Debt-Issuance Gross Profit Delta and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Debt-Issuance Gross Profit Delta (DGPDelta), 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 DGPDelta achieves an annualized gross (net) Sharpe ratio of 0.45 (0.33), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (15) bps/month with a t-statistic of 2.67 (2.13), 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, Net external financing, Asset growth, Inventory Growth, change in net operating assets) is 17 bps/month with a t-statistic of 2.39.

1 Introduction

Market efficiency remains a central question in financial economics, with mounting evidence that certain firm characteristics can predict future stock returns. While the literature has extensively documented various accounting-based signals, the interaction between debt issuance decisions and operating performance metrics remains underexplored. This gap is particularly notable given the theoretical links between financing choices and firm fundamentals established by Myers and Majluf (1984) and Baker and Wurgler (2002a).

Prior research has separately examined how changes in debt levels (Bradshaw et al. (2006)) and gross profitability (Novy-Marx (2013)) relate to future returns. However, the dynamic relationship between these two dimensions - specifically how changes in debt financing affect the predictive power of profitability metrics - has not been systematically investigated. This oversight is significant given that debt issuance decisions may reveal management's private information about future operating performance.

We propose that the interaction between debt issuance and gross profitability changes (Debt-Issuance Gross Profit Delta or DGPDelta) contains valuable information about future stock returns. Our hypothesis builds on two established theoretical frameworks. First, the pecking order theory of Myers and Majluf (1984) suggests that firms prefer debt to equity financing when they have positive private information. Second, the q-theory of investment (Cochrane (1991)) predicts that firms expand operations when expected returns on capital are high.

When firms simultaneously increase debt and improve gross profitability, this may signal both management's confidence in future prospects and realized improvements in operating efficiency. Following Baker and Wurgler (2002b), managers time their financing decisions based on private information. Therefore, debt issuance concurrent with profitability improvements likely indicates genuine operating enhancements rather than temporary fluctuations.

Conversely, declining gross profitability alongside debt issuance may signal potential financial distress, as described in Campbell et al. (2008). This combination could indicate that firms are borrowing to cover operating shortfalls rather than to fund profitable growth opportunities, suggesting lower future returns.

Our empirical analysis reveals that DGPDelta strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on DGPDelta quintiles generates a monthly alpha of 19 basis points (t-statistic = 2.67) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.45, placing it in the top 12% of documented return predictors.

Importantly, the predictive power of DGPDelta persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 24 basis points (t-statistic = 2.68) among stocks above the 80th percentile of market capitalization. This suggests that the signal's predictive ability is not confined to small, illiquid stocks.

The signal remains robust after controlling for related predictors. When we simultaneously control for six closely related anomalies (including change in financial liabilities, net debt financing, and asset growth) and the Fama-French six factors, DGPDelta still generates a monthly alpha of 17 basis points (t-statistic = 2.39).

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures the interaction between financing decisions and operating performance, extending work by Bradshaw et al. (2006) on debt issuance and Novy-Marx (2013) on gross profitability. Unlike previous studies that examine these dimensions separately, we show that their interaction provides incremental predictive power.

Second, we contribute to the literature on financing-based return predictors (Baker and Wurgler (2002b), Pontiff and Woodgate (2008)) by demonstrating that the information content of debt issuance varies systematically with changes in operating performance. This finding helps reconcile mixed evidence on the relationship between external financing and future returns.

Finally, our results have important implications for both academic research and investment practice. For researchers, we highlight the value of examining interactions between different types of firm characteristics. For practitioners, we document a robust return predictor that remains effective among large, liquid stocks and survives transaction costs, with a net Sharpe ratio of 0.33.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Debt-Issuance Gross Profit Delta. 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 GP for gross profit. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt during the fiscal year, while gross profit (GP) measures the difference between revenue and cost of goods sold, providing a fundamental indicator of a company's operational efficiency.construction of the signal follows a difference-based approach, where we first calculate the change in DLTIS by subtracting its lagged value from the current value, and then scale this difference by the previous period's gross profit (GP). This scaled difference captures the relative magnitude of changes in debt issuance compared to the firm's operational performance baseline. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financing decisions in proportion to the firm's core business performance. We construct this measure using end-of-fiscal-year values for both DLTIS and GP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DGPDelta signal. Panel A plots the time-series of the mean, median, and interquartile range for DGPDelta. On average, the cross-sectional mean (median) DGPDelta is 0.03 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DGPDelta data. The signal's interquartile range spans -0.31 to 0.36. Panel B of Figure 1 plots the time-series of the coverage of the DGPDelta signal for the CRSP universe. On average, the DGPDelta signal is available for 6.20% of CRSP names, which on average make up 7.45% of total market capitalization.

4 Does DGPDelta predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DGPDelta 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 DGPDelta portfolio and sells the low DGPDelta 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 DGPDelta strategy earns an average return of 0.22% per month with a t-statistic of 3.16. The annualized Sharpe ratio of the strategy is 0.45. The alphas range from 0.19% to 0.27% per month and have t-statistics exceeding 2.67 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 0.26, with a t-statistic of 5.47 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 559 stocks and an average market capitalization of at least $1,249 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 2.99. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for sixteen 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 -11-18bps/month. The lowest return, (-11 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.83. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DGPDelta trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in seventeen cases.

Table 3 provides direct tests for the role size plays in the DGPDelta strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DGPDelta, as well as average returns and alphas for long/short trading DGPDelta 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 DGPDelta strategy achieves an average return of 29 bps/month with a t-statistic of 3.33. Among these large cap stocks, the alphas for the DGPDelta strategy relative to the five most common factor models range from 24 to 33 bps/month with t-statistics between 2.68 and 3.77.

