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

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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 in the cross-section of stocks, debate persists about whether these patterns represent genuine market inefficiencies or compensation for risk. A particularly important yet understudied channel is how firms' financing decisions interact with their real operations to affect future performance and returns.

Despite the theoretical importance of the interplay between financing and operations, existing research has largely examined debt levels and operational metrics in isolation. This gap is notable given that debt financing can both enable growth and constrain operational flexibility, suggesting a complex relationship that may not be fully priced by market participants.

We propose that the impact of debt on sales growth (DISG) provides a unique window into how financing decisions affect operational outcomes and, ultimately, stock returns. Building on Myers (1977)'s debt overhang theory, we argue that high debt levels can impair a firm's ability to pursue revenue-generating opportunities, particularly when facing competitive pressures or economic uncertainty. This mechanism suggests that firms whose debt levels are constraining sales growth may face heightened business risk.

The relationship between DISG and expected returns can be understood through two complementary channels. First, following Opler and Titman (1994), firms with debt-constrained growth may face higher costs of financial distress as their inability to grow revenues makes it harder to service existing debt obligations. Second, drawing on Berk et al. (1999), constraints on revenue growth may increase the firm's systematic risk by reducing its operational flexibility to respond to adverse market conditions.

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These theoretical mechanisms suggest that stocks with more negative DISG (indicating greater debt constraints on sales growth) should earn higher expected returns as compensation for both financial distress risk and reduced operational flexibility. This prediction is distinct from previously documented relationships between leverage and returns (George and Hwang, 2001) or between investment and returns (Titman et al., 2004).

Our empirical analysis strongly supports the predicted relationship between DISG and future stock returns. A value-weighted long-short portfolio strategy based on DISG generates monthly abnormal returns of 17 basis points relative to the Fama-French six-factor model, with a t-statistic of 2.51. The strategy achieves an annualized gross Sharpe ratio of 0.45, placing it in the top 12% of documented return predictors.

Importantly, the predictive power of DISG remains robust after controlling for size. Among the largest quintile of stocks, the DISG strategy earns monthly abnormal returns of 28 basis points (t-statistic = 3.11), addressing concerns that the effect might be limited to small, illiquid stocks. The strategy's performance persists after accounting for transaction costs, with a net Sharpe ratio of 0.34.

Further analysis demonstrates that DISG's predictive power is distinct from related anomalies. Controlling for the six most closely related predictors including change in financial liabilities, net debt financing, and asset growth, DISG continues to generate significant abnormal returns of 17 basis points per month (t-statistic = 2.45).

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the interaction between financing decisions and operational outcomes, extending work by Opler and Titman (1994) on financial constraints and Titman et al. (2004) on investment-based anomalies. Unlike previous research that examines debt or growth in isolation, DISG provides

a unified measure of how financing choices affect operational flexibility.

Second, we contribute to the growing literature on factor investing by documenting a robust return predictor that performs well among large, liquid stocks. Our findings complement recent work by Novy-Marx and Velikov (2023) on evaluating trading strategies, showing that DISG generates economically meaningful returns even after accounting for implementation costs and various methodological considerations.

Finally, our results have important implications for understanding market efficiency and risk pricing. The persistent abnormal returns associated with DISG suggest either that markets systematically underestimate the impact of debt-constrained growth on firm value, or that DISG captures a previously unidentified dimension of systematic risk. These findings open new avenues for research on the intersection of corporate financing decisions and asset prices.

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 cash proceeds from issuing long-term debt 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

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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

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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$^{\text{th}}$ 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%

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[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,

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[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 significance of Debt Impact on Sales Growth (DISG) 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 DISG generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.45 (0.34 net of transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that DISG captures unique information about firm performance and future stock returns that is not fully reflected

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[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.

in current market prices.

Particularly noteworthy is the signal's ability to maintain its predictive power when tested against the Fama-French five-factor model plus momentum, as well as six closely related strategies from the factor zoo. The consistent alpha of 17 basis points per month (t-statistic of 2.45) in the presence of these controls underscores the distinctive nature of the DISG signal and its potential value for investment professionals.

However, several limitations should be considered. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market conditions. Second, transaction costs and market impact could affect the real-world implementation of DISG-based strategies, particularly for larger portfolios.

Future research could explore the international validity of the DISG signal, its interaction with other established anomalies, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the DISG effect could provide valuable insights into firm behavior and market efficiency. Researchers might also consider examining how the signal's effectiveness varies across different firm characteristics and market conditions to better understand its practical applications and limitations.
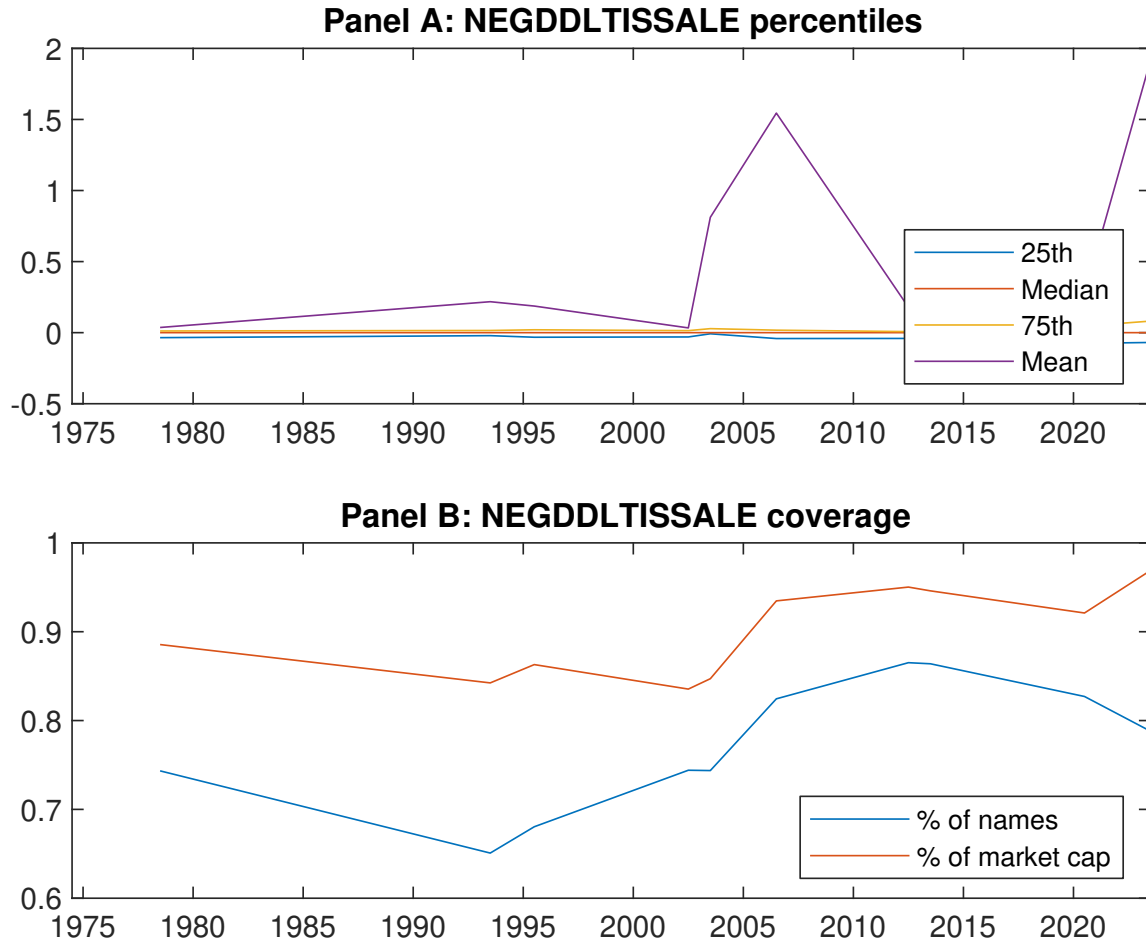
Figure 1: Times series of DISG percentiles and coverage.
This figure plots descriptive statistics for DISG. Panel A shows cross-sectional percentiles of DISG over the sample. Panel B plots the monthly coverage of DISG relative to the universe of CRSP stocks with available market capitalizations.

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.

	(L)	(2)	(3)	(4)	(H)	(H-L)
Panel A: Excess returns and alphas on DISG-sorted portfolios						
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}
	(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]
Size quintiles	(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

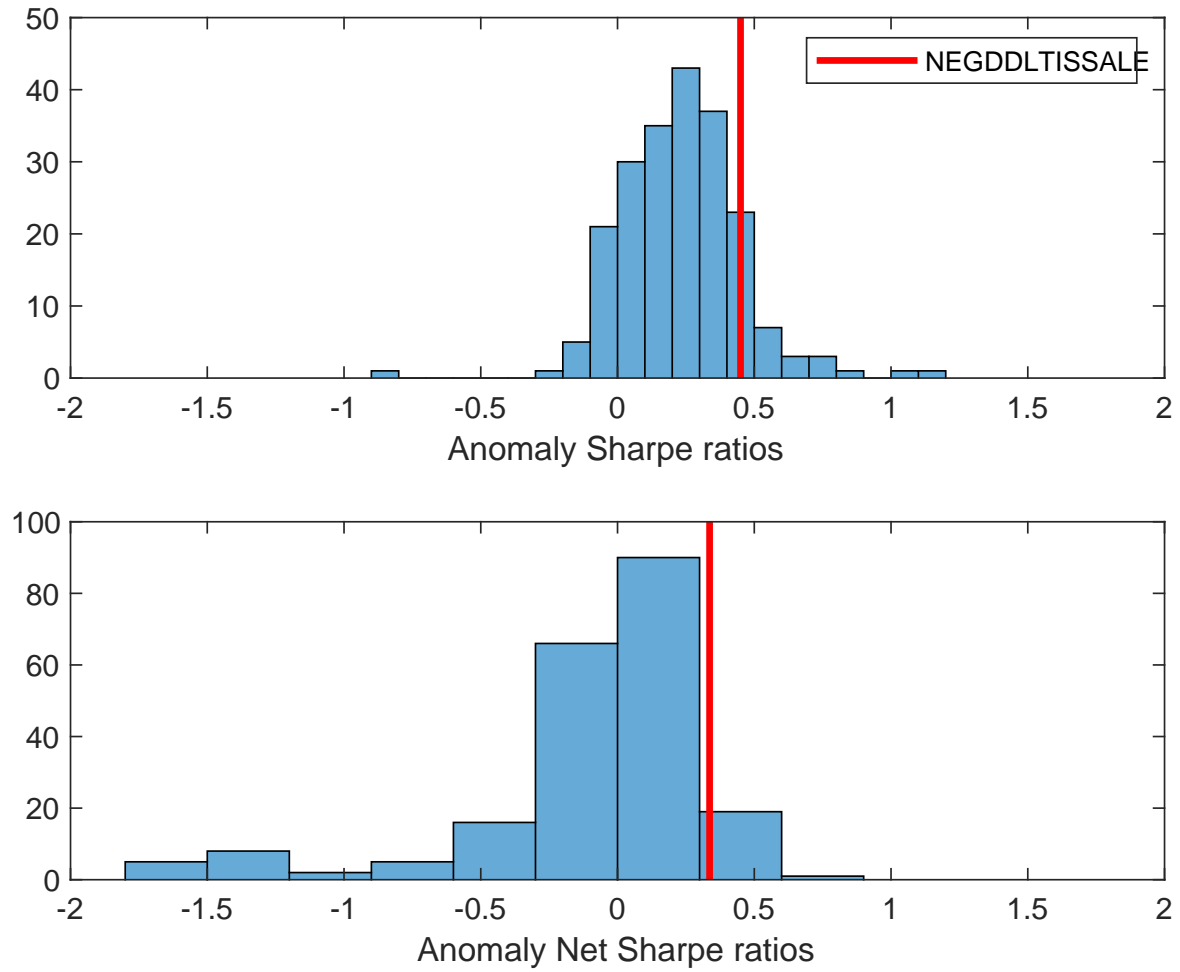|		DISG Quintiles					DISG Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
	(1)	389	391	390	391	386	36	33	32	33	34
	(2)	107	107	107	107	107	59	59	58	60	59
Size quintiles	(3)	76	77	76	77	76	104	106	101	104	104
	(4)	64	65	65	65	64	224	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.
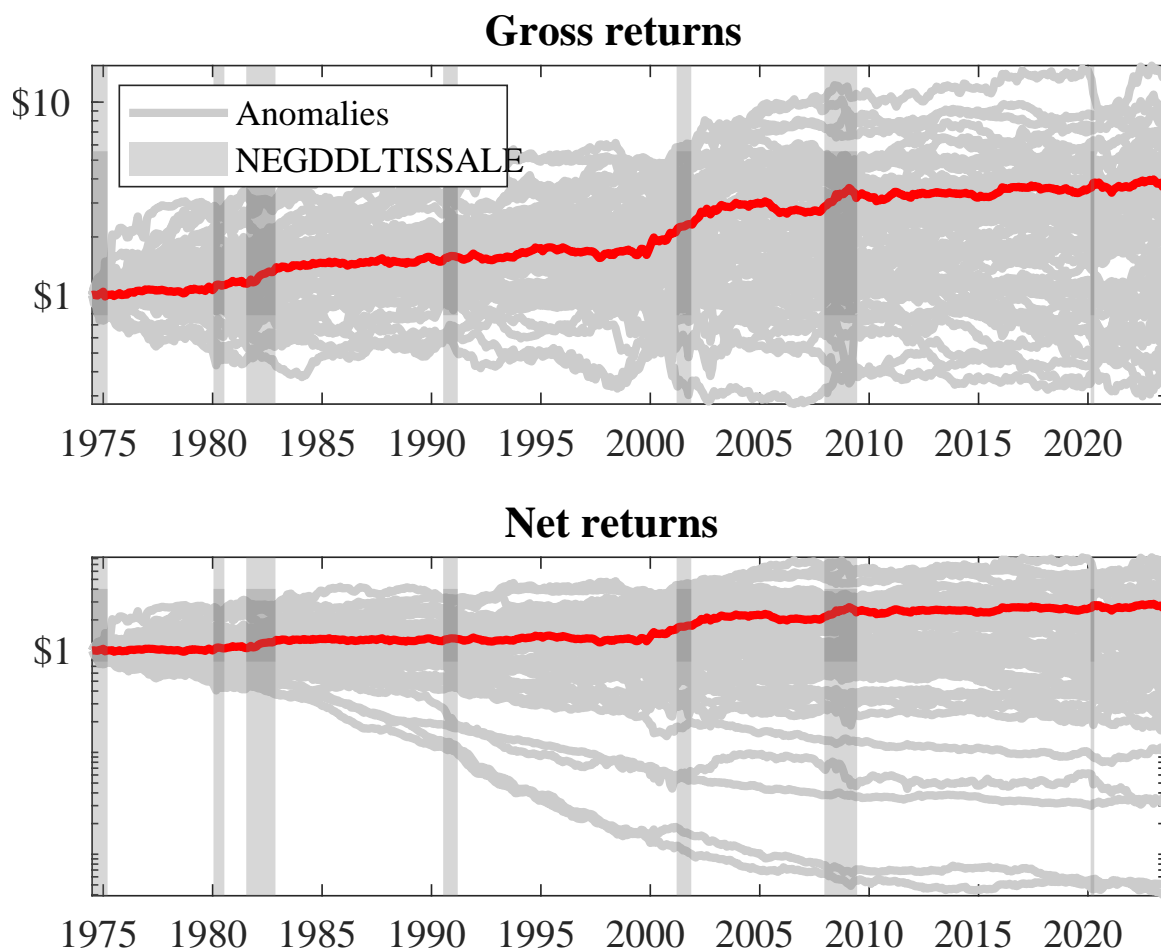
Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the DISG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel B plots results for net strtaegy returns.
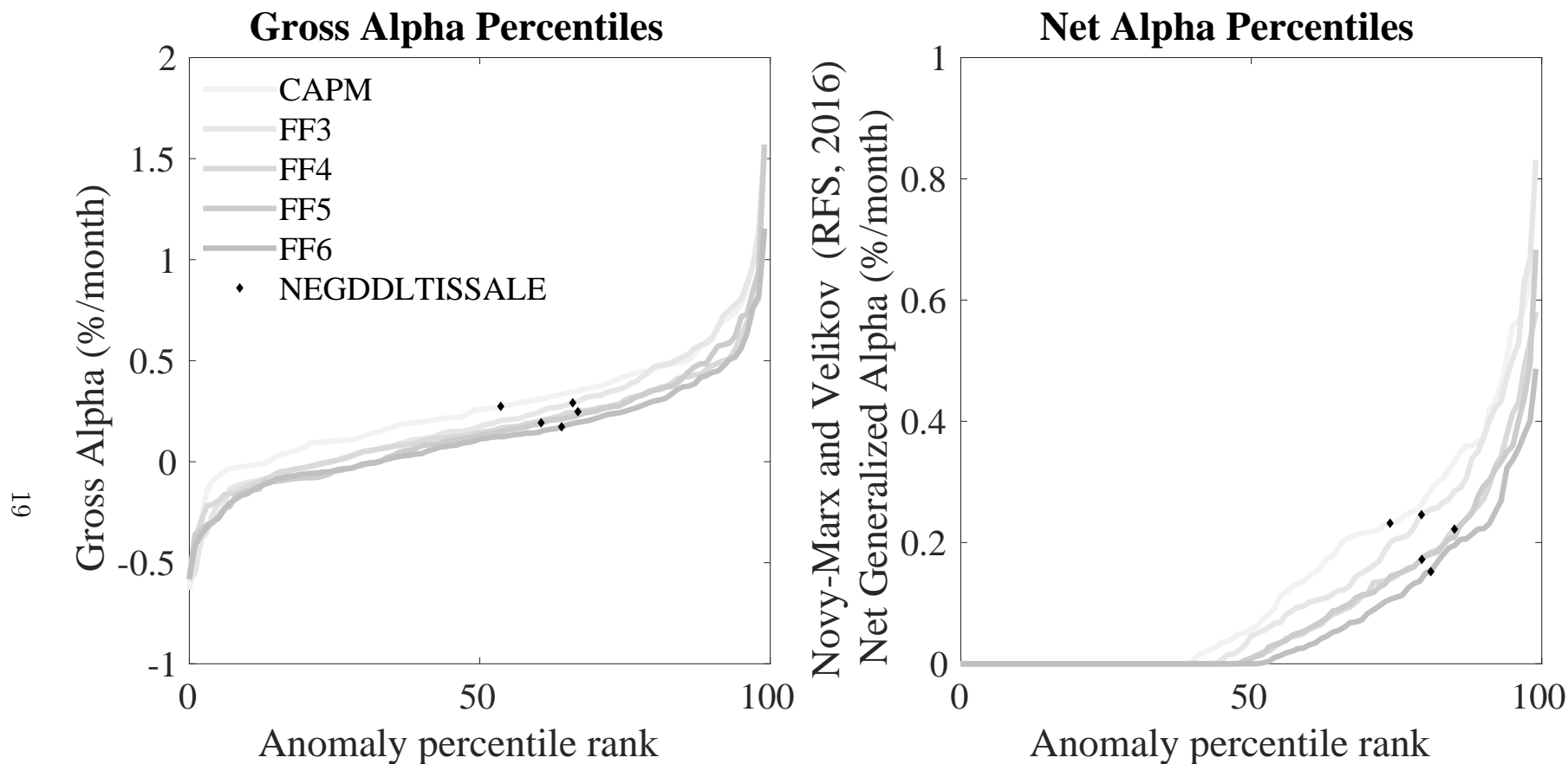
Gross Alpha Percentiles

Net Alpha Percentiles

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.
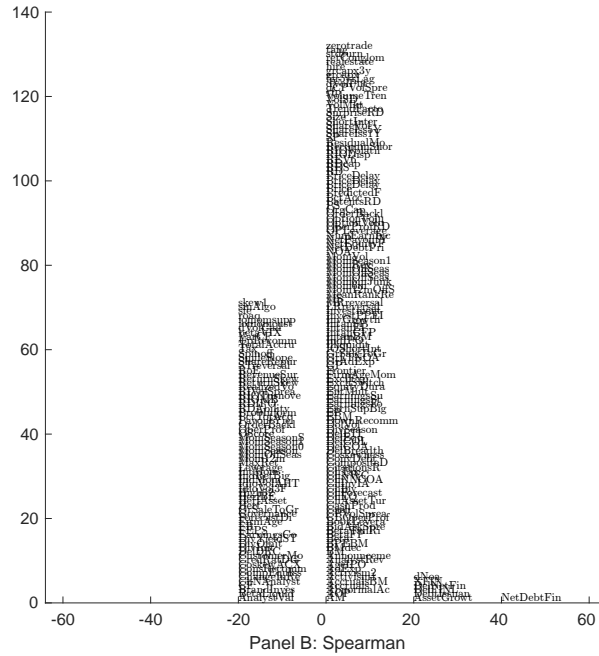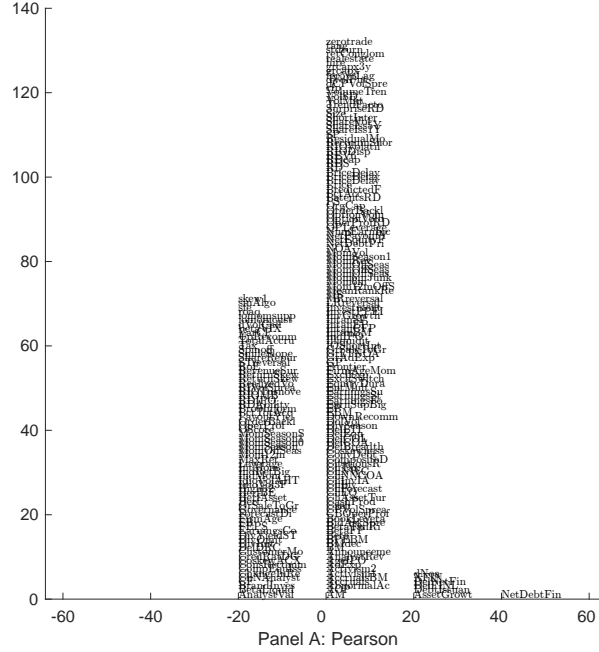
Figure 5: Distribution of correlations.

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.
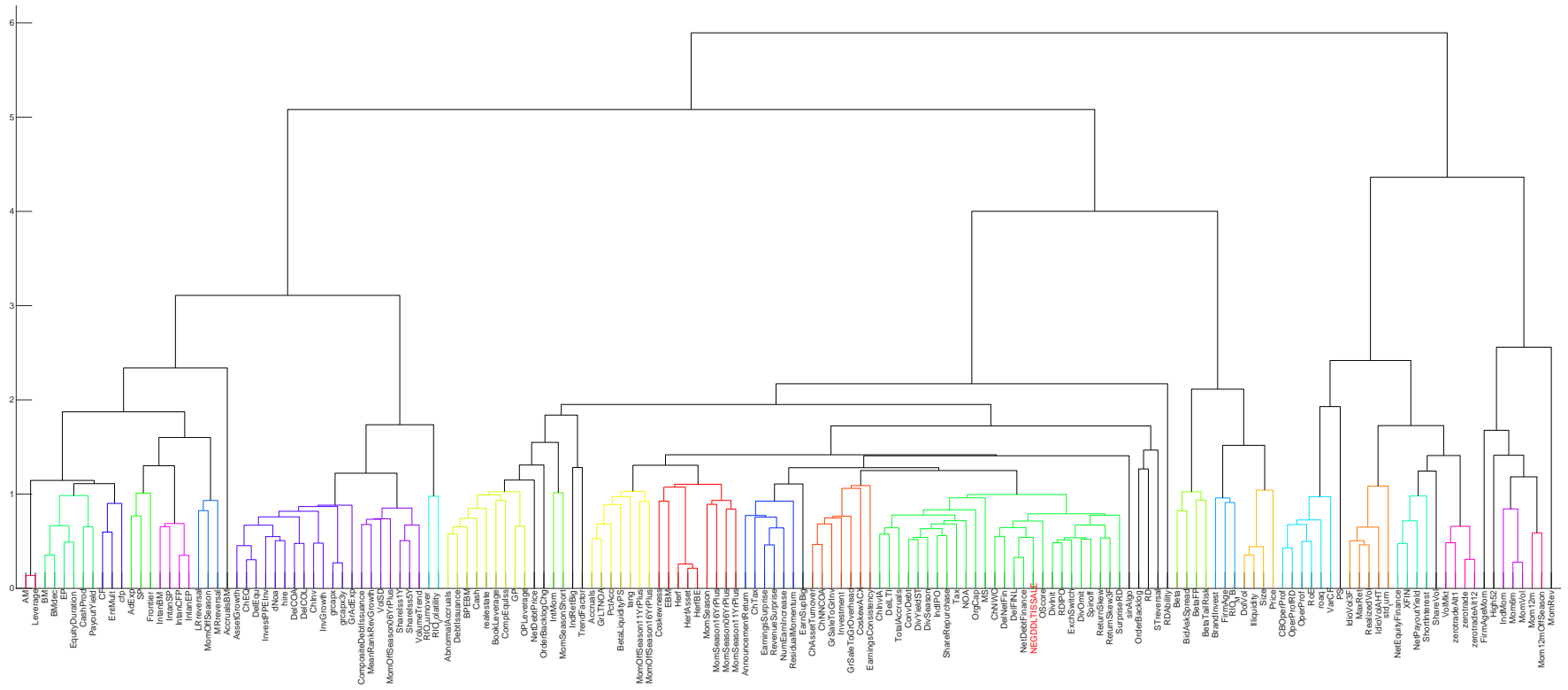
Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.
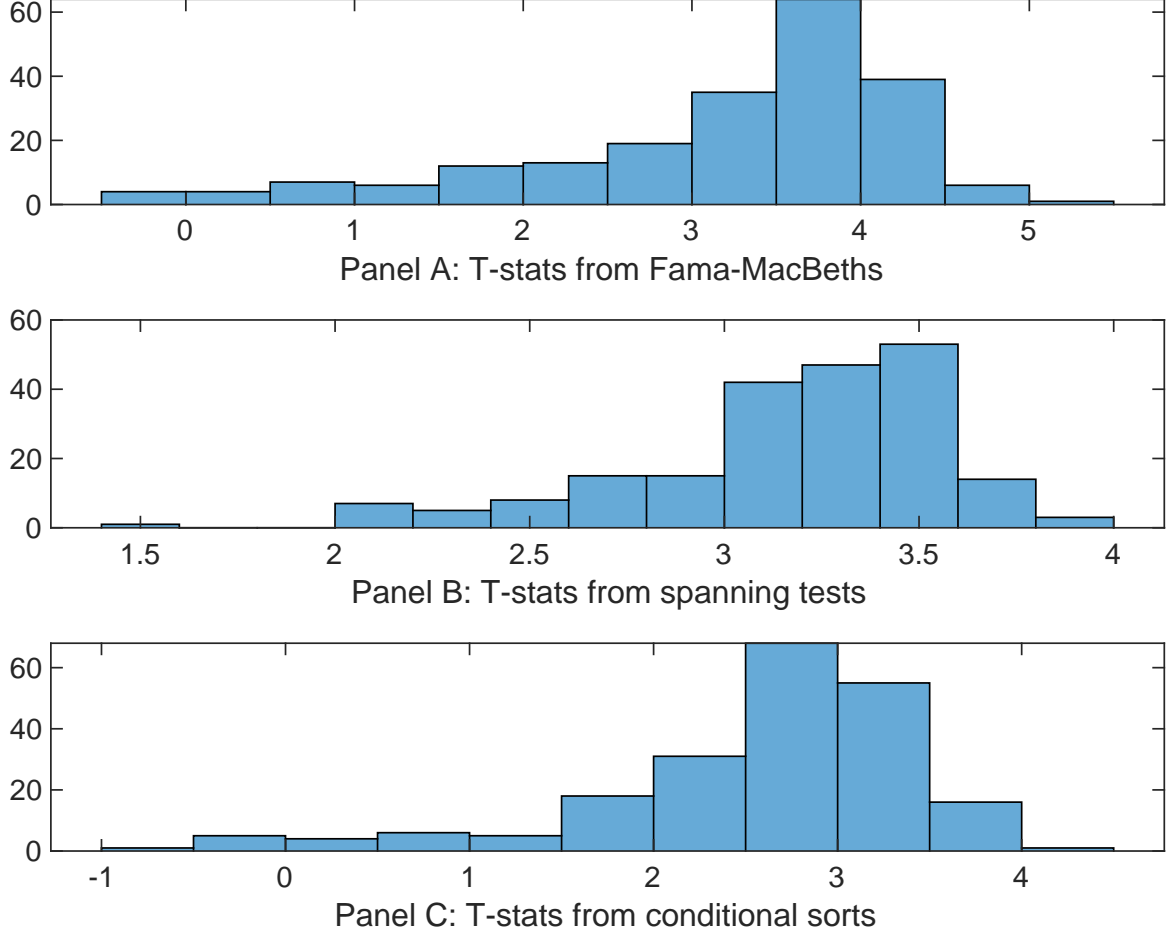
Figure 7: Distribution of t-stats on conditioning strategies

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.

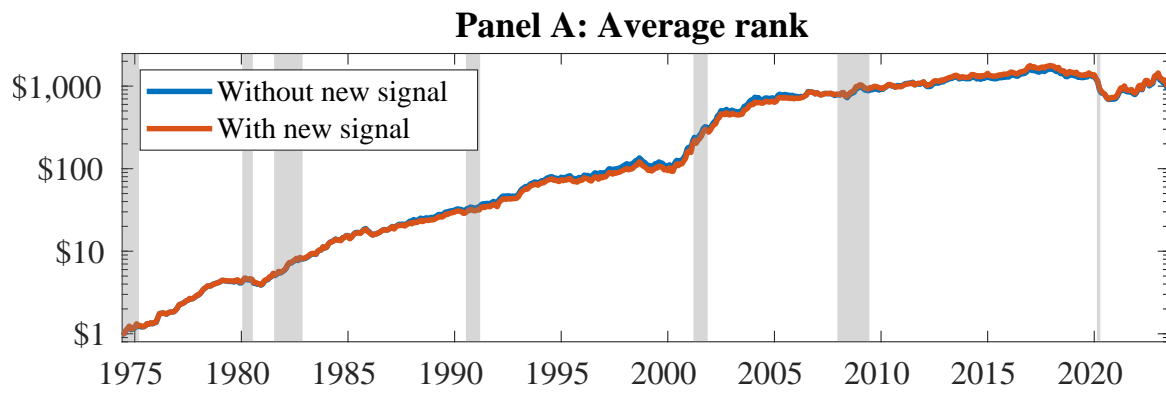|							
Intercept	0.16	0.16	0.16	0.18	0.20	0.18	0.17
	[2.40]	[2.40]	[2.40]	[2.60]	[2.94]	[2.61]	[2.45]
Anomaly 1	21.09						11.34
	[5.28]						[2.13]
Anomaly 2		22.38					10.92
		[5.88]					[2.07]
Anomaly 3			14.42				10.35
			[4.14]				[2.79]
Anomaly 4				7.02			5.01
				[2.58]			[1.79]
Anomaly 5					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

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 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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