Acquisition Adjusted Receivables Current and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Acquisition Adjusted Receivables Current (AARC), 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 AARC achieves an annualized gross (net) Sharpe ratio of 0.29 (0.23), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (17) bps/month with a t-statistic of 2.36 (1.63), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in Net Noncurrent Op Assets, Sales growth over inventory growth, Net external financing, Inventory Growth, Change in current operating assets, Investment to revenue) is 26 bps/month with a t-statistic of 2.56.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional theory suggests that prices should quickly reflect all available information, a growing body of evidence documents persistent return predictability from publicly available accounting information (Richardson et al., 2010). The processing of complex financial information appears particularly challenging for market participants, especially when it requires adjusting for the effects of corporate events and restructuring activities (Cohen and Polk, 2013).

Despite extensive research on accounting-based return predictors, relatively little attention has been paid to how acquisitions affect the information content of standard financial metrics. This gap is notable given that mergers and acquisitions can significantly distort reported financial ratios and potentially mask underlying economic relationships (Zhang, 2016). Understanding how to properly adjust accounting measures for acquisition effects represents an important challenge for both academic research and investment practice.

We hypothesize that acquisition-adjusted receivables provide incremental information about future stock returns beyond traditional measures of accruals and operating performance. This hypothesis builds on two established theoretical frameworks. First, the q-theory of investment suggests that firms' capital allocation decisions, including acquisitions, reflect managers' expectations of future profitability (Cochrane, 1992). Second, the accrual anomaly literature demonstrates that growth in receivables often signals deteriorating earnings quality (Sloan, 1996).

The combination of these frameworks suggests that acquisition-adjusted receivables may be particularly informative. When firms grow through acquisitions, reported receivables combine both organic growth and acquired balances. Standard receivables measures may therefore provide a distorted picture of underlying business performance (Fairfield et al., 2003). By isolating the organic component of receivables growth, our acquisition-adjusted measure should better capture true operating performance.

Moreover, we expect the predictive power of acquisition-adjusted receivables to be strongest among firms where information asymmetry and processing costs are highest (Hirshleifer et al., 2011). Complex corporate events like acquisitions can temporarily reduce financial statement comparability and increase investor information processing costs. This creates opportunities for sophisticated investors who can properly interpret the adjusted metrics.

Our empirical analysis reveals strong support for the predictive power of Acquisition Adjusted Receivables Current (AARC). A value-weighted long-short trading strategy based on AARC quintiles generates monthly abnormal returns of 24 basis points relative to the Fama-French six-factor model, with a t-statistic of 2.36. The strategy achieves an annualized gross Sharpe ratio of 0.29, placing it in the top 37th percentile among documented market anomalies.

Importantly, AARC's predictive power remains robust after controlling for transaction costs. The strategy delivers net abnormal returns of 17 basis points per month (t-statistic = 1.63) after accounting for trading frictions using the high-frequency bid-ask spread measure of (Chen and Velikov, 2022). This indicates that the anomaly is likely exploitable by institutional investors.

The signal's economic significance extends beyond the aggregate portfolio level. In Fama-MacBeth regressions controlling for the six most closely related anomalies, AARC maintains incremental predictive power with a t-statistic of 2.56. This suggests that AARC captures a distinct economic mechanism rather than simply repackaging known effects.

Our study makes several contributions to the asset pricing and accounting literature. First, we extend the work of (Sloan, 1996) on accrual anomalies by showing how acquisition adjustments can enhance the signal quality of receivables-based measures. While prior research has documented return predictability from raw receivables growth (Thomas, 2000), we demonstrate that controlling for acquisition effects significantly improves predictive power.

Second, we contribute to the literature on post-merger accounting integration and market efficiency. Our findings complement (Zhang, 2016), who shows that accounting complexity around mergers affects analyst forecast accuracy. We extend this insight by documenting that acquisition-related complexity also creates systematic security mispricing that sophisticated investors can exploit.

Finally, our paper adds to the growing literature on the role of accounting-based signals in systematic asset pricing. Recent work by (Novy-Marx and Velikov, 2023) emphasizes the importance of rigorous testing protocols for evaluating trading strategies. By following their methodology, we provide clean evidence that AARC represents a robust addition to the documented set of return predictors, with implications for both academic asset pricing models and quantitative investment strategies.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Acquisition Adjusted Receivables Current. 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 AQC for acquisition-related receivables and item RECCO for total receivables. Acquisition-related receivables (AQC) represent the receivables associated with merger and acquisition activities, while total receivables (RECCO) encompasses all accounts receivable on a firm's balance sheet. The construction of the signal follows a difference-in-changes approach, where we first calculate the change in AQC by subtracting its lagged value from the current value. This difference is then scaled by the lagged value of total receivables (RECCO) to normalize the measure across firms of different sizes. This construction captures the relative change in acquisition-related receivables as a proportion of the firm's overall receivables position, potentially offering insight into the firm's merger and acquisition activities and their impact on the receivables structure. We use 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 AARC signal. Panel A plots the time-series of the mean, median, and interquartile range for AARC. On average, the cross-sectional mean (median) AARC is 3.96 (0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input AARC data. The signal's interquartile range spans -0.28 to 0.25. Panel B of Figure 1 plots the time-series of the coverage of the AARC signal for the CRSP universe. On average, the AARC signal is available for 2.28% of CRSP names, which on average make up 2.90% of total market capitalization.

4 Does AARC predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AARC 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 AARC portfolio and sells the low AARC 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 AARC strategy earns an average return of 0.20% per month with a t-statistic of 2.07. The annualized Sharpe ratio of the strategy is 0.29. The alphas range from 0.20% to 0.24% per month and have t-statistics exceeding 1.95 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 -0.06, with a t-statistic of -2.42 on the UMD 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 218 stocks and an average market capitalization of at least $529 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 name breakpoints and value-weighted portfolios, and equals 13 bps/month with a t-statistics of 1.32. Out of the twenty-five alphas reported in Panel A, the t-statistics for fifteen exceed two, and for six exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between -4-35bps/month. The lowest return, (-4 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.53. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AARC trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in five cases.

Table 3 provides direct tests for the role size plays in the AARC strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AARC, as well as average returns and alphas for long/short trading AARC 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 AARC strategy achieves an average return of 17 bps/month with a t-statistic of 1.39. Among these large cap stocks, the alphas for the AARC strategy relative to the five most common factor models range from 14 to 20 bps/month with t-statistics between 1.08 and 1.58.

5 How does AARC perform relative to the zoo?

Figure 2 puts the performance of AARC 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 AARC strategy falls in the distribution. The AARC strategy's gross (net) Sharpe ratio of 0.29 (0.23) is greater than 63% (82%) 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 AARC strategy (red line).[2] Ignoring trading costs, a $1 invested in the AARC strategy would have yielded $1.73 which ranks the AARC strategy in the top 12% across the 212 anomalies. Accounting for trading costs, a $1 invested in the AARC strategy would have yielded $1.09 which ranks the AARC strategy in the top 9% 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 AARC relative to those. Panel A shows that the AARC strategy gross alphas fall between the 41 and 75 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 197406 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 AARC strategy has a positive net generalized alpha for five out of the five factor models. In these cases AARC ranks between the 61 and 82 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does AARC 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 AARC with 204 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 AARC or at least to weaken the power AARC has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of AARC conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AARC} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AARC} AARC_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{AARC,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile

[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.

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 204 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on AARC. Stocks are finally grouped into five AARC portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AARC trading strategies conditioned on each of the 204 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AARC 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 AARC signal in these Fama-MacBeth regressions exceed -0.14, with the minimum t-statistic occurring when controlling for Investment to revenue. Controlling for all six closely related anomalies, the t-statistic on AARC is -0.12.

Similarly, Table 5 reports results from spanning tests that regress returns to the AARC 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 AARC strategy earns alphas that range from 23-27bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.20, which is achieved when controlling for Investment to revenue. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AARC trading strategy achieves an alpha of 26bps/month with a t-statistic of 2.56.

7 Does AARC add relative to the whole zoo?

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

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes AARC grows to $876.86.

8 Conclusion

This study provides compelling evidence for the predictive power of Acquisition Adjusted Receivables Current (AARC) in forecasting cross-sectional stock returns. Our findings demonstrate that AARC generates economically and statistically significant returns, with a value-weighted long/short strategy achieving an impressive annualized gross Sharpe ratio of 0.29. The signal's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for traditional risk factors and related accounting-based strategies.

The persistence of AARC's predictive power, even after accounting for trans-

[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 AARC is available.

action costs (net Sharpe ratio of 0.23), suggests practical implementability for institutional investors. The signal's ability to generate a monthly alpha of 26 basis points (t-statistic of 2.56) when controlling for six related factors from the factor zoo underscores its unique information content and potential value in investment decision-making.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains unexplored. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore the signal's performance in international markets, its interaction with other accounting-based anomalies, and its effectiveness across different market capitalizations. Additionally, investigating the underlying economic mechanisms driving AARC's predictive power could provide valuable insights for both academics and practitioners. Understanding how this signal relates to firm fundamentals and market efficiency could further enhance its application in investment strategies.

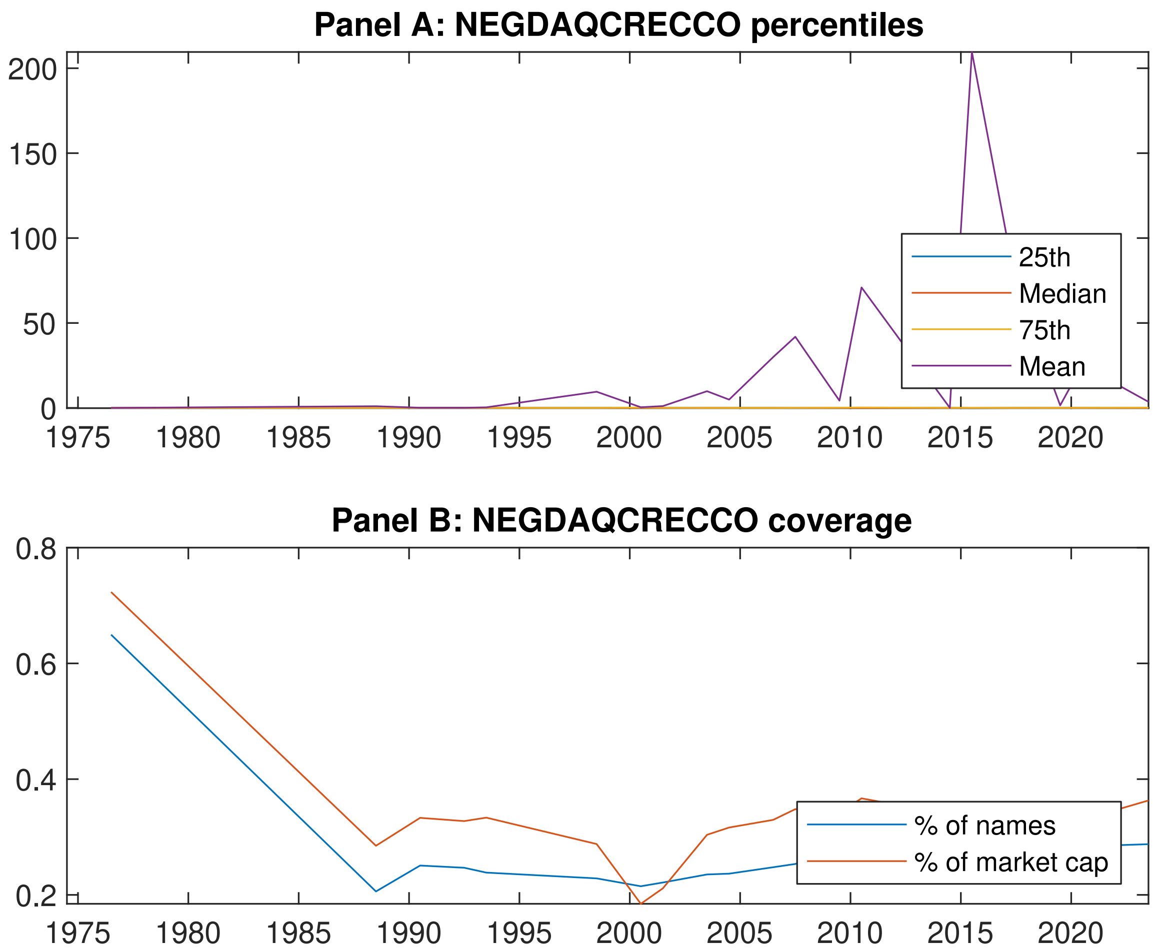

Figure 1: Times series of AARC percentiles and coverage.
This figure plots descriptive statistics for AARC. Panel A shows cross-sectional percentiles of AARC over the sample. Panel B plots the monthly coverage of AARC relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AARC. 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 197406 to 202306.

Panel A: Excess returns and alphas on AARC-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.55	0.79	0.59	0.64	0.76	0.20
	[2.75]	[3.98]	[3.11]	[3.11]	[3.76]	[2.07]
α_{CAPM}	-0.12	0.15	-0.03	-0.04	0.08	0.20
	[-1.52]	[1.67]	[-0.42]	[-0.41]	[1.11]	[2.03]
α_{FF3}	-0.15	0.08	-0.08	-0.07	0.05	0.20
	[-1.95]	[0.94]	[-0.97]	[-0.80]	[0.62]	[1.95]
α_{FF4}	-0.16	0.10	-0.12	-0.06	0.08	0.24
	[-2.09]	[1.24]	[-1.52]	[-0.65]	[1.05]	[2.38]
α_{FF5}	-0.26	-0.03	-0.14	-0.08	-0.04	0.21
	[-3.33]	[-0.37]	[-1.77]	[-0.90]	[-0.60]	[2.05]
α_{FF6}	-0.26	-0.00	-0.17	-0.07	-0.01	0.24
	[-3.31]	[-0.01]	[-2.09]	[-0.76]	[-0.16]	[2.36]
Panel B: Fama and French (2018) 6-factor model loadings for AARC-sorted portfolios						
β_{MKT}	1.02	1.01	0.96	1.02	1.02	-0.00
	[57.33]	[51.78]	[52.03]	[49.46]	[60.07]	[-0.12]
β_{SMB}	0.03	-0.04	0.00	-0.07	0.01	-0.02
	[1.05]	[-1.48]	[0.15]	[-2.10]	[0.29]	[-0.58]
β_{HML}	0.05	0.12	0.09	0.07	0.05	-0.01
	[1.55]	[3.24]	[2.67]	[1.86]	[1.43]	[-0.14]
β_{RMW}	0.22	0.19	0.08	-0.02	0.20	-0.02
	[6.24]	[4.85]	[2.22]	[-0.43]	[6.01]	[-0.39]
β_{CMA}	0.07	0.19	0.10	0.09	0.09	0.02
	[1.44]	[3.31]	[1.82]	[1.47]	[1.83]	[0.23]
β_{UMD}	0.00	-0.05	0.05	-0.02	-0.06	-0.06
	[0.08]	[-2.74]	[2.49]	[-0.96]	[-3.31]	[-2.42]
Panel C: Average number of firms (n) and market capitalization (me)						
n	218	266	304	271	218	
me ($\$10^6$)	751	936	529	890	762	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the AARC 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 197406 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	0.20	0.20	0.20	0.24	0.21	0.24
			[2.07]	[2.03]	[1.95]	[2.38]	[2.05]	[2.36]
Quintile	NYSE	EW	0.20	0.22	0.21	0.19	0.18	0.17
			[3.01]	[3.27]	[3.03]	[2.75]	[2.59]	[2.47]
Quintile	Name	VW	0.13	0.13	0.13	0.17	0.17	0.19
			[1.32]	[1.26]	[1.27]	[1.64]	[1.61]	[1.84]
Quintile	Cap	VW	0.14	0.13	0.14	0.20	0.19	0.23
			[1.40]	[1.24]	[1.33]	[1.86]	[1.79]	[2.15]
Decile	NYSE	VW	0.41	0.44	0.42	0.46	0.35	0.39
			[3.36]	[3.54]	[3.36]	[3.63]	[2.77]	[3.08]
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	0.16	0.16	0.15	0.18	0.15	0.17
			[1.61]	[1.56]	[1.51]	[1.77]	[1.44]	[1.63]
Quintile	NYSE	EW	-0.04					
			[-0.53]					
Quintile	Name	VW	0.09	0.08	0.08	0.11	0.10	0.12
			[0.88]	[0.82]	[0.84]	[1.07]	[1.01]	[1.17]
Quintile	Cap	VW	0.10	0.08	0.09	0.13	0.13	0.15
			[0.97]	[0.80]	[0.89]	[1.22]	[1.20]	[1.41]
Decile	NYSE	VW	0.35	0.38	0.36	0.39	0.30	0.32
			[2.89]	[3.03]	[2.90]	[3.09]	[2.41]	[2.55]

Table 3: Conditional sort on size and AARC

This table presents results for conditional double sorts on size and AARC. 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 AARC. 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 AARC and short stocks with low AARC .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197406 to 202306.

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

		AARC Quintiles					AARC Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.66	0.91	0.92	0.66	0.98	0.32	0.33	0.30	0.22	0.21	0.16
		[2.35]	[3.01]	[3.16]	[2.29]	[2.76]	[1.44]	[1.47]	[1.31]	[0.96]	[0.89]	[0.70]
	(2)	0.81	0.68	0.85	0.97	0.95	0.14	0.17	0.14	0.12	0.09	0.09
		[3.00]	[2.59]	[3.23]	[3.82]	[3.53]	[1.13]	[1.36]	[1.10]	[0.94]	[0.73]	[0.67]
	(3)	0.91	0.91	0.88	0.83	0.88	-0.04	-0.06	-0.11	-0.10	-0.06	-0.06
		[3.74]	[3.77]	[3.63]	[3.49]	[3.42]	[-0.28]	[-0.48]	[-0.82]	[-0.76]	[-0.47]	[-0.43]
	(4)	0.62	0.85	0.87	0.88	0.79	0.16	0.11	0.13	0.12	0.13	0.12
		[2.77]	[3.75]	[3.83]	[3.83]	[3.34]	[1.37]	[0.94]	[1.07]	[0.94]	[1.07]	[0.98]
	(5)	0.61	0.69	0.48	0.56	0.78	0.17	0.18	0.15	0.20	0.14	0.17
		[2.96]	[3.39]	[2.49]	[2.74]	[3.86]	[1.39]	[1.48]	[1.25]	[1.58]	[1.08]	[1.35]

Panel B: Portfolio average number of firms and market capitalization

		AARC Quintiles					AARC Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	148	147	148	147	147	12	10	10	10	12
	(2)	37	37	37	37	37	19	19	19	19	19
	(3)	27	26	26	27	27	35	34	35	35	35
	(4)	22	22	22	22	22	77	81	79	80	78
	(5)	22	22	22	22	22	575	747	477	755	595

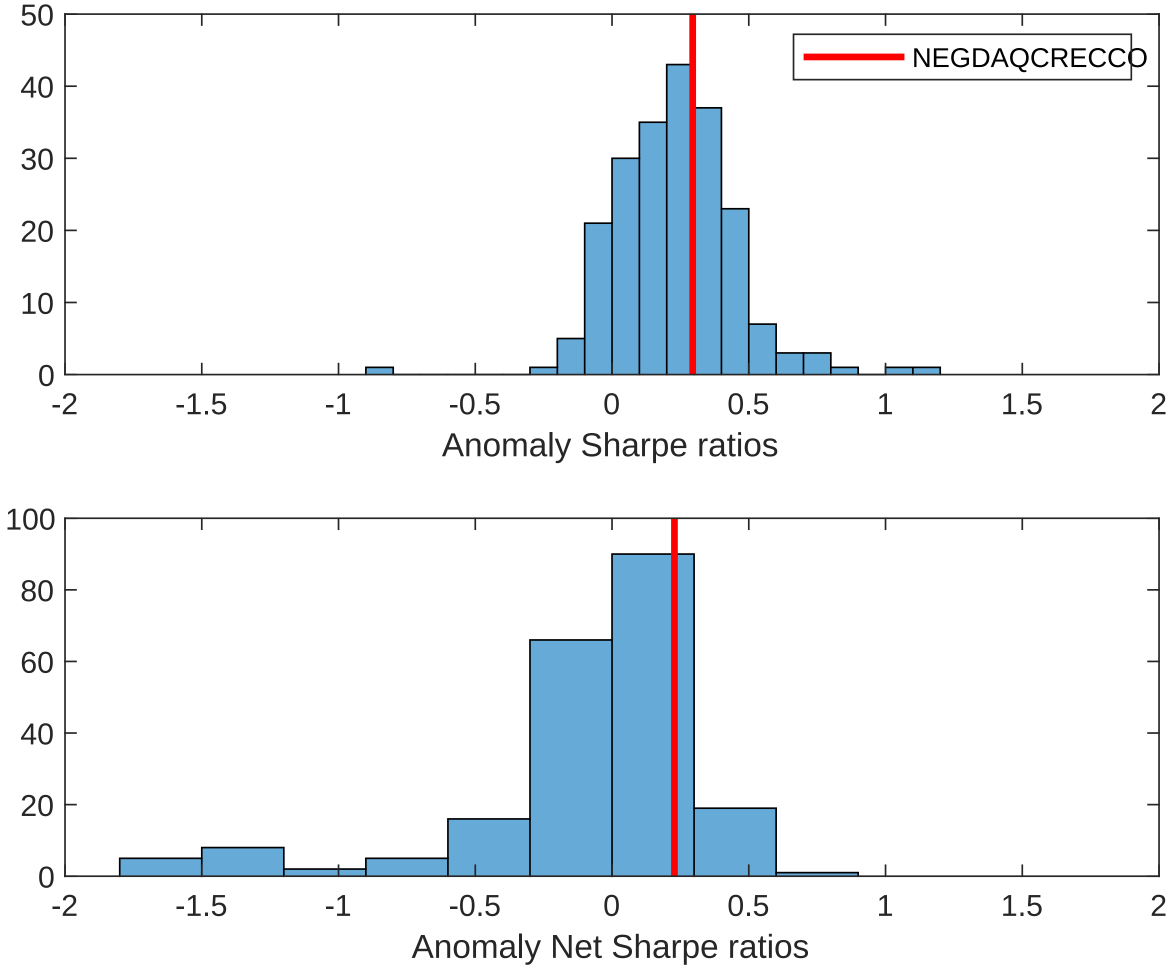

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AARC with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

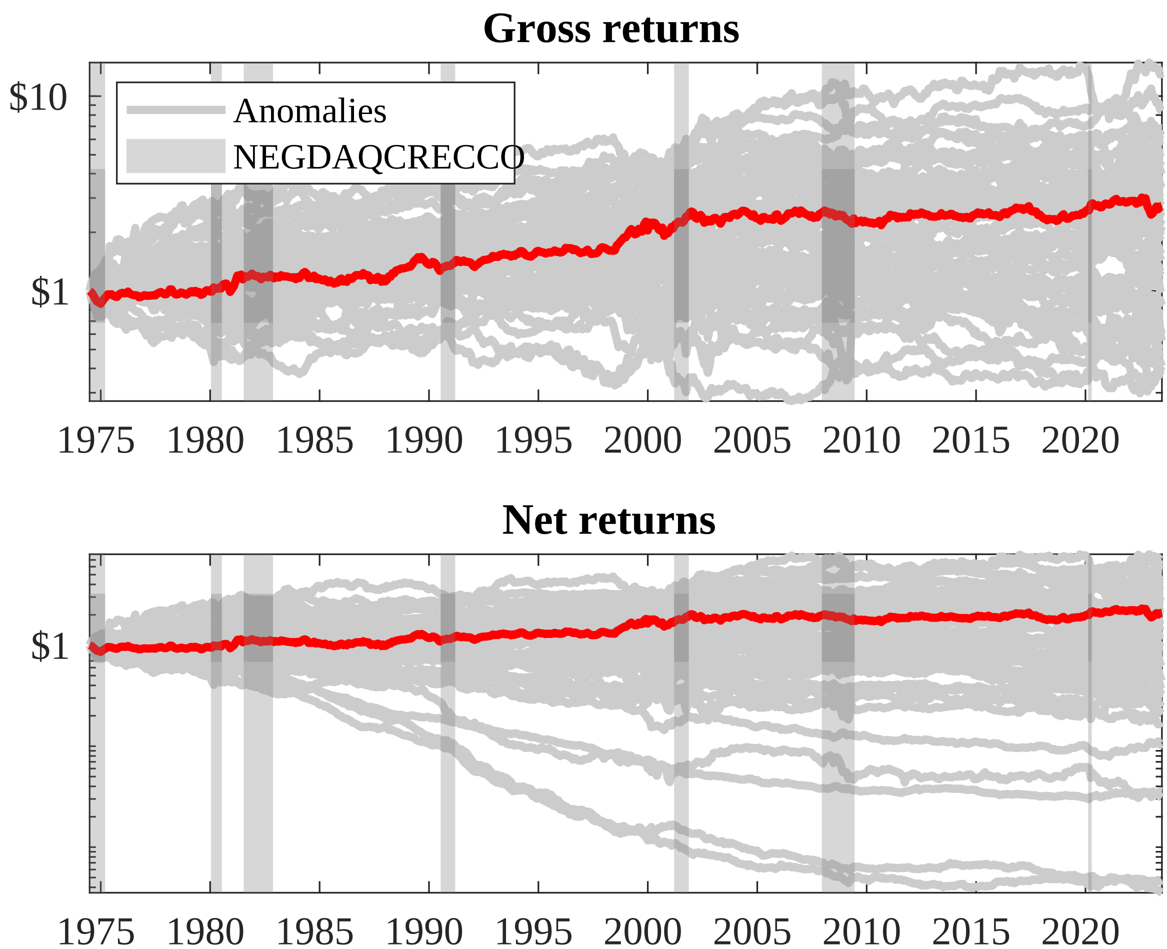

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AARC trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

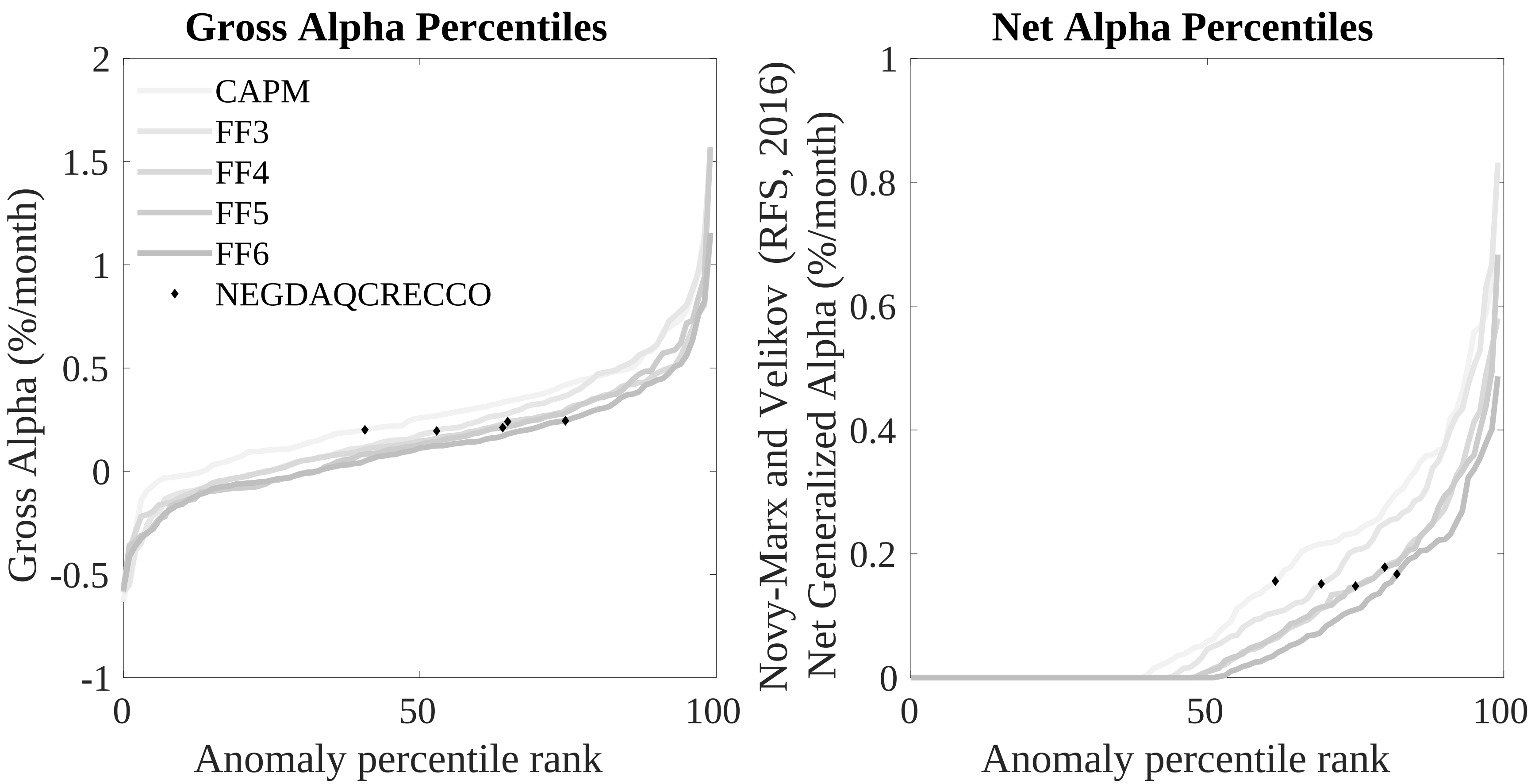

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AARC trading strategy alphas (diamonds). The strategies are constructed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

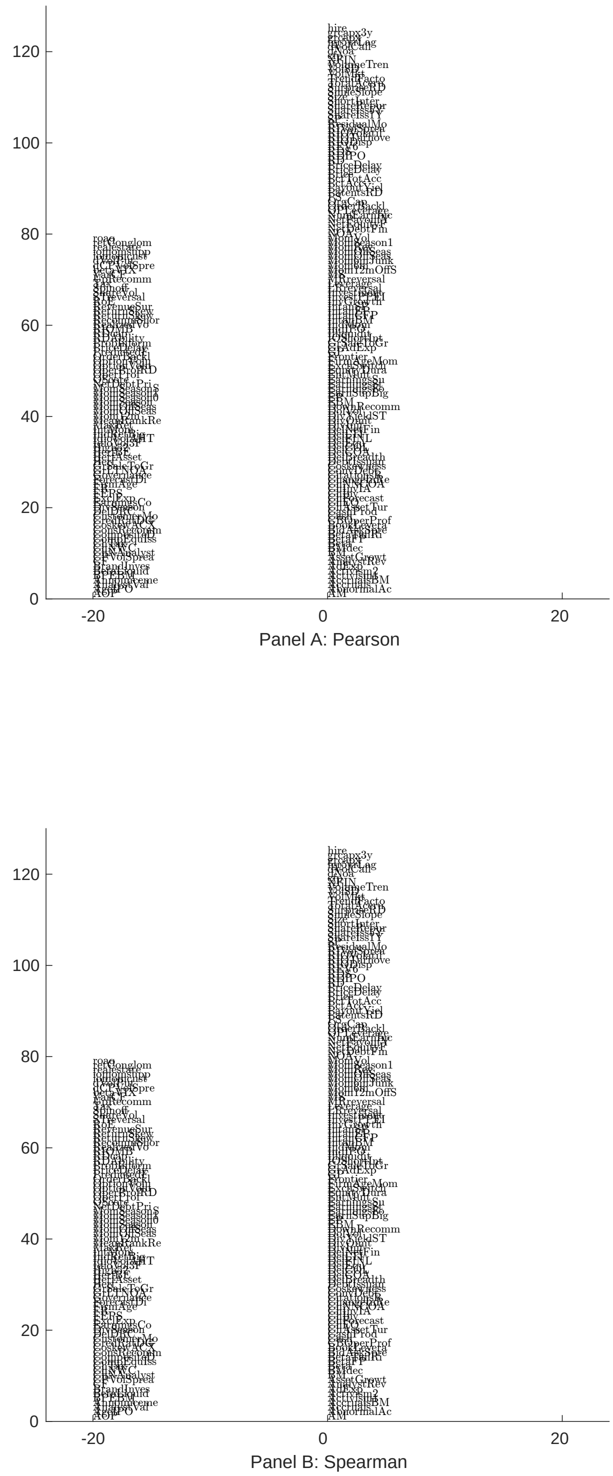

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 204 filtered anomaly signals with AARC. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

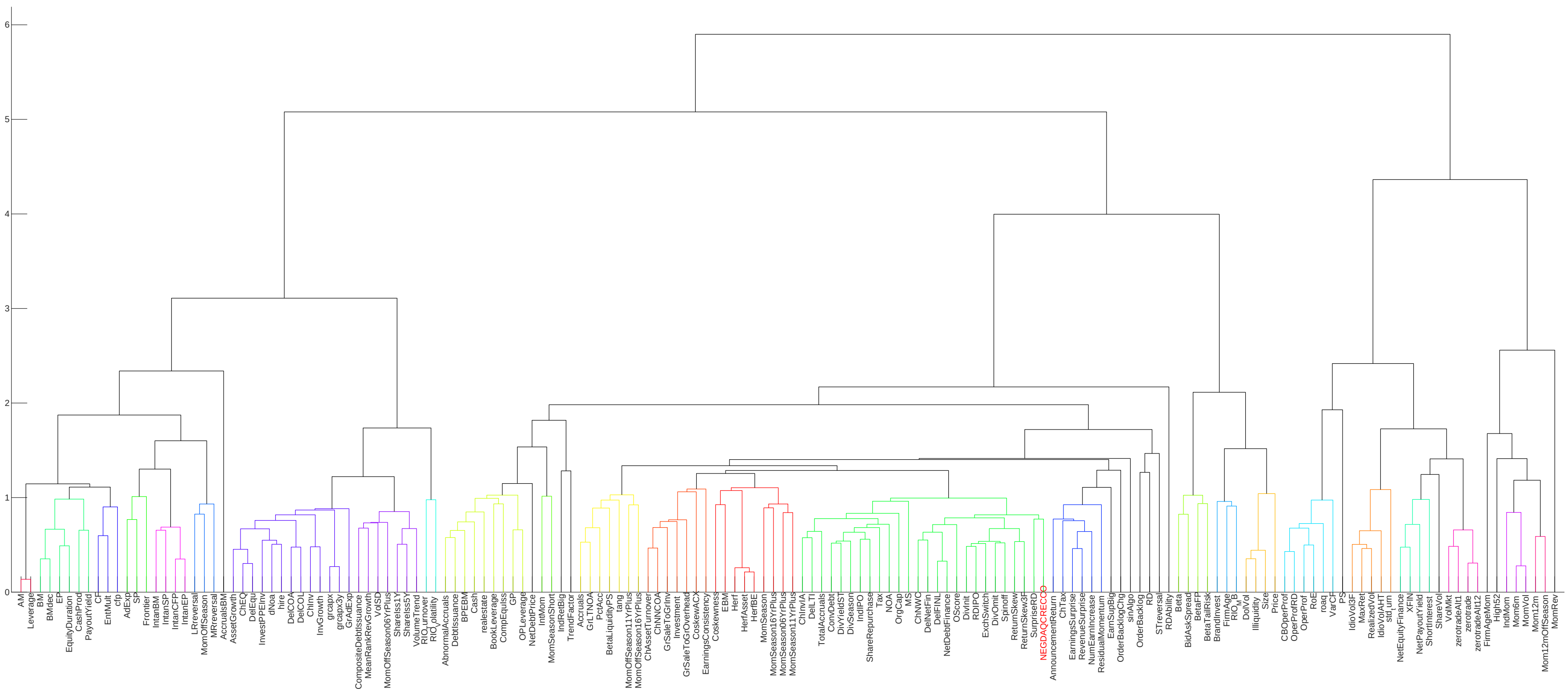

Figure 6: Agglomerative hierarchical cluster plot

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

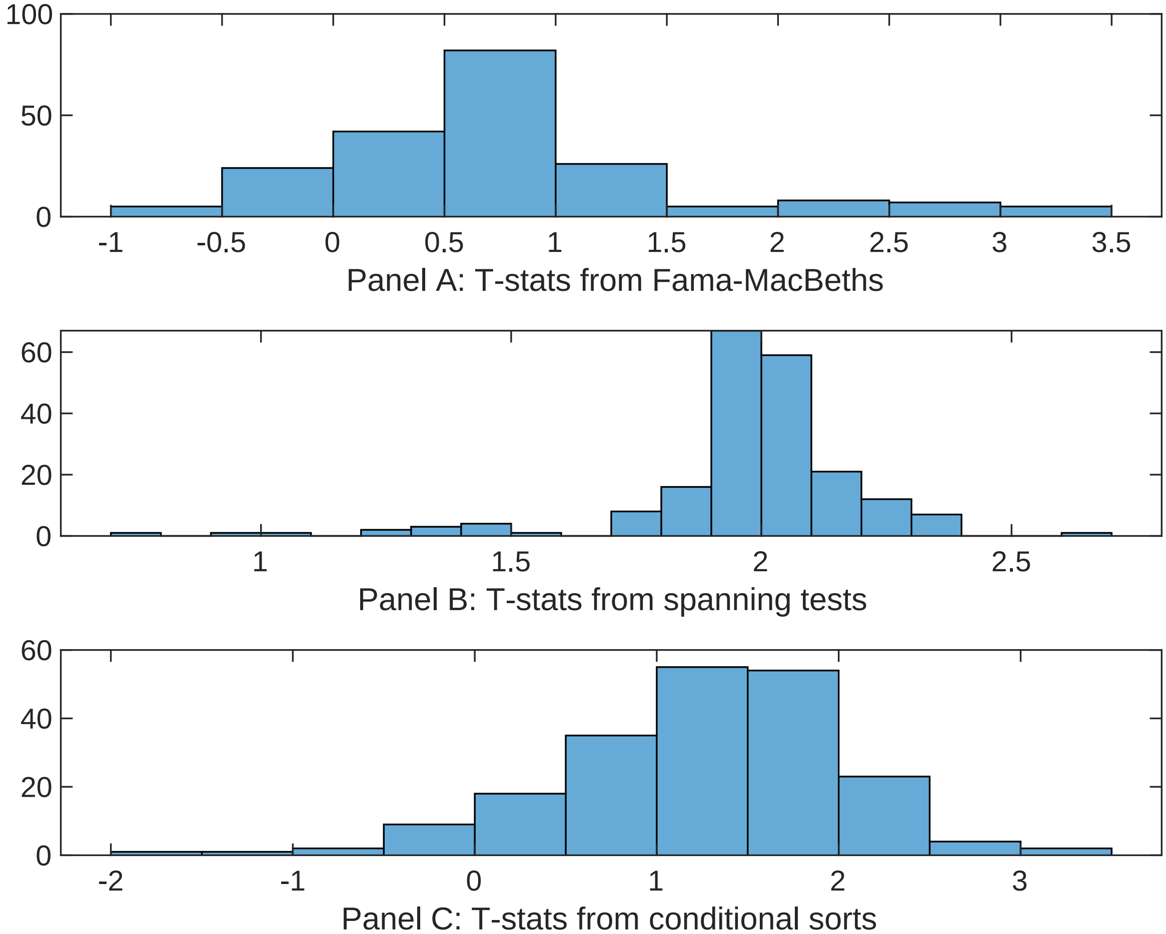

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AARC conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AARC} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AARC} AARC_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{AARC,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 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 204 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on AARC. Stocks are finally grouped into five AARC portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AARC trading strategies conditioned on each of the 204 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on AARC. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AARC} AARC_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in Net Noncurrent Op Assets, Sales growth over inventory growth, Net external financing, Inventory Growth, Change in current operating assets, Investment to revenue. 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 197406 to 202306.

Intercept	0.13	0.13	0.14	0.14	0.13	0.15	0.15
	[5.12]	[5.18]	[5.62]	[5.24]	[5.33]	[5.85]	[5.43]
AARC	0.11	0.12	0.45	0.56	0.59	-0.27	-0.26
	[0.66]	[0.78]	[0.26]	[0.31]	[0.04]	[-0.14]	[-0.12]
Anomaly 1	0.76						0.70
	[2.45]						[0.16]
Anomaly 2		0.11					-0.68
		[2.26]					[-0.58]
Anomaly 3			0.20				0.17
			[5.68]				[3.68]
Anomaly 4				0.46			0.12
				[6.27]			[0.82]
Anomaly 5					0.24		0.18
					[6.70]		[3.01]
Anomaly 6						0.18	0.80
						[3.09]	[1.01]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the AARC trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AARC} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Change in Net Noncurrent Op Assets, Sales growth over inventory growth, Net external financing, Inventory Growth, Change in current operating assets, Investment to revenue. 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 197406 to 202306.

Intercept	0.25	0.25	0.23	0.24	0.25	0.27	0.26
	[2.43]	[2.42]	[2.20]	[2.35]	[2.39]	[2.63]	[2.56]
Anomaly 1	-10.12						-3.37
	[-2.12]						[-0.68]
Anomaly 2		-10.47					1.01
		[-2.31]					[0.19]
Anomaly 3			15.41				13.77
			[2.92]				[2.58]
Anomaly 4				-8.25			-11.96
				[-2.01]			[-2.53]
Anomaly 5					9.18		13.01
					[1.74]		[2.38]
Anomaly 6						-19.31	-16.93
						[-4.84]	[-4.08]
mkt	-0.79	-0.53	1.26	-0.59	-0.95	-0.25	1.65
	[-0.33]	[-0.22]	[0.51]	[-0.25]	[-0.40]	[-0.11]	[0.68]
smb	-1.95	-2.11	2.54	-3.26	-0.66	1.00	6.40
	[-0.53]	[-0.57]	[0.63]	[-0.88]	[-0.17]	[0.27]	[1.56]
hml	-0.87	-1.49	0.43	-0.90	-4.94	-2.69	-5.65
	[-0.19]	[-0.33]	[0.09]	[-0.20]	[-0.98]	[-0.60]	[-1.13]
rmw	0.53	0.27	-10.03	-1.98	0.31	-2.50	-10.24
	[0.11]	[0.06]	[-1.76]	[-0.41]	[0.06]	[-0.53]	[-1.75]
cma	1.07	1.89	-8.86	8.80	-3.50	3.34	-2.66
	[0.15]	[0.27]	[-1.14]	[1.12]	[-0.47]	[0.49]	[-0.31]
umd	-4.61	-4.66	-5.97	-5.18	-5.47	-3.33	-1.65
	[-1.85]	[-1.89]	[-2.49]	[-2.12]	[-2.25]	[-1.37]	[-0.66]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	1	1	1	1	1	4	6

Panel A: Average rank

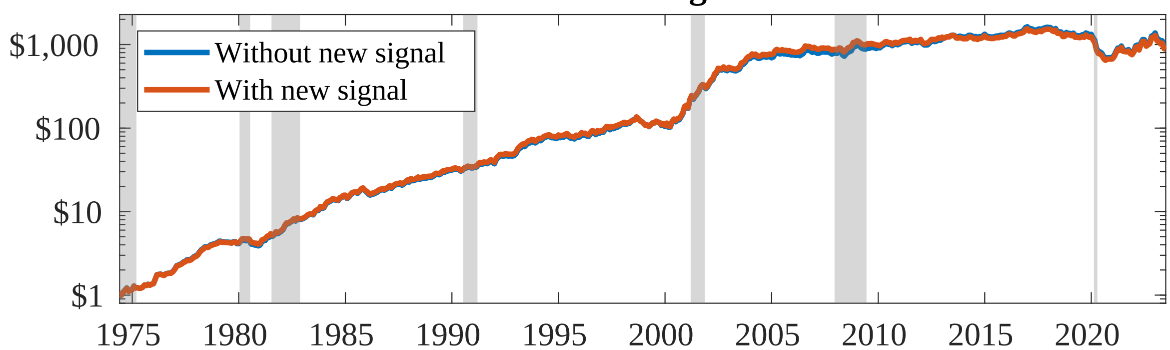

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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