Cash Profitability Index and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Cash Profitability Index (CPI), 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 CPI achieves an annualized gross (net) Sharpe ratio of 0.41 (0.37), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (16) bps/month with a t-statistic of 2.26 (1.71), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Realized (Total) Volatility, net income / book equity, Price, Maximum return over month) is 24 bps/month with a t-statistic of 2.54.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn excess returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different market conditions and time periods is frequently questioned (Hou et al., 2020).

A particularly intriguing puzzle in asset pricing is the relationship between various measures of profitability and future stock returns. While traditional measures like return on equity show some predictive power (Fama and French, 2015), they may be distorted by accrual accounting choices and fail to capture the true economic profitability of firms (Novy-Marx, 2013).

We propose that the Cash Profitability Index (CPI), which measures a firm's ability to generate cash-based operating profits relative to invested capital, provides a more reliable signal of future stock returns than traditional accounting-based measures. The theoretical foundation for this relationship stems from q-theory of investment (Cochrane, 1991), which suggests that firms with higher productivity of capital should earn higher expected returns.

Cash-based measures are particularly informative because they are less subject to manipulation and accounting distortions than accrual-based metrics (Dechow and Dichev, 2002). Moreover, cash profitability better reflects a firm's current operating efficiency and its ability to generate real economic value (Ball et al., 2016).

The predictive power of CPI may also stem from investors' limited attention to cash flow information (Hirshleifer and Teoh, 2003) and their tendency to focus on earnings-based metrics. This behavioral bias could lead to systematic underreaction to information contained in cash profitability measures, creating predictable patterns in future returns.

Our empirical analysis reveals that CPI is a robust predictor of cross-sectional stock returns. A value-weighted long-short strategy based on CPI quintiles generates a significant monthly alpha of 21 basis points (t-statistic = 2.26) relative to the Fama-French six-factor model. The strategy's economic significance is substantial, achieving an annualized Sharpe ratio of 0.41 before trading costs and 0.37 after accounting for transaction costs.

Importantly, CPI's predictive power remains strong among large-cap stocks, with the highest size quintile generating a monthly alpha of 31 basis points (t-statistic = 2.88). This finding suggests that the anomaly is not driven by small, illiquid stocks that are costly to trade.

The signal's robustness is further demonstrated by its performance against the factor zoo. CPI's gross Sharpe ratio exceeds 84% of documented anomalies, while its net Sharpe ratio (after trading costs) ranks even higher, surpassing 94% of competing strategies.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of (Novy-Marx, 2013) on gross profitability by showing that cash-based measures provide incremental predictive power beyond traditional profitability metrics. Second, we contribute to the growing literature on quality investing (Asness et al., 2019) by introducing a new measure that captures fundamental firm quality.

Third, our findings complement recent work on the role of accounting information in asset pricing (Ball et al., 2016) by demonstrating the importance of cash-based metrics in predicting returns. The robust performance of CPI among large-cap stocks distinguishes it from many documented anomalies that work primarily in small caps (Hou et al., 2020).

Finally, our results have important implications for both academic research and investment practice. For academics, they highlight the need to consider cash-based measures when studying firm profitability and stock returns. For practitioners, CPI offers a transparent and implementable strategy that remains profitable after accounting for transaction costs.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Cash Profitability Index, which measures the ratio of cash holdings to operating income before depreciation. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CH for cash and short-term investments and item OIADP for operating income before depreciation. Cash and short-term investments (CH) represent the firm's most liquid assets, including cash on hand and marketable securities that can be readily converted to cash. Operating income before depreciation (OIADP) provides a measure of core operating performance by capturing the firm's ability to generate earnings from its primary business activities before accounting for non-cash expenses like depreciation. The construction of the signal follows a straightforward ratio format, where we divide CH by OIADP for each firm in each year of our sample. This ratio captures the relative scale of a firm's cash holdings against its operational income, offering insight into the firm's cash management efficiency and operating performance. By focusing on this relationship, the signal aims to reflect aspects of liquidity position and operational profitability in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both CH and OIADP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CPI signal. Panel A plots the time-series of the mean, median, and interquartile range for CPI. On average, the cross-sectional mean (median) CPI is 0.95 (0.32) over the 1971 to 2023 sample, where the starting date is determined by the availability of the input CPI data. The signal's interquartile range spans -1.21 to 1.77. Panel B of Figure 1 plots the time-series of the coverage of the CPI signal for the CRSP universe. On average, the CPI signal is available for 6.98% of CRSP names, which on average make up 7.47% of total market capitalization.

4 Does CPI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CPI 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 CPI portfolio and sells the low CPI 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 CPI strategy earns an average return of 0.29% per month with a t-statistic of 2.99. The annualized Sharpe ratio of the strategy is 0.41. The alphas range from 0.14% to 0.21% per month and have t-statistics exceeding 1.56 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 0.16, with a t-statistic of 7.49 on the MKT factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 492 stocks and an average market capitalization of at least $1,187 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 24 bps/month with a t-statistics of 2.72. Out of the twenty-five alphas reported in Panel A, the t-statistics for eleven exceed two, and for three 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 19-35bps/month. The lowest return, (19 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.42. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CPI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-one cases, and significantly expands the achievable frontier in five cases.

Table 3 provides direct tests for the role size plays in the CPI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CPI, as well as average returns and alphas for long/short trading CPI 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 CPI strategy achieves an average return of 28 bps/month with a t-statistic of 2.43. Among these large cap stocks, the alphas for the CPI strategy relative to the five most common factor models range from 13 to 31 bps/month with t-statistics between 1.19 and 2.88.

