Operating Liquidity Margin and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Operating Liquidity Margin (OLM), 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 OLM achieves an annualized gross (net) Sharpe ratio of 0.30 (0.27), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 26 (17) bps/month with a t-statistic of 2.47 (1.70), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (operating profits / book equity, Predicted Analyst forecast error, Analyst earnings per share, Share turnover volatility, IPO and age, Operating leverage) is 24 bps/month with a t-statistic of 2.12.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While numerous accounting-based measures have been documented to forecast returns, the role of operating liquidity in asset pricing remains understudied. Operating liquidity - a firm's ability to convert operating activities into cash - represents a fundamental aspect of business performance that may contain important information about future profitability and risk. Despite its economic importance, prior literature has focused primarily on traditional liquidity measures like trading volume and bid-ask spreads, leaving the predictive power of operating liquidity largely unexplored.

This gap is particularly notable given that operating liquidity captures distinct information about a firm's operational efficiency and working capital management that is not fully reflected in conventional profitability or liquidity metrics. While measures like operating profits and trading volume are well-established return predictors, they may not fully capture the speed and efficiency with which firms convert operations into cash flow - a critical determinant of financial flexibility and distress risk.

We hypothesize that Operating Liquidity Margin (OLM) predicts stock returns through multiple economic channels. First, following Ben-Melech and Bergman (2009), firms with higher operating liquidity face lower financial constraints and have greater flexibility to fund profitable investments, leading to higher expected returns. This mechanism builds on the insight that the ability to quickly convert operations to cash reduces reliance on external financing.

Second, operating liquidity may serve as an indicator of management quality and operational efficiency, consistent with Dechow and Dichev (2002). More capable managers implement processes that minimize working capital requirements while maintaining smooth operations. This operational excellence should translate into superior long-term performance. Additionally, as argued by Fama and French (2006), measures of operating efficiency contain information about expected profitability and therefore expected returns.

Third, operating liquidity could proxy for risk factors not captured by traditional measures. Following **?**, firm characteristics that predict returns must reflect either mispricing or underlying economic risks. Higher operating liquidity could indicate lower sensitivity to aggregate funding liquidity shocks (Brunnermeier and Pedersen, 2009), suggesting OLM captures systematic risk exposure.

Our empirical analysis reveals that OLM strongly predicts cross-sectional stock returns. A value-weighted long-short strategy that buys stocks with high OLM and sells stocks with low OLM generates a monthly alpha of 26 basis points (t-statistic = 2.47) relative to the Fama-French six-factor model. The strategy's economic significance is substantial, achieving an annualized gross Sharpe ratio of 0.30, placing it in the top 35th percentile of documented anomalies.

Importantly, OLM's predictive power remains robust after controlling for transaction costs. The strategy delivers a net alpha of 17 basis points per month (t-statistic = 1.70) after accounting for trading frictions using the high-frequency bid-ask spread measure of Chen and Velikov (2022). This indicates that the OLM effect is implementable in practice and not merely a paper trading phenomenon.

The signal's predictive power extends across the size spectrum but is particularly strong among large-cap stocks, where the long-short strategy generates a monthly alpha of 33 basis points (t-statistic = 2.72) relative to the Fama-French six-factor model. This finding is notable since many documented anomalies are concentrated in small, illiquid stocks.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures a fundamental aspect of firm operations previously overlooked in return prediction. While Hou et al. (2015) examine operating profitability and Ng and Sivakumar (2011) study working capital accruals, OLM uniquely captures the efficiency of converting operations to cash flow.

Second, we extend the literature on financial constraints and stock returns. Prior work by Whited and Wu (2006) and Hadlock and Pierce (2010) focuses on identifying constrained firms through various metrics, but does not directly examine operating liquidity as a constraint measure. Our findings suggest that operating liquidity contains distinct information about constraints and expected returns.

Third, we contribute to the growing literature on quality factors in asset pricing. While Asness et al. (2013) propose a composite quality measure incorporating profitability, growth, and safety, we show that operating liquidity represents an important dimension of quality not captured by existing metrics. The robustness of OLM's predictive power to controlling for prominent quality factors suggests it captures unique information about firm fundamentals.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Operating Liquidity Margin, defined as the ratio of current assets to earnings before interest, taxes, depreciation, and amortization (EBITDA). We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item ACT for current assets and item EBITDA for earnings. Current assets (ACT) represent the firm's short-term assets, which are expected to be converted to cash or consumed within a year, including cash, receivables, and inventories. EBITDA, on the other hand, provides a measure of core operating performance by isolating operating income from non-operating expenses and tax effects. The construction of the Operating Liquidity Margin follows a straightforward ratio format, where we divide ACT by EBITDA for each firm in each year of our sample. This ratio captures the relative scale of a firm's liquid or short-term assets against its operational income, offering insight into how efficiently the firm utilizes current assets to generate earnings. By focusing on this relationship, the signal aims to reflect aspects of liquidity management and operational efficiency in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both ACT and EBITDA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the OLM signal. Panel A plots the time-series of the mean, median, and interquartile range for OLM. On average, the cross-sectional mean (median) OLM is 1.75 (2.69) over the 1964 to 2023 sample, where the starting date is determined by the availability of the input OLM data. The signal's interquartile range spans -2.42 to 5.73. Panel B of Figure 1 plots the time-series of the coverage of the OLM signal for the CRSP universe. On average, the OLM signal is available for 6.29% of CRSP names, which on average make up 7.06% of total market capitalization.

