Online Appendix for

"Predicting the Performance of Equity Anomalies in Frontier Emerging Markets: A Markov Switching Model Approach"

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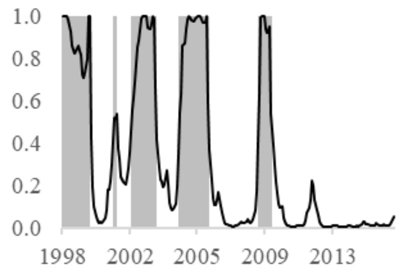
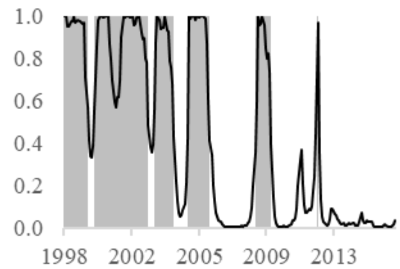
Abstract

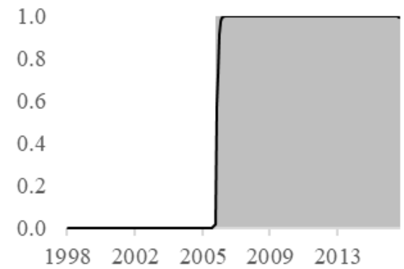
The appendix includes additional figures and tables for the manuscript. Figure A1 presents the time series probability of being in the regimes of significant positive returns for value-weighted meta-anomalies. Table A1 shows the description and implementation of the anomalies investigated in this study. Table A2 reports the performance of individual anomalies



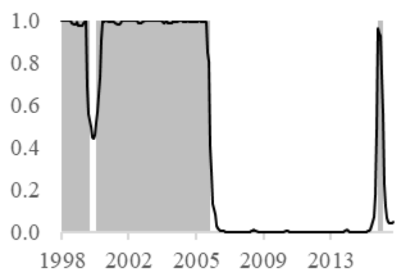
Panel A: Value



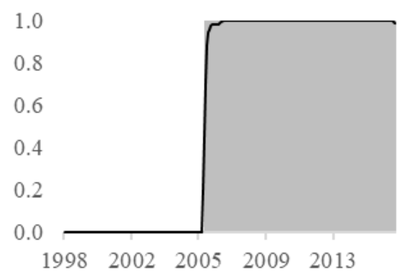
Panel B: Dividends



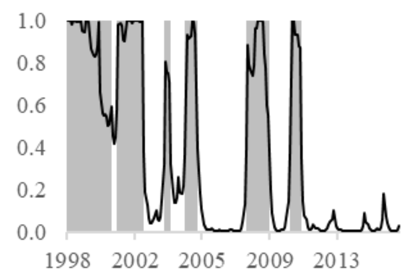
Panel C: Profitability



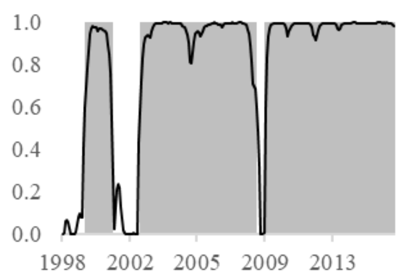
Panel D: Credit risk and indebtedness



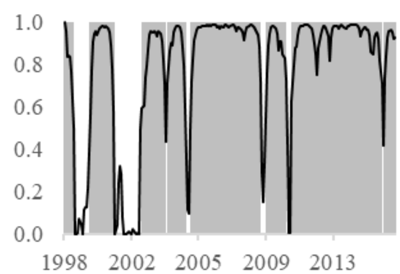
Panel E: Fundamental analysis



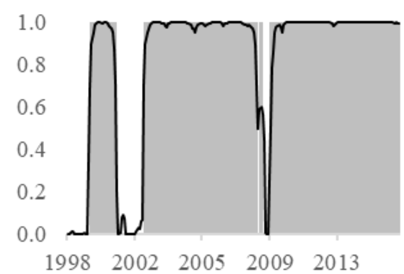
Panel F: Short-term reversal



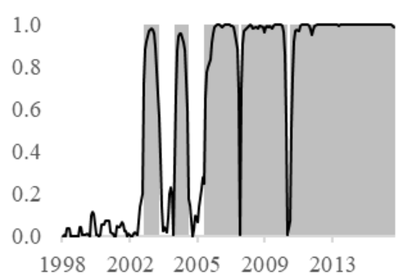
Panel G: Momentum



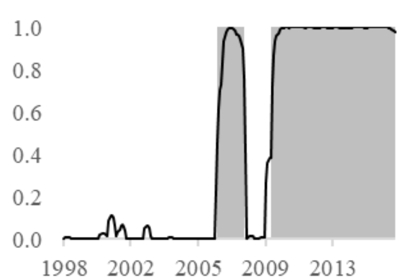
Panel H: Trend



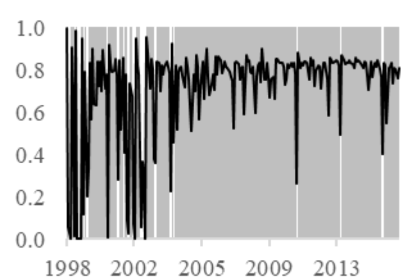
Panel I: 52-week high



Panel J: Seasonalities



Panel K: Analyst coverage



Panel L: Market frictions and others

Figure A1: Time Series Probability of being in the Regimes of Significant Positive Returns for Value-Weighted Meta-Anomalies

Note. This figure displays the regime probabilities of being in the regimes of significant positive returns for meta-anomalies (Regime I). The shaded are is the period when the probability exceeds 0.5.

Table A1

Description and Implementation of the Investigated Anomalies

The table provides detailed information on the anomalies examined in this study. The sample of the anomalies closely follows Zaremba (2017) and builds also on Zaremba and Czapkiewicz (2017).

No.	Abbr.	Name	Description	Key references	Implementation details
Group 1: Value vs growth					
1	EP	Earnings-to-price	Stocks of firms with low price-to-earnings ratio outperform firms with high price-to-earnings ratio.	Basu (1983)	We rank firms on their ratios of trailing four-quarter net profit in month *t*-5 to total firm capitalization in month *t*-1. We go long (short) the firms with the high (low) ratio.
2	BM	Book-to-market	Stocks of firms with high book-to-market ratio outperform firms with low book-to-market ratio.	Rosenberg *et al.*(1985)	We rank firms on their book-to-market ratios calculated based on book value in month *t*-5. We go long (short) the firms with the high (low) ratio.
3	CFP	Cash flow-to-price	Stocks of firms with low price-to-cash flow ratio outperform firms with high price-to-cash flow ratio.	Lakonishok *et al.*(1994), Desai *et al.*(2004)	We rank firms on their ratios of trailing four-quarter cash flow from operations in month t-5 to total stock firm capitalization in month *t*-1. We go long (short) the firms with the high (low) ratio.
4	SP	Sales-to-price	Stocks of firms with low price-to-sales ratio outperform firms with high price-to-sales ratio	Barbee *et al.*(1996), Lewellen (2014)	We rank firms on their ratios of trailing four-quarter sales in month t-5 to total capitalization in month *t*-1. We go long (short) the firms with the high (low) ratio.
5	EBEV	EBITDA-to-EV	Firms with low EV-to-EBITDA ratio outperform firms with high EV-to-EBITDA ratio.	Loughran and Wellman (2011)	We rank firms on their ratios of trailing four-quarter EBITDA in month t-5 to the enterprise value (EV) of a stock firm in month *t*-1. We go long (short) the firms with the high (low) ratio.
6	SEV	Sales-to-EV	Stocks of firms with low EV-to-sales ratio outperform firms with high EV-to-sales ratio	Toniato *et al.*(2013)	We rank firms on their ratios of trailing four-quarter sales in month t-5 to the enterprise value of a stock firm in month *t*-1. We go long (short) the firms with the high (low) ratio.
7	EBP	EBITDA-to-price	Firms with low price-to-EBITDA ratio outperform firms with high price-to-EBITDA ratio	Mesale (2008)	We rank firms on their ratios of trailing four-quarter EBITDA in month t-5 to total capitalization in month *t*-1. We go long (short) the firms with the high (low) ratio.

8	SG	Sales growth	Stocks of firms with low sales growth outperform firms with high sales growth.	Lakonishok *et al.*(1994)	We rank firms on their average sales growth over past 5 years as of month *t*-5. We go long (short) the firms with the low (high) growth.
9	BMCap	Size-enhanced book-to-market ratio	The book-to-market effect is stronger among the small firms.	Loughran (1997), Griffin and Lemmon (2002)	Firstly, we sort stocks on their stock market capitalization, as characterized in anomaly (136), and determine the median. Next, we rank the below-median (small) firms on their book-to-firm ratios (the anomaly [2]). We go long (short) the firms with the high (low) ratio.
10	BMGPA	Gross profitability-enhanced book-to-market ratio	The book-to-market is enhanced by additional sort on the gross profits-to-asset ratio.	Novy-Marx (2013)	We rank stocks separately on GPA and BM. Then, we form portfolios based on the averaged rank. We go long (short) the stocks with high (low) GPA and BM
Group 2: Dividends					
11	DY	Dividend yield	Stocks of firms with high dividend yield outperform firms with low dividend yield .	Litzenberger and Ramaswamy (1979)	We rank firms on their dividend yield, calculated as the sum of all the dividend paid in months *t*-12 to *t*-1, to the total capitalization in month *t*-1. We go long (short) the firms with the high (low) yield.
12	DYCh	Change in dividend yield	The change in dividend yield positively predicts returns.	Lev and Thiagarajan (1993), Abarbanell and Bushee (1998)	We rank firms on a change in the dividend yield (DY) from *t*-13 to *t*-1. We go long (short) the firms with the high (low) change.
13	DCh	Change in absolute dividends	The change in the absolute value of dividends positively predicts returns.	Benartzi *et al.*(1997)	We rank firms on percent change of the absolute value of dividend in the *t*-13 to *t*-1 period. We go long (short) the firms with the high (low) change.
Group 3: Profitability					
14	ROA	Return on assets	Firms with high return on assets outperform firms with low return on assets.	Balakrishnan *et al.*(2010), Kogan and Papanikolaou (2013)	We sort firms on the ratio of trailing four-quarter net profit to total assets in month *t*-5 . We go long (short) the firms with the high (low) ratio.
15	ROE	Return on equity	Firms with high return on equity outperform firms with low return on equity.	Haugen and Baker (1996), Chen *et al.*(2011), Wang and Yu (2013)	We sort firms on the ratio of trailing four-quarter net profit to common equity in month *t*-5. We go long (short) the firms with the high (low) ratio.
16	ROIC	Return on invested capital	Return on invested capital positively predicts return.	Brown and Rowe (2007).	We sort firms on the EBIT divided by the invested capital, i.e., total equity plus total debt minus cash and short-term investments, at *t*-5. We go long (short) the stocks with the high (low) ratio.

17	GPA	Gross profitability	Stocks of firms with high gross profitability outperform firms with low gross profitability.	Novy-Marx (2013)	We rank firms on the ratio of trailing four-quarter gross profit to total assets in month *t*5. We go long (short) the firms with the high (low) ratio.
18	CFA	Cash flow-to-assets ratio	Stocks of firms with high cash flow-to-assets ratio outperform stocks of firms with low cash flow-to-price ratio.	Jansen (2016)	We rank firms on their ratios of trailing four-quarter free cash flow to total assets in month *t*-5. We go long (short) the firms with the high (low) ratio.
Group 4: Credit risk and indebtedness					
19	Cred1	Credit risk anomaly (1)	Firms with high Altman's (1968) *z*-score outperform firms with low *z*-score.	Dichev (1998)	We rank firms on the their Altman's (1968) *z*-score based on data from month *t*-5. We go long (short) the stocks with the low (high) default probability.
20	Cred2	Credit risk anomaly (2)	Firms in financial distress underperform financially healthy firms.	Avramov *et al.*(2009), Greenwood and Hanson (2012), Campbell *et al.*(2008), Ohlson (1980), Shumway (2001)	We rank firms on the their Bloomberg estimate of default probability in month *t*-1. We go long (short) the stocks with the low (high) default probability.
21	DM	Leverage	Stocks of firms with high debt-to-market equity ratio outperform firms with low debt-to-market equity ratio.	Bhandari (1988)	We rank the firms on the ratio of the balance sheet value of total debt to the stock market value of equity (capitalization) in month *t*-5 We go long (short) the firms with the high (low) ratio.
22	LevCh	Change in leverage	Change in leverage negatively predicts returns	Piotroski (2000)	We rank firms on the change of the ratio of total debt to total assets in the period from *t*-17 to *t*-5. We go long (short) the firms with the low (high) change.
23	LTDCh	Change in long-term debt	Change in long term debt negatively predicts performance.	Richardson *et al.*(2005)	We follow the replication approach of Green *et al.*(2016). We rank the firms on percent change in long-term debt from *t*-17 to *t*-5. We go long (short) the stocks with the low (high) change.
24	CFD	Cash flow to debt	Firms with high cash flow-to-debt ratio outperform firms with low cash flow-to-debt ratio.	Ou and Penman (1989)	We rank stocks on the ratio of a ratio of trailing 12-month cash flow from operation to total long-term and short-term debt in month *t*-5. We go long (short) the firms with a high (low) ratio.
Group 5: Investment and intangibles					

25	AG	Asset growth	Stocks of firms with low asset growth outperform firms with high asset growth.	Cooper *et al.*(2008)	We rank firms on their total percentage asset growth from in the *t*-17 to *t*-5 period. We go long (short) the firms with the low (high) asset growth.
26	Invest	Investment	Change in fixed assets and inventories negatively predicts return.	Chen and Zhang (2010)	We rank firms on change in gross property, plant, and equipment plus annual change in inventories in the *t*-17 to *t*-5 period all divided by total assets at *t*-17. We go long (short) the firms with the low (high) change.
27	IG	Investment growth	Stocks of firms with low investment growth outperform firms with high investment growth.	Xing (2008)	We rank firms on their total percentage change in the capital expenditures in the *t*-16 to *t*-4 period. We go long (short) the firms with the low (high) asset growth.
28	HR	Hiring rate	Stocks of firms with low hiring rate outperform firms with high hiring rate.	Belo *et al.*(2014)	We rank firms on the 12-month change in the number of employees in month *t-5*. We go long (short) the firms with the low (high) change.
29	CIA	Capital investments	Capital investments scaled by total assets negatively predicts returns.'	Titman *et al.*(2004)	We rank firms on aggregated capital expenditures in the *t*-17 to *t*-5 period scaled by balance sheet total assets in *t*-5. We go long (short) the firms with the low (high) value of capital expenditures.
30	I2Ch	2-year change in investments.	2-year change in capital expenditures negatively predict returns.	Anderson *et al.*(2006)	We rank first on the percent change in capital expenditures from *t*-29 to *t*-5. We go long (short) the stocks with the low (high) change.
31	OL	Operating leverage	Stocks of firms with high operating leverage outperform firms with low operating leverage.	Novy-Marx (2011)	We rank firms on their operating leverage defined as Novy-Marx (2011), i.e., the trailing four-quarter operating costs to total assets, as of month *t*-5. We go long (short) the firms with the high (low) leverage.
Group 6: Accruals					
32	OA	Operating accruals	Stocks of firms with the low level of operating accruals outperform firms with high level of operating accruals.	Sloan (1996), Hafzalla *et al.*(2011)	We rank the firms on the cumulative operating accruals, i.e., the difference between the net profit and the cash flow from operations, for the 12 months ending *t*-5 scaled by total balance sheet assets. We go long (short) the firms with the low (high) accruals.

33	TA	Total accruals	Stocks of firms with low level of total accruals outperform firms with high level of total accruals.	Richardson *et al.*(2005), Hafzalla *et al.*(2011)	We rank the firms on the cumulative total accruals, i.e., the difference between the net profit and the total cash flow, for the 12 months ending *t5* scaled by total balance sheet assets. We go long (short) the firms with the low (high) accruals.
34	POA	Percent operating accruals	Stocks of firms with low level of percent operating accruals outperform firms with high level of percent operating accruals.	Hafzalla *et al.*(2011)	We rank the firms on the cumulative operating accruals, i.e., the difference between the net profit and the cash flow from operations, for the 12 months ending *t5* scaled by the absolute value of the net profit. We go long (short) the firms with the low (high) accruals.
35	PTA	Percent total accruals	Stocks of firms with low level of percent total accruals outperform firms with high level of percent total accruals.	Hafzalla *et al.*(2011)	We rank the firms on the cumulative total accruals, i.e., the difference between the net profit and the total cash flow, for the 12 months ending *t5* scaled by the absolute value of the net profit. We go long (short) the firms with the low (high) accruals.
36	AcIvol	Idiosyncratic volatility-enhanced accruals	The accruals anomaly is stronger within the stocks of firms with high idiosyncratic volatility.	Mashruwala *et al.(*2006)	Firstly, we sort stocks on idiosyncratic volatility as characterized in anomaly (79) and determine the median. Secondly, we rank the above-median stocks on their operating accruals, defined as in the anomaly (32). We go long (short) the stocks with the low (high) accruals.
37	NOAg	Net operating assets growth	Growth in net operating assets negatively predicts returns.	Fairfield (2003)	We rank firms on the change in net operating assets *t*-17 to *t*-5. We drop the firms with the negative operating assets in *t*-17. We go long (short) the firms with the low (high) change.
38	NOAc	Net operating assets change	Growth in net operating assets scaled by total assets negatively predicts returns.	Hirshleifer *et al.*(2004)	We rank firms on the change in net operating assets scaled by total assets *t*-17 to *t*-5. We go long (short) the firms with the low (high) change.
39	InG	Inventory growth	Stocks of firms with low inventory growth outperform firms with high inventory growth.	Belo and Lin (2011)	We rank firms on the inventory growth from month *t*-17 to *t-5*. We go long (short) the firms with the low (high) growth.
40	InC	Inventory change	Stocks of firms with low change of the inventory to assets ratio outperform firms with high change the inventory to assets ratio	Thomas and Zhang (2002)	We rank firms on the change of the inventory to assets ratio from month *t*-17 to *t5*. We go long (short) the firms with the low (high) change.
Group 7: Fundamental analysis					

41	CH	Cash holdings	The level of cash holdings positively predicts returns.	Palazzo (2012)	We rank firms on the ratio of short-term investment to total assets. We go long (short) the firms with the high (low) ratio.
42	CR	Current ratio	Firms with high (low) current ratio outperform (underperform) the market.	Ou and Penman (1989)	We rank firms on their current ratios, i.e., current assets divided by current liabilities, at month t-5. We go long (short) the stocks with the high (low) ratio
43	CRCh	Change in current ratio	The growth of current ratio positively predicts returns.	Ou and Penman (1989)	We rank firms on the percent change of their current ratios, i.e., current assets divided by current liabilities, in months t-17 to t-5. We go long (short) the stocks with the high (low) change.
44	QR	Quick ratio	Firms with high (low) quick ratio outperform (underperform) the market.	Ou and Penman (1989)	We rank firms on their quick ratios, i.e., current assets minus inventories divided by current liabilities, at month t-5. We go long (short) the stocks with the high (low) ratio
45	QRCh	Change in quick ratio	The growth of quick ratio positively predicts returns.	Ou and Penman (1989)	We rank firms on the percent change of their quick ratios, i.e., current assets minus inventories divided by current liabilities, in months *t*-17 to *t*-5. We go long (short) the stocks with the high (low) change.
46	GM	Gross margin	Companies with high gross margin outperform companies with low gross margin.	Lev and Thiagarajan (1993), Abarbanell and Bushee (1998), Witkowska (2006)	We sort firms on their ratio of trailing four-quarter gross profit to trailing four-quarter sales in month *t*-5.
47	GMCh	Change in gross margin	Change in gross margin positively predicts returns	Piotroski (2000)	We rank firms on the change in gross margin from *t*-17 to *t*-5. We go long (short) the firms with the high (low) change.
48	AT	Asset turnover	Stocks of firms with high asset turnover outperform firms with low asset turnover.	Haugen and Baker (1996)	We rank firms on the ratio of trailing four-quarter sales to assets in month *t*5. We go long (short) the firms with the high (low) ratio.
49	ATCh	Change in asset turnover	Change in asset turnover positively predicts returns.	Soliman (2008)	We rank firms on the change of asset turnover (measured as in the anomaly [48]) from month *t*-17 to *t*-5. We go long (short) the firms with high (low) change.
50	PM	Profit margin	Firms with high profit margin outperform firms with low profit margin.	Soliman (2008)	We rank firms on the their trailing 12-month profit margin in month *t*-5. We go long (short) the firms with the high (low) profit margin.
51	PMCh	Change in profit margin	Change in profit margins positively predicts returns.	Soliman (2008)	We rank firms on the change of profit margin (measured as in the anomaly [50]) from month *t*-17 to *t*-5. We go long (short) the firms with high (low) change.

52	Depr	Depreciation-to-fixed assets ratio	Firms with high depreciation-to-fixed assets ratio overperform.	Holthausen and Larcker (1992)	We rank their ratio of trailing 12-month depreciation and amortization to balance sheet net fixed assets at *t*-5. We go long (short) the firms with the high (low) ratio.
53	DeprCh	Percentage change in depreciation-to-fixed assets ratio	Firms with increasing depreciation-to-fixed assets ratio outperform firms with decreasing ratio.	Holthausen and Larcker (1992)	We rank change in the depreciation-to-fixed assets ratio (measured as in the anomaly [52]) from month *t*-17 to *t*-5. We go long (short) the firms with high (low) change.
54	SR	Sales-to-receivables ratio	Firms with high sales-to-receivables ratio outperform firms with low sales-to-receivables ratio.	Ou and Penman (1989)	We rank firms on their ratios of trailing four-quarter sales to receivables in month *t*-5. We go long (short) the firms with the highest (lowest) ratio.
55	SC	Sales-to-cash ratio	Firms with high sales-to-cash ratio outperform firms with the low sales-to-cash ratio.	Ou and Penman (1989)	We rank firms on their ratios of trailing four-quarter sales to cash in month *t*-5. We go long (short) the firms with the highest (lowest) ratio.
56	SGIG	Sales growth-to-inventory growth	The difference between sales change and inventory change positively predicts returns.	Lev and Thiagarajan (1993), Abarbanell and Bushee (1998)	We rank firms on the difference between sales growth and inventory growth in the period from *t*-17 to *t*-5. We go long (short) the firms with the high (low) difference.
57	SChRCh	Sales growth minus receivables growth	The differences between sales growth and receivables growth positively predict future returns.	Abarbanell and Bushee (1998)	We rank firms on the difference between the percentage sales growth from month *t*-17 to *t*-5 and the receivables growth from month *t*-17 to *t*-5. We go long (short) the firms with the highest (lowest) difference.
58	GMGSG	Gross margin growth minus sales growth	The difference between gross margin change and sales change positively predicts returns.	Abarbanell and Bushee (1998)	We rank firms on the difference between the absolute change in gross margin and the percent sales growth the period from *t*-17 to *t*-5. We go long (short) the firms with the high (low) difference.
59	EarVol	Earnings volatility	Earnings volatility positively predicts the returns	Francis *et al.*(2004)	We follow the replication approach of Green *et al.*(2016). We rank firms on the standard deviation for 16 quarters of the return on assets. We go long (short) the stocks with the high (low) volatility.
60	CfVol	Cash flow volatility	Cash flow volatility negatively predicts the returns	Huang (2009)	We follow the replication approach of Green *et al.*(2016). We rank firms on the standard deviation for 16 quarters of the ratio of cash flow from operations to sales. We go long (short) the stocks with the low (high) volatility.

61	TS140.Cons	Percentage positive earnings quarters	Firms consistently improving earnings overperform.	Barth, Ellion, and Finn (1999)	We rank firms on the percentage of year-on-year increases of quarterly EPS within previous 20 quarters (as of month *t*-5). We drop firms with lest than 16 quarters of data. We go long (short) firms with the highest (lowest) percentage of increases.
Group 8: Issuance					
62	IPO	Initial public offerings	Firms underperform the market in the three years following their IPO.	Loughran and Ritter (1995)	We rank firms on the time since IPO. We go long (short) the stocks with the number of months since IPO higher (lower) than 36.
63	CEI	Composite equity issuance	Stocks of firms with low composite equity issuance over past 5 years outperform firms with high composite equity issuance over past 5 years.	Daniel and Titman (2006)	We rank firms the difference between the natural logarithm of total market capitalization in month *t*-60 divided by the total market capitalization in month *t*-1 and the cumulative stock price appreciation in months *t*-60 to *t*-1 (in logarithmic terms). We go long (short) the firms with the low (high) value of this difference.
64	NSI	Net stock issuance	Stocks of firms with low net stock issuance over last year outperform firms with high net stock issuance over last year.	Pontiff and Woodgate (2008)	We rank firms on the growth of the share capital from month *t*-17 to *t*5. We go long (short) the firms with the low (high) growth.
65	Age	Age	Young public companies tend to underperform the older counterparts.	Jiang *et al.*(2005)	We rank stocks on the time that since first Bloomberg coverage. We long (short) the stocks with old (young) stocks.
66	Ext	External financing	Future returns are negatively related to the change in net external financing.	Bradshaw *et al.*(2006), Richardson and Sloan (2003)	We rank firms on the total change in short-term debt, long-term debt, and shareholder equity due to equity issuances, repurchases, and dividends from month *t*-17 to *t*-5. We go long (short) the firms with the low (high) change in external financing.
67	TECh	Change in common shareholder equity	Firms with the high (low) change in common shareholder equity overperform (underperform).	Richardson *et al.*(2005)	We rank firms on the change in common shareholder equity from month *t*-17 to *t*-5. We go long (short) the firms with high (low) change.
Group 9: Liquidity					
68	Turn	Turnover	Stocks of firms with low turnover outperform firms with high turnover.	Brennan *et al.*(1998)	We rank firms on the average turnover (i.e., dollar trading volume) over past 6 months. We go long (short) the firms with the low (high) turnover.

69	TR	Turnover ratio	Stocks of firms with low turnover ratio outperform firms with the high turnover ratio.	Datar *et al.*(1998)	We rank the firms on the ratio of daily turnover to total market capitalization averaged over last 6 months. We go long (short) the firms with the low (high) turnover ratio.
70	TRV	Turnover ratio variability	The variability of turnover ratio negatively predicts returns.	Chordia *et al.*(2001)	We rank firms on the variance of monthly turnover ratios calculated based on the *t*-36 to *t*-1 period. We go long (short) the firms with the low (high) variance.
71	TurnV	Turnover variability	The variability of turnover negatively predicts returns.	Chordia *et al.*(2001)	We rank firms on the variance of monthly turnover calculated based on the *t*-36 to *t*-1 period. We go long (short) the firms with the low (high) variance.
72	Amih	Amihud measure	Stocks with low liquidity measured with the Amihud ratio outperform stocks with high liquidity.	Amihud (2002)	We rank stocks on their Amihud measures calculated based on monthly data in months *t*-12 to *t*-1. We go long (short) the stocks with high (low) Amihud illiquidity measure.
73	AmihSmall	Size-enhanced Amihud	The illiquidity effect measured with the Amihud ratio is stronger among small firms.	Bali, Engle, and Murray (2016)	Firstly, we sort stocks on size as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median (small) firms on their Amihud measure as characterized in the anomaly (72). We go long (short) the highest (lowest) Amihud measure.
74	AmihStRev	Short-term reversal enhanced Amihud	The illiquidity effect measured with the Amihud ratio is stronger among with recent price decrease.	Bali, Engle, and Murray (2016)	Firstly, we sort stocks on the short-term return as characterized in the anomaly (95). Secondly, we rank the below-median (low short-term return) firms on their Amihud measure as characterized in the anomaly (72). We go long (short) the highest (lowest) Amihud measure.
75	Spread	Bid-ask spread	Stocks of firms with wide bid-ask spread tend to outperform stocks of firms with tight bid-ask spread.	Amihud and Mendelson (1986)	We rank firms on the bid-ask spread in *t*-1. We go long (short) the stocks with the wide (tight) spread.
76	TR12	Annual turnover	Stocks with low average monthly turnover over previous 12 months outperform stocks with high turnover.	Lewellen (2015)	We rank stocks on average monthly turnover over previous 12 months. We go long (short) stocks with a low (high) turnover.
Group 10: Low-volatility					

77	Beta	Beta	Stocks with low beta outperform stocks with high beta.	Frazzini and Pedersen (2014)	We rank stocks on the coefficient of regression of their returns on returns of the market portfolio, *i.e.*, capitalization-weighted portfolio of all the stocks, calculated for months *t*-24 to *t*-1. We go long (short) the stocks with the low (high) coefficient. We delever (lever) the long (short) side of the trade to equalized their 24-month betas following the approach of Frazzini and Pedersen (2014).
78	SD	Volatility	Stocks with low return volatility outperform markets with high volatility.	Ang (2006a). Baker *et al.*(2011)	We rank stocks on the standard deviation of the monthly returns in months *t*-24 to *t*-1. We go long (short) the stocks with the low (high) volatility. We delever (lever) the long (short) side of the trade to equalized their 24-month betas measured as in the anomaly (77) following the approach of Frazzini and Pedersen (2014).
79	IVolFF3	Idiosyncratic volatility (FF3)	Stocks with high idiosyncratic volatility outperform firms with low idiosyncratic volatility.*	Ang *et al.*(2006a, 2009)	We rank stocks on the idiosyncratic volatility from the Fama-French (1993) three-factor model, as characterized in the section on portfolio evaluation, calculated for months *t*-24 to *t*-1. We go long (short) the stocks with the low (high) idiosyncratic risk. We delever (lever) the long (short) side of the trade to equalized their 24-month betas measured as in the anomaly (77) following the approach of Frazzini and Pedersen (2014).
80	IvolMKT	Idiosyncratic volatility (CAPM)	Stocks with low idiosyncratic volatility outperform firms with high idiosyncratic volatility.	Merton (1987), Malkiel and Xu (2002)	We rank stocks on the idiosyncratic volatility from the CAPM, as characterized in the section on portfolio evaluation, calculated for months *t*-24 to *t*-1. We go long (short) the stocks with the low (high) idiosyncratic risk. We delever (lever) the long (short) side of the trade to equalized their 24-month betas measured as in the anomaly (77) following the approach of Frazzini and Pedersen (2014).
81	OilBeta	Oil beta	Stocks with low oil beta outperform stocks with high oil beta.	Huang and Miao (2016)	We rank stocks on the coefficient of regression of their excess returns on excess returns of the generic light sweet crude oil futures, calculated for months *t*-24 to *t*-1. We go long (short) the stocks with the low (high) coefficient.
Group 11: Extreme and downside risk					
82	DownVol	Downside volatility	Stocks with high downside risk outperform stocks with low downside risk.	Ang *et al.*(2006b)	We rank stocks on the downside deviation of the monthly returns in months *t*-24 to *t*-1. We go long (short) the stocks with the high (low) downside volatility

83	VaR	Value at risk	Stocks with high value at risk outperform stocks with low value at risk.	Bali and Cakici (2004)	We rank stocks on their 5% VaR, *i.e.*, the absolute value of the 5th percentile of returns in months *t*-24 to *t*-1. We go long (short) the stocks with the high (low) VaR.
84	Kurt	Kurtosis	Stocks with high kurtosis of returns outperform stocks with low kurtosis of returns.	Dittmar (2002), Amaya *et al.*(2015)	We rank stocks on the kurtosis of monthly returns in t-24 to t-1 period (min. 20 observations). We go long (short) the stocks with the high (low) past return.
Group 12: Skewness					
85	Skew	Total skewness	Stocks with low skewness of returns outperform stocks with high skewness of returns.	Amaya *et al.*(2015), Bali, Engle, and Murray (2016)	We rank stocks on the skewness of monthly returns in t-24 to t-1 period (min. 20 observations). We go long (short) the stocks with the low (high) skewness.
86	CoSkew	Systematic skewness	Stocks with high (low) systematic skewness underperform (overperform).	Harvey and Siddique (2000)	We sort stocks on their systematic skewness calculated following Harvey and Siddique (2000) based on returns in months *t*-24 to *t*-1. We go long (short) stocks with low (high) systematic skewness.
87	IdSkew	Idiosyncratic skewness	Stocks with high (low) idiosyncratic skewness underperform (overperform).	Boyer, Mitton, & Vorkink (2010)	We follow the approach of (XXX). We rank stocks on the skewness of monthly residuals from the three-factor model of Fama and French (1993) in months *t*-24 to *t*-1. We go long (short) the stocks with low (high) skewness.
1					
88	LtRev36	Long-term reversal (36 months)	Firms with high (low) returns in the previous 3 years exhibit return reversal.	DeBondt and Thaler (1985)	We follow the approach of Green *et al.*(2014). We rank stocks based on their cumulative return in months *t*-36 to *t*-13. We go long (short) the stocks with the low (high) return.
89	LtRev60	Long-term reversal (60 months)	Firms with high (low) returns in the previous 5 years exhibit return reversal.	DeBondt and Thaler (1985)	We follow the approach of Jacobs (2015). We rank stocks based on their cumulative return in months *t*-60 to *t*-13. We go long (short) the stocks with the low (high) return.
90	LtRev36Ivol	Idiosyncratic volatility-enhanced long-term reversal (36 months)	Long-term reversal is stronger across firms with high idiosyncratic volatility.	McLean (2010)	Firstly, we sort stocks on idiosyncratic volatility as characterized in anomaly (79) and determine the median. Secondly, we rank the above-median stocks on their cumulative returns in months *t*-36 to *t*-13. We go long (short) the stocks with the low (high) return.
91	LtRev60Ivol	Idiosyncratic volatility-enhanced long-term reversal (60 months)	Long-term reversal is stronger across firms with high idiosyncratic volatility.	McLean (2010)	Firstly, we sort stocks on idiosyncratic volatility as characterized in anomaly (79) and determine the median. Secondly, we rank the above-median stocks on their

					cumulative returns in months *t*-60 to *t*-13. We go long (short) the stocks with the low (high) return.
92	LtRev36Small	Size-enhanced long-term reversal (36 months)	Long-term reversal is stronger across small companies.	Blackburn and Cakici (2016)	Firstly, we sort stocks on total stock market capitalization as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median stocks on their cumulative returns in months *t*-36 to *t*-13. We go long (short) the stocks with the low (high) return.
93	LtRev60Small	Size-enhanced long-term reversal (60 months)	Long-term reversal is stronger across small companies.	Blackburn and Cakici (2016)	Firstly, we sort stocks on total stock market capitalization as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median stocks on their cumulative returns in months *t*-60 to *t*-13. We go long (short) the stocks with the low (high) return.
94	RevMonth	Stock-reversal month (*t*-13) to (*t*-18)	The mean return in months *t*-18 to *t*-13 negatively predicts future returns.	Jegadeesh and Titman (1993)	We rank stocks based on their cumulative return in months *t*-18 to *t*-13. We go long (short) the stocks with the lowest (highest) return.
Group 14: Short-term reversal					
95	StRev	Short-term reversal	Firms with the highest (lowest) return in the previous month exhibit return reversal.	Lehmann (1990), Jegadeesh (1990)	We rank stocks based on their raw return in month *t*-1. We go long (short) the stocks with the low (high) return.
96	StRevSmall	Size-enhanced short-term reversal	The short-term reversal effect is stronger among small firms.	Bali, Engle, and Murray (2016)	Firstly, we sort stocks on size as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median (small) firms on total return in month *t*-1. We go long (short) the lowest (highest) return.
97	StRevLMom	Momentum-enhanced short-term reversal	The short-term reversal effect is stronger among high-momentum firms.	Bali, Engle, and Murray (2016)	Firstly, we sort stocks on long-term momentum as characterized in anomaly (99) and determine the median. Secondly, we rank the above-median stocks on total return in month *t-1*. We go long (short) the lowest (highest) return.
Group 15: Momentum					
98	StMom	Short-term momentum	Stocks of firms that outperformed over past 6 months continue to outperform over the next month.	Jegadeesh and Titman (1993)	We rank stocks based on their cumulative return in months *t*-1 to *t*-6. We go long (short) the stocks with the high (low) return.

99	LtMom	Long-term momentum	Past-year winners outperform past-year losers	Fama and French (1996)	We rank stocks based on their cumulative return in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
100	IntMom	Intermediate momentum	Intermediate returns (*i.e.* in months t-12 to t-7) cause momentum.	Novy-Marx (2012)	We rank stocks based on their cumulative return in months *t*-12 to *t*-7. We go long (short) the stocks with the high (low) return.
101	MomAge	Age-enhanced momentum	Momentum is stronger among young companies.	Zhang (2006)	Firstly, we sort stocks on their age as characterized in anomaly (65) and determine the median. Secondly, we rank the below-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
102	MomIvol	Idiosyncratic volatility-enhanced momentum	Momentum is stronger among stocks with high idiosyncratic volatility.	Jiang *et al.*(2005)	Firstly, we sort stocks on the idiosyncratic volatility as characterized in anomaly (79) and determine the median. Secondly, we rank the above-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
103	MomSmall	Size-enhanced momentum	Momentum is stronger among small firms.	Jegadeesh and Titman (1993), Hong *et al.*(2000), Zhang (2006)	Firstly, we sort stocks on the size as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
104	MomBM	Book-to-market ratio-enhanced momentum	Momentum is stronger among companies with high book-to-market ratios.	Asness (1997), Daniel and Titman (1999), Sagi and Seasholes (2007)	Firstly, we sort stocks on the book-to-market ratio as characterized in anomaly (2) and determine the median. Secondly, we rank the above-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
105	MomTR	Liquidity-enhanced momentum	Momentum is stronger across liquid stocks.	Lee and Swaminathan (2000)	Firstly, we sort stocks on the turnover ratio as characterized in anomaly (69) and determine the median. Secondly, we rank the above-median stocks on their cumulative returns in months *t*-12 to *t*-2.
106	Mom52H	52-week high-enhanced momentum	Momentum is stronger among the firms near their 52-weeks high.	George and Hwang (2004)	Firstly, we sort stocks on the distance to the 52-weeks high, as characterized in anomaly (124), and determine the median. Secondly, we rank the above-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.

107 MomNeg	Analyst coverage-enhanced momentum	Momentum is stronger among the neglected companies.	Hong *et al.*(2000)	Firstly, we discard the stocks followed by at least one analyst. Secondly, we rank the stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
108 MomR2	R^2-enhanced momentum	Momentum is stronger among the companies with low R^2.	Hou *et al.*(2006)	Firstly, we sort stocks on the R^2 from the three-factor model of Fama and French (1993) based on returns in 4months *t*-24 to *t*-1 (at least 12 observations required). Secondly, we rank the below-median stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
109 MomCons	Return consistency-enhanced momentum	Momentum is stronger among stocks with consistent positive or negative returns.	Grinblatt and Moskowitz (2004)	We rank stocks based on their cumulative return in months *t*-1 to *t*-6. We go long (short) the stocks with the high (low) return. We discard stocks with less than 5 positive (negative) returns in the ranking period from the long (short) portfolio.
110 MomCred1	Credit risk-enhanced momentum (1)	Momentum is stronger among firms with high credit risk.	Avramov *et al.*(2009)	Firstly, we sort stocks on the credit risk as characterized in anomaly (19) and determine the median. Secondly, we rank the high credit risk stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
111 MomCred2	Credit risk-enhanced momentum (2)	Momentum is stronger among firms with high credit risk.	Avramov *et al.*(2009)	Firstly, we sort stocks on the credit risk as characterized in anomaly (20) and determine the median. Secondly, we rank the high credit risk stocks on their cumulative returns in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) return.
112 MomSkew	Skewness-enhanced momentum	Stocks with high (low) momentum and low (high) idiosyncratic skewness outperform stocks with low (high) momentum and high (low) skewness.	Jacobs, Regale, and Weber (2016)	We average the ranks of stocks sorted on long-term momentum (anomaly [99]) and idiosyncratic skewness (anomaly [87]). We go long (short) the stocks with high (low) rank.
113 RALtMom	Risk-adjusted momentum	Stocks of firms with high (low) normalized returns over past year continue to outperform (underperform) over the next month.	Shaik (2011)	We rank stocks based on their cumulative return in months *t*-12 to *t*-2 divided by the standard deviation of monthly returns in this period. We go long (short) the stocks with the high (low) normalized return.

114 TSMom	Time series momentum	The stocks with the positive return in previous 12 months outperform the stocks with the negative return in previous 12 months.	Moskowitz *et al.*(2012)	We go long (short) stocks with the positive (negative) cumulative excess return in previous 12 months.
115 AlphaMom	Alpha momentum	Stocks with high momentum in three-factor model alphas outperform stocks with low momentum in the alphas.	Huhn and Scholz (2016)	Firstly, we calculate monthly alphas based the three-factor model of Fama and French (1993). Secondly, we sort stocks on an average of the alphas in months
116 Acc	Momentum acceleration	Change in 6-month momentum positively predicts returns.	Ardila *et al.*(2015)	We sort firms on the difference between cumulative returns in months *t*-6 to *t*-1 and *t*-12 to *t*-7. We go long (short) the stocks with the high (low) difference.
Group 16: Trend				
117 MA6A	6-month moving average (absolute)	The stocks with the price above (below) 200-trading day moving average outperform (underperform) the market.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-6 to *t*-2. We go long (short) the stocks the positive (negative) value of this ratio.
118 MA12A	12-month moving average (absolute)	The stocks with the price above (below) 250-trading day moving average outperform (underperform) the market.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-12 to *t*-2. We go long (short) the stocks the positive (negative) value of this ratio.
119 MA6B	6-month moving average (band)	The stocks with the price at least 25% above (below) 200-trading day moving average outperform (underperform) the market.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-6 to *t*-2. We go long (short) the stocks with the ratio of price to moving average equal at least 1.25 (at most 0.75).
120 MA12B	12-month moving average (band)	The stocks with the price at least 25% above (below) 250-trading day moving average outperform (underperform) the market.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-12 to *t*-2. We go long (short) the stocks with the ratio of price to moving average equal at least 1.25 (at most 0.75).
121 MA6Q	6-month moving average (ratio)	The ratio of current price to the 200-trading day moving average positively predicts returns.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-6 to *t*-2. We go long (short) the stocks with the high (low) ratio.

122 MA12Q	12-month moving average (ratio)	The ratio of current price to the 250-trading day moving average positively predicts returns.	Huddart *et al.*(2009), Han *et al.*(2013)	We sort stocks on the relation of price in month *t*-1 to the mean price in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) ratio.
Group 17: 52-week high				
123 52HA	52-week high (absolute)	Companies at their 52-weeks high outperform the companies below the 52-weeks high.	George and Hwang (2004)	We rank firms on the ratio of the price at the and of *t*-1 to the maximum price in months *t*-12 to *t*-2. We go long the stocks with the ratio equal 1 and short the stocks with the ratio below 1.
124 52HQ	52-week high (ratio)	Companies near their 52-weeks high outperform the market far from the 52-weeks high.	George and Hwang (2004)	We rank firms on the ratio of the price at the and of *t*-1 to the maximum price in months *t*-12 to *t*-2. We go long (short) the stocks with the high (low) value of the ratio.
125 52HAL	Lagged 52-week high (absolute)	Companies at their 52-weeks high three months ago outperform the companies below the 52-weeks high three months ago.	Chen and Yang (2016)	We rank firms on the ratio of the price at the and of *t*-1 to the maximum price in months *t*-15 to *t*-4. We go long the stocks with the ratio equal 1 and short the stocks with the ratio below 1.
126 52HQL	Lagged 52-week high (ratio)	Companies near their 52-weeks high three months ago outperform the market far from the 52-weeks high three months ago.	Chen and Yang (2016)	We rank firms on the ratio of the price at the and of *t*-1 to the maximum price in months *t*-15 to *t-4*. We go long (short) the stocks with the high (low) value of the ratio.
127 52HQSmall	Size-enhanced 52-week effect	The 52-week effect is stronger among small companies.	Burghof and Prothmann (2011)	Firstly, we sort stocks on the size as characterized in anomaly (136) and determine the median. Secondly, we rank the below-median stocks on their ratio of the price at the and of t-1 to the maximum price in months t-12 to t-2. We go long (short) the stocks with the high (low) return.
128 52HQBM	B/M ratio-enhanced 52-week effect	The 52-week effect is stronger among high book-to-market ratio companies.	Burghof and Prothmann (2011)	Firstly, we sort stocks on the book-to-market ratio as characterized in anomaly (2) and determine the median. Secondly, we rank the below-median stocks on their ratio of the price at the and of t-1 to the maximum price in months t-12 to t-2 We go long (short) the stocks with the high (low) return.
Group 18: Seasonalities				
129 SeasMom5	Seasonality momentum (5 years)	Stocks tend to have high (low) returns in the same calendar month in consecutive years.	Heston and Sadka (2008)	We rank stocks on the average returns in the same calendar month in the last 5 years, as available. We go long (short) the stocks with the high (low) mean return.

130 SeasMom20	Seasonality momentum (20 years)	Stocks tend to have high (low) returns in the same calendar month in consecutive years.	Keloharju, Linnainmaa, and Nyberg (2016)	We rank stocks on the average returns in the same calendar month in the last 20 years, as available. We go long (short) the stocks with the high (low) mean return.
131 OtherJan	The other January effect	Performance in January positively predicts performance during rest of the year.	Cooper *et al.*(2006)	We rank stocks on their past return in the most recent January. We go long (short) the stocks with the high (low) past return.
Group 19: Analyst coverage				
132 Neg	Analyst coverage	Neglected firms tend to outperform the market.	Arbel and Strebel (1982)	We rank the securities based on the number of analysts that covers them. We go long (short) the stocks with the low (high) coverage.
133 CovCh	Change in analyst coverage	Change in the number of analysts covering a company positively predicts returns.	Scherbina (2008)	We rank firms on the change in the number of analysts covering a company (measured as in the anomaly [132]) from months t-4 to t-1. We go long (short) the stocks with the high (low) change.
134 Rec	Average recommendation	Stocks with favorable analysts recommendations outperform stocks with poor analyst recommendations.	Jegadeesh *et al.*(2004)	We assign numeric variables from 1 to 5 to the analyst recommendations. We rank stocks based on an average analyst recommendation in month t-1. In the case of missing values, we use average lagged values from months t-3 to t-2. We go long (short) the stocks with the highest (lowest) analysts' recommendations.
135 RecCh	Change in recommendation	Companies with improving analysts' recommendations outperform companies with deteriorating analysts' recommendations.	Jegadeesh *et al.*(2004)	We rank stocks on the change in average analyst recommendation (measured as in the anomaly [134]) from month t-4 to month t-1.
Group 20: Market frictions and others				
136 Cap	Total market capitalization	Firms with low total market capitalization outperform firms with high total market capitalization.	Banz (1981)	We rank firms based on their total market capitalization at t-1. We go long (short) the firms with the low (high) capitalization.
137 CapBeta	Beta-enhanced size effect	The small firm effect is stronger among low-beta firms.	Bali, Engle, and Murray (2016)	Firstly, we sort stocks on beta as characterized in anomaly (77) and determine the median. Secondly, we rank the below-median beta stocks on their total stock market capitalization in month t-1. We go long (short) the small (large) companies.

138 LP	Price	Stocks of firms with low price outperform firms with high price	Bhardwaj and Brooks (1992)	We rank firms on their prices at the end of month *t*-1. We go long (short) the firms with the low (high) price.
139 Sin	Stock stocks	Stocks belonging to "sin" industries overperform.	Hong and Kacperczyk (2009)	We go long the firms belonging to one of the following industries according to the Bloomberg Industry Classification Standard: 1) Alcoholic Beverages, 2) Tobacco, 3) Casinos and Gaming. We go short the other firms.
140 PEAD	Post-earnings announcement drift	Stock with positive earnings surprises outperform stocks with negative earnings surprises.	Chordia and Shivakumar (2006)	Earnings surprises are computed as the difference between actual earnings and earnings four quarters ago, scaled by the standard deviation of earnings surprises over the previous 8 quarters. We go long (short) stocks with the high (low) earnings surprise.

Table A2

Performance of Individual Anomalies

No.	Abbr.	Equal-weighted portfolios: Average return R	*t*-stat	Alpha a	*t*-stat	Value-weighted portfolios: Average return R	*t*-stat	Alpha a	*t*-stat
				Group 1: Value vs growth					
1	EP	1.15**	*(4.69)*	1.15**	*(3.89)*	0.21	*(0.56)*	0.22	*(0.61)*
2	BM	0.63**	*(2.71)*	0.63*	*(2.31)*	-0.04	*(-0.04)*	-0.03	*(-0.07)*
3	CFP	1.16**	*(4.14)*	1.16**	*(4.20)*	0.82*	*(2.03)*	0.82*	*(1.98)*
4	SP	1.12**	*(4.66)*	1.12**	*(3.73)*	0.68*	*(2.45)*	0.69	*(1.91)*
5	EBEV	1.48**	*(5.20)*	1.48**	*(5.81)*	0.79	*(1.77)*	0.79*	*(2.16)*
6	SEV	1.18**	*(4.49)*	1.18**	*(3.82)*	1.19**	*(3.64)*	1.20**	*(3.17)*
7	EBP	1.38**	*(4.67)*	1.39**	*(4.88)*	0.68	*(1.71)*	0.68	*(1.52)*
8	SG	-0.36	*(-0.92)*	-0.36	*(-1.03)*	-0.81	*(-1.15)*	-0.81	*(-1.19)*
9	BMCap	0.91**	*(2.89)*	0.91*	*(2.27)*	0.85*	*(2.57)*	0.85*	*(2.12)*
10	BMGPA	0.53	*(1.30)*	0.52	*(1.30)*	0.37	*(0.89)*	0.36	*(0.76)*
				Group 2: Dividends					
11	DY	0.40*	*(2.00)*	0.39	*(1.57)*	0.49	*(1.46)*	0.49	*(1.69)*
12	DYCh	-0.23	*(-1.19)*	-0.22	*(-1.09)*	0.26	*(0.62)*	0.27	*(0.68)*
13	DCh	0.40*	*(2.38)*	0.41**	*(2.75)*	0.23	*(0.78)*	0.23	*(0.86)*
				Group 3: Profitability					
14	ROA	0.25	*(0.93)*	0.24	*(0.74)*	0.49	*(1.03)*	0.49	*(1.12)*
15	ROE	0.46	*(1.78)*	0.46	*(1.55)*	1.31*	*(2.42)*	1.30*	*(2.52)*
16	ROIC	0.35	*(1.08)*	0.34	*(1.09)*	0.48	*(0.88)*	0.46	*(0.68)*
17	GPA	0.18	*(0.52)*	0.18	*(0.40)*	-0.05	*(-0.04)*	-0.07	*(-0.13)*
18	CFA	0.59**	*(3.73)*	0.59**	*(3.25)*	0.12	*(0.51)*	0.12	*(0.34)*
				Group 4: Credit risk and indebtedness					
19	Cred1	0.50	*(1.05)*	0.58	*(1.09)*	0.45	*(0.67)*	0.59	*(0.80)*
20	Cred2	0.35	*(1.86)*	0.38*	*(2.14)*	0.79*	*(2.04)*	0.87*	*(2.01)*
21	DM	-0.36	*(-1.58)*	-0.35	*(-1.39)*	-0.48	*(-1.25)*	-0.48	*(-1.15)*
22	LevCh	0.68**	*(3.59)*	0.68**	*(3.36)*	0.69	*(1.56)*	0.68	*(1.66)*
23	LTDCh	0.31	*(1.27)*	0.30	*(1.48)*	-0.25	*(-0.53)*	-0.23	*(-0.50)*
24	CFD	1.00**	*(4.50)*	1.00**	*(4.00)*	0.70	*(1.63)*	0.70	*(1.32)*
				Group 5: Investment and intangibles					
25	AG	-0.41	*(-1.60)*	-0.41	*(-1.14)*	-0.42	*(-0.99)*	-0.42	*(-0.91)*
26	Invest	-0.20	*(-0.54)*	-0.20	*(-0.61)*	0.12	*(0.31)*	0.11	*(0.23)*
27	IG	0.22	*(0.93)*	0.22	*(0.73)*	0.02	*(0.16)*	0.02	*(0.04)*
28	HR	0.31	*(1.08)*	0.31	*(0.89)*	0.16	*(0.39)*	0.16	*(0.28)*
29	CIA	-0.10	*(-0.33)*	-0.10	*(-0.30)*	-0.29	*(-0.64)*	-0.30	*(-0.56)*
30	I2Ch	0.09	*(0.44)*	0.09	*(0.36)*	-0.52	*(-0.86)*	-0.52	*(-0.76)*
31	OL	0.25	*(1.22)*	0.25	*(0.88)*	-0.01	*(0.19)*	-0.01	*(-0.04)*
				Group 6: Accruals					
32	OA	0.47*	*(2.10)*	0.47	*(1.71)*	0.57	*(1.00)*	0.58	*(0.98)*
33	TA	0.30	*(1.24)*	0.31	*(0.96)*	-0.44	*(-0.98)*	-0.43	*(-0.81)*
34	POA	0.38	*(1.42)*	0.39	*(1.09)*	0.46	*(0.99)*	0.48	*(0.90)*
35	PTA	0.24	*(1.12)*	0.24	*(0.78)*	-0.37	*(-0.93)*	-0.37	*(-0.89)*
36	AcIvol	0.38	*(1.73)*	0.36	*(1.27)*	-0.19	*(-0.42)*	-0.23	*(-0.49)*
37	NOAg	0.24	*(1.03)*	0.25	*(0.77)*	0.01	*(-0.02)*	0.01	*(0.02)*
38	NOAc	0.19	*(0.91)*	0.19	*(0.62)*	-0.08	*(-0.23)*	-0.08	*(-0.15)*
39	InG	0.30	*(1.23)*	0.29	*(0.94)*	0.07	*(0.19)*	0.07	*(0.13)*

40	InC	0.13	*(0.65)*	0.12	*(0.40)*	0.24	*(0.43)*	0.23	*(0.41)*
	Group 7: Fundamental analysis								
41	CH	0.32	*(1.04)*	0.32	*(1.07)*	-0.66	*(-1.66)*	-0.66	*(-1.29)*
42	CR	0.47	*(1.55)*	0.46	*(1.14)*	0.53	*(1.24)*	0.52	*(0.96)*
43	CRCh	0.11	*(0.41)*	0.10	*(0.53)*	0.13	*(0.40)*	0.13	*(0.35)*
44	QR	0.39	*(1.50)*	0.38	*(1.15)*	0.35	*(0.77)*	0.34	*(0.61)*
45	QRCh	0.28	*(1.29)*	0.28	*(1.21)*	0.66	*(1.51)*	0.66	*(1.86)*
46	GM	-0.38	*(-1.16)*	-0.39	*(-0.95)*	-0.02	*(-0.18)*	-0.03	*(-0.05)*
47	GMCh	0.51	*(1.73)*	0.50	*(1.71)*	0.83	*(1.44)*	0.83	*(1.44)*
48	AT	0.85**	*(3.92)*	0.85**	*(3.53)*	0.55	*(1.33)*	0.55	*(1.50)*
49	ATCh	-0.04	*(-0.27)*	-0.04	*(-0.16)*	0.45	*(0.64)*	0.44	*(0.65)*
50	PM	-0.29	*(-1.26)*	-0.30	*(-0.92)*	0.45	*(0.87)*	0.44	*(0.77)*
51	PMCh	0.68**	*(2.91)*	0.67**	*(2.72)*	0.71	*(1.46)*	0.71	*(1.53)*
52	Depr	0.34	*(1.06)*	0.34	*(1.17)*	-0.01	*(0.06)*	-0.01	*(-0.01)*
53	DeprCh	-0.07	*(-0.17)*	-0.07	*(-0.28)*	-0.24	*(-0.55)*	-0.23	*(-0.50)*
54	SR	0.48*	*(2.05)*	0.47	*(1.91)*	0.58	*(1.28)*	0.57	*(1.40)*
55	SC	0.15	*(0.89)*	0.16	*(0.66)*	0.04	*(0.13)*	0.04	*(0.11)*
56	SGIG	0.58**	*(2.94)*	0.58*	*(2.47)*	0.15	*(0.24)*	0.15	*(0.27)*
57	SChRCh	0.24	*(1.32)*	0.25	*(1.22)*	-0.63	*(-1.38)*	-0.63	*(-1.29)*
58	GMGSG	-0.07	*(-0.11)*	-0.07	*(-0.17)*	-0.22	*(-0.27)*	-0.22	*(-0.32)*
59	EarVol	0.14	*(0.29)*	0.14	*(0.38)*	-0.29	*(-0.69)*	-0.28	*(-0.51)*
60	CfVol	0.17	*(0.28)*	0.16	*(0.34)*	0.37	*(0.48)*	0.35	*(0.46)*
61	TS140.Cons	0.72*	*(2.04)*	0.71	*(1.57)*	1.25*	*(2.06)*	1.25	*(1.60)*
	Group 8: Issuance								
62	IPO	0.39	*(1.54)*	0.39	*(1.62)*	0.03	*(0.08)*	0.04	*(0.12)*
63	CEI	0.39	*(1.21)*	0.41	*(1.19)*	0.16	*(0.41)*	0.21	*(0.59)*
64	NSI	0.39	*(1.01)*	0.40	*(1.39)*	0.42	*(0.91)*	0.41	*(0.82)*
65	Age	0.50*	*(2.00)*	0.50	*(1.59)*	0.17	*(0.43)*	0.18	*(0.50)*
66	Ext	0.34	*(1.45)*	0.33	*(1.29)*	0.21	*(0.51)*	0.21	*(0.54)*
67	TECh	-0.01	*(-0.07)*	-0.01	*(-0.06)*	-0.61	*(-1.55)*	-0.61	*(-1.42)*
	Group 9: Liquidity								
68	Turn	0.12	*(0.33)*	0.10	*(0.32)*	-0.36	*(-0.75)*	-0.38	*(-0.83)*
69	TR	-0.11	*(-0.41)*	-0.12	*(-0.35)*	-0.29	*(-0.74)*	-0.29	*(-0.89)*
70	TRV	0.71*	*(2.20)*	0.75	*(1.92)*	0.38	*(1.12)*	0.42	*(0.99)*
71	TurnV	0.16	*(0.63)*	0.16	*(0.51)*	-0.70	*(-1.34)*	-0.72	*(-1.44)*
72	Amih	0.49	*(1.54)*	0.48	*(1.63)*	0.12	*(0.48)*	0.10	*(0.26)*
73	AmihSmall	0.67*	*(1.98)*	0.66	*(1.55)*	0.52	*(1.54)*	0.51	*(1.20)*
74	AmihStRev	1.18**	*(2.69)*	1.17**	*(3.68)*	0.54	*(1.23)*	0.53	*(1.09)*
75	Spread	-0.55	*(-1.59)*	-0.54	*(-1.59)*	-0.95	*(-1.80)*	-0.93	*(-2.76)*
76	TR12	0.06	*(0.14)*	0.05	*(0.17)*	-0.16	*(-0.41)*	-0.15	*(-0.44)*
	Group 10: Low-volatility								
77	Beta	1.69**	*(3.21)*	1.66**	*(2.90)*	1.44*	*(2.51)*	1.42*	*(2.09)*
78	SD	0.63	*(1.55)*	0.68	*(1.72)*	1.11*	*(2.37)*	1.15*	*(2.23)*
79	IVolFF3	0.68	*(1.74)*	0.71*	*(1.99)*	0.94	*(1.94)*	0.96	*(1.88)*
80	IvolMKT	0.58	*(1.55)*	0.62	*(1.64)*	1.05*	*(2.34)*	1.08*	*(2.18)*
81	OilBeta	0.15	*(0.88)*	0.15	*(0.66)*	0.12	*(0.38)*	0.11	*(0.43)*
	Group 11: Extreme and downside risk								
82	DownVol	-0.12	*(-0.49)*	-0.11	*(-0.45)*	-0.56	*(-1.39)*	-0.53	*(-1.13)*
83	VaR	-0.12	*(-0.43)*	-0.11	*(-0.40)*	-0.54	*(-1.32)*	-0.52	*(-1.01)*
84	Kurt	-0.14	*(-0.92)*	-0.14	*(-1.05)*	-0.42	*(-1.45)*	-0.43	*(-1.69)*
	Group 12: Skewness								
85	Skew	0.18	*(1.15)*	0.18	*(1.01)*	0.54	*(1.82)*	0.55	*(1.57)*
86	CoSkew	0.14	*(0.72)*	0.15	*(0.58)*	0.27	*(0.80)*	0.28	*(0.98)*

87	IdSkew	-0.01	*(-0.06)*	-0.01	*(-0.07)*	0.09	*(0.26)*	0.13	*(0.40)*
	Group 13: Long-term reversal								
88	LtRev36	0.23	*(0.84)*	0.23	*(0.95)*	0.13	*(0.23)*	0.13	*(0.32)*
89	LtRev60	0.41	*(1.57)*	0.42	*(1.49)*	0.14	*(0.36)*	0.11	*(0.21)*
90	LtRev36Ivol	0.21	*(0.62)*	0.21	*(0.64)*	0.31	*(0.53)*	0.29	*(0.57)*
91	LtRev60Ivol	0.54	*(1.27)*	0.54	*(1.35)*	0.45	*(0.74)*	0.42	*(0.77)*
92	LtRev36Small	0.17	*(0.60)*	0.16	*(0.55)*	0.18	*(0.67)*	0.17	*(0.59)*
93	LtRev60Small	0.12	*(0.22)*	0.12	*(0.32)*	0.21	*(0.45)*	0.20	*(0.53)*
94	RevMonth	0.73**	*(3.65)*	0.73*	*(2.46)*	0.47	*(1.21)*	0.47	*(0.96)*
	Group 14: Short-term reversal								
95	StRev	-1.49**	*(-6.66)*	-1.49	*(-5.81)*	-1.03*	*(-2.21)*	-1.03	*(-2.46)*
96	StRevSmall	-1.29**	*(-5.05)*	-1.29	*(-4.52)*	-1.45**	*(-5.37)*	-1.45	*(-5.09)*
97	StRevLMom	-0.75**	*(-2.47)*	-0.75	*(-2.70)*	-0.33	*(-0.43)*	-0.34	*(-0.61)*
	Group 15: Momentum								
98	StMom	1.30**	*(4.58)*	1.30**	*(4.35)*	0.38	*(0.79)*	0.38	*(0.80)*
99	LtMom	1.39**	*(5.11)*	1.38**	*(4.74)*	0.78*	*(1.98)*	0.77	*(1.46)*
100	IntMom	1.19**	*(5.08)*	1.19**	*(4.36)*	0.96**	*(2.80)*	0.95*	*(2.16)*
101	MomAge	1.50**	*(4.46)*	1.50**	*(4.75)*	1.43**	*(3.63)*	1.42**	*(3.28)*
102	MomIvol	1.26**	*(3.93)*	1.31**	*(3.81)*	0.99*	*(2.05)*	1.06*	*(2.20)*
103	MomSmall	1.60**	*(5.74)*	1.59**	*(5.66)*	1.54**	*(5.19)*	1.54**	*(5.26)*
104	MomBM	1.19**	*(3.01)*	1.19**	*(3.18)*	1.06*	*(2.13)*	1.05*	*(2.39)*
105	MomTR	1.63**	*(3.83)*	1.62**	*(3.76)*	1.70**	*(3.19)*	1.69**	*(2.75)*
106	Mom52H	1.34**	*(5.51)*	1.35**	*(5.74)*	1.02**	*(3.05)*	1.02**	*(2.97)*
107	MomNeg	1.47**	*(5.33)*	1.47**	*(5.42)*	0.90*	*(2.17)*	0.88	*(1.74)*
108	MomR2	1.56**	*(7.20)*	1.58**	*(6.46)*	1.41**	*(4.65)*	1.42**	*(3.94)*
109	MomCons	1.51**	*(3.13)*	1.51**	*(3.26)*	1.02	*(1.64)*	1.02	*(1.91)*
110	MomCred1	1.65**	*(2.58)*	1.74*	*(2.56)*	1.58*	*(2.14)*	1.67*	*(2.27)*
111	MomCred2	1.40**	*(4.51)*	1.43**	*(3.92)*	0.61	*(1.23)*	0.67	*(1.21)*
112	MomSkew	0.91**	*(4.91)*	0.93**	*(4.02)*	0.81*	*(2.35)*	0.87*	*(2.05)*
113	RALtMom	1.56**	*(6.46)*	1.55**	*(6.17)*	1.02**	*(3.43)*	1.01**	*(3.08)*
114	TSMom	1.26**	*(7.19)*	1.25**	*(6.68)*	0.88**	*(3.05)*	0.87*	*(2.37)*
115	AlphaMom	1.09**	*(5.80)*	1.09**	*(4.73)*	0.64*	*(2.06)*	0.64*	*(2.31)*
116	Acc	0.02	*(0.04)*	0.02	*(0.08)*	-0.31	*(-0.77)*	-0.31	*(-0.61)*
	Group 16: Trend								
117	MA6A	0.97**	*(5.35)*	0.97**	*(4.33)*	0.32	*(0.84)*	0.32	*(0.85)*
118	MA12A	1.09**	*(5.96)*	1.09**	*(5.03)*	0.60*	*(2.12)*	0.59	*(1.87)*
119	MA6B	0.63	*(1.00)*	0.63	*(0.81)*	0.09	*(0.02)*	0.09	*(0.07)*
120	MA12B	1.33**	*(2.85)*	1.32*	*(2.42)*	0.32	*(0.51)*	0.30	*(0.44)*
121	MA6Q	1.35**	*(4.79)*	1.34**	*(3.98)*	0.60	*(1.17)*	0.59	*(1.16)*
122	MA12Q	1.48**	*(5.24)*	1.48**	*(4.51)*	0.59	*(1.48)*	0.59	*(1.26)*
	Group 17: the 52-week high effect								
123	52HA	1.72**	*(7.26)*	1.71**	*(6.25)*	1.31**	*(3.49)*	1.30**	*(3.06)*
124	52HQ	1.61**	*(5.72)*	1.60**	*(4.60)*	0.81	*(1.93)*	0.79	*(1.81)*
125	52HAL	0.71**	*(3.36)*	0.71**	*(3.67)*	0.45	*(1.36)*	0.44	*(1.27)*
126	52HQL	1.02**	*(3.84)*	1.01**	*(4.08)*	0.90**	*(2.64)*	0.88*	*(2.36)*
127	52HQSmall	1.49**	*(5.19)*	1.49**	*(4.76)*	1.51**	*(4.84)*	1.50**	*(4.16)*
128	52HQBM	1.38**	*(3.10)*	1.36**	*(2.95)*	1.54**	*(2.80)*	1.51**	*(2.68)*
	Group 18: Seasonalities								
129	SeasMom5	0.58**	*(2.73)*	0.58**	*(2.80)*	0.47	*(1.19)*	0.46	*(1.22)*
130	SeasMom20	0.69**	*(3.38)*	0.69**	*(4.09)*	0.57	*(1.45)*	0.57	*(1.61)*
131	OtherJan	0.89**	*(3.28)*	0.89**	*(4.02)*	0.44	*(1.00)*	0.44	*(1.25)*
	Group 19: Analyst coverage								
132	Neg	0.10	*(0.34)*	0.09	*(0.36)*	0.07	*(0.26)*	0.07	*(0.25)*

133	CovCh	0.23	*(0.86)*	0.24	*(1.07)*	0.04	*(0.22)*	0.04	*(0.17)*
134	Rec	1.06**	*(2.63)*	1.05	*(1.95)*	0.74	*(1.54)*	0.73	*(1.04)*
135	RecCh	1.63**	*(3.35)*	1.64**	*(3.12)*	1.43**	*(2.70)*	1.43**	*(3.25)*
	Group 20: Market frictions and others								
136	Cap	0.36*	*(2.02)*	0.36*	*(2.01)*	0.38	*(1.65)*	0.37	*(1.70)*
137	CapBeta	-0.16	*(-0.57)*	-0.14	*(-0.31)*	-0.12	*(-0.39)*	-0.10	*(-0.26)*
138	LP	0.42	*(1.70)*	0.42	*(1.64)*	-0.17	*(-0.54)*	-0.17	*(-0.55)*
139	Sin	0.66**	*(3.08)*	0.65**	*(2.80)*	0.65	*(1.66)*	0.64	*(1.44)*
140	PEAD	0.13	*(0.58)*	0.13	*(0.40)*	0.11	*(0.16)*	0.11	*(0.20)*
	Summary statistics								
Average		0.54	*1.96*	0.54	1.82	0.35	*0.85*	0.35	0.79
N(5%)		62		56		32		28	

Notes: This table reports the performance on the equal-weighted and value-weighted long-short anomaly portfolios formed on the basis of one-way sorts with a 30%-breakpoint. *No.* is the number of anomalies considered. *Abbreviation is* the abbreviation for a specific anomaly. *R* is the mean monthly return, α is the intercept from the CAPM, and *t*-stat are the corresponding *t*-statistics. The asterisks, * and ** , indicate values that are significantly different from zero at the 5% and 1% levels of significance. The numbers in brackets are bootstrap (Newey-West (1987) robust standard error) *t*-statistics for the means (alphas). The table also presents the average statistics for all the anomalies. *N(p<5%)* is the number of means that are positive and significantly different from zero at the 5% level of significance. The abbreviations of the strategies are explained in detail in Table A1 in the Online Appendix.

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