5 How does CPI perform relative to the zoo?

Figure 2 puts the performance of CPI 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 CPI strategy falls in the distribution. The CPI strategy's gross (net) Sharpe ratio of 0.41 (0.37) is greater than 84% (94%) 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 CPI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CPI strategy would have yielded \$4.03 which ranks the CPI strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CPI strategy would have yielded \$3.19 which ranks the CPI 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 CPI relative to those. Panel A shows that the CPI strategy gross alphas fall between the 35 and 70 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 197106 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The CPI strategy has a positive net generalized alpha for five out of the five factor models. In these cases CPI ranks between the 60 and 81 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CPI 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 CPI signal in these Fama-MacBeth regressions exceed -0.59, with the minimum t-statistic occurring when controlling for Maximum return over month. Controlling for all six closely related anomalies, the t-statistic on CPI is -0.57.

Similarly, Table 5 reports results from spanning tests that regress returns to the CPI 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 CPI strategy earns alphas that range from 22-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.34, which is achieved when controlling for Maximum return over month. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CPI trading strategy achieves an alpha of 24bps/month with a t-statistic of 2.54.

7 Does CPI add relative to the whole zoo?

Finally, we can ask how much adding CPI to the entire factor zoo could improve investment performance. Figure 8 plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the CPI 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

[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 CPI is available.

on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 156-anomaly combination strategy grows to $1203.74, while $1 investment in the combination strategy that includes CPI grows to $1347.21.

8 Conclusion

Our comprehensive analysis of the Cash Profitability Index (CPI) reveals its significant potential as a robust predictor of stock returns in the cross-section of equities. The empirical evidence demonstrates that a value-weighted long/short trading strategy based on CPI generates economically meaningful and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.41 (0.37 net). The strategy's persistence in generating significant abnormal returns, even after controlling for well-established factors and related anomalies, underscores CPI's unique informational content in asset pricing.

Particularly noteworthy is the signal's ability to maintain its predictive power when accounting for transaction costs, as evidenced by the net returns analysis. The strategy's monthly alpha of 24 bps relative to both standard factors and closely related anomalies suggests that CPI captures distinct aspects of firm performance not fully reflected in existing metrics.

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, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore several promising directions. First, investigating the interaction between CPI and other established anomalies could yield insights into potential complementarities or substitution effects. Second, examining the signal's performance in different market capitalizations and international markets could assess its broader applicability. Finally, analyzing the underlying economic mechanisms driving the CPI premium could enhance our understanding of market efficiency and price formation processes.

In conclusion, our findings suggest that CPI represents a valuable addition to the investment practitioner's toolkit, offering meaningful predictive power for stock returns while maintaining robustness to transaction costs and common risk factors.

