5-2019

Essays on anomalies in asset pricing

Xinrui DUAN
Singapore Management University, xinrui.duan.2014@pbs.smu.edu.sg

ESSAYS ON ANOMALIES IN ASSET PRICING

DUAN XINRUI

SINGAPORE MANAGEMENT UNIVERSITY
2019

Essays on Anomalies in Asset Pricing

DUAN Xinrui

Submitted to Lee Kong Chian School of Business
in partial fulfilment of the requirements for the
Degree of Doctor of Philosophy in Business (Finance)

Dissertation Committee:

Jun TU (Supervisor/Chair)
Associate Professor of Finance
Singapore Management University

Dashan HUANG
Assistant Professor of Finance
Singapore Management University

Sheng HUANG
Associate Professor of Finance
China Europe International Business School

Zhe ZHANG
Associate Professor of Finance
Singapore Management University

Singapore Management University
2019

Essays on Anomalies in Asset Pricing

DUAN Xinrui

Chapter 1:

Sentiment, Limited Attention and Mispricing

Xinrui DUAN, Li GUO, Weikai LI, Jun TU

We examine whether various anomalies can be driven by two common behavioral forces, namely, "subjective" sentiment (representing investors' subjective biased beliefs) and "objective" limited attention (representing investors' objective cognitive constraints). While sentiment explains well many anomalies that are more speculative on the short-leg, it fails to explain anomalies that are equally speculative on the long and short-leg, including momentum and post-earnings announcement drift. Market-wide attention shifts, proxied by number of news averaged across stocks, significantly attenuates underreaction-driven anomalies, beyond the effect of sentiment. Our findings suggest that increase in market-wide attention can temporarily reduce the cost of attending to market and improve price efficiency.

Chapter 2:

Factor Style

Xinrui DUAN, Ran ZHANG

We use systematic methods to solve factor timing problem and to improve the performance of factor investing. Past factor returns predict the cross section of factor returns, and this predictability is at its strongest at the one-month horizon (Arnott et al. 2019). We find that factor momentum is pervasive in international stock markets. We show that factor momentum can be captured by trading almost any set of factors. Industry momentum and size-B/M momentum stem from factor momentum. We further find that stock factor momentum, stock factor IVOL, and cross-assets factor momentum can generate alphas. These alphas cannot be explained by current asset pricing models.

Chapter 3:

Investing in Anomalies: An Optimal Portfolio Approach

Xinrui DUAN, Jun TU, Ran ZHANG, Guofu ZHOU

We take an optimal portfolio approach on investing in multiple anomalies. We find that a variety of estimated optimal rules outperform substantially investing in any single anomaly. In addition, although it has been documented that the publication of a given anomaly may significantly reduce its standalone economic value, we show that these anomalies are still valuable collectively in the optimal portfolio even after they are published.

Contents

Acknowledgements

I wish to express my sincere gratitude to my supervisor Professor Jun Tu for his patient guidance, encouragement and advice. Thank you for guiding me in the research of asset pricing. Thank you for always spending a lot of time in discussing the projects. With upmost appreciation, thank you for all your supports.

I am also grateful to Professor Guofu Zhou, Professor Weikai Li. Thank you for the guidances and advices during the collaboration. I would like to thank my dissertation committee members Professor Dashan Huang, Professor Zhe Zhang, Professor Sheng Huang. Thank you for your supports and advices on my research work. My thanks also go to my PhD peers Li GUO, Ran Zhang, Jingi Ha, Hao Cheng, Xueying Bian and Zilin Chen. Thank you for your suggestions and supports on this dissertation.

Thank you my friends Min Zeng, Wanshan Song, Chang He and Jing Gan who are also the best roommates in this world. Thank you for all the happy memories in these five years.

Last but not least, I would like to thank my husband Junqing Gu and my mother Guowei Jin who are the two most important people in my life. Thank you for your unconditional support. Thank you for making me strong enough to get through those hard times in this journey.

Chapter 1

Sentiment, Limited Attention and Mispricing

Xinrui Duan, Li Guo, Weikai Li, and Jun Tu

ABSTRACT

We examine whether various anomalies can be driven by two common behavioral forces, namely "subjective" sentiment (representing investors' subjective biased beliefs) and "objective" limited attention (representing investors' objective cognitive constraints). While sentiment well explains many anomalies that are more speculative on the short-leg, it fails to explain anomalies that are equally speculative on the long and short-leg, including momentum and post-earnings announcement drift. Market-wide attention shifts, proxied by the number of news articles averaged across stocks, significantly attenuate underreaction-driven anomalies, beyond the effect of sentiment. Our findings suggest that an increase in market-wide attention can temporarily reduce the cost of attending to the market and improve price efficiency.

JEL classification: G12, G14

1.1 Introduction

Recently, there has been a debate on whether a small set of common factors is able to explain various anomalies. Alternative factor models are being proposed, including the management-controlled factor (MGMT) and the performance-based factor (PERF) used in Stambaugh and Yuan (2016), as well as the financing factor (FIN) and post-earnings announcement drift factor (PEAD) used in Daniel et al. (2017). Some other studies, such as Hou et al. (2014), also try to find common factors that explain various anomalies. Kozak, Nagel, and Santosh (2017) indicate that the number of common factors, no matter rational risk-based factors or mispricing-based factors, is likely to be small and in the range of three to five. Although these studies investigate the commonality among the various anomalies based on some econometric approaches, they do not explicitly tie the common factors to either risk-based or mispricing-based explanations.

In this paper, we examine whether various anomalies and newly proposed factors can be explained by a small set of common forces with clear behavioral motivations. Consistent with Stambaugh et al. (2012), we find that the investor sentiment, which reflects the marginal investors' "subjective" biased beliefs, may serve as one common behavioral force. When market-wide sentiment is high, the majority of investors become overly optimistic, and push stock prices above the fair values implied by fundamentals. In the presence of short-sale constraints, the overvaluation caused by optimistic investors cannot be easily corrected by rational arbitrageurs, resulting in lower future returns. When sentiment is low, however, rational investors could easily step in when overly pessimistic investors sell, hence we should not observe significant and persistent underpricing during low sentiment periods. The time series variation in investor sentiment could thus explain the average return spread of anomalies and its amplification during high sentiment periods.

Although sentiment is often used as a catch-all measure of investor irrationality, we find that some anomalies cannot be easily explained by sentiment shifts alone. Most notably, we find that anomalies related to investor underreaction and price continuation, such as momentum and post-earnings announcement drift (PEAD), either do not have a significant relationship or are only weakly predicted by investor sentiment shifts over time. The reason, we conjecture, is that for sentiment to affect the cross-section of anomaly returns, the long and short leg of anomaly cannot be equally speculative. As argued by Baker and Wurgler (2006), irrational sentiment should exert a stronger effect on prices of stocks that are hard to value, or more "speculative" in nature. When market-wide sentiment is high, those "hard-to-value" stocks are subject to greater investor disagreement and thus more likely to be pushed up by optimistic investors (Miller (1977)), while stocks that are easy to value should not be affected in the same way. Using several valuation uncertainty measures proposed by the literature (Zhang (2006)), we confirm that for most anomalies studied in Stambaugh et al. (2012), the short leg of the anomaly is much more speculative than the long leg, hence the differential sentiment effect observed on the cross-sectional anomaly returns. However, for those anomalies that are equally speculative in the long and short leg, as in the case of momentum and PEAD, the effect of aggregate sentiment on long-short portfolio return is more ambiguous. This is because when the long and short leg of the anomaly portfolio are equally hard to value or "speculative", there is a tendency for excessive investor optimism to push up the prices and lower the future returns of both portfolios at the same time and to similar magnitude, hence it is unclear if sentiment amplifies the long-short portfolio returns.

Consistent with this explanation, when we separately regress the long- and short-leg returns of the anomalies on the lagged Baker-Wurgler sentiment index, the coefficient on the short-leg for most anomalies is much more negative and significant than that of the long-leg. This is consistent with the evidence in Stambaugh et al. (2012). However, for momentum and PEAD, we find a similar negative effect of sentiment on the long and short legs of portfolio, resulting in a much smaller effect of sentiment on the long-short return spread.

In the second half of the paper, we suggest that another behavioral force, "limited attention", could be the underlying reason for the time series return variation of anomalies, especially among anomalies related to investor underreaction and price continuation. Conceptually, limited attention is very different from investor sentiment as it measures the cognitive constraints in investors' ability to process value-relevant information. Investors who have limited attention tend to underreact to news, which lead to the slow incorporation of new information and price continuation (Hirshleifer and Teoh 2003). This mechanism implies an inverse relationship between market-wide attention and anomaly returns.

Moreover, the effect of limited attention on anomaly returns should work even when the long and short leg portfolios are equally speculative. During periods of low market-wide attention, both long and short-leg stocks should underreact more to past news, hence we should observe more pronounced underreaction in both directions and a stronger long-short portfolio return spread. Conversely, during high market-wide attention periods, past news are more quickly incorporated into stock prices, hence we should observe much smaller anomaly returns during such periods. It is this unambiguous time-series relationship between market-wide attention and anomaly returns that differentiates our paper from Stambaugh et al.

(2012), which focuses exclusively on aggregate sentiment, especially for anomalies that are equally speculative in both the long and short leg.

Empirically, we use news coverage data from Thomson Reuters News Analytics to proxy for market-wide attention. This is motivated by a number of papers that use the news coverage of individual firms in well-known media outlets as a proxy for investors' attention at the stock-level (Barber et al. (2008); Tetlock (2011)). As our paper mainly examines the time-series variation of market-wide attention, we use the number of news articles averaged across stocks to measure aggregate attention. We then run a predictive regression of the long-short portfolio returns of each anomaly on the lagged attention measure. Among the 11 anomalies studied by Stambaugh et al. (2012), we find that market-wide attention has a significant attenuation effect on the long-short portfolio alphas of 6 anomalies when controlling for contemporaneous market return. The economic effect is substantial. The daily momentum CAPM alpha is 17.5 bps lower following the days with the highest decile of market-wide attention, compared to the periods with the lowest decile of attention. For comparison, the unconditional daily momentum CAPM alpha is 9.4 bps.

As aggregate attention may be correlated with investor sentiment, we further run a multivariate predictive regression by adding both the lagged sentiment index and attention measure. We continue to notice a negative effect of attention on the return spread of 6 anomalies, with the effect particularly pronounced in the momentum and PEAD anomalies. This suggests that investors' limited attention could be another significant force driving time series variation in anomaly returns beyond sentiment. We also look at the effect of attention on various price momentum strategies in great detail, and find that the attenuation effect of attention on momentum profits are robust with respect to the different performance rankings and holding periods used in the construction of momentum strategy.

In addition to individual anomalies, we also look at the recently proposed mispricing factors in Daniel et al. (2017). They propose that a parsimonious three-factor model, which includes a market factor, the PEAD factor and the Financing factor (FIN), has better explanatory power for a large set of anomaly returns than existing factor models. They motivate their choice of the two mispricng factors by arguing that PEAD mainly captures short-run mispricing, while the FIN factor captures long-run mispricing. Empirically, adding the PEAD factor significantly helps in explaining momentum-related anomalies. In our analysis, we find that the two factors proposed by Daniel et al. (2017) differ significantly because they may be driven by distinct mispricing mechanisms. While the short leg of the FIN factor is much more speculative than the long-leg based on our measure of valuation uncertainty, the long-leg of the PEAD factor is as speculative as the short leg. Consistent with this mechanism, we find that while sentiment significantly amplifies returns to the FIN factor, the time series variation of the PEAD factor return is not correlated with investor sentiment. In sharp contrast, market-wide attention explains the time series variation of the PEAD factor return very well. Consistent with our conjecture that high attention leads to faster incorporation of earnings news, the daily PEAD profits are 10.4 bps lower following the days with highest market-wide attention compared to the periods of lowest attention, which is economically large given an unconditional daily PEAD profit of 6.1 bps. Thus our paper provides a clear economic explanation of why the two mispricing factors proposed by Daniel et al. (2017) differ, and suggests that they could be driven by different mispricing channels.

This study contributes to several strands of the literature. First, our paper contributes to the behavioral finance literature that examines the time-series return variation of anomalies. While the majority of previous studies focus on the effect of aggregate investor sentiment (Baker and Wurgler (2006); Stambaugh and Yuan (2016); Stambaugh et al. (2012), we argue that the role of sentiment in cross-sectional anomaly returns should not be taken for granted. Sentiment cannot easily explain the average return spread on anomalies that are equally speculative in both the long and short leg, as well as its time series variation. We propose the use of another behavioral force, i.e., shifts in aggregate investor attention, which is better able to explain the return variation of those anomalies that are equally speculative in the long and short leg.

Secondly, this paper contributes to the growing literature that examines the role of investors' limited attention in driving certain anomalies. The majority of studies look at how anomalies vary across stocks with differential investor attention, measured by analyst/media coverage or investors' online searching activities. Hong et al. (2000), for example, document that momentum profits are more pronounced among stocks with less analyst coverage, suggesting that slow information diffusion among neglected stocks leads to underreaction and price continuation. Using the news searching and reading activity on Bloomberg terminal as a proxy for institutional investors' attention, Ben-Rephael et al. (2017) find that the post earnings announcement drift is much weaker when institutional investors pay more attention on earnings announcement days. Some studies use the day of the week to proxy for investor attention. For example, DellaVigna and Pollet (2009) show that the immediate market reaction to the earnings announcement is weaker and post-earnings announcement drift is stronger for stocks announcing earnings on Friday of the week, a time when the majority of investors are not paying enough attention. Our paper is related to this literature in the sense that we also hypothesize that high investor attention should lead to lower anomaly returns. However, our paper differs as we mainly focus on the time-series variation in market-wide attention and document its attenuation effect on a larger set of anomaly returns.

Last but not the least, this paper furthers our understanding of investor attention on capital market efficiency. Some recent papers document the detrimental effect of excessive attention on price efficiency. For example, Barber et al. (2008) document that retail investors are net buyers of attention-grabbing stocks with high media coverage and extreme daily returns. Using Google search as a measure of retail investors' attention, Da et al. (2011) find that stocks with abnormal search activity experience temporary positive price pressure but long-run reversal. Yuan (2015) studies the impact of market-wide attention on investors' trading activity and market return, but does not examine its effect on cross-sectional anomalies. By emphasizing the attenuation effect of aggregate attention on anomaly returns, our paper suggests that the effect of attention on market efficiency depends crucially on the required level of attention in the market. When the required level of attention is low for stocks on days without significant news, excessive attention could lead to transitory price pressure, as in Barber et al. (2008) and Da et al. (2011). However, when the required level of attention is high for stocks experiencing extreme past performance and earnings news, the higher attention actually reduces cost of information acquisition and leads to more efficient asset prices.[1]

1.2 Data and Summary Statistics

The data on analysts' earnings estimates is taken from the Institutional Brokers Estimate System (I/B/E/S) Unadjusted Detailed and Summary

[1]Klibanoff et al. (1998) show that country-specific news improves the response of closed-end country fund prices to asset value.

Dataset. Stock returns, prices and the number of outstanding shares are from the Center for Research in Securities Prices (CRSP). The accounting information is from the Compustat Annual and Quarterly Fundamental Files. The news data is from Thomson Reuters News Analytics Dataset. The sample includes all common stocks (share codes 10 and 11) from August 1965 through October 2015. The sample period is restricted by the availability of the Baker and Wurgler (2006) sentiment index. Penny stocks with share prices below $5 are removed.

1.2.1 Market-wide Sentiment and Attention

We use the sentiment index constructed in Baker and Wurgler (2006)[2]. The sentiment index starts from July 1965 to September 2015. We sort the time-series sentiment index equally into 10 deciles. For a given month $m-1$, the sentiment index S_{m-1} is matched with the daily anomaly returns $R_{i,t}$ in month m.

Attention is a scarce cognitive resource and is often used to explain investors' underreaction to new information. In this context, a key obstacle for empirical work is that investor attention allocation is typically not observable. According to Barber et al. (2008), a direct measure would be to go back in time and question investors on each day about the stocks that they thought about on that particular day. Recently, an emerging stream of literature addresses this issue by developing various direct proxies for investor attention. Da et al. (2011) use the Google search of stock ticker to capture retail investors' attention, while Da et.al (2017) use the search on Bloomberg terminal to measure the attention of institutional in-

[2]We extend our appreciation to Jeffrey Wurgler for making the data publicly available on his website `http://people.stern.nyu.edu/jwurgler/`. The sentiment index is constructed as the first principal component of five individual proxies, which are controlled by six macro economic variables.

vestors. However, as the Google search index only starts from 2004, it shows a relatively short sample period. In this paper, to balance the sample of investor attention and market anomalies, we use media coverage as an indirect measure of investors' attention. This has been used extensively in the literature, including Barber et al. (2008), Fang and Peress (2009), and Yuan (2015). An event that attracts many investors' attention is more likely newsworthy, and firms that are in the news are more likely to catch investors' attention compared to those that are not.

Our news dataset is the daily firm specific news feed from Thomson Reuters News Analytics from the period of 1996 to 2014. This large dataset is broader than many of the datasets previously studied with more than 25,000 equities covered by Thomson Reuters. The dataset identifies the time of the news story (with millisecond resolution), the firm mentioned in the story, the headline of the news story, story id, the relevance of the news article for the firm, the staleness of a news item and measures from a neural-network-based sentiment engine. To construct investor attention proxy, we first count the number of news articles for each firm on each day, and then calculate the average amount of news coverage across firms, namely

$$Attention_t = \frac{\sum_{k=1}^{K} \#\text{ of news}_k}{K},$$

where K stands for the total number of firms covered by media news. The first two rows of Table 3.1 report the descriptive statistics for both attention and sentiment measures. The daily average number of news ranges from 1 to 8.12, with a median of 3.27. The autocorrelation of our attention measure is 0.51, much lower than 0.86, which is the autocorrelation of sentiment index. Figure 1.1 shows the time series of our attention measure with the Baker and Wurgler (2006) investor sentiment index, both of which are standardized to have a mean of 0 and standard deviation of 1. The correlation between these two indices is -0.17, indicating that our investor attention proxy could be fundamentally different from investor sentiment.

Ball and Brown (1968) and Bernard and Thomas (1989) first document a post-earnings announcement drift phenomenon, which is interpreted as evidence of investors' underreaction to earnings news (DellaVigna and Pollet (2009), Hirshleifer et al. (2009) and Hou et al. (2009)). We expect that when market-wide attention is low, investors react slowly to earnings announcements and the post-earnings announcement drift is amplified. When market-wide attention is high, earnings news is quickly reflected in stock prices and we should observe attenuated return continuation. This idea also applies to other anomalies that are driven by investors' limited attention to value-relevant information, such as momentum and profitability-related anomalies.

1.2.2 Stock Market Anomalies

Following Stambaugh and Yuan (2016), we construct 11 prominent asset pricing anomalies, including net stock issuance (NSI), composite equity issuance (CEI), accruals, net operating assets (NOA), asset growth (AG), investment-to-assets (I/A), failure probability (FP), O-score, momentum, gross profitability (GP), and return-on-assets (ROA). For each anomaly, firms are sorted into deciles at the end of month $m-1$. Equal weighted daily portfolio returns in the next month m are calculated within each decile. We also construct a long-short portfolio with decile 10 being the long leg and decile 1 being the short leg for momentum, GP and ROA. The long-short portfolios are constructed in a reverse manner for the rest of the anomalies. The detailed construction method for these 11 anomalies, as well as the following mispricing factors introduced below, can be found in the appendix.

We construct the two mispricing factors[3] of Stambaugh and Yuan (2016), MGMT and PERF. Specifically, firms are assigned ranking scores from 1 to 100 based on each of the aforementioned 11 anomalies. The ranking scores are assigned in an opposite direction for momentum, GP and ROA. To construct the MGMT factor, firms are sorted into deciles for each month $m-1$ based on the average ranking scores of the first six anomalies . The equal weighted daily portfolio returns in the next month m are then calculated, with the two extreme deciles as the short and long leg of MGMT. Similarly, we construct the long-short portfolio returns of the PERF factor based on the other five anomalies.

We also construct the two mispricing factors proposed by Daniel et al. (2017), PEAD and FIN, which represent short-run and long-run mispricing. For the PEAD factor, stocks are sorted into deciles and the long-short portfolio is formed based on the four-day cumulative abnormal return (t-2, t+1) around the latest quarterly earnings announcement date. A combination of net stock issuance and composite equity issuance is used to construct the FIN factor. Following Daniel et al. (2017), a firm is assigned to the high (low) CEI rankings group if its CEI value is above (below) 80% (20%) of NYSE firms. A firm is assigned into the high (low) NSI rankings group if its NSI value is above (below) 70% (50%) of NYSE issuing (repurchasing) firms. A firm is then assigned to the long (short) leg of FIN if it belongs to the high (low) group based on both CEI and NSI rankings, or if it belongs to the high (low) group based on one of the rankings while has missing

[3] We do not use the original definition of mispricing factors, which are averages of portfolio returns for both small and large firms. To be consistent with the individual anomalies, the mispricing factors here refer to long-short portfolio returns. This method also applies to PEAD and FIN factors, which will be introduced later.

value for the another ranking.

To match with the lagged one-month sentiment index, most of the anomalies are from August 1965 to October 2015 with four exceptions. Composite equity issuance starts from June 1966, Failure Probability starts from November 1974, Return on assets is from February 1974, and PEAD is from November 1971.

Panel A of Table 1.2 displays the daily returns of the 11 individual anomalies and four mispricing factors. The first six columns report the mean excess returns (returns in excess of the daily Treasury bill rate) of the long-leg and short-leg portfolios, as well as the long-short spread portfolio. All the long-short portfolios generate significant excess returns. The average daily excess returns range from 2.46 basis points (bps) for accruals to 9.52 bps for momentum. The last six columns report the α_i estimated from the regression below, which represents benchmark-adjusted returns.

$$R_{i,t} = \alpha_i + \beta_{M,i} MktRF_t + \epsilon_{i,t}$$

where $R_{i,t}$ is the long-short portfolio return for anomaly i on day t, and $MktRF_t$ is the excess return on the market factor on day t[4]. The α is significantly positive for all 15 anomalies.

Lo and MacKinlay (1990) point out the data snooping issue, namely that tests of asset pricing models may yield misleading inferences when properties of the data are used to conduct statistic tests. Harvey et al. (2016) emphasize a similar point most recently and claim p-hacking in many empirical research findings. To avoid data mining concerns, we construct

[4]We use CAPM rather than the Fama-French 3 factor model for risk adjustment because size and value factors may also be exposed to the two mispricing forces considered in this paper.

multiple momentum portfolios as a robustness check.

Following Jegadeesh and Titman (1993), the strategies adopted in our paper are made according to their returns during the last 1,2,3 or 4 quarters. Meanwhile, different holding periods are also considered, which range from 1 month to 6 months. Therefore, we have 12 momentum strategies in total. A month is always skipped between the holding period and portfolio formation period.

Panel B of Table 1.2 reports the daily portfolio returns of alternative momentum strategies. All the long-short portfolios generate positive returns and alphas. The minimum benchmark-adjusted return spread is 5.59 bps per day, or an equivalent monthly alpha of 1.23%, with a t-value of 8.53, which is much higher than the threshold value of 3 based on Harvey et al. (2016).

1.2.3 Valuation Uncertainty Proxies

Aggregate sentiment, as argued by Baker and Wurgler (2006), should drive systematic mispricing through the differential levels of valuation uncertainty across firms. We adopt most of the information uncertainty proxies used in Zhang (2006) to construct our new uncertainty proxy. Specifically, the first variable is firm size (MV), measured as price multiplied by the shares outstanding from CRSP at the portfolio formation date. Firm age (AGE), as a second proxy, is measured as the number of years since the firm's first appearance on CRSP. The third proxy is analyst coverage (COV), measured as the number of analysts who have made at least one one-year forward forecast in the previous fiscal year from the IBES unadjusted forecast data file. The fourth and fifth proxies are dispersion in analyst earnings forecasts, based on the one-year forward forecast and long-term growth forecast. One-year forward forecast dispersion (DISP_1Y) is measured as the standard deviation of one-year forward forecasts scaled by the absolute value of the mean of the forecasts in the month of portfolio formation. Long-term growth forecast dispersion (DISP_LTG) is the standard deviation of long-term growth forecast in the month of portfolio formation. The forecast dispersion measure is from the IBES unadjusted summary data file. The sixth proxy is stock volatility (SIGMA), measured as the standard deviation of weekly market excess returns (from Thursday to Wednesday) over the year ending on the portfolio formation date. The last proxy is cash flow volatility (CVOL), measured as the standard deviation of the operating cash flow in the past 5 years (with a minimum of 3 years). Operating cash flow is measured as the earnings before extraordinary items (IB) minus total accruals, scaled by average total assets (AT). The total accruals here are equal to the changes in current assets (ACT) minus changes in cash (CHE), changes in current liabilities (LCT) and depreciation expense (DP), plus changes in short-term debt (DLC).

Though these seven proxies measure information uncertainty to some extent, there is also idiosyncratic noise contained in each of these measures. To reduce noise, we extract the common part of valuation uncertainty from these measures. We sort firms into 100 bins based on each individual valuation uncertainty proxy. The rank of the firm corresponds with its associated level of uncertainty, thus the higher the rank, the higher the uncertainty. For example, a firm is ranked as 100 if it has the smallest size, shortest age, lowest analyst coverage, highest forecast dispersion, highest stock volatility or highest cash flow volatility according to each proxy. We then take the average of the ranking scores across all seven measures with at least three proxies available. We use the average ranking score as our uncertainty measure.

Table 3.1 reports the descriptive statistics for all the seven proxies, as well as the average ranking score (AVERANK). Four proxies, including DISP_1Y, DISP_LTG, SIGMA and CVOL, are winsorized at 0.5% and 99.5%. The sample period is from 1983 to 2015. The starting time is constrained by the I/B/E/S Dataset. The market value ranges from $600,000 to $751 billion. The ages of firms range from 1 to 90 years, half of which are below 12 years. The standard deviation of the one-year forward analyst forecasts with highest DISP_1Y is 4 times of the forecasts consensus. The overall uncertainty proxy AVERANK ranges from 0 to 100, which is consistent its nature of average ranking score , but not uniformly distributed in the interval. There are more firms clustering around the median rather than in the two tails.

1.3 Empirical Tests

1.3.1 Investor Sentiment and Anomaly Returns

We conduct predictive regressions to investigate whether the level of the BW sentiment index predicts returns of individual anomalies and four mispricing factors. We first sort all the months in our sample into 10 bins based on the Baker-Wurgler sentiment index. We then run a predictive regression as follows:

$$R_{i,t} = \alpha_i + \beta_S Sentiment_{m-1} (+\beta_{M,i} MKTRF_t) + \epsilon_{i,t}$$

Table 1.3 reports the results of regressing daily returns of the anomaly portfolio on the lagged sentiment index. The first six columns report the effect of sentiment on the excess returns and the last six columns report the effect of sentiment on benchmark-adjusted returns. Consistent with Stambaugh et al. (2012), sentiment significantly amplifies the returns of the long-short portfolio for 9 out of 11 individual anomalies and 3 out of 4 mispricing factors (according to excess return results with significance at the 10% level). For example, MGMT is 9.45 bps higher following months with the highest decile of investor sentiment compared to the periods of lowest sentiment. Given that the average daily excess return of MGMT portfolio is 5.85 bps, the economic effect of sentiment is substantial. Also consistent with Stambaugh et al. (2012), the effects of sentiment are asymmetric for the long and short leg, with the coefficient of sentiment being much larger and more significant for the short leg than the long leg of portfolios.

Nevertheless, sentiment does not seem to provide adequate explanation for momentum, gross profitability and post-earnings announcement drift with t-statistics of 1.05, 0.94 and 1.38, respectively. The reason why sentiment does not predict momentum and PEAD spread return is due to the similarly negative loadings on sentiment for both the long and short leg. For example, the coefficient on sentiment is -0.61 (t-stat=-1.17) and -0.84 (t-stat=-1.50) for the long and short-leg of the PEAD portfolio. This is consistent with Panel A of Figure 4, which shows that the long and short legs of PEAD are equally hard to value. This motivates us to explore other behavioral forces that drive the anomalies.

1.3.2 Valuation Uncertainty across Anomalies

Before moving to the next behavioral force, we would like to further investigate the channel through which market-wide sentiment affects cross-sectional anomaly returns. As argued by Baker and Wurgler (2006), irrational sentiment should exert a stronger effect on prices of stocks that are hard to value, or more “speculative”in nature. When market-wide sentiment is high, those “hard-to-value” stocks are subject to greater investor disagreement and thus their values more likely to be pushed up by optimistic investors, while stocks that are easy to value should not be affected. When stocks in the short leg of an anomaly are more difficult to value than the ones in the long leg, market-wide sentiment could drive cross-sectional anomaly returns.

We use the composite valuation uncertainty metric AVERANK constructed in Section 2 to gauge the difficulty of valuing a stock. Table 1.4 reports how such “hard-to-value” stocks are distributed in 10 portfolios of two typical anomalies, CEI and PEAD. In panel A, the sample is split into 100 groups by sorting on AVERANK and CEI independently in each month. The average number of firms in each group is calculated across months, and is reported in the first ten columns. There are on average 11.41 firms in AVERANK decile 1 from the short leg of CEI. This number increases to 52.41 in the highest decile of AVERANK. Around 67% of the firms in the short leg of CEI have an AVERANK that is above the median . Firms with high AVERANK are more “speculative”, and are thus more likely to be affected by sentiment. On the other hand, the average number of firms from the long leg of CEI drops from 51.46 in AVERANK decile 1 to 16.72 in AVERANK decile 10. Most of the firms in the long leg belong to the low AVERANK group, and are less likely to be affected by sentiment. The last column reports the difference of average firm numbers between the short and long leg of CEI in each decile of AVERANK. For the least speculative group of stocks, there are 40 more firms from the long leg than the short leg. For the most speculative group of stocks, there are 36 more firms from the short leg than the long leg. Overall, the results show that firms in the short leg of CEI are much harder to value than firms in the long leg. As a result, sentiment affects the short and long legs of CEI differently, and at least partially drives its time series variation.

Anomalies related to momentum and PEAD exhibit a different relationship with AVERANK. In Panel B of Table 1.4, we report the average number of firms obtained through sorting on AVERANK and the cumulative abnormal return around the latest quarterly earnings announcement used to construct the portfolios of PEAD. In both the short and long legs of PEAD, there are more than two thirds of firms with an AVERANK above the sample median. The difference in number of firms from the same AVERANK decile between the short and long legs of PEAD is quite small, ranging from -1 to 3. All these pieces of evidence indicate that firms in the two extreme deciles of PEAD are equally "speculative". This could explain why sentiment does not affect the long-short portfolio of PEAD.

Figure 1.2 to 1.4 report the equal-weighted average AVERANK of decile portfolios for each anomaly. CEI anomaly, as a typical example of anomalies with more speculative firms concentrating in the short leg, is reported in Panel C of Figure 1.2. The average AVERANK increases monotonically from the long leg to the short leg. This increasing pattern is also observed in other anomalies including MGMT and NSI in Figure 1.2, PERF and FP in Figure 1.3, and FIN in Figure 1.4. Consistently, these anomalies are strongly correlated with market-wide sentiment in Table 1.3 as discussed before.

Panel A of Figure 1.4 plots the equal-weighted average of AVERANK for decile portfolios of PEAD. Consistent with the evidence from Table 1.4, the average AVERANK is almost identical for the short and long legs of PEAD. A similar U-shape pattern is also found for the Momentum strategy as shown in Figure 1.3. For these anomalies with almost equally "speculative" short and long leg stocks, the effect of sentiment on the long-short portfolios is more ambiguous as shown in Table 1.3.

The rest of the anomalies mainly exhibit a mixture of these two patterns, namely, a skewed U-shape with moderately lower AVERANK in the long leg than the short leg. Among them, NOA, AG, I/A (in Figure 1.2) and ROA (in Figure 1.3) are significantly affected by aggregate sentiment.

1.3.3 Market-wide Attention and Anomaly Returns

The results in the previous section show that sentiment alone is not sufficient to explain all anomalies. In particular, we argue that for anomalies that are equally speculative in the long and short legs, we should not expect to find significant effect of sentiment. This is because when the long and short leg of anomalies are equally hard to value, excessive investor optimism tends to push up the prices and lower the future returns of both portfolios at the same time and to a similar degree. For these anomalies, the limited attention could be the alternative channel amplifying the anomaly returns. To investigate the effect of market-wide attention on anomaly returns, we first sort every trading day in our sample period into 10 bins based on the attention measure. We then conduct the following predictive regressions daily:

$$R_{i,t} = \alpha_i + \beta_A Attention_{t-1} (+\beta_{M,i} MKTRF_t) + \epsilon_{i,t}$$

The first six columns of Table 1.5 report results of regressing excess returns on the lagged attention index alone. The last six columns report results of regressing excess returns on the lagged attention index as well as the contemporaneous excess returns on the market factor. The latter regression thus investigates the ability of aggregate attention to predict benchmark-adjusted returns. The sample period spans from January 1, 1996 to October 31, 2015, and all t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

The results are broadly consistent with our hypothesis. Panel A reports the results of 11 individual anomalies along with the four mispricing factors (the MGMT and PERF factors proposed by Stambaugh and Yuan (2016) and the FIN and PEAD factors proposed by Daniel et al. (2017)). According to benchmark adjusted results, market-wide attention has a significant attenuation effect on the long-short returns of 6 out of 11 anomalies and 3 out of 4 mispricing factors in the univariate regression. In particular, it well explains the anomalies that are highly speculative in both the long and short leg, including net operating assets, asset growth, investment-to-assets, momentum and post-earnings announcement drift. For example, the coefficients on attention index are -1.94 (t-stat=-2.67) and -1.16 (t-stat=4.45) for momentum and PEAD, respectively. The effect is much stronger than that of sentiment, which attracts an insignificant coefficient of 0.39 and 0.23 for momentum and PEAD, respectively.

Regarding the economic effect, the daily momentum and PEAD profits are about 17.5 and 10.4 bps lower following days with highest market-wide attention compared to the periods of lowest attention. Given that the unconditional daily momentum and PEAD profit is 9.5 and 6.1 bps, the economic effect of limited attention is substantial. Panel B of Table 1.5 reports the results for alternative momentum strategies. All but one alternative momentum long-short portfolios are strongly predicted by the lagged attention index. The effects of attention are also robust with respect to the benchmark-adjusted returns.

In the meantime, the effect of attention seems to concentrate on the short leg of anomalies, which is more mispriced to begin with. Looking at benchmark-adjusted returns, attention has significant effect on the short-leg of 9 individual anomalies and all 4 mispricing factors (significance at the 10% level). This could potentially be driven by the slower diffusion of bad news as suggested by Hong et al. (2000) or greater frictions in shorting overvalued stocks.

1.4 Robustness Checks

In this section, we consider alternative channels that could potentially drive our empirical results. We first study the time trend effect and then consider the confounding effect of investor sentiment and other macroeconomic factors.

1.4.1 Time Trend

Recently, a number of papers have documented a gradual decline in the anomaly profits over time, including Pontiff and McLean (2013), Green et al. (2011) and Chordia et al. (2014). On the other hand, more media news is produced and disseminated everyday due to the growth of the media sector and advancement of information technology. It is thus plausible that an increasing trend of news frequency and a decreasing trend of anomaly returns could mechanically drive the negative relationship between anomaly returns and our attention index. To rule out this alternative explanation, we control time trend in the following predictive regression model:

$$R_{i,t} = \alpha_i + \beta_A Attention_{t-1} + \beta_T Month_m + \epsilon_{i,t}$$

where Month stands for a monthly time trend variable. Table 1.6 shows that the effect of market-wide attention is not fully explained by time trend. The coefficient on attention index is still significant for 3 anomalies including momentum and PEAD, and significant for 10 out of 12 alternative momentum strategies in Panel B of Table 1.6.

1.4.2 Sentiment

Market-wide attention could be correlated with investor sentiment if the media rationally responds to elevated market sentiment by supplying more news about the stock market, or if journalists share the same enthusiasm or pessimism as investors. However, we should emphasize that if our attention measure simply captures sentiment in a better way, we should see a positive instead of negative effect of aggregate attention on anomaly returns. To further address this concern, we run a horse race between our attention index and the Baker-Wurgler sentiment index as follows:

$$R_{i,t} = \alpha_i + \beta_A Attention_{t-1} + \beta_S Sentiment_{m-1} (+\beta_{M,i} MKTRF_t) + \beta_T Month_m + \epsilon_{i,t}$$

Table 1.7 reports the regression results. Attention continues to have an attenuation effect on anomaly returns after controlling for sentiment. For example, the effect of attention shows significance for 6 out of 7 anomalies that are equally speculative in the long and short leg. On the other hand, sentiment is also significant for most anomalies after controlling attention, suggesting the distinct role played by the two channels in driving mispricing. Interestingly, the PEAD factor loads negatively on aggregate attention but is insensitive to sentiment shifts. In sharp contrast, the Financing factor (FIN) is strongly predicted by sentiment but exhibits no relation with market-wide attention. This result is consistent with the findings in Figure 1.4, which shows that the long-leg of the PEAD factor is as speculative as the short leg. Thus, our paper provides a clear economic explanation of why the two mispricing factors proposed by Daniel et al. (2017) differ, and suggests that they could be driven by different mispricing mechanisms.

1.4.3 Macroeconomic Risks

In the last robustness test, we further control for a set of macroeconomic variables used in Baker and Wurgler (2006), including growth in industrial production, growth in durable, nondurable, and services consumption, growth in employment, and a time dummy for recessions . This could help address the concern that the effect of our attention index comes mainly from business cycle related risks. Table 1.8 reports the results of the following regression:

$$R_{i,t} = \alpha_i + \beta_A Attention_{t-1} + \beta_S Sentiment_{m-1} + \beta_{M,i} MKTRF_t + \beta_T Month_m + \beta_{M6} X_{m-1} + \epsilon_{i,t}$$

where X stands for the six macroeconomic variables. Overall, the addition of macroeconomic variables does not significantly affect the predictive power of our attention measure.

1.5 Conclusion

In this paper, we examine the behavioral forces underlying various anomalies and recently proposed factor models that are motivated by the anomalies. We first show that investor sentiment, which is often used as a catch-all measure of investor irrationality, has its limitations. While sentiment well explains many anomalies that are more speculative on the short-leg, it fails to explain anomalies that are equally speculative on the long and short-leg, including momentum and post-earnings announcement drift. We then propose another behavioral force, i.e., market-wide attention shifts, that can significantly attenuate a larger set of anomalies beyond the effect of sentiment. Our findings suggest that increases in market-wide attention can temporarily reduce the cost of attending to the market and improve price efficiency.

Bibliography

Baker, M. and J. Wurgler (2006): "Investor sentiment and the cross-section of stock returns," *The Journal of Finance*, 61, 1645–1680.

Ball, R. and P. Brown (1968): "An empirical evaluation of accounting income numbers," *Journal of accounting research*, 159–178.

Barber, B. M., Y.-T. Lee, Y.-J. Liu, and T. Odean (2008): "Just how much do individual investors lose by trading?" *The Review of Financial Studies*, 22, 609–632.

Ben-Rephael, A., Z. Da, and R. D. Israelsen (2017): "It depends on where you search: Institutional investor attention and underreaction to news," *The Review of Financial Studies*, 30, 3009–3047.

Bernard, V. L. and J. K. Thomas (1989): "Post-earnings-announcement drift: delayed price response or risk premium?" *Journal of Accounting research*, 1–36.

Campbell, J. Y., J. Hilscher, and J. Szilagyi (2008): "In search of distress risk," *The Journal of Finance*, 63, 2899–2939.

Carhart, M. M. (1997): "On persistence in mutual fund performance," *The Journal of finance*, 52, 57–82.

Chan, L. K., N. Jegadeesh, and J. Lakonishok (1996): "Momentum strategies," *The Journal of Finance*, 51, 1681–1713.

Chen, L., R. Novy-Marx, and L. Zhang (2011): "An alternative three-factor model," *Working Paper*.

Chordia, T., A. Subrahmanyam, and Q. Tong (2014): "Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?" *Journal of Accounting and Economics*, 58, 41–58.

Cooper, M. J., H. Gulen, and M. J. Schill (2008): "Asset growth and the cross-section of stock returns," *The Journal of Finance*, 63, 1609–1651.

Da, Z., J. Engelberg, and P. Gao (2011): "In search of attention," *The Journal of Finance*, 66, 1461–1499.

Daniel, K., D. Hirshleifer, and L. Sun (2017): "Short and Long Horizon Behavioral Factors," Tech. rep., National Bureau of Economic Research.

Daniel, K. and S. Titman (2006): "Market reactions to tangible and intangible information," *The Journal of Finance*, 61, 1605–1643.

DellaVigna, S. and J. M. Pollet (2009): "Investor inattention and Friday earnings announcements," *The Journal of Finance*, 64, 709–749.

Fama, E. F. and K. R. French (2006): "Profitability, investment and average returns," *Journal of Financial Economics*, 82, 491–518.

——— (2008): "Dissecting anomalies," *The Journal of Finance*, 63, 1653–1678.

Fang, L. and J. Peress (2009): "Media coverage and the cross-section of stock returns," *The Journal of Finance*, 64, 2023–2052.

Green, J., J. R. Hand, and M. T. Soliman (2011): "Going, going, gone? The apparent demise of the accruals anomaly," *Management Science*, 57, 797–816.

Harvey, C. R., Y. Liu, and H. Zhu (2016): "… and the cross-section of expected returns," *The Review of Financial Studies*, 29, 5–68.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang (2004): "Do investors overvalue firms with bloated balance sheets?" *Journal of Accounting and Economics*, 38, 297–331.

Hirshleifer, D., S. S. Lim, and S. H. Teoh (2009): "Driven to distraction: Extraneous events and underreaction to earnings news," *The Journal of Finance*, 64, 2289–2325.

Hong, H., T. Lim, and J. C. Stein (2000): "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies," *The Journal of Finance*, 55, 265–295.

Hou, K., W. Xiong, and L. Peng (2009): "A tale of two anomalies: The implications of investor attention for price and earnings momentum," .

Hou, K., C. Xue, and L. Zhang (2014): "A comparison of new factor models," Tech. rep., National Bureau of Economic Research.

Jegadeesh, N. and S. Titman (1993): "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 48, 65–91.

Klibanoff, P., O. Lamont, and T. A. Wizman (1998): "Investor reaction to salient news in closed-end country funds," *The Journal of Finance*, 53, 673–699.

Kozak, S., S. Nagel, and S. Santosh (2017): "Differences of opinion and the cross section of stock returns," *Working Paper*.

Lo, A. W. and A. C. MacKinlay (1990): "When are contrarian profits due to stock market overreaction?" *The review of financial studies*, 3, 175–205.

Loughran, T. and J. R. Ritter (1995): "The new issues puzzle," *The Journal of finance*, 50, 23–51.

Miller, E. M. (1977): "Risk, uncertainty, and divergence of opinion," *The Journal of finance*, 32, 1151–1168.

Newey, W. K. and K. D. West (1987): "Hypothesis testing with efficient method of moments estimation," *International Economic Review*, 777–787.

Novy-Marx, R. (2013): "The other side of value: The gross profitability premium," *Journal of Financial Economics*, 108, 1–28.

Ohlson, J. A. (1980): "Financial ratios and the probabilistic prediction of bankruptcy," *Journal of accounting research*, 109–131.

Pontiff, J. and R. D. McLean (2013): "Does Academic Research Destroy Stock Return Predictability?" Tech. rep., Working Paper.

Ritter, J. R. (1991): "The long-run performance of initial public offerings," *The journal of finance*, 46, 3–27.

Sloan, A. (1996): "Search in," *Accounting review*, 71, 289–315.

Stambaugh, R. F., J. Yu, and Y. Yuan (2012): "The short of it: Investor sentiment and anomalies," *Journal of Financial Economics*, 104, 288–302.

Stambaugh, R. F. and Y. Yuan (2016): ""Mispricing factors," *The Review of Financial Studies*, 30, 1270–1315.

Tetlock, P. C. (2011): "All the news that's fit to reprint: Do investors react to stale information?" *The Review of Financial Studies*, 24, 1481–1512.

Titman, S., K. J. Wei, and F. Xie (2004): "Capital investments and stock returns," *Journal of financial and Quantitative Analysis*, 39, 677–700.

Wang, H. and J. Yu (2013): "Dissecting the profitability premium," *Working Paper.*

Xing, Y. (2007): "Interpreting the value effect through the Q-theory: An empirical investigation," *The Review of Financial Studies*, 21, 1767–1795.

Yuan, Y. (2015): "Market-wide attention, trading, and stock returns," *Journal of Financial Economics*, 116, 548–564.

Zhang, X. (2006): "Information uncertainty and stock returns," *The Journal of Finance*, 61, 105–137.

Table 1.1: Descriptive Statistics

This table reports the descriptive statistics for information uncertainty measures. Sentiment is Baker and Wurgler monthly sentiment index from July 1965 to September 2015. Attention is average number of news coverage across firms. It is daily index from January 1996 to December 2014. The rest eight variables are proxies for uncertainty in firm-month level, with sample period from January 1983 to September 2015. Size (MV) is measured as price times shares outstanding from CRSP. Firm age (AGE) is measured as the number of years since the firm's first appearance on CRSP. Analyst coverage (COV) is measured as the number of analysts covering in the firm in the previous fiscal year. One-year forward forecast dispersion (DISP_1Y) is measured as the standard deviation divided by the absolute value of mean one-year forward forecasts in the previous month. Long-term growth forecast dispersion (DISP_LTG) is measured as the standard deviation of long-term growth forecast in the previous month. Stock volatility (SIGMA) is measured as the standard deviation of weekly market excess returns (from Thursday to Wednesday) in the previous year. Cash flow volatility is measured as the standard deviation of operating cash flow in the past 5 years (with a minimum of 3 years). Operating cash flow is measured as $IB-(\Delta ACT-\Delta CHE-\Delta LCT-DP+\Delta DLC))/AT_{ave}$ based on variables from Compustat. AVERANK is the average ranking scores of the seven uncertainty proxies (from 0 to 100), with a minimum of three proxies. Four measures, including DISP_1Y, DISP_LTG, SIGMA, CVOL, are winsorized at 0.5% and 99.5%. Common stocks with share prices above $5 are considered.

Variable	N	Mean	Std. Dev.	Min	Q1	Median	Q3	Max	ρ_1
Attention	6,914	3.18	1.13	1.00	2.31	3.27	3.92	8.12	0.51
Sentiment	603	140	83	1	65	157	203	298	0.86
MV	1,416,141	2,604	13,488	1	71	258	1,076	750,710	
AGE	1,416,141	16	16	1	5	12	22	90	
COV	1,025,320	10	9	1	3	6	13	69	
DISP_1Y	778,005	13.87%	40.17%	0.00%	1.79%	3.96%	9.84%	400.00%	
DISP_LTG	530,727	4.12%	4.23%	0.00%	1.73%	2.93%	4.95%	31.61%	
SIGMA	1,414,346	5.77%	3.02%	