4 Does OLM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on OLM 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 OLM portfolio and sells the low OLM 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 OLM strategy earns an average return of 0.32% per month with a t-statistic of 2.34. The annualized Sharpe ratio of the strategy is 0.30. The alphas range from 0.09% to 0.26% per month and have t-statistics exceeding 0.73 everywhere. The lowest alpha is with respect to the CAPM 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 0.42, with a t-statistic of 11.61 on the SMB 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 447 stocks and an average market capitalization of at least $858 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 2.46. Out of the twenty-five alphas reported in Panel A, the t-statistics for nine exceed two, and for two 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 20-43bps/month. The lowest return, (20 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.73. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the OLM 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 three cases.

Table 3 provides direct tests for the role size plays in the OLM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and OLM, as well as average returns and alphas for long/short trading OLM 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 OLM strategy achieves an average return of 29 bps/month with a t-statistic of 1.98. Among these large cap stocks, the alphas for the OLM strategy relative to the five most common factor models range from 5 to 33 bps/month with t-statistics between 0.40 and 2.72.

5 How does OLM perform relative to the zoo?

Figure 2 puts the performance of OLM 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 OLM strategy falls in the distribution. The OLM strategy's gross (net) Sharpe ratio of 0.30 (0.27) is greater than 65% (88%) 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 OLM strategy (red line).[2] Ignoring trading costs, a \$1 invested in the OLM strategy would have yielded \$5.52 which ranks the OLM strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the OLM strategy would have yielded \$4.22 which ranks the OLM strategy in the top 3% 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 OLM relative to those. Panel A shows that the OLM strategy gross alphas fall between the 20 and 76 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 196406 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 OLM strategy has a positive net generalized alpha for five out of the five factor models. In these cases OLM ranks between the 51 and 83 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on OLM 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 OLM signal in these Fama-MacBeth regressions exceed 0.00, with the minimum t-statistic occurring when controlling for Predicted Analyst forecast error. Controlling for all six closely related anomalies, the t-statistic on OLM is NaN.

Similarly, Table 5 reports results from spanning tests that regress returns to the OLM 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 OLM strategy earns alphas that range from 19-40bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.98, which is achieved when controlling for Predicted Analyst forecast error. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the OLM trading strategy achieves an alpha of 24bps/month with a t-statistic of 2.12.

7 Does OLM add relative to the whole zoo?

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

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 155-anomaly combination strategy grows to $3137.77, while $1 investment in the combination strategy that includes OLM grows to $3317.15.

8 Conclusion

This study provides compelling evidence for the significance of Operating Liquidity Margin (OLM) as a valuable predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on OLM generates economically meaningful and statistically significant returns, even after accounting for transaction costs and controlling for established risk factors. The strategy's ability to maintain positive abnormal returns when benchmarked against both the Fama-French five-factor model plus momentum, and additional related factors from the factor zoo, suggests that OLM captures unique information about

[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 OLM is available.

future stock returns that is not fully reflected in existing pricing factors.

The robustness of OLM's predictive power, evidenced by its significant gross Sharpe ratio of 0.30 and net Sharpe ratio of 0.27, indicates its potential practical value for investment professionals. The persistence of abnormal returns after accounting for transaction costs (net alpha of 17 bps/month) suggests that the signal could be implementable in real-world trading strategies, though with somewhat diminished economic benefits.

However, several limitations should be noted. The study's findings may be sensitive to the specific time period examined and the methodological choices in signal construction. Future research could explore the signal's performance across different market regimes, international markets, and asset classes. Additionally, investigating the underlying economic mechanisms driving the OLM-return relationship and potential interactions with other firm characteristics could provide valuable insights. Further analysis of the signal's stability and potential decay over time would also be beneficial for understanding its long-term viability as a return predictor.

