Stock Depreciation Gradient and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Depreciation Gradient (SDG), 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 SDG achieves an annualized gross (net) Sharpe ratio of 0.60 (0.53), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (24) bps/month with a t-statistic of 3.06 (3.06), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 20 bps/month with a t-statistic of 2.62.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to identify reliable signals that predict cross-sectional variation in stock returns. While hundreds of potential predictors have been documented in the literature, many fail to generate economically meaningful returns after accounting for transaction costs or lack theoretical foundations (Harvey et al., 2016; Chen and Zimmermann, 2022). The depreciation of corporate assets represents a fundamental aspect of firm operations that has received limited attention in the asset pricing literature, despite its direct connection to firm value and investment decisions.

Prior research has focused primarily on aggregate measures of investment and capital expenditure (Titman et al., 2004; Cooper et al., 2008), but has not specifically examined how the pattern of depreciation across a firm's asset base affects expected returns. This gap is particularly notable given that depreciation schedules reflect management's expectations about asset productivity and economic obsolescence, potentially containing valuable information about future cash flows and risks.

We propose that the Stock Depreciation Gradient (SDG), defined as the slope of a firm's depreciation schedule across its asset vintages, provides a novel window into management's private information about asset productivity and future investment opportunities. Building on the q-theory of investment (Tobin, 1969; Cochrane and Saa-Requejo, 2000), firms with steeper depreciation gradients may be signaling expectations of more rapid technological obsolescence or declining productivity of existing assets.

The theoretical link between depreciation patterns and expected returns operates through two primary channels. First, following (Zhang, 2005), firms with accelerated depreciation schedules face greater adjustment costs when responding to productivity shocks, leading to higher systematic risk. Second, as argued by (Berk and Green, 2004), steeper depreciation gradients may indicate reduced growth options and flexibility in the firm's asset base, requiring higher expected returns to compensate investors.

These mechanisms suggest that firms with steeper depreciation gradients (more negative SDG) should earn lower expected returns compared to firms with flatter depreciation schedules. This relationship should be particularly pronounced among firms with greater capital intensity and technological exposure, where the information content of depreciation decisions is most relevant for valuation.

Our empirical analysis confirms a strong relationship between SDG and future stock returns. A value-weighted long-short portfolio that buys stocks with high SDG and sells stocks with low SDG generates monthly abnormal returns of 24 basis points relative to the Fama-French six-factor model, with a t-statistic of 3.06. The strategy achieves an annualized gross Sharpe ratio of 0.60, placing it in the 96th percentile among documented anomalies.

Importantly, the predictive power of SDG remains robust after controlling for transaction costs. The strategy maintains a net Sharpe ratio of 0.53 and continues to generate significant abnormal returns across different portfolio construction approaches. The effect persists among large-cap stocks, with the long-short portfolio earning monthly returns of 26 basis points (t-statistic = 2.73) among stocks above the 80th percentile of market capitalization.

Spanning tests demonstrate that SDG captures unique information not contained in related anomalies. Controlling for the six most closely related predictors and the Fama-French six factors, the strategy maintains a monthly alpha of 20 basis points (t-statistic = 2.62). This indicates that SDG represents a distinct source of predictable variation in stock returns rather than simply repackaging known effects.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that exploits detailed accounting information about firms' depreciation policies, extending the literature on investment-based return predictability (Titman et al., 2004; Cooper et al., 2008). Unlike existing measures that focus on aggregate investment levels, SDG captures management's forward-looking assessments of asset productivity embedded in depreciation choices.

Second, we contribute to the growing literature on accounting-based anomalies (Sloan, 1996; Richardson et al., 2005) by showing how the temporal pattern of depreciation expenses, rather than just their magnitude, contains valuable information for predicting returns. Our findings suggest that careful analysis of financial statement details can reveal subtle signals about future firm performance.

Third, our results have important implications for both academic research and investment practice. For researchers, we demonstrate that firm depreciation policies contain more information than previously recognized, opening new avenues for investigating how accounting choices reflect and affect firm risk. For practitioners, we document a robust return predictor that remains effective among large, liquid stocks and survives transaction costs, making it feasible to implement in practice.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Stock Depreciation Gradient. 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 CSTK for common stock and item DP for depreciation and amortization. Common stock (CSTK) represents the total value of common shares issued by the company, while depreciation and amortization (DP) reflects the systematic allocation of asset costs over their useful lives, capturing the gradual reduction in value of the firm's assets. The construction of the signal follows a difference-based approach, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year's depreciation and amortization (DP). This gradient measure captures the relative change in equity capital structure normalized by the firm's depreciation expense, potentially offering insight into how firms manage their capital structure in relation to their asset base depreciation. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and asset management efficiency in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and DP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SDG signal. Panel A plots the time-series of the mean, median, and interquartile range for SDG. On average, the cross-sectional mean (median) SDG is -0.38 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SDG data. The signal's interquartile range spans -0.19 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SDG signal for the CRSP universe. On average, the SDG signal is available for 6.41% of CRSP names, which on average make up 7.62% of total market capitalization.

4 Does SDG predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SDG 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 SDG portfolio and sells the low SDG 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 SDG strategy earns an average return of 0.36% per month with a t-statistic of 4.55. The annualized Sharpe ratio of the strategy is 0.60. The alphas range from 0.24% to 0.38% per month and have t-statistics exceeding 3.06 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 0.33, with a t-statistic of 6.20 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 565 stocks and an average market capitalization of at least $1,454 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 cap breakpoints and value-weighted portfolios, and equals 31 bps/month with a t-statistics of 3.85. 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 27-33bps/month. The lowest return, (27 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.40. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SDG trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the SDG strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SDG, as well as average returns and alphas for long/short trading SDG 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 SDG strategy achieves an average return of 26 bps/month with a t-statistic of 2.73. Among these large cap stocks, the alphas for the SDG strategy relative to the five most common factor models range from 21 to 27 bps/month with t-statistics between 2.17 and 2.81.

5 How does SDG perform relative to the zoo?

Figure 2 puts the performance of SDG 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 SDG strategy falls in the distribution. The SDG strategy's gross (net) Sharpe ratio of 0.60 (0.53) is greater than 96% (99%) 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 SDG strategy (red line).[2] Ignoring trading costs, a $1 invested in the SDG strategy would have yielded $9.24 which ranks the SDG strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SDG strategy would have yielded $6.89 which ranks the SDG strategy in the top 0% 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 SDG relative to those. Panel A shows that the SDG strategy gross alphas fall between the 71 and 75 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 196606 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 SDG strategy has a positive net generalized alpha for five out of the five factor models. In these cases SDG ranks between the 86 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SDG 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 SDG signal in these Fama-MacBeth regressions exceed 2.59, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SDG is 2.13.

Similarly, Table 5 reports results from spanning tests that regress returns to the SDG 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 SDG strategy earns alphas that range from 21-26bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.73, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SDG trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.62.

7 Does SDG add relative to the whole zoo?

Finally, we can ask how much adding SDG 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 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the SDG 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 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes SDG grows to $2280.28.

8 Conclusion

This study provides compelling evidence for the effectiveness of Stock Depreciation Gradient (SDG) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on SDG delivers economically and statistically significant results, with an impressive annualized gross Sharpe ratio of 0.60 and net Sharpe ratio of 0.53. The strategy's persistence in generating significant abnormal returns, even after controlling for the Fama-French five factors and momentum (24 bps/month), underscores its unique predictive power.

Particularly noteworthy is the signal's continued significance (20 bps/month al-

[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 SDG is available.

pha) when tested against six closely related factors from the factor zoo, suggesting that SDG captures distinct information not fully explained by existing investment strategies. These results remain robust after accounting for transaction costs, indicating practical implementability for institutional investors.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be explored. Additionally, the study period may not fully capture the signal's behavior across different market regimes.

Future research could extend this work by examining SDG's performance in international markets, investigating its interaction with other established factors, and exploring potential variations in its effectiveness across different market conditions and sectors. Furthermore, research into the underlying economic mechanisms driving SDG's predictive power could provide valuable insights for both academics and practitioners.

In conclusion, SDG represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that persists even after controlling for well-known factors and transaction costs.

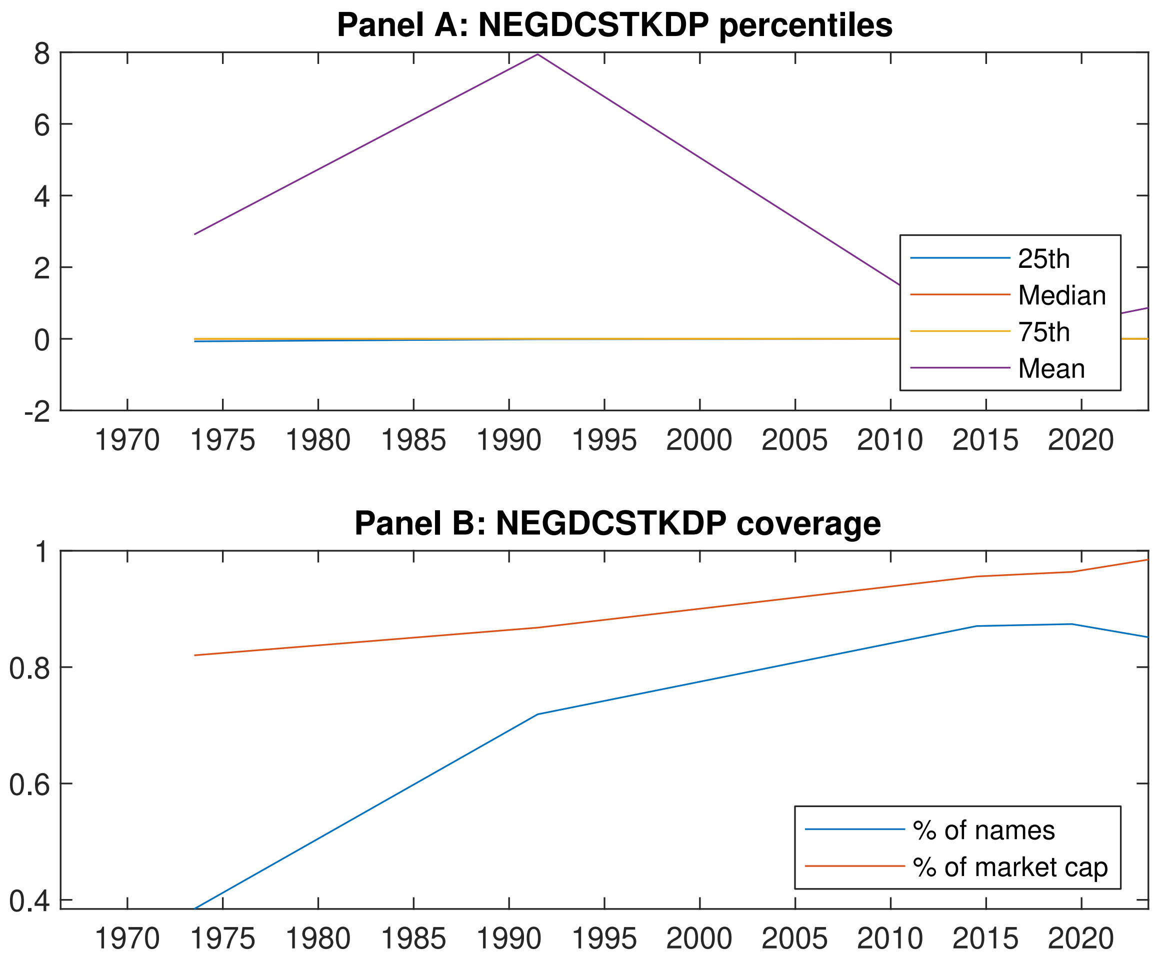

Figure 1: Times series of SDG percentiles and coverage.
This figure plots descriptive statistics for SDG. Panel A shows cross-sectional percentiles of SDG over the sample. Panel B plots the monthly coverage of SDG relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SDG. 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 196606 to 202306.

Panel A: Excess returns and alphas on SDG-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.49	0.65	0.68	0.77	0.36
	[2.30]	[2.61]	[3.36]	[4.07]	[4.54]	[4.55]
α_{CAPM}	-0.15	-0.11	0.04	0.16	0.24	0.38
	[-2.82]	[-2.37]	[0.83]	[3.30]	[5.00]	[4.91]
α_{FF3}	-0.15	-0.09	0.07	0.12	0.20	0.35
	[-2.85]	[-1.97]	[1.37]	[2.76]	[4.33]	[4.43]
α_{FF4}	-0.13	-0.05	0.09	0.08	0.18	0.31
	[-2.42]	[-1.19]	[1.76]	[1.76]	[3.93]	[3.91]
α_{FF5}	-0.16	-0.04	0.11	0.03	0.10	0.26
	[-3.10]	[-0.88]	[2.05]	[0.61]	[2.21]	[3.34]
α_{FF6}	-0.15	-0.02	0.12	-0.00	0.09	0.24
	[-2.77]	[-0.34]	[2.29]	[-0.02]	[2.11]	[3.06]
Panel B: Fama and French (2018) 6-factor model loadings for SDG-sorted portfolios						
β_{MKT}	0.98	1.02	1.02	0.99	0.98	0.01
	[78.19]	[96.88]	[80.29]	[95.25]	[93.49]	[0.44]
β_{SMB}	-0.01	0.03	0.03	-0.06	-0.01	-0.01
	[-0.36]	[1.92]	[1.49]	[-3.94]	[-0.75]	[-0.19]
β_{HML}	0.05	-0.04	-0.06	0.03	0.02	-0.02
	[2.00]	[-2.20]	[-2.33]	[1.72]	[1.18]	[-0.68]
β_{RMW}	0.11	-0.07	-0.04	0.11	0.13	0.02
	[4.60]	[-3.28]	[-1.72]	[5.41]	[6.36]	[0.52]
β_{CMA}	-0.10	-0.07	-0.08	0.22	0.22	0.33
	[-2.88]	[-2.43]	[-2.29]	[7.45]	[7.51]	[6.20]
β_{UMD}	-0.03	-0.04	-0.02	0.04	0.00	0.03
	[-2.03]	[-3.58]	[-1.76]	[4.23]	[0.47]	[1.63]
Panel C: Average number of firms (n) and market capitalization (me)						
n	795	683	565	673	744	
me ($\$10^6$)	1689	1454	1973	2209	2400	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SDG 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 196606 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	0.36	0.38	0.35	0.31	0.26	0.24
			[4.55]	[4.91]	[4.43]	[3.91]	[3.34]	[3.06]
Quintile	NYSE	EW	0.53	0.60	0.52	0.44	0.38	0.33
			[7.99]	[9.55]	[9.02]	[7.77]	[6.92]	[6.05]
Quintile	Name	VW	0.36	0.38	0.34	0.30	0.27	0.24
			[4.64]	[4.80]	[4.32]	[3.73]	[3.43]	[3.07]
Quintile	Cap	VW	0.31	0.33	0.30	0.26	0.27	0.24
			[3.85]	[4.07]	[3.73]	[3.15]	[3.38]	[2.98]
Decile	NYSE	VW	0.37	0.39	0.33	0.27	0.29	0.25
			[3.89]	[4.10]	[3.47]	[2.84]	[3.04]	[2.61]
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	0.32	0.35	0.32	0.30	0.25	0.24
			[4.06]	[4.46]	[4.04]	[3.79]	[3.21]	[3.06]
Quintile	NYSE	EW	0.32	0.39	0.31	0.27	0.17	0.15
			[4.43]	[5.51]	[4.83]	[4.28]	[2.73]	[2.42]
Quintile	Name	VW	0.32	0.35	0.31	0.29	0.26	0.25
			[4.15]	[4.41]	[3.99]	[3.70]	[3.33]	[3.15]
Quintile	Cap	VW	0.27	0.30	0.27	0.25	0.26	0.24
			[3.40]	[3.68]	[3.38]	[3.08]	[3.20]	[2.98]
Decile	NYSE	VW	0.33	0.36	0.30	0.27	0.27	0.25
			[3.45]	[3.70]	[3.17]	[2.85]	[2.81]	[2.63]

Table 3: Conditional sort on size and SDG

This table presents results for conditional double sorts on size and SDG. 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 SDG. 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 SDG and short stocks with low SDG .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

Panel A: portfolio average returns and time-series regression results

		SDG Quintiles					SDG Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.41	0.63	0.89	0.96	0.98	0.57	0.63	0.56	0.50	0.44	0.40
		[1.56]	[2.39]	[3.39]	[3.79]	[4.08]	[7.33]	[8.16]	[7.75]	[6.87]	[6.09]	[5.52]
	(2)	0.49	0.65	0.88	0.89	0.95	0.45	0.52	0.41	0.37	0.34	0.31
		[2.05]	[2.65]	[3.58]	[3.77]	[4.23]	[4.97]	[5.72]	[4.86]	[4.25]	[3.97]	[3.58]
	(3)	0.62	0.58	0.79	0.83	0.93	0.31	0.35	0.29	0.28	0.22	0.22
		[2.85]	[2.62]	[3.35]	[3.95]	[4.55]	[3.92]	[4.50]	[3.81]	[3.54]	[2.87]	[2.76]
	(4)	0.48	0.60	0.82	0.79	0.80	0.32	0.36	0.28	0.27	0.12	0.12
		[2.40]	[2.83]	[3.91]	[3.92]	[4.21]	[4.00]	[4.42]	[3.69]	[3.42]	[1.60]	[1.60]
	(5)	0.46	0.48	0.49	0.55	0.72	0.26	0.27	0.25	0.21	0.25	0.22
		[2.65]	[2.60]	[2.67]	[3.16]	[4.33]	[2.73]	[2.81]	[2.56]	[2.17]	[2.53]	[2.25]

Panel B: Portfolio average number of firms and market capitalization

		SDG Quintiles					SDG Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	390	388	387	386	387	32	33	40	29	29
	(2)	106	106	105	105	105	55	56	56	55	56
	(3)	77	76	75	75	76	96	93	95	97	98
	(4)	64	64	64	64	64	199	201	207	210	212
	(5)	59	59	59	59	59	1375	1408	1684	1576	1738

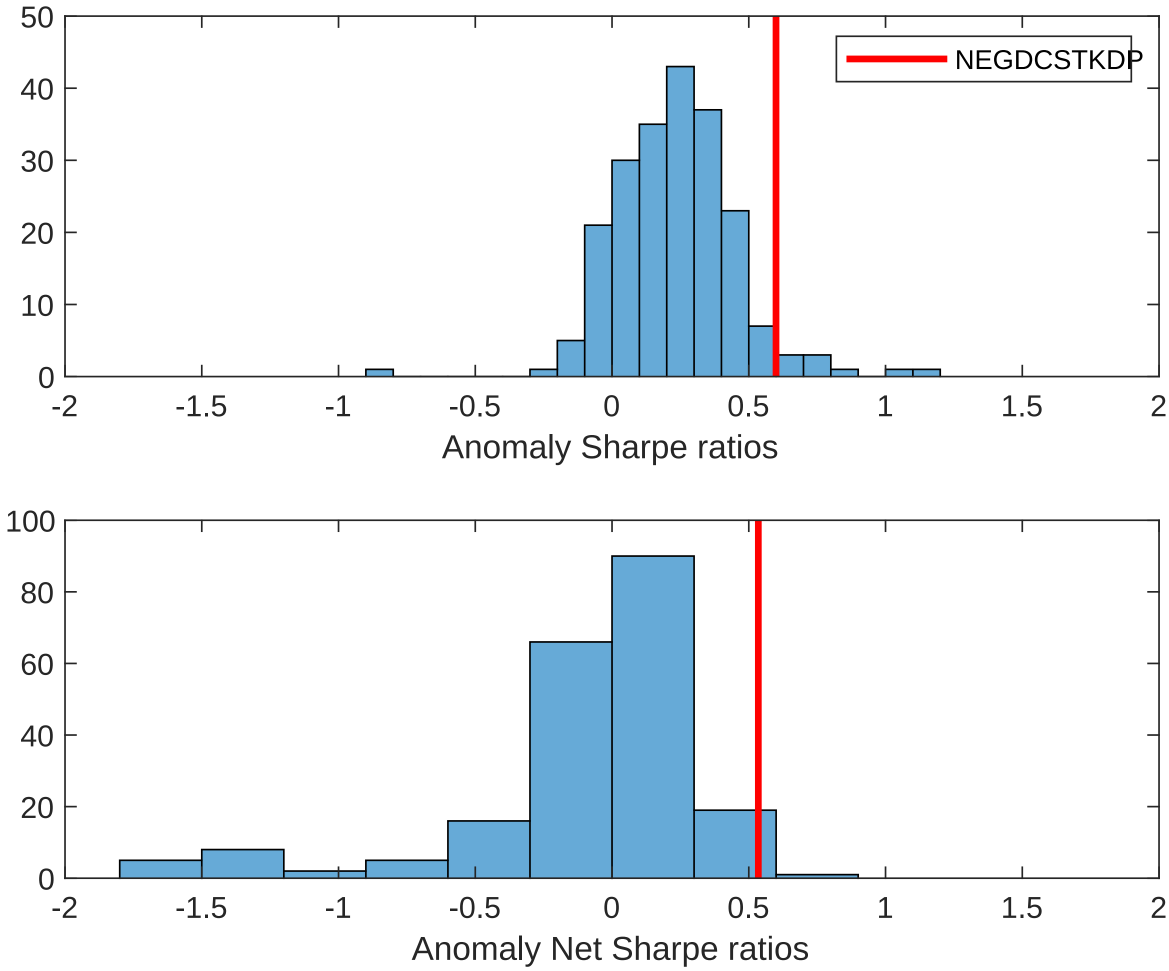

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SDG with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

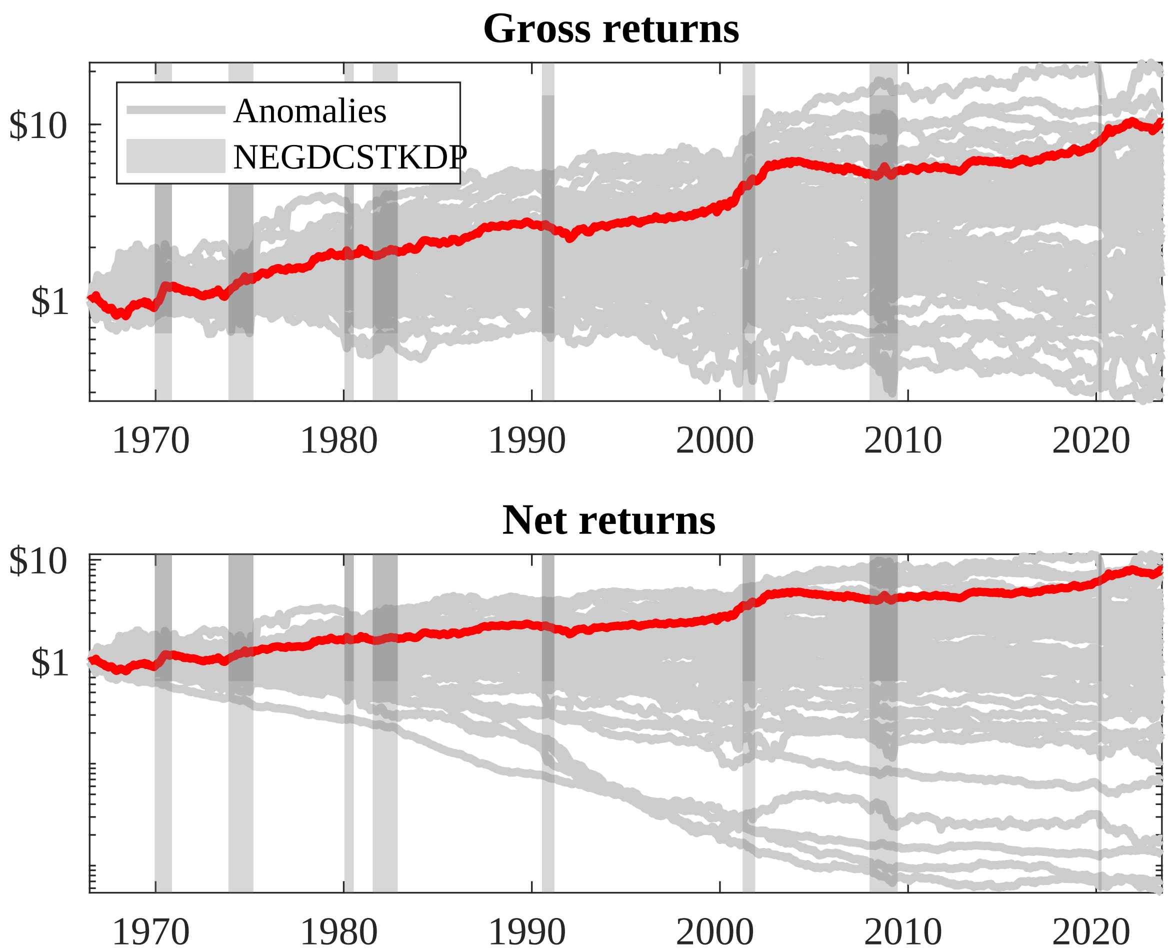

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SDG trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

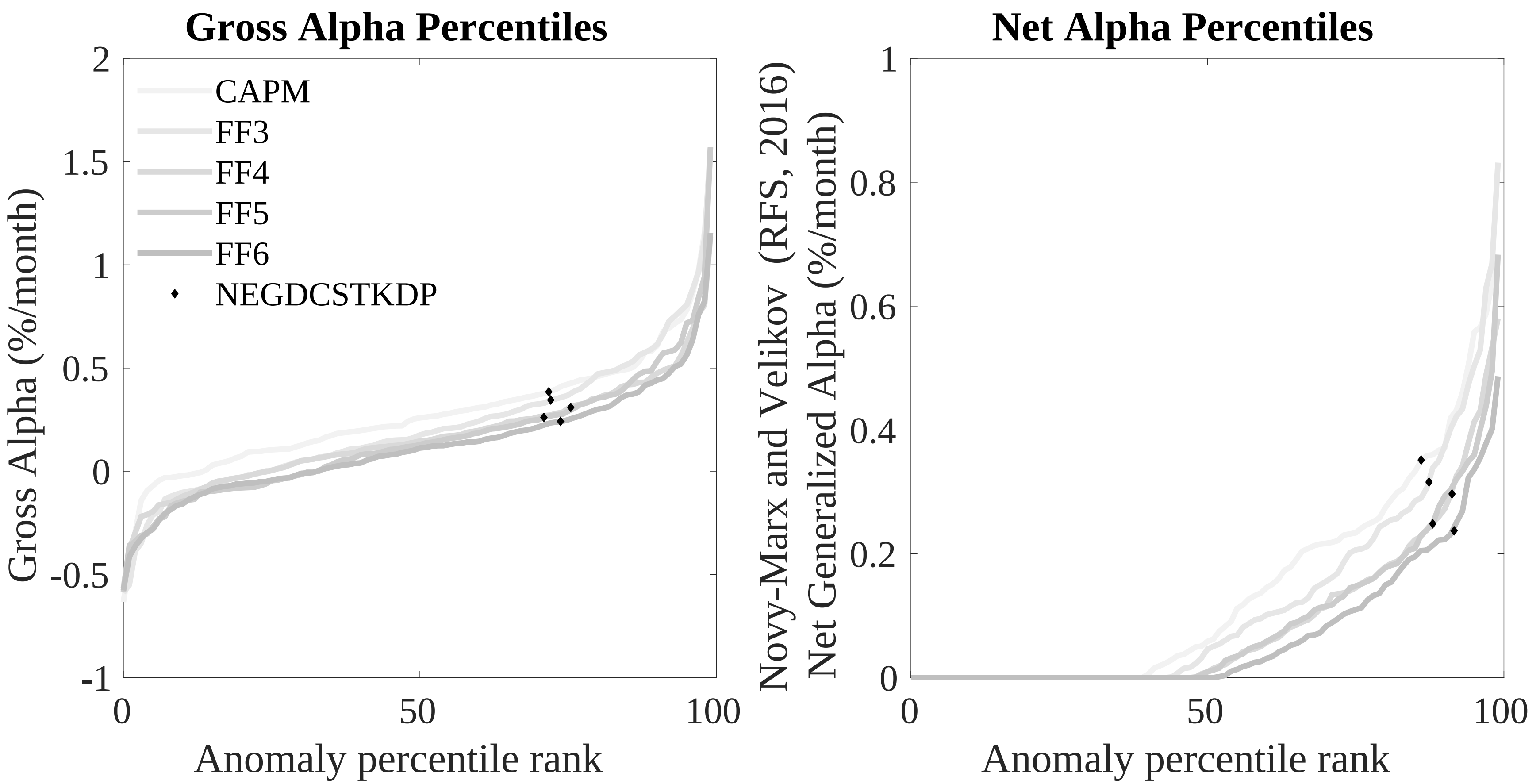

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SDG trading strategy alphas (diamonds). The strategies are constructed using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

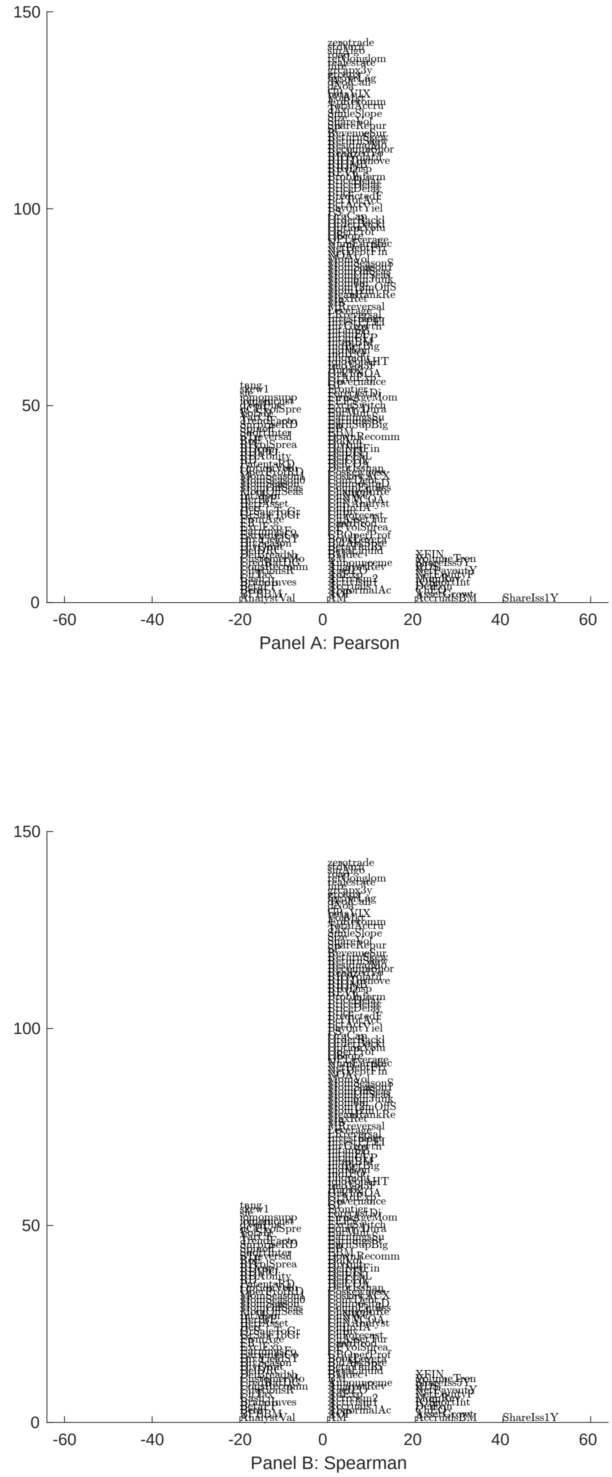

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SDG. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

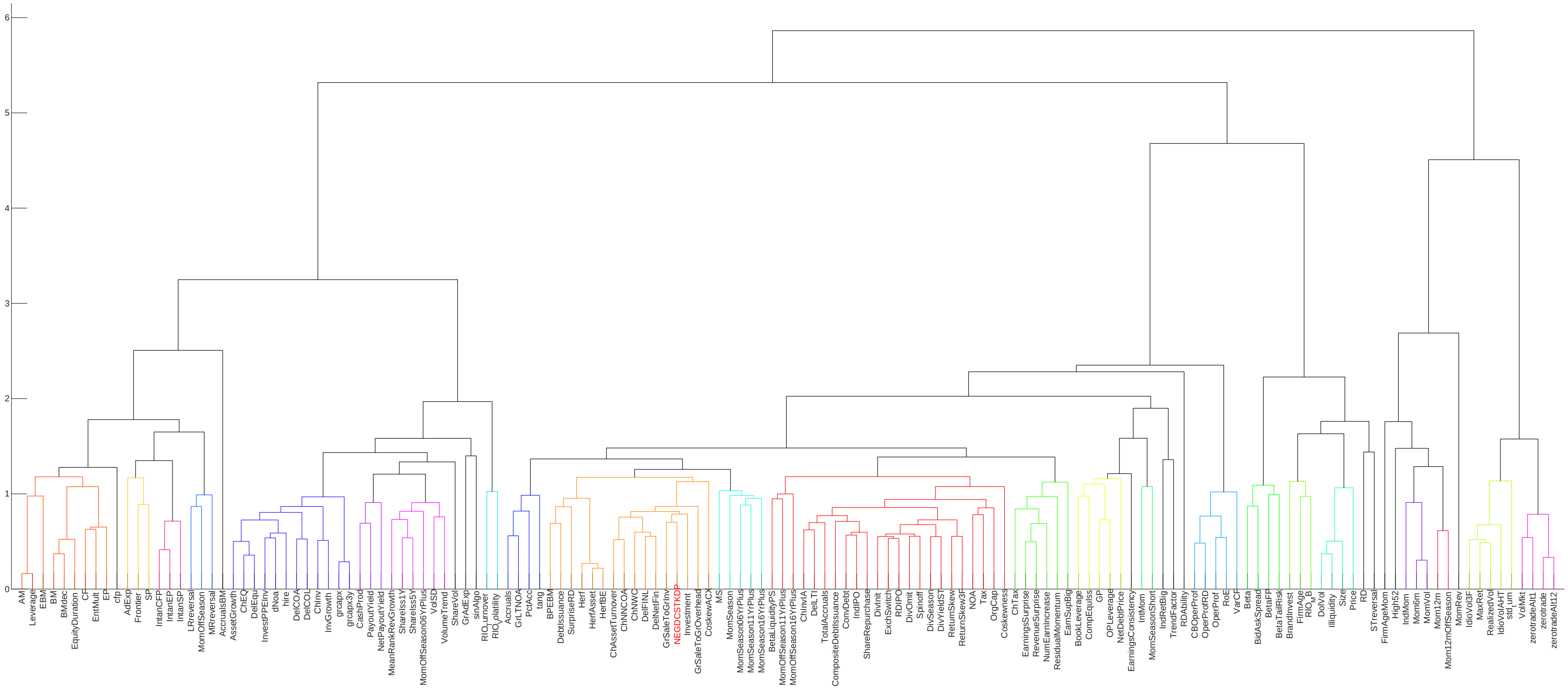

Figure 6: Agglomerative hierarchical cluster plot

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

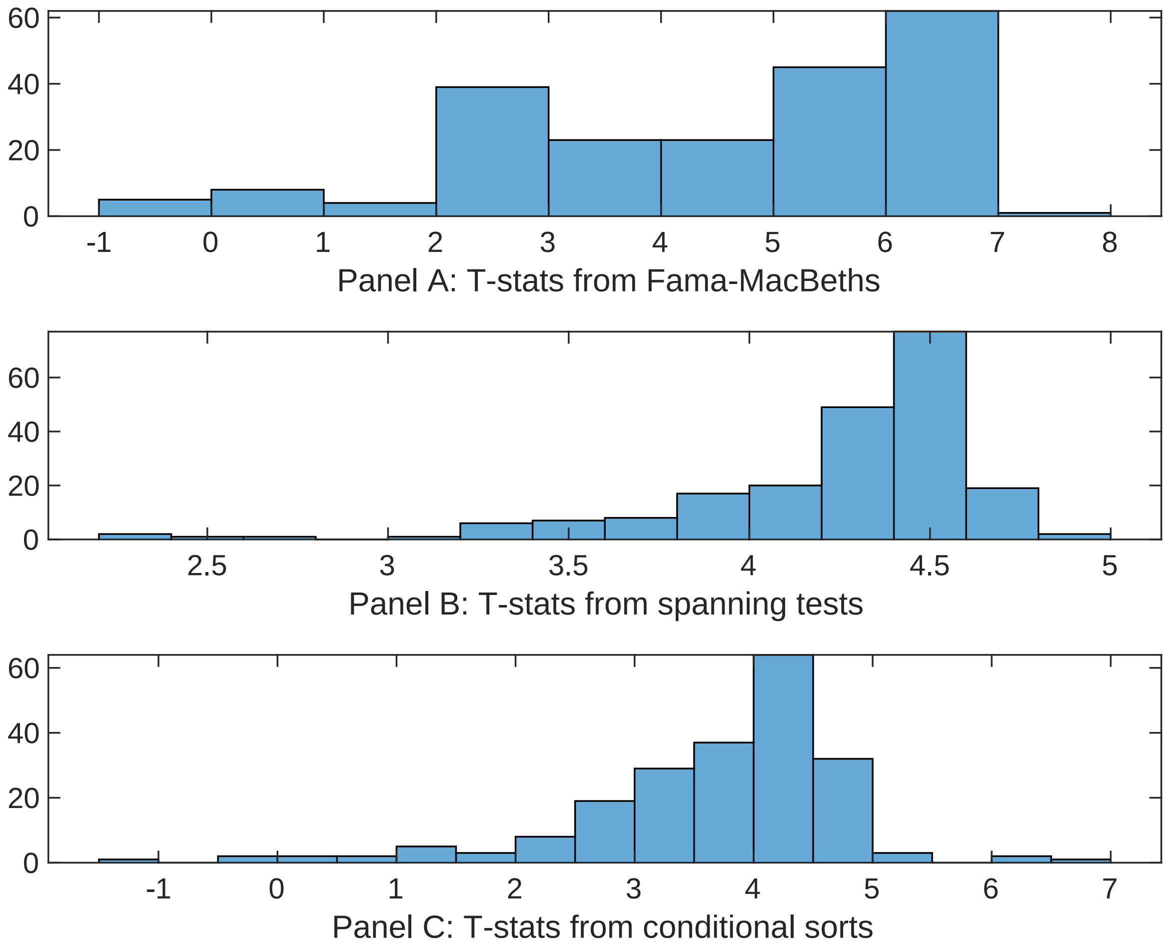

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SDG conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDG} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDG} SDG_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SDG,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SDG. Stocks are finally grouped into five SDG portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDG 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 SDG. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SDG} SDG_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.13	0.18	0.12	0.13	0.13	0.14	0.13
	[5.67]	[7.20]	[5.26]	[6.02]	[5.58]	[6.04]	[5.15]
SDG	0.13	0.12	0.79	0.13	0.12	0.96	0.64
	[5.66]	[5.52]	[2.59]	[5.20]	[5.62]	[4.35]	[2.13]
Anomaly 1	0.26						0.99
	[5.84]						[2.45]
Anomaly 2		0.48					-0.16
		[4.32]					[-0.01]
Anomaly 3			0.28				0.23
			[2.46]				[2.17]
Anomaly 4				0.37			0.37
				[4.24]			[0.42]
Anomaly 5					0.15		-0.21
					[4.14]		[-0.38]
Anomaly 6						0.10	0.68
						[8.70]	[6.45]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	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 SDG trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SDG} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.22	0.24	0.23	0.21	0.26	0.25	0.20
	[2.84]	[3.14]	[2.97]	[2.73]	[3.25]	[3.09]	[2.62]
Anomaly 1	22.16						16.03
	[5.59]						[3.49]
Anomaly 2		30.97					38.70
		[7.28]					[6.22]
Anomaly 3			11.57				1.81
			[3.80]				[0.52]
Anomaly 4				9.66			-1.84
				[2.35]			[-0.42]
Anomaly 5					14.73		-12.42
					[3.54]		[-2.14]
Anomaly 6						1.63	-17.29
						[0.31]	[-3.15]
mkt	2.81	1.96	3.03	2.50	0.71	0.95	3.85
	[1.54]	[1.09]	[1.61]	[1.31]	[0.38]	[0.51]	[2.06]
smb	0.99	-1.30	2.33	-0.35	-0.48	-0.38	1.73
	[0.38]	[-0.50]	[0.86]	[-0.13]	[-0.18]	[-0.14]	[0.64]
hml	-4.60	-5.71	-6.12	-4.26	-3.93	-2.10	-6.42
	[-1.29]	[-1.63]	[-1.62]	[-1.12]	[-1.09]	[-0.58]	[-1.72]
rmw	-5.28	3.28	-4.47	0.27	3.11	1.60	-2.85
	[-1.40]	[0.93]	[-1.12]	[0.07]	[0.86]	[0.44]	[-0.68]
cma	22.48	1.68	24.89	30.61	17.09	30.44	20.74
	[4.02]	[0.25]	[4.29]	[5.56]	[2.51]	[3.69]	[2.56]
umd	2.91	2.71	4.19	3.30	3.47	3.04	1.69
	[1.62]	[1.52]	[2.29]	[1.81]	[1.89]	[1.63]	[0.94]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	14	16	12	11	11	9	19

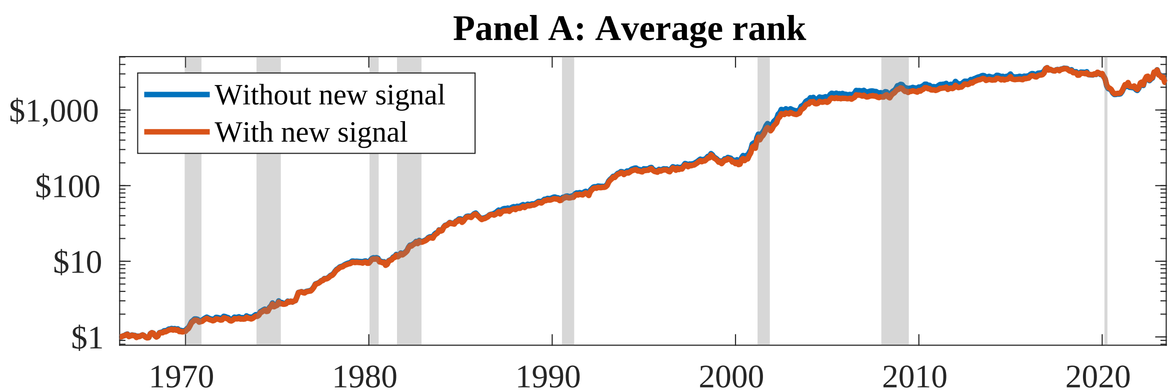

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines indicate combination trading strategies that utilize the 155 anomalies as well as SDG. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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