5 How does DGPDelta perform relative to the zoo?

Figure 2 puts the performance of DGPDelta 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

[1] The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

ratio for the DGPDelta strategy falls in the distribution. The DGPDelta strategy's gross (net) Sharpe ratio of 0.45 (0.33) is greater than 88% (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 DGPDelta strategy (red line).[2] Ignoring trading costs, a $1 invested in the DGPDelta strategy would have yielded $2.53 which ranks the DGPDelta strategy in the top 8% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DGPDelta strategy would have yielded $1.51 which ranks the DGPDelta strategy in the top 7% 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 DGPDelta relative to those. Panel A shows that the DGPDelta strategy gross alphas fall between the 53 and 66 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% (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 DGPDelta strategy has a positive net generalized alpha for five out of the five factor models. In these cases DGPDelta ranks between the 72 and 84 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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 DGPDelta 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 DGPDelta with 210 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price DGPDelta or at least to weaken the power DGPDelta has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DGPDelta conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{DGPDelta}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DGPDelta} DGPDelta_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DGPDelta,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort

[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.

stocks into quintiles based on DGPDelta. Stocks are finally grouped into five DGPDelta portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DGPDelta trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DGPDelta 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 DGPDelta signal in these Fama-MacBeth regressions exceed -0.35, 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 DGPDelta is -0.29.

Similarly, Table 5 reports results from spanning tests that regress returns to the DGPDelta 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 DGPDelta strategy earns alphas that range from 17-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.47, 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 DGPDelta trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.39.

7 Does DGPDelta add relative to the whole zoo?

Finally, we can ask how much adding DGPDelta 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 DGPDelta 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 DGPDelta grows to $1009.09.

8 Conclusion

Our comprehensive analysis of the Debt-Issuance Gross Profit Delta (DGPDelta) signal reveals its significant potential as a predictor of cross-sectional stock returns. The empirical results demonstrate that a value-weighted long/short strategy based on DGPDelta generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.45 (0.33 net). The signal'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.

The persistence of DGPDelta's predictive power, evidenced by a monthly alpha of 17 bps (t-statistic = 2.39) after controlling for related factors, suggests that it captures unique information about future stock returns that is not fully reflected in existing asset pricing factors. This finding has important implications for both

[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 DGPDelta is available.

academic research and practical investment management, as it contributes to our understanding of the relationship between debt issuance, profitability, and stock returns.

However, several limitations should be noted. First, transaction costs and market impact could affect the real-world implementation of trading strategies based on this signal. Second, the study's findings may be sensitive to the specific time period examined and market conditions. Future research could explore the signal's performance in international markets, investigate its interaction with other established anomalies, and examine its underlying economic mechanisms. Additionally, researchers might consider studying how the signal's predictive power varies across different market regimes and firm characteristics.

In conclusion, while DGPDelta shows promise as a robust predictor of stock returns, further investigation is warranted to fully understand its practical applications and theoretical implications in asset pricing.