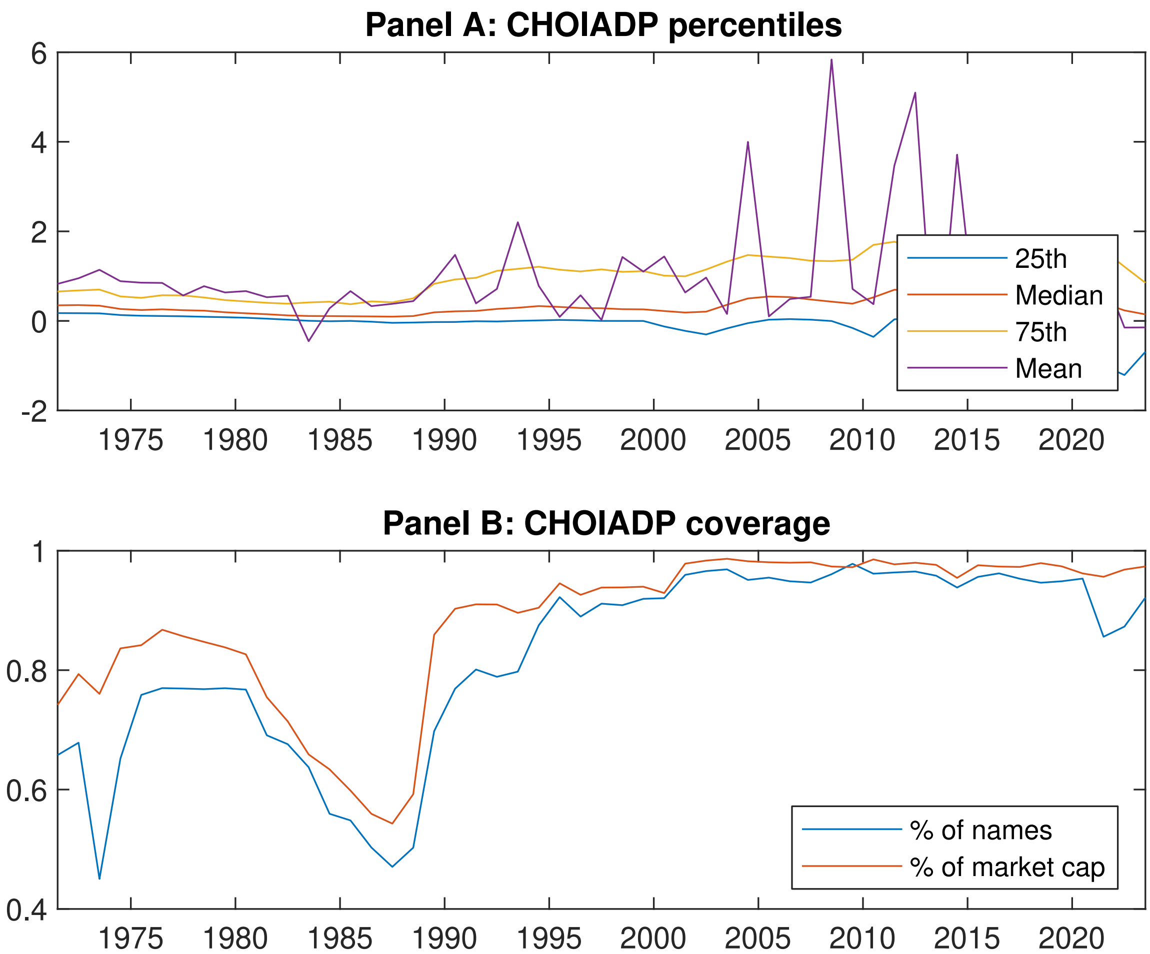


Figure 1: Times series of CPI percentiles and coverage.
This figure plots descriptive statistics for CPI. Panel A shows cross-sectional percentiles of CPI over the sample. Panel B plots the monthly coverage of CPI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CPI. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 197106 to 202306.

Panel A: Excess returns and alphas on CPI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.58	0.63	0.66	0.74	0.29
	[2.37]	[3.36]	[3.41]	[3.25]	[3.30]	[2.99]
α_{CAPM}	-0.14	0.04	0.04	0.02	0.04	0.17
	[-2.07]	[0.80]	[0.94]	[0.31]	[0.57]	[1.91]
α_{FF3}	-0.12	0.03	0.02	0.01	0.02	0.14
	[-1.93]	[0.55]	[0.42]	[0.30]	[0.27]	[1.56]
α_{FF4}	-0.13	0.02	0.01	0.04	0.05	0.17
	[-1.98]	[0.48]	[0.26]	[0.73]	[0.76]	[1.92]
α_{FF5}	-0.03	-0.12	-0.08	-0.00	0.15	0.19
	[-0.52]	[-2.60]	[-1.93]	[-0.02]	[2.74]	[2.04]
α_{FF6}	-0.04	-0.11	-0.08	0.02	0.17	0.21
	[-0.67]	[-2.38]	[-1.86]	[0.35]	[2.94]	[2.26]
Panel B: Fama and French (2018) 6-factor model loadings for CPI-sorted portfolios						
β_{MKT}	0.95	0.95	1.01	1.05	1.11	0.16
	[63.76]	[90.43]	[98.67]	[89.72]	[83.65]	[7.49]
β_{SMB}	0.04	-0.09	0.01	0.06	0.13	0.09
	[2.02]	[-5.84]	[0.39]	[3.29]	[6.63]	[2.68]
β_{HML}	-0.02	-0.01	0.02	-0.02	0.10	0.12
	[-0.60]	[-0.64]	[0.87]	[-0.75]	[3.99]	[2.86]
β_{RMW}	-0.24	0.30	0.22	0.06	-0.26	-0.02
	[-8.28]	[14.74]	[11.07]	[2.73]	[-10.05]	[-0.48]
β_{CMA}	-0.02	0.15	0.10	-0.01	-0.17	-0.14
	[-0.52]	[4.79]	[3.40]	[-0.28]	[-4.35]	[-2.31]
β_{UMD}	0.01	-0.01	-0.00	-0.03	-0.02	-0.03
	[1.02]	[-1.22]	[-0.32]	[-2.37]	[-1.46]	[-1.60]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1193	492	555	666	994	
me ($\$10^6$)	1187	2499	2903	2253	1819	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CPI strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 197106 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.29	0.17	0.14	0.17	0.19	0.21
			[2.99]	[1.91]	[1.56]	[1.92]	[2.04]	[2.26]
Quintile	NYSE	EW	0.39	0.46	0.36	0.23	0.10	0.01
			[3.04]	[3.69]	[3.15]	[2.06]	[1.04]	[0.13]
Quintile	Name	VW	0.35	0.44	0.27	0.24	-0.03	-0.04
			[2.18]	[2.75]	[1.93]	[1.65]	[-0.25]	[-0.35]
Quintile	Cap	VW	0.24	0.12	0.11	0.14	0.21	0.23
			[2.72]	[1.45]	[1.36]	[1.80]	[2.69]	[2.91]
Decile	NYSE	VW	0.40	0.41	0.30	0.32	0.20	0.21
			[3.04]	[3.10]	[2.45]	[2.56]	[1.60]	[1.73]
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	0.26	0.14	0.11	0.13	0.13	0.16
			[2.68]	[1.57]	[1.25]	[1.48]	[1.45]	[1.71]
Quintile	NYSE	EW	0.19	0.24	0.14	0.07		
			[1.42]	[1.84]	[1.16]	[0.58]		
Quintile	Name	VW	0.30	0.39	0.25	0.23		
			[1.88]	[2.47]	[1.74]	[1.59]		
Quintile	Cap	VW	0.21	0.09	0.08	0.10	0.15	0.17
			[2.41]	[1.09]	[1.02]	[1.30]	[1.91]	[2.15]
Decile	NYSE	VW	0.35	0.36	0.27	0.28	0.15	0.19
			[2.70]	[2.76]	[2.16]	[2.25]	[1.23]	[1.49]

