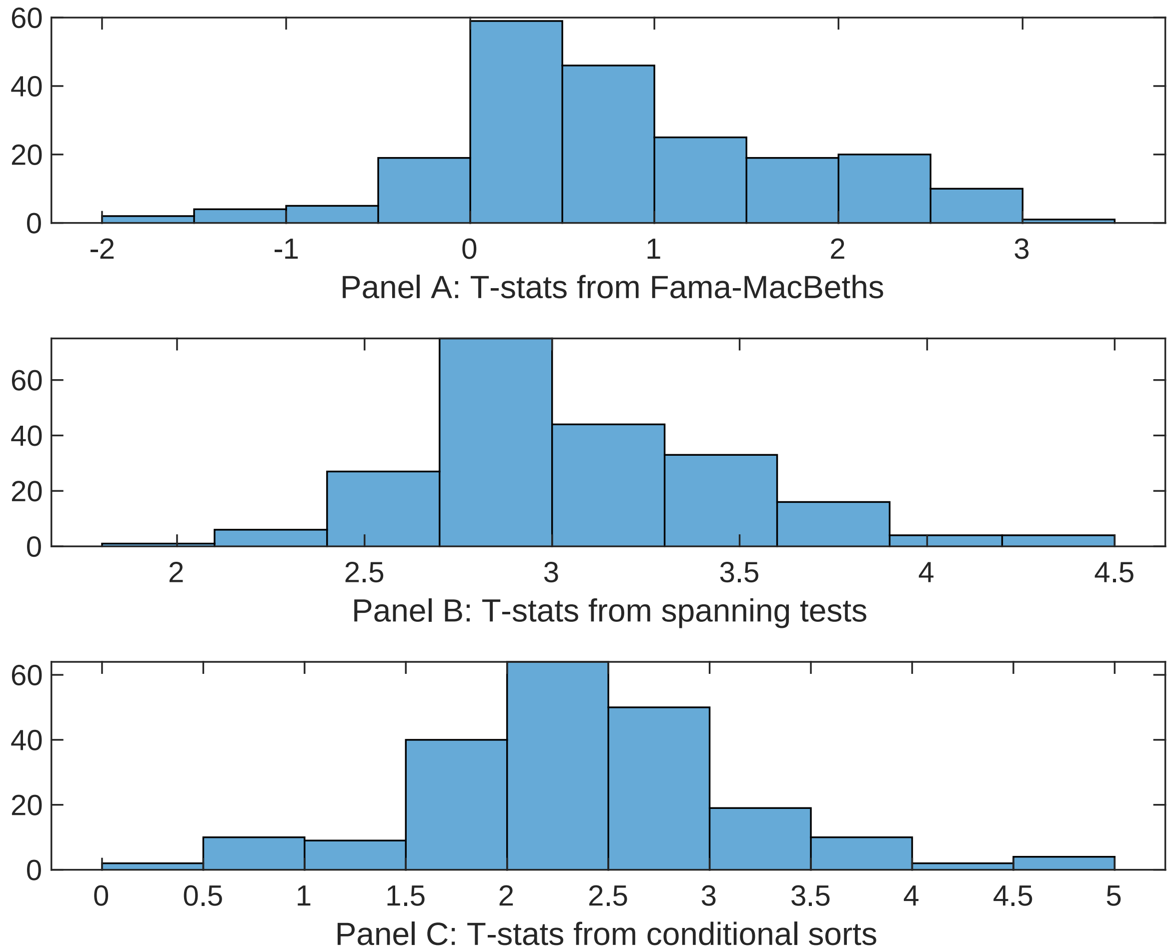

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of PLS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PLS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PLS} PLS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{PLS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 PLS. Stocks are finally grouped into five PLS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted PLS 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 PLS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{PLS} PLS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Price, Realized (Total) Volatility, net income / book equity, Analyst earnings per share. 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 197106 to 202306.

