Debt Impact on Sales Growth and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Debt Impact on Sales Growth (DISG), 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 DISG achieves an annualized gross (net) Sharpe ratio of 0.45 (0.34), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 17 (15) bps/month with a t-statistic of 2.51 (2.18), 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, Employment growth, Asset growth) is 17 bps/month with a t-statistic of 2.45.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While extensive literature documents various return predictors, the role of debt in shaping firms' operational decisions and subsequent stock returns remains incompletely understood (Baker and Wurgler, 2002). The interaction between financial leverage and operational performance represents a particularly important yet understudied channel through which capital structure decisions may affect firm value and stock returns (Rajan and Zingales, 1995).

Prior research has largely focused on examining either the direct effects of leverage on returns (George and Hwang, 2010) or the impact of operational metrics on stock performance (Novy-Marx, 2013). However, the dynamic interaction between debt levels and operational outcomes - specifically how leverage constrains or enables sales growth - has received limited attention as a potential return predictor, despite its economic importance in determining firm value.

We hypothesize that the Debt Impact on Sales Growth (DISG) metric captures valuable information about firms' financial constraints and operational efficiency that is not fully reflected in stock prices. This hypothesis builds on theoretical work by Myers (1977) showing that debt overhang can restrict firms' ability to pursue growth opportunities. When high debt levels impair sales growth, it may signal both financial distress and deteriorating competitive position (**?**).

The slow incorporation of this information into prices could occur through several mechanisms. First, investors may struggle to properly assess the complex interaction between capital structure and operational performance (Hirshleifer and Teoh, 2003). Second, limits to arbitrage may prevent rapid price adjustment even when sophisticated investors identify mispricing (Shleifer and Vishny, 1997). Third, the gradual nature of how debt constraints manifest in operational outcomes could lead to underreaction (Hong and Stein, 1999).

Importantly, DISG differs from simple measures of either leverage or sales growth alone. By capturing their interaction, it provides insight into how effectively firms deploy debt financing to drive revenue expansion (Lang and Stulz, 1994). Firms with positive DISG scores successfully leverage debt to fuel growth, while negative scores indicate debt may be constraining rather than enabling expansion.

Our empirical analysis reveals that DISG strongly predicts future stock returns. A value-weighted long-short strategy based on DISG quintiles generates monthly abnormal returns of 17 basis points (t-statistic = 2.51) 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.

The predictive power of DISG remains robust across various methodological specifications. The signal maintains significance when controlling for size, with the long-short strategy earning a monthly alpha of 28 basis points (t-statistic = 3.11) among large-cap stocks. Importantly, these results hold after accounting for transaction costs, with the strategy delivering a net Sharpe ratio of 0.34.

Further analysis demonstrates that DISG's predictive ability is distinct from related anomalies. Controlling for the six most closely related predictors - including measures of debt financing, asset growth, and employment growth - the strategy continues to generate significant abnormal returns of 17 basis points monthly (t-statistic = 2.45). This persistence suggests DISG captures a unique dimension of mispricing.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that bridges the gap between capital structure and operational performance research streams. While prior work has examined leverage (George and Hwang, 2010) and growth (Cooper et al., 2008) separately, DISG uniquely captures their interaction.

Second, we extend the literature on financial constraints and stock returns (Whited and Wu, 2006; Hadlock and Pierce, 2010) by showing how debt's impact on sales growth provides an important signal about firm value. Our findings suggest markets are slow to incorporate information about the efficiency with which firms deploy debt financing to drive growth.

Third, our results contribute to the growing body of work on return predictor evaluation and validation (Novy-Marx and Velikov, 2023; Hou et al., 2020). Using comprehensive robustness tests, we demonstrate that DISG represents a distinct and economically meaningful addition to the 'factor zoo.' The signal's predictive power persists after controlling for transaction costs and related anomalies, suggesting it captures a unique dimension of systematic mispricing.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the impact of debt issuance changes on sales growth. 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 SALE for total sales revenue. Long-term debt issuance (DLTIS) represents the amount of new long-term debt issued by the firm during the fiscal year, while sales (SALE) captures the firm's total revenue from its primary business operations. The construction of the signal follows a change-based approach, where we first calculate the year-over-year change in DLTIS by subtracting the previous year's value from the current year's value. This difference is then scaled by the previous year's sales to normalize the measure across firms of different sizes. This ratio captures the relative magnitude of changes in debt financing relative to the firm's operational scale, offering insight into how aggressively firms are leveraging their revenue base to fund expansion or operations. By focusing on this relationship, the signal aims to reflect aspects of capital structure decisions and their potential impact on firm growth in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both DLTIS and SALE to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the DISG signal. Panel A plots the time-series of the mean, median, and interquartile range for DISG. On average, the cross-sectional mean (median) DISG is -0.47 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input DISG data. The signal's interquartile range spans -0.12 to 0.15. Panel B of Figure 1 plots the time-series of the coverage of the DISG signal for the CRSP universe. On average, the DISG signal is available for 6.18% of CRSP names, which on average make up 7.45% of total market capitalization.

4 Does DISG predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on DISG 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 DISG portfolio and sells the low DISG 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 DISG 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 0.17% to 0.29% per month and have t-statistics exceeding 2.51 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 0.35, with a t-statistic of 7.73 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 533 stocks and an average market capitalization of at least $1,597 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 16 bps/month with a t-statistics of 3.51. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for eighteen exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between -9-24bps/month. The lowest return, (-9 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.51. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the DISG 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 DISG strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and DISG, as well as average returns and alphas for long/short trading DISG 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 DISG strategy achieves an average return of 28 bps/month with a t-statistic of 3.11. Among these large cap stocks, the alphas for the DISG strategy relative to the five most common factor models range from 17 to 34 bps/month with t-statistics between 1.86 and 3.76.

5 How does DISG perform relative to the zoo?

Figure 2 puts the performance of DISG 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 DISG strategy falls in the distribution. The DISG strategy's gross (net) Sharpe ratio of 0.45 (0.34) 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 DISG strategy (red line).[2] Ignoring trading costs, a $1 invested in the DISG strategy would have yielded $2.61 which ranks the DISG strategy in the top 7% across the 212 anomalies. Accounting for trading costs, a $1 invested in the DISG strategy would have yielded $1.61 which ranks the DISG 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 DISG relative to those. Panel A shows that the DISG strategy gross alphas fall between the 54 and 67 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 197406 to 202306 sample. For example, 45%

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

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

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The DISG strategy has a positive net generalized alpha for five out of the five factor models. In these cases DISG ranks between the 74 and 85 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on DISG 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 DISG signal in these Fama-MacBeth regressions exceed -0.08, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on DISG is -0.45.

Similarly, Table 5 reports results from spanning tests that regress returns to the DISG 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 DISG strategy earns alphas that range from 16-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.40, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the DISG trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.45.

7 Does DISG add relative to the whole zoo?

Finally, we can ask how much adding DISG 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 DISG 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 DISG grows to $996.13.

8 Conclusion

This study provides compelling evidence for the effectiveness of Debt Impact on Sales Growth (DISG) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short strategy based on DISG generates economically meaningful and statistically significant returns, with an annualized gross Sharpe ratio of 0.45 (0.34 net). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factors and related anomalies.

The persistence of DISG's predictive power, evidenced by monthly abnormal

[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 DISG is available.

returns of 17 basis points (gross) relative to both the Fama-French five-factor model plus momentum and an expanded model including six closely related anomalies, suggests that this signal captures unique information about future stock returns. These results remain economically significant even after accounting for transaction costs, indicating practical implementability for institutional investors.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we control for various related anomalies, the underlying economic mechanisms driving DISG's predictive power deserve further investigation.

Future research could explore several promising directions. First, examining DISG's performance across different market regimes and economic cycles could provide insights into its reliability under varying conditions. Second, investigating potential interactions between DISG and other established anomalies might reveal valuable complementarities for portfolio construction. Finally, studying the signal's effectiveness in international markets could test its universal applicability and potential for global investment strategies.

In conclusion, DISG represents a robust addition to the existing arsenal of return predictors, offering both statistical significance and practical applicability for investment professionals.

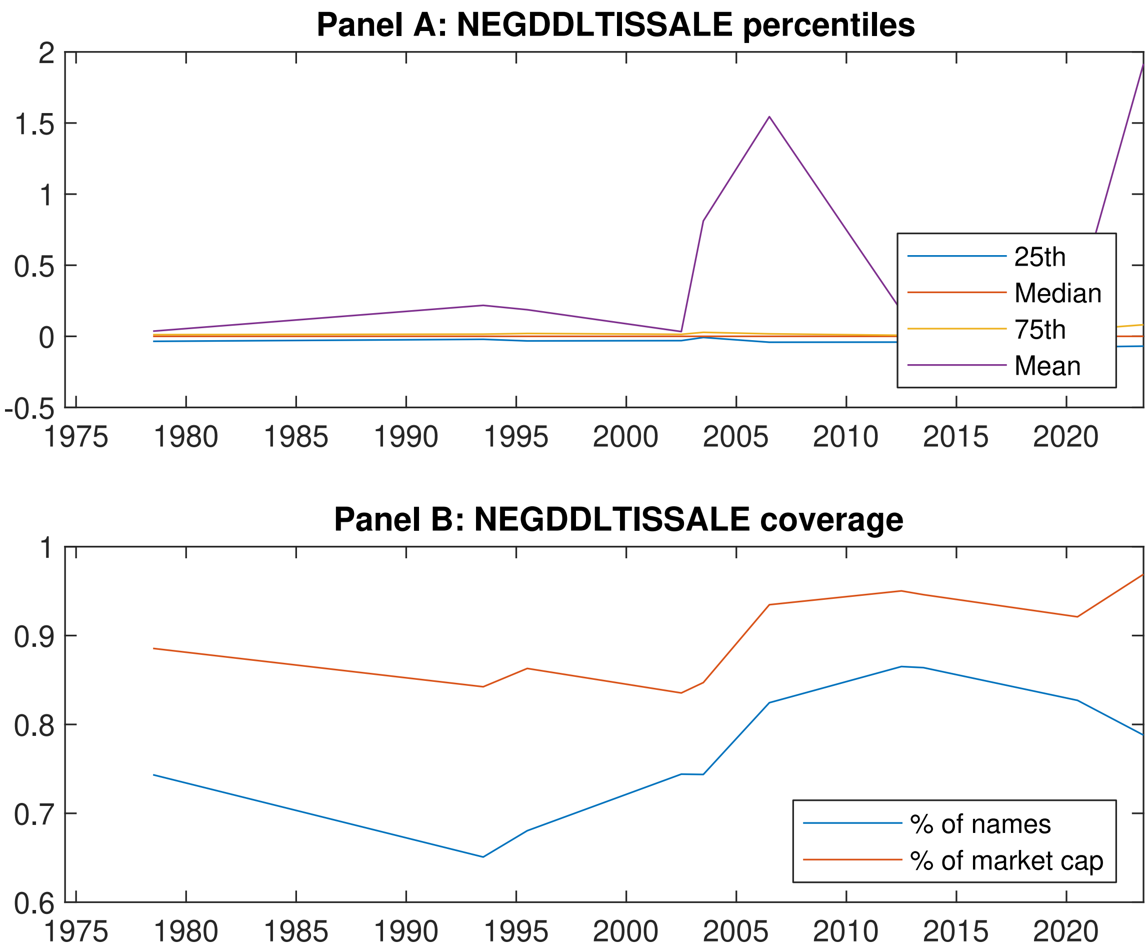

Figure 1: Times series of DISG percentiles and coverage.
This figure plots descriptive statistics for DISG. Panel A shows cross-sectional percentiles of DISG over the sample. Panel B plots the monthly coverage of DISG relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on DISG. 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 DISG-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.57	0.68	0.71	0.80	0.80	0.22
	[2.71]	[3.73]	[3.45]	[4.40]	[4.04]	[3.16]
α_{CAPM}	-0.17	0.05	-0.00	0.17	0.11	0.27
	[-3.14]	[0.97]	[-0.04]	[3.43]	[2.13]	[3.94]
α_{FF3}	-0.20	0.02	0.06	0.16	0.09	0.29
	[-3.87]	[0.33]	[1.11]	[3.24]	[1.79]	[4.18]
α_{FF4}	-0.17	0.04	0.11	0.11	0.08	0.25
	[-3.19]	[0.87]	[1.95]	[2.28]	[1.57]	[3.52]
α_{FF5}	-0.14	-0.05	0.09	0.06	0.05	0.19
	[-2.71]	[-1.16]	[1.68]	[1.17]	[1.01]	[2.82]
α_{FF6}	-0.12	-0.03	0.12	0.03	0.05	0.17
	[-2.34]	[-0.63]	[2.23]	[0.63]	[0.97]	[2.51]
Panel B: Fama and French (2018) 6-factor model loadings for DISG-sorted portfolios						
β_{MKT}	1.06	0.97	0.99	0.97	1.02	-0.04
	[88.37]	[92.16]	[77.35]	[88.51]	[85.40]	[-2.67]
β_{SMB}	0.03	-0.12	0.02	-0.00	0.06	0.03
	[1.51]	[-7.08]	[1.19]	[-0.28]	[3.03]	[1.14]
β_{HML}	0.15	0.10	-0.16	-0.03	-0.04	-0.20
	[6.70]	[5.02]	[-6.55]	[-1.23]	[-1.82]	[-6.46]
β_{RMW}	-0.03	0.14	0.02	0.13	-0.01	0.02
	[-1.16]	[6.80]	[0.63]	[6.14]	[-0.26]	[0.68]
β_{CMA}	-0.18	0.07	-0.11	0.17	0.18	0.35
	[-5.10]	[2.45]	[-3.02]	[5.36]	[5.11]	[7.73]
β_{UMD}	-0.03	-0.04	-0.05	0.05	0.00	0.03
	[-2.66]	[-4.05]	[-4.10]	[4.08]	[0.20]	[2.17]
Panel C: Average number of firms (n) and market capitalization (me)						
n	670	533	1049	586	644	
me ($\$10^6$)	1658	2664	2202	2636	1597	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the DISG 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	0.29	0.25	0.19	0.17
			[3.16]	[3.94]	[4.18]	[3.52]	[2.82]	[2.51]
Quintile	NYSE	EW	0.16	0.18	0.18	0.18	0.17	0.17
			[3.51]	[3.93]	[3.86]	[3.77]	[3.50]	[3.53]
Quintile	Name	VW	0.23	0.28	0.30	0.24	0.23	0.19
			[3.26]	[3.99]	[4.25]	[3.45]	[3.24]	[2.78]
Quintile	Cap	VW	0.24	0.29	0.31	0.26	0.20	0.17
			[3.60]	[4.29]	[4.60]	[3.84]	[2.97]	[2.59]
Decile	NYSE	VW	0.31	0.40	0.39	0.33	0.26	0.23
			[3.32]	[4.33]	[4.27]	[3.52]	[2.92]	[2.54]
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	0.23	0.25	0.22	0.17	0.15
			[2.37]	[3.29]	[3.49]	[3.16]	[2.44]	[2.18]
Quintile	NYSE	EW	-0.09					
			[-1.51]					
Quintile	Name	VW	0.17	0.24	0.25	0.22	0.20	0.18
			[2.47]	[3.34]	[3.54]	[3.14]	[2.78]	[2.48]
Quintile	Cap	VW	0.19	0.25	0.27	0.24	0.17	0.15
			[2.84]	[3.65]	[3.90]	[3.53]	[2.55]	[2.26]
Decile	NYSE	VW	0.24	0.35	0.34	0.30	0.24	0.21
			[2.57]	[3.72]	[3.68]	[3.29]	[2.60]	[2.32]

Table 3: Conditional sort on size and DISG

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

		DISG Quintiles					DISG Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.67	1.01	1.03	1.11	0.72	0.05	0.06	0.05	0.04	0.06	0.05
		[2.38]	[3.72]	[3.78]	[3.77]	[2.59]	[0.61]	[0.78]	[0.63]	[0.49]	[0.74]	[0.65]
	(2)	0.77	1.00	0.83	1.01	0.84	0.07	0.11	0.08	0.08	0.05	0.06
		[2.88]	[3.92]	[3.31]	[4.06]	[3.31]	[0.85]	[1.34]	[1.00]	[1.05]	[0.66]	[0.74]
	(3)	0.78	0.89	0.88	0.96	0.86	0.08	0.13	0.14	0.11	0.14	0.11
		[3.15]	[3.95]	[3.61]	[4.21]	[3.70]	[1.03]	[1.67]	[1.85]	[1.40]	[1.70]	[1.41]
	(4)	0.72	0.85	0.90	0.81	0.88	0.16	0.18	0.18	0.14	0.13	0.11
		[3.21]	[3.95]	[3.99]	[3.81]	[4.05]	[1.99]	[2.31]	[2.25]	[1.80]	[1.66]	[1.40]
	(5)	0.47	0.66	0.64	0.74	0.75	0.28	0.33	0.34	0.28	0.19	0.17
		[2.27]	[3.62]	[3.16]	[3.96]	[3.87]	[3.11]	[3.64]	[3.76]	[3.09]	[2.17]	[1.86]

Panel B: Portfolio average number of firms and market capitalization

		DISG Quintiles Average n					DISG Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	389	391	390	391	386	36	33	32	33	34
	(2)	107	107	107	107	107	59	59	58	60	59
	(3)	76	77	76	77	76	104	106	101	104	104
	(4)	64	65	65	65	64	224	231	222	229	222
	(5)	59	59	59	59	59	1422	1994	1759	2032	1441

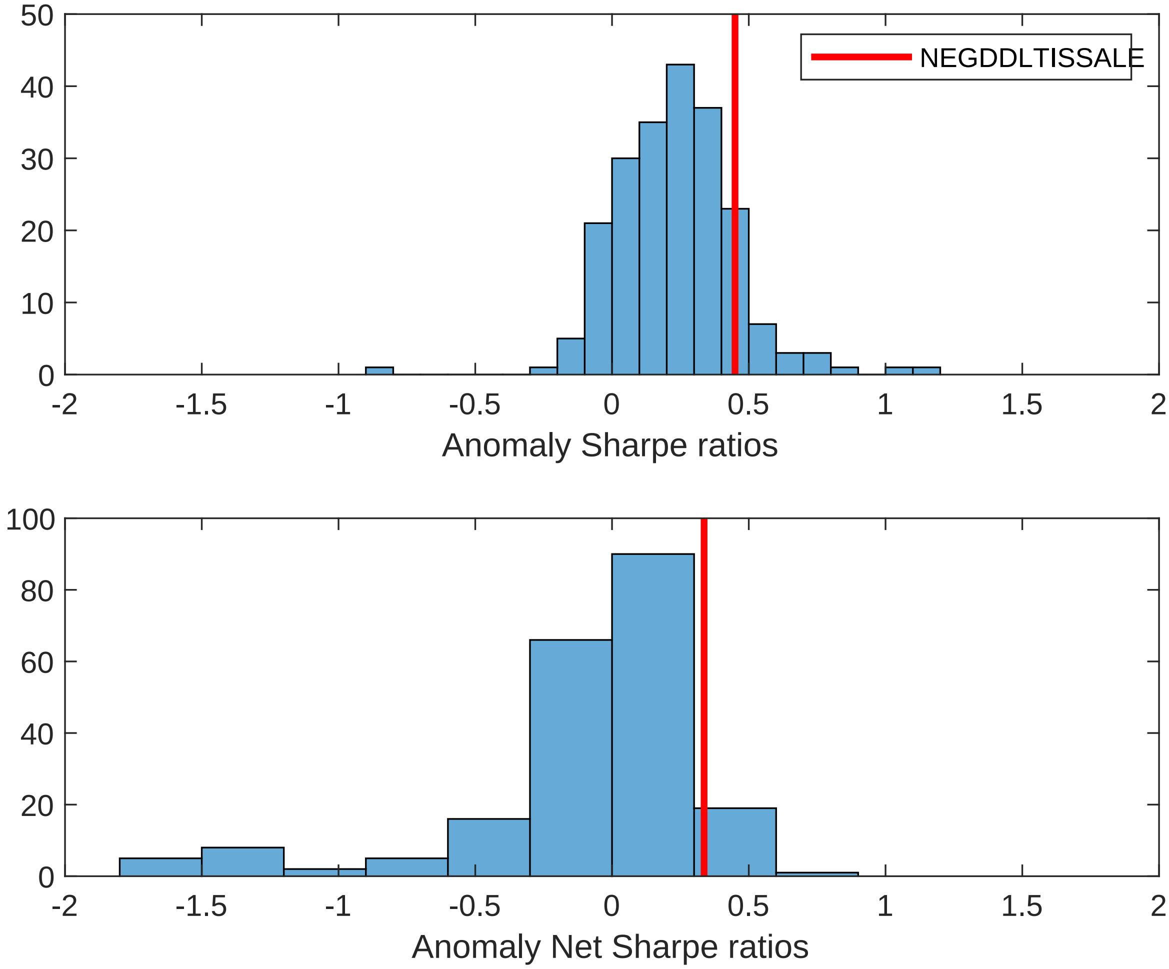

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the DISG with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

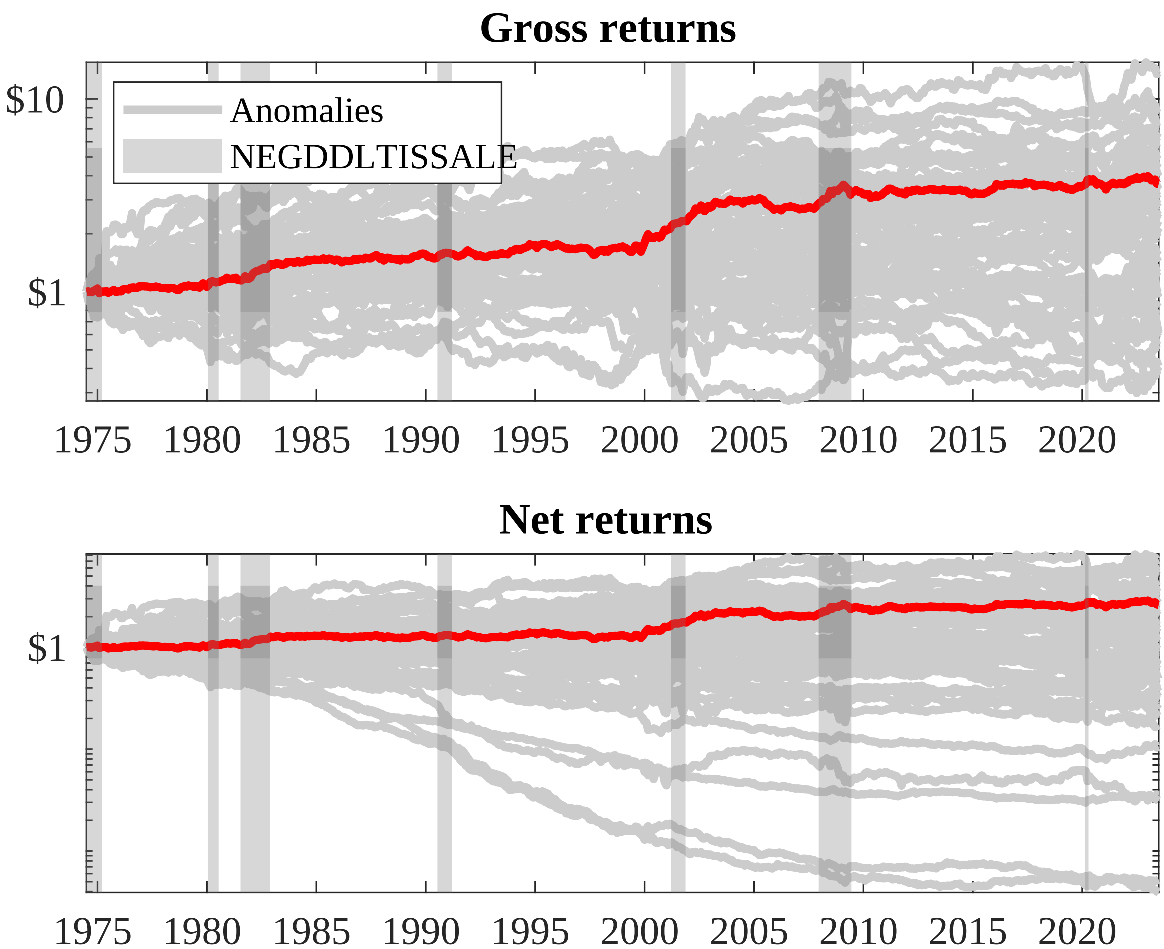

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DISG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

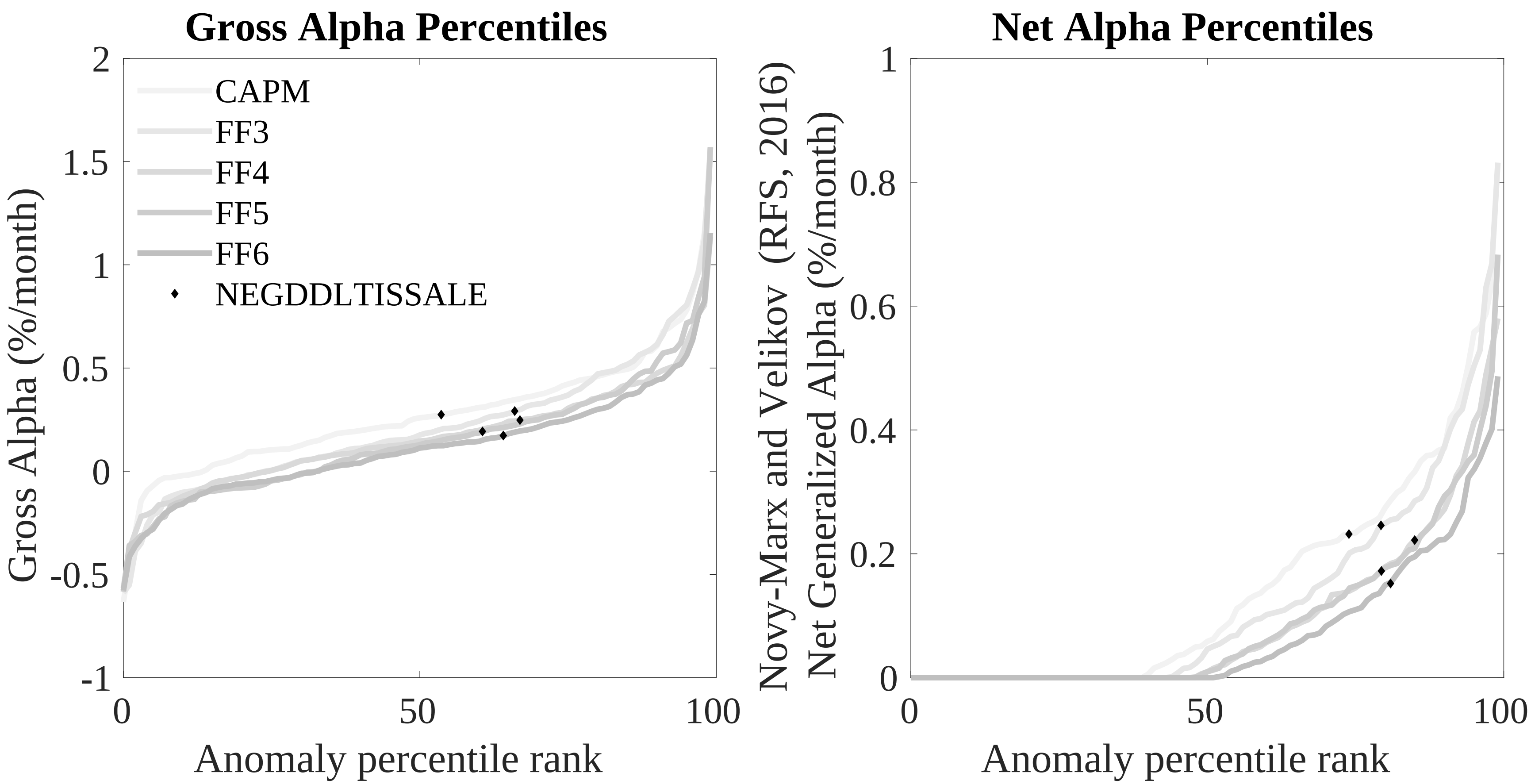

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the DISG 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.

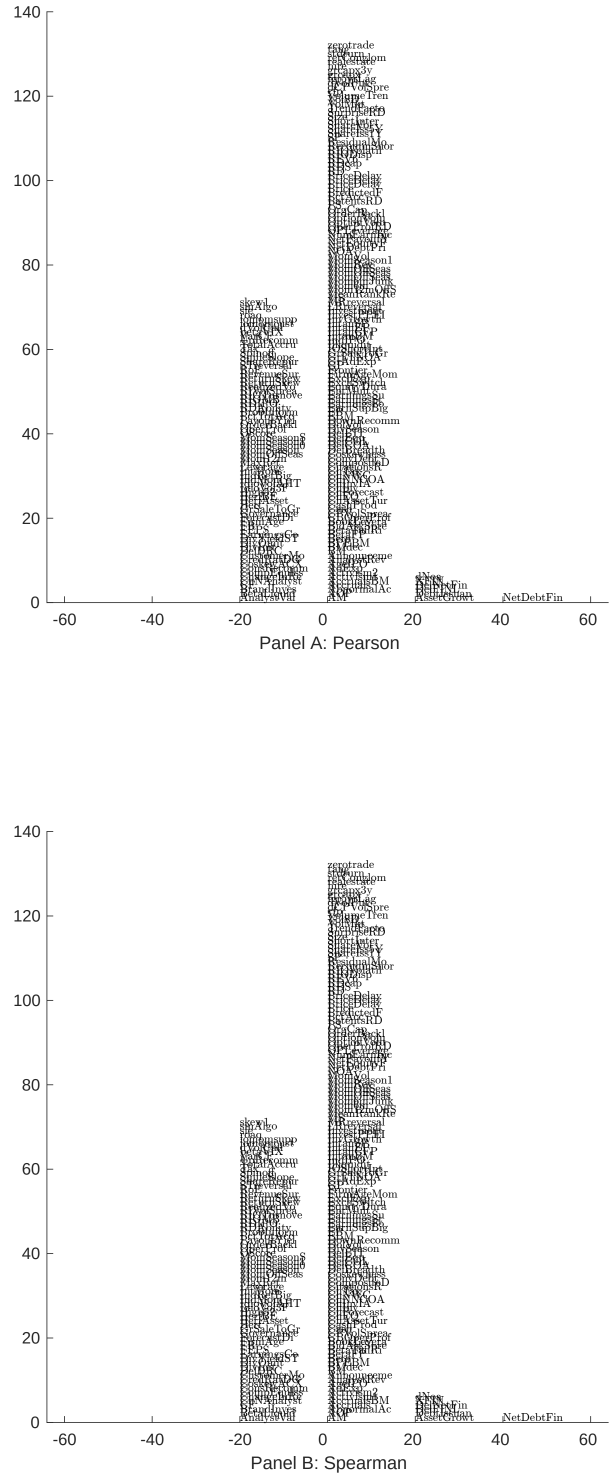

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with DISG. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

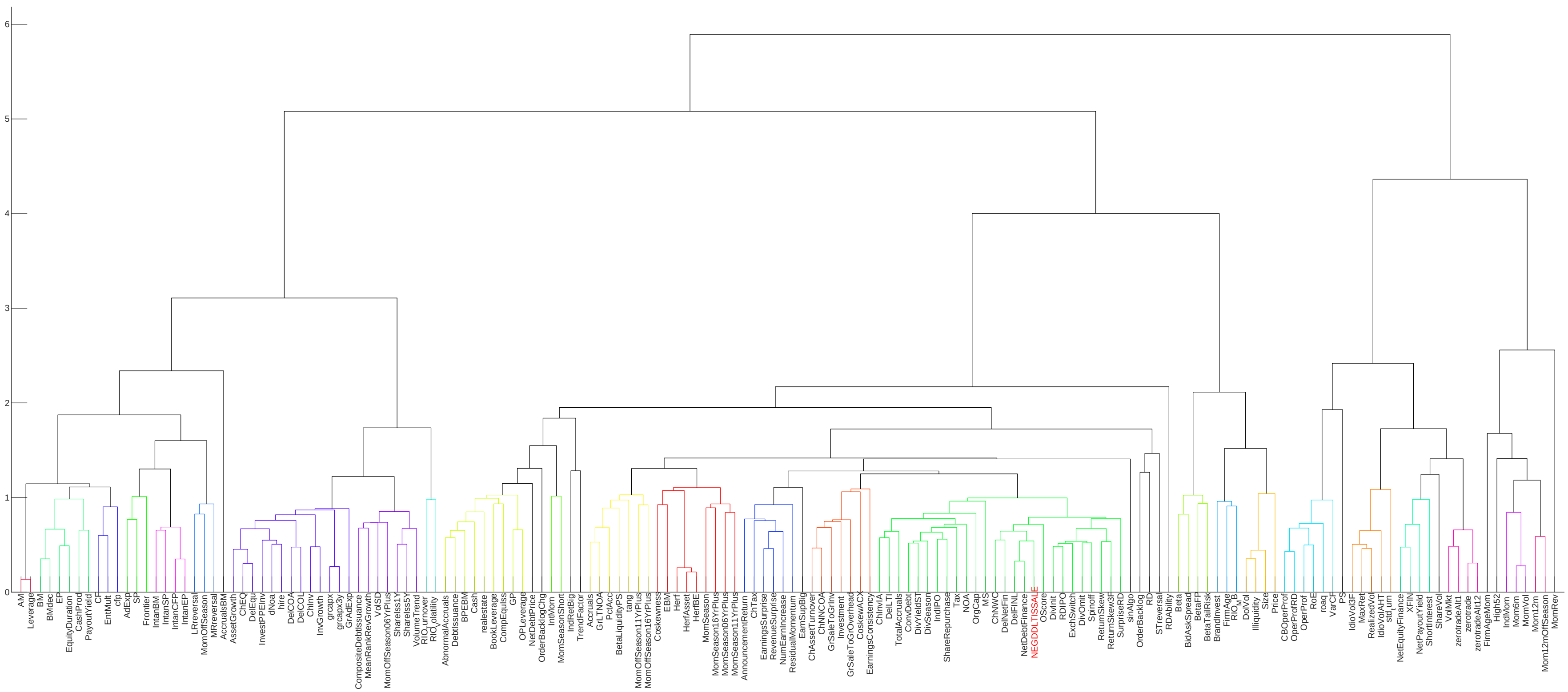

Figure 6: Agglomerative hierarchical cluster plot

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

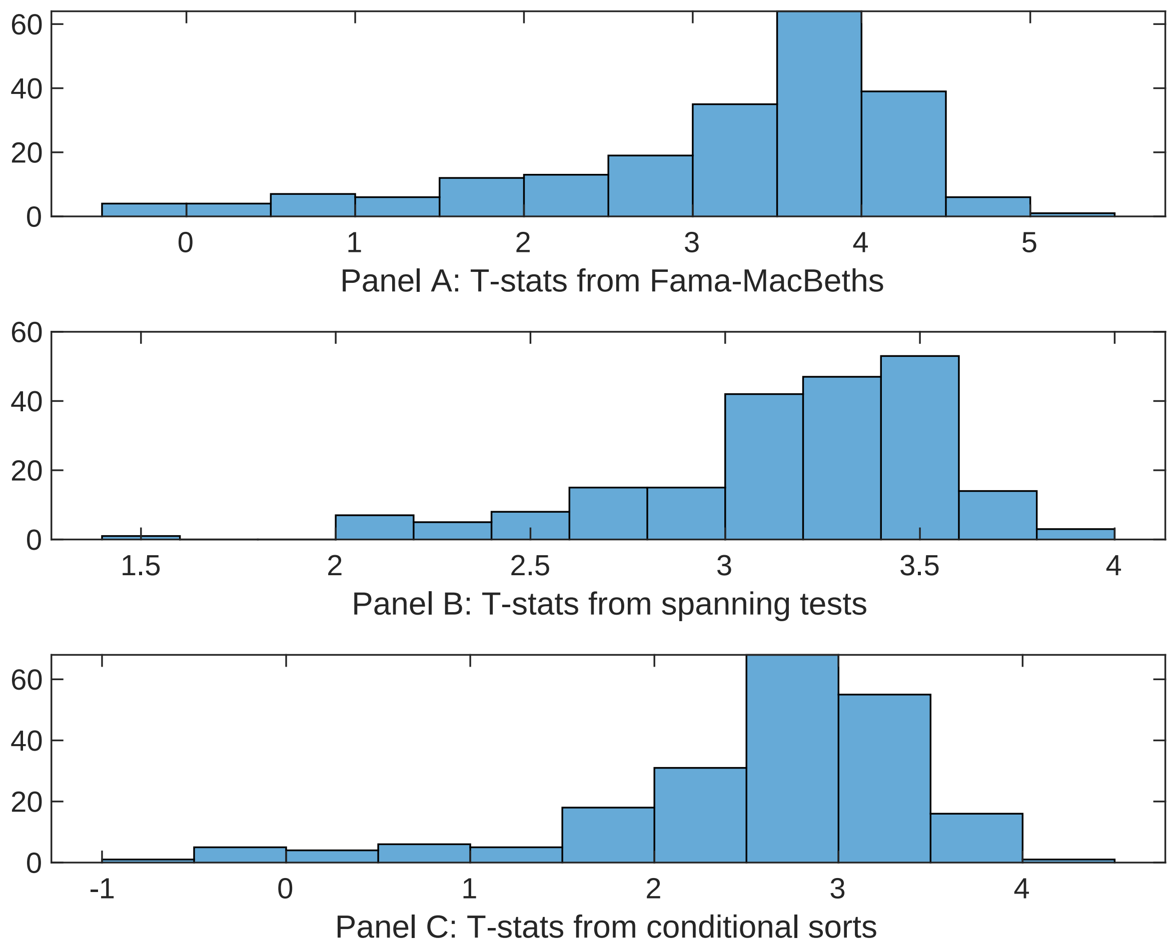

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of DISG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{DISG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{DISG} DISG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{DISG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 DISG. Stocks are finally grouped into five DISG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted DISG 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 DISG. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{DISG} DISG_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Net debt financing, Net external financing, Inventory Growth, Employment growth, 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	0.14	0.15	0.15
	[5.61]	[5.58]	[5.87]	[5.48]	[5.57]	[6.05]	[5.82]
DISG	0.18	0.85	0.65	0.30	0.19	-0.54	-0.37
	[0.00]	[0.13]	[1.09]	[3.70]	[2.95]	[-0.08]	[-0.45]
Anomaly 1	0.18						-0.58
	[9.39]						[-1.26]
Anomaly 2		0.21					0.11
		[9.41]					[1.67]
Anomaly 3			0.19				0.93
			[6.50]				[1.69]
Anomaly 4				0.38			0.76
				[6.65]			[1.35]
Anomaly 5					0.93		0.32
					[6.12]		[0.23]
Anomaly 6						0.11	0.77
						[9.33]	[3.98]
# 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 DISG trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{DISG} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Employment growth, 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	0.16	0.16	0.16	0.18	0.20	0.18	0.17
	[2.40]	[2.40]	[2.40]	[2.60]	[2.94]	[2.61]	[2.45]
Anomaly 1	21.09						11.34
	[5.28]						[2.13]
Anomaly 2		22.38					10.92
		[5.88]					[2.07]
Anomaly 3			14.42				10.35
			[4.14]				[2.79]
Anomaly 4				7.02			5.01
				[2.58]			[1.79]
Anomaly 5					9.90		5.92
					[2.57]		[1.47]
Anomaly 6						6.89	-3.10
						[1.53]	[-0.65]
mkt	-4.22	-4.47	-2.52	-4.66	-4.27	-4.44	-2.97
	[-2.71]	[-2.89]	[-1.54]	[-2.94]	[-2.69]	[-2.79]	[-1.83]
smb	0.67	1.06	7.20	3.27	2.99	1.86	5.23
	[0.28]	[0.44]	[2.69]	[1.33]	[1.22]	[0.74]	[1.85]
hml	-18.49	-19.25	-17.94	-19.79	-21.30	-19.79	-18.87
	[-6.18]	[-6.48]	[-5.90]	[-6.50]	[-6.82]	[-6.47]	[-6.17]
rmw	0.94	0.73	-6.08	3.52	2.91	2.58	-4.48
	[0.30]	[0.23]	[-1.62]	[1.11]	[0.92]	[0.82]	[-1.19]
cma	27.79	29.08	25.15	28.56	25.71	26.22	15.28
	[5.90]	[6.32]	[4.91]	[5.49]	[4.43]	[3.61]	[2.07]
umd	1.51	1.71	3.49	2.90	3.05	3.82	0.65
	[0.93]	[1.07]	[2.20]	[1.79]	[1.89]	[2.36]	[0.40]
# months	588	588	588	588	588	588	588
$\bar{R}^2$(%)	19	20	17	16	16	15	21

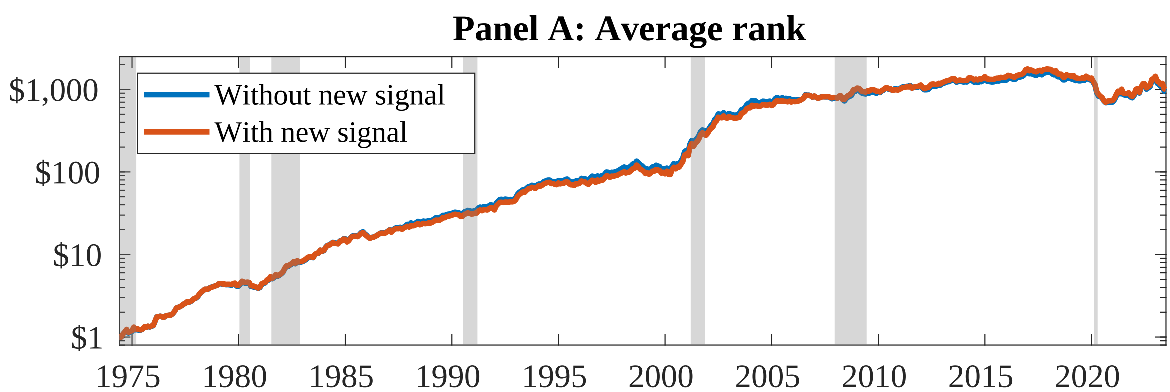

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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