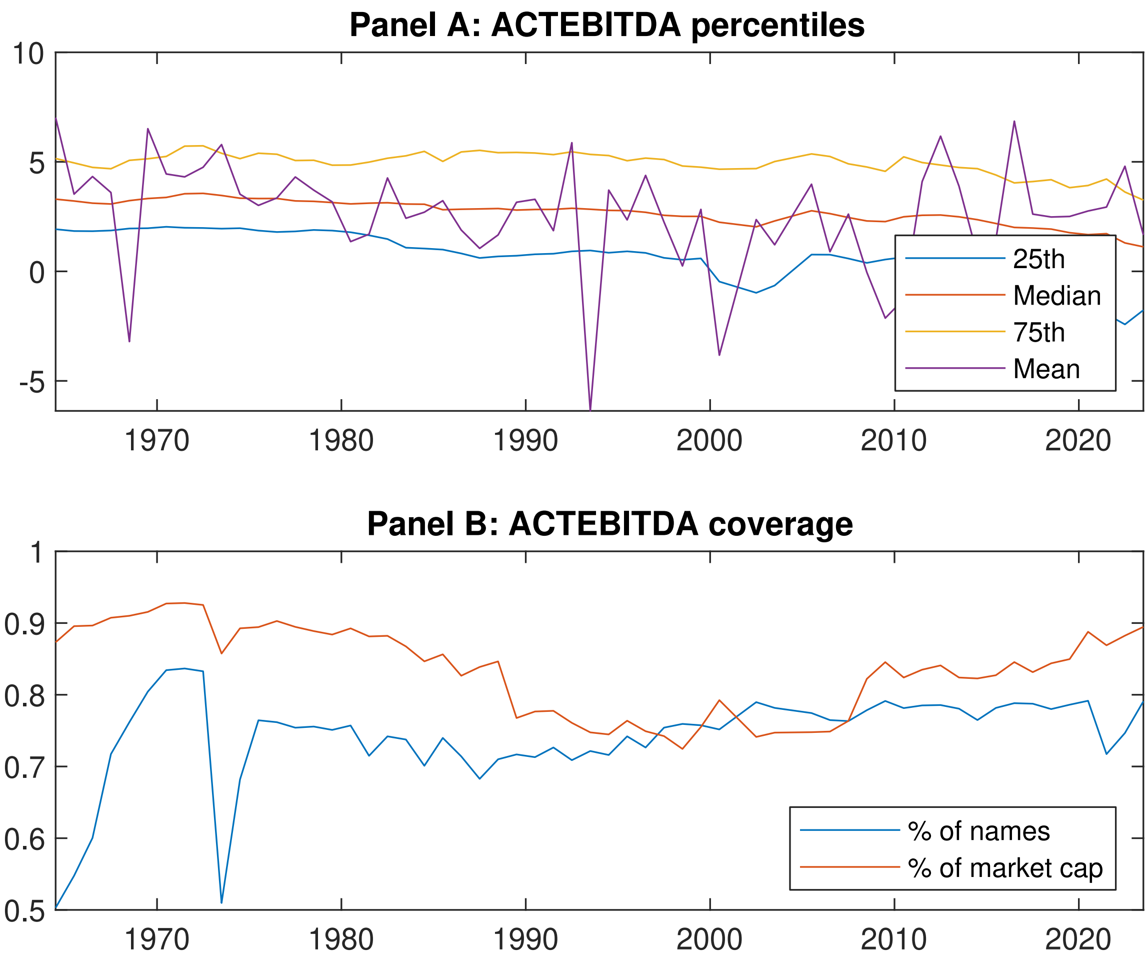

Figure 1: Times series of OLM percentiles and coverage.
This figure plots descriptive statistics for OLM. Panel A shows cross-sectional percentiles of OLM over the sample. Panel B plots the monthly coverage of OLM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on OLM. 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 196406 to 202306.

Panel A: Excess returns and alphas on OLM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40	0.59	0.63	0.63	0.73	0.32
	[2.55]	[3.75]	[3.46]	[3.06]	[3.09]	[2.34]
α_{CAPM}	-0.07	0.10	0.05	-0.02	0.02	0.09
	[-1.12]	[2.06]	[1.10]	[-0.24]	[0.17]	[0.73]
α_{FF3}	-0.07	0.12	0.09	0.02	0.04	0.12
	[-1.12]	[2.81]	[2.14]	[0.28]	[0.63]	[1.14]
α_{FF4}	-0.08	0.09	0.11	0.07	0.08	0.16
	[-1.24]	[2.08]	[2.51]	[1.23]	[1.11]	[1.55]
α_{FF5}	-0.02	-0.01	0.06	0.06	0.21	0.23
	[-0.26]	[-0.36]	[1.44]	[1.07]	[3.21]	[2.20]
α_{FF6}	-0.03	-0.03	0.08	0.10	0.23	0.26
	[-0.43]	[-0.71]	[1.80]	[1.78]	[3.47]	[2.47]
Panel B: Fama and French (2018) 6-factor model loadings for OLM-sorted portfolios						
β_{MKT}	0.85	0.95	1.02	1.08	1.12	0.27
	[54.13]	[100.75]	[99.41]	[77.72]	[70.80]	[10.84]
β_{SMB}	-0.06	-0.10	0.02	0.18	0.36	0.42
	[-2.69]	[-7.06]	[1.07]	[9.07]	[15.63]	[11.61]
β_{HML}	0.03	-0.11	-0.13	-0.14	-0.24	-0.28
	[1.14]	[-5.89]	[-6.79]	[-5.37]	[-7.94]	[-5.75]
β_{RMW}	-0.15	0.24	0.08	-0.04	-0.42	-0.27
	[-4.83]	[13.10]	[4.18]	[-1.51]	[-13.49]	[-5.52]
β_{CMA}	-0.03	0.21	0.01	-0.09	-0.03	-0.00
	[-0.57]	[7.85]	[0.37]	[-2.36]	[-0.64]	[-0.05]
β_{UMD}	0.02	0.02	-0.02	-0.06	-0.03	-0.05
	[1.12]	[2.23]	[-2.40]	[-4.53]	[-1.85]	[-1.88]
Panel C: Average number of firms (n) and market capitalization (me)						
n	943	447	486	578	859	
me ($\$10^6$)	1413	2607	1876	1414	858	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the OLM 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 196406 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	0.32	0.09	0.12	0.16	0.23	0.26
			[2.34]	[0.73]	[1.14]	[1.55]	[2.20]	[2.47]
Quintile	NYSE	EW	0.38	0.37	0.27	0.21	0.05	0.01
			[3.46]	[3.37]	[2.50]	[1.89]	[0.49]	[0.10]
Quintile	Name	VW	0.49	0.46	0.36	0.34	0.04	0.04
			[3.38]	[3.18]	[2.56]	[2.36]	[0.29]	[0.33]
Quintile	Cap	VW	0.30	0.09	0.15	0.18	0.23	0.25
			[2.46]	[0.85]	[1.64]	[1.93]	[2.38]	[2.55]
Decile	NYSE	VW	0.35	0.11	0.13	0.11	0.13	0.12
			[2.23]	[0.78]	[0.97]	[0.81]	[0.98]	[0.86]

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	0.06	0.08	0.11	0.16	0.17
			[2.11]	[0.52]	[0.80]	[1.07]	[1.58]	[1.70]
Quintile	NYSE	EW	0.20	0.17	0.07	0.04		
			[1.73]	[1.46]	[0.63]	[0.34]		
Quintile	Name	VW	0.43	0.42	0.32	0.31	0.03	0.04
			[2.95]	[2.85]	[2.27]	[2.18]	[0.23]	[0.34]
Quintile	Cap	VW	0.28	0.07	0.12	0.14	0.17	0.17
			[2.29]	[0.66]	[1.30]	[1.49]	[1.76]	[1.81]
Decile	NYSE	VW	0.30	0.07	0.07	0.07	0.06	0.05
			[1.92]	[0.50]	[0.58]	[0.52]	[0.48]	[0.40]

Table 3: Conditional sort on size and OLM

This table presents results for conditional double sorts on size and OLM. 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 OLM. 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 OLM and short stocks with low OLM .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196406 to 202306.