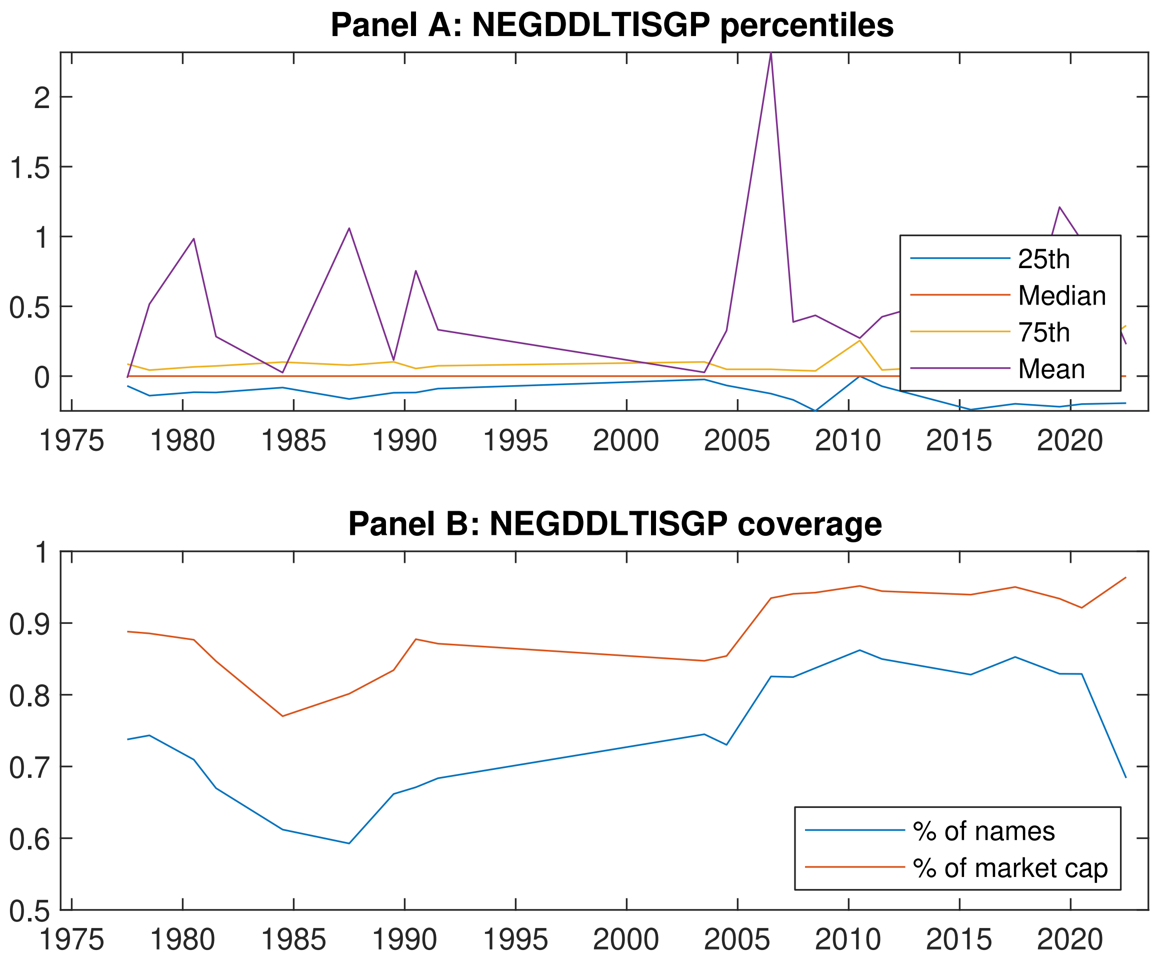

Figure 1: Times series of DGPDelta percentiles and coverage.
This figure plots descriptive statistics for DGPDelta. Panel A shows cross-sectional percentiles of DGPDelta over the sample. Panel B plots the monthly coverage of DGPDelta relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DGPDelta. 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 DGPDelta-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.59	0.64	0.73	0.80	0.81	0.22
	[2.70]	[3.50]	[3.61]	[4.42]	[3.96]	[3.16]
α_{CAPM}	-0.17	0.01	0.03	0.17	0.10	0.27
	[-2.92]	[0.13]	[0.51]	[3.76]	[1.79]	[3.85]
α_{FF3}	-0.22	-0.03	0.09	0.17	0.05	0.27
	[-3.95]	[-0.71]	[1.79]	[3.86]	[1.01]	[3.88]
α_{FF4}	-0.20	0.00	0.13	0.13	0.05	0.24
	[-3.49]	[0.11]	[2.52]	[3.03]	[0.84]	[3.40]
α_{FF5}	-0.18	-0.08	0.11	0.08	0.03	0.20
	[-3.19]	[-1.82]	[2.10]	[1.94]	[0.47]	[2.89]
α_{FF6}	-0.17	-0.05	0.14	0.07	0.02	0.19
	[-2.96]	[-1.14]	[2.60]	[1.51]	[0.42]	[2.67]
Panel B: Fama and French (2018) 6-factor model loadings for DGPDelta-sorted portfolios						
β_{MKT}	1.09	0.97	0.98	0.97	1.04	-0.05
	[83.76]	[95.74]	[81.13]	[96.34]	[81.12]	[-2.91]
β_{SMB}	0.08	-0.11	-0.01	-0.03	0.12	0.05
	[3.78]	[-7.16]	[-0.31]	[-2.25]	[6.29]	[1.92]
β_{HML}	0.18	0.11	-0.16	-0.07	0.05	-0.13
	[7.10]	[5.63]	[-7.06]	[-3.49]	[2.02]	[-4.04]
β_{RMW}	0.01	0.12	0.02	0.09	0.01	0.01
	[0.25]	[5.87]	[0.98]	[4.44]	[0.55]	[0.24]
β_{CMA}	-0.16	0.05	-0.08	0.19	0.10	0.26
	[-4.21]	[1.66]	[-2.14]	[6.54]	[2.73]	[5.47]
β_{UMD}	-0.02	-0.05	-0.05	0.03	0.00	0.02
	[-1.55]	[-5.30]	[-3.72]	[3.24]	[0.31]	[1.47]
Panel C: Average number of firms (n) and market capitalization (me)						
n	640	559	1060	610	621	
me ($\$10^6$)	1292	2925	2331	2963	1249	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DGPDelta 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	0.22	0.27	0.27	0.24	0.20	0.19
			[3.16]	[3.85]	[3.88]	[3.40]	[2.89]	[2.67]
Quintile	NYSE	EW	0.14	0.16	0.15	0.16	0.14	0.15
			[2.99]	[3.34]	[3.21]	[3.31]	[3.02]	[3.18]
Quintile	Name	VW	0.19	0.24	0.24	0.21	0.17	0.15
			[2.82]	[3.55]	[3.61]	[3.08]	[2.47]	[2.23]
Quintile	Cap	VW	0.22	0.25	0.26	0.23	0.18	0.17
			[3.30]	[3.83]	[4.02]	[3.44]	[2.80]	[2.53]
Decile	NYSE	VW	0.24	0.30	0.28	0.26	0.21	0.21
			[2.85]	[3.45]	[3.22]	[2.97]	[2.43]	[2.36]
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	0.17	0.22	0.22	0.21	0.17	0.15
			[2.33]	[3.09]	[3.11]	[2.88]	[2.31]	[2.13]
Quintile	NYSE	EW	-0.11					
			[-1.83]					
Quintile	Name	VW	0.14	0.20	0.20	0.18	0.14	0.12
			[1.99]	[2.90]	[2.93]	[2.67]	[2.02]	[1.82]
Quintile	Cap	VW	0.17	0.21	0.22	0.20	0.16	0.14
			[2.53]	[3.21]	[3.36]	[3.07]	[2.37]	[2.15]
Decile	NYSE	VW	0.18	0.23	0.22	0.21	0.16	0.15
			[2.01]	[2.65]	[2.46]	[2.34]	[1.77]	[1.70]