Table 3: Conditional sort on size and CPI

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

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

		CPI Quintiles					CPI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.33	0.27	0.72	0.82	0.92	0.59	0.73	0.57	0.51	0.22	0.19
		[1.01]	[0.87]	[2.88]	[3.46]	[3.57]	[3.60]	[4.62]	[4.06]	[3.61]	[1.77]	[1.55]
	(2)	0.47	0.69	0.81	0.79	0.83	0.36	0.50	0.34	0.33	0.13	0.13
		[1.54]	[2.90]	[3.37]	[3.28]	[3.49]	[2.58]	[3.76]	[2.94]	[2.80]	[1.28]	[1.26]
	(3)	0.54	0.65	0.79	0.82	0.72	0.18	0.24	0.11	-0.02	-0.10	-0.20
		[2.08]	[3.05]	[3.45]	[3.57]	[3.11]	[1.43]	[1.85]	[0.91]	[-0.20]	[-0.86]	[-1.70]
	(4)	0.54	0.68	0.67	0.75	0.82	0.28	0.20	0.16	0.12	0.16	0.12
		[2.48]	[3.42]	[3.20]	[3.37]	[3.36]	[2.67]	[1.93]	[1.59]	[1.16]	[1.50]	[1.15]
	(5)	0.42	0.59	0.55	0.57	0.69	0.28	0.13	0.13	0.18	0.28	0.31
		[2.35]	[3.51]	[3.09]	[2.83]	[3.16]	[2.43]	[1.19]	[1.22]	[1.64]	[2.67]	[2.88]

Panel B: Portfolio average number of firms and market capitalization

		CPI Quintiles					CPI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	446	436	452	455	455	35	30	43	45	43
	(2)	121	121	121	121	121	63	64	67	67	66
	(3)	83	84	84	83	83	108	111	113	110	109
	(4)	67	67	68	68	67	222	232	232	232	233
	(5)	59	60	60	60	59	1213	2014	2033	1653	1525

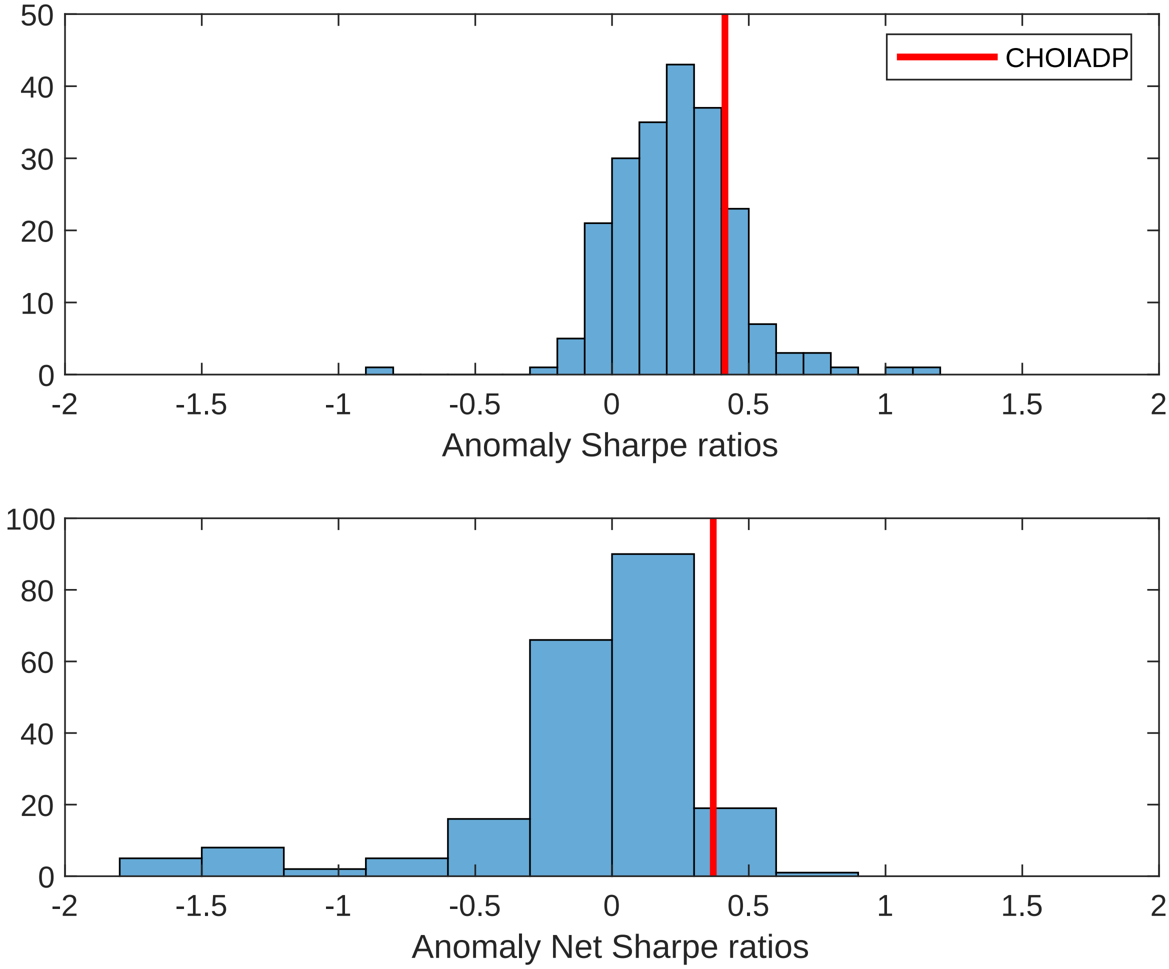


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CPI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

