Debt-Equity Liquidity Gap and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Debt-Equity Liquidity Gap (DELG), 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 DELG achieves an annualized gross (net) Sharpe ratio of 0.50 (0.38), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (18) bps/month with a t-statistic of 2.97 (2.54), 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 19 bps/month with a t-statistic of 2.82.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns. While the literature has extensively studied various market anomalies, the role of relative liquidity between a firm's debt and equity securities remains largely unexplored. This gap is particularly notable given the interconnected nature of debt and equity markets and their importance in price discovery.

Prior research has examined debt and equity markets in isolation, focusing on either bond liquidity premiums Bao et al. (2011) or stock market liquidity Amihud and Mendelson (1986). However, the relative liquidity between these markets may contain valuable information about firm fundamentals and future stock performance, as market participants choose between trading in either market based on their information and trading costs.

We propose that the Debt-Equity Liquidity Gap (DELG) - the difference between standardized measures of bond and stock market liquidity - predicts future stock returns through two primary mechanisms. First, following Chen and Ludvigson (2009), when informed traders face differential trading costs across markets, they may choose to trade in the more liquid market, leading to temporary price pressure in one market that subsequently reverses. This creates predictable return patterns as prices converge across markets.

Second, building on Goldstein and Yang (2014), the relative liquidity between debt and equity markets may reflect the nature of information being traded. Debt market liquidity tends to increase when credit-relevant information dominates, while equity market liquidity rises with information about future growth opportunities. Therefore, DELG may capture the market's evolving assessment of a firm's risk-return tradeoff.

These mechanisms suggest that firms with higher DELG (relatively more liquid debt markets) should subsequently underperform firms with lower DELG, as prices adjust to reflect the information content embedded in the relative liquidity measures Sadka and Scherbina (2007).

Our empirical analysis confirms the strong predictive power of DELG for future stock returns. A value-weighted long-short portfolio that buys stocks with high DELG and shorts those with low DELG generates significant abnormal returns of 21 basis points per month (t-statistic = 2.97) after controlling for the Fama-French five factors plus momentum. The strategy achieves an annualized Sharpe ratio of 0.50 before trading costs and 0.38 after accounting for transaction costs.

The predictive power of DELG remains robust across various methodological choices and subsamples. Notably, the signal maintains its effectiveness among large-cap stocks, with the long-short strategy earning 32 basis points per month (t-statistic = 3.69) in the largest size quintile. This suggests that the DELG effect is not merely a small-stock phenomenon.

Further supporting the robustness of our findings, DELG continues to predict returns even after controlling for six closely related anomalies, including changes in financial liabilities and net external financing. The strategy generates an alpha of 19 basis points per month (t-statistic = 2.82) when controlling for these related signals and standard risk factors simultaneously.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel cross-market signal that bridges the gap between the bond market liquidity literature Bao et al. (2011) and stock market liquidity research Amihud and Mendelson (1986). While prior work has studied these markets separately, we show that their relative liquidity dynamics contain valuable information about future stock returns.

Second, we extend the growing literature on cross-market information flows Goldstein and Yang (2014) by demonstrating how the debt-equity liquidity gap reflects the nature of information being incorporated into prices. Our findings suggest that market participants' choice of trading venue reveals their private information, creating predictable patterns in stock returns.

Finally, our results have important implications for market efficiency and investment practice. The persistence of DELG's predictive power among large-cap stocks and after controlling for transaction costs suggests that institutional constraints or limits to arbitrage may prevent the immediate elimination of this cross-market mispricing. This finding contributes to our understanding of market frictions and their role in asset price formation.

2 Data

Our study investigates the predictive power of the Debt-Equity Liquidity Gap signal for cross-sectional returns, derived from firms' financing activities reported in COMPUSTAT. 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 CEQL for common/ordinary equity. Long-term debt issuance (DLTIS) represents the cash proceeds from issuing long-term debt during the fiscal year, while common equity (CEQL) reflects the book value of shareholders' equity excluding preferred stock. The construction of the Debt-Equity Liquidity Gap follows a difference-based approach, where we first calculate the change in long-term debt issuance by subtracting the previous year's DLTIS from the current year's value. This difference is then scaled by the previous year's common equity (CEQL) to normalize the measure across firms of different sizes. This signal captures the relative change in a firm's debt financing activities in proportion to its equity base, providing insight into the dynamics of capital structure decisions and their potential impact on firm value. The construction ensures that the signal reflects both the magnitude and direction of changes in debt financing relative to the firm's equity foundation, making it comparable across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DELG signal. Panel A plots the time-series of the mean, median, and interquartile range for DELG. On average, the cross-sectional mean (median) DELG is -0.30 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DELG data. The signal's interquartile range spans -0.17 to 0.16. Panel B of Figure 1 plots the time-series of the coverage of the DELG signal for the CRSP universe. On average, the DELG signal is available for 6.29% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does DELG predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DELG 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 DELG portfolio and sells the low DELG 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 DELG strategy earns an average return of 0.24% per month with a t-statistic of 3.52. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.21% to

0.31% per month and have t-statistics exceeding 2.97 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 0.29, with a t-statistic of 6.31 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 557 stocks and an average market capitalization of at least $1,388 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 22 bps/month with a t-statistics of 4.74. 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 -3-22bps/month. The lowest return, (-3 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.53. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DELG 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 DELG strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DELG, as well as average returns and alphas for long/short trading DELG 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 DELG strategy achieves an average return of 32 bps/month with a t-statistic of 3.69. Among these large cap stocks, the alphas for the DELG strategy relative to the five most common factor models range from 24 to 37 bps/month with t-statistics between 2.78 and 4.32.

5 How does DELG perform relative to the zoo?

Figure 2 puts the performance of DELG 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 DELG strategy falls in the distribution. The DELG strategy's gross (net) Sharpe ratio of 0.50 (0.38) is greater than 92% (95%) 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 DELG strategy (red line).[2] Ignoring trading costs, a $1 invested in the DELG strategy would have yielded $3.12 which ranks the DELG strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DELG strategy would have yielded $1.95 which ranks the DELG strategy in the top 6% 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 DELG relative to those. Panel A shows that the DELG strategy gross alphas fall between the 59 and 71 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 DELG strategy has a positive net generalized alpha for five out of the five factor models. In these cases DELG ranks between the 79 and 87 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[2] The figure assumes an initial investment of $1 in T-bills and $1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

6 Does DELG 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 DELG 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 DELG or at least to weaken the power DELG has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of DELG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DELG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DELG} DELG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DELG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DELG. Stocks are finally grouped into five DELG 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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DELG 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 DELG signal in these Fama-MacBeth regressions exceed 1.64, 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 DELG is 0.63.

Similarly, Table 5 reports results from spanning tests that regress returns to the DELG 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 DELG strategy earns alphas that range from 20-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.86, 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 DELG trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.82.

7 Does DELG add relative to the whole zoo?

Finally, we can ask how much adding DELG 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 DELG 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 DELG grows to $993.83.

8 Conclusion

This study provides compelling evidence for the predictive power of the Debt-Equity Liquidity Gap (DELG) in forecasting cross-sectional stock returns. Our findings demonstrate that DELG represents a robust and economically significant signal, generating impressive risk-adjusted returns even after accounting for transaction costs. The strategy's performance, characterized by an annualized net Sharpe ratio of 0.38 and monthly abnormal returns of 18 basis points after costs, remains significant when controlling for standard risk factors and related anomalies.

Particularly noteworthy is the signal's resilience when tested against the Fama-French five-factor model augmented with momentum, as well as its persistent significance when controlling for six closely related strategies from the factor zoo. The alpha of 19 basis points per month (t-statistic = 2.82) in the presence of these controls suggests that DELG captures unique information about future stock returns that is not subsumed by existing factors.

However, several limitations warrant consideration. First, our analysis focuses

[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 DELG is available.

primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we account for transaction costs, the implementation challenges in different market conditions and for different types of investors deserve further investigation.

Future research could explore several promising directions. First, examining the interaction between DELG and other market anomalies could yield insights into the underlying economic mechanisms. Second, investigating the signal's performance during different market regimes and economic cycles could enhance our understanding of its reliability. Finally, extending the analysis to international markets and different asset classes could test the signal's broader applicability.

In conclusion, DELG emerges as a valuable addition to the quantitative investor's toolkit, offering meaningful economic gains even after accounting for transaction costs and existing factors. These findings contribute to our understanding of market efficiency and the role of debt-equity dynamics in asset pricing.

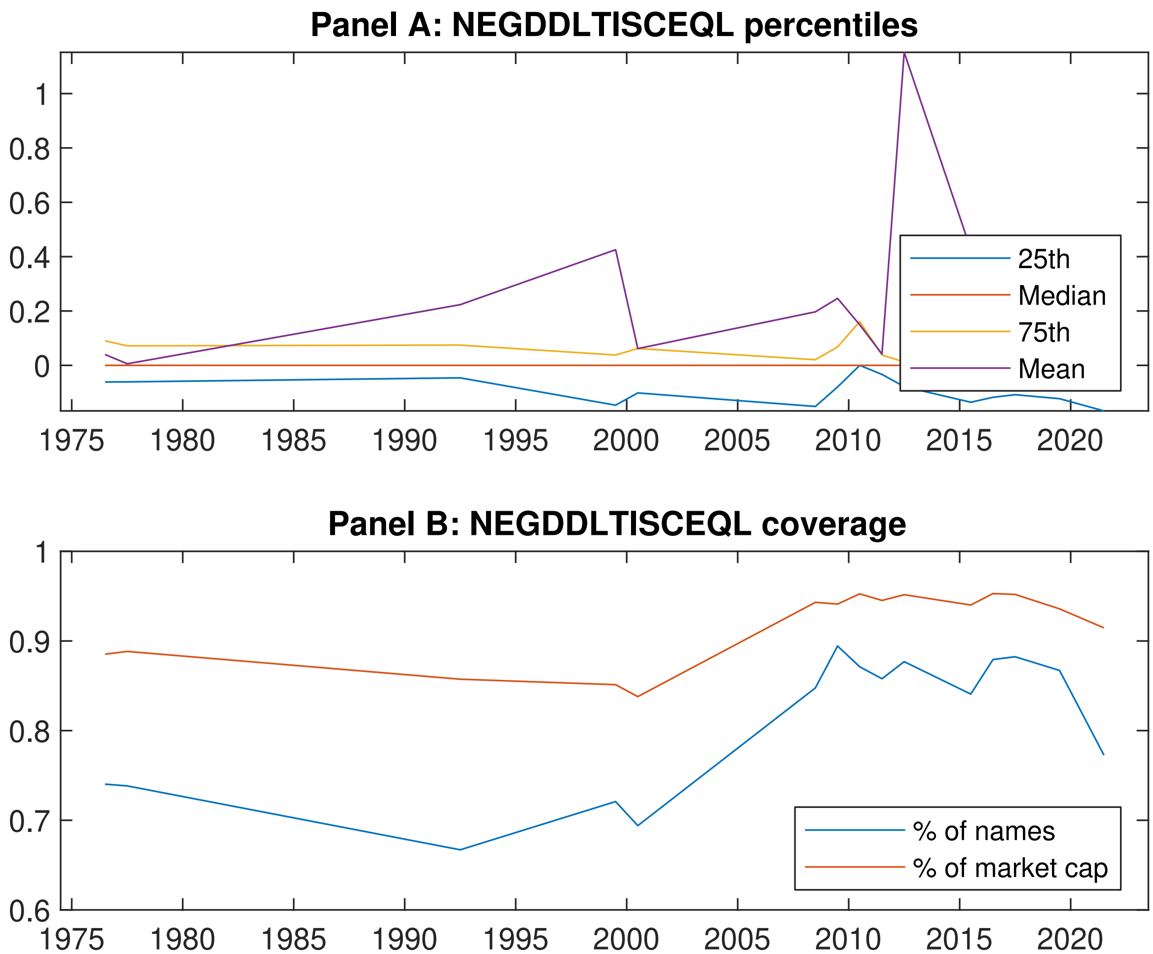

Figure 1: Times series of DELG percentiles and coverage.
This figure plots descriptive statistics for DELG. Panel A shows cross-sectional percentiles of DELG over the sample. Panel B plots the monthly coverage of DELG relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DELG. 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 DELG-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.59	0.67	0.69	0.78	0.84	0.24
	[2.71]	[3.63]	[3.43]	[4.27]	[4.18]	[3.52]
α_{CAPM}	-0.17	0.03	-0.00	0.14	0.14	0.31
	[-3.02]	[0.60]	[-0.07]	[3.00]	[2.72]	[4.50]
α_{FF3}	-0.19	-0.02	0.06	0.14	0.12	0.31
	[-3.43]	[-0.36]	[1.01]	[2.82]	[2.33]	[4.46]
α_{FF4}	-0.16	0.01	0.09	0.10	0.11	0.27
	[-2.91]	[0.20]	[1.68]	[2.01]	[2.07]	[3.87]
α_{FF5}	-0.19	-0.06	0.10	0.06	0.03	0.22
	[-3.41]	[-1.44]	[1.85]	[1.27]	[0.69]	[3.25]
α_{FF6}	-0.17	-0.04	0.13	0.04	0.03	0.21
	[-3.07]	[-0.95]	[2.26]	[0.82]	[0.68]	[2.97]
Panel B: Fama and French (2018) 6-factor model loadings for DELG-sorted portfolios						
β_{MKT}	1.09	0.98	0.97	0.97	1.03	-0.06
	[85.06]	[97.16]	[75.02]	[87.38]	[89.20]	[-3.54]
β_{SMB}	0.11	-0.11	-0.01	-0.03	0.13	0.02
	[5.50]	[-7.15]	[-0.59]	[-1.70]	[7.21]	[0.82]
β_{HML}	0.07	0.14	-0.14	-0.02	-0.04	-0.12
	[3.00]	[7.34]	[-5.67]	[-0.90]	[-2.02]	[-3.89]
β_{RMW}	0.10	0.11	-0.04	0.07	0.13	0.02
	[4.01]	[5.38]	[-1.70]	[3.25]	[5.45]	[0.74]
β_{CMA}	-0.14	0.04	-0.09	0.16	0.15	0.29
	[-3.82]	[1.47]	[-2.52]	[5.06]	[4.45]	[6.31]
β_{UMD}	-0.03	-0.04	-0.04	0.04	-0.00	0.03
	[-2.42]	[-3.74]	[-3.06]	[3.32]	[-0.01]	[1.94]
Panel C: Average number of firms (n) and market capitalization (me)						
n	652	557	1087	609	626	
me ($\$10^6$)	1453	2847	2160	2922	1388	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the DELG 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	0.24	0.31	0.31	0.27	0.22	0.21
			[3.52]	[4.50]	[4.46]	[3.87]	[3.25]	[2.97]
Quintile	NYSE	EW	0.22	0.25	0.24	0.22	0.20	0.19
			[4.74]	[5.31]	[5.06]	[4.55]	[4.14]	[3.89]
Quintile	Name	VW	0.24	0.31	0.30	0.26	0.24	0.21
			[3.55]	[4.72]	[4.61]	[3.86]	[3.59]	[3.16]
Quintile	Cap	VW	0.24	0.29	0.29	0.23	0.19	0.16
			[3.76]	[4.51]	[4.50]	[3.61]	[3.04]	[2.54]
Decile	NYSE	VW	0.29	0.38	0.38	0.33	0.31	0.28
			[2.98]	[3.96]	[3.97]	[3.39]	[3.20]	[2.88]
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	0.19	0.26	0.26	0.24	0.19	0.18
			[2.68]	[3.75]	[3.70]	[3.41]	[2.74]	[2.54]
Quintile	NYSE	EW	-0.03					
			[-0.53]					
Quintile	Name	VW	0.18	0.27	0.26	0.23	0.20	0.19
			[2.69]	[4.03]	[3.90]	[3.54]	[3.06]	[2.83]
Quintile	Cap	VW	0.20	0.26	0.26	0.23	0.18	0.16
			[2.97]	[3.97]	[3.92]	[3.49]	[2.73]	[2.43]
Decile	NYSE	VW	0.22	0.33	0.33	0.30	0.27	0.25
			[2.27]	[3.35]	[3.34]	[3.05]	[2.76]	[2.56]

Table 3: Conditional sort on size and DELG

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

		DELG Quintiles					DELG Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.73	0.92	0.98	0.91	0.81	0.08	0.12	0.11	0.05	0.03	0.01
		[2.62]	[3.37]	[3.54]	[3.22]	[2.90]	[0.87]	[1.25]	[1.15]	[0.57]	[0.37]	[0.06]
	(2)	0.76	0.98	0.82	0.90	0.93	0.16	0.19	0.16	0.16	0.11	0.11
		[2.84]	[3.84]	[3.25]	[3.66]	[3.60]	[2.05]	[2.38]	[2.06]	[2.06]	[1.33]	[1.42]
	(3)	0.83	0.84	0.85	0.86	0.94	0.11	0.17	0.17	0.12	0.14	0.11
		[3.28]	[3.82]	[3.47]	[3.83]	[4.01]	[1.47]	[2.20]	[2.14]	[1.53]	[1.78]	[1.40]
	(4)	0.72	0.82	0.93	0.74	0.93	0.21	0.26	0.25	0.21	0.21	0.19
		[3.09]	[3.99]	[4.09]	[3.53]	[4.27]	[2.76]	[3.41]	[3.21]	[2.68]	[2.67]	[2.34]
	(5)	0.48	0.66	0.61	0.70	0.80	0.32	0.36	0.37	0.30	0.29	0.24
		[2.36]	[3.70]	[3.00]	[3.82]	[4.12]	[3.69]	[4.19]	[4.32]	[3.49]	[3.27]	[2.78]

Panel B: Portfolio average number of firms and market capitalization

		DELG Quintiles					DELG Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	396	399	399	399	395	37	34	33	33	36
	(2)	108	108	108	108	108	60	60	58	60	60
	(3)	77	77	76	77	77	105	106	102	103	106
	(4)	64	65	65	65	64	224	230	224	227	225
	(5)	59	59	59	59	59	1348	2018	1858	2001	1423

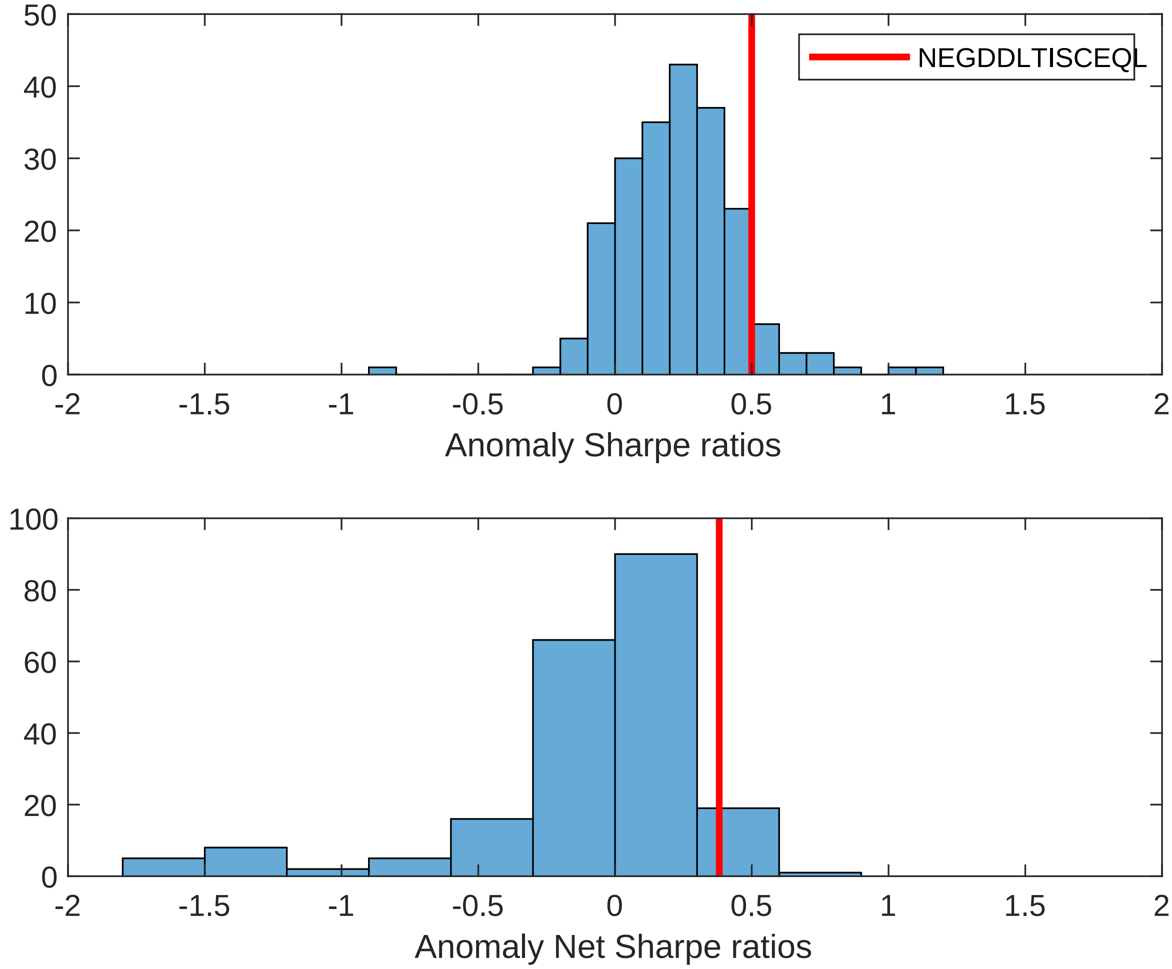

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DELG with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

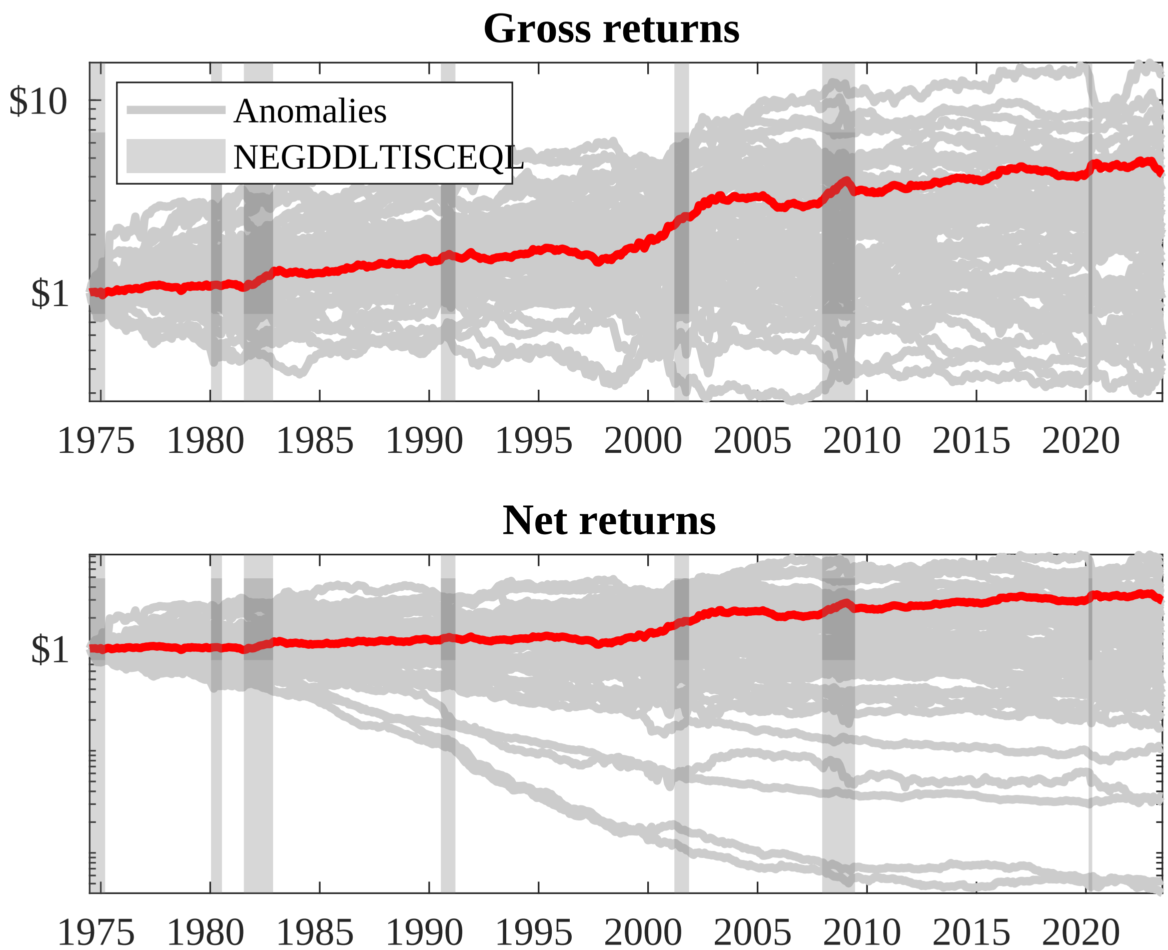

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DELG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

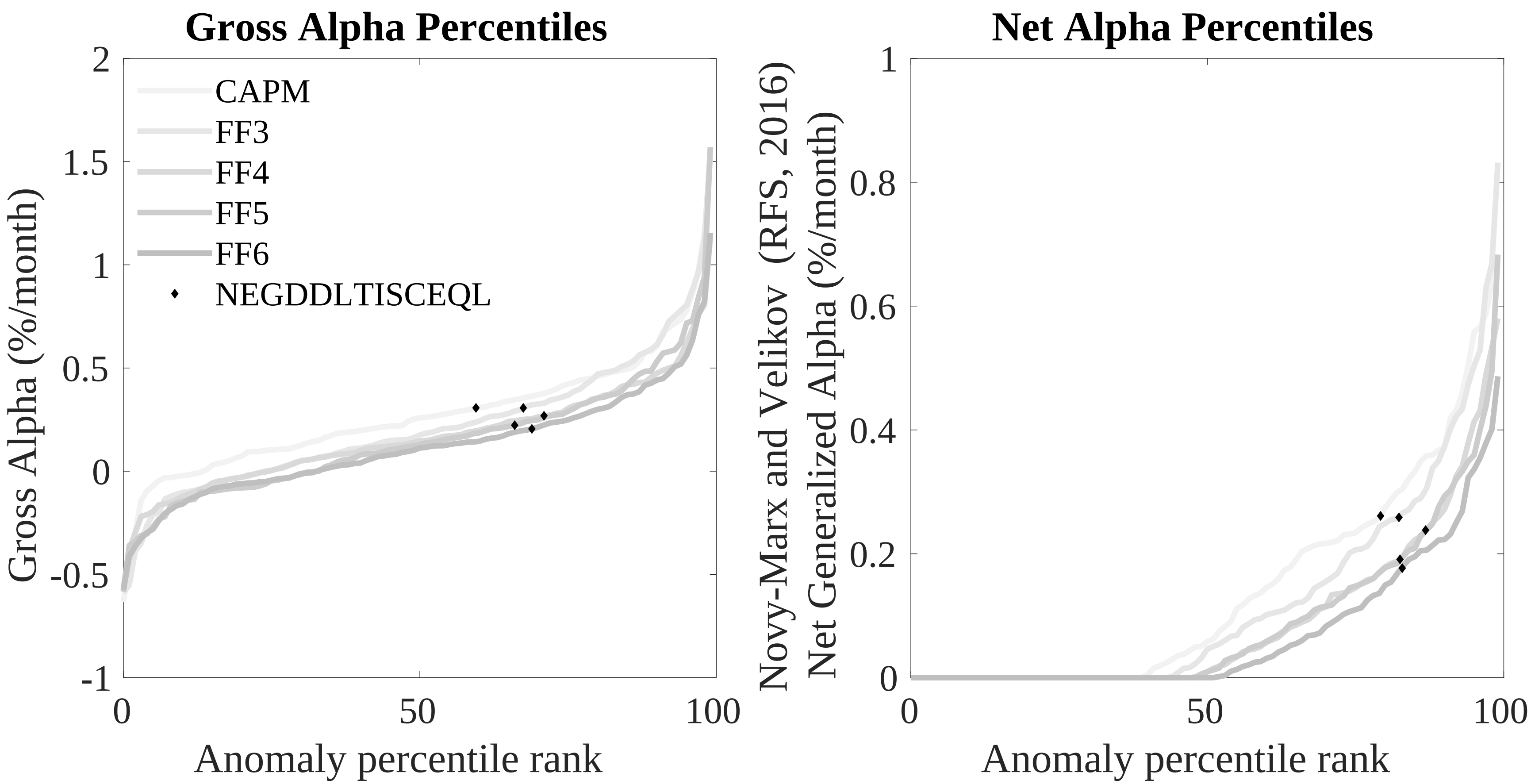

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DELG trading strategy alphas (diamonds). The strategies are constructed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

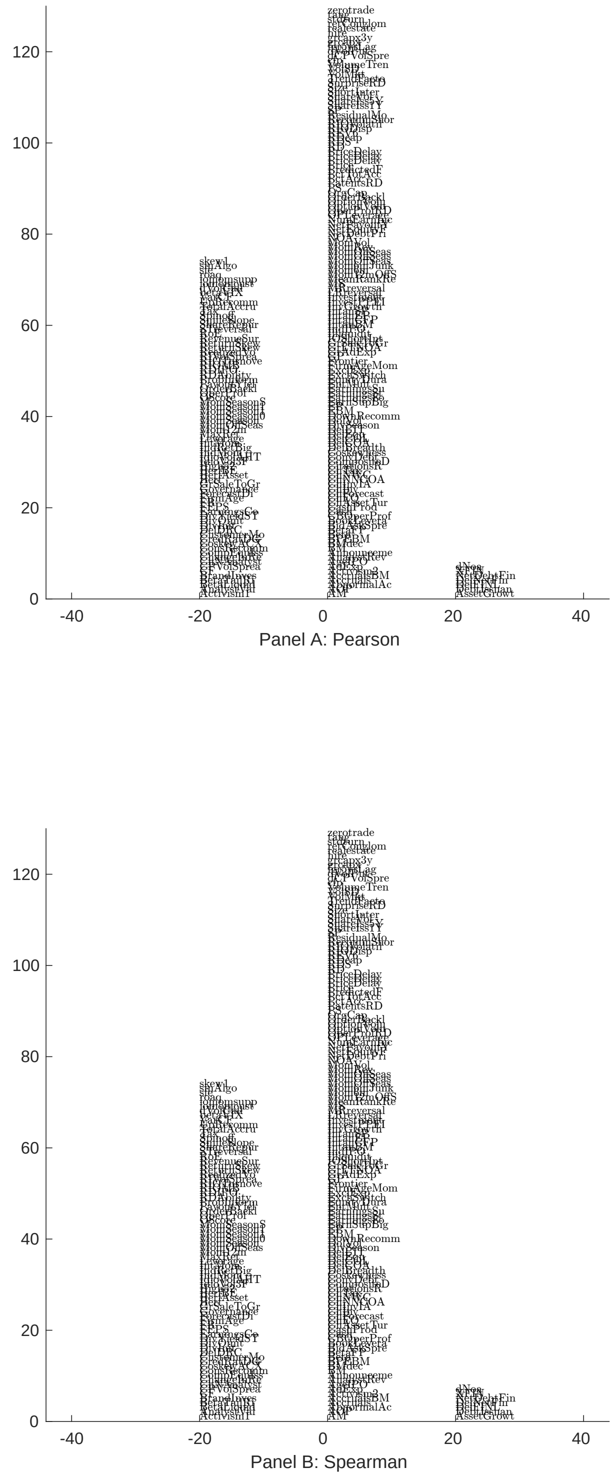

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DELG. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

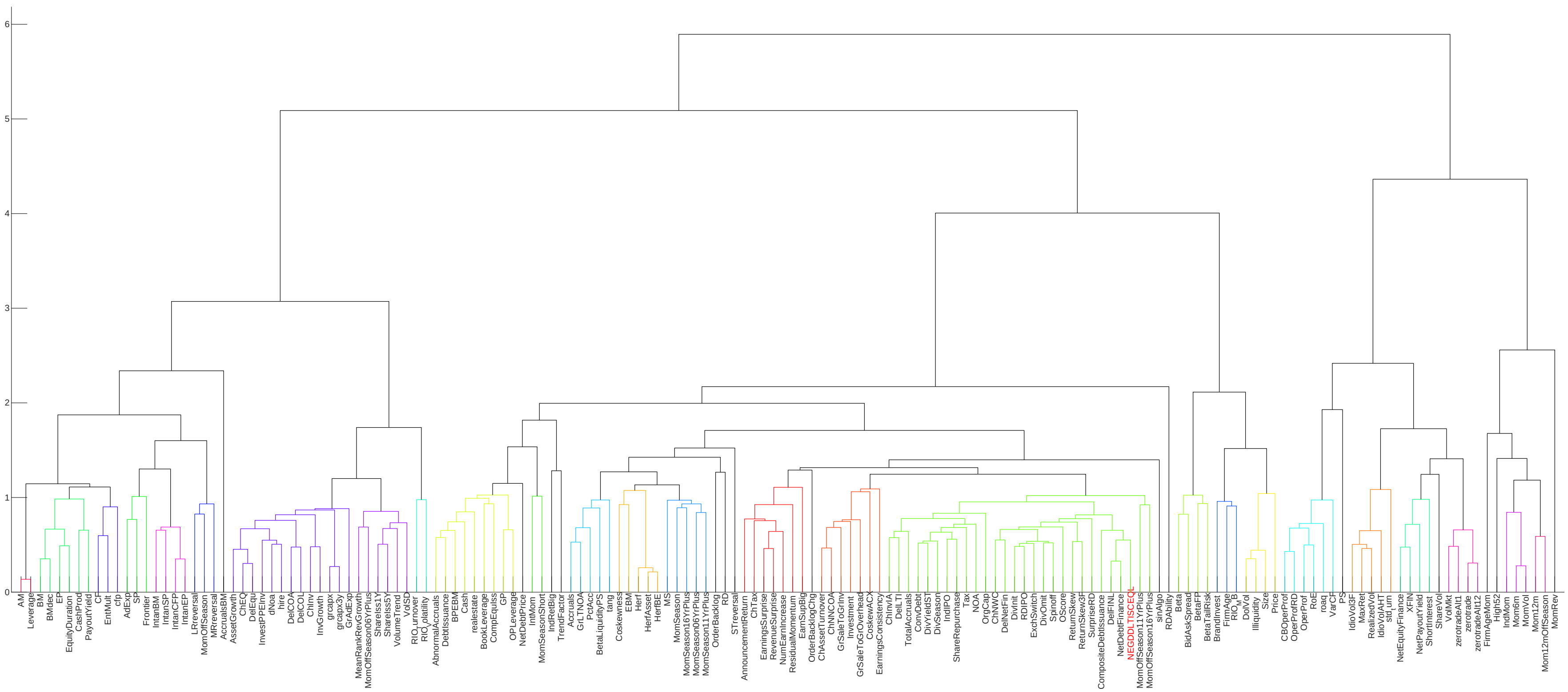

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

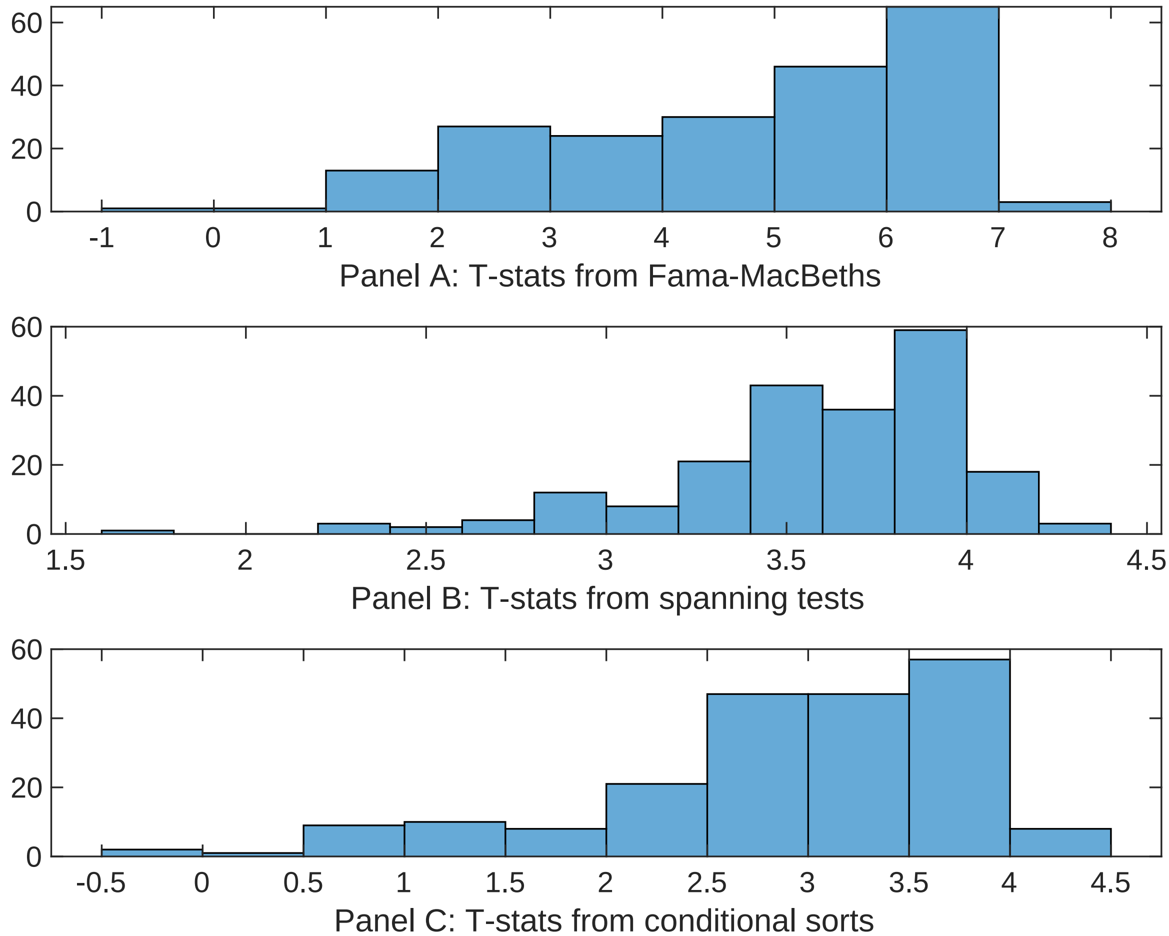

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DELG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DELG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DELG} DELG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DELG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DELG. Stocks are finally grouped into five DELG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DELG 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 DELG. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DELG} DELG_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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
	[5.52]	[5.49]	[5.86]	[5.96]	[5.46]	[5.81]	[5.83]
DELG	0.50	0.58	0.77	0.42	0.12	0.39	0.18
	[2.06]	[2.37]	[2.93]	[1.66]	[4.51]	[1.64]	[0.63]
Anomaly 1	0.17						-0.11
	[9.11]						[-2.40]
Anomaly 2		0.19					0.11
		[8.56]					[1.73]
Anomaly 3			0.18				0.95
			[6.10]				[1.69]
Anomaly 4				0.11			0.45
				[9.18]			[2.07]
Anomaly 5					0.40		0.26
					[6.94]		[0.47]
Anomaly 6						0.14	0.88
						[10.11]	[4.99]
# 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 DELG trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DELG} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.20	0.20	0.20	0.21	0.21	0.20	0.19
	[2.87]	[2.88]	[2.86]	[3.06]	[3.06]	[2.92]	[2.82]
Anomaly 1	18.34						12.83
	[4.54]						[2.31]
Anomaly 2		18.73					7.70
		[4.85]					[1.44]
Anomaly 3			13.84				10.35
			[3.94]				[2.76]
Anomaly 4				6.32			-0.59
				[1.40]			[-0.12]
Anomaly 5					6.82		6.51
					[2.49]		[2.32]
Anomaly 6						4.91	-4.75
						[1.20]	[-1.05]
mkt	-5.40	-5.62	-3.75	-5.59	-5.80	-5.62	-4.24
	[-3.42]	[-3.57]	[-2.27]	[-3.49]	[-3.63]	[-3.51]	[-2.59]
smb	0.34	0.72	6.43	1.34	2.67	2.04	4.31
	[0.14]	[0.30]	[2.39]	[0.53]	[1.08]	[0.82]	[1.51]
hml	-10.58	-11.24	-9.96	-11.72	-11.73	-11.92	-9.43
	[-3.49]	[-3.73]	[-3.26]	[-3.81]	[-3.83]	[-3.85]	[-3.07]
rmw	0.75	0.62	-6.13	2.18	3.09	2.28	-4.87
	[0.24]	[0.20]	[-1.62]	[0.68]	[0.97]	[0.72]	[-1.28]
cma	22.53	23.84	19.38	20.77	22.56	24.98	13.94
	[4.73]	[5.11]	[3.75]	[2.84]	[4.31]	[4.50]	[1.91]
umd	1.38	1.62	3.10	3.41	2.53	2.99	0.79
	[0.85]	[1.00]	[1.94]	[2.09]	[1.55]	[1.84]	[0.48]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	15	16	14	13	13	12	17

Panel A: Average rank

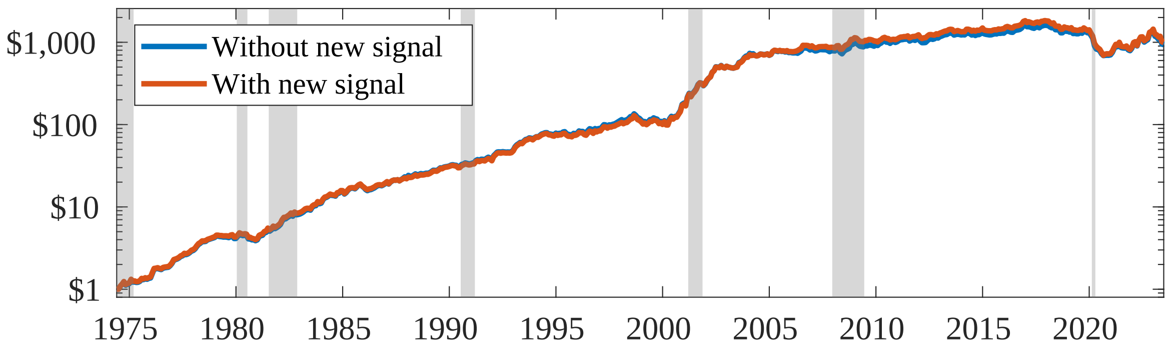

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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