Intercept	0.13	0.14	0.12	0.15	0.12	0.10	0.17
	[7.11]	[7.65]	[4.10]	[8.33]	[4.73]	[3.46]	[8.80]
PLS	-0.22	-0.25	0.35	-0.33	0.35	0.58	-0.35
	[-0.29]	[-0.31]	[0.37]	[-0.40]	[0.36]	[0.58]	[-0.40]
Anomaly 1	0.90						-0.54
	[1.65]						[-0.91]
Anomaly 2		0.15					0.95
		[3.50]					[0.79]
Anomaly 3			0.59				0.20
			[1.23]				[5.52]
Anomaly 4				0.14			0.17
				[3.47]			[1.49]
Anomaly 5					0.94		0.13
					[0.08]		[1.35]
Anomaly 6						0.83	0.16
						[1.46]	[4.48]
# months	619	619	624	619	624	564	564
$\bar{R}^2(\%)$	2	2	1	2	0	2	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the PLS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{PLS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Price, Realized (Total) Volatility, net income / book equity, Analyst earnings per share. 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 197106 to 202306.

Intercept	0.33	0.33	0.32	0.33	0.32	0.37	0.38
	[3.60]	[3.66]	[3.52]	[3.60]	[3.55]	[3.92]	[3.97]
Anomaly 1	-4.56						-1.94
	[-1.49]						[-0.37]
Anomaly 2		-5.74					4.23
		[-1.82]					[0.67]
Anomaly 3			-0.53				-2.58
			[-0.14]				[-0.59]
Anomaly 4				-6.65			-10.23
				[-2.53]			[-2.04]
Anomaly 5					-7.39		-3.93
					[-1.46]		[-0.65]
Anomaly 6						3.72	8.55
						[0.98]	[1.94]
mkt	15.49	15.28	17.63	14.05	16.40	18.28	14.92
	[6.37]	[6.43]	[8.03]	[5.70]	[7.29]	[7.61]	[5.56]
smb	8.40	8.01	13.33	8.11	10.27	13.09	11.82
	[1.92]	[1.94]	[2.66]	[2.20]	[2.86]	[3.09]	[2.14]
hml	10.81	11.11	9.15	11.68	8.21	8.26	9.64
	[2.61]	[2.68]	[2.26]	[2.83]	[2.03]	[1.88]	[2.07]
rmw	-16.33	-16.42	-20.48	-15.16	-13.48	-23.14	-19.01
	[-3.24]	[-3.47]	[-4.46]	[-3.26]	[-2.19]	[-3.95]	[-2.70]
cma	-23.93	-23.54	-24.29	-22.51	-25.86	-26.77	-24.28
	[-3.82]	[-3.76]	[-3.98]	[-3.59]	[-4.18]	[-4.14]	[-3.55]
umd	-5.61	-5.34	-6.77	-4.99	-6.38	-6.66	-7.30
	[-2.60]	[-2.46]	[-2.29]	[-2.31]	[-3.06]	[-2.85]	[-2.27]
# months	620	620	624	620	624	565	565
$\bar{R}^2(\%)$	30	31	30	31	30	28	29

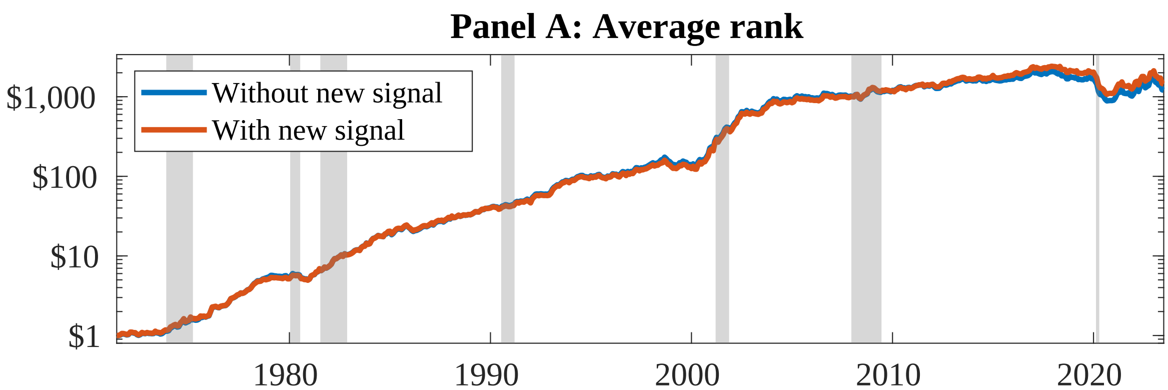

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines indicate combination trading strategies that utilize the 156 anomalies as well as PLS. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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