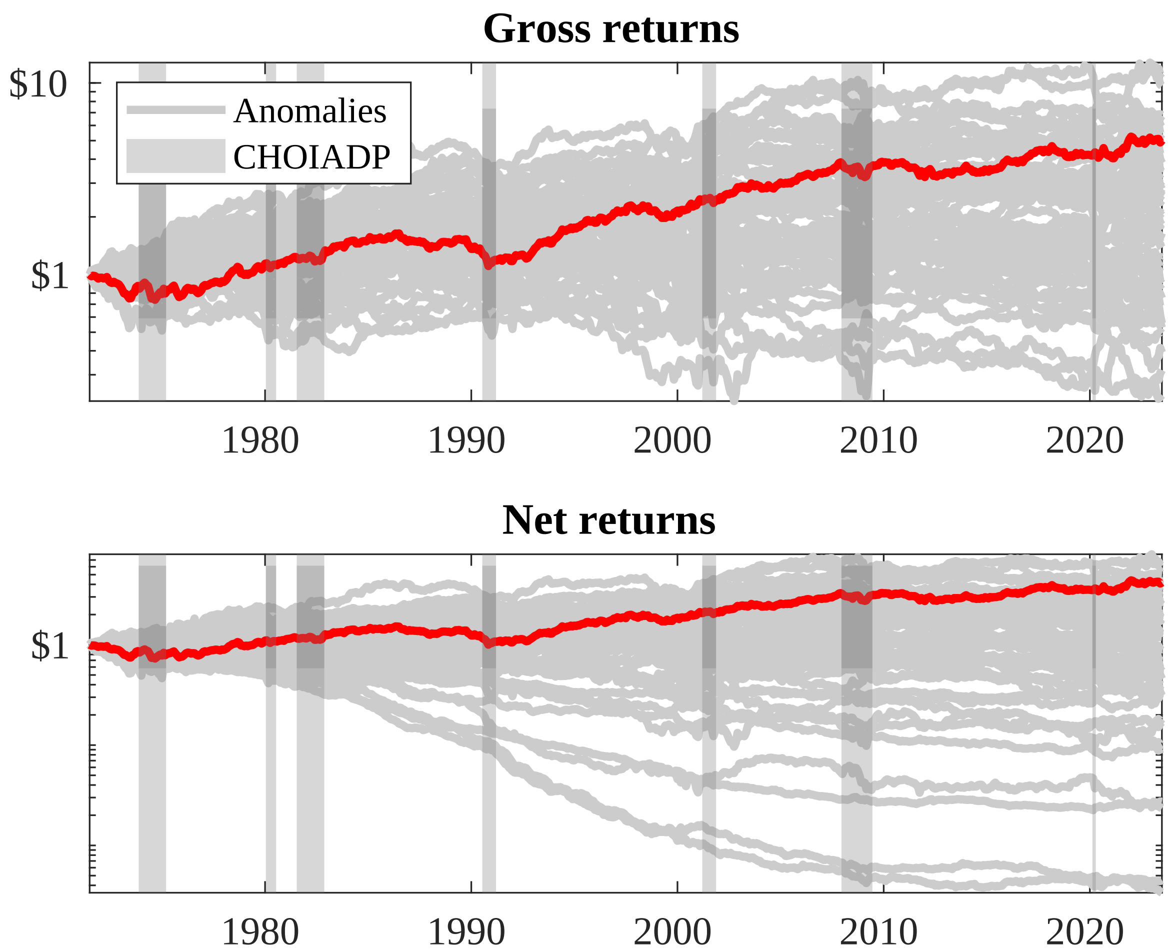


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CPI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

