Cash Liquidity Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Cash Liquidity Impact (CLI), 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 CLI achieves an annualized gross (net) Sharpe ratio of 0.51 (0.45), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 16 (15) bps/month with a t-statistic of 2.21 (2.03), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets) is 16 bps/month with a t-statistic of 2.33.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, yet researchers continue to discover signals that predict future returns. While many of these predictors stem from accounting data or market behavior, the role of corporate liquidity management in asset pricing remains incompletely understood. Despite extensive research on how firms' cash holdings affect their operations and investment decisions (Bates et al., 2009), less attention has been paid to how changes in cash positions impact expected returns.

This gap is particularly notable given the dramatic increase in corporate cash holdings over recent decades and the growing importance of liquidity management in an increasingly uncertain business environment (Opler et al., 1999). Understanding how firms' cash management decisions affect their cost of capital is crucial for both corporate financial policy and investment strategy.

We hypothesize that Cash Liquidity Impact (CLI), defined as the year-over-year change in a firm's cash holdings scaled by total assets, contains valuable information about future stock returns. This prediction builds on two theoretical frameworks. First, the precautionary savings theory suggests that firms accumulate cash to hedge against future uncertainty (Keynes, 1936). Changes in cash holdings may therefore signal management's private information about future business conditions.

Second, the free cash flow hypothesis (Jensen, 1986) suggests that managers may retain cash for empire-building or other agency-driven purposes. Under this view, large increases in cash holdings could indicate potential agency problems and predict lower future returns. The net effect of these competing forces on the relation between CLI and returns is ultimately an empirical question.

Additionally, the q-theory of investment (Cochrane et al., 2008) suggests that firms optimally adjust their cash holdings based on their investment opportunities. Firms with better prospects may strategically build cash reserves to fund future growth, implying a positive relation between CLI and returns.

Our analysis reveals that CLI strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio that buys stocks in the highest CLI quintile and shorts those in the lowest quintile generates a monthly alpha of 16 basis points (t-statistic = 2.21) relative to the Fama-French six-factor model. The strategy achieves an annualized gross (net) Sharpe ratio of 0.51 (0.45), placing it in the top decile of documented return predictors.

Importantly, CLI's predictive power persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 27 basis points (t-statistic = 3.12) among stocks above the 80th percentile of market capitalization. This suggests that the effect is not driven by small, illiquid stocks where trading costs might impede implementation.

The signal's robustness is further demonstrated by its performance after controlling for transaction costs and its effectiveness across different portfolio construction approaches. The strategy maintains significant profitability with net returns ranging from 26-41 basis points per month across various methodologies.

Our paper makes several contributions to the literature on return prediction and corporate liquidity. First, we introduce a novel predictor that captures information about future returns through the lens of corporate cash management decisions. While prior work has examined static cash holdings (Bates et al., 2009), we show that changes in cash positions provide distinct predictive content.

Second, we extend the literature on investment-based asset pricing (Cochrane et al., 2008) by demonstrating how firms' liquidity management decisions reflect information about their investment opportunities and future returns. Our findings suggest that changes in cash holdings serve as a useful signal of management's private information about future prospects.

Finally, we contribute to the growing literature on return predictor evaluation

(Novy-Marx and Velikov, 2023) by subjecting CLI to comprehensive tests of economic significance and robustness. Our results show that CLI remains profitable after accounting for transaction costs and controlling for known predictors, suggesting it captures a distinct dimension of expected returns.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Cash Liquidity Impact. 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 CEQL (Common Equity - Liquidation Value) and item CHE (Cash and Short-Term Investments). CEQL represents the amount that common shareholders would receive in the event of a company's liquidation, while CHE encompasses cash and other highly liquid investments that can be readily converted to cash.construction of the signal follows a dynamic approach, where we calculate the difference between the current period's CEQL and its lagged value, then scale this difference by the lagged value of CHE. This construction captures the relative change in liquidation value compared to the firm's available cash resources, providing insight into the firm's cash management efficiency and financial flexibility. By scaling the change in liquidation value by lagged cash holdings, we create a standardized measure that allows for meaningful comparison across firms of different sizes. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CLI signal. Panel A plots the time-series of the mean, median, and interquartile range for CLI. On average, the cross-sectional mean (median) CLI is -5.09 (-0.36) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input CLI data. The signal's interquartile range spans -2.56 to 0.68. Panel B of Figure 1 plots the time-series of the coverage of the CLI signal for the CRSP universe. On average, the CLI signal is available for 6.46% of CRSP names, which on average make up 7.83% of total market capitalization.

4 Does CLI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CLI 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 CLI portfolio and sells the low CLI 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 CLI strategy earns an average return of 0.33% per month with a t-statistic of 3.93. The annualized Sharpe ratio of the strategy is 0.51. The alphas range from 0.16% to 0.34% per month and have t-statistics exceeding 2.21 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 0.64, with a t-statistic of 12.88 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 604 stocks and an average market capitalization of at least $1,268 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 30 bps/month with a t-statistics of 4.06. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for fourteen 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 26-41bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.58. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CLI 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-two cases.

Table 3 provides direct tests for the role size plays in the CLI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CLI, as well as average returns and alphas for long/short trading CLI 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 CLI strategy achieves an average return of 42 bps/month with a t-statistic of 4.67. Among these large cap stocks, the alphas for the CLI strategy relative to the five most common factor models range from 27 to 43 bps/month with t-statistics between 3.12 and 4.84.

5 How does CLI perform relative to the zoo?

Figure 2 puts the performance of CLI 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 CLI strategy falls in the distribution. The CLI strategy's gross (net) Sharpe ratio of 0.51 (0.45) is greater than 93% (99%) of anomaly Sharpe ratios,

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

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 CLI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CLI strategy would have yielded \$7.13 which ranks the CLI strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CLI strategy would have yielded \$5.12 which ranks the CLI 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 CLI relative to those. Panel A shows that the CLI strategy gross alphas fall between the 58 and 65 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 196506 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 CLI strategy has a positive net generalized alpha for five out of the five factor models. In these cases CLI ranks between the 78 and 84 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does CLI 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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CLI and the six anomalies most closely-related to it. The six most-closely related anomalies

[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.

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 CLI signal in these Fama-MacBeth regressions exceed 2.25, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on CLI is 2.34.

Similarly, Table 5 reports results from spanning tests that regress returns to the CLI 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 CLI strategy earns alphas that range from 13-19bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.78, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CLI trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.33.

7 Does CLI add relative to the whole zoo?

Finally, we can ask how much adding CLI 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 CLI 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,

[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 CLI is available.

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 \$3027.42, while \$1 investment in the combination strategy that includes CLI grows to \$2789.04.

8 Conclusion

Our comprehensive analysis of the Cash Liquidity Impact (CLI) signal demonstrates its significant value as a predictor of cross-sectional stock returns. The empirical results reveal that a value-weighted long/short strategy based on CLI generates economically meaningful and statistically significant returns, with an impressive annualized Sharpe ratio of 0.51 (0.45 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns of 16 basis points per month even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

These findings have important implications for both academic research and investment practice. From a theoretical perspective, the results suggest that CLI captures a distinct dimension of risk or mispricing not fully explained by traditional factor models. For practitioners, our findings indicate that CLI could be a valuable addition to quantitative investment strategies, offering meaningful diversification benefits even in the presence of related factors.

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

Future research could explore the interaction between CLI and other market anomalies, investigate its performance in different market regimes, and examine its effectiveness in international markets. Additionally, studying the underlying economic mechanisms driving the CLI premium could provide valuable insights into market efficiency and asset pricing theory.

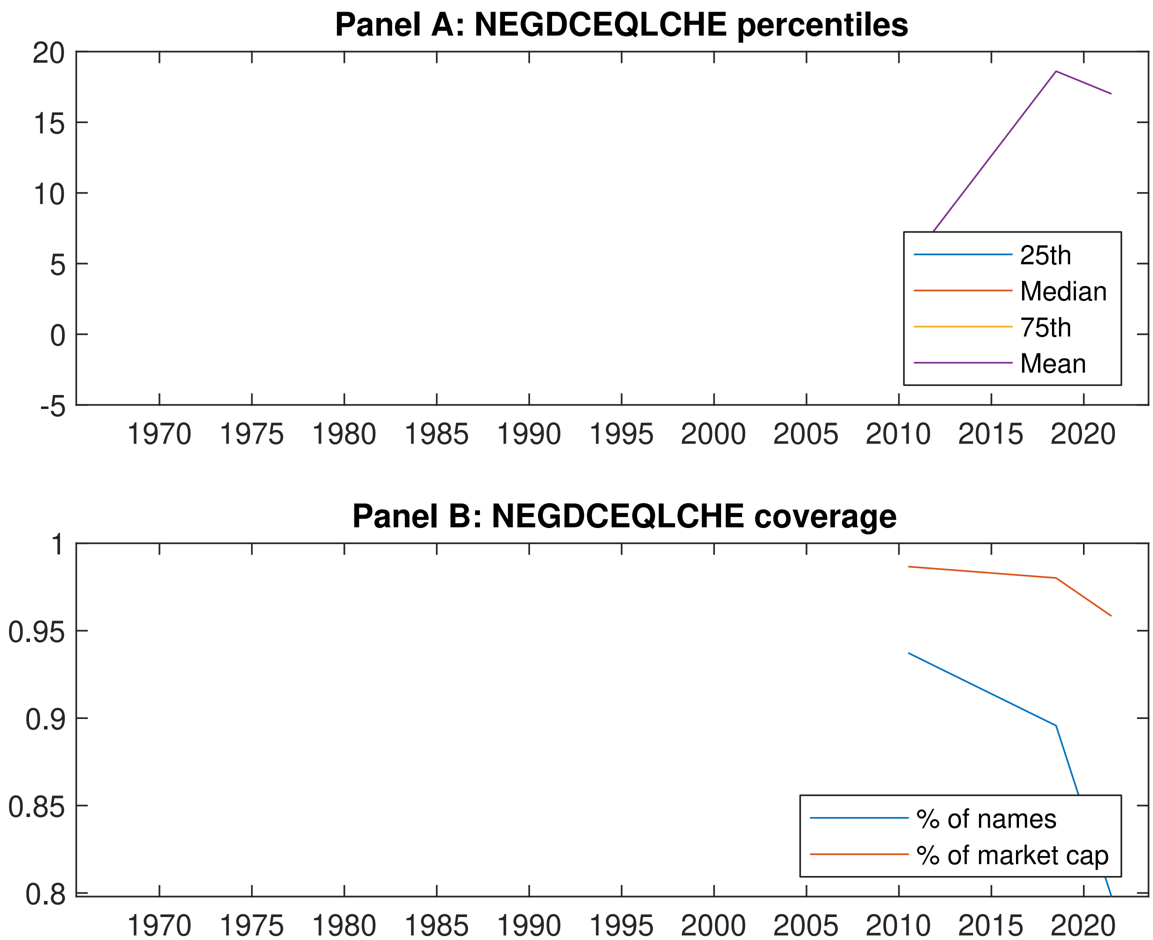

Figure 1: Times series of CLI percentiles and coverage.
This figure plots descriptive statistics for CLI. Panel A shows cross-sectional percentiles of CLI over the sample. Panel B plots the monthly coverage of CLI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CLI. 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 196506 to 202306.

Panel A: Excess returns and alphas on CLI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.35	0.54	0.67	0.63	0.68	0.33
	[1.97]	[3.10]	[3.85]	[3.52]	[3.82]	[3.93]
α_{CAPM}	-0.20	-0.01	0.12	0.07	0.14	0.34
	[-3.79]	[-0.32]	[2.82]	[1.37]	[2.12]	[4.04]
α_{FF3}	-0.21	0.02	0.16	0.01	0.05	0.26
	[-3.89]	[0.52]	[4.08]	[0.19]	[0.81]	[3.19]
α_{FF4}	-0.20	0.03	0.15	0.02	0.04	0.23
	[-3.53]	[0.70]	[3.76]	[0.46]	[0.59]	[2.79]
α_{FF5}	-0.24	0.03	0.17	-0.04	-0.06	0.17
	[-4.43]	[0.83]	[4.26]	[-0.79]	[-1.16]	[2.35]
α_{FF6}	-0.22	0.04	0.16	-0.02	-0.06	0.16
	[-4.14]	[0.91]	[3.97]	[-0.45]	[-1.07]	[2.21]
Panel B: Fama and French (2018) 6-factor model loadings for CLI-sorted portfolios						
β_{MKT}	0.97	0.97	0.99	1.06	1.03	0.05
	[76.45]	[100.45]	[101.27]	[99.75]	[79.19]	[2.91]
β_{SMB}	0.05	-0.04	-0.09	-0.06	0.12	0.06
	[2.97]	[-2.76]	[-6.69]	[-4.03]	[6.23]	[2.43]
β_{HML}	0.07	-0.02	-0.06	0.12	-0.01	-0.09
	[2.95]	[-0.82]	[-3.09]	[6.04]	[-0.59]	[-2.56]
β_{RMW}	0.16	0.05	-0.01	0.05	0.03	-0.14
	[6.61]	[2.72]	[-0.44]	[2.42]	[1.14]	[-3.94]
β_{CMA}	-0.15	-0.15	-0.06	0.13	0.49	0.64
	[-4.30]	[-5.37]	[-2.07]	[4.29]	[13.30]	[12.88]
β_{UMD}	-0.02	-0.00	0.01	-0.02	-0.01	0.01
	[-1.50]	[-0.52]	[1.51]	[-2.07]	[-0.52]	[0.70]
Panel C: Average number of firms (n) and market capitalization (me)						
n	628	604	679	788	803	
me ($\$10^6$)	1351	2025	2587	2523	1268	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CLI 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 196506 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	0.34	0.26	0.23	0.17	0.16
			[3.93]	[4.04]	[3.19]	[2.79]	[2.35]	[2.21]
Quintile	NYSE	EW	0.49	0.49	0.40	0.42	0.49	0.51
			[4.57]	[4.49]	[3.97]	[4.12]	[5.50]	[5.68]
Quintile	Name	VW	0.31	0.33	0.23	0.21	0.14	0.13
			[3.63]	[3.80]	[2.84]	[2.48]	[1.85]	[1.75]
Quintile	Cap	VW	0.30	0.32	0.27	0.26	0.19	0.19
			[4.06]	[4.29]	[3.65]	[3.49]	[2.86]	[2.95]
Decile	NYSE	VW	0.47	0.49	0.38	0.34	0.24	0.22
			[4.32]	[4.51]	[3.66]	[3.18]	[2.45]	[2.25]
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	0.29	0.30	0.23	0.21	0.16	0.15
			[3.43]	[3.48]	[2.77]	[2.56]	[2.15]	[2.03]
Quintile	NYSE	EW	0.27	0.28	0.20	0.22	0.25	0.26
			[2.42]	[2.43]	[1.87]	[2.05]	[2.66]	[2.83]
Quintile	Name	VW	0.27	0.28	0.20	0.18	0.12	0.11
			[3.11]	[3.21]	[2.40]	[2.21]	[1.62]	[1.53]
Quintile	Cap	VW	0.26	0.28	0.24	0.24	0.18	0.18
			[3.58]	[3.82]	[3.27]	[3.21]	[2.76]	[2.77]
Decile	NYSE	VW	0.41	0.43	0.34	0.32	0.22	0.21
			[3.82]	[3.97]	[3.27]	[3.02]	[2.33]	[2.21]

Table 3: Conditional sort on size and CLI

This table presents results for conditional double sorts on size and CLI. 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 CLI. 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 CLI and short stocks with low CLI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

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

		CLI Quintiles					CLI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.54	0.79	0.95	0.99	0.71	0.18	0.13	0.02	-0.01	0.07	0.05
		[2.11]	[3.26]	[4.17]	[3.66]	[2.31]	[1.22]	[0.85]	[0.17]	[-0.06]	[0.53]	[0.37]
	(2)	0.64	0.70	0.85	0.94	0.87	0.23	0.25	0.18	0.18	0.28	0.28
		[2.61]	[2.95]	[3.76]	[4.29]	[3.52]	[2.22]	[2.38]	[1.72]	[1.68]	[2.97]	[2.92]
	(3)	0.58	0.77	0.81	0.89	0.82	0.24	0.25	0.17	0.14	0.27	0.24
		[2.62]	[3.49]	[3.80]	[4.28]	[3.71]	[2.17]	[2.24]	[1.61]	[1.31]	[2.68]	[2.40]
	(4)	0.50	0.67	0.78	0.84	0.80	0.31	0.28	0.18	0.21	0.12	0.16
		[2.48]	[3.30]	[3.83]	[4.20]	[3.86]	[3.43]	[3.09]	[2.11]	[2.46]	[1.45]	[1.90]
	(5)	0.28	0.57	0.59	0.57	0.70	0.42	0.43	0.38	0.36	0.27	0.27
		[1.62]	[3.34]	[3.36]	[3.10]	[4.19]	[4.67]	[4.84]	[4.25]	[3.98]	[3.12]	[3.10]

Panel B: Portfolio average number of firms and market capitalization

		CLI Quintiles					CLI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	392	392	392	386	370	37	38	34	30	24
	(2)	109	109	109	109	108	56	57	56	56	55
	(3)	79	79	79	79	78	97	96	97	97	96
	(4)	66	66	66	66	66	206	205	211	206	207
	(5)	61	61	61	61	60	1143	1571	1819	1783	1479

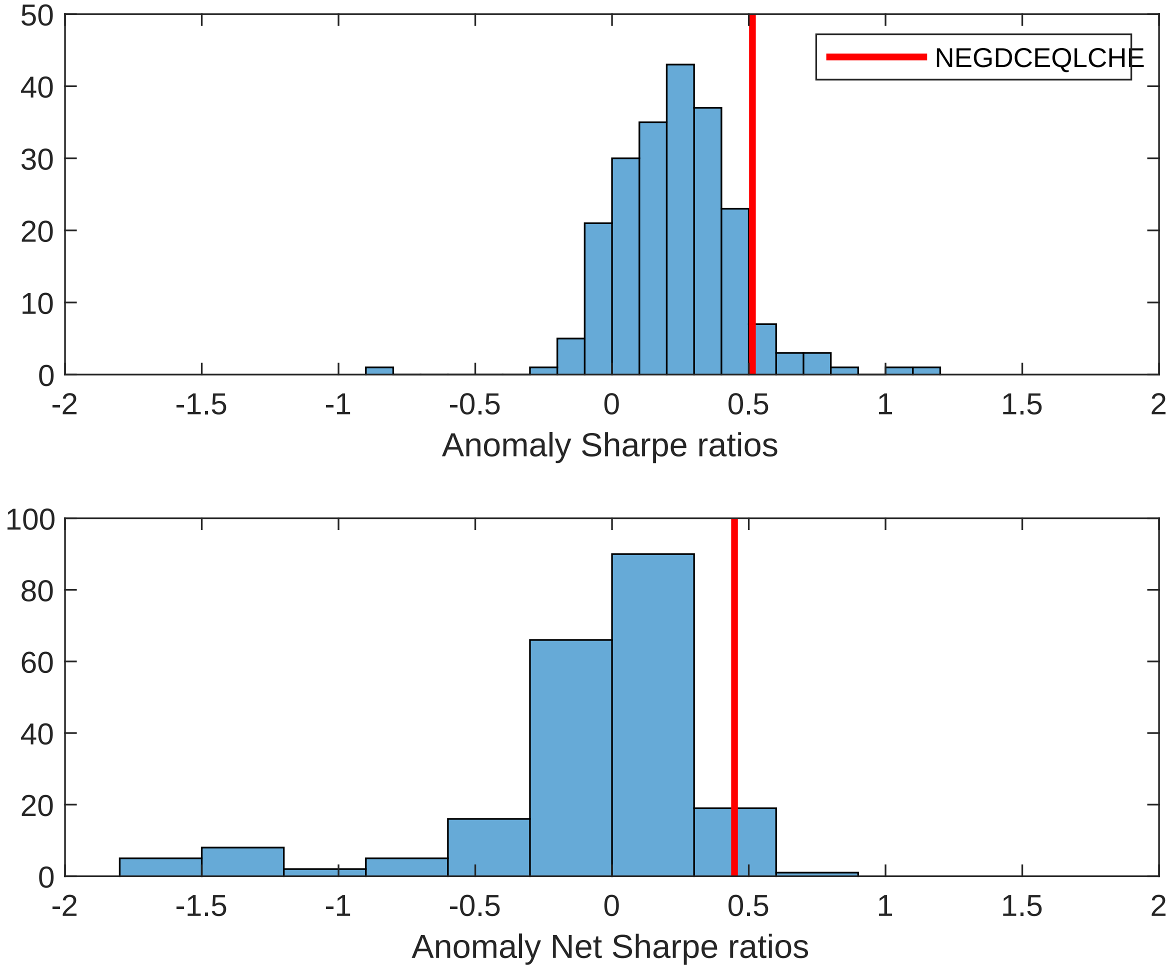

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CLI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

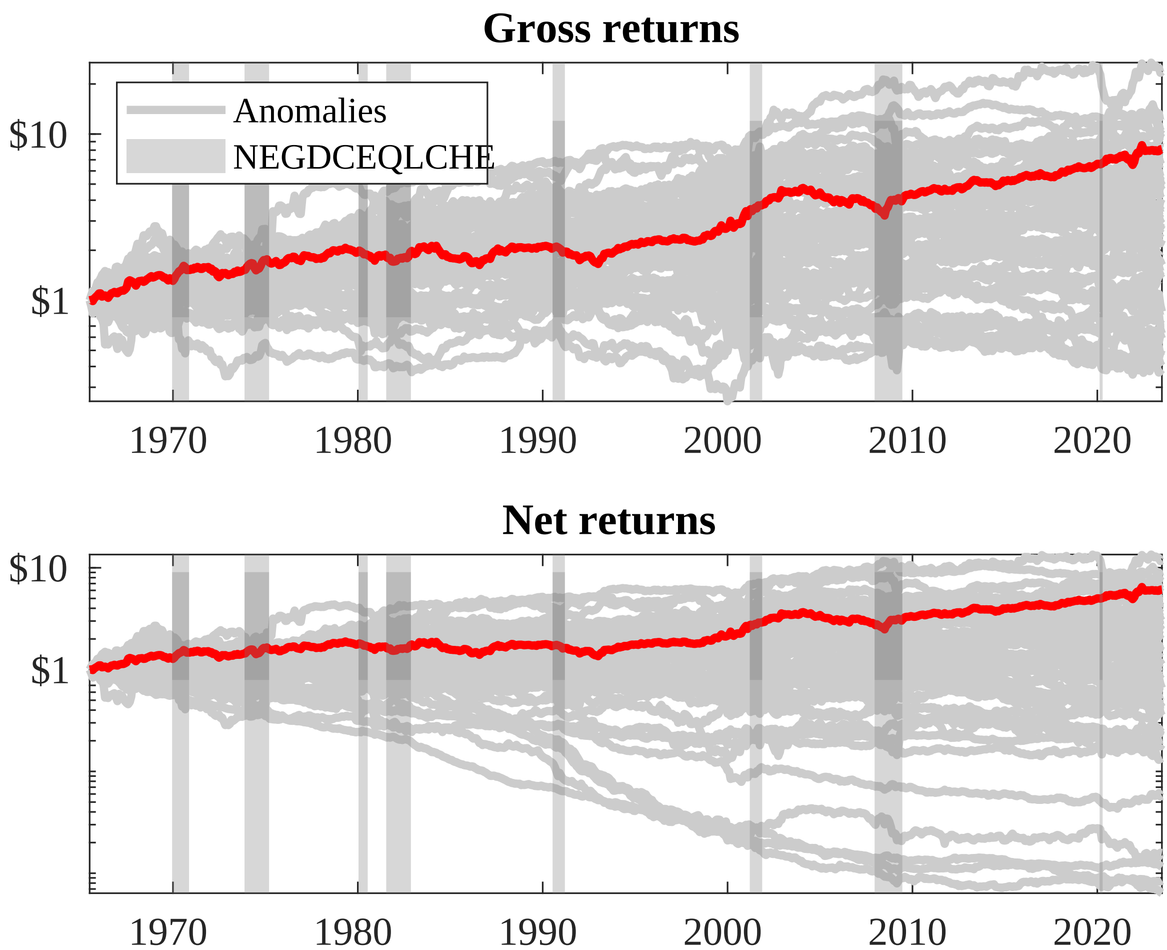

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CLI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

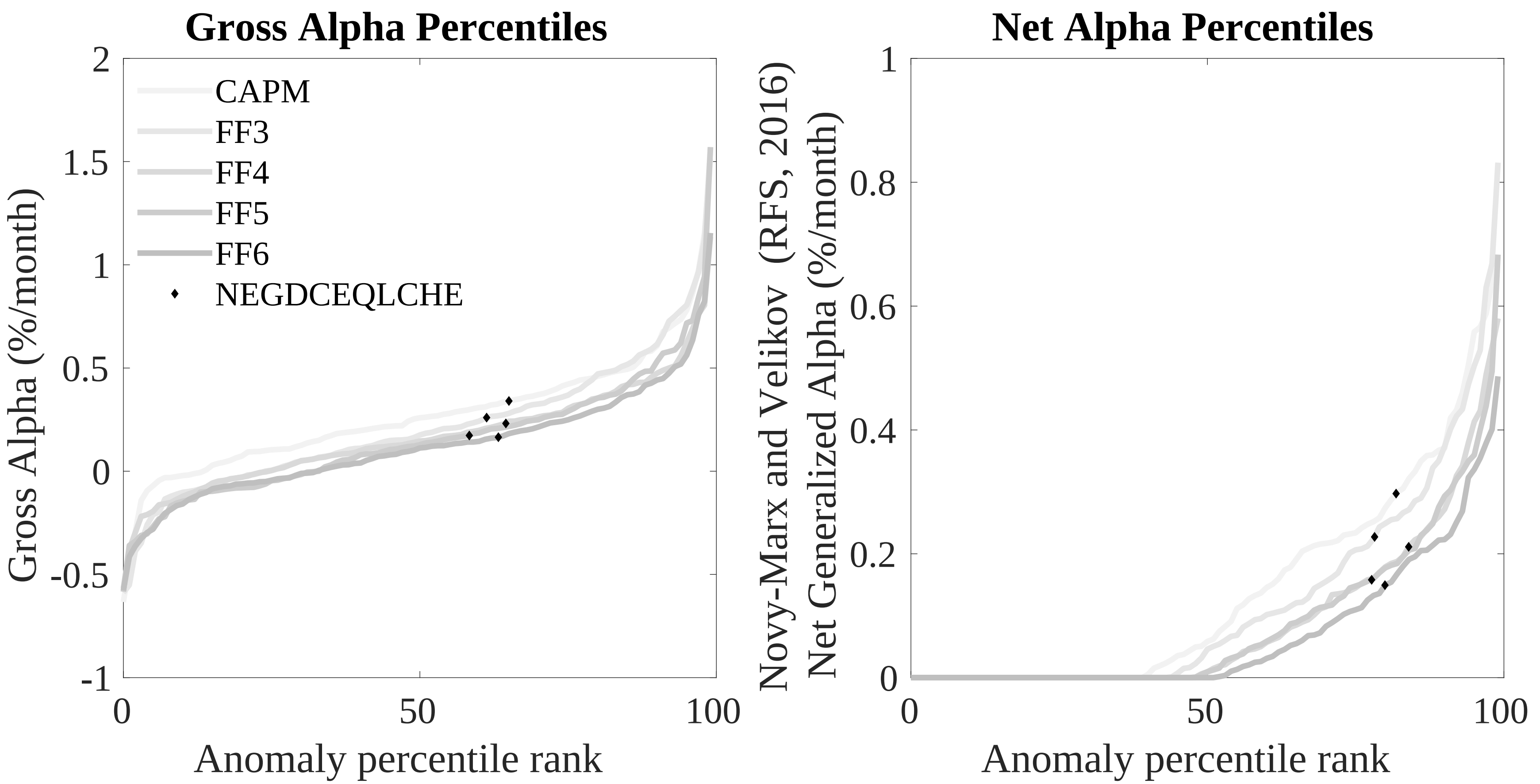

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CLI trading strategy alphas (diamonds). The strategies are constructed using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

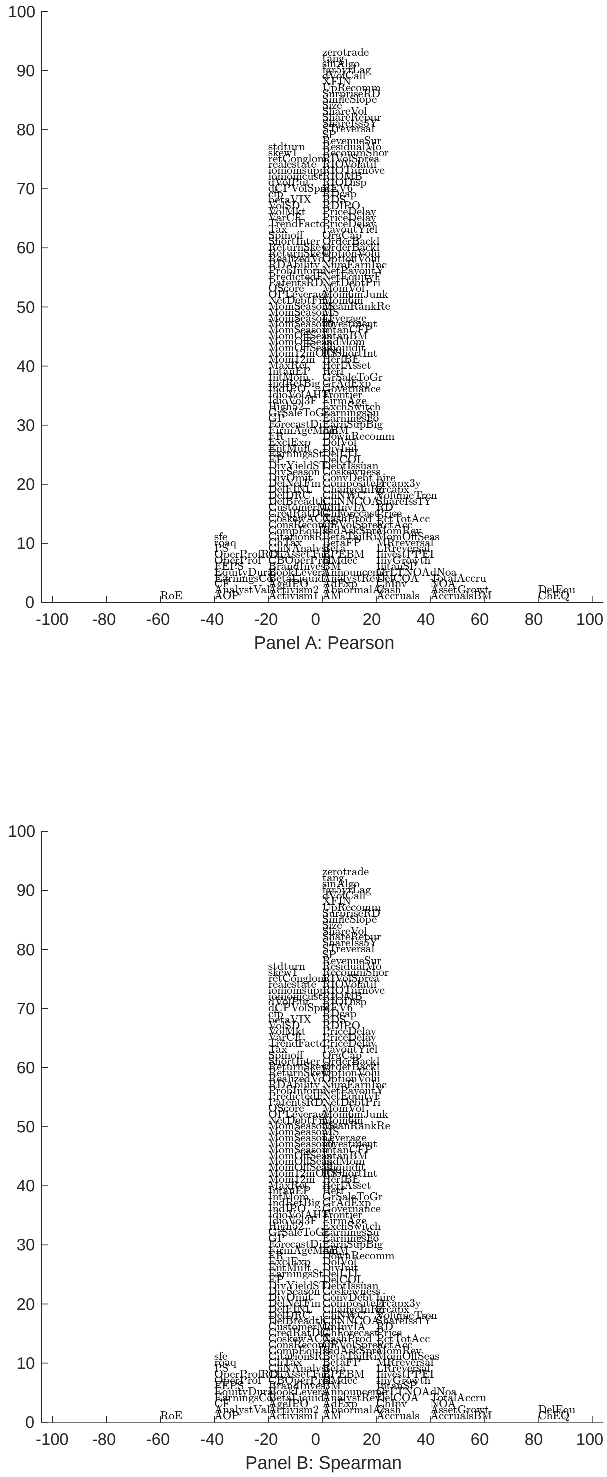

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with CLI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

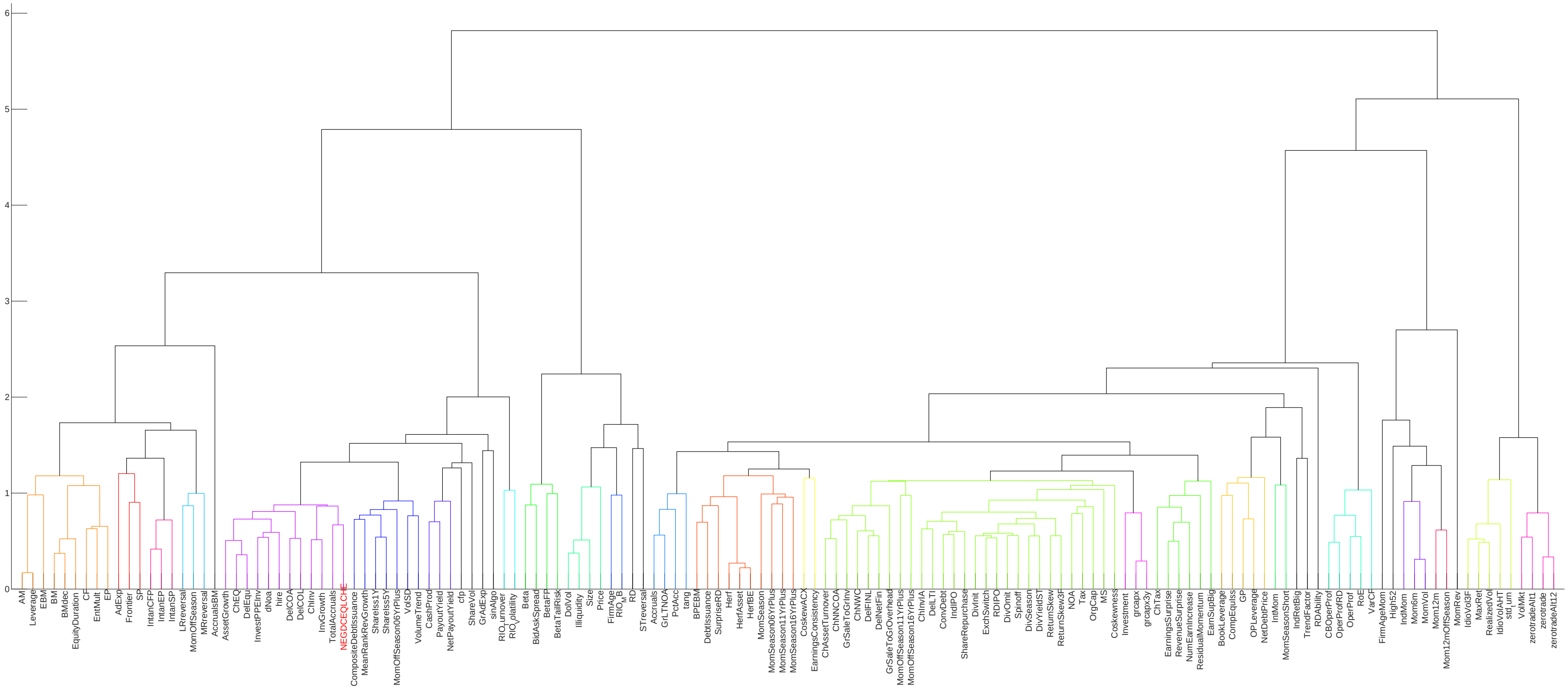

Figure 6: Agglomerative hierarchical cluster plot

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

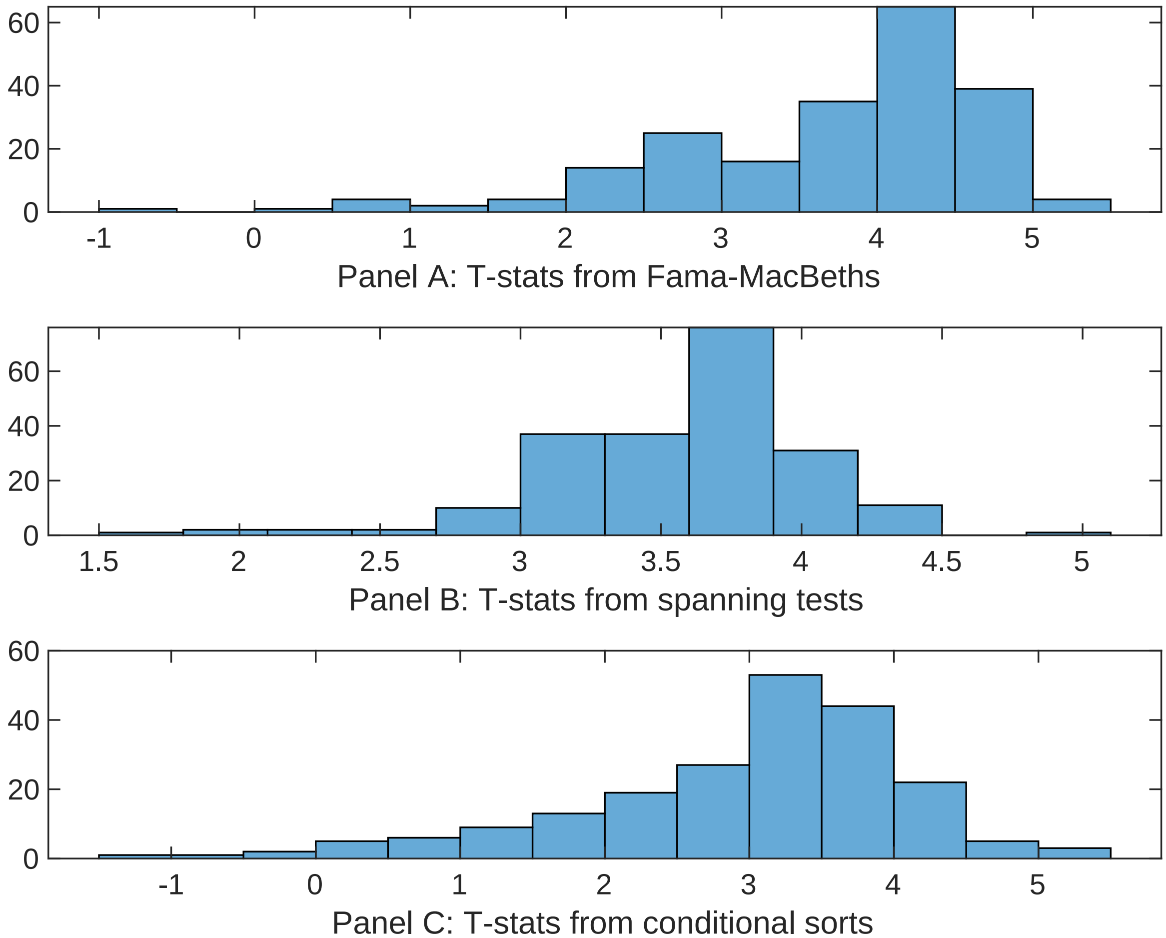

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CLI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CLI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CLI} CLI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CLI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CLI. Stocks are finally grouped into five CLI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CLI 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 CLI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CLI} CLI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets. 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 196506 to 202306.

Intercept	0.13	0.18	0.14	0.13	0.12	0.14	0.13
	[5.69]	[7.55]	[6.15]	[5.99]	[5.43]	[5.98]	[6.36]
CLI	0.13	0.14	0.11	0.13	0.25	0.16	0.11
	[2.52]	[3.07]	[2.25]	[2.52]	[4.24]	[3.10]	[2.34]
Anomaly 1	0.15						0.67
	[4.26]						[1.20]
Anomaly 2		0.47					-0.79
		[4.60]					[-0.57]
Anomaly 3			0.10				0.29
			[9.79]				[1.70]
Anomaly 4				0.13			0.63
				[10.40]			[3.17]
Anomaly 5					0.41		-0.31
					[2.15]		[-1.40]
Anomaly 6						0.16	0.54
						[8.66]	[2.38]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	0	0	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 CLI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CLI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets. 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 196506 to 202306.

Intercept	0.19	0.15	0.17	0.13	0.15	0.16	0.16
	[2.72]	[2.14]	[2.32]	[1.78]	[1.98]	[2.09]	[2.33]
Anomaly 1	43.26						26.46
	[11.91]						[4.85]
Anomaly 2		45.61					28.25
		[12.01]					[5.16]
Anomaly 3			22.88				-7.16
			[4.72]				[-1.37]
Anomaly 4				17.65			7.65
				[4.09]			[1.64]
Anomaly 5					13.43		-6.01
					[3.81]		[-1.62]
Anomaly 6						13.52	3.69
						[3.83]	[1.05]
mkt	4.60	6.75	5.36	5.31	4.87	4.94	5.85
	[2.84]	[4.17]	[3.07]	[3.02]	[2.77]	[2.81]	[3.64]
smb	5.63	4.77	4.31	6.84	6.36	6.06	5.68
	[2.41]	[2.04]	[1.68]	[2.70]	[2.50]	[2.38]	[2.42]
hml	-14.56	-14.53	-9.86	-10.25	-8.69	-10.37	-16.63
	[-4.64]	[-4.64]	[-2.93]	[-3.03]	[-2.58]	[-3.06]	[-5.34]
rmw	-9.32	-11.17	-13.88	-13.23	-11.57	-13.59	-10.11
	[-2.93]	[-3.54]	[-4.07]	[-3.86]	[-3.33]	[-3.96]	[-3.22]
cma	19.89	19.78	36.92	51.37	57.61	54.45	12.75
	[3.35]	[3.35]	[4.79]	[8.63]	[10.83]	[9.62]	[1.75]
umd	2.60	0.71	2.10	0.79	1.60	1.15	1.11
	[1.63]	[0.44]	[1.21]	[0.45]	[0.92]	[0.66]	[0.69]
# months	696	696	696	696	696	696	696
$\bar{R}^2(\%)$	41	41	31	31	30	31	43

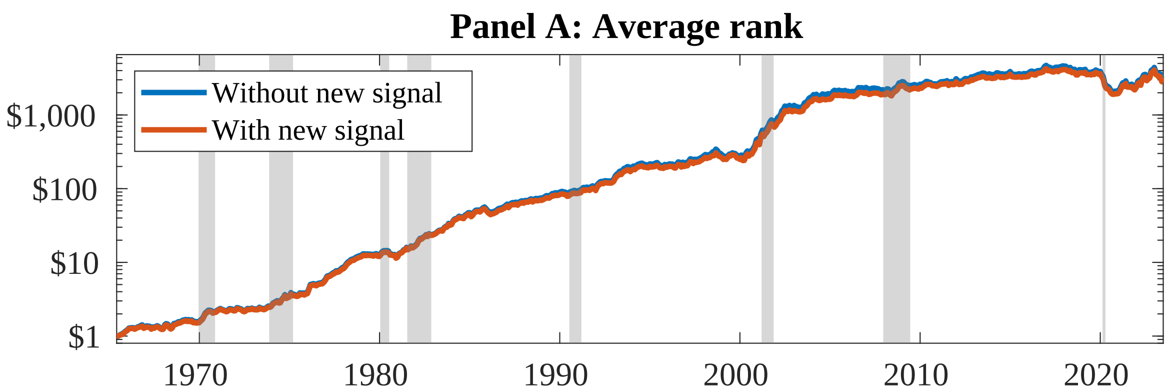

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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