Table 3: Conditional sort on size and DGPDelta

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

Size quintiles		DGPDelta Quintiles					DGPDelta Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
	(1)	0.71	0.96	1.02	1.07	0.75	0.04	0.05	0.05	0.05	0.03	0.04
		[2.57]	[3.45]	[3.76]	[3.65]	[2.74]	[0.60]	[0.66]	[0.60]	[0.67]	[0.33]	[0.45]
	(2)	0.79	0.97	0.84	0.97	0.87	0.08	0.12	0.09	0.08	0.04	0.04
		[2.99]	[3.80]	[3.35]	[3.85]	[3.42]	[1.01]	[1.52]	[1.20]	[1.02]	[0.56]	[0.52]
	(3)	0.83	0.84	0.89	0.93	0.89	0.06	0.11	0.12	0.11	0.12	0.11
		[3.35]	[3.72]	[3.63]	[4.05]	[3.84]	[0.84]	[1.49]	[1.60]	[1.47]	[1.49]	[1.42]
	(4)	0.71	0.85	0.90	0.84	0.85	0.14	0.16	0.16	0.12	0.13	0.10
		[3.16]	[3.98]	[3.98]	[3.95]	[3.92]	[1.75]	[2.04]	[1.96]	[1.52]	[1.51]	[1.24]
	(5)	0.51	0.62	0.66	0.69	0.80	0.29	0.32	0.33	0.31	0.24	0.24
		[2.49]	[3.44]	[3.24]	[3.78]	[4.07]	[3.33]	[3.65]	[3.77]	[3.45]	[2.77]	[2.68]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles		DGPDelta Quintiles Average n					DGPDelta Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
	(1)	390	392	392	392	388	36	33	32	33	34
	(2)	107	107	107	107	107	59	59	58	60	59
	(3)	77	77	76	77	76	106	105	102	104	104
	(4)	64	64	65	65	64	222	233	223	229	221
	(5)	59	59	59	59	59	1270	2052	1888	2097	1341

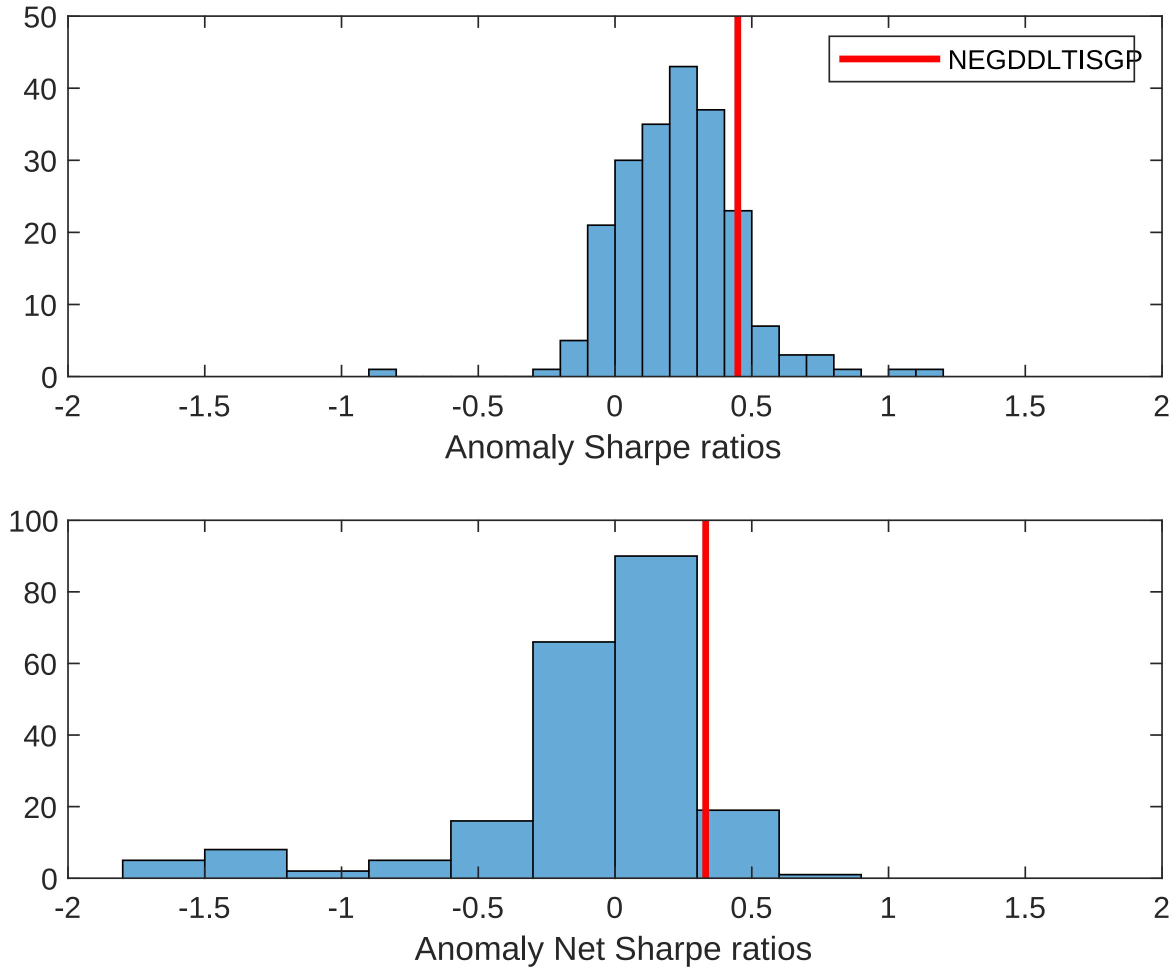

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DGPDelta with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