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

		OLM Quintiles					OLM Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.49	0.52	0.68	0.88	0.87	0.38	0.43	0.29	0.28	0.02	0.03
		[1.60]	[1.80]	[2.72]	[3.53]	[3.12]	[2.71]	[3.03]	[2.13]	[2.01]	[0.15]	[0.23]
	(2)	0.67	0.74	0.72	0.84	0.76	0.09	0.07	-0.06	-0.07	-0.34	-0.32
		[2.45]	[3.26]	[3.14]	[3.52]	[2.88]	[0.70]	[0.55]	[-0.53]	[-0.53]	[-3.02]	[-2.81]
	(3)	0.56	0.83	0.72	0.86	0.68	0.12	0.01	-0.07	-0.12	-0.28	-0.31
		[2.42]	[4.14]	[3.42]	[3.83]	[2.70]	[0.90]	[0.09]	[-0.53]	[-0.91]	[-2.24]	[-2.42]
	(4)	0.51	0.68	0.79	0.74	0.80	0.29	0.10	0.12	0.11	0.10	0.09
		[2.70]	[3.62]	[3.97]	[3.50]	[3.29]	[2.14]	[0.83]	[1.05]	[0.96]	[0.80]	[0.77]
	(5)	0.34	0.57	0.55	0.57	0.63	0.29	0.05	0.17	0.19	0.31	0.33
		[2.20]	[3.65]	[3.36]	[3.06]	[2.87]	[1.98]	[0.40]	[1.41]	[1.62]	[2.64]	[2.72]

Panel B: Portfolio average number of firms and market capitalization

		OLM Quintiles					OLM Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	371	369	379	380	378	24	26	34	34	27
	(2)	101	101	101	102	101	48	50	50	50	48
	(3)	71	72	72	71	71	82	85	85	84	82
	(4)	60	60	61	60	60	175	184	185	183	176
	(5)	53	54	54	54	54	1056	1451	1492	1340	1118

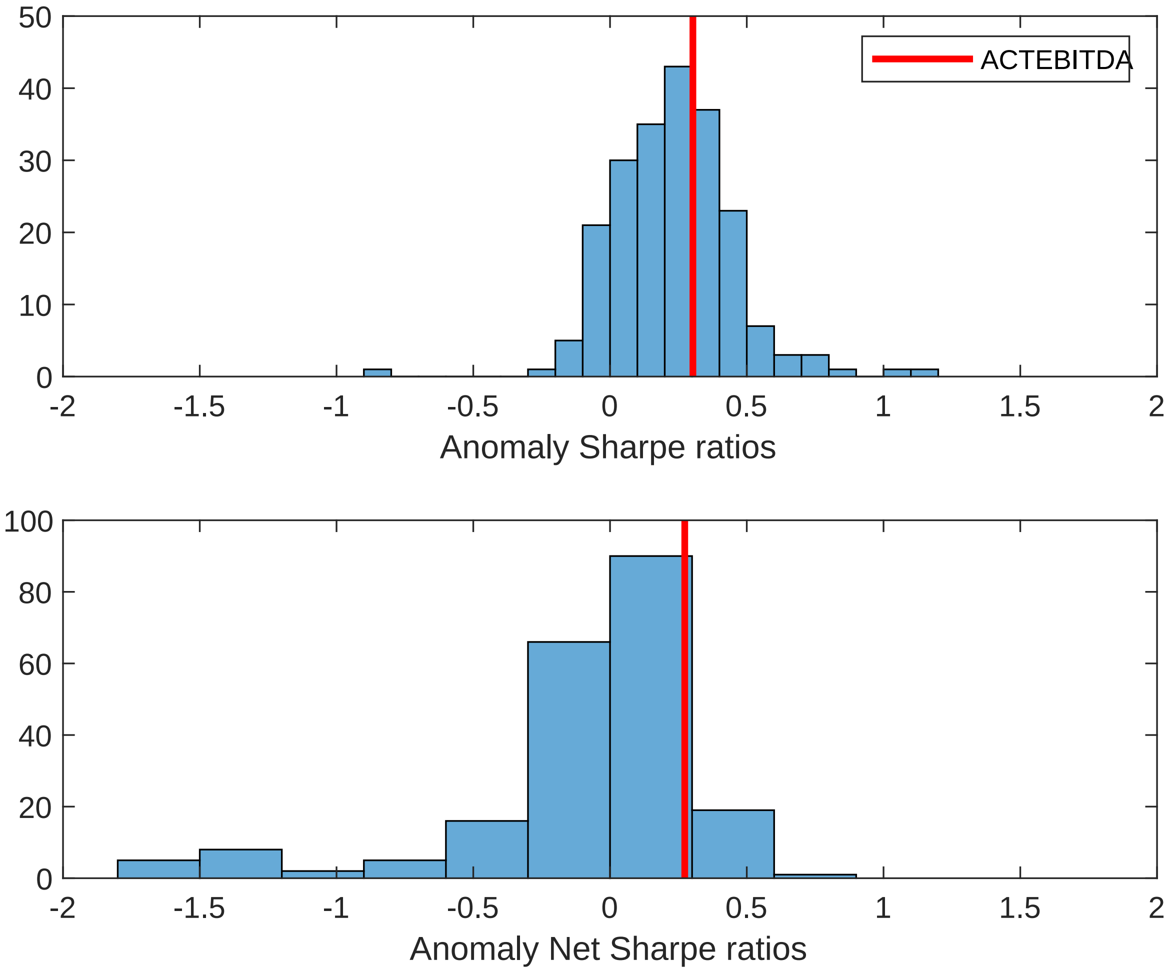

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the OLM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

