# Debt Capital Gap and the Cross Section of Stock Returns

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**Abstract**

This paper studies the asset pricing implications of Debt Capital Gap (DCG), 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 DCG achieves an annualized gross (net) Sharpe ratio of 0.56 (0.44), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 26 (24) bps/month with a t-statistic of 3.56 (3.26), 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, Inventory Growth, change in ppe and inv/assets, Asset growth) is 25 bps/month with a t-statistic of 3.45.

# 1 Introduction

Market efficiency remains a central question in financial economics, with substantial debate around whether and how quickly asset prices incorporate new information. While traditional theory suggests that readily available accounting information should be fully reflected in stock prices, a growing body of evidence documents persistent return predictability based on public financial statements. One particularly understudied area is how firms' debt financing decisions and resulting capital structure changes affect future stock returns.

Prior research has largely focused on equity-based measures of investment and financing activities, while the granular dynamics of debt capital allocation have received less attention. This gap is notable given that debt financing represents the primary source of external capital for most public firms and that changes in debt structure can significantly impact firm risk and future profitability.

We propose that the Debt Capital Gap (DCG) - the difference between a firm's actual and predicted optimal debt levels - contains valuable information about future stock returns. This hypothesis builds on Myers and Majluf (1984)'s pecking order theory, which suggests that information asymmetries lead firms to prefer debt over equity financing, and Jensen and Meckling (1976)'s agency theory showing that deviation from optimal leverage can destroy firm value.

The predictive power of DCG likely stems from two economic mechanisms. First, following Rajan and Zingales (1995), firms face adjustment costs in moving toward optimal capital structure, creating observable gaps between actual and target leverage that persist over time. Second, as argued by Frank and Goyal (2009), managers may opportunistically time debt markets, temporarily deviating from optimal leverage to exploit favorable financing conditions.

Importantly, market participants appear to underreact to the information contained in DCG, possibly due to the complexity of properly benchmarking a firm's debt levels against dynamic industry conditions. This builds on Hirshleifer and Teoh (2003)'s limited attention theory, suggesting that investors may struggle to fully process the implications of sophisticated financial metrics.

Our empirical analysis reveals strong evidence that DCG predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high DCG and shorts those with low DCG generates monthly abnormal returns of 26 basis points (t-statistic = 3.56) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.56, placing it in the top 5% of documented cross-sectional predictors.

The predictive power of DCG is particularly strong among large-cap stocks, with the long-short strategy earning monthly abnormal returns of 36 basis points (t-statistic = 4.12) within the largest size quintile. This finding is notable as many documented anomalies are concentrated in small, illiquid stocks.

Critically, DCG's predictive ability remains robust after controlling for related financing-based predictors. When we simultaneously control for the six most closely related anomalies and the Fama-French six factors, the DCG strategy still generates monthly alpha of 25 basis points (t-statistic = 3.45).

Our study makes several contributions to the asset pricing literature. First, we extend the work of Titman and Wessels (1988) and Leary and Roberts (2005) on capital structure by showing that deviations from optimal leverage have important implications for future stock returns. While these studies focused on the determinants of capital structure, we demonstrate its asset pricing consequences.

Second, we contribute to the growing literature on financing-based return predictors pioneered by Ikenberry et al. (1995) and Loughran and Ritter (1995). While prior work has emphasized equity financing events, we show that debt financing decisions contain distinct predictive information not captured by existing metrics.

Finally, our findings have implications for the efficient markets debate and the broader factor investing literature. The persistence and robustness of the DCG effect, particularly among large-cap stocks, suggests that even sophisticated investors may struggle to fully process complex financing information. This supports behavioral theories of market inefficiency while offering practitioners a novel tool for security selection.

## 2 Data

Our study investigates the predictive power of the Debt Capital Gap signal for cross-sectional returns, which captures the relative change in long-term debt issuance scaled by invested capital. 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 ICAPT for invested capital. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while invested capital (ICAPT) measures the total capital invested in the business, including both equity and debt financing. The construction of the signal involves calculating the year-over-year change in DLTIS (current year minus previous year) and scaling this difference by the previous year's invested capital (ICAPT). This scaled difference captures the relative magnitude of changes in debt financing activities compared to the firm's existing capital base. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financing decisions in a manner that is both economically meaningful and comparable across firms of different sizes. 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 DCG signal. Panel A plots the time-series of the mean, median, and interquartile range for DCG. On average, the cross-sectional mean (median) DCG is -0.04 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DCG data. The signal's interquartile range spans -0.10 to 0.09. Panel B of Figure 1 plots the time-series of the coverage of the DCG signal for the CRSP universe. On average, the DCG signal is available for 6.29% of CRSP names, which on average make up 7.46% of total market capitalization.

# 4 Does DCG predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DCG 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 DCG portfolio and sells the low DCG 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 DCG strategy earns an average return of 0.29% per month with a t-statistic of 3.91. The annualized Sharpe ratio of the strategy is 0.56. The alphas range from 0.26% to 0.34% per month and have t-statistics exceeding 3.56 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 0.27, with a t-statistic of 5.58 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 534 stocks and an average market capitalization of at least $1,365 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 18 bps/month with a t-statistics of 3.90. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-two 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 -8-26bps/month. The lowest return, (-8 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.32. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DCG 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 DCG strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DCG, as well as average returns and alphas for long/short trading DCG 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 $80^{\text{th}}$ NYSE percentile), the DCG strategy achieves an average return of 36 bps/month with a t-statistic of 4.12. Among these large cap stocks, the alphas for the DCG strategy relative to the five most common factor models range from 28 to 40 bps/month with t-statistics between 3.18 and 4.56.

# 5 How does DCG perform relative to the zoo?

Figure 2 puts the performance of DCG 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 DCG strategy falls in the distribution. The DCG strategy's gross (net) Sharpe ratio of 0.56 (0.44) is greater than 95% (99%) of anomaly Sharpe ratios,

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

respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the DCG strategy (red line).[2] Ignoring trading costs, a \$1 invested in the DCG strategy would have yielded \$4.41 which ranks the DCG strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the DCG strategy would have yielded \$2.85 which ranks the DCG strategy in the top 3% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the DCG relative to those. Panel A shows that the DCG strategy gross alphas fall between the 63 and 76 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 DCG strategy has a positive net generalized alpha for five out of the five factor models. In these cases DCG ranks between the 82 and 92 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 DCG 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 DCG 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 DCG or at least to weaken the power DCG has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DCG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{DCG}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DCG} DCG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{DCG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on DCG. Stocks are finally grouped into five DCG 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.

DCG trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DCG 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 DCG signal in these Fama-MacBeth regressions exceed 0.81, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DCG is 0.04.

Similarly, Table 5 reports results from spanning tests that regress returns to the DCG 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 DCG strategy earns alphas that range from 26-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.59, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DCG trading strategy achieves an alpha of 25bps/month with a t-statistic of 3.45.

# 7 Does DCG add relative to the whole zoo?

Finally, we can ask how much adding DCG 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 DCG 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 DCG 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 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes DCG grows to $988.74.

# 8 Conclusion

This study provides compelling evidence for the significance of Debt Capital Gap (DCG) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on DCG delivers economically and statistically significant results, with an impressive annualized gross Sharpe ratio of 0.56 (0.44 net). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that DCG captures unique information about future stock returns that is not fully reflected in current market prices.

Particularly noteworthy is the strategy's ability to maintain significant alpha (25 bps/month) when controlling for both the Fama-French five-factor model plus momentum and six closely related anomalies from the factor zoo. This robustness indicates that DCG is not merely capturing previously documented effects but represents a distinct signal for return prediction.

However, several limitations should be acknowledged. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, transaction costs and market impact could affect the strategy's real-world implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore several promising directions. First, investigating the economic mechanisms underlying the DCG effect could provide deeper insights into why this signal works. Second, examining how DCG interacts with other firm characteristics and market conditions could reveal important conditional relationships. Finally, testing the signal's effectiveness in different asset classes and international markets would help establish its broader applicability.

In conclusion, our findings suggest that DCG represents a valuable addition to the quantitative investor's toolkit, offering meaningful improvements to portfolio performance when properly implemented.

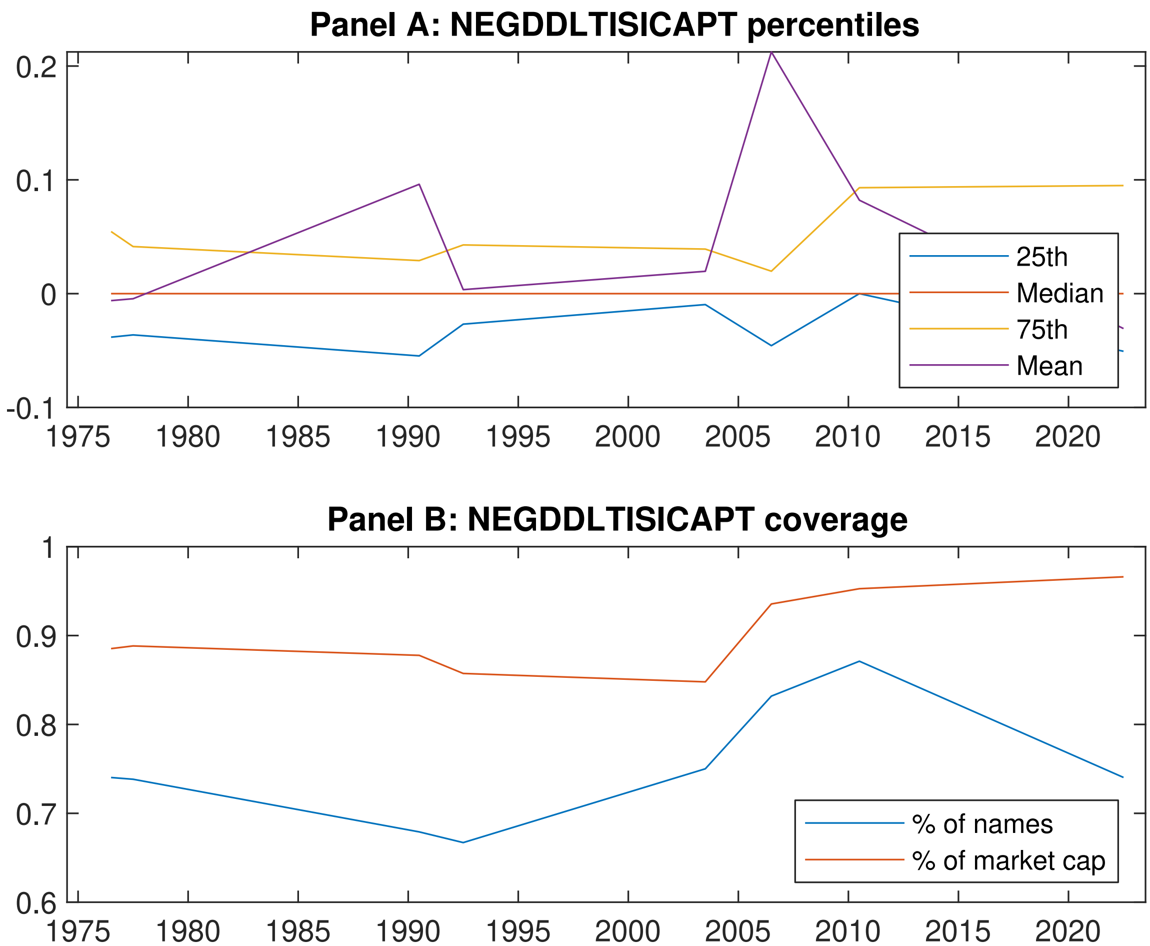


**Figure 1:** Times series of DCG percentiles and coverage.
This figure plots descriptive statistics for DCG. Panel A shows cross-sectional percentiles of DCG over the sample. Panel B plots the monthly coverage of DCG relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DCG. 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 DCG-sorted portfolios | | | | | | |
|---|---|---|---|---|---|---|
| | (L) | (2) | (3) | (4) | (H) | (H-L) |
| $r^e$ | 0.58 | 0.68 | 0.69 | 0.76 | 0.87 | 0.29 |
| | [2.70] | [3.72] | [3.42] | [4.20] | [4.27] | [3.91] |
| $\alpha_{CAPM}$ | -0.17 | 0.05 | -0.01 | 0.13 | 0.16 | 0.33 |
| | [-3.22] | [0.92] | [-0.10] | [2.70] | [3.01] | [4.57] |
| $\alpha_{FF3}$ | -0.18 | 0.00 | 0.05 | 0.11 | 0.16 | 0.34 |
| | [-3.37] | [0.04] | [0.82] | [2.38] | [3.07] | [4.63] |
| $\alpha_{FF4}$ | -0.15 | 0.02 | 0.09 | 0.07 | 0.15 | 0.29 |
| | [-2.75] | [0.45] | [1.68] | [1.55] | [2.77] | [3.98] |
| $\alpha_{FF5}$ | -0.18 | -0.04 | 0.10 | 0.02 | 0.11 | 0.29 |
| | [-3.43] | [-1.07] | [1.68] | [0.49] | [2.01] | [3.92] |
| $\alpha_{FF6}$ | -0.16 | -0.03 | 0.13 | 0.00 | 0.10 | 0.26 |
| | [-3.01] | [-0.67] | [2.23] | [0.06] | [1.92] | [3.56] |
| Panel B: Fama and French (2018) 6-factor model loadings for DCG-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 1.07 | 0.98 | 0.97 | 0.97 | 1.03 | -0.04 |
| | [88.42] | [103.25] | [74.41] | [89.49] | [84.23] | [-2.49] |
| $\beta_{\text{SMB}}$ | 0.12 | -0.13 | -0.00 | -0.03 | 0.13 | 0.02 |
| | [6.33] | [-8.50] | [-0.20] | [-1.96] | [7.08] | [0.58] |
| $\beta_{\text{HML}}$ | 0.02 | 0.15 | -0.13 | 0.00 | -0.10 | -0.12 |
| | [1.01] | [7.98] | [-5.03] | [0.02] | [-4.22] | [-3.79] |
| $\beta_{\text{RMW}}$ | 0.11 | 0.10 | -0.04 | 0.10 | 0.06 | -0.06 |
| | [4.62] | [5.24] | [-1.57] | [4.69] | [2.31] | [-1.65] |
| $\beta_{\text{CMA}}$ | -0.14 | 0.04 | -0.09 | 0.18 | 0.14 | 0.27 |
| | [-3.85] | [1.38] | [-2.44] | [5.66] | [3.87] | [5.58] |
| $\beta_{\text{UMD}}$ | -0.04 | -0.03 | -0.05 | 0.04 | 0.01 | 0.05 |
| | [-3.13] | [-2.98] | [-4.09] | [3.27] | [0.53] | [2.64] |
| Panel C: Average number of firms ($n$) and market capitalization ($me$) | | | | | | |
| $n$ | 681 | 534 | 1080 | 585 | 655 | |
| me ($\$10^6$) | 1431 | 2929 | 2151 | 2899 | 1365 | |

**Table 2:** Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DCG 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 | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.29 | 0.33 | 0.34 | 0.29 | 0.29 | 0.26 |
| | | | [3.91] | [4.57] | [4.63] | [3.98] | [3.92] | [3.56] |
| Quintile | NYSE | EW | 0.18 | 0.21 | 0.20 | 0.18 | 0.18 | 0.17 |
| | | | [3.90] | [4.51] | [4.22] | [3.76] | [3.89] | [3.62] |
| Quintile | Name | VW | 0.28 | 0.34 | 0.35 | 0.30 | 0.29 | 0.26 |
| | | | [3.93] | [4.85] | [5.00] | [4.24] | [4.12] | [3.69] |
| Quintile | Cap | VW | 0.25 | 0.30 | 0.30 | 0.25 | 0.21 | 0.18 |
| | | | [3.81] | [4.53] | [4.55] | [3.74] | [3.20] | [2.76] |
| Decile | NYSE | VW | 0.33 | 0.39 | 0.38 | 0.38 | 0.26 | 0.27 |
| | | | [3.47] | [4.11] | [4.01] | [3.92] | [2.75] | [2.88] |
| Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas | | | | | | | | |
| Portfolios | Breaks | Weights | $r^e_{net}$ | $\alpha^*_{\text{CAPM}}$ | $\alpha^*_{\text{FF3}}$ | $\alpha^*_{\text{FF4}}$ | $\alpha^*_{\text{FF5}}$ | $\alpha^*_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.23 | 0.29 | 0.30 | 0.27 | 0.26 | 0.24 |
| | | | [3.10] | [4.01] | [4.05] | [3.74] | [3.49] | [3.26] |
| Quintile | NYSE | EW | -0.08 | | | | | |
| | | | [-1.32] | | | | | |
| Quintile | Name | VW | 0.22 | 0.30 | 0.31 | 0.28 | 0.26 | 0.23 |
| | | | [3.08] | [4.17] | [4.28] | [3.91] | [3.61] | [3.35] |
| Quintile | Cap | VW | 0.20 | 0.26 | 0.26 | 0.23 | 0.19 | 0.17 |
| | | | [3.02] | [3.97] | [3.95] | [3.56] | [2.85] | [2.57] |
| Decile | NYSE | VW | 0.26 | 0.33 | 0.32 | 0.32 | 0.22 | 0.22 |
| | | | [2.68] | [3.42] | [3.34] | [3.31] | [2.35] | [2.33] |

**Table 3:** Conditional sort on size and DCG

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

| | | DCG Quintiles | | | | | DCG Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| Size quintiles | (1) | 0.73 | 0.89 | 0.99 | 0.90 | 0.83 | 0.10 | 0.12 | 0.11 | 0.07 | 0.08 | 0.06 |
| | | [2.63] | [3.26] | [3.57] | [3.21] | [2.94] | [1.16] | [1.38] | [1.25] | [0.73] | [0.93] | [0.62] |
| | (2) | 0.75 | 0.98 | 0.82 | 0.94 | 0.90 | 0.15 | 0.19 | 0.17 | 0.17 | 0.14 | 0.14 |
| | | [2.78] | [3.87] | [3.24] | [3.77] | [3.54] | [1.90] | [2.37] | [2.16] | [2.08] | [1.70] | [1.70] |
| | (3) | 0.83 | 0.84 | 0.85 | 0.89 | 0.92 | 0.09 | 0.15 | 0.14 | 0.10 | 0.12 | 0.10 |
| | | [3.28] | [3.80] | [3.49] | [3.98] | [3.90] | [1.11] | [1.92] | [1.77] | [1.20] | [1.56] | [1.19] |
| | (4) | 0.75 | 0.83 | 0.89 | 0.73 | 0.95 | 0.20 | 0.25 | 0.24 | 0.19 | 0.21 | 0.18 |
| | | [3.21] | [3.97] | [3.99] | [3.49] | [4.35] | [2.57] | [3.14] | [2.98] | [2.38] | [2.57] | [2.18] |
| | (5) | 0.49 | 0.65 | 0.62 | 0.64 | 0.85 | 0.36 | 0.39 | 0.40 | 0.34 | 0.32 | 0.28 |
| | | [2.43] | [3.60] | [3.16] | [3.42] | [4.40] | [4.12] | [4.46] | [4.56] | [3.79] | [3.63] | [3.18] |

Panel B: Portfolio average number of firms and market capitalization

| | | DCG Quintiles<br>Average $n$ | | | | | DCG Quintiles<br>Average market capitalization ($\$10^6$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | (L) | (2) | (3) | (4) | (H) |
| Size quintiles | (1) | 398 | 400 | 399 | 400 | 395 | 37 | 34 | 33 | 34 | 35 |
| | (2) | 108 | 108 | 108 | 108 | 108 | 60 | 61 | 58 | 61 | 60 |
| | (3) | 77 | 77 | 77 | 77 | 77 | 105 | 107 | 102 | 104 | 105 |
| | (4) | 64 | 65 | 65 | 65 | 64 | 223 | 233 | 222 | 228 | 224 |
| | (5) | 59 | 59 | 59 | 59 | 59 | 1361 | 2102 | 1714 | 2086 | 1386 |

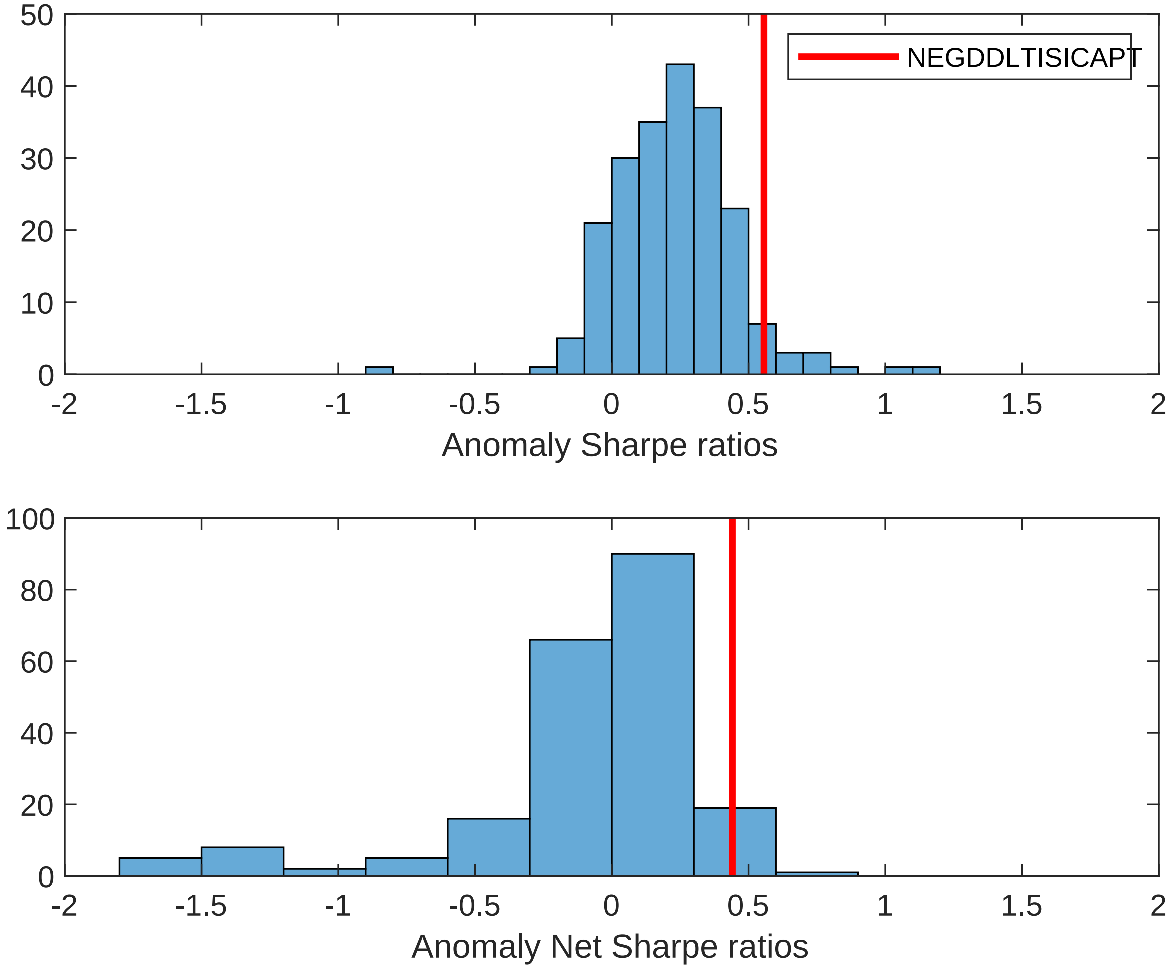


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DCG with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

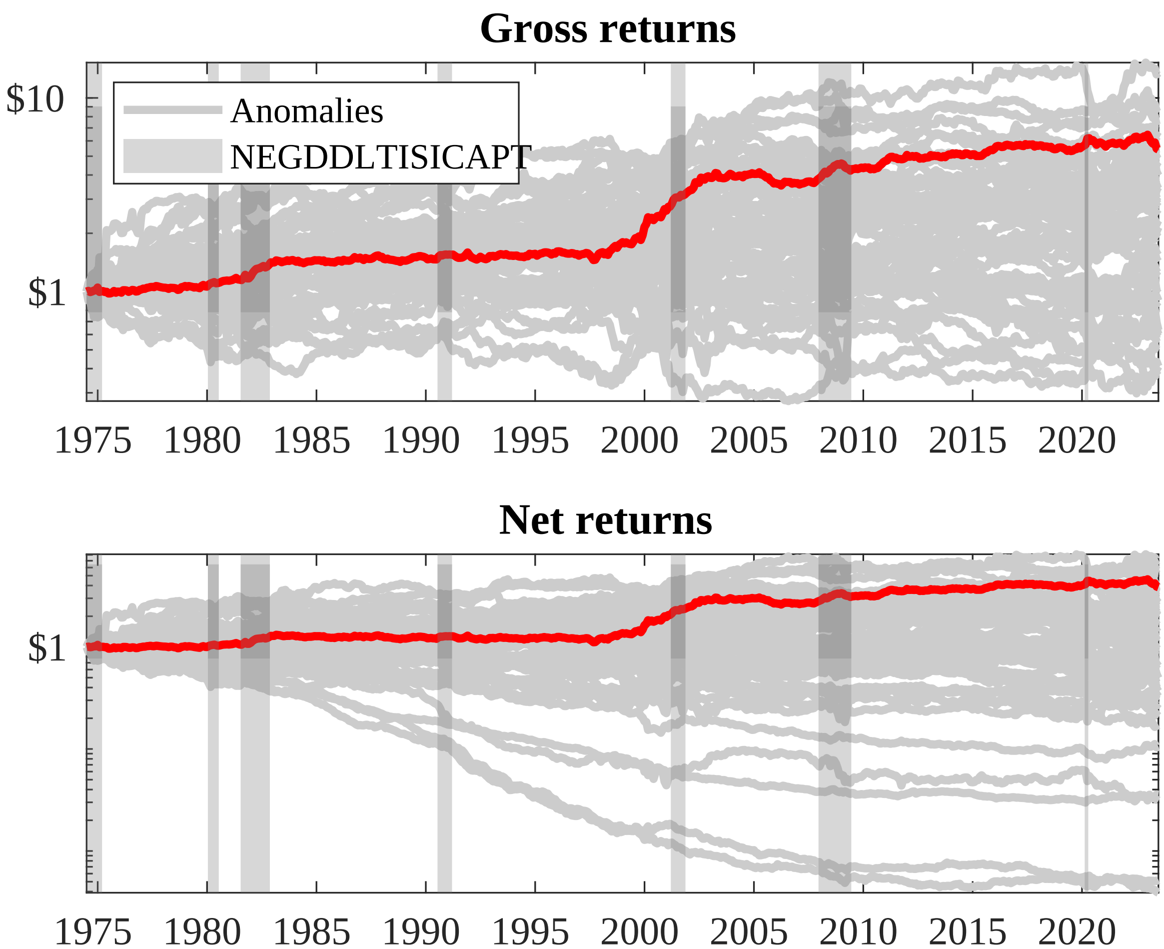


**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DCG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

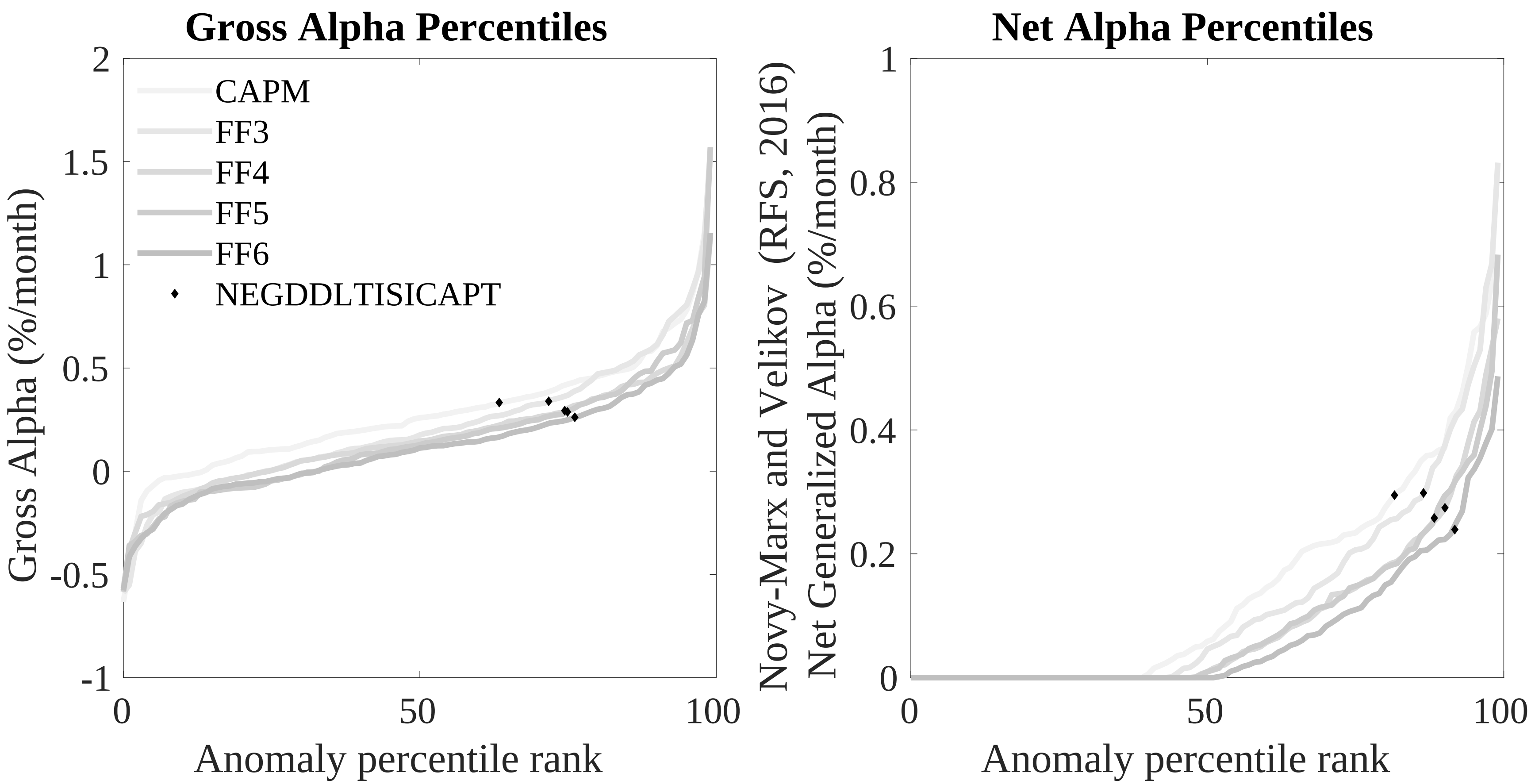


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DCG trading strategy alphas (diamonds). The strategies are constructed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

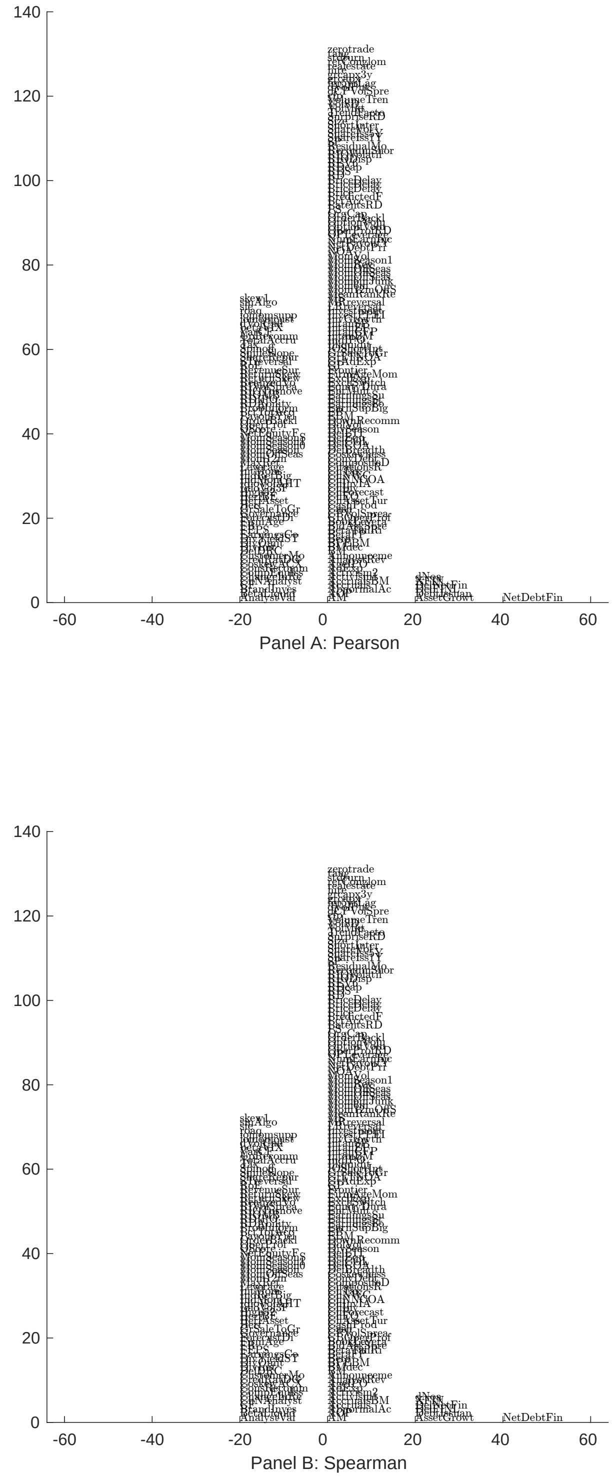


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DCG. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

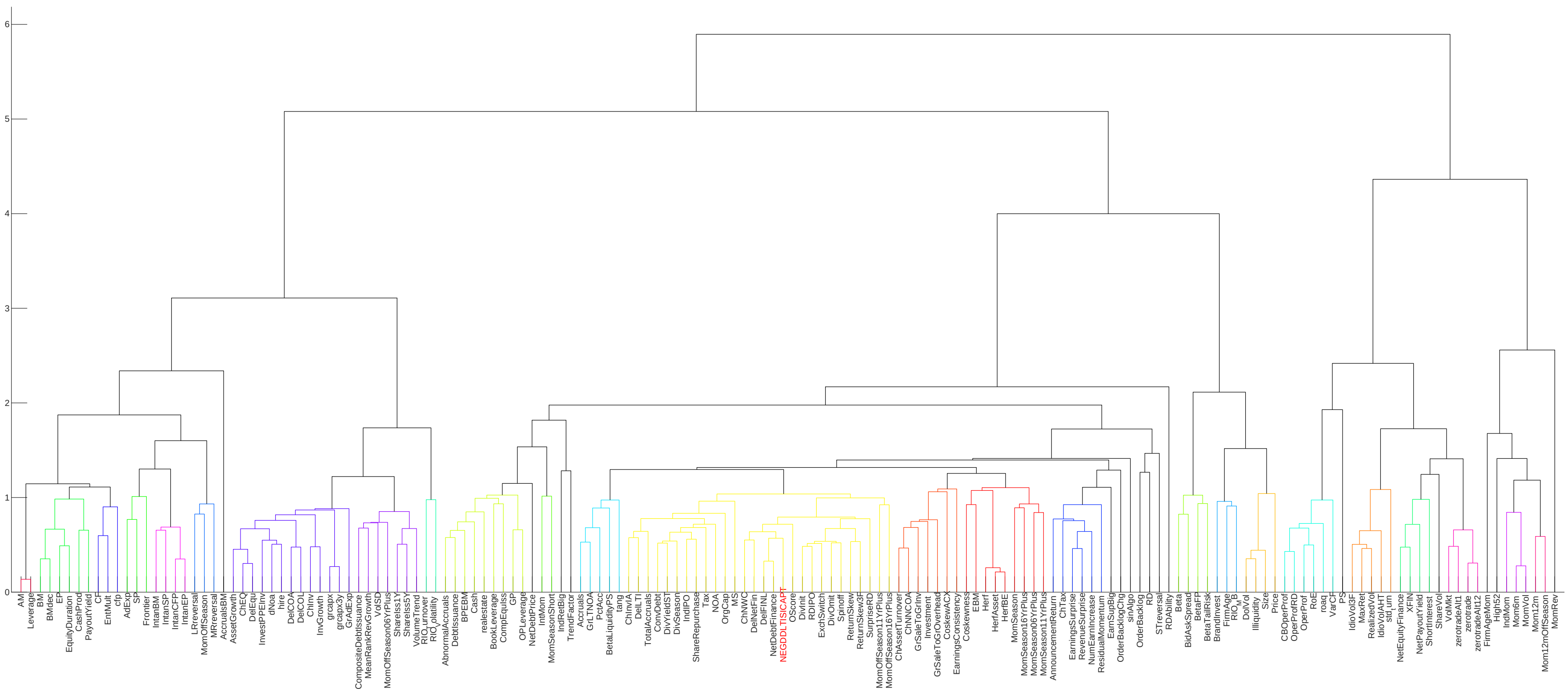

**Figure 6:** Agglomerative hierarchical cluster plot

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

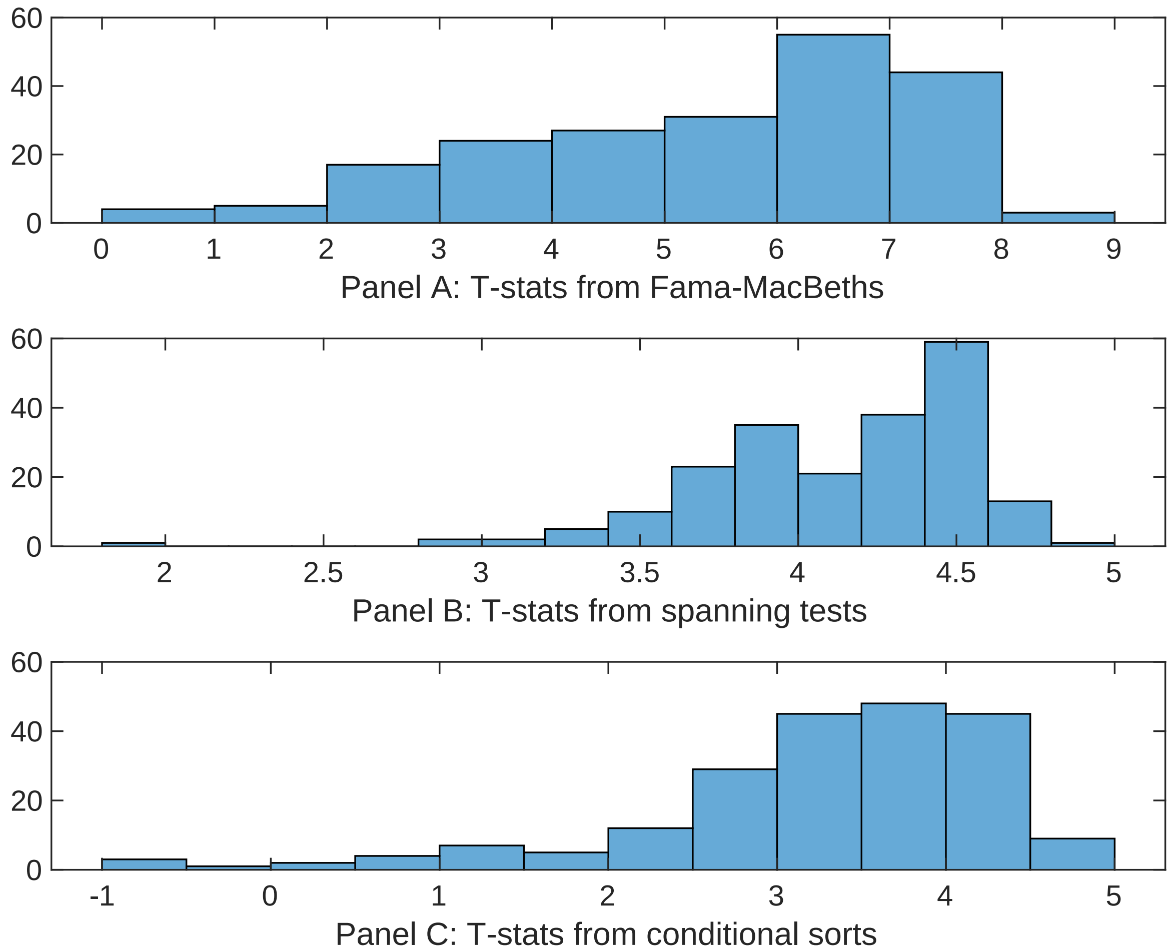


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DCG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{DCG}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DCG} DCG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{DCG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DCG. Stocks are finally grouped into five DCG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DCG 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 DCG. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DCG} DCG_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are Change in financial liabilities, Net debt financing, Net external financing, Inventory Growth, change in ppe and inv/assets, Asset growth. 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 | 0.14 | 0.15 | 0.15 | 0.15 |
| | [5.52] | [5.49] | [5.86] | [5.48] | [5.89] | [5.96] | [5.89] |
| DCG | 0.10 | 0.12 | 0.17 | 0.36 | 0.17 | 0.52 | 0.27 |
| | [1.70] | [1.88] | [2.63] | [5.38] | [2.81] | [0.81] | [0.04] |
| Anomaly 1 | 0.17 | | | | | | -0.86 |
| | [8.89] | | | | | | [-1.81] |
| Anomaly 2 | | 0.19 | | | | | 0.12 |
| | | [8.22] | | | | | [1.79] |
| Anomaly 3 | | | 0.18 | | | | 0.10 |
| | | | [5.85] | | | | [1.82] |
| Anomaly 4 | | | | 0.38 | | | 0.14 |
| | | | | [6.66] | | | [0.23] |
| Anomaly 5 | | | | | 0.16 | | 0.76 |
| | | | | | [7.56] | | [2.74] |
| Anomaly 6 | | | | | | 0.11 | 0.57 |
| | | | | | | [8.92] | [2.68] |
| # 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 DCG trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DCG} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Inventory Growth, change in ppe and inv/assets, Asset growth. 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 | 0.26 | 0.26 | 0.26 | 0.28 | 0.28 | 0.28 | 0.25 |
| | [3.61] | [3.61] | [3.59] | [3.78] | [3.75] | [3.76] | [3.45] |
| Anomaly 1 | 18.96 | | | | | | 10.87 |
| | [4.45] | | | | | | [1.91] |
| Anomaly 2 | | 21.01 | | | | | 10.02 |
| | | [5.16] | | | | | [1.77] |
| Anomaly 3 | | | 15.25 | | | | 11.44 |
| | | | [4.12] | | | | [2.82] |
| Anomaly 4 | | | | 7.00 | | | 6.25 |
| | | | | [2.42] | | | [2.07] |
| Anomaly 5 | | | | | 7.35 | | 2.02 |
| | | | | | [2.18] | | [0.56] |
| Anomaly 6 | | | | | | 2.62 | -6.95 |
| | | | | | | [0.55] | [-1.38] |
| mkt | -4.31 | -4.53 | -2.47 | -4.72 | -4.71 | -4.52 | -3.11 |
| | [-2.59] | [-2.74] | [-1.42] | [-2.80] | [-2.79] | [-2.67] | [-1.79] |
| smb | -0.16 | 0.13 | 6.44 | 2.25 | 1.66 | 1.27 | 4.95 |
| | [-0.06] | [0.05] | [2.27] | [0.86] | [0.64] | [0.48] | [1.64] |
| hml | -11.08 | -11.75 | -10.34 | -12.27 | -12.90 | -12.10 | -10.33 |
| | [-3.46] | [-3.70] | [-3.21] | [-3.80] | [-3.95] | [-3.72] | [-3.19] |
| rmw | -6.50 | -6.76 | -14.17 | -4.08 | -4.79 | -5.04 | -12.63 |
| | [-1.95] | [-2.04] | [-3.55] | [-1.21] | [-1.43] | [-1.50] | [-3.11] |
| cma | 20.27 | 21.21 | 16.37 | 20.35 | 20.86 | 23.31 | 14.27 |
| | [4.02] | [4.31] | [3.01] | [3.68] | [3.75] | [3.02] | [1.86] |
| umd | 2.59 | 2.69 | 4.36 | 3.77 | 4.34 | 4.51 | 1.64 |
| | [1.49] | [1.58] | [2.59] | [2.19] | [2.55] | [2.62] | [0.94] |
| # months | 588 | 588 | 588 | 588 | 588 | 588 | 588 |
| $\bar{R}^2(\%)$ | 13 | 14 | 13 | 11 | 11 | 10 | 16 |

## Panel A: Average rank

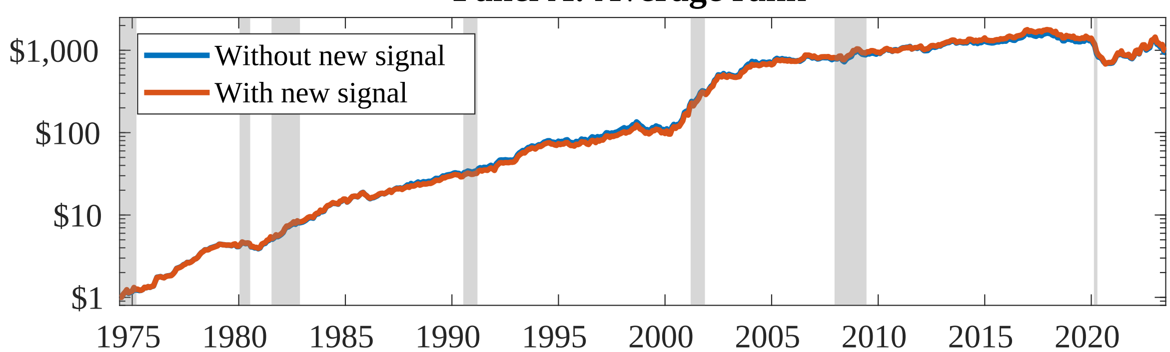


**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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