Receipts Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Receipts Impact (RI), 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 RI achieves an annualized gross (net) Sharpe ratio of 0.43 (0.36), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 37 (34) bps/month with a t-statistic of 3.92 (3.66), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Accruals, Growth in long term operating assets, Inventory Growth, Momentum and LT Reversal, Change in Net Working Capital, Growth in book equity) is 25 bps/month with a t-statistic of 2.69.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). These patterns, often called anomalies, challenge our understanding of how information is incorporated into asset prices. While hundreds of return predictors have been documented, many fail to survive transaction costs or more rigorous statistical testing (Hou et al., 2020).

One particularly puzzling aspect of market efficiency relates to how investors process complex accounting information. While standard theory suggests that sophisticated investors should arbitrage away any predictable patterns, evidence shows that certain accounting-based signals continue to predict returns (Richardson et al., 2010). This persistence raises important questions about the mechanisms through which accounting information is incorporated into prices.

We propose that Receipts Impact (RI), which measures the change in a firm's operating receipts relative to its asset base, contains valuable information about future profitability that is not fully reflected in stock prices. Our hypothesis builds on theoretical work showing that changes in operating activities provide signals about management's private information (Demerjian et al., 2012). When managers observe positive future prospects, they often adjust operating policies before this information becomes public (Beneish and Lee, 2008).

The predictive power of RI likely stems from two complementary mechanisms. First, increases in operating receipts relative to assets may signal improving operational efficiency and future profitability (**?**). Second, because operating receipts are less subject to manipulation than accrual-based measures, they may provide a more reliable signal of fundamental performance (**?**).

Moreover, behavioral models suggest that investors may underreact to complex accounting information, particularly when it requires combining multiple financial statement items (?). The construction of RI involves comparing changes across different financial statements, potentially making it difficult for investors to fully incorporate this information into prices.

Our empirical analysis reveals that RI strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks in the highest RI quintile and shorts stocks in the lowest RI quintile generates monthly abnormal returns of 37 basis points (t-statistic = 3.92) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.43, placing it in the top 14% of documented anomalies.

Importantly, the predictive power of RI persists after controlling for transaction costs. The strategy generates net returns of 34 basis points per month (t-statistic = 3.66) after accounting for trading frictions using the high-frequency bid-ask spread measure of Chen and Velikov (2022). This indicates that the anomaly is economically exploitable.

The return predictability is particularly strong among large-cap stocks, with the long-short strategy generating monthly returns of 36 basis points (t-statistic = 3.26) among stocks above the 80th percentile of market capitalization. This finding is notable because many anomalies are concentrated in small, illiquid stocks where implementation is challenging.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel accounting-based predictor that captures information about future returns not contained in existing anomalies. When we control for the six most closely related anomalies and the Fama-French factors simultaneously, RI continues to generate significant abnormal returns of 25 basis points per month (t-statistic = 2.69).

Second, we extend the literature on how accounting information is incorporated into stock prices (Richardson et al., 2010). While prior work has focused primarily on accrual-based measures (Sloan, 1996), we show that examining changes in actual cash receipts provides incremental predictive power. This suggests that market participants may not fully process the information contained in firms' operating activities.

Finally, our findings have important implications for market efficiency and investment practice. The persistence of the RI effect among large, liquid stocks challenges the notion that sophisticated investors quickly arbitrage away predictable patterns in returns. Moreover, the robust performance after transaction costs suggests that RI could be valuable for institutional investors seeking to enhance portfolio returns.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Receipts Impact measure. 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 RECTR for trade receivables and item NOPIO for net operating income. Trade receivables (RECTR) represent the amounts due from customers for goods and services sold in the ordinary course of business, while net operating income (NOPIO) measures a company's operating performance before considering non-operating items and financing costs. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's trade receivables and its lagged value, then scale this difference by the previous period's net operating income. This scaled difference captures the relative change in a firm's receivables position compared to its operational scale, potentially offering insights into working capital management efficiency and the quality of reported earnings. By focusing on this relationship, the signal aims to detect significant shifts in receivables that might signal changes in business conditions or accounting practices. We construct this measure using end-of-fiscal-year values for both RECTR and NOPIO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the RI signal. Panel A plots the time-series of the mean, median, and interquartile range for RI. On average, the cross-sectional mean (median) RI is -4.47 (-0.43) over the 1978 to 2023 sample, where the starting date is determined by the availability of the input RI data. The signal's interquartile range spans -9.62 to 4.98. Panel B of Figure 1 plots the time-series of the coverage of the RI signal for the CRSP universe. On average, the RI signal is available for 4.81% of CRSP names, which on average make up 6.39% of total market capitalization.

4 Does RI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on RI 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 RI portfolio and sells the low RI 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 RI strategy earns an average return of 0.27% per month with a t-statistic of 2.89. The annualized Sharpe ratio of the strategy is 0.43. The alphas range from 0.31% to 0.38% per month and have t-statistics exceeding 3.37 everywhere. The lowest alpha is with respect to the FF4 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 -0.20, with a t-statistic of -4.78 on the RMW factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 492 stocks and an average market capitalization of at least $1,526 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 NYSE breakpoints and equal-weighted portfolios, and equals 14 bps/month with a t-statistics of 2.69. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for nineteen 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 -9-23bps/month. The lowest return, (-9 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.37. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the RI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the RI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and RI, as well as average returns and alphas for long/short trading RI 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 RI strategy achieves an average return of 36 bps/month with a t-statistic of 3.26. Among these large cap stocks, the alphas for the RI strategy relative to the five most common factor models range from 44 to 48 bps/month with t-statistics between 3.94 and 4.29.

5 How does RI perform relative to the zoo?

Figure 2 puts the performance of RI 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 RI strategy falls in the distribution. The RI strategy's gross (net) Sharpe ratio of 0.43 (0.36) is greater than 86% (93%) 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 RI strategy (red line).[2] Ignoring trading costs, a $1 invested in the RI strategy would have yielded $2.94 which ranks the RI strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a $1 invested in the RI strategy would have yielded $2.17 which ranks the RI strategy in the top 4% 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 RI relative to those. Panel A shows that the RI strategy gross alphas fall between the 62 and 85 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 197806 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 RI strategy has a positive net generalized alpha for five out of the five factor models. In these cases RI ranks between the 81 and 95 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does RI 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 RI with 209 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 RI or at least to weaken the power RI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of RI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{RI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{RI} RI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{RI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on RI. Stocks are finally grouped into five RI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

RI trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on RI 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 RI signal in these Fama-MacBeth regressions exceed 2.41, with the minimum t-statistic occurring when controlling for Inventory Growth. Controlling for all six closely related anomalies, the t-statistic on RI is 2.87.

Similarly, Table 5 reports results from spanning tests that regress returns to the RI 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 RI strategy earns alphas that range from 32-37bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.47, which is achieved when controlling for Inventory Growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the RI trading strategy achieves an alpha of 25bps/month with a t-statistic of 2.69.

7 Does RI add relative to the whole zoo?

Finally, we can ask how much adding RI 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 157 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 157 anomalies augmented with the RI signal.[4] We consider one different methods for combining signals.

[4]We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capitalization on CRSP in the period for which RI is available.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, \$1 investment in the 157-anomaly combination strategy grows to \$190.39, while \$1 investment in the combination strategy that includes RI grows to \$254.29.

8 Conclusion

This study provides compelling evidence for the effectiveness of Receipts Impact (RI) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on RI generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.43 (0.36 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for traditional risk factors and related anomalies from the factor zoo.

The persistence of the signal's alpha (25 bps/month) when controlling for six closely related strategies suggests that RI captures unique information content not explained by existing factors. This indicates that RI provides incremental value to investors' trading strategies and portfolio management decisions. The high statistical significance (t-statistic of 2.69) further reinforces the reliability of these findings.

However, several limitations should be considered. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market conditions. Second, transaction costs and market impact could affect the strategy's practical implementation, particularly for larger portfolios.

Future research could explore several promising directions. First, investigating the underlying economic mechanisms driving the RI signal's predictive power would enhance our understanding of this anomaly. Second, examining the signal's performance in international markets could test its global applicability. Finally, studying potential interactions between RI and other established factors could reveal valuable insights for portfolio optimization and risk management.

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

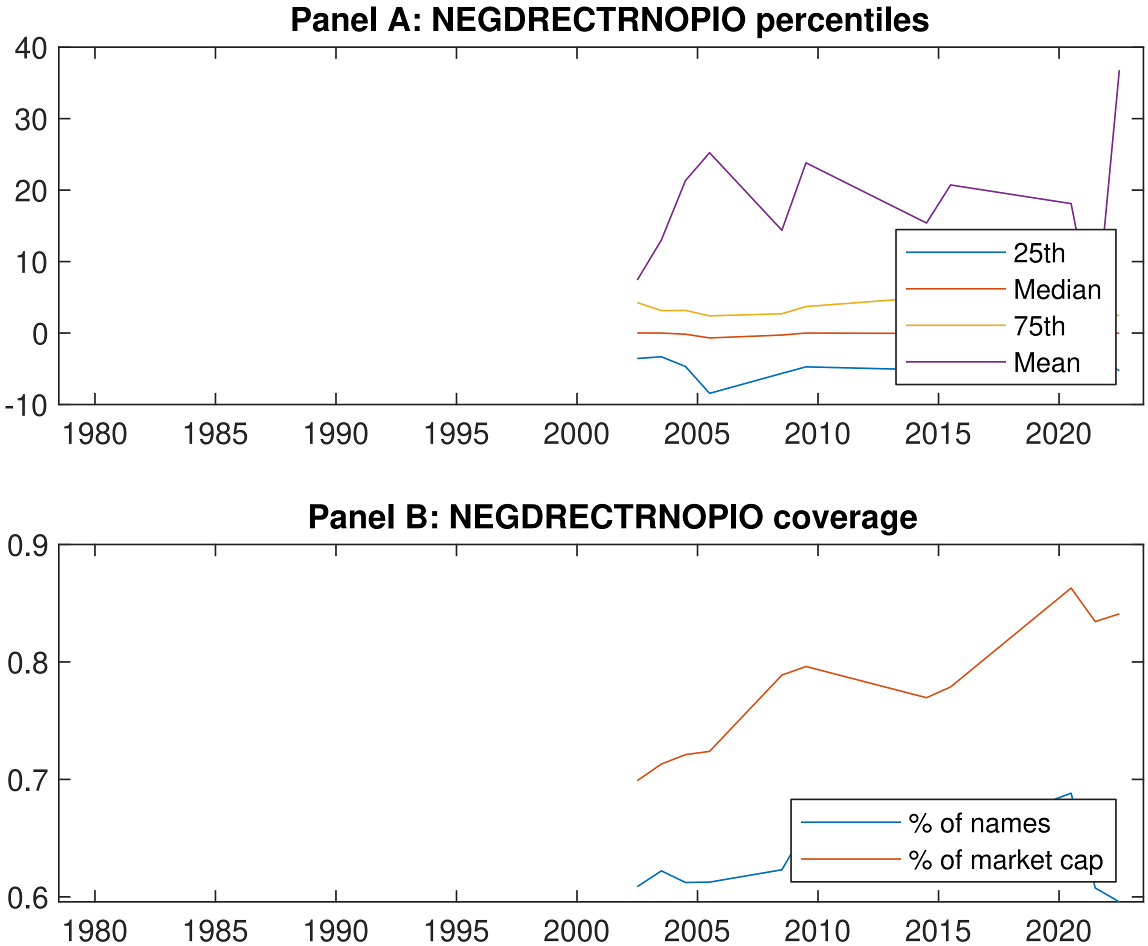


Figure 1: Times series of RI percentiles and coverage.
This figure plots descriptive statistics for RI. Panel A shows cross-sectional percentiles of RI over the sample. Panel B plots the monthly coverage of RI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on RI. 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 197806 to 202306.

Panel A: Excess returns and alphas on RI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.63	0.69	0.73	0.70	0.90	0.27
	[2.74]	[3.40]	[4.08]	[3.75]	[4.10]	[2.89]
α_{CAPM}	-0.17	-0.01	0.12	0.07	0.15	0.32
	[-2.81]	[-0.23]	[2.13]	[1.06]	[2.13]	[3.45]
α_{FF3}	-0.14	0.03	0.12	0.05	0.20	0.34
	[-2.34]	[0.52]	[2.35]	[0.77]	[3.00]	[3.67]
α_{FF4}	-0.13	0.04	0.09	0.07	0.19	0.31
	[-2.11]	[0.81]	[1.74]	[1.18]	[2.79]	[3.37]
α_{FF5}	-0.16	0.03	0.02	0.01	0.23	0.38
	[-2.64]	[0.57]	[0.35]	[0.11]	[3.34]	[4.13]
α_{FF6}	-0.15	0.04	0.01	0.03	0.22	0.37
	[-2.48]	[0.76]	[0.11]	[0.49]	[3.17]	[3.92]
Panel B: Fama and French (2018) 6-factor model loadings for RI-sorted portfolios						
β_{MKT}	1.11	0.98	0.94	0.94	1.03	-0.09
	[79.43]	[74.50]	[77.66]	[63.85]	[64.29]	[-3.90]
β_{SMB}	0.05	-0.03	-0.12	-0.08	0.07	0.02
	[2.29]	[-1.59]	[-6.45]	[-3.32]	[2.67]	[0.48]
β_{HML}	-0.06	-0.12	-0.12	-0.02	-0.16	-0.09
	[-2.44]	[-5.00]	[-5.31]	[-0.81]	[-5.13]	[-2.19]
β_{RMW}	0.12	0.02	0.08	0.02	-0.08	-0.20
	[4.53]	[0.80]	[3.55]	[0.71]	[-2.56]	[-4.78]
β_{CMA}	-0.13	-0.04	0.26	0.17	0.01	0.15
	[-3.32]	[-1.01]	[7.70]	[4.06]	[0.33]	[2.37]
β_{UMD}	-0.02	-0.02	0.02	-0.04	0.02	0.03
	[-1.17]	[-1.58]	[1.99]	[-3.14]	[1.17]	[1.60]
Panel C: Average number of firms (n) and market capitalization (me)						
n	596	492	512	507	590	
me ($\$10^6$)	1559	2416	2611	1856	1526	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the RI 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 197806 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	0.27	0.32	0.34	0.31	0.38	0.37
			[2.89]	[3.45]	[3.67]	[3.37]	[4.13]	[3.92]
Quintile	NYSE	EW	0.14	0.16	0.14	0.15	0.17	0.17
			[2.69]	[3.11]	[2.81]	[2.91]	[3.34]	[3.39]
Quintile	Name	VW	0.25	0.31	0.32	0.31	0.36	0.35
			[2.58]	[3.21]	[3.39]	[3.21]	[3.77]	[3.63]
Quintile	Cap	VW	0.20	0.25	0.26	0.26	0.31	0.31
			[2.41]	[3.02]	[3.02]	[2.97]	[3.65]	[3.58]
Decile	NYSE	VW	0.25	0.29	0.32	0.29	0.41	0.39
			[2.07]	[2.43]	[2.70]	[2.43]	[3.46]	[3.23]
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	0.23	0.29	0.30	0.29	0.35	0.34
			[2.45]	[3.09]	[3.28]	[3.12]	[3.79]	[3.66]
Quintile	NYSE	EW	-0.09					
			[-1.37]					
Quintile	Name	VW	0.21	0.27	0.29	0.28	0.32	0.32
			[2.14]	[2.83]	[2.98]	[2.88]	[3.36]	[3.29]
Quintile	Cap	VW	0.17	0.23	0.23	0.23	0.28	0.28
			[1.97]	[2.68]	[2.67]	[2.66]	[3.26]	[3.24]
Decile	NYSE	VW	0.20	0.26	0.28	0.26	0.37	0.36
			[1.67]	[2.13]	[2.34]	[2.20]	[3.10]	[2.99]

Table 3: Conditional sort on size and RI

This table presents results for conditional double sorts on size and RI. 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 RI. 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 RI and short stocks with low RI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197806 to 202306.

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

		RI Quintiles					RI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.75	0.79	0.76	0.81	0.81	0.06	0.08	0.06	0.08	0.04	0.06
		[2.63]	[2.79]	[2.43]	[2.73]	[2.86]	[0.74]	[0.99]	[0.72]	[0.93]	[0.52]	[0.70]
	(2)	0.80	0.78	0.79	0.86	0.88	0.08	0.10	0.07	0.12	0.13	0.17
		[2.85]	[3.02]	[2.96]	[3.30]	[3.19]	[0.91]	[1.05]	[0.76]	[1.32]	[1.45]	[1.80]
	(3)	0.85	0.84	0.75	0.82	0.85	0.00	0.03	-0.01	-0.03	-0.05	-0.06
		[3.28]	[3.41]	[3.18]	[3.36]	[3.40]	[0.05]	[0.35]	[-0.06]	[-0.28]	[-0.57]	[-0.67]
	(4)	0.77	0.84	0.78	0.76	0.84	0.08	0.07	0.06	0.04	0.10	0.08
		[3.14]	[3.69]	[3.62]	[3.48]	[3.44]	[0.87]	[0.80]	[0.68]	[0.39]	[1.09]	[0.87]
	(5)	0.58	0.61	0.76	0.70	0.94	0.36	0.44	0.45	0.44	0.48	0.47
		[2.52]	[3.05]	[4.12]	[3.95]	[4.47]	[3.26]	[4.04]	[4.13]	[3.94]	[4.29]	[4.17]

Panel B: Portfolio average number of firms and market capitalization

		RI Quintiles					RI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	287	286	285	284	284	29	28	26	27	27
	(2)	86	87	86	86	86	52	52	52	52	52
	(3)	63	63	63	63	63	93	94	92	93	93
	(4)	55	55	55	55	55	211	211	210	209	209
	(5)	50	50	50	50	50	1295	1774	2011	1654	1324

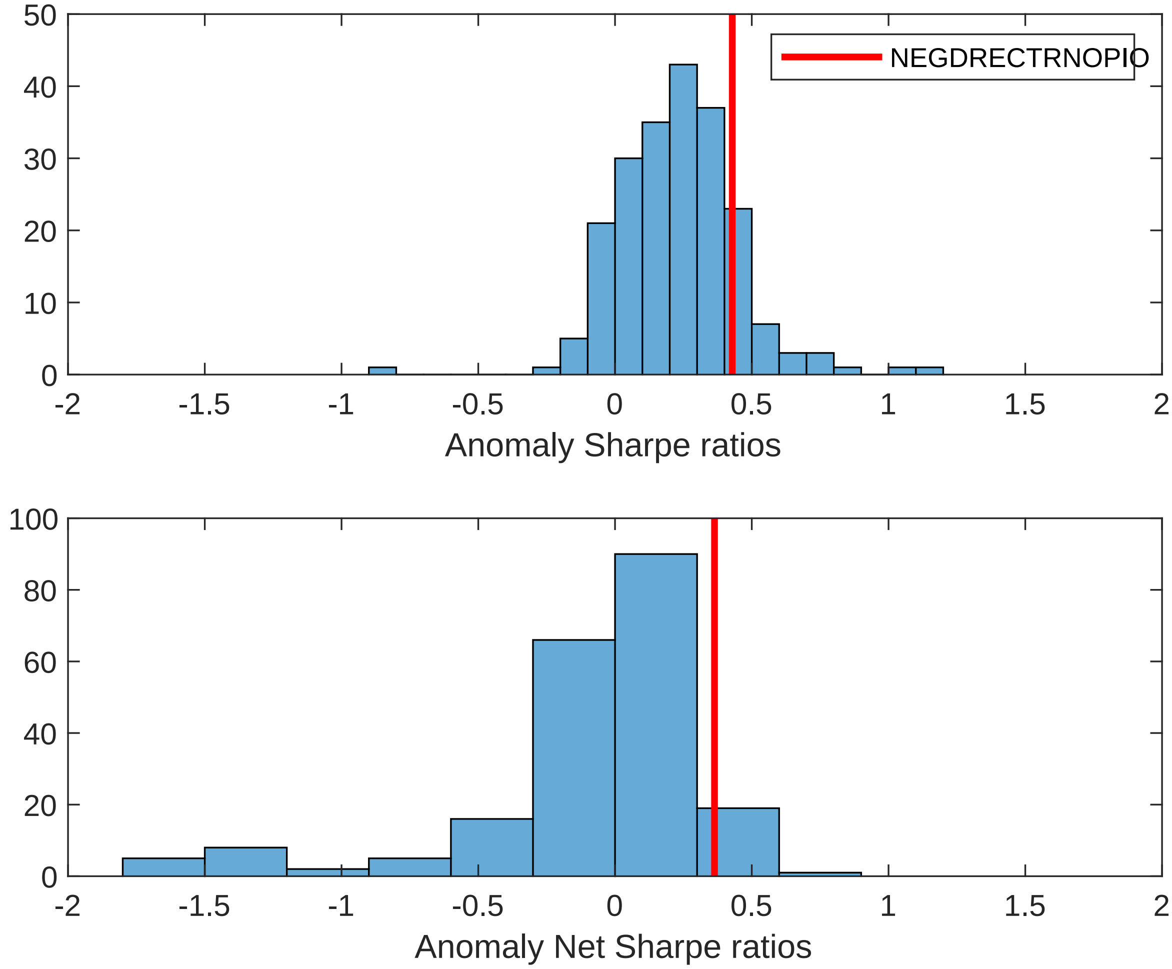


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the RI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

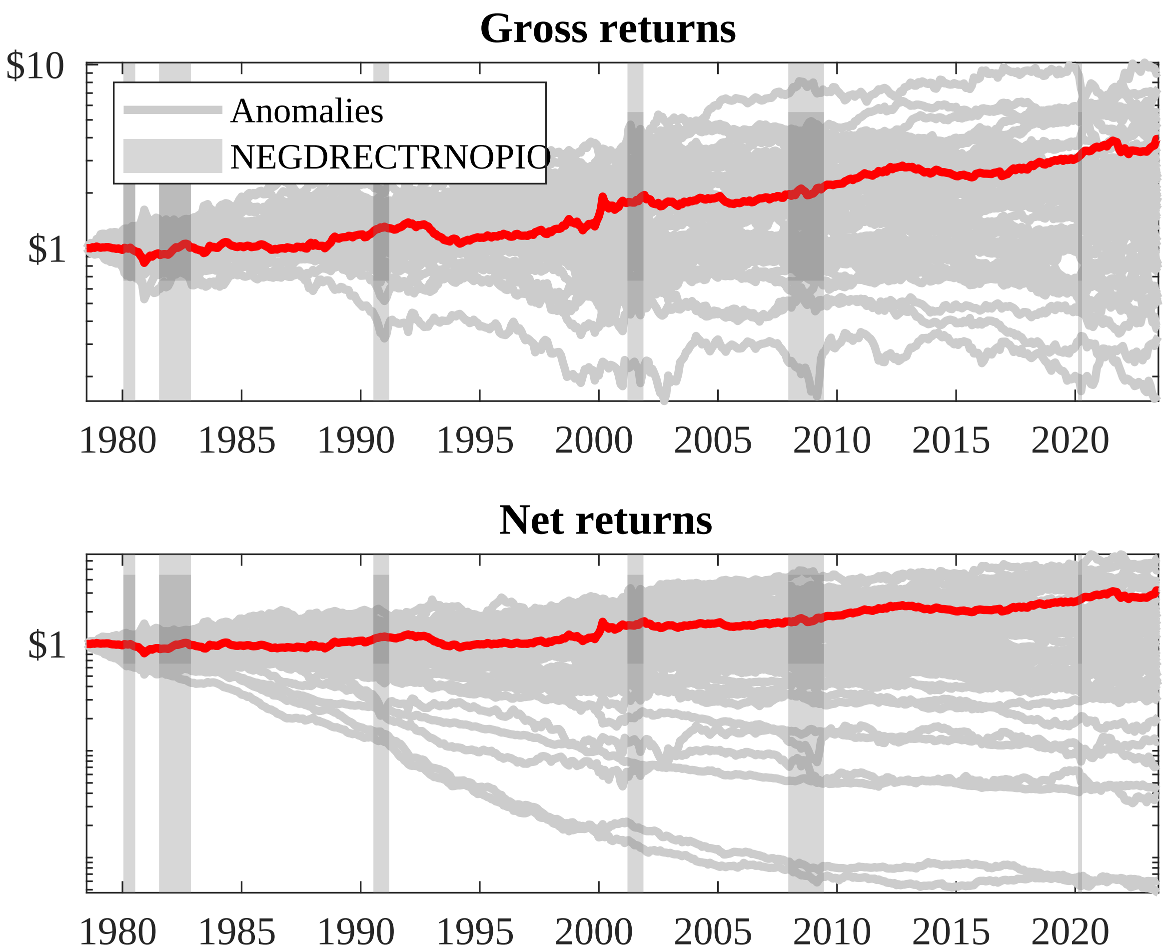


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the RI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

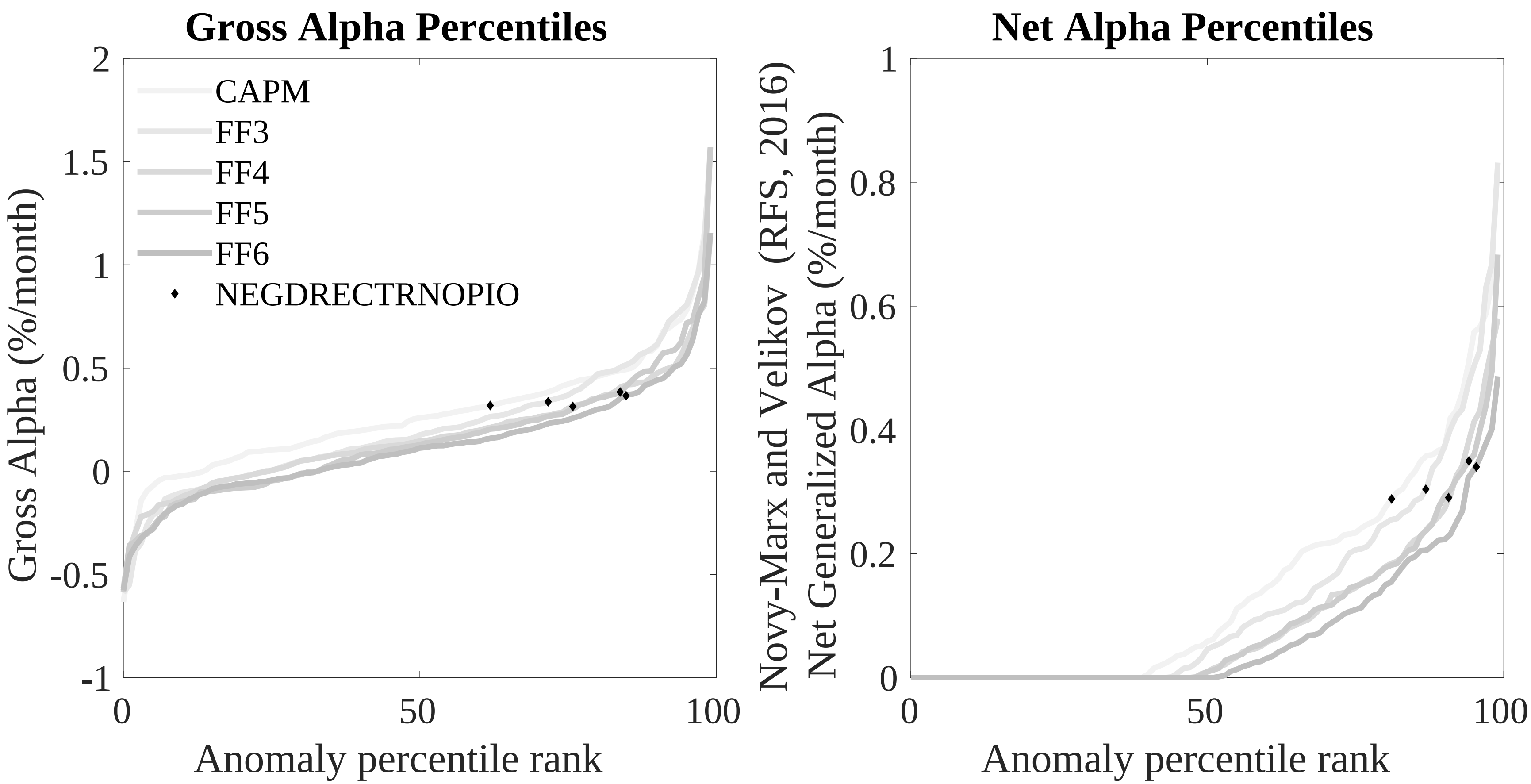
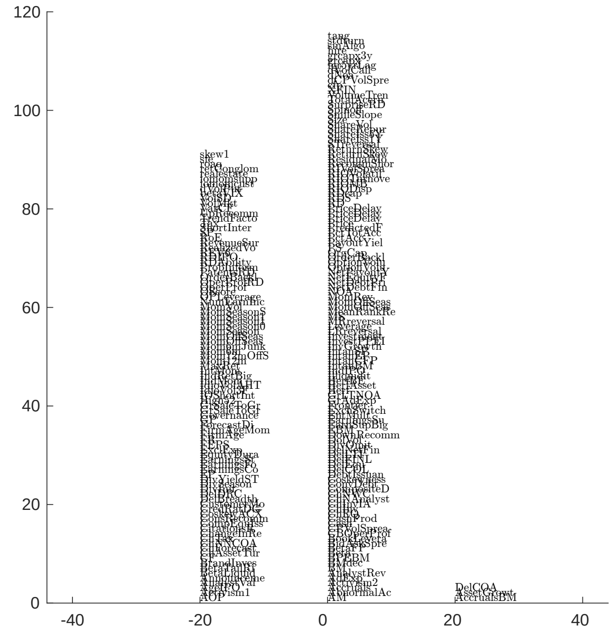
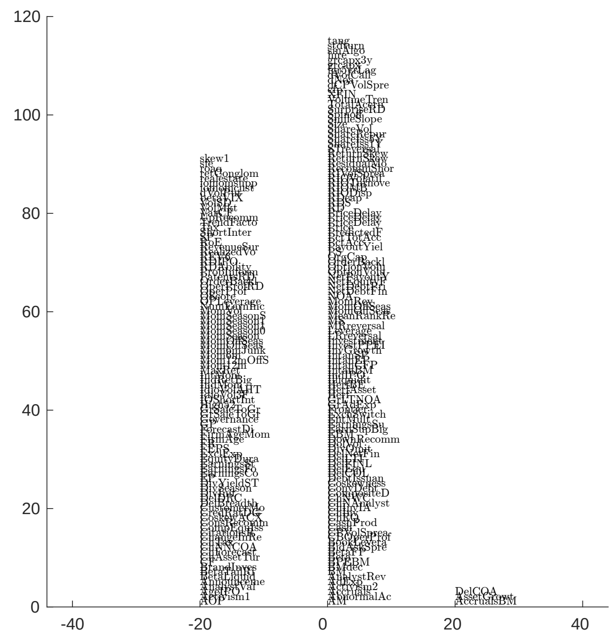


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the RI trading strategy alphas (diamonds). The strategies are constructed using 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 209 filtered anomaly signals with RI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

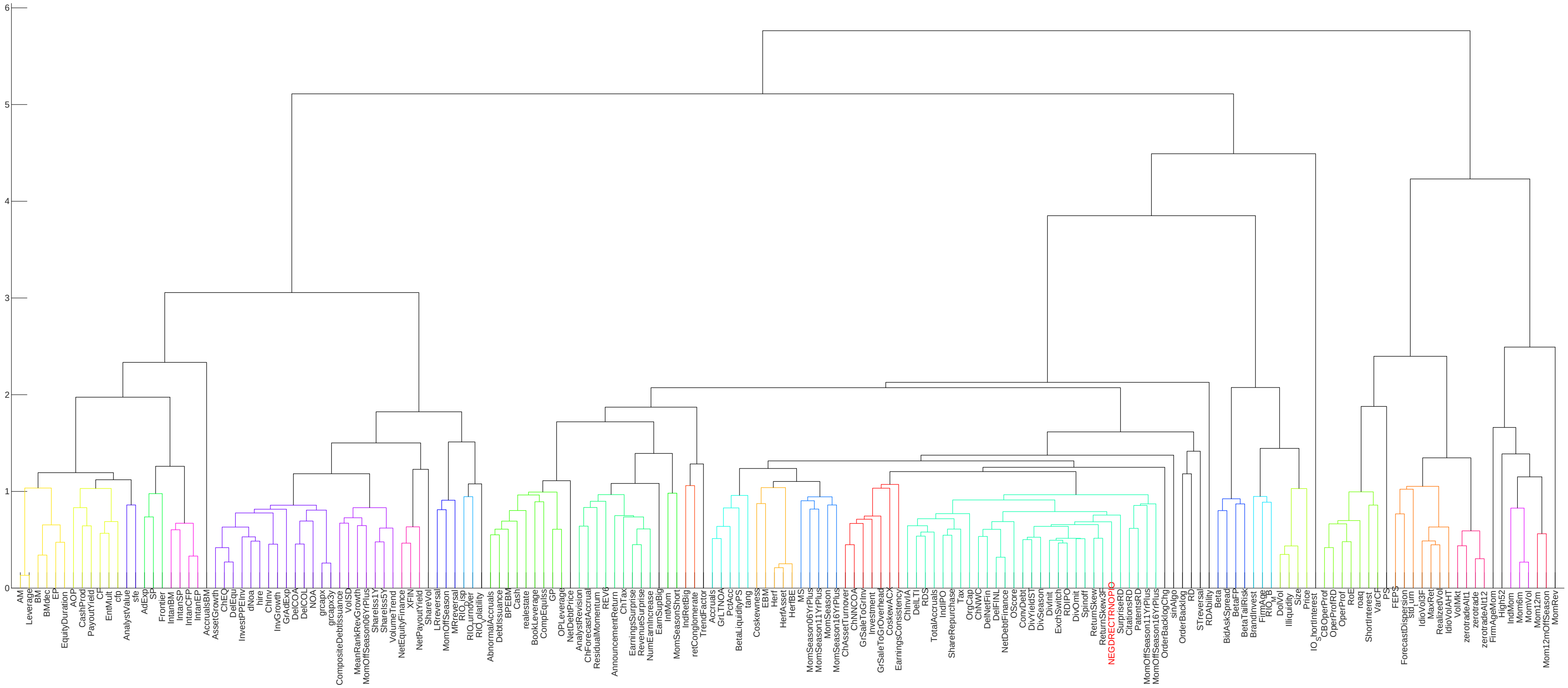


Figure 6: Agglomerative hierarchical cluster plot

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

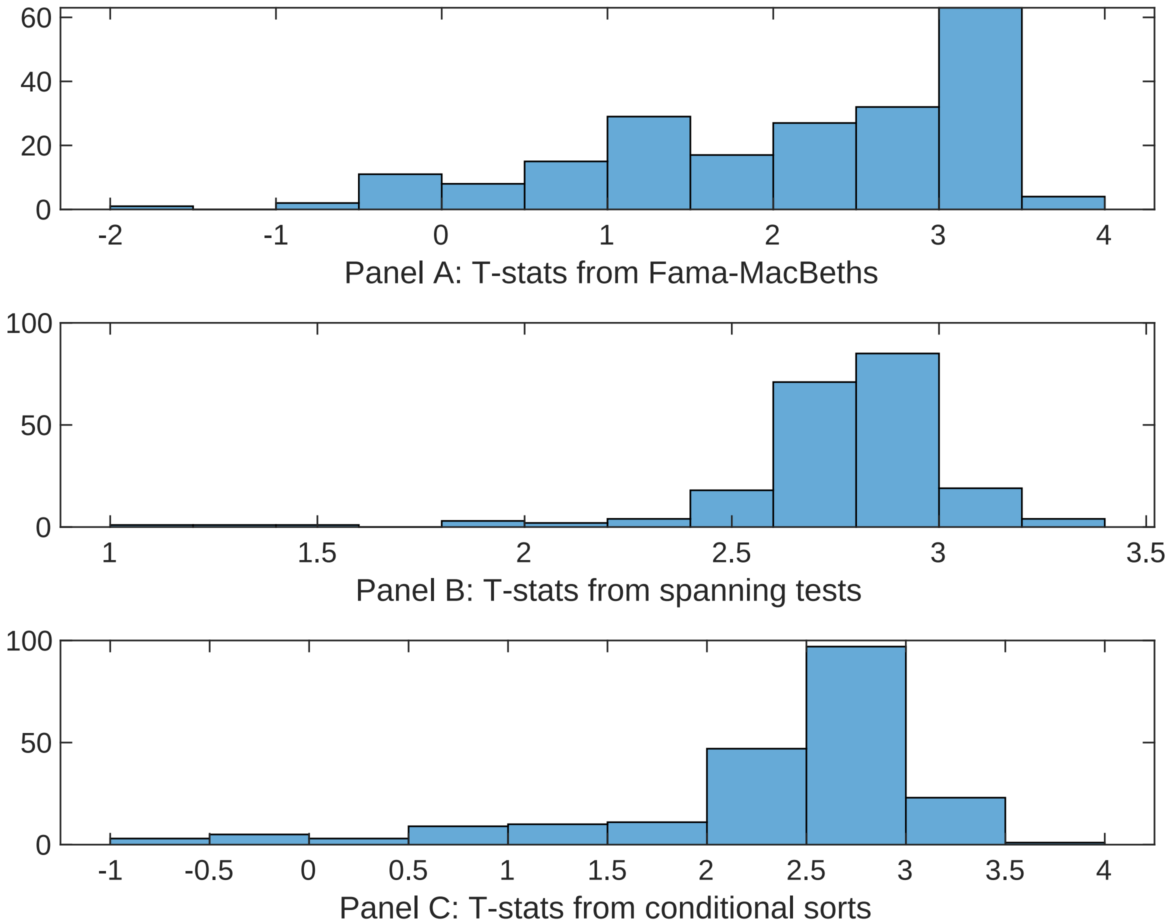


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of RI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{RI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{RI} RI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{RI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on RI. Stocks are finally grouped into five RI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted RI trading strategies conditioned on each of the 209 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on RI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{RI} RI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Accruals, Growth in long term operating assets, Inventory Growth, Momentum and LT Reversal, Change in Net Working Capital, Growth in book equity. 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 197806 to 202306.

Intercept	0.12	0.12	0.12	0.58	0.12	0.17	0.12
	[4.59]	[4.75]	[4.87]	[1.53]	[4.74]	[6.73]	[2.95]
RI	0.69	0.87	0.63	0.32	0.84	0.66	0.28
	[2.63]	[3.23]	[2.41]	[3.29]	[3.12]	[2.54]	[2.87]
Anomaly 1	0.12						0.20
	[3.59]						[0.14]
Anomaly 2		0.37					-0.11
		[1.39]					[-1.40]
Anomaly 3			0.33				0.30
			[5.45]				[1.58]
Anomaly 4				1.00			0.69
				[3.48]			[2.34]
Anomaly 5					0.60		-0.12
					[1.98]		[-0.08]
Anomaly 6						0.41	0.31
						[5.20]	[2.60]
# months	540	540	540	532	540	540	529
$\bar{R}^2$(%)	0	0	0	1	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the RI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{RI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Accruals, Growth in long term operating assets, Inventory Growth, Momentum and LT Reversal, Change in Net Working Capital, Growth in book equity. 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 197806 to 202306.

Intercept	0.32	0.35	0.34	0.33	0.34	0.37	0.25
	[3.47]	[3.79]	[3.60]	[3.57]	[3.69]	[3.98]	[2.69]
Anomaly 1	17.05						11.93
	[4.64]						[2.38]
Anomaly 2		14.57					4.97
		[3.42]					[0.92]
Anomaly 3			16.45				10.52
			[3.48]				[2.25]
Anomaly 4				1.59			1.08
				[1.41]			[0.98]
Anomaly 5					17.39		13.02
					[3.61]		[2.48]
Anomaly 6						12.57	10.05
						[2.38]	[1.90]
mkt	-7.59	-7.42	-8.15	-7.93	-8.94	-7.95	-6.80
	[-3.51]	[-3.38]	[-3.74]	[-3.64]	[-4.11]	[-3.62]	[-3.18]
smb	4.44	2.67	3.09	1.07	2.03	1.02	5.55
	[1.31]	[0.79]	[0.91]	[0.32]	[0.61]	[0.30]	[1.64]
hml	-3.61	-7.24	-9.96	-8.67	-6.73	-9.73	-4.33
	[-0.85]	[-1.75]	[-2.41]	[-2.07]	[-1.62]	[-2.33]	[-1.02]
rmw	-15.01	-17.16	-17.45	-19.37	-18.69	-20.15	-11.65
	[-3.47]	[-3.98]	[-4.07]	[-4.58]	[-4.42]	[-4.76]	[-2.71]
cma	7.58	10.43	2.82	14.67	11.94	1.37	-9.05
	[1.22]	[1.68]	[0.41]	[2.32]	[1.94]	[0.17]	[-1.09]
umd	2.83	4.46	2.84	2.25	3.16	3.38	1.44
	[1.35]	[2.11]	[1.34]	[0.93]	[1.50]	[1.60]	[0.60]
# months	540	540	540	536	540	540	536
$\bar{R}^2(\%)$	12	11	11	10	11	10	16

Panel A: Average rank

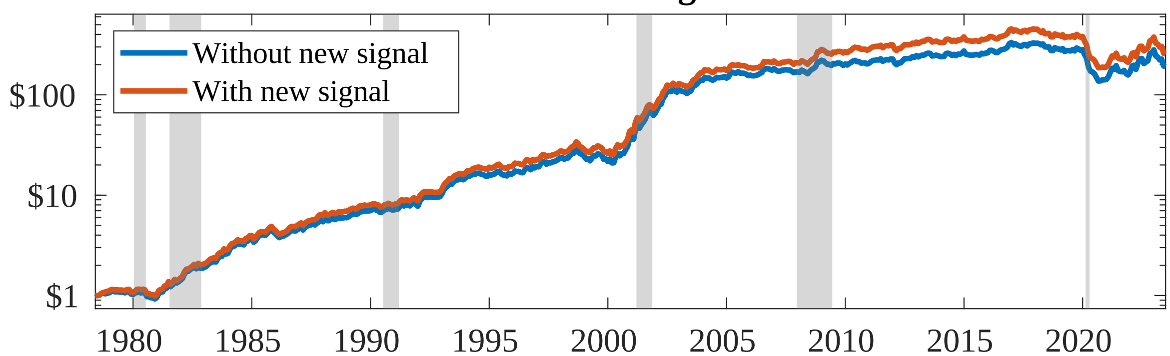


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 157 anomalies. The red solid lines indicate combination trading strategies that utilize the 157 anomalies as well as RI. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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