Equity Impact Divergence and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity Impact Divergence (EID), 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 EID achieves an annualized gross (net) Sharpe ratio of 0.50 (0.38), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 20 (18) bps/month with a t-statistic of 2.83 (2.54), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in net operating assets) is 19 bps/month with a t-statistic of 2.76.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns (Harvey et al., 2016). While many documented predictors capture information about firm fundamentals or investor behavior, the role of equity financing decisions in driving cross-sectional return patterns deserves deeper investigation. Despite extensive research on capital structure and stock returns, we still lack a complete understanding of how firms' equity issuance and repurchase decisions signal future performance.

Prior work has examined various aspects of equity financing in isolation, such as share issuance (Pontiff and Woodgate, 2008) or repurchase announcements (Ikenberry et al., 1995). However, the literature has not fully explored how the divergence between firms' actual and expected equity financing activities may contain valuable information about future returns. This gap is particularly notable given theoretical arguments that managers time the market when making equity financing decisions (Baker and Wurgler, 2002).

We propose that the divergence between realized and expected equity financing activities (Equity Impact Divergence, or EID) provides a novel signal about future stock returns. Our hypothesis builds on market timing theories suggesting that managers exploit private information when making equity issuance decisions (Myers and Majluf, 1984). When managers deviate from expected financing patterns, this likely reflects their superior information about firm prospects.

The theoretical mechanism operates through two channels. First, following (Baker and Wurgler, 2002), managers are more likely to issue equity when they believe their stock is overvalued and repurchase when undervalued. Second, as argued by (Green and Hand, 2011), market participants may not fully incorporate the information content of these financing decisions. These effects should be particularly strong when actual equity financing activities diverge significantly from expected levels based on firm characteristics.

Importantly, our hypothesis suggests that both positive and negative EID can be informative. Large positive divergences (more equity issuance than expected) may signal overvaluation, while large negative divergences (less issuance or more repurchases than expected) may indicate undervaluation. This bi-directional prediction distinguishes our work from studies focused solely on issuance or repurchase events.

Our empirical analysis reveals that EID strongly predicts future stock returns. A value-weighted long-short portfolio strategy that buys stocks with high EID and shorts those with low EID generates significant abnormal returns. Specifically, this strategy earns a monthly alpha of 20 basis points (t-statistic = 2.83) relative to the Fama-French six-factor model, translating to an annualized Sharpe ratio of 0.50 before trading costs.

The predictive power of EID remains robust after controlling for size. Among the largest quintile of stocks, the EID strategy achieves an average monthly return of 33 basis points (t-statistic = 3.71). This finding is particularly notable given that many documented anomalies are concentrated in small stocks. The strategy's performance persists after accounting for transaction costs, with a net Sharpe ratio of 0.38.

Importantly, EID's predictive ability survives controls for related anomalies. When we simultaneously control for the six most closely related predictors including net debt financing and asset growth, the strategy still generates an alpha of 19 basis points per month (t-statistic = 2.76). This indicates that EID captures unique information not contained in previously documented signals.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures information from the divergence between actual and expected equity financing activities. While prior work has examined equity issuance (Pontiff and Woodgate, 2008) and repurchases (Ikenberry et al., 1995) separately, we show that their unexpected component jointly provides valuable predictive information.

Second, we extend the market timing literature by demonstrating that managers' deviations from expected financing patterns contain information about future returns. This builds on theoretical work by (Baker and Wurgler, 2002) and (Myers and Majluf, 1984) while providing new empirical evidence on how financing decisions reflect private information. Our findings suggest that sophisticated investors can profit from managers' market timing attempts.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining unexpected components of corporate actions rather than just their levels. For practitioners, we document a robust predictor that works well among large, liquid stocks and remains profitable after transaction costs. The strategy's performance among large stocks is particularly valuable given recent evidence on the declining profitability of many well-known anomalies.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Equity Impact Divergence. 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 SEQ for stockholders' equity. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while stockholders' equity (SEQ) represents the total equity capital of the firm, including common and preferred stock, capital surplus, and retained earnings. The construction of the signal follows a change-based format, where we calculate the difference between current DLTIS and its lagged value, and then scale this difference by the lagged value of SEQ for each firm in each year of our sample. This scaled difference captures the relative magnitude of changes in long-term debt issuance compared to the firm's equity base, offering insight into the dynamics of capital structure decisions and their potential impact on firm value. By focusing on this relationship, the signal aims to reflect aspects of financing policy changes and their relative significance in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both DLTIS and SEQ to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EID signal. Panel A plots the time-series of the mean, median, and interquartile range for EID. On average, the cross-sectional mean (median) EID is -0.30 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input EID data. The signal's interquartile range spans -0.16 to 0.16. Panel B of Figure 1 plots the time-series of the coverage of the EID signal for the CRSP universe. On average, the EID signal is available for 6.30% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does EID predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EID 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 EID portfolio and sells the low EID 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 EID strategy earns an average return of 0.25% per month with a t-statistic of 3.52. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.20% to 0.32% per month and have t-statistics exceeding 2.83 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 6.93 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 556 stocks and an average market capitalization of at least $1,396 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 21 bps/month with a t-statistics of 4.47. 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 -5-23bps/month. The lowest return, (-5 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.74. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EID 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 EID strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EID, as well as average returns and alphas for long/short trading EID 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 EID strategy achieves an average return of 33 bps/month with a t-statistic of 3.71. Among these large cap stocks, the alphas for the EID strategy relative to the five most common factor models range from 25 to 38 bps/month with t-statistics between 2.79 and 4.33.

5 How does EID perform relative to the zoo?

Figure 2 puts the performance of EID 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 EID strategy falls in the distribution. The EID strategy's gross (net) Sharpe ratio of 0.50 (0.38) is greater than 92% (95%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the EID strategy (red line).[2] Ignoring trading costs, a $1 invested in the EID strategy would have yielded $3.39 which ranks the EID strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EID strategy would have yielded $2.14 which ranks the EID strategy in the top 5% 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 EID relative to those. Panel A shows that the EID strategy gross alphas fall between the 62 and 72 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 EID strategy has a positive net generalized alpha for five out of the five factor models. In these cases EID ranks between the 80 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does EID 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 EID 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 EID or at least to weaken the power EID has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EID conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EID} EID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EID. Stocks are finally grouped into five EID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EID trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EID 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 EID signal in these Fama-MacBeth regressions exceed 1.28, with the minimum t-statistic occurring when controlling for change in net operating assets. Controlling for all six closely related anomalies, the t-statistic on EID is 0.32.

Similarly, Table 5 reports results from spanning tests that regress returns to the EID 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 EID strategy earns alphas that range from 19-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.78, which is achieved when controlling for change in net operating assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EID trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.76.

7 Does EID add relative to the whole zoo?

Finally, we can ask how much adding EID 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 EID 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 EID grows to $977.36.

8 Conclusion

This study provides compelling evidence for the effectiveness of Equity Impact Divergence (EID) as a significant predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on EID generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.50 (0.38 after transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factors and related anomalies.

The persistence of EID's predictive power, evidenced by monthly abnormal re-

[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 EID is available.

turns of 20 basis points (18 basis points net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information not fully reflected in existing factor models. Furthermore, the signal's ability to maintain its explanatory power even after controlling for six closely related anomalies (with an alpha of 19 bps/month) underscores its distinctive nature and potential value for investment professionals.

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 account for transaction costs, the implementation challenges in different market conditions and for different investor types deserve further investigation.

Future research could explore the signal's performance across different market regimes, its interaction with other established anomalies, and its effectiveness in international markets. Additionally, investigating the underlying economic mechanisms driving the EID effect could provide valuable insights into market efficiency and asset pricing theory. These findings contribute significantly to our understanding of return predictability and offer practical implications for investment strategy development.

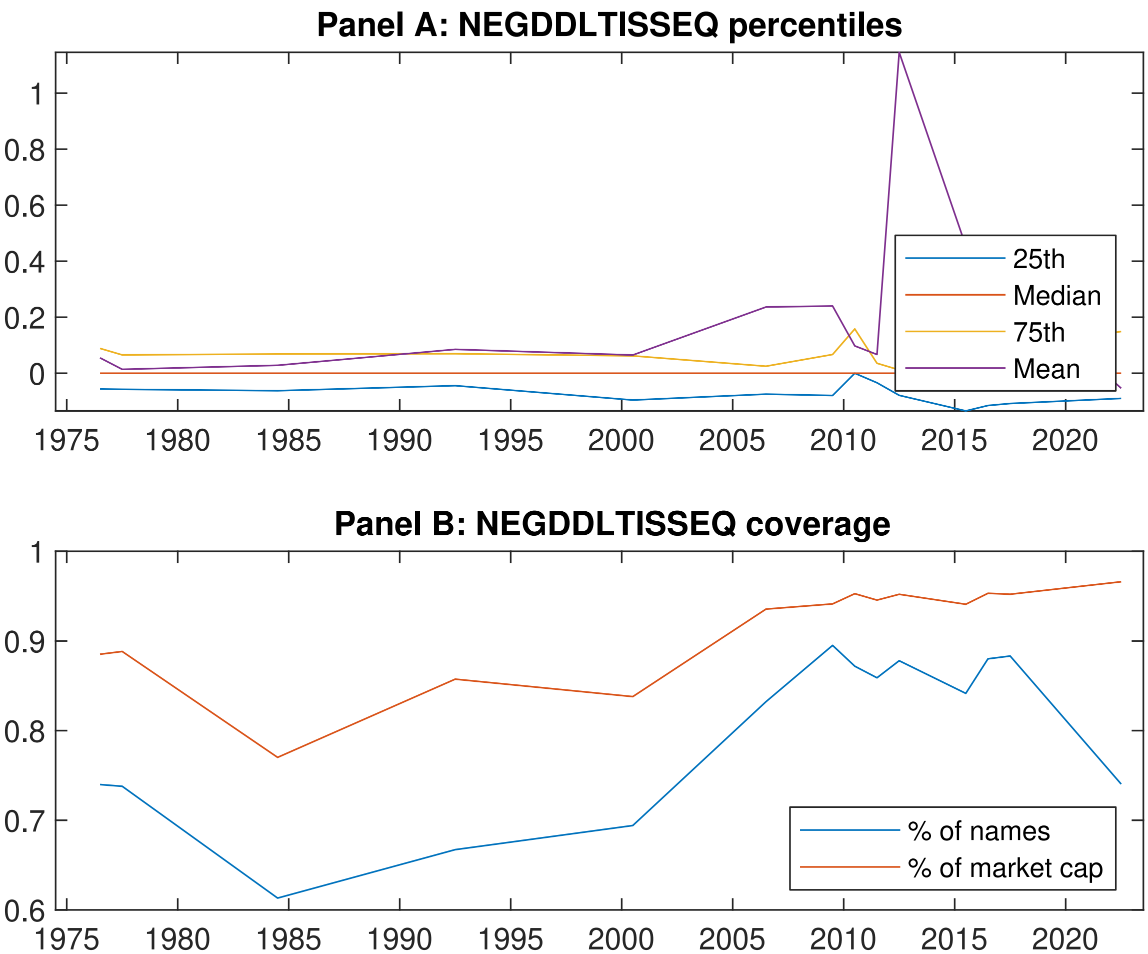

Figure 1: Times series of EID percentiles and coverage.
This figure plots descriptive statistics for EID. Panel A shows cross-sectional percentiles of EID over the sample. Panel B plots the monthly coverage of EID relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EID. 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 EID-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.60	0.67	0.70	0.77	0.85	0.25
	[2.72]	[3.66]	[3.46]	[4.22]	[4.22]	[3.52]
α_{CAPM}	-0.17	0.04	0.00	0.13	0.15	0.32
	[-2.97]	[0.71]	[0.02]	[2.85]	[2.85]	[4.49]
α_{FF3}	-0.19	-0.01	0.06	0.12	0.13	0.32
	[-3.40]	[-0.18]	[1.10]	[2.63]	[2.52]	[4.52]
α_{FF4}	-0.16	0.01	0.10	0.09	0.12	0.27
	[-2.80]	[0.24]	[1.82]	[1.83]	[2.20]	[3.83]
α_{FF5}	-0.19	-0.06	0.11	0.06	0.04	0.22
	[-3.34]	[-1.32]	[1.98]	[1.18]	[0.70]	[3.17]
α_{FF6}	-0.16	-0.04	0.13	0.04	0.03	0.20
	[-2.94]	[-0.91]	[2.42]	[0.74]	[0.68]	[2.83]
Panel B: Fama and French (2018) 6-factor model loadings for EID-sorted portfolios						
β_{MKT}	1.09	0.98	0.97	0.96	1.04	-0.05
	[84.54]	[98.88]	[75.67]	[88.56]	[88.45]	[-3.19]
β_{SMB}	0.12	-0.11	-0.01	-0.03	0.13	0.01
	[5.88]	[-7.45]	[-0.64]	[-1.62]	[7.00]	[0.39]
β_{HML}	0.08	0.14	-0.14	-0.01	-0.06	-0.14
	[3.21]	[7.27]	[-5.63]	[-0.58]	[-2.67]	[-4.49]
β_{RMW}	0.11	0.11	-0.05	0.06	0.14	0.03
	[4.20]	[5.44]	[-1.79]	[2.71]	[6.07]	[1.06]
β_{CMA}	-0.16	0.04	-0.10	0.16	0.17	0.33
	[-4.22]	[1.43]	[-2.58]	[4.94]	[4.94]	[6.93]
β_{UMD}	-0.04	-0.03	-0.04	0.04	0.00	0.04
	[-2.92]	[-3.06]	[-3.30]	[3.28]	[0.13]	[2.42]
Panel C: Average number of firms (n) and market capitalization (me)						
n	657	556	1086	609	629	
me ($\$10^6$)	1452	2856	2201	2869	1396	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EID 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	0.25	0.32	0.32	0.27	0.22	0.20
			[3.52]	[4.49]	[4.52]	[3.83]	[3.17]	[2.83]
Quintile	NYSE	EW	0.21	0.24	0.23	0.21	0.20	0.19
			[4.47]	[5.07]	[4.83]	[4.43]	[4.14]	[3.96]
Quintile	Name	VW	0.24	0.31	0.32	0.26	0.25	0.21
			[3.53]	[4.68]	[4.68]	[3.84]	[3.66]	[3.17]
Quintile	Cap	VW	0.26	0.31	0.31	0.25	0.21	0.18
			[3.88]	[4.65]	[4.64]	[3.71]	[3.23]	[2.70]
Decile	NYSE	VW	0.29	0.37	0.38	0.31	0.29	0.25
			[3.02]	[3.90]	[3.92]	[3.19]	[3.03]	[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	0.20	0.27	0.28	0.25	0.20	0.18
			[2.71]	[3.83]	[3.83]	[3.49]	[2.79]	[2.54]
Quintile	NYSE	EW	-0.05					
			[-0.74]					
Quintile	Name	VW	0.19	0.27	0.27	0.24	0.22	0.20
			[2.69]	[4.00]	[3.97]	[3.56]	[3.17]	[2.89]
Quintile	Cap	VW	0.21	0.27	0.27	0.24	0.19	0.17
			[3.11]	[4.12]	[4.08]	[3.63]	[2.93]	[2.62]
Decile	NYSE	VW	0.23	0.32	0.32	0.28	0.26	0.23
			[2.31]	[3.28]	[3.28]	[2.91]	[2.61]	[2.35]

Table 3: Conditional sort on size and EID

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

	EID Quintiles					EID Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.72	0.92	0.98	0.90	0.82	0.10	0.14	0.13	0.07	0.06	0.03
	[2.57]	[3.37]	[3.57]	[3.18]	[2.93]	[1.13]	[1.53]	[1.37]	[0.79]	[0.60]	[0.29]
(2)	0.76	0.99	0.81	0.92	0.91	0.15	0.19	0.16	0.17	0.12	0.13
	[2.82]	[3.90]	[3.22]	[3.71]	[3.55]	[1.96]	[2.38]	[2.07]	[2.14]	[1.51]	[1.63]
(3)	0.84	0.84	0.86	0.87	0.94	0.10	0.15	0.16	0.12	0.15	0.12
	[3.30]	[3.83]	[3.49]	[3.86]	[3.96]	[1.29]	[1.98]	[1.99]	[1.54]	[1.83]	[1.55]
(4)	0.73	0.82	0.91	0.75	0.94	0.21	0.25	0.24	0.20	0.21	0.18
	[3.13]	[3.99]	[4.07]	[3.56]	[4.26]	[2.70]	[3.26]	[3.09]	[2.57]	[2.66]	[2.32]
(5)	0.48	0.66	0.61	0.69	0.81	0.33	0.37	0.38	0.31	0.29	0.25
	[2.36]	[3.70]	[3.00]	[3.76]	[4.16]	[3.71]	[4.17]	[4.33]	[3.51]	[3.26]	[2.79]

Panel B: Portfolio average number of firms and market capitalization

	EID Quintiles Average n					EID Quintiles Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	397	400	400	400	395	37	34	33	33	36
(2)	108	108	108	108	108	60	60	59	60	60
(3)	77	77	77	77	77	105	106	102	104	106
(4)	64	65	65	65	64	224	231	223	228	224
(5)	59	59	59	59	59	1342	2019	1864	1997	1427

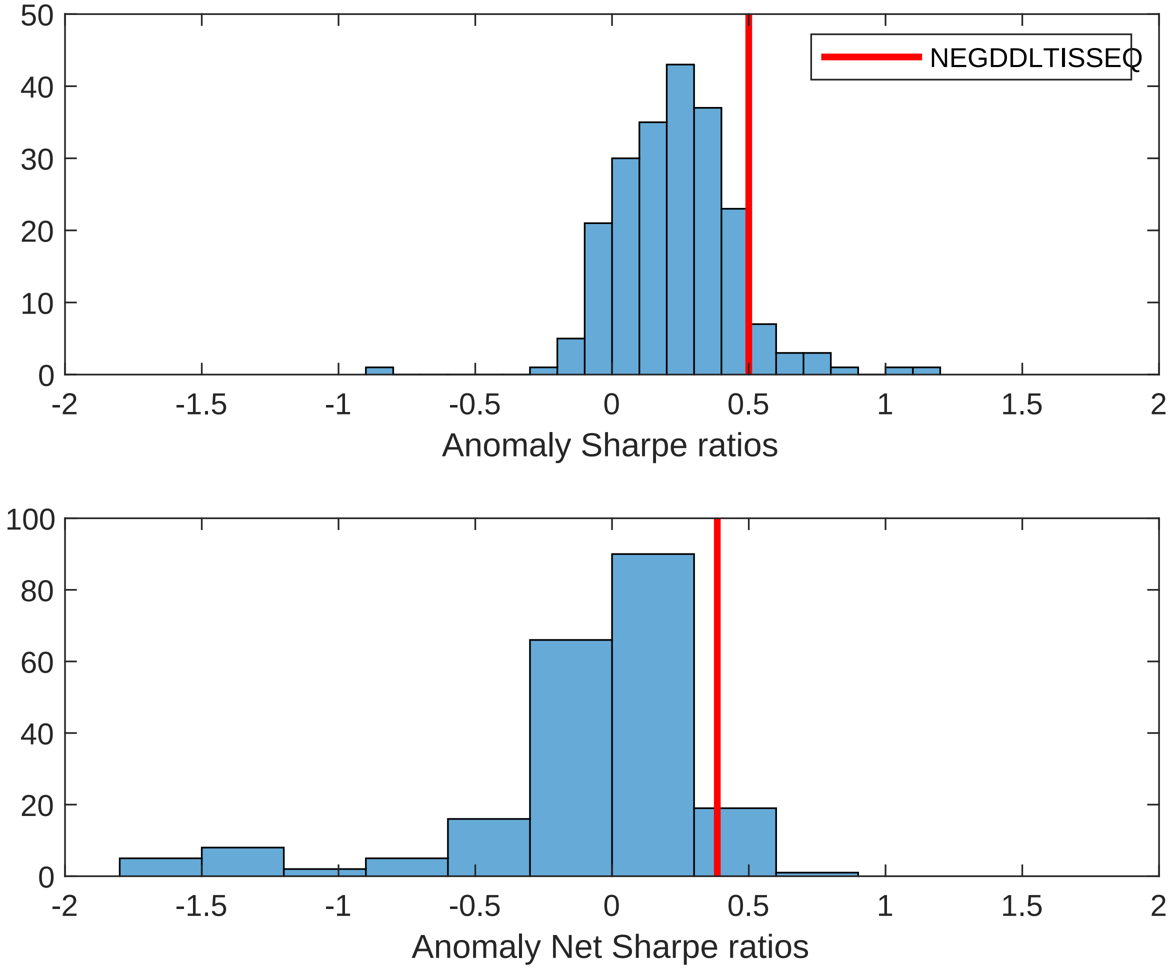

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EID with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

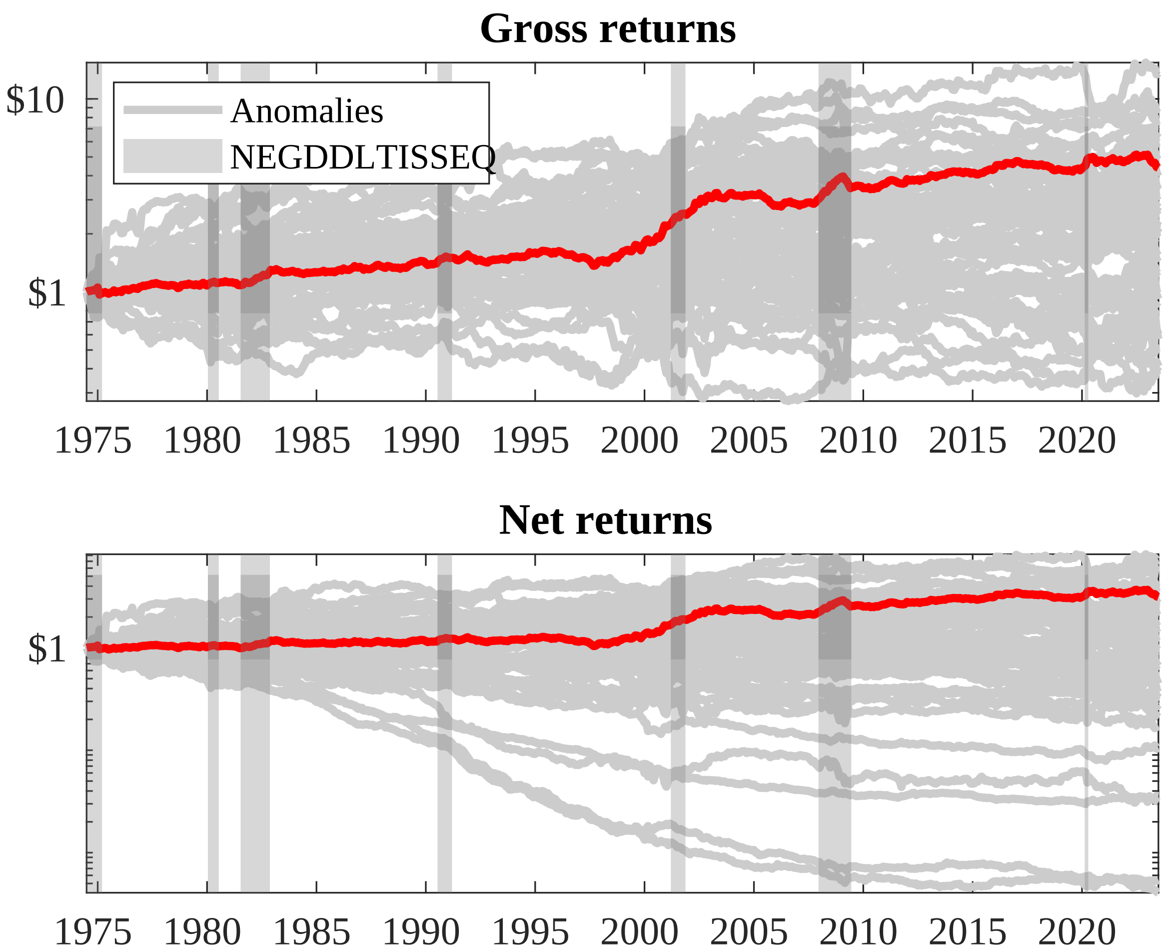

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EID trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

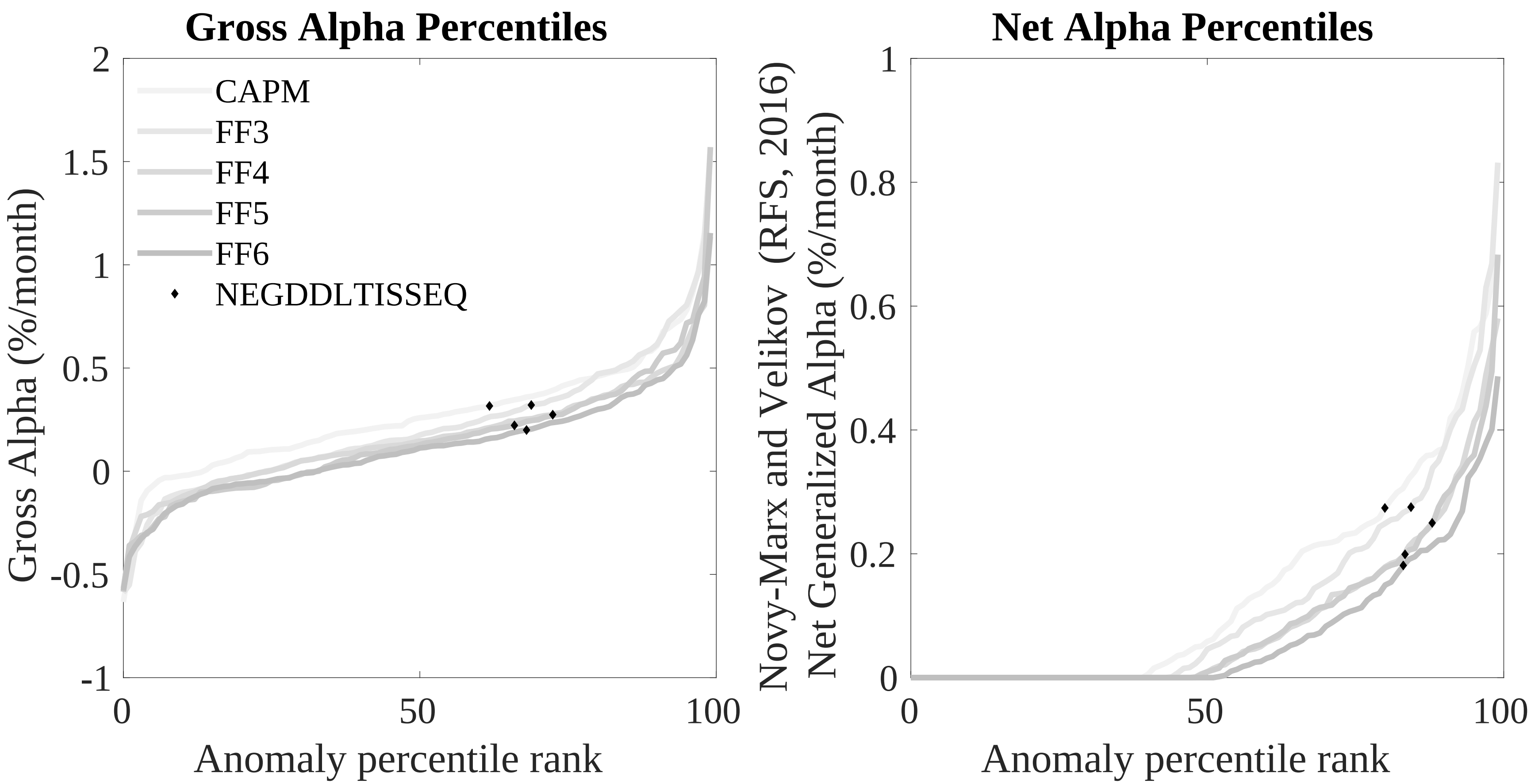

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EID trading strategy alphas (diamonds). The strategies are constructed using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

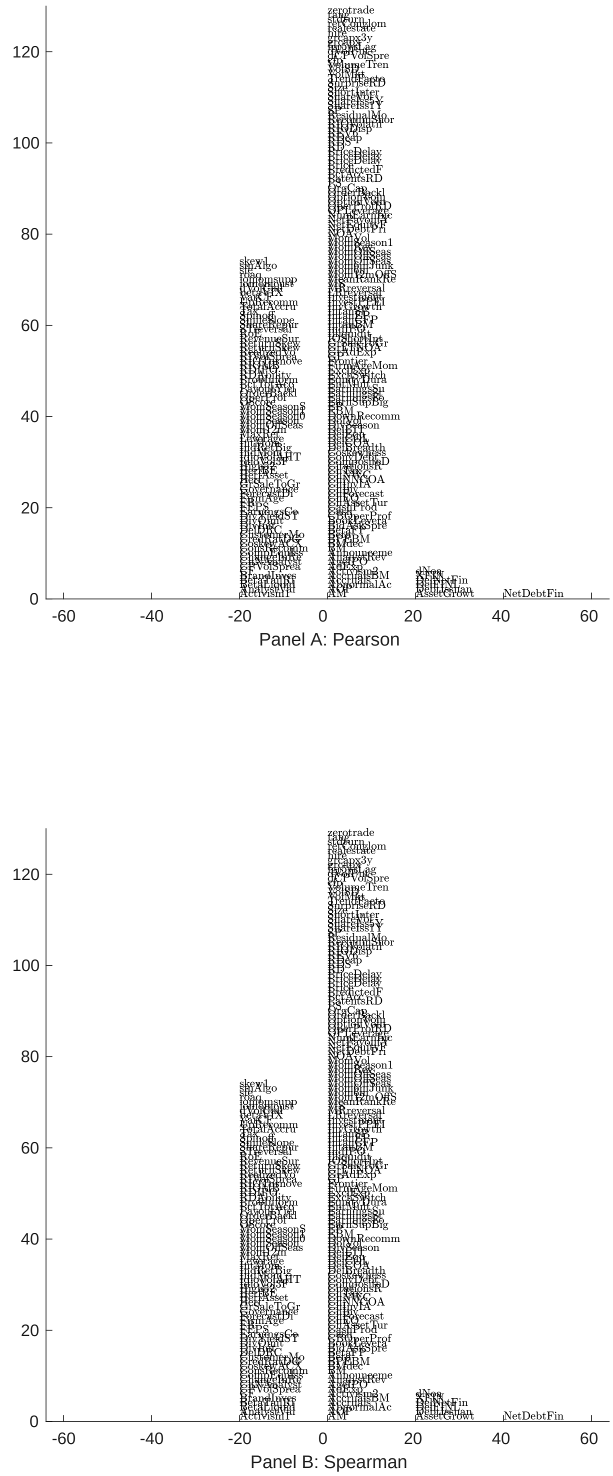

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with EID. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

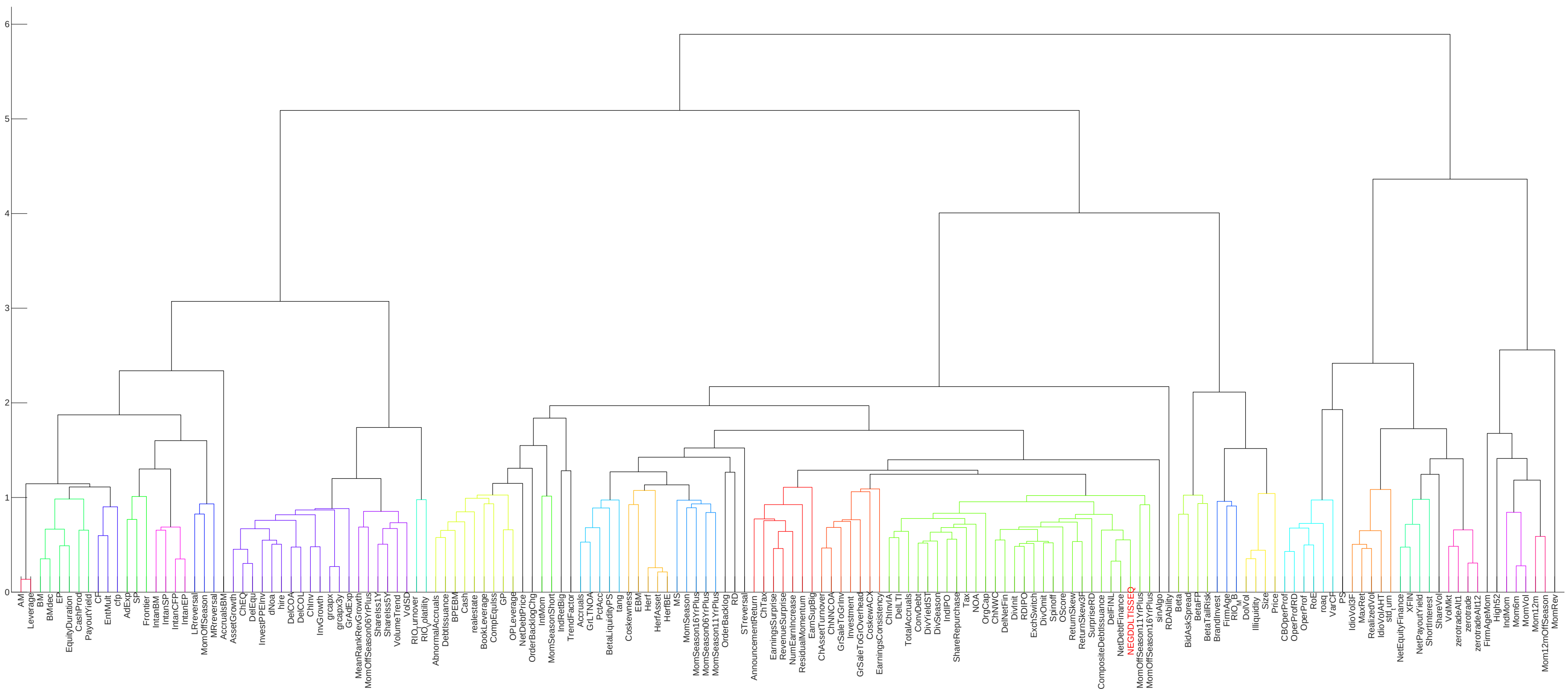

Figure 6: Agglomerative hierarchical cluster plot

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

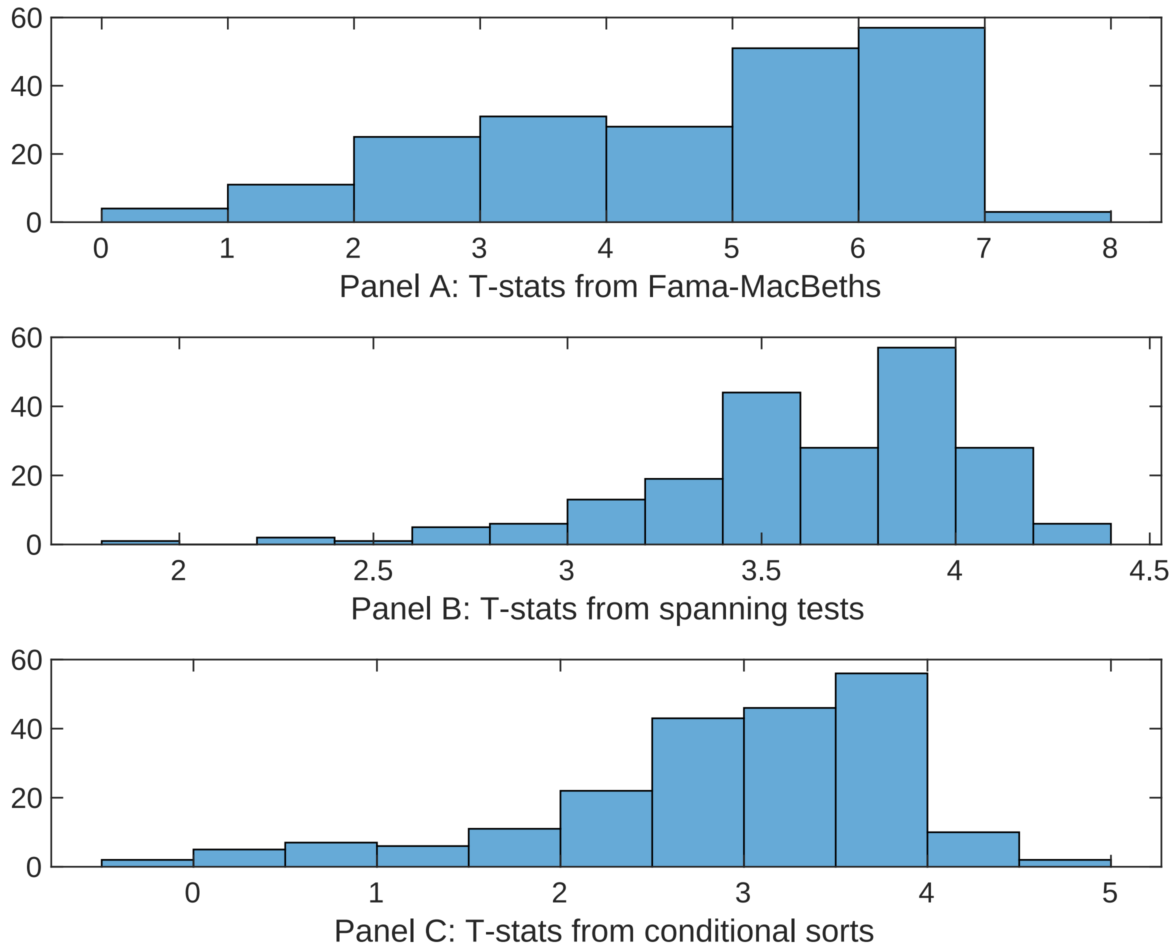

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EID conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EID} EID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EID. Stocks are finally grouped into five EID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EID 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 EID. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EID} EID_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in net operating assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.14	0.14	0.14	0.15	0.14	0.14	0.15
	[5.48]	[5.51]	[5.85]	[5.95]	[5.45]	[5.80]	[5.82]
EID	0.57	0.45	0.79	0.37	0.13	0.33	0.10
	[2.09]	[1.70]	[2.76]	[1.35]	[4.31]	[1.28]	[0.32]
Anomaly 1	0.20						0.11
	[8.63]						[1.71]
Anomaly 2		0.17					-0.11
		[9.26]					[-2.35]
Anomaly 3			0.19				0.98
			[6.09]				[1.74]
Anomaly 4				0.11			0.44
				[9.15]			[2.02]
Anomaly 5					0.40		0.28
					[6.93]		[0.51]
Anomaly 6						0.14	0.88
						[10.09]	[4.98]
# 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 EID trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EID} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in net operating assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

Intercept	0.19	0.19	0.20	0.21	0.21	0.20	0.19
	[2.78]	[2.78]	[2.78]	[2.97]	[2.97]	[2.82]	[2.76]
Anomaly 1	21.32						12.42
	[5.43]						[2.28]
Anomaly 2		18.99					10.31
		[4.61]					[1.82]
Anomaly 3			13.33				8.40
			[3.71]				[2.20]
Anomaly 4				8.10			1.80
				[1.75]			[0.36]
Anomaly 5					7.48		6.84
					[2.67]		[2.39]
Anomaly 6						5.38	-5.14
						[1.29]	[-1.12]
mkt	-5.16	-4.94	-3.36	-5.13	-5.37	-5.16	-4.08
	[-3.24]	[-3.07]	[-1.99]	[-3.14]	[-3.30]	[-3.16]	[-2.45]
smb	-0.41	-0.68	5.30	0.20	1.78	1.09	2.41
	[-0.17]	[-0.27]	[1.92]	[0.08]	[0.70]	[0.43]	[0.83]
hml	-13.18	-12.52	-11.99	-13.77	-13.73	-13.94	-11.75
	[-4.30]	[-4.05]	[-3.83]	[-4.38]	[-4.39]	[-4.41]	[-3.76]
rmw	1.43	1.72	-4.81	3.21	4.20	3.32	-2.83
	[0.45]	[0.53]	[-1.24]	[0.99]	[1.29]	[1.02]	[-0.73]
cma	26.56	25.70	23.10	21.93	25.36	28.02	15.28
	[5.60]	[5.28]	[4.38]	[2.94]	[4.75]	[4.94]	[2.05]
umd	2.25	2.17	3.95	4.32	3.31	3.82	1.58
	[1.37]	[1.30]	[2.42]	[2.61]	[1.99]	[2.30]	[0.94]
# months	588	588	588	588	588	588	588
$\bar{R}^2(\%)$	18	17	16	14	15	14	19

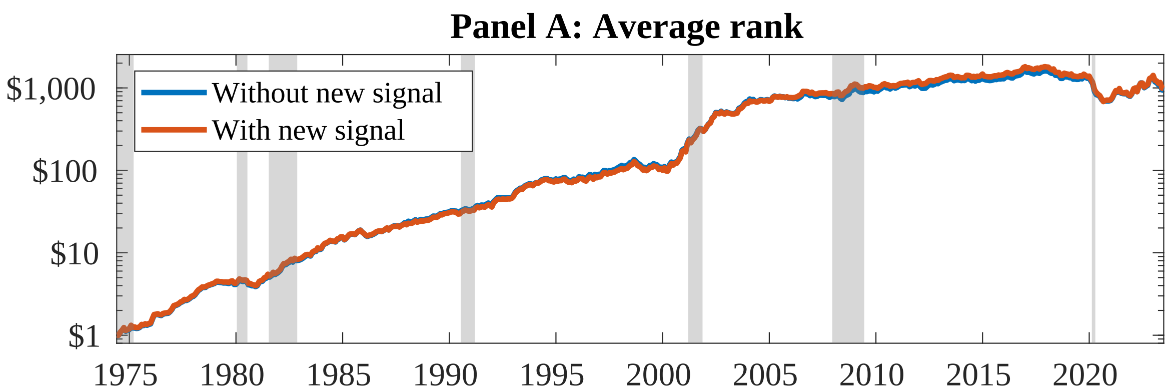

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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

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