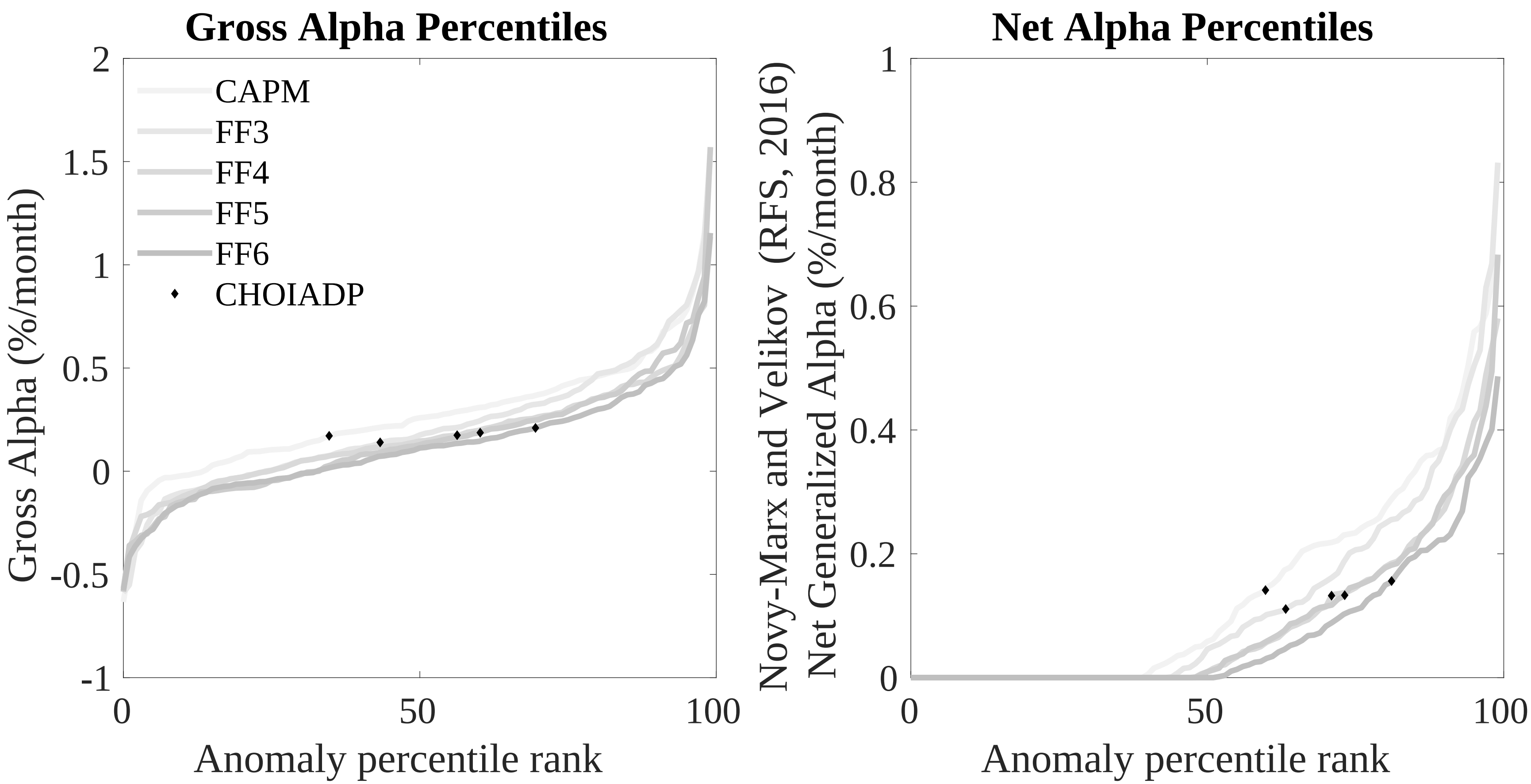
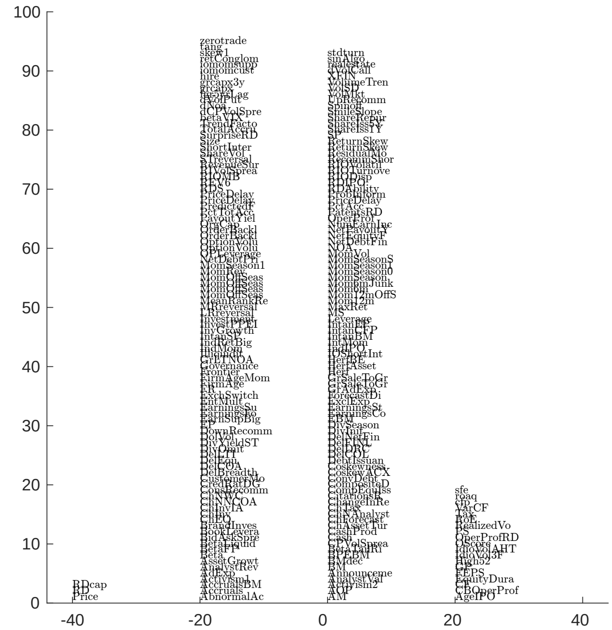
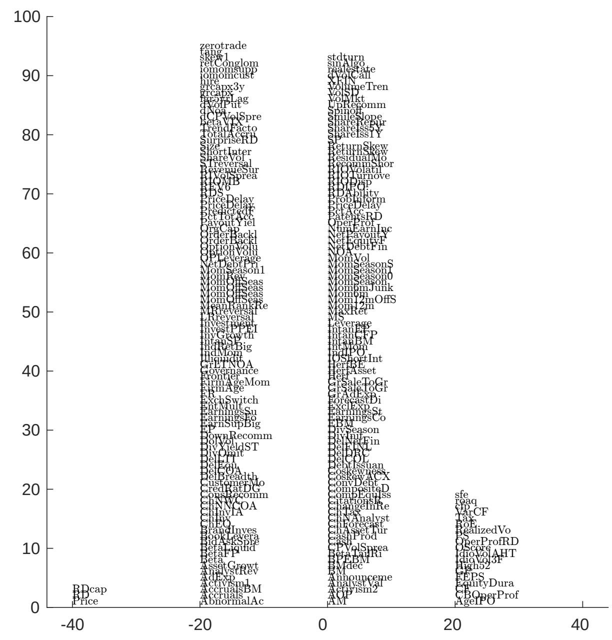


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CPI trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

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

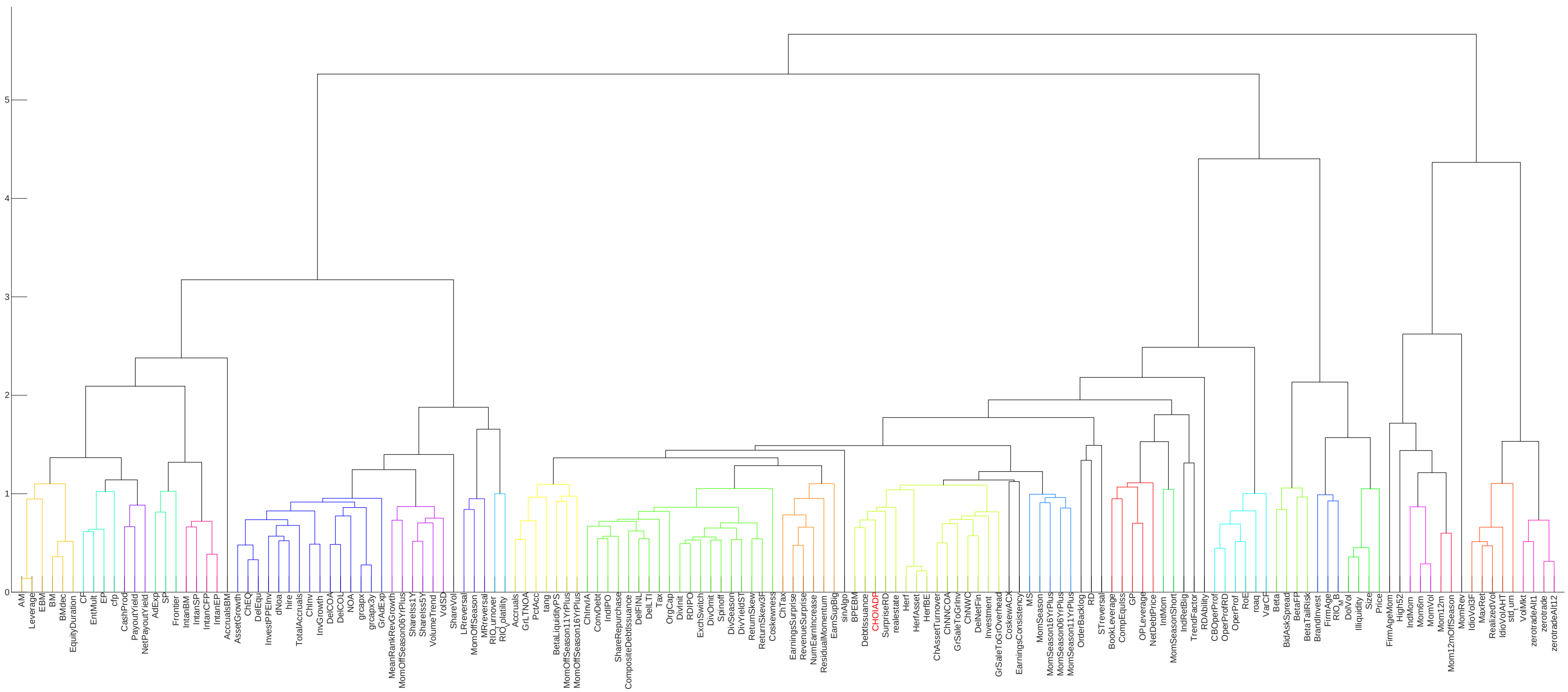


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

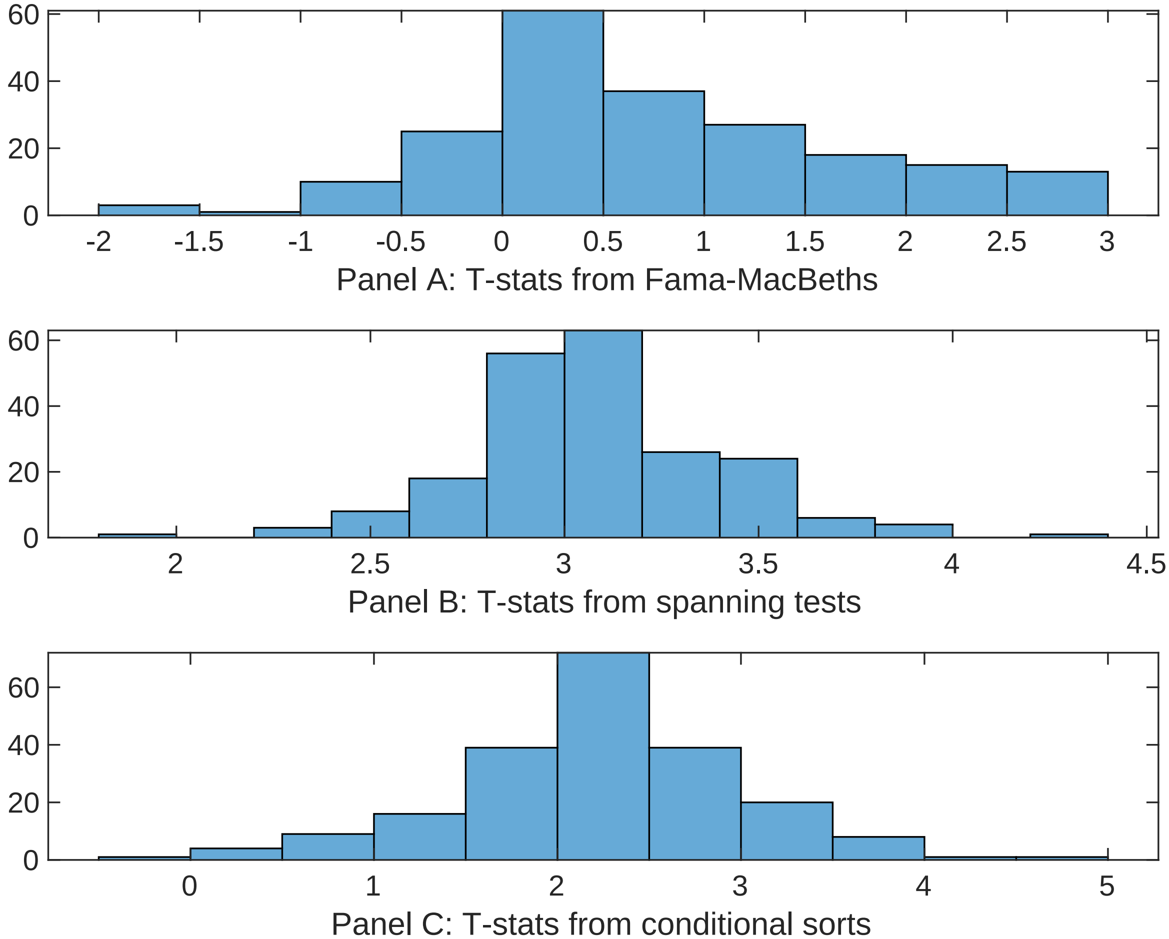


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CPI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CPI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CPI} CPI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CPI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CPI. Stocks are finally grouped into five CPI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CPI 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 CPI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CPI} CPI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Realized (Total) Volatility, net income / book equity, Price, Maximum return over month. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197106 to 202306.

Intercept	0.13	0.14	0.15	0.12	0.12	0.15	0.15
	[7.13]	[7.67]	[8.35]	[4.74]	[4.10]	[7.74]	[7.93]
CPI	-0.16	-0.21	-0.27	0.17	0.25	-0.38	-0.30
	[-0.30]	[-0.35]	[-0.45]	[0.24]	[0.37]	[-0.59]	[-0.57]
Anomaly 1	0.91						0.22
	[1.66]						[0.52]
Anomaly 2		0.15					-0.13
		[3.50]					[-1.19]
Anomaly 3			0.14				-0.23
			[3.48]				[-0.19]
Anomaly 4				0.66			-0.17
				[0.06]			[-0.26]
Anomaly 5					0.59		0.70
					[1.22]		[2.37]
Anomaly 6						0.64	0.11
						[5.81]	[9.85]
# months	619	619	619	624	624	619	619
$\bar{R}^2(\%)$	2	2	2	0	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the CPI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CPI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Idiosyncratic risk (AHT), Idiosyncratic risk (3 factor), Realized (Total) Volatility, net income / book equity, Price, Maximum return over month. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197106 to 202306.

Intercept	0.22	0.23	0.22	0.22	0.22	0.22	0.24
	[2.41]	[2.50]	[2.42]	[2.35]	[2.34]	[2.42]	[2.54]
Anomaly 1	-1.43						5.99
	[-0.46]						[1.16]
Anomaly 2		-5.21					-4.52
		[-1.63]					[-0.70]
Anomaly 3			-4.41				-5.43
			[-1.64]				[-0.89]
Anomaly 4				-12.33			-11.54
				[-2.40]			[-2.06]
Anomaly 5					-3.51		-5.43
					[-0.94]		[-1.27]
Anomaly 6						-4.34	1.03
						[-1.45]	[0.17]
mkt	15.83	14.58	14.24	14.85	17.34	14.69	14.05
	[6.39]	[6.02]	[5.66]	[6.50]	[7.76]	[6.00]	[5.46]
smb	8.00	5.00	6.25	5.16	13.04	6.78	10.05
	[1.80]	[1.19]	[1.66]	[1.41]	[2.55]	[1.83]	[1.86]
hml	13.49	14.58	14.55	11.20	13.14	14.33	13.48
	[3.19]	[3.46]	[3.45]	[2.72]	[3.19]	[3.40]	[2.99]
rmw	-2.47	0.01	-0.18	7.97	-5.16	-0.66	5.10
	[-0.48]	[0.00]	[-0.04]	[1.27]	[-1.10]	[-0.14]	[0.78]
cma	-15.56	-14.30	-14.08	-16.73	-13.97	-14.46	-16.49
	[-2.44]	[-2.24]	[-2.20]	[-2.66]	[-2.24]	[-2.27]	[-2.48]
umd	-3.24	-2.53	-2.55	-3.37	-5.52	-2.87	-5.65
	[-1.47]	[-1.14]	[-1.16]	[-1.59]	[-1.83]	[-1.32]	[-1.84]
# months	620	620	620	624	624	620	620
$\bar{R}^2$(%)	17	18	18	18	17	18	18

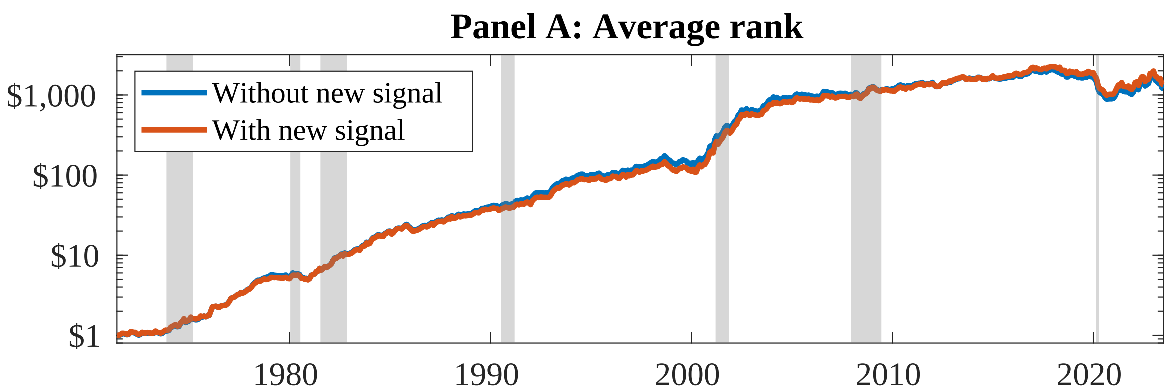


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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