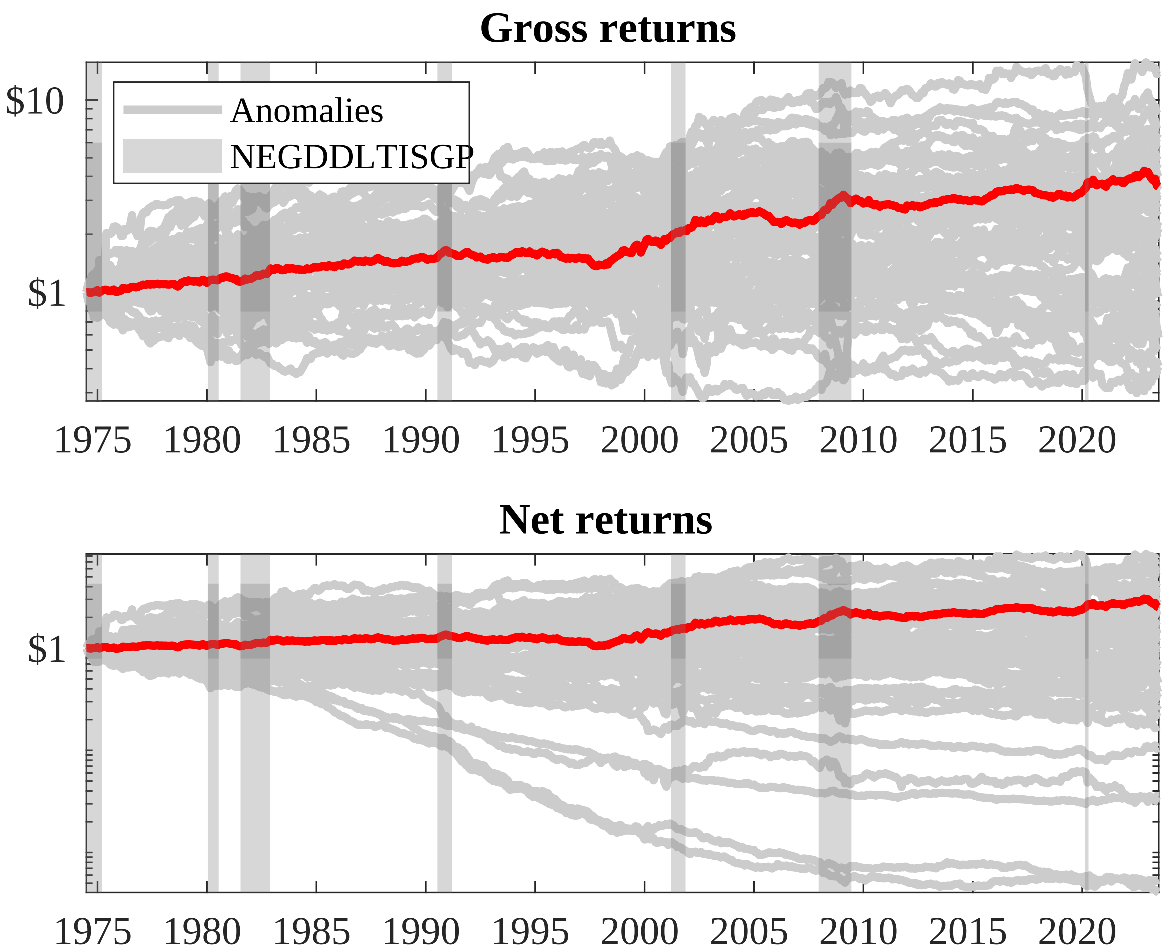

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DGPDelta trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

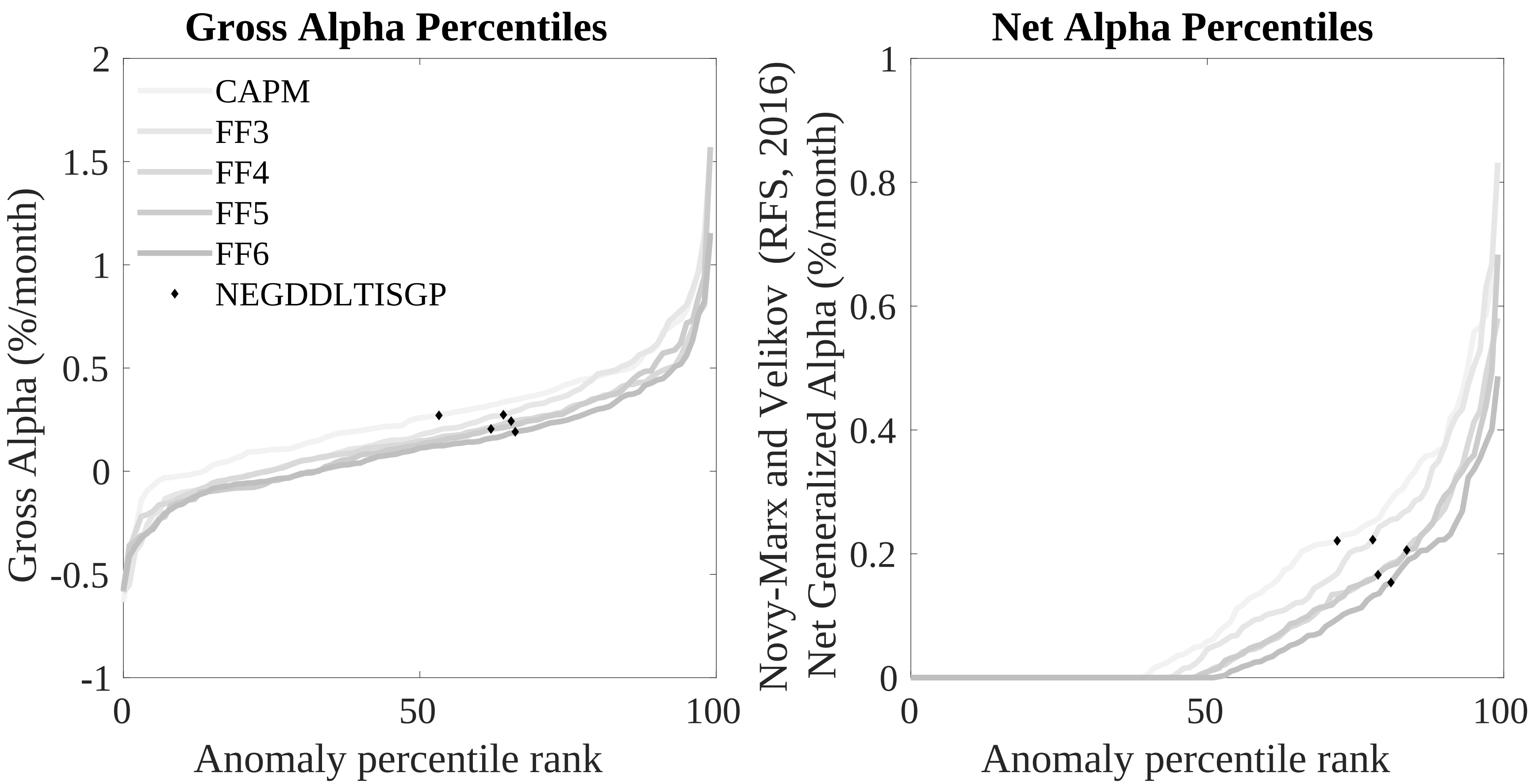

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DGPDelta trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.

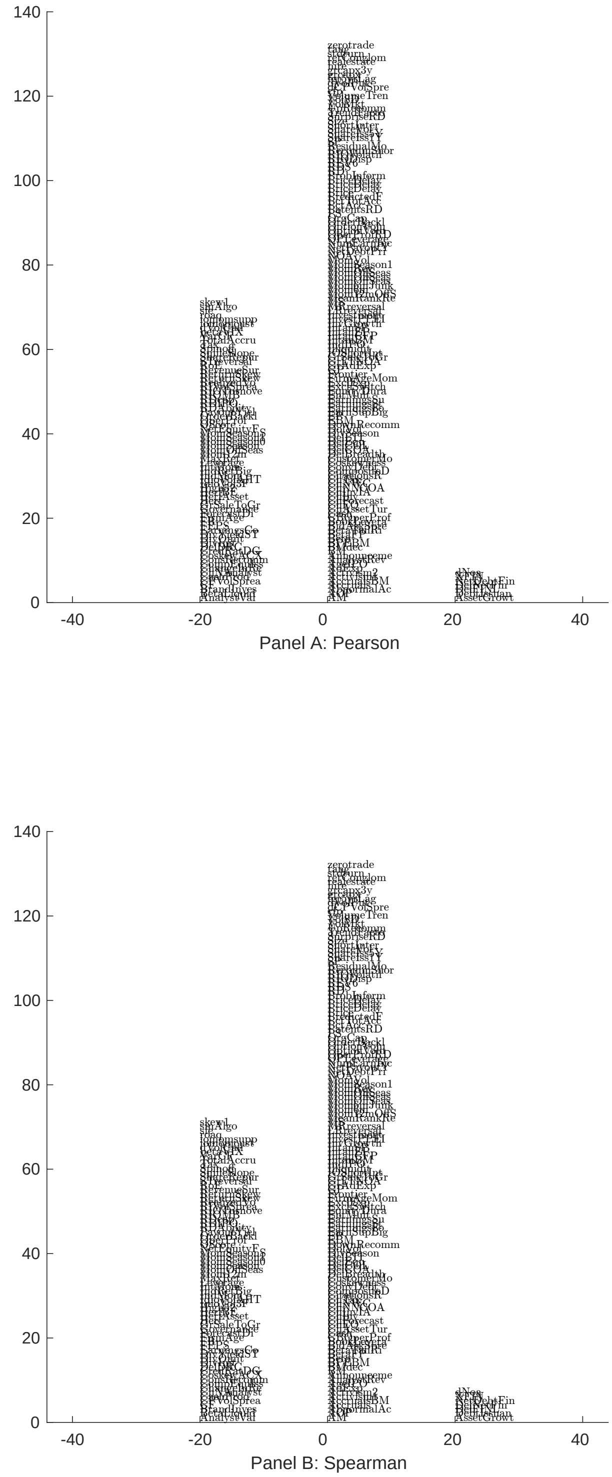

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DGPDelta. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

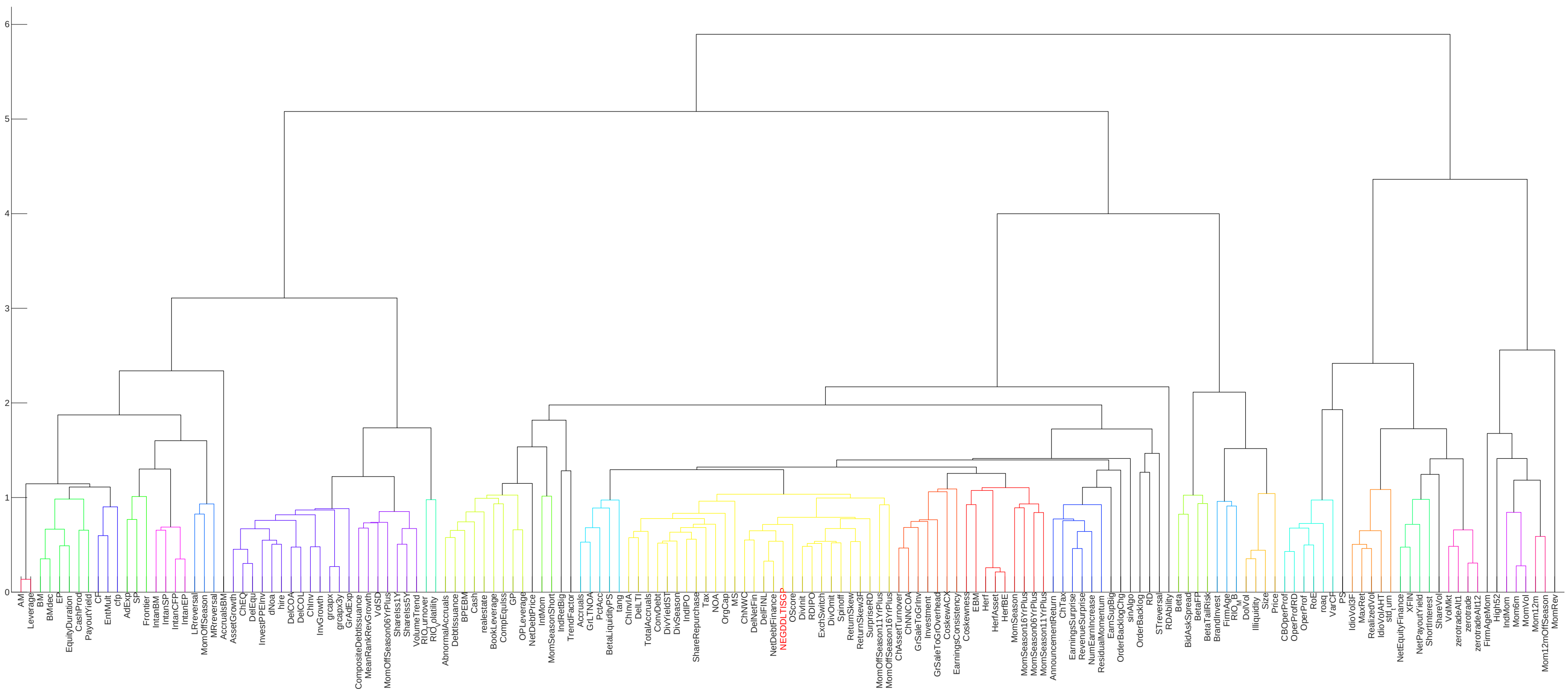

Figure 6: Agglomerative hierarchical cluster plot

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

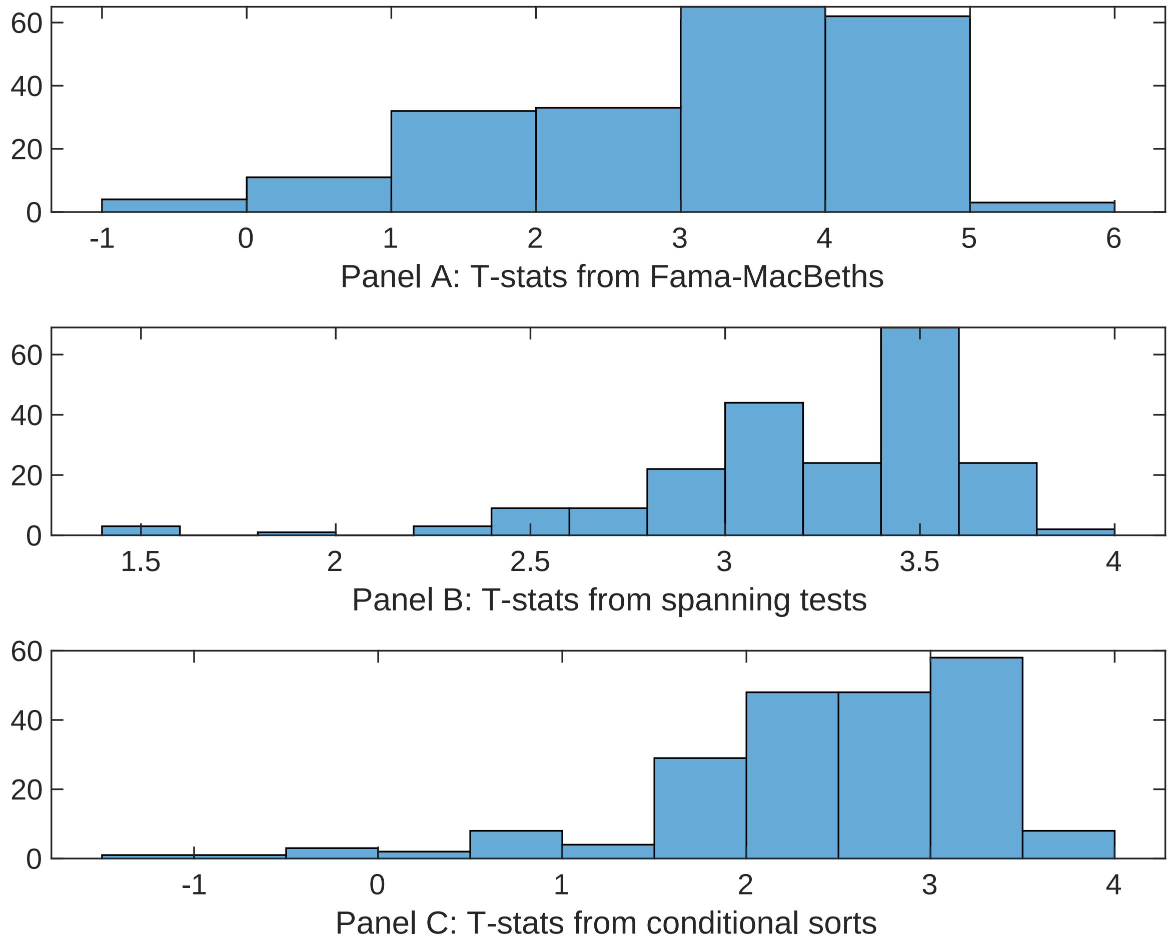

Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of DGPDelta conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{DGPDelta}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DGPDelta} DGPDelta_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{DGPDelta,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on DGPDelta. Stocks are finally grouped into five DGPDelta portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DGPDelta trading strategies conditioned on each of the 210 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on DGPDelta. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DGPDelta} DGPDelta_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Asset growth, 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	0.14	0.15	0.14	0.14	0.15
	[5.60]	[5.56]	[5.88]	[6.03]	[5.47]	[5.90]	[5.84]
DGPDelta	0.64	0.48	0.28	-0.11	0.83	-0.59	-0.72
	[0.04]	[0.27]	[1.59]	[-0.06]	[3.50]	[-0.35]	[-0.29]
Anomaly 1	0.18						-0.11
	[9.67]						[-2.31]
Anomaly 2		0.21					0.11
		[9.54]					[1.76]
Anomaly 3			0.19				0.93
			[6.33]				[1.65]
Anomaly 4				0.11			0.46
				[9.29]			[2.09]
Anomaly 5					0.39		0.20
					[6.81]		[0.36]
Anomaly 6						0.15	0.88
						[10.41]	[4.95]
# 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 DGPDelta trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DGPDelta} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Net external financing, Asset growth, 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	0.17	0.17	0.18	0.20	0.19	0.18	0.17
	[2.47]	[2.50]	[2.50]	[2.71]	[2.70]	[2.51]	[2.39]
Anomaly 1	26.78						20.27
	[6.52]						[3.58]
Anomaly 2		24.77					8.74
		[6.27]					[1.61]
Anomaly 3			15.41				10.84
			[4.24]				[2.84]
Anomaly 4				7.42			-1.06
				[1.58]			[-0.21]
Anomaly 5					6.59		5.99
					[2.32]		[2.10]
Anomaly 6						8.20	-3.89
						[1.94]	[-0.85]
mkt	-4.59	-4.91	-2.83	-4.88	-5.09	-4.91	-3.37
	[-2.86]	[-3.06]	[-1.66]	[-2.94]	[-3.07]	[-2.97]	[-2.02]
smb	2.27	3.01	9.62	3.92	5.34	4.77	6.42
	[0.91]	[1.20]	[3.45]	[1.50]	[2.07]	[1.86]	[2.21]
hml	-11.47	-12.47	-11.09	-13.06	-13.02	-13.53	-10.34
	[-3.72]	[-4.04]	[-3.50]	[-4.10]	[-4.10]	[-4.23]	[-3.31]
rmw	-1.09	-1.07	-8.27	0.98	1.85	1.18	-7.07
	[-0.34]	[-0.33]	[-2.12]	[0.30]	[0.56]	[0.36]	[-1.82]
cma	16.91	19.48	15.51	16.57	19.96	19.72	8.46
	[3.49]	[4.08]	[2.91]	[2.19]	[3.68]	[3.43]	[1.14]
umd	-0.07	0.48	2.45	2.81	1.90	2.23	-0.65
	[-0.04]	[0.29]	[1.48]	[1.67]	[1.13]	[1.33]	[-0.39]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	15	15	11	9	10	9	17

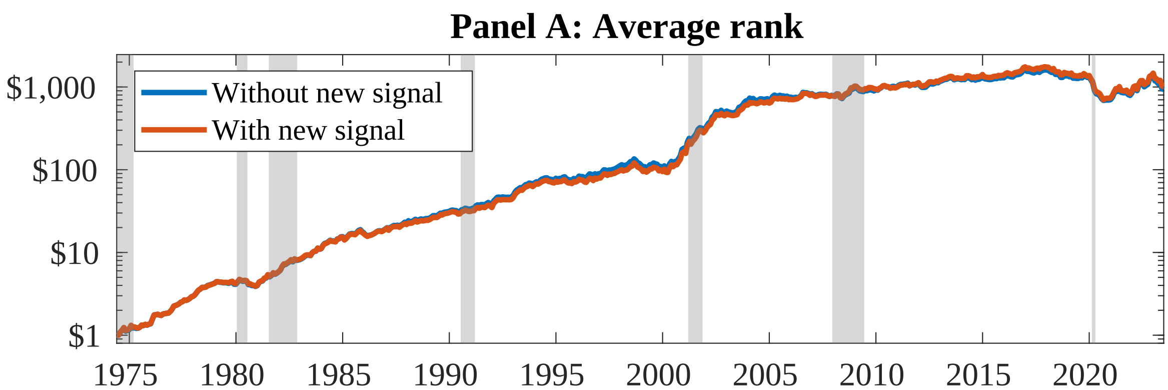

Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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