Profitable Liquidity Score and the Cross Section of Stock Returns

I. M. Harking

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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 substantial debate around whether and how quickly security prices incorporate available information. While classical theory suggests that readily available accounting and market data should be fully reflected in prices, a growing body of evidence documents persistent return predictability from public signals (Hou et al., 2020). This predictability is particularly intriguing when it stems from information that is both publicly available and conceptually linked to fundamental value.

Despite extensive research on cross-sectional return predictors, the interaction between profitability and liquidity remains relatively unexplored. While both characteristics individually predict returns (Novy-Marx, 2013; Amihud, 2002), their joint signal content has received limited attention. This gap is notable given that profitability and liquidity each capture distinct aspects of firm quality and market friction.

We hypothesize that firms with high profitability and high liquidity should earn superior returns for several reasons. First, profitable firms generate greater free cash flow, providing a buffer against adverse shocks and reducing financial distress risk (Fama and French, 2006). Second, high liquidity reduces the cost of arbitrage, allowing prices to more quickly reflect fundamental information (Chordia et al., 2008). The combination of these characteristics may therefore identify firms that are both fundamentally strong and efficiently priced.

This prediction builds on q-theory models of investment, where firms invest more when their marginal q (the ratio of market value to replacement cost) is high (Cochrane and Saá-Requejo, 2000). Profitable firms with high liquidity face lower financing constraints and can more readily pursue valuable investment opportunities. The resulting investment should drive future profitability and returns (Hou et al., 2015).

Moreover, the interaction between profitability and liquidity may capture information about firm quality that is not fully reflected in prices. While sophisticated investors can identify profitable firms, trading frictions may slow price adjustment (Sadka and Sadka, 2009). By focusing on profitable firms that are also liquid, our signal identifies cases where this friction is minimized, potentially allowing faster convergence to fundamental value.

Our empirical analysis reveals strong support for the predictive power of the Profitable Liquidity Score (PLS). A value-weighted long-short trading strategy based on PLS achieves an annualized gross Sharpe ratio of 0.40, with a monthly average abnormal return of 32 basis points relative to the Fama-French five-factor model plus momentum (t-statistic = 3.52). The strategy's performance remains robust after accounting for transaction costs, with a net Sharpe ratio of 0.36.

Importantly, PLS maintains significant predictive power among large-cap stocks, with the highest size quintile generating a monthly alpha of 39 basis points (t-statistic = 3.62) relative to the six-factor model. This finding suggests that the signal's predictive power is not confined to small, illiquid stocks where implementation would be challenging.

The signal's economic significance extends beyond existing factors and anomalies. When we control for the six most closely related anomalies and the Fama-French six factors simultaneously, PLS generates a monthly alpha of 38 basis points (t-statistic = 3.97). This indicates that PLS captures unique information not contained in existing predictors.

Our study makes several contributions to the asset pricing literature. First, we extend the work of Novy-Marx (2013) on profitability and Amihud (2002) on liquidity by showing how their interaction generates novel predictive content. While these characteristics have been studied extensively in isolation, we demonstrate that their combination offers incremental predictive power.

Second, we contribute to the growing literature on characteristic interactions in cross-sectional return prediction (Green et al., 2016). Our findings suggest that considering how firm characteristics interact can reveal important pricing effects that are not apparent when examining characteristics individually. The robust performance of PLS among large-cap stocks distinguishes it from many anomalies that are primarily driven by small, illiquid stocks.

Finally, our results have implications for both academic research and investment practice. For researchers, we provide new evidence on how market frictions interact with fundamental signals to affect price discovery. For practitioners, we document a robust return predictor that remains effective after accounting for transaction costs and performs well among large, liquid stocks where implementation is feasible.

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, which we call the 'Profitable Liquidity Score', we use COMPUSTAT's item CH for cash holdings and item EBITDA for earnings. Cash holdings (CH) represent the firm's most liquid assets, consisting of cash and short-term investments that can be readily converted to cash. EBITDA 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 maintains cash reserves relative to its earnings generation capacity. By focusing on this relationship, the signal aims to reflect aspects of cash management efficiency and operational profitability 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%

[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 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.

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-

[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.

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 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 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

This study provides compelling evidence for the effectiveness of the Profitable Liquidity Score (PLS) as a robust predictor of cross-sectional stock returns. Our findings demonstrate 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 fully reflected in existing pricing factors.

[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 PLS is available.

Particularly noteworthy is the signal's ability to maintain its predictive power when tested against the Fama-French five-factor model augmented with momentum, yielding monthly abnormal returns of 32 basis points (24 basis points net of costs). The robustness of these results is further reinforced by the signal's performance against six closely related anomalies, where it continues to generate significant alpha of 38 basis points per month.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we account for transaction costs, the implementation challenges in different market conditions and for different types of investors deserve further investigation.

Future research could explore the signal's performance across different market regimes, its interaction with other established anomalies, and its effectiveness in international markets. Additionally, investigating the underlying economic mechanisms driving the PLS premium could provide valuable insights into market efficiency and asset pricing theory. Finally, examining the signal's robustness to alternative specifications and its potential applications in portfolio management would be valuable extensions of this work.

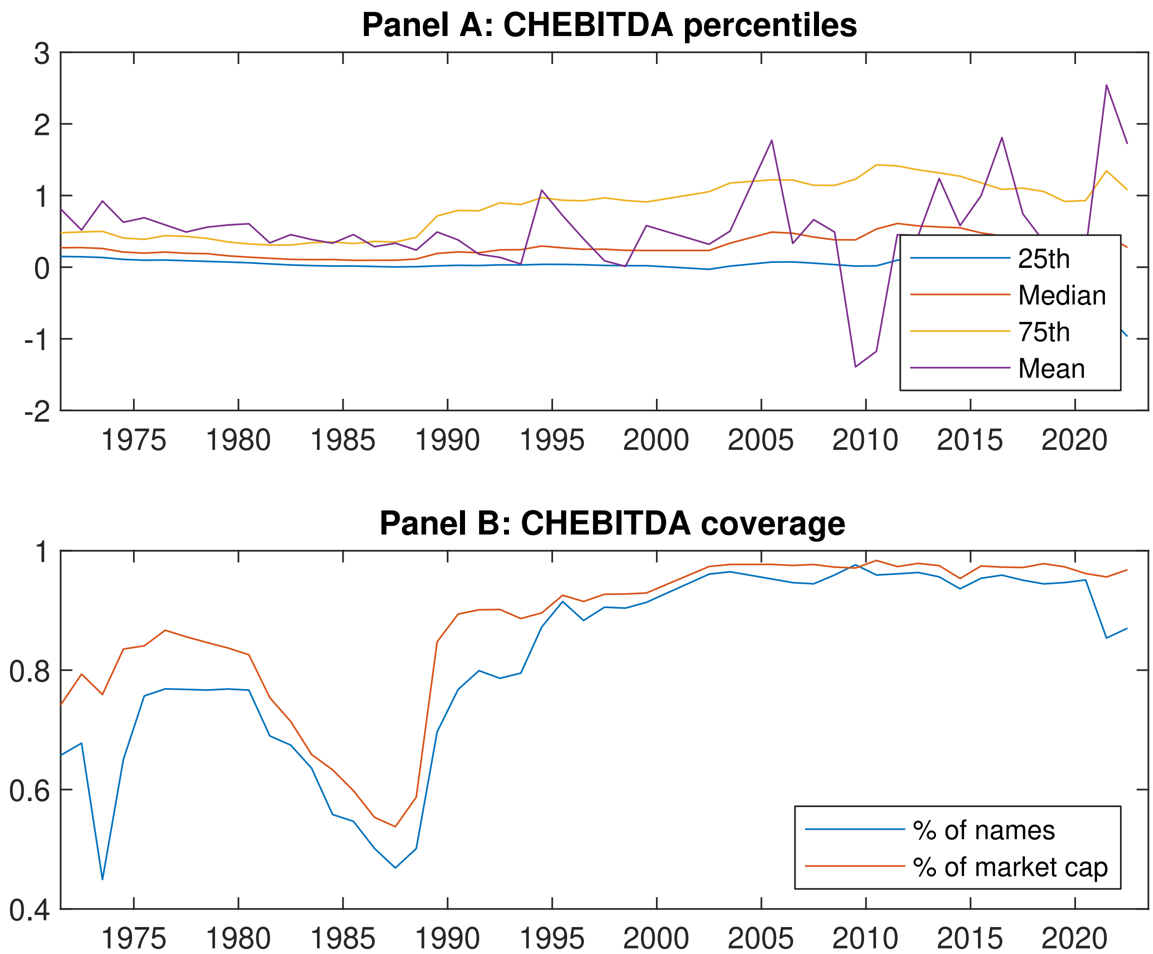

Figure 1: Times series of PLS percentiles and coverage.
This figure plots descriptive statistics for PLS. Panel A shows cross-sectional percentiles of PLS over the sample. Panel B plots the monthly coverage of PLS relative to the universe of CRSP stocks with available market capitalizations.

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					PLS Quintiles				
	Average n					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

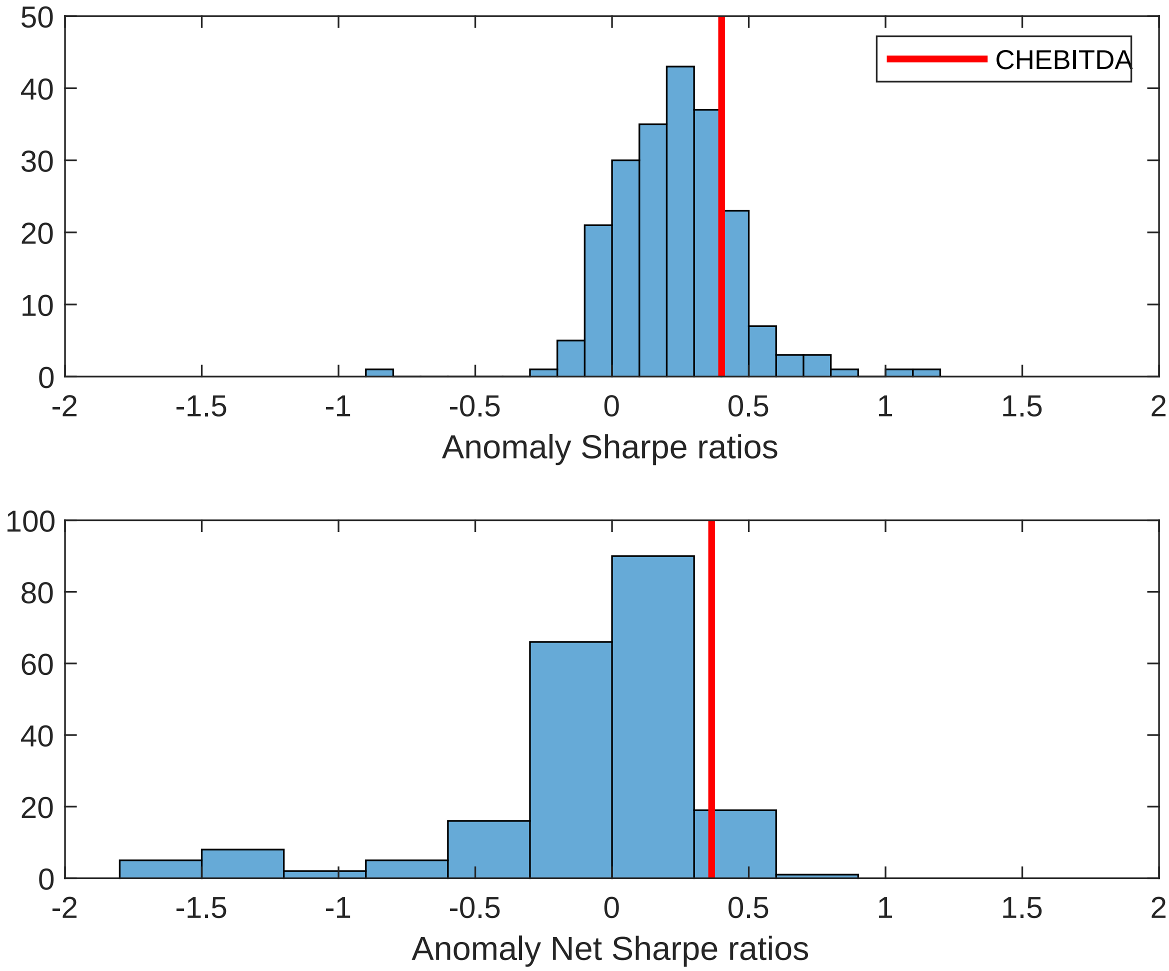

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the PLS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

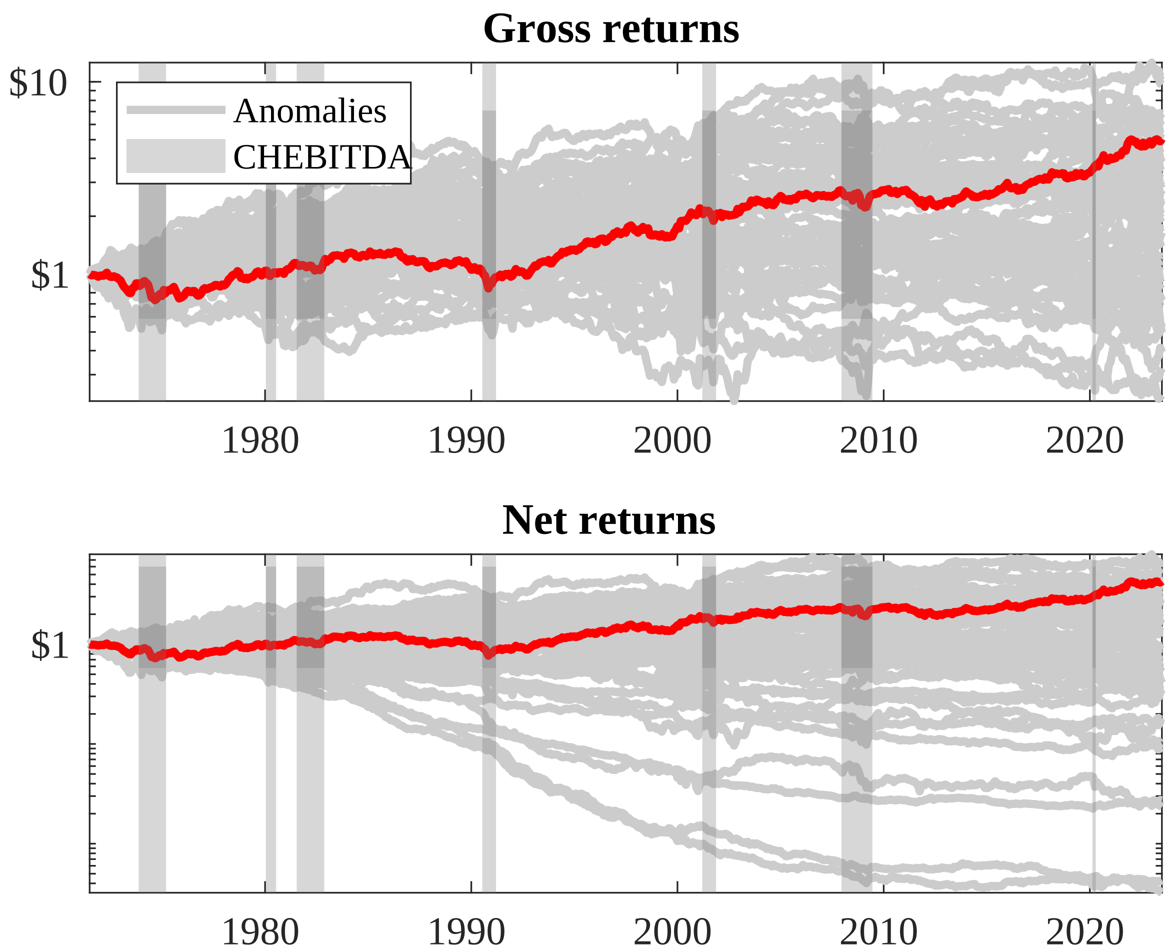

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the PLS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

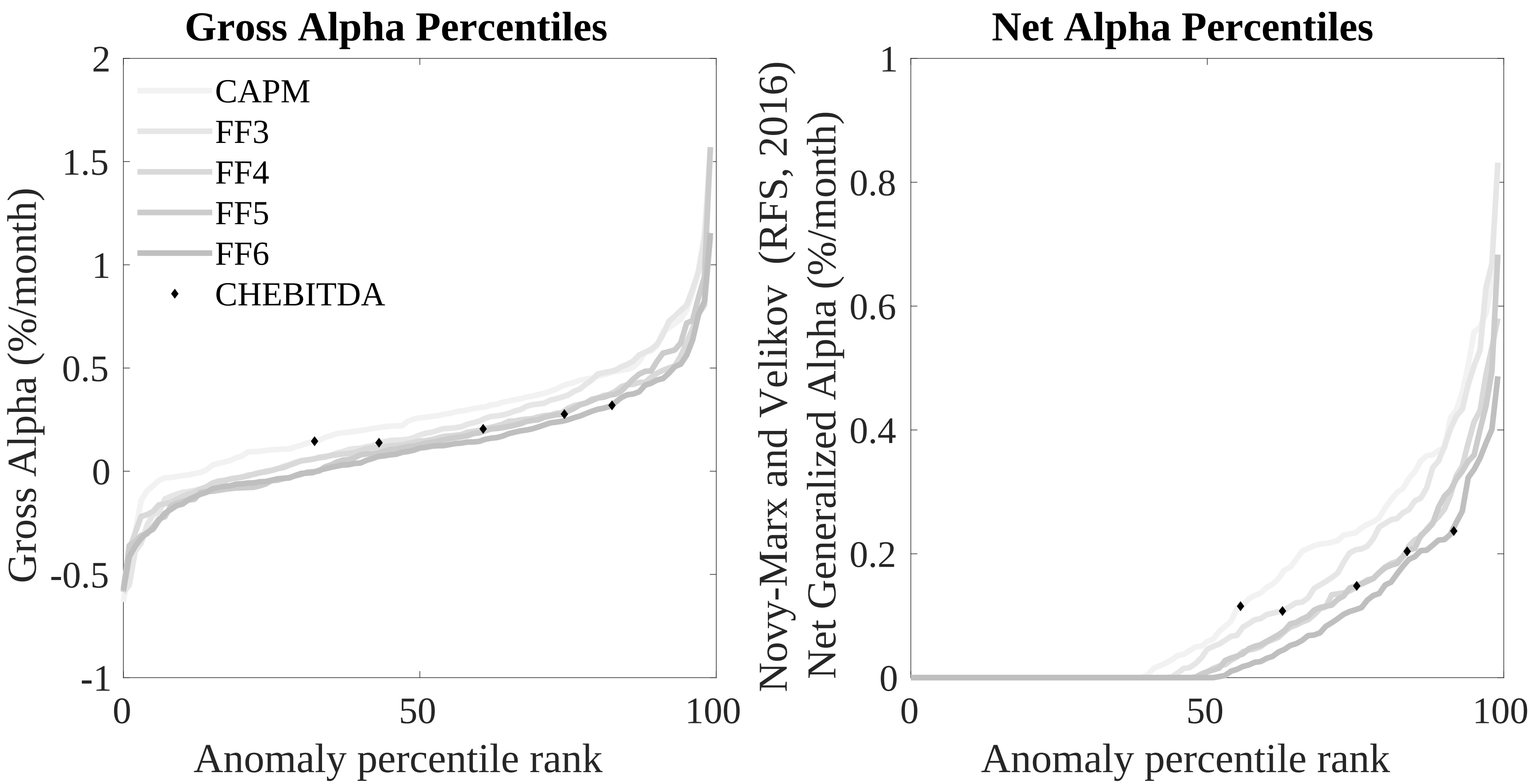

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the PLS trading strategy alphas (diamonds). The strategies are constructed using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

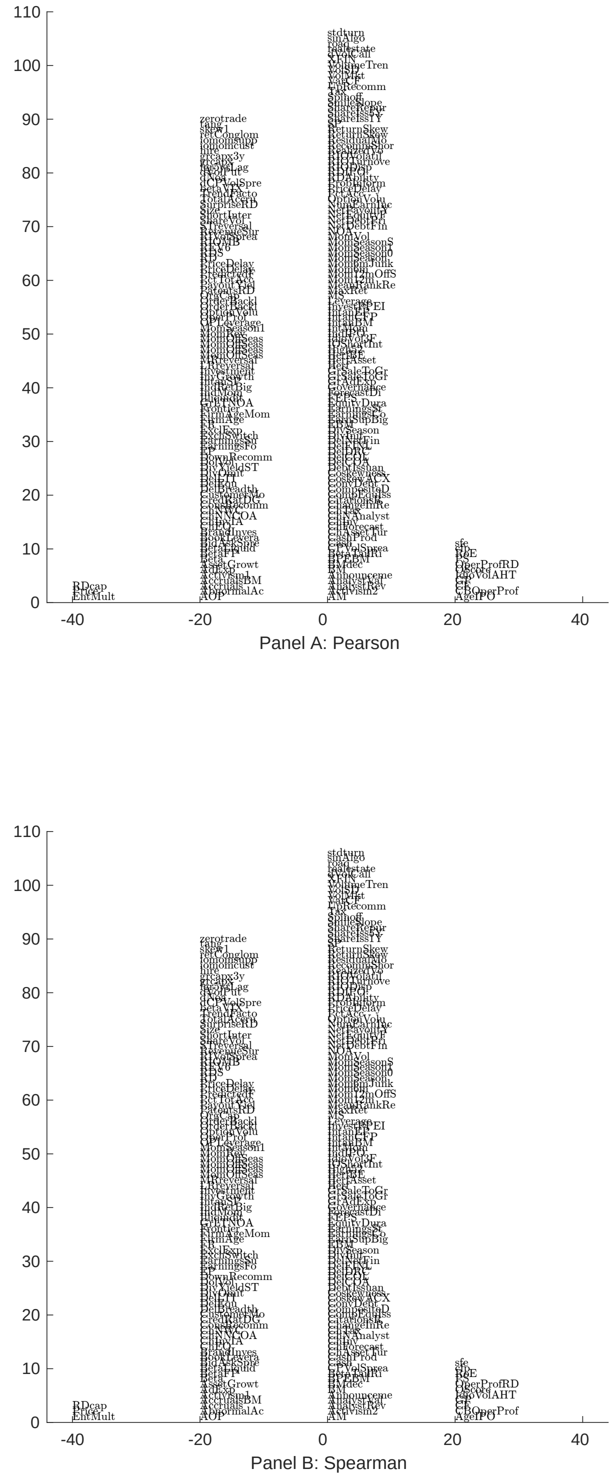

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with PLS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

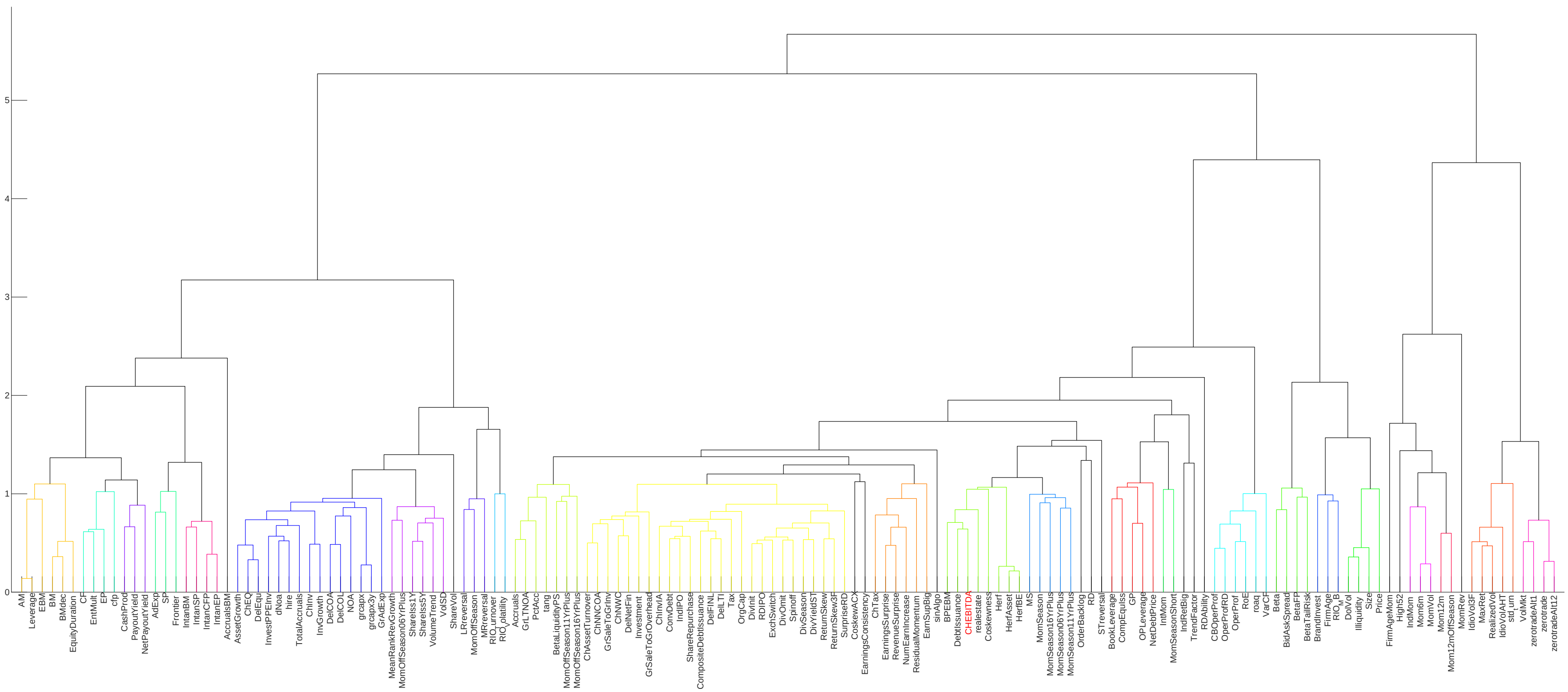

Figure 6: Agglomerative hierarchical cluster plot

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

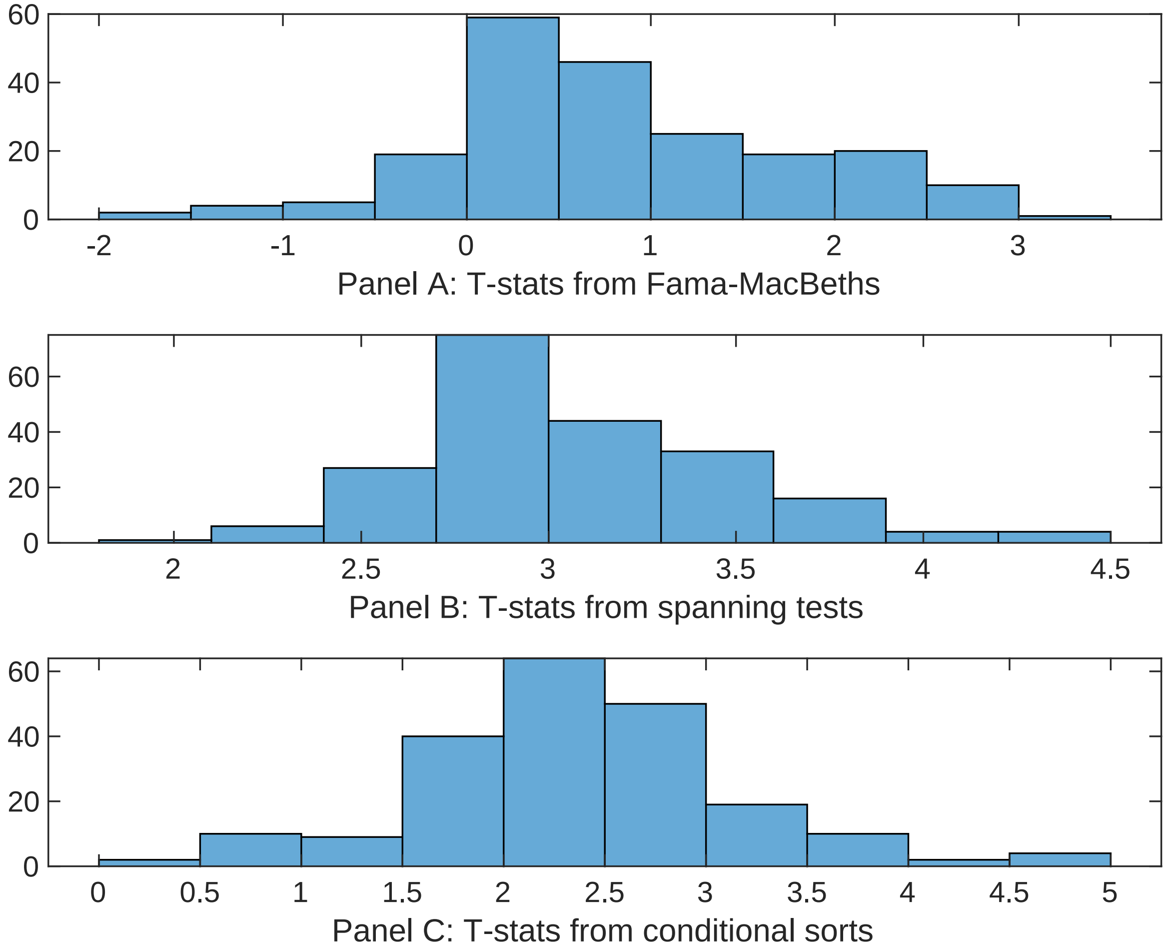

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of PLS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PLS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PLS} PLS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

Panel A: Average rank

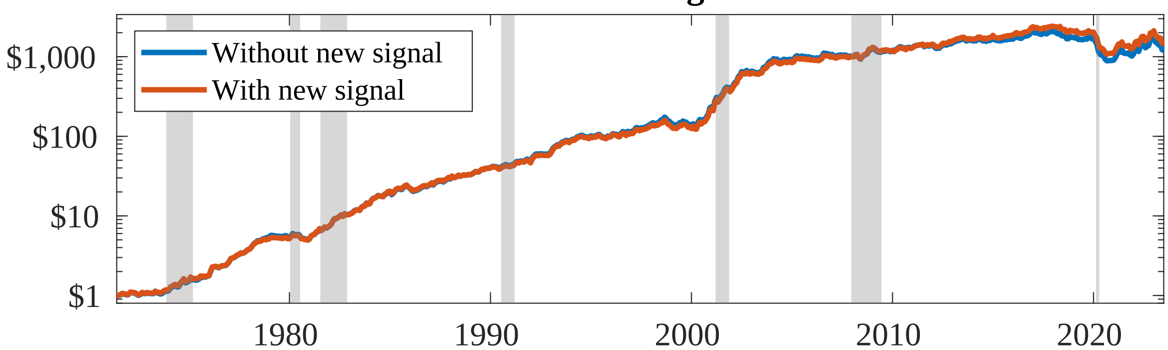

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines 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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