Rent-scaled Debt Emission Deviation and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Rent-scaled Debt Emission Deviation (RSDED), 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 RSDED achieves an annualized gross (net) Sharpe ratio of 0.52 (0.42), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (19) bps/month with a t-statistic of 2.81 (2.49), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in financial liabilities, Net debt financing, Asset growth, Net external financing, Inventory Growth, change in net operating assets) is 20 bps/month with a t-statistic of 2.66.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns (Harvey et al., 2016). While extensive research has documented various accounting-based anomalies, the role of firms' financing decisions in predicting returns remains incompletely understood (Baker and Wurgler, 2002). In particular, the interaction between firms' debt issuance decisions and their underlying economic fundamentals has received limited attention in the cross-sectional asset pricing literature.

Recent work suggests that examining debt issuance in isolation may miss important information content embedded in its relationship to firms' real activities (Leary and Roberts, 2005). The ratio of debt emissions to rental expenses (rent-scaled debt emission) provides a natural measure of the alignment between firms' financing and operating decisions, as rental commitments represent a key alternative to debt financing of capital assets (**?**).

We propose that deviations from typical industry rent-scaled debt emission patterns (RSDED) contain valuable information about future stock returns. Our hypothesis builds on two theoretical frameworks. First, the trade-off theory of capital structure suggests that firms face costs when their leverage deviates from optimal levels (Kraus and Litzenberger, 1973). Rental expenses represent fixed commitments similar to debt service, implying that large deviations in rent-scaled debt emissions likely reflect suboptimal financing choices.

Second, the q-theory of investment indicates that firms' financing decisions should align with their investment opportunities and operating needs (Cochrane, 1991). Abnormal rent-scaled debt emissions may signal agency problems where managers are either over-investing using debt financing or failing to pursue valuable growth opportunities (Jensen and Meckling, 1976). This misalignment between financing and real decisions should predict lower future returns as the costs of misallocation materialize.

Importantly, the market may not fully incorporate this information due to the complexity of evaluating the joint optimality of financing and operating decisions (?). The relative opacity of rental arrangements compared to debt contracts could further impede efficient price formation (?).

Our empirical analysis reveals that RSDED strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high RSDED and shorts those with low RSDED generates a monthly alpha of 21 basis points (t-statistic = 2.81) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.52 before trading costs and 0.42 after accounting for transaction costs.

The predictive power of RSDED is robust across various methodological choices. The signal maintains significant predictability when using different portfolio construction approaches, with net returns ranging from 1-30 basis points per month across specifications. Importantly, RSDED's predictive ability persists among large-cap stocks, with the long-short strategy generating a monthly alpha of 23 basis points (t-statistic = 2.45) among stocks above the 80th NYSE size percentile.

Further tests demonstrate that RSDED captures unique information beyond known predictors. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the RSDED strategy still generates a monthly alpha of 20 basis points (t-statistic = 2.66). The strategy's gross (net) Sharpe ratio of 0.52 (0.42) exceeds 94% (98%) of documented anomalies in the literature.

Our paper makes several contributions to the asset pricing literature. First, we extend the growing body of work on financing-based return predictors (Bradshaw et al., 2006; Lewellen and Resutek, 2016) by showing how the interaction between financing and operating decisions contains valuable information about future returns. Our findings suggest that considering debt emissions in isolation, without accounting for their relationship to firms' operational scale, misses important pricing implications.

Second, we contribute to the literature on operating leverage and asset pricing (?Novy-Marx, 2011) by demonstrating that the alignment between financial and operating leverage decisions affects expected returns. Our results highlight the importance of examining firms' joint financing and operating choices rather than studying these decisions in isolation.

Finally, our work adds to the broader literature on market efficiency and the limits of arbitrage (?). The persistence of RSDED's predictive power, particularly among large-cap stocks, suggests that even sophisticated investors may struggle to properly value complex interactions between firms' financing and operating decisions. This finding has important implications for understanding market efficiency and the sources of cross-sectional return predictability.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Rent-scaled Debt Emission Deviation. 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 DLTIS for long-term debt issuance and item XRENT for rental expenses. Long-term debt issuance (DLTIS) represents the cash proceeds from the issuance of long-term debt during the fiscal year, while rental expenses (XRENT) capture the firm's periodic payments for leased assets and properties.construction of the signal follows a difference-based approach, where we first calculate the change in debt issuance by subtracting the previous year's DLTIS from the current year's value. This difference captures the year-over-year variation in a firm's long-term debt financing activities. We then scale this difference by the previous year's rental expenses (XRENT) to normalize the measure across firms of different sizes and to account for their operational scale as reflected in their rental commitments. This scaling choice provides a meaningful way to compare debt emission deviations across firms with different rental expense profiles. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the RSDED signal. Panel A plots the time-series of the mean, median, and interquartile range for RSDED. On average, the cross-sectional mean (median) RSDED is -3.46 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input RSDED data. The signal's interquartile range spans -5.36 to 4.91. Panel B of Figure 1 plots the time-series of the coverage of the RSDED signal for the CRSP universe. On average, the RSDED signal is available for 5.23% of CRSP names, which on average make up 6.46% of total market capitalization.

4 Does RSDED predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on RSDED 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 RSDED portfolio and sells the low RSDED 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 RSDED strategy earns an average return of 0.28% per month with a t-statistic of 3.69. The annualized Sharpe ratio of the strategy is 0.52. The alphas range from 0.21% to 0.32% per month and have t-statistics exceeding 2.81 everywhere. The lowest alpha is with respect to the FF6 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 0.34, with a t-statistic of 6.81 on the CMA 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 484 stocks and an average market capitalization of at least $1,566 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

24 bps/month with a t-statistics of 3.43. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 1-30bps/month. The lowest return, (1 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.16. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the RSDED trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the RSDED strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and RSDED, as well as average returns and alphas for long/short trading RSDED 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 RSDED strategy achieves an average return of 33 bps/month with a t-statistic of 3.60. Among these large cap stocks, the alphas for the RSDED strategy relative to the five most common factor models range from 23 to 36 bps/month with t-statistics between 2.45 and 3.84.

5 How does RSDED perform relative to the zoo?

Figure 2 puts the performance of RSDED 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 RSDED strategy falls in the distribution. The RSDED strategy's gross (net) Sharpe ratio of 0.52 (0.42) is greater than 94% (98%) 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 RSDED strategy (red line).[2] Ignoring trading costs, a \$1 invested in the RSDED strategy would have yielded \$3.85 which ranks the RSDED strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the RSDED strategy would have yielded \$2.55 which ranks the RSDED 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 RSDED relative to those. Panel A shows that the RSDED strategy gross alphas fall between the 63 and 74 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 RSDED strategy has a positive net generalized alpha for five out of the five factor models. In these cases RSDED ranks between the 81 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does RSDED 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 RSDED 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 RSDED or at least to weaken the power RSDED has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of RSDED conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{RSDED} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{RSDED} RSDED_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{RSDED,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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

[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.

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 RSDED. Stocks are finally grouped into five RSDED portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted RSDED trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on RSDED 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 RSDED signal in these Fama-MacBeth regressions exceed 0.28, with the minimum t-statistic occurring when controlling for change in net operating assets. Controlling for all six closely related anomalies, the t-statistic on RSDED is -0.79.

Similarly, Table 5 reports results from spanning tests that regress returns to the RSDED 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 RSDED strategy earns alphas that range from 20-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.68, which is achieved when controlling for change in net operating assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the RSDED trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.66.

7 Does RSDED add relative to the whole zoo?

Finally, we can ask how much adding RSDED 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 RSDED 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 RSDED grows to $1087.20.

8 Conclusion

This study provides compelling evidence for the effectiveness of Rent-scaled Debt Emission Deviation (RSDED) 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 RSDED generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.52 (0.42 net). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

[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 RSDED is available.

The persistence of the signal's predictive power, evidenced by a monthly alpha of 20 bps with a t-statistic of 2.66 after controlling for related factors, suggests that RSDED captures unique information about future stock returns that is not fully reflected in existing pricing factors. This has important implications for both academic research and practical investment management, as it introduces a novel and effective tool for portfolio construction and risk management.

However, several limitations should be noted. First, the study's findings may be sensitive to the specific time period examined and market conditions. Second, transaction costs and market impact could affect the real-world implementation of the strategy, particularly for smaller stocks or during periods of market stress.

Future research could explore the international validity of the RSDED signal, its interaction with other established anomalies, and its performance during different market regimes. Additionally, investigating the underlying economic mechanisms driving the RSDED premium would enhance our understanding of this anomaly and its role in asset pricing theory. Researchers might also consider examining how the signal's effectiveness varies across different industry sectors and firm characteristics.

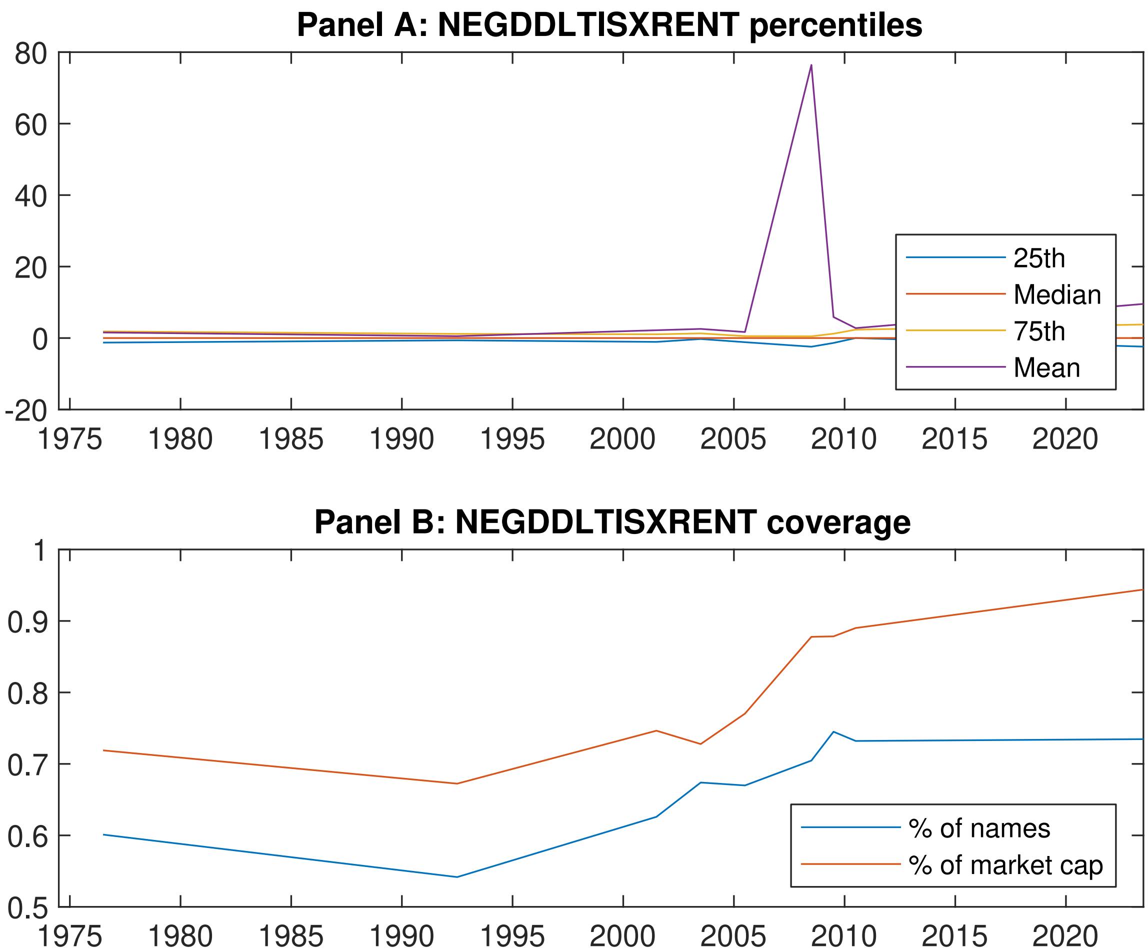

Figure 1: Times series of RSDED percentiles and coverage.
This figure plots descriptive statistics for RSDED. Panel A shows cross-sectional percentiles of RSDED over the sample. Panel B plots the monthly coverage of RSDED relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on RSDED. 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 RSDED-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.61	0.65	0.72	0.76	0.89	0.28
	[2.89]	[3.40]	[3.50]	[3.89]	[4.46]	[3.69]
α_{CAPM}	-0.13	-0.02	0.01	0.08	0.20	0.32
	[-2.41]	[-0.31]	[0.20]	[1.52]	[3.72]	[4.34]
α_{FF3}	-0.14	-0.05	0.08	0.09	0.18	0.32
	[-2.67]	[-1.11]	[1.37]	[1.70]	[3.39]	[4.26]
α_{FF4}	-0.11	-0.01	0.12	0.08	0.17	0.28
	[-2.12]	[-0.32]	[2.13]	[1.37]	[3.13]	[3.70]
α_{FF5}	-0.10	-0.08	0.11	0.08	0.13	0.23
	[-1.85]	[-1.78]	[1.92]	[1.40]	[2.40]	[3.05]
α_{FF6}	-0.08	-0.05	0.14	0.07	0.13	0.21
	[-1.55]	[-1.16]	[2.43]	[1.19]	[2.36]	[2.81]
Panel B: Fama and French (2018) 6-factor model loadings for RSDED-sorted portfolios						
β_{MKT}	1.06	1.00	0.98	0.99	1.03	-0.03
	[85.13]	[97.12]	[72.84]	[76.31]	[83.51]	[-1.63]
β_{SMB}	0.01	-0.10	0.04	-0.01	0.02	0.01
	[0.59]	[-6.54]	[2.04]	[-0.59]	[1.28]	[0.50]
β_{HML}	0.09	0.11	-0.19	-0.03	-0.04	-0.13
	[3.91]	[5.33]	[-7.39]	[-1.20]	[-1.51]	[-3.90]
β_{RMW}	0.00	0.08	-0.01	0.01	0.02	0.02
	[0.02]	[4.11]	[-0.56]	[0.42]	[0.66]	[0.46]
β_{CMA}	-0.16	0.02	-0.07	0.02	0.19	0.34
	[-4.31]	[0.82]	[-1.78]	[0.65]	[5.17]	[6.81]
β_{UMD}	-0.03	-0.05	-0.05	0.02	0.00	0.03
	[-2.16]	[-4.78]	[-3.78]	[1.46]	[0.16]	[1.68]
Panel C: Average number of firms (n) and market capitalization (me)						
n	506	484	924	536	484	
me ($\$10^6$)	1634	2464	1775	2460	1566	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the RSDED 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	0.28	0.32	0.32	0.28	0.23	0.21
			[3.69]	[4.34]	[4.26]	[3.70]	[3.05]	[2.81]
Quintile	NYSE	EW	0.25	0.27	0.26	0.24	0.24	0.23
			[4.80]	[5.26]	[4.99]	[4.52]	[4.79]	[4.54]
Quintile	Name	VW	0.24	0.29	0.29	0.26	0.21	0.19
			[3.43]	[4.07]	[4.02]	[3.53]	[2.89]	[2.67]
Quintile	Cap	VW	0.31	0.34	0.34	0.32	0.26	0.25
			[4.13]	[4.53]	[4.58]	[4.15]	[3.47]	[3.30]
Decile	NYSE	VW	0.36	0.45	0.45	0.36	0.29	0.24
			[3.37]	[4.20]	[4.21]	[3.38]	[2.77]	[2.33]
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	0.22	0.28	0.28	0.26	0.20	0.19
			[2.96]	[3.71]	[3.63]	[3.35]	[2.68]	[2.49]
Quintile	NYSE	EW	0.01	0.04	0.02	0.02		
			[0.16]	[0.64]	[0.36]	[0.28]		
Quintile	Name	VW	0.19	0.25	0.25	0.23	0.18	0.17
			[2.70]	[3.50]	[3.45]	[3.21]	[2.52]	[2.36]
Quintile	Cap	VW	0.26	0.30	0.31	0.29	0.24	0.23
			[3.46]	[4.00]	[4.03]	[3.83]	[3.11]	[2.96]
Decile	NYSE	VW	0.30	0.39	0.39	0.34	0.27	0.23
			[2.78]	[3.61]	[3.64]	[3.22]	[2.54]	[2.22]

Table 3: Conditional sort on size and RSDED

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

	RSDED Quintiles					RSDED Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.74	0.99	1.05	1.04	0.89	0.14	0.15	0.13	0.11	0.12	0.11
	[2.60]	[3.37]	[3.62]	[3.29]	[3.08]	[1.94]	[2.03]	[1.77]	[1.46]	[1.61]	[1.43]
(2)	0.82	0.95	0.88	0.97	0.96	0.15	0.20	0.19	0.18	0.19	0.18
	[2.99]	[3.59]	[3.33]	[3.66]	[3.77]	[1.65]	[2.29]	[2.14]	[2.07]	[2.05]	[2.03]
(3)	0.83	0.84	0.92	0.95	0.96	0.13	0.18	0.17	0.14	0.13	0.11
	[3.35]	[3.54]	[3.56]	[4.01]	[4.10]	[1.58]	[2.09]	[2.03]	[1.58]	[1.54]	[1.29]
(4)	0.70	0.92	0.93	0.84	0.89	0.19	0.22	0.20	0.17	0.13	0.11
	[3.10]	[4.08]	[3.96]	[3.75]	[4.13]	[2.38]	[2.79]	[2.50]	[2.11]	[1.56]	[1.38]
(5)	0.51	0.59	0.61	0.74	0.84	0.33	0.36	0.35	0.32	0.25	0.23
	[2.53]	[3.08]	[2.96]	[3.77]	[4.32]	[3.60]	[3.84]	[3.77]	[3.32]	[2.64]	[2.45]

Panel B: Portfolio average number of firms and market capitalization

	RSDED Quintiles: Average n					RSDED Quintiles: Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	325	324	324	324	321	31	27	27	27	30
(2)	91	91	92	91	91	52	52	51	52	53
(3)	65	65	65	65	65	94	94	90	93	93
(4)	56	55	56	56	55	206	212	202	209	205
(5)	52	52	52	52	52	1368	1863	1519	1855	1395

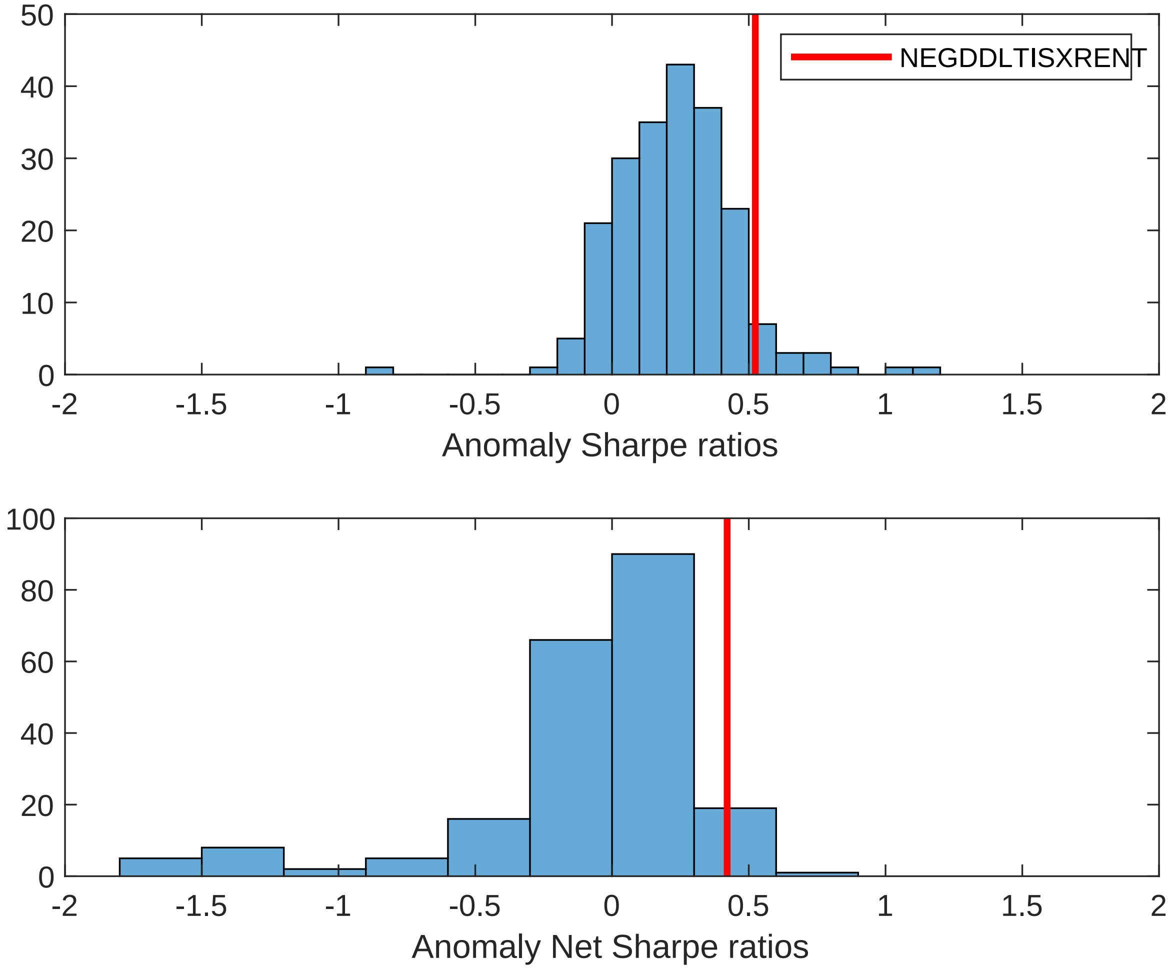

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the RSDED with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

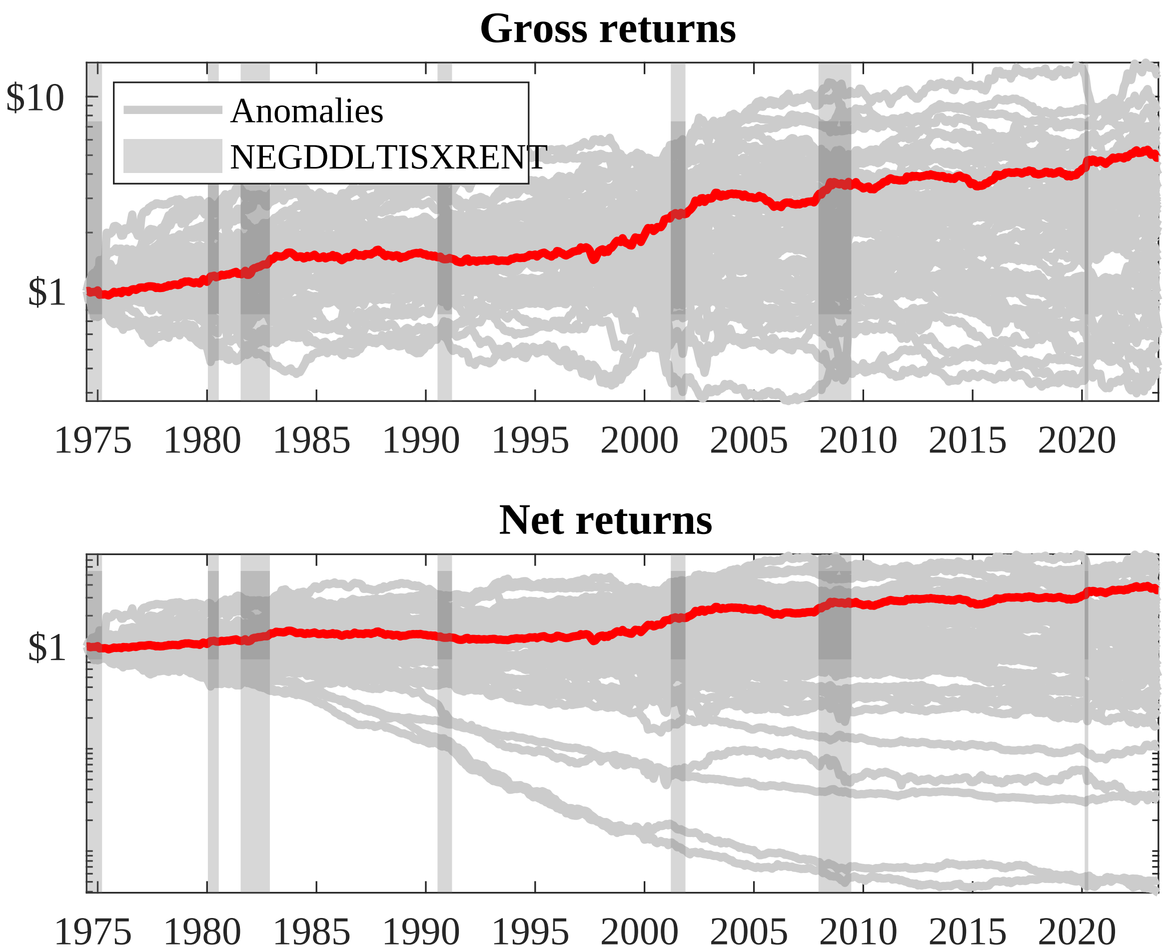

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the RSDED trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

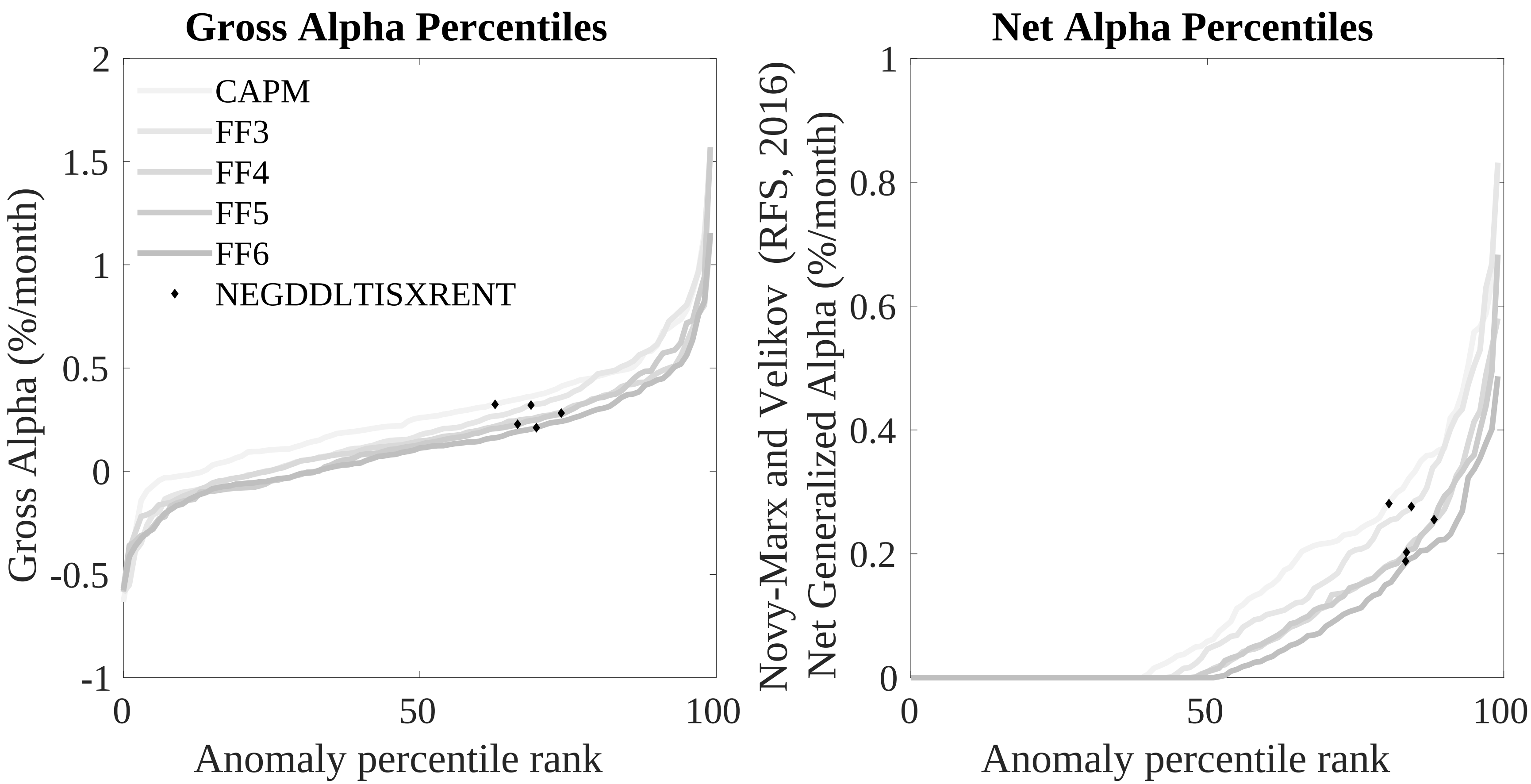

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the RSDED trading strategy alphas (diamonds). The strategies are constructed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

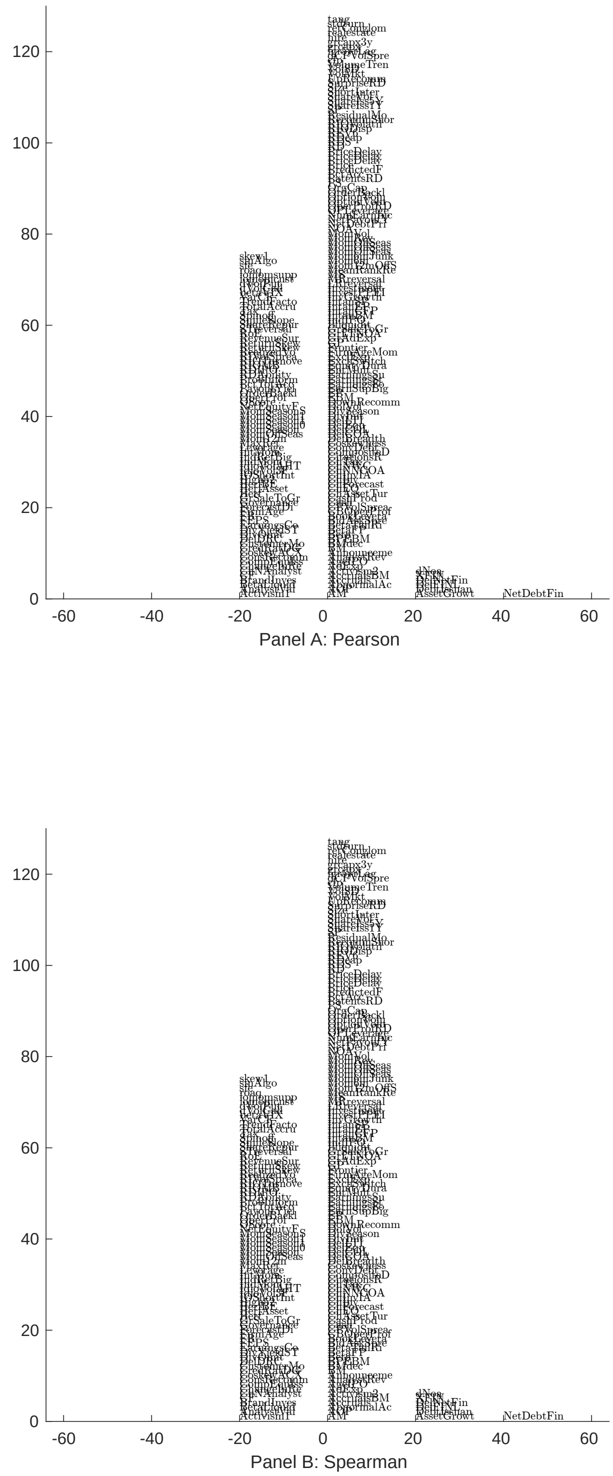

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with RSDED. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

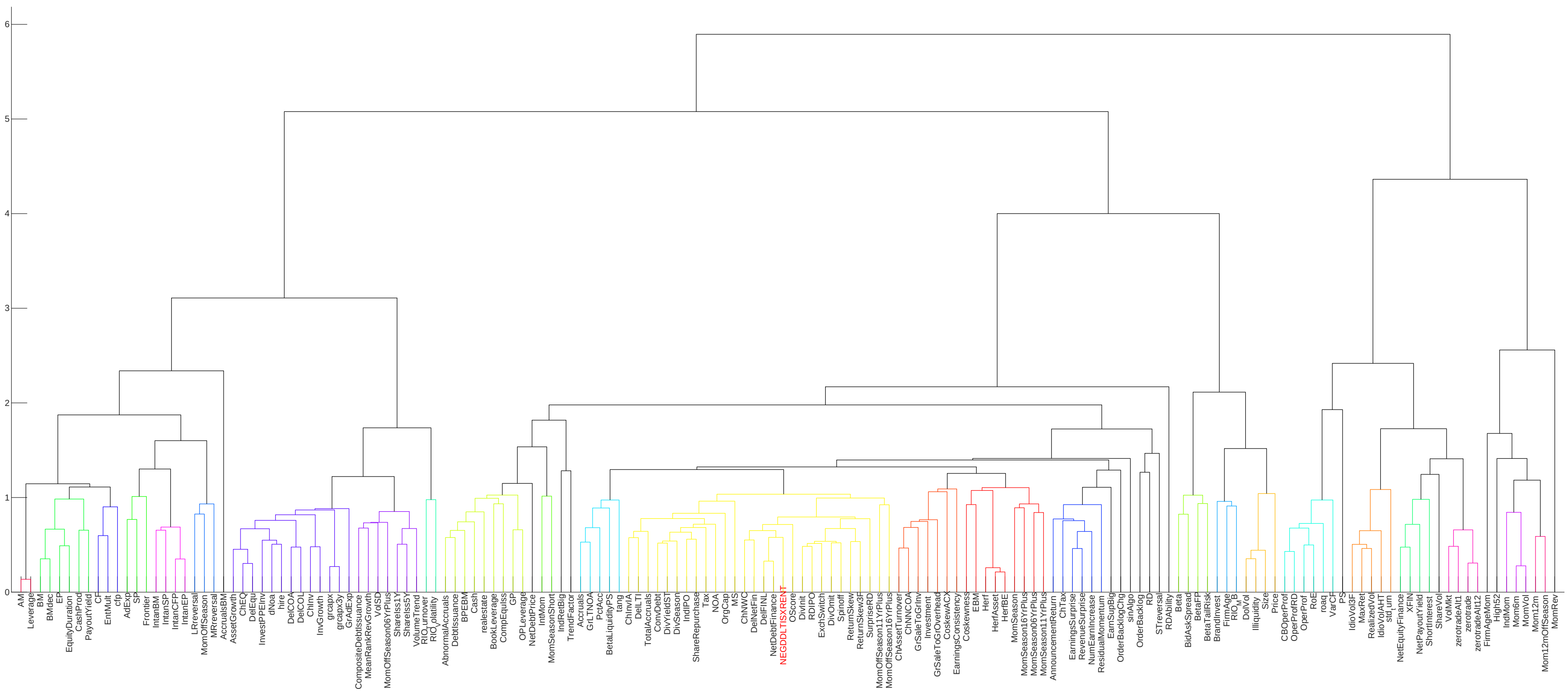

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

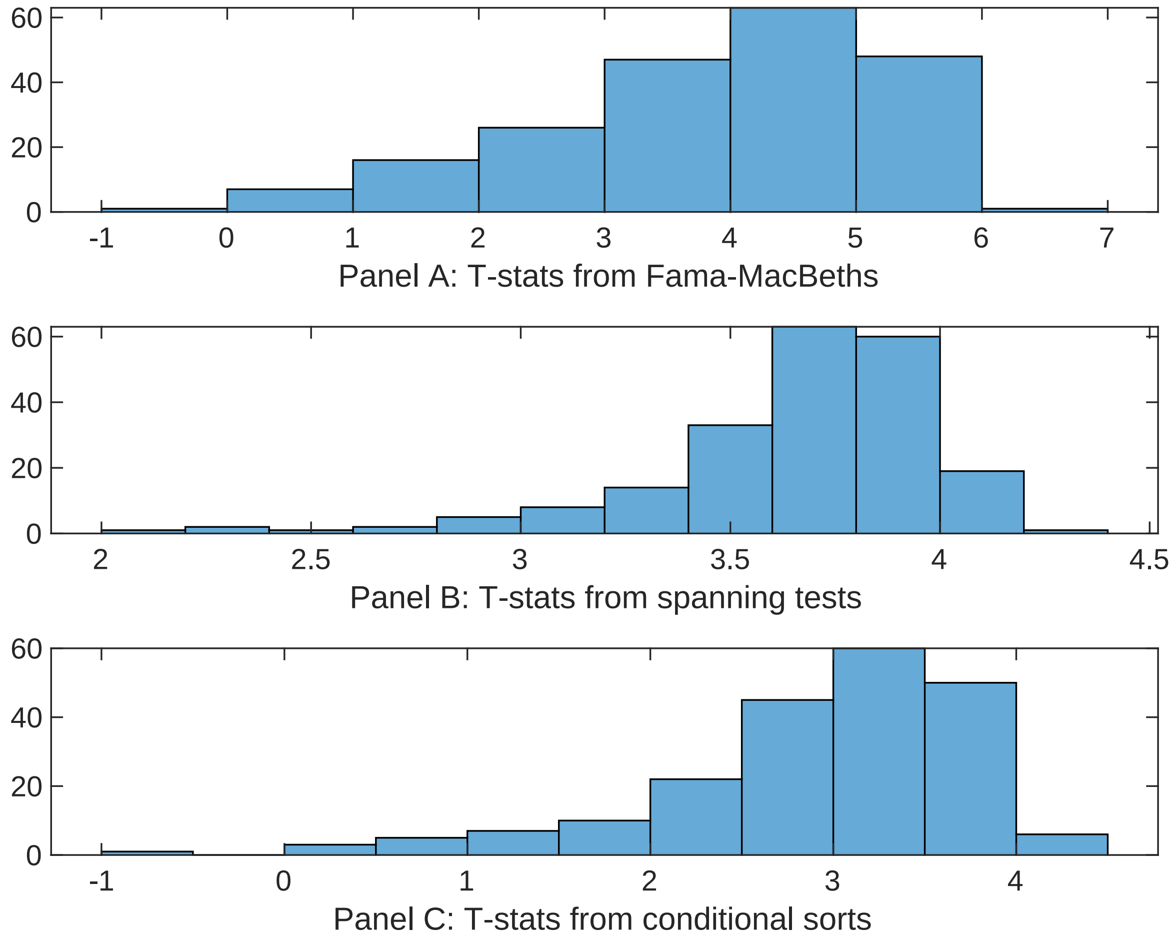

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of RSDED conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{RSDED} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{RSDED} RSDED_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{RSDED,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 RSDED. Stocks are finally grouped into five RSDED portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted RSDED 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 RSDED. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{RSDED} RSDED_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Asset growth, Net external financing, Inventory Growth, change in net operating assets. 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	0.14	0.14	0.15	0.15	0.14	0.15	0.15
	[5.48]	[5.45]	[5.90]	[5.85]	[5.46]	[5.77]	[5.84]
RSDED	0.43	0.71	0.33	0.13	0.33	0.21	-0.79
	[0.58]	[0.96]	[0.41]	[1.63]	[3.37]	[0.28]	[-0.79]
Anomaly 1	0.18						-0.90
	[9.22]						[-1.81]
Anomaly 2		0.21					0.88
		[8.78]					[1.36]
Anomaly 3			0.11				0.48
			[9.00]				[2.17]
Anomaly 4				0.19			0.11
				[6.31]			[2.02]
Anomaly 5					0.38		-0.25
					[6.35]		[-0.04]
Anomaly 6						0.14	0.79
						[10.04]	[4.29]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	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 RSDED trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{RSDED} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 financial liabilities, Net debt financing, Asset growth, Net external financing, Inventory Growth, change in net operating assets. 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	0.20	0.20	0.22	0.20	0.22	0.20	0.20
	[2.68]	[2.71]	[2.89]	[2.69]	[2.87]	[2.69]	[2.66]
Anomaly 1	20.33						16.76
	[4.63]						[2.76]
Anomaly 2		17.51					3.79
		[4.14]					[0.65]
Anomaly 3			12.06				4.65
			[2.46]				[0.87]
Anomaly 4				13.25			9.19
				[3.46]			[2.25]
Anomaly 5					8.50		7.45
					[2.85]		[2.43]
Anomaly 6						7.67	-4.19
						[1.72]	[-0.85]
mkt	-2.64	-2.88	-2.83	-1.09	-3.11	-2.88	-1.62
	[-1.54]	[-1.68]	[-1.63]	[-0.60]	[-1.79]	[-1.66]	[-0.91]
smb	-0.48	0.17	0.13	5.60	2.21	1.44	2.78
	[-0.18]	[0.06]	[0.05]	[1.90]	[0.82]	[0.54]	[0.89]
hml	-11.70	-12.47	-13.18	-11.24	-13.01	-13.40	-10.93
	[-3.55]	[-3.78]	[-3.95]	[-3.36]	[-3.91]	[-3.98]	[-3.27]
rmw	0.05	0.17	1.67	-6.33	2.78	1.82	-4.53
	[0.01]	[0.05]	[0.48]	[-1.53]	[0.80]	[0.52]	[-1.09]
cma	26.99	29.27	18.72	24.89	26.19	28.05	11.75
	[5.20]	[5.73]	[2.36]	[4.42]	[4.60]	[4.64]	[1.47]
umd	0.97	1.49	3.42	2.88	2.15	2.67	0.63
	[0.54]	[0.84]	[1.94]	[1.65]	[1.21]	[1.51]	[0.34]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	13	13	11	12	11	11	15

Panel A: Average rank

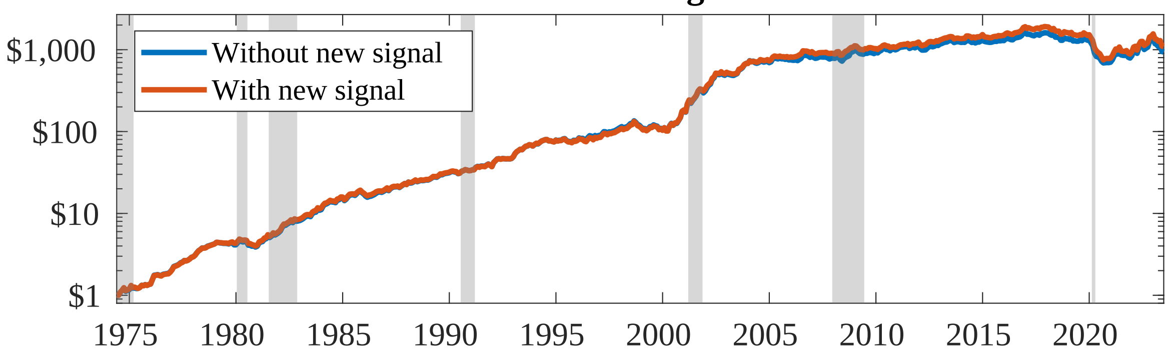

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

References

Baker, M. and Wurgler, J. (2002). Market timing and capital structure. *Journal of Finance*, 57(1):1–32.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, 42(1-2):53–85.

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

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

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

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance*, 46(1):209–237.

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

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

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

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

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Kraus, A. and Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance*, 28(4):911–922.

Leary, M. T. and Roberts, M. R. (2005). Do firms rebalance their capital structures? *Journal of Finance*, 60(6):2575–2619.

Lewellen, J. and Resutek, R. J. (2016). The predictive power of investment and accruals. *Review of Financial Studies*, 29(10):2687–2723.

Novy-Marx, R. (2011). Operating leverage. *Review of Finance*, 15(1):103–134.

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

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