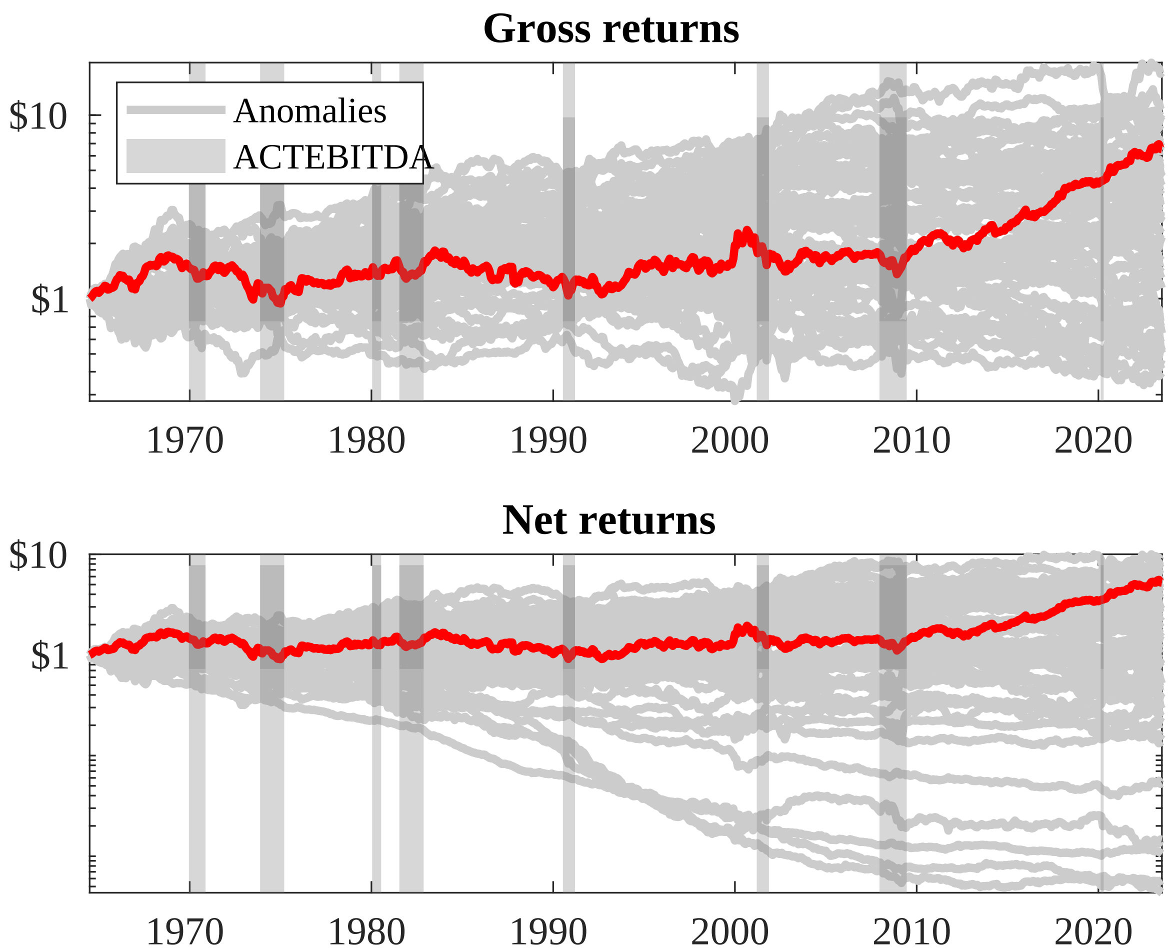

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the OLM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

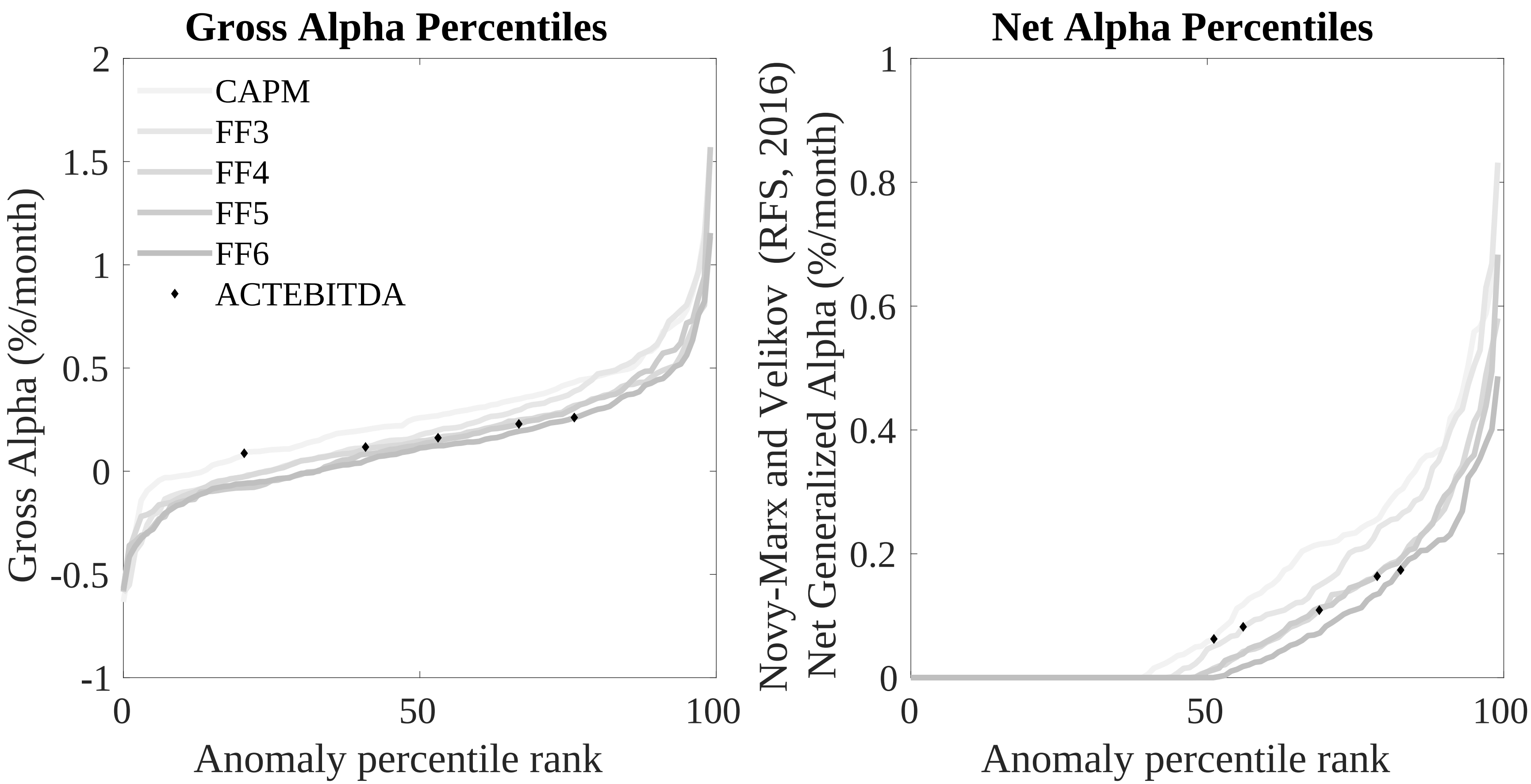

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the OLM trading strategy alphas (diamonds). The strategies are constructed using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

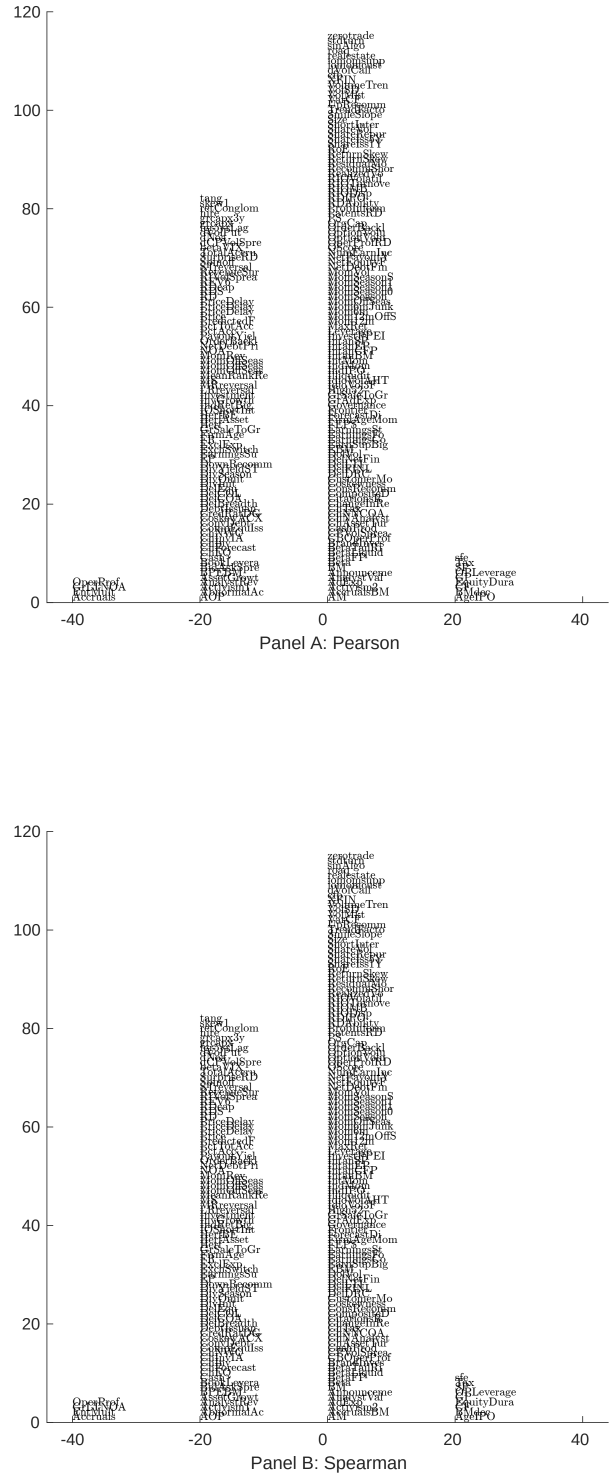

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with OLM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

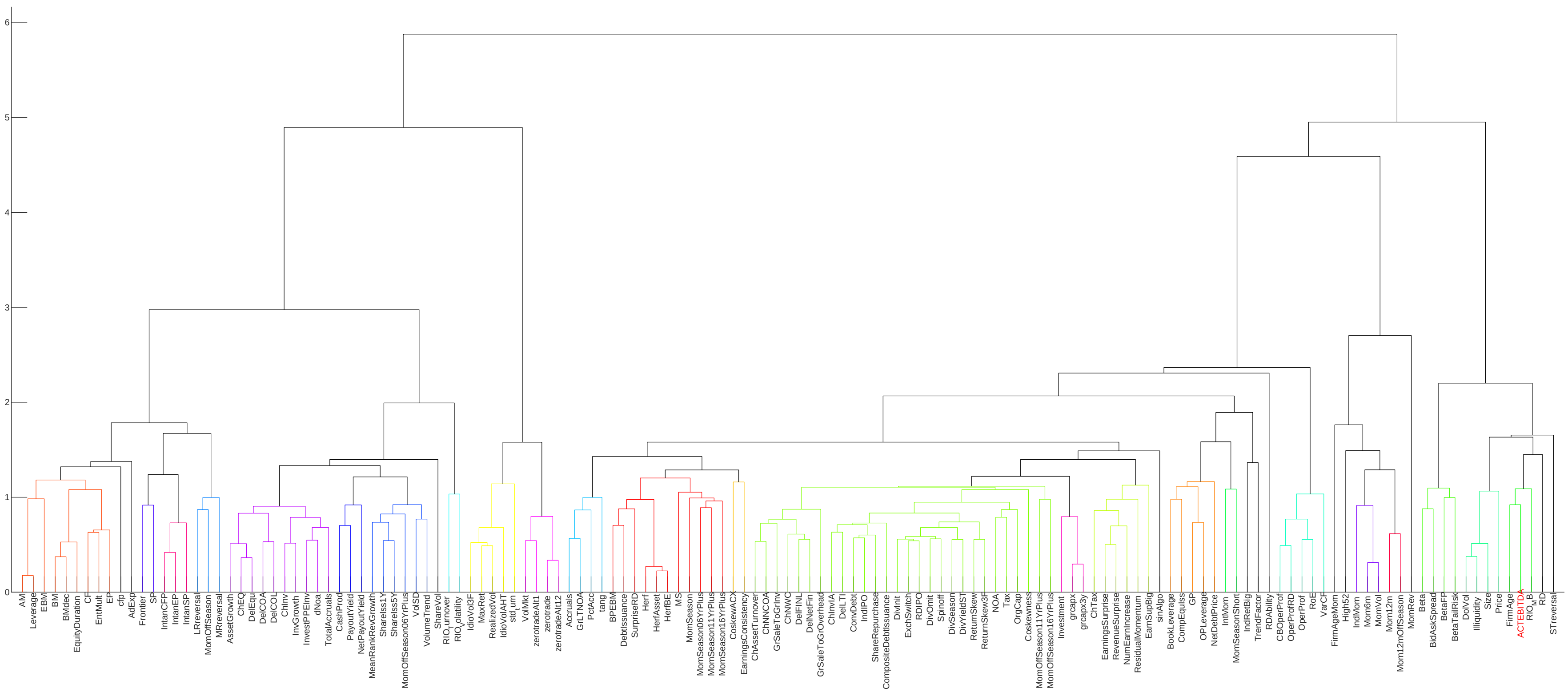

Figure 6: Agglomerative hierarchical cluster plot

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

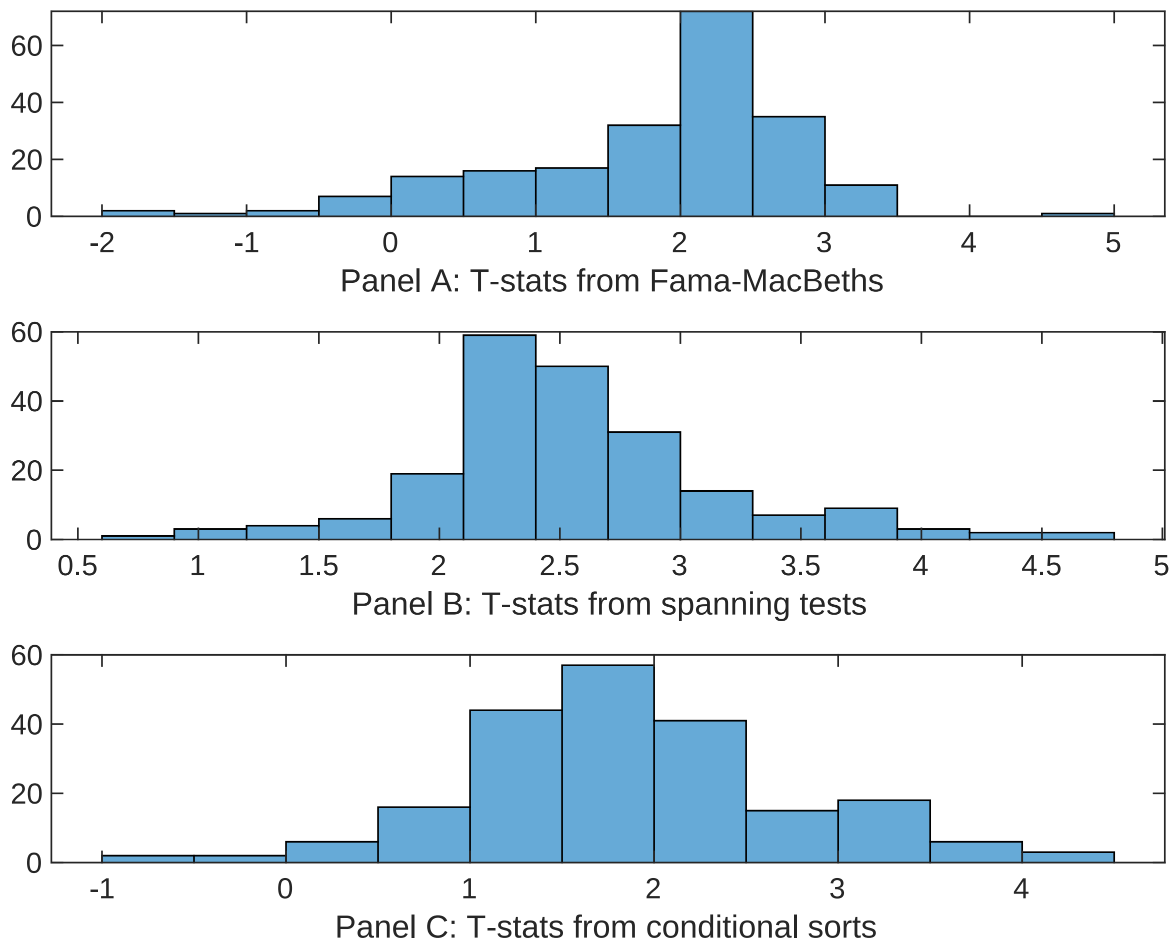

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of OLM conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{OLM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OLM} OLM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{OLM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 OLM. Stocks are finally grouped into five OLM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted OLM 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 OLM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{OLM} OLM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are operating profits / book equity, Predicted Analyst forecast error, Analyst earnings per share, Share turnover volatility, IPO and age, Operating leverage. 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 196406 to 202306.

Intercept	0.91	0.11	0.10	0.17	0.86	0.97	
	[3.91]	[5.25]	[3.46]	[7.15]	[1.95]	[4.21]	
OLM	0.12	0.33	0.38	0.44	0.26	0.58	
	[3.12]	[0.00]	[1.47]	[0.20]	[0.58]	[2.15]	
Anomaly 1	0.50						
	[3.81]						
Anomaly 2		0.78					
		[0.29]					
Anomaly 3			0.70				
			[1.16]				
Anomaly 4				0.76			
				[4.67]			
Anomaly 5					0.27		
					[0.59]		
Anomaly 6						0.16	
						[4.07]	
# months	703	480	564	703	463	708	0
$\bar{R}^2(\%)$	1	2	1	1	0	0	

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the OLM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{OLM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 operating profits / book equity, Predicted Analyst forecast error, Analyst earnings per share, Share turnover volatility, IPO and age, Operating leverage. 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 196406 to 202306.

Intercept	0.34	0.24	0.33	0.24	0.40	0.19	0.24
	[3.45]	[1.98]	[2.77]	[2.30]	[3.14]	[2.04]	[2.12]
Anomaly 1	-43.15						-32.06
	[-9.42]						[-5.62]
Anomaly 2		-25.78					-20.91
		[-6.95]					[-5.97]
Anomaly 3			-5.29				7.46
			[-1.13]				[1.55]
Anomaly 4				8.92			12.60
				[2.96]			[3.80]
Anomaly 5					2.26		0.29
					[0.92]		[0.13]
Anomaly 6						45.16	30.04
						[11.94]	[6.31]
mkt	21.54	25.31	27.00	31.56	27.84	28.58	30.37
	[9.00]	[8.41]	[9.12]	[11.24]	[9.39]	[12.70]	[9.20]
smb	32.82	37.41	32.69	48.31	36.35	22.97	27.83
	[9.30]	[8.35]	[6.26]	[12.50]	[7.78]	[6.27]	[5.16]
hml	-27.81	-17.30	-28.08	-28.73	-29.65	-2.70	-10.93
	[-6.23]	[-3.01]	[-5.17]	[-5.87]	[-5.12]	[-0.57]	[-1.77]
rmw	11.15	-17.56	-27.01	-36.45	-35.83	-53.70	-29.23
	[1.78]	[-3.02]	[-3.74]	[-6.95]	[-5.66]	[-11.03]	[-3.28]
cma	-3.33	2.47	-0.13	-5.46	-6.24	-7.99	-4.01
	[-0.51]	[0.31]	[-0.02]	[-0.79]	[-0.75]	[-1.25]	[-0.53]
umd	-0.29	-4.65	-3.33	-6.57	-3.38	-5.65	-6.76
	[-0.13]	[-1.67]	[-1.15]	[-2.65]	[-1.17]	[-2.54]	[-2.35]
# months	704	480	565	704	507	708	476
$\bar{R}^2$(%)	56	55	50	52	50	58	63

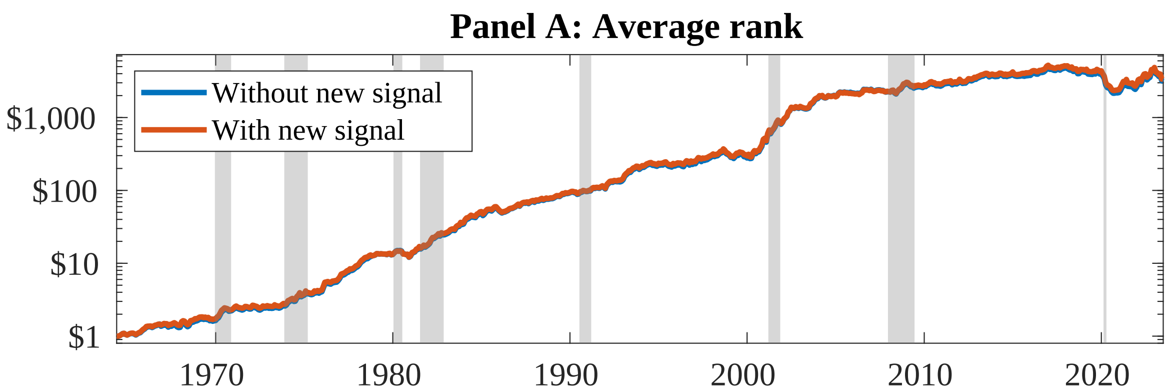

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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