Nonop Liability Contrast and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

Abstract

This paper studies the asset pricing implications of Nonop Liability Contrast (NLC), 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 NLC achieves an annualized gross (net) Sharpe ratio of 0.31 (0.22), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 26 (20) bps/month with a t-statistic of 3.47 (2.65), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Growth in long term operating assets, Inventory Growth, Change in Net Noncurrent Op Assets, net income / book equity, Analyst Value, Accruals) is 29 bps/month with a t-statistic of 3.40.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices (Fama and French, 2015). While accounting information plays a crucial role in price discovery, the literature has primarily focused on operating metrics, leaving the pricing implications of non-operating items relatively unexplored (Sloan et al., 2018).

This gap is particularly notable given that non-operating liabilities represent significant off-balance-sheet obligations that may contain important information about future firm performance and risk. Recent evidence suggests that investors often struggle to fully process complex financial information (Hirshleifer et al., 2020), making the examination of non-operating liability contrasts (NLC) - the difference between reported and normalized non-operating liabilities - a promising avenue for understanding market efficiency.

We develop three hypotheses linking NLC to expected returns. First, following (Campbell and Shiller, 1988), large deviations in non-operating liabilities from their normalized levels may signal changes in future cash flow expectations. When actual non-operating liabilities exceed normalized levels, this could indicate deteriorating operational flexibility and increased financial risk (Titman and Wessels, 1988).

Second, building on (Hirshleifer et al., 2020), we posit that the complexity of non-operating liability accounting creates information processing frictions. Investors may struggle to distinguish temporary from permanent changes in non-operating obligations, leading to systematic mispricing that resolves as information is gradually incorporated into prices.

Third, drawing from (Fama and French, 1993), we hypothesize that NLC captures systematic risk exposure. Firms with high NLC may be more sensitive to aggregate funding conditions and credit market stress, commanding a risk premium in equilibrium.

Our analysis reveals that NLC strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio formed on NLC generates a monthly alpha of 26 basis points (t-statistic = 3.47) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.31, placing it in the top third of documented return predictors.

Importantly, the predictive power of NLC persists among large-capitalization stocks, with the highest size quintile generating a monthly alpha of 35 basis points (t-statistic = 3.62). This suggests that the effect is not confined to small, illiquid securities where trading costs might impede implementation.

The signal's robustness is further demonstrated by its performance after accounting for transaction costs. The strategy delivers a net Sharpe ratio of 0.22 and maintains significant risk-adjusted returns across various portfolio construction approaches, with net alphas ranging from 13 to 20 basis points monthly.

Our study makes several contributions to the asset pricing literature. First, we extend the work of (Sloan et al., 2018) on accounting-based return predictors by documenting a novel signal derived from non-operating liabilities. While prior research has focused primarily on operating metrics, we show that non-operating items contain important pricing-relevant information.

Second, we contribute to the growing literature on investor attention and information processing frictions (Hirshleifer et al., 2020). Our findings suggest that the complexity of non-operating liability accounting creates systematic mispricing that sophisticated investors can exploit. The persistence of the NLC effect among large stocks distinguishes it from many previously documented anomalies.

Finally, our results have implications for the efficient markets debate and asset pricing theory. The robust predictive power of NLC, even after controlling for standard risk factors and transaction costs, challenges the notion that readily available accounting information is fully incorporated into prices. This finding adds to our understanding of how accounting information is processed by market participants and priced in equilibrium.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the change in current liabilities relative to non-operating income. 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 LCT for current liabilities and item NOPIO for non-operating income. Current liabilities (LCT) represent the firm's short-term obligations that are due within one year, including accounts payable, short-term debt, and other current liabilities. Non-operating income (NOPIO) represents income or expenses that are not related to the company's core business operations. The construction of our signal, 'Nonop Liability Contrast', follows a change-based approach, where we calculate the difference between current LCT and its lagged value, and then scale this change by lagged NOPIO. This scaled difference captures the relative change in short-term obligations against the backdrop of non-core business income, potentially offering insight into how firms manage their short-term liabilities in relation to their non-operating activities. By focusing on this relationship, the signal aims to reflect aspects of liability management and non-core business performance in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both variables to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the NLC signal. Panel A plots the time-series of the mean, median, and interquartile range for NLC. On average, the cross-sectional mean (median) NLC is -0.78 (-1.15) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input NLC data. The signal's interquartile range spans -16.25 to 10.71. Panel B of Figure 1 plots the time-series of the coverage of the NLC signal for the CRSP universe. On average, the NLC signal is available for 4.85% of CRSP names, which on average make up 6.54% of total market capitalization.

4 Does NLC predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on NLC 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 NLC portfolio and sells the low NLC 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 NLC strategy earns an average return of 0.17% per month with a t-statistic of 2.38. The annualized Sharpe ratio of the strategy is 0.31. The alphas range from 0.19% to 0.26% per month and have t-statistics exceeding 2.51 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 -0.18, with a t-statistic of -5.13 on the RMW 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 469 stocks and an average market capitalization of at least $1,213 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 15 bps/month with a t-statistics of 2.27. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twelve 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 2-14bps/month. The lowest return, (2 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.41. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the NLC trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in thirteen cases.

Table 3 provides direct tests for the role size plays in the NLC strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and NLC, as well as average returns and alphas for long/short trading NLC 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 NLC strategy achieves an average return of 23 bps/month with a t-statistic of 2.45. Among these large cap stocks, the alphas for the NLC strategy relative to the five most common factor models range from 27 to 35 bps/month with t-statistics between 2.82 and 3.62.

5 How does NLC perform relative to the zoo?

Figure 2 puts the performance of NLC 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 NLC strategy falls in the distribution. The NLC strategy's gross (net) Sharpe ratio of 0.31 (0.22) is greater than 66% (81%) 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 NLC strategy (red line).[2] Ignoring trading costs, a \$1 invested in the NLC strategy would have yielded \$2.18 which ranks the NLC strategy in the top 12% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the NLC strategy would have yielded \$1.23 which ranks the NLC strategy in the top 10% 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 NLC relative to those. Panel A shows that the NLC strategy gross alphas fall between the 38 and 77 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 NLC strategy has a positive net generalized alpha for five out of the five factor models. In these cases NLC ranks between the 60 and 85 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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 NLC 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 NLC with 208 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 NLC or at least to weaken the power NLC has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of NLC conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NLC} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NLC} NLC_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{NLC,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on NLC. Stocks are finally grouped into five NLC 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.

NLC trading strategies conditioned on each of the 208 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on NLC 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 NLC signal in these Fama-MacBeth regressions exceed 0.51, with the minimum t-statistic occurring when controlling for Analyst Value. Controlling for all six closely related anomalies, the t-statistic on NLC is -0.10.

Similarly, Table 5 reports results from spanning tests that regress returns to the NLC 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 NLC strategy earns alphas that range from 24-36bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.23, which is achieved when controlling for Analyst Value. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the NLC trading strategy achieves an alpha of 29bps/month with a t-statistic of 3.40.

7 Does NLC add relative to the whole zoo?

Finally, we can ask how much adding NLC 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 NLC signal.[4] We consider one different methods for combining signals.

[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 NLC is available.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, \$1 investment in the 155-anomaly combination strategy grows to \$3027.42, while \$1 investment in the combination strategy that includes NLC grows to \$2817.12.

8 Conclusion

This study provides compelling evidence for the significance of Nonop Liability Contrast (NLC) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on NLC generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.31 (0.22 net). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that NLC captures unique information about future stock returns that is not fully incorporated in existing pricing factors.

Particularly noteworthy is the signal's ability to maintain its predictive power when accounting for transaction costs, as evidenced by the significant net returns. The robust performance against both the Fama-French five-factor model plus momentum and an extended model including six closely related anomalies (with alphas of 20-29 bps/month) underscores the distinctive nature of the information captured by NLC.

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 control for various known factors, the evolving nature of financial markets means that other undiscovered factors might explain part of our findings.

Future research could explore several promising directions. First, investigating the economic mechanisms underlying the NLC signal's predictive power could provide valuable insights into market inefficiencies. Second, examining the signal's performance across different market regimes and economic cycles could help understand its reliability under varying conditions. Finally, exploring potential enhancements to the signal through machine learning techniques or combination with other predictors could yield even more powerful forecasting tools.

In conclusion, our findings suggest that NLC represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that persists after accounting for transaction costs and known factors.

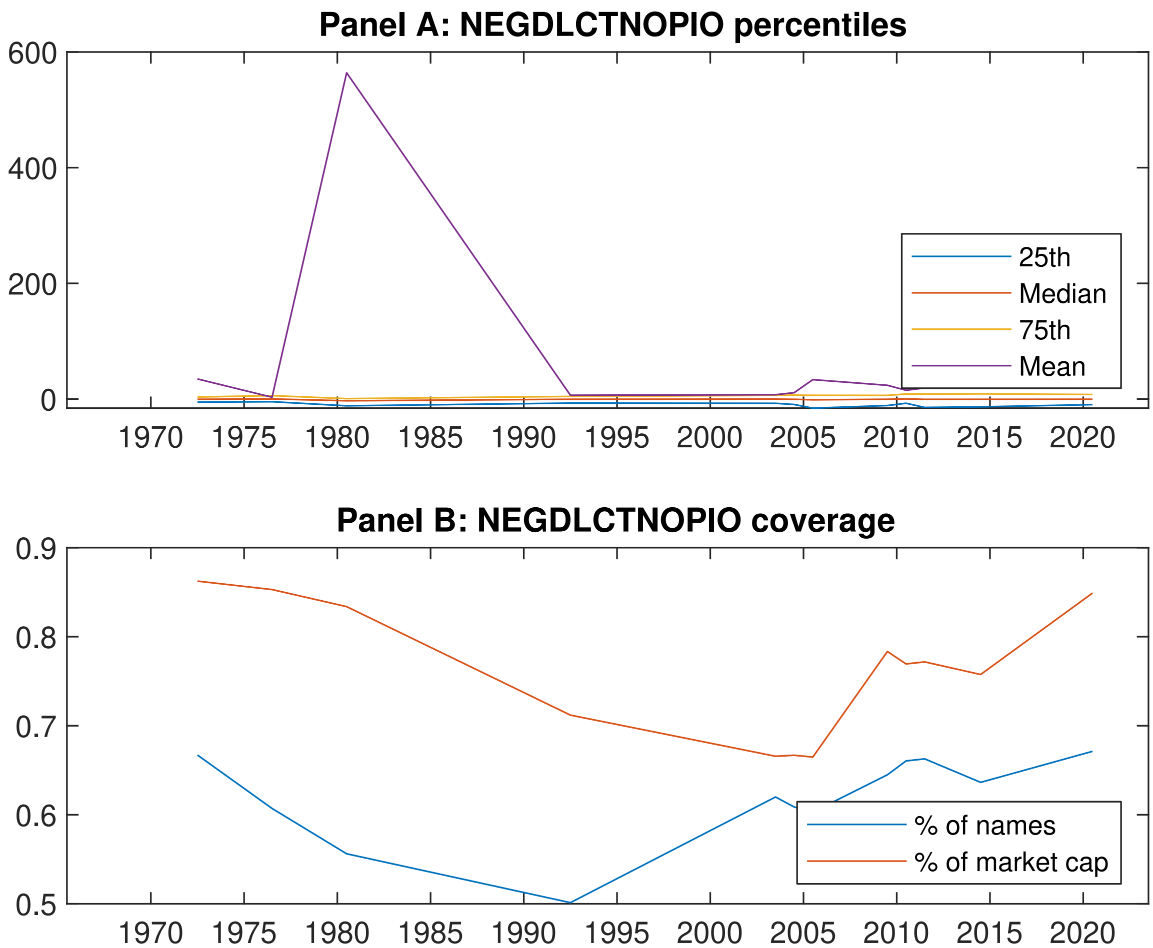


Figure 1: Times series of NLC percentiles and coverage.
This figure plots descriptive statistics for NLC. Panel A shows cross-sectional percentiles of NLC over the sample. Panel B plots the monthly coverage of NLC relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on NLC. 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 NLC-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.56	0.59	0.56	0.57	0.73	0.17
	[2.92]	[3.36]	[3.44]	[3.56]	[3.87]	[2.38]
α_{CAPM}	-0.05	0.04	0.05	0.07	0.14	0.19
	[-0.93]	[0.77]	[1.06]	[1.42]	[2.42]	[2.57]
α_{FF3}	0.01	0.09	0.04	0.05	0.20	0.19
	[0.21]	[2.12]	[0.88]	[0.95]	[3.48]	[2.51]
α_{FF4}	0.01	0.10	0.03	0.03	0.21	0.20
	[0.18]	[2.19]	[0.55]	[0.58]	[3.73]	[2.71]
α_{FF5}	-0.01	0.09	-0.01	-0.05	0.24	0.25
	[-0.14]	[1.96]	[-0.16]	[-0.99]	[4.27]	[3.35]
α_{FF6}	-0.01	0.09	-0.02	-0.05	0.26	0.26
	[-0.16]	[2.01]	[-0.32]	[-1.05]	[4.40]	[3.47]
Panel B: Fama and French (2018) 6-factor model loadings for NLC-sorted portfolios						
β_{MKT}	1.04	0.97	0.95	0.96	0.98	-0.05
	[93.82]	[92.05]	[83.37]	[87.18]	[71.80]	[-2.93]
β_{SMB}	0.05	-0.04	-0.08	-0.09	0.07	0.03
	[2.93]	[-2.78]	[-4.94]	[-5.84]	[3.79]	[1.09]
β_{HML}	-0.12	-0.11	0.00	-0.05	-0.14	-0.02
	[-5.49]	[-5.51]	[0.10]	[-2.47]	[-5.25]	[-0.63]
β_{RMW}	0.11	0.06	0.05	0.03	-0.07	-0.18
	[4.89]	[2.77]	[2.17]	[1.52]	[-2.76]	[-5.13]
β_{CMA}	-0.11	-0.07	0.14	0.37	-0.09	0.02
	[-3.38]	[-2.25]	[4.22]	[11.87]	[-2.32]	[0.31]
β_{UMD}	0.00	-0.01	0.01	0.01	-0.02	-0.02
	[0.18]	[-0.51]	[0.99]	[0.49]	[-1.14]	[-0.98]
Panel C: Average number of firms (n) and market capitalization (me)						
n	541	469	469	480	561	
me ($\$10^6$)	1430	1807	1900	1356	1213	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the NLC 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	0.17	0.19	0.19	0.20	0.25	0.26
			[2.38]	[2.57]	[2.51]	[2.71]	[3.35]	[3.47]
Quintile	NYSE	EW	0.25	0.26	0.23	0.23	0.24	0.24
			[6.51]	[6.71]	[6.12]	[5.94]	[6.28]	[6.15]
Quintile	Name	VW	0.18	0.20	0.20	0.22	0.25	0.27
			[2.37]	[2.59]	[2.55]	[2.80]	[3.24]	[3.42]
Quintile	Cap	VW	0.15	0.19	0.17	0.16	0.21	0.20
			[2.27]	[2.76]	[2.49]	[2.34]	[3.09]	[2.96]
Decile	NYSE	VW	0.20	0.21	0.23	0.23	0.32	0.31
			[2.05]	[2.10]	[2.33]	[2.28]	[3.25]	[3.13]

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	0.13	0.15	0.14	0.15	0.19	0.20
			[1.69]	[1.98]	[1.90]	[2.04]	[2.56]	[2.65]
Quintile	NYSE	EW	0.02	0.03	0.00	0.01		
			[0.41]	[0.61]	[0.02]	[0.12]		
Quintile	Name	VW	0.13	0.16	0.15	0.16	0.19	0.20
			[1.69]	[1.98]	[1.92]	[2.10]	[2.46]	[2.56]
Quintile	Cap	VW	0.11	0.15	0.13	0.13	0.17	0.16
			[1.59]	[2.18]	[1.91]	[1.85]	[2.46]	[2.40]
Decile	NYSE	VW	0.14	0.16	0.17	0.17	0.25	0.24
			[1.45]	[1.60]	[1.77]	[1.76]	[2.50]	[2.44]

Table 3: Conditional sort on size and NLC

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

	NLC Quintiles					NLC Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.55	0.87	0.87	0.85	0.83	0.28	0.30	0.29	0.23	0.27	0.22
	[2.13]	[3.33]	[3.26]	[3.35]	[3.20]	[3.77]	[4.00]	[3.93]	[3.07]	[3.52]	[2.88]
(2)	0.68	0.74	0.83	0.81	0.88	0.20	0.20	0.20	0.24	0.22	0.26
	[2.77]	[3.14]	[3.52]	[3.50]	[3.67]	[2.46]	[2.50]	[2.47]	[2.94]	[2.69]	[3.06]
(3)	0.77	0.80	0.75	0.76	0.75	-0.02	-0.00	-0.03	-0.07	-0.04	-0.07
	[3.48]	[3.74]	[3.48]	[3.62]	[3.47]	[-0.31]	[-0.02]	[-0.44]	[-0.93]	[-0.55]	[-0.91]
(4)	0.60	0.76	0.71	0.71	0.77	0.17	0.17	0.16	0.15	0.20	0.20
	[2.91]	[3.88]	[3.52]	[3.69]	[3.72]	[2.37]	[2.40]	[2.18]	[2.06]	[2.80]	[2.68]
(5)	0.49	0.50	0.61	0.51	0.72	0.23	0.27	0.27	0.29	0.34	0.35
	[2.58]	[2.91]	[3.72]	[3.21]	[3.95]	[2.45]	[2.84]	[2.82]	[3.03]	[3.47]	[3.62]

Panel B: Portfolio average number of firms and market capitalization

	NLC Quintiles					NLC Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	261	263	263	261	260	22	23	21	21	21
(2)	79	79	79	79	79	40	40	40	40	41
(3)	60	60	60	60	60	72	72	71	72	72
(4)	54	54	53	54	54	166	165	161	162	164
(5)	50	50	50	50	50	1043	1259	1720	1247	949

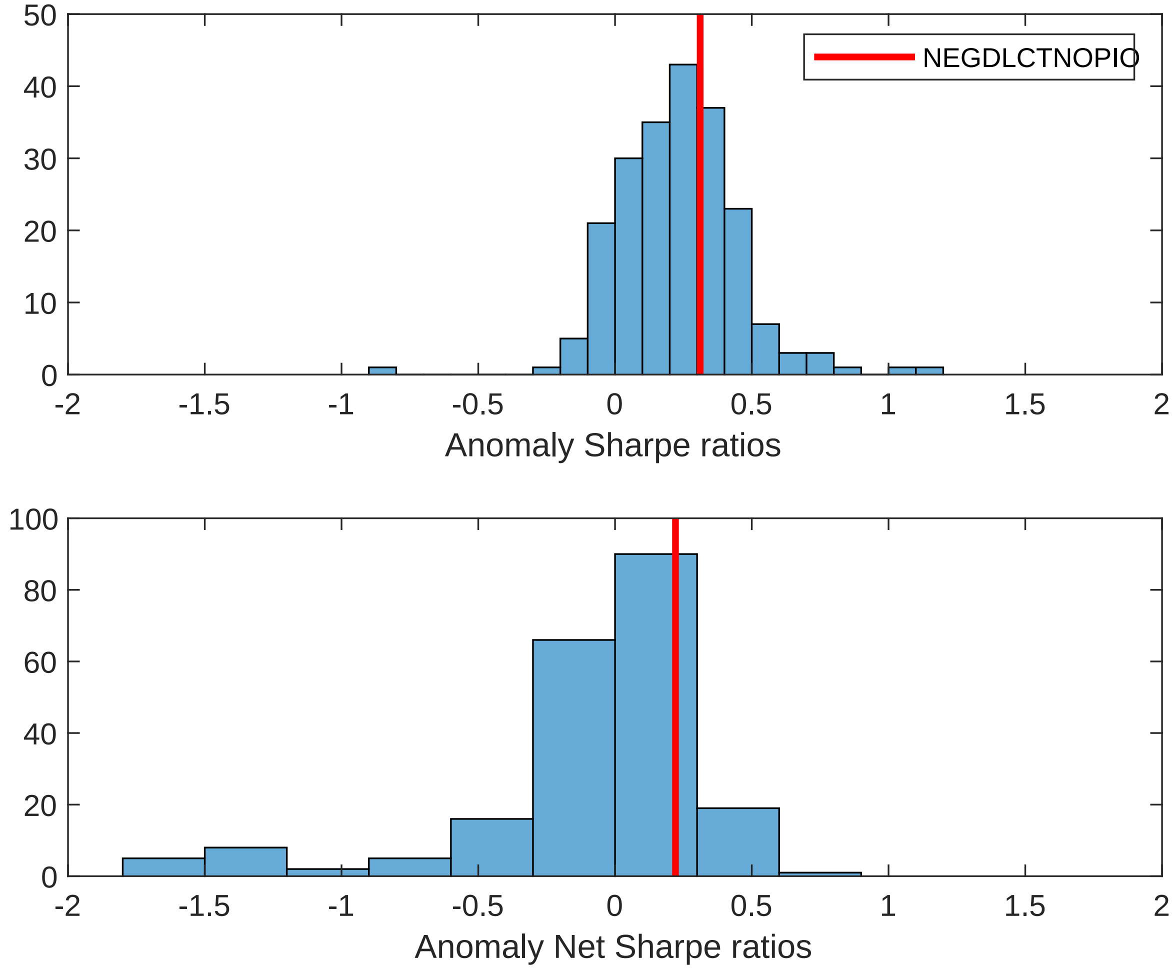


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the NLC with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

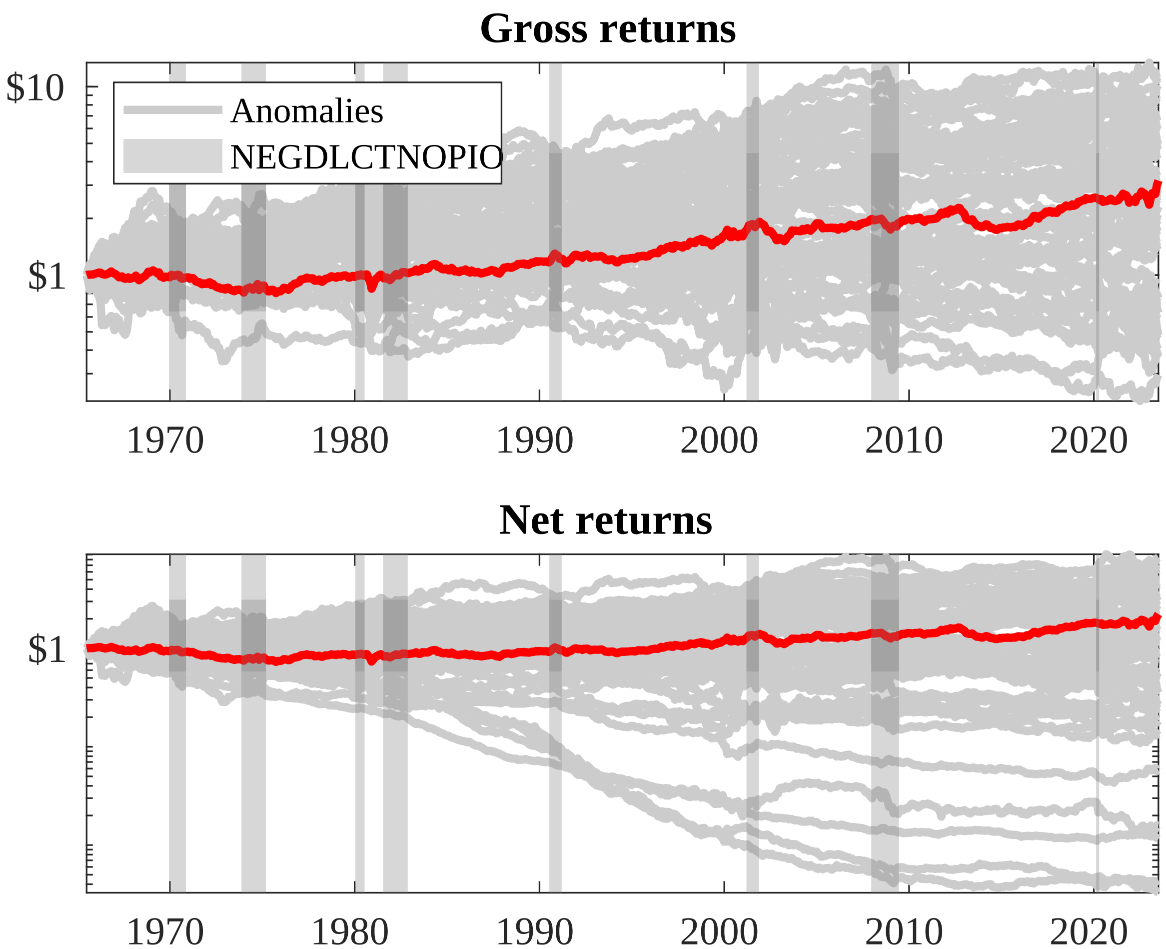


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the NLC trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

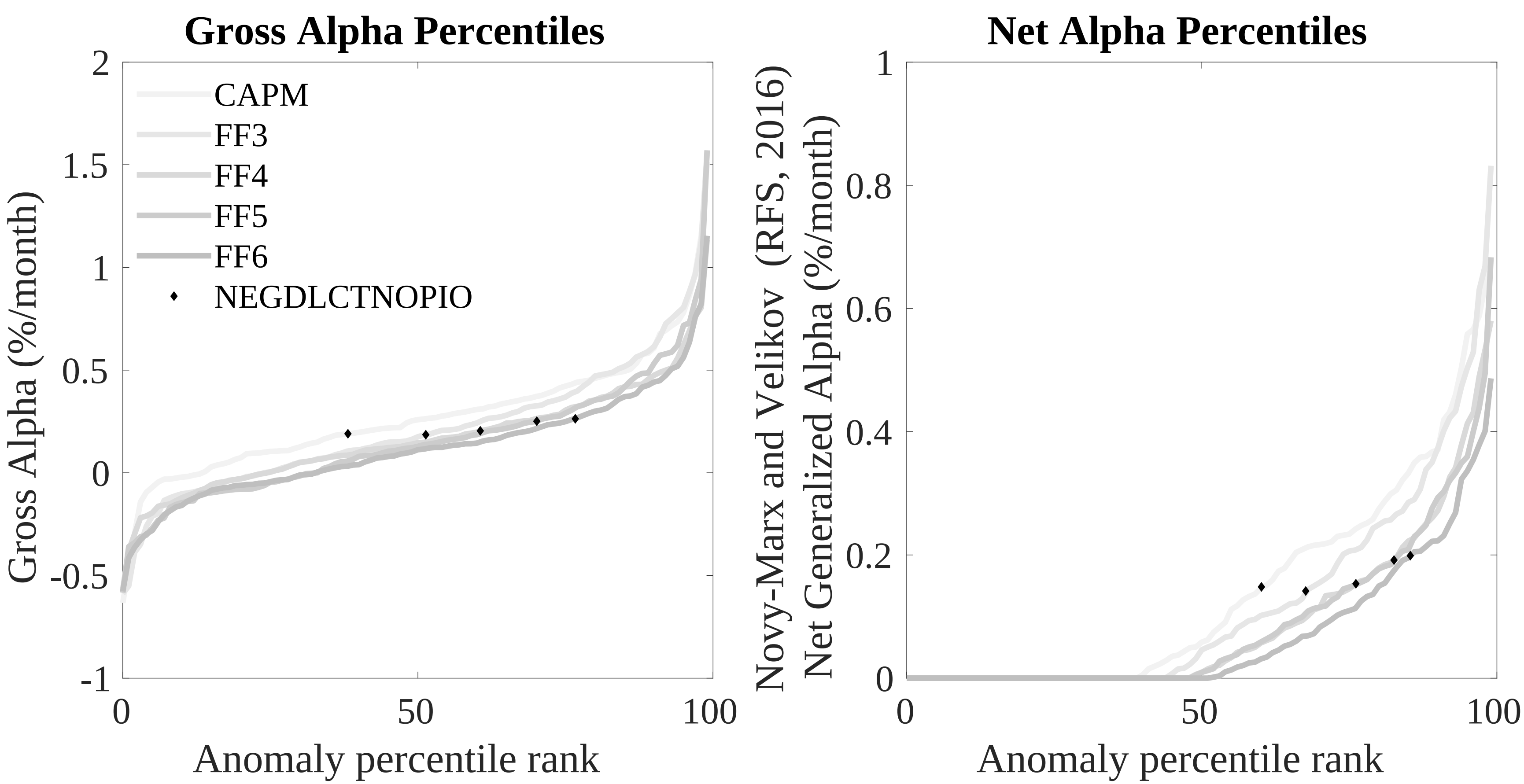
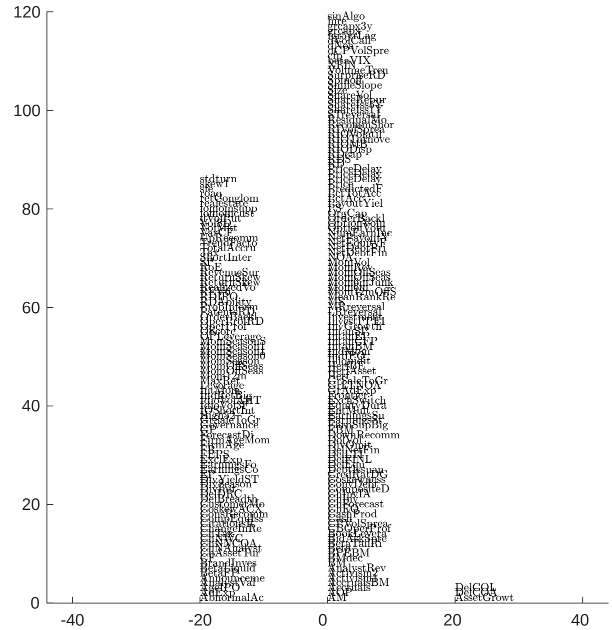


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the NLC trading strategy alphas (diamonds). The strategies are constructed using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



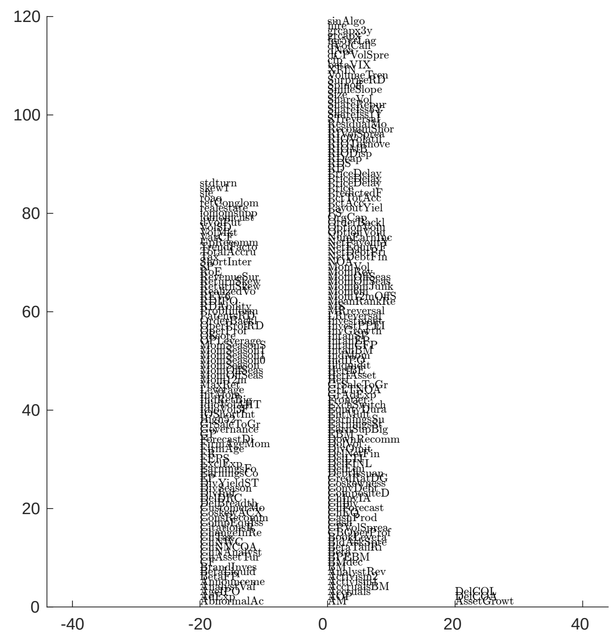


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 208 filtered anomaly signals with NLC. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

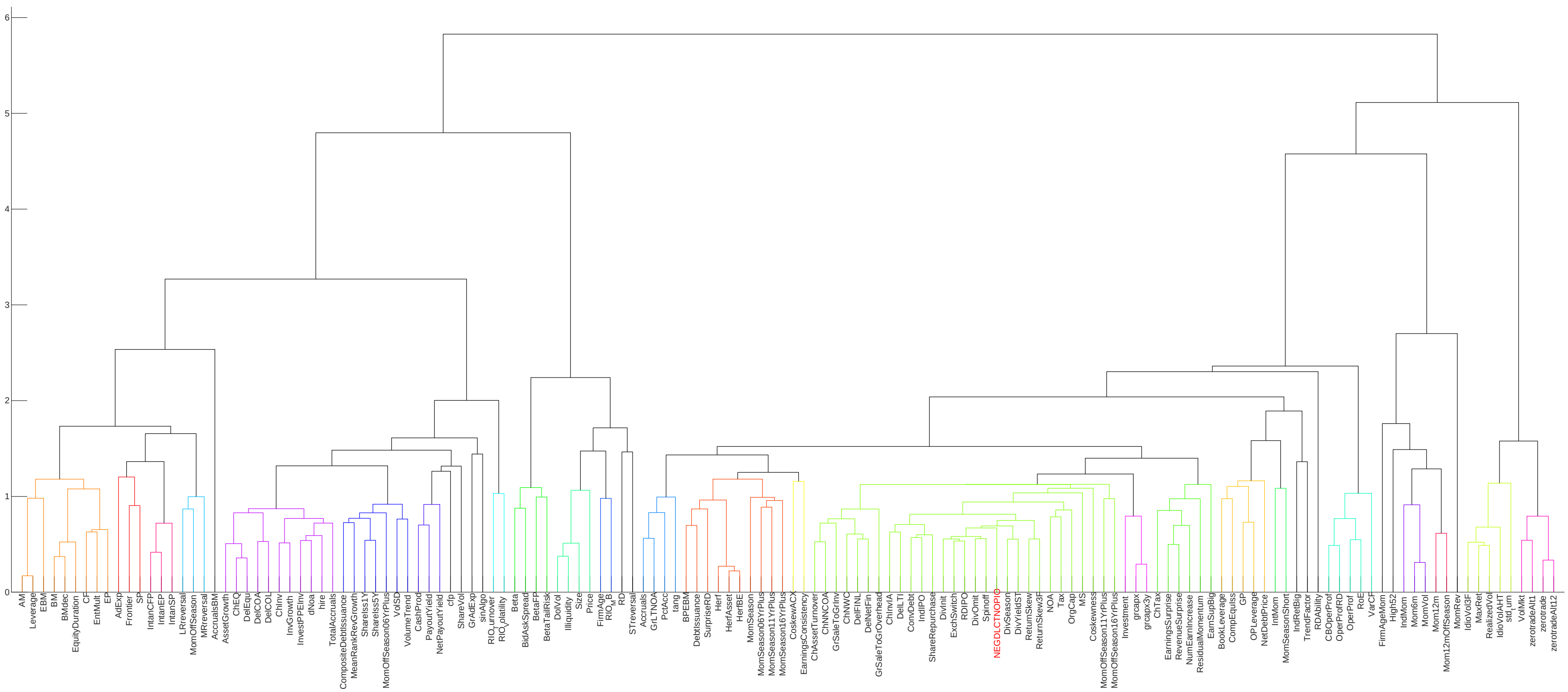


Figure 6: Agglomerative hierarchical cluster plot

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

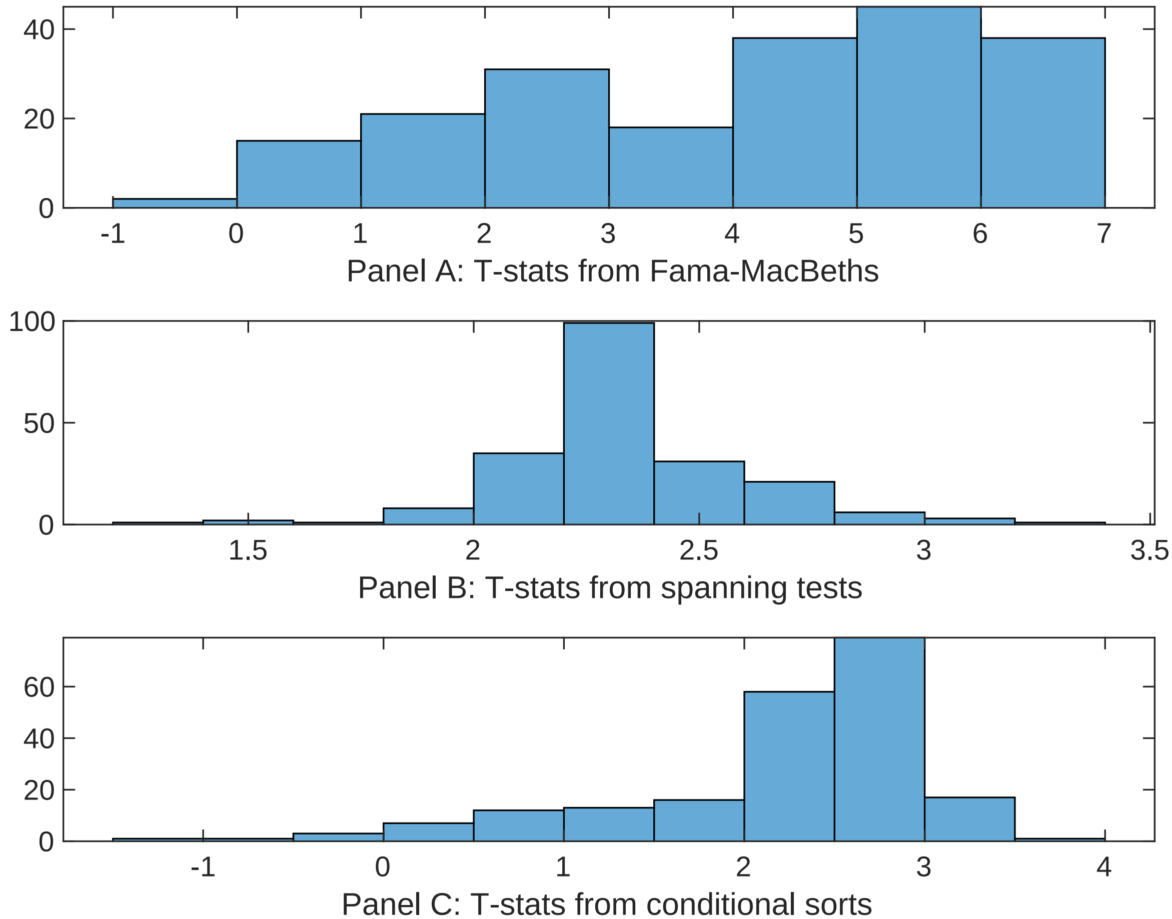


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of NLC conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NLC} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NLC}NLC_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{NLC,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on NLC. Stocks are finally grouped into five NLC portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NLC trading strategies conditioned on each of the 208 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies

This table presents Fama-MacBeth results of returns on NLC. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{NLC} NLC_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in long term operating assets, Inventory Growth, Change in Net Noncurrent Op Assets, net income / book equity, Analyst Value, Accruals. 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	0.12	0.12	0.12	0.12	0.11	0.12	0.10
	[5.27]	[5.49]	[5.29]	[5.27]	[4.24]	[5.10]	[4.22]
NLC	0.85	0.66	0.90	0.83	0.11	0.72	-0.21
	[5.91]	[4.73]	[6.19]	[5.38]	[0.51]	[5.14]	[-0.10]
Anomaly 1	0.65						0.14
	[2.60]						[3.07]
Anomaly 2		0.34					0.22
		[6.60]					[2.74]
Anomaly 3			0.11				0.22
			[5.15]				[5.09]
Anomaly 4				-0.12			0.42
				[-0.64]			[1.69]
Anomaly 5					0.13		0.81
					[1.16]		[0.75]
Anomaly 6						0.16	-0.29
						[5.08]	[-0.06]
# months	696	696	696	696	564	696	564
$\bar{R}^2$(%)	0	0	0	0	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the NLC trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{NLC} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Growth in long term operating assets, Inventory Growth, Change in Net Noncurrent Op Assets, net income / book equity, Analyst Value, Accruals. 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	0.25	0.24	0.28	0.27	0.36	0.25	0.29
	[3.36]	[3.23]	[3.69]	[3.58]	[4.11]	[3.28]	[3.40]
Anomaly 1	13.63						7.96
	[3.90]						[1.47]
Anomaly 2		15.00					20.12
		[3.94]					[4.52]
Anomaly 3			-12.19				-9.88
			[-3.47]				[-2.18]
Anomaly 4				0.56			5.67
				[0.13]			[1.12]
Anomaly 5					-8.24		-7.76
					[-2.81]		[-2.63]
Anomaly 6						7.03	4.44
						[2.28]	[1.00]
mkt	-3.87	-4.63	-4.97	-4.92	-3.45	-4.48	-1.25
	[-2.15]	[-2.60]	[-2.79]	[-2.60]	[-1.66]	[-2.48]	[-0.57]
smb	5.46	4.79	3.36	3.10	0.61	4.32	6.88
	[2.06]	[1.83]	[1.30]	[1.07]	[0.19]	[1.62]	[1.86]
hml	-0.60	-2.34	-1.04	-1.26	3.14	0.15	4.46
	[-0.18]	[-0.68]	[-0.30]	[-0.36]	[0.74]	[0.04]	[1.04]
rmw	-14.57	-15.90	-17.24	-19.16	-13.41	-16.17	-10.47
	[-4.02]	[-4.49]	[-4.92]	[-3.65]	[-3.22]	[-4.42]	[-1.77]
cma	-2.89	-8.96	1.09	0.98	-5.09	-1.33	-21.36
	[-0.56]	[-1.60]	[0.22]	[0.19]	[-0.87]	[-0.26]	[-3.28]
umd	-1.34	-2.58	-0.22	-1.70	-0.94	-2.26	-0.62
	[-0.76]	[-1.46]	[-0.12]	[-0.95]	[-0.47]	[-1.27]	[-0.30]
# months	696	696	696	696	564	696	564
$\bar{R}^2(\%)$	7	7	7	5	5	6	10

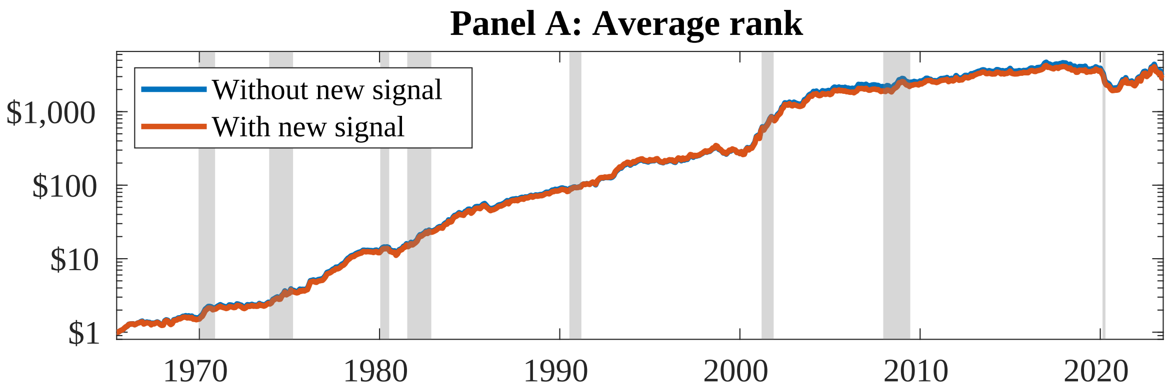


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

References

Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, 1(3):195–228.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Hirshleifer, D., Luo, J., and Teoh, S. H. (2020). Behavioral finance. *Review of Financial Studies*, 33(5):2217–2266.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper.*

Sloan, R. G., Soliman, M. T., and Zhu, C. (2018). A unified model of earnings, revenues, and accruals. *Journal of Accounting and Economics*, 66(1):1–24.

Titman, S. and Wessels, R. (1988). The determinants of capital structure choice. *Journal of Finance*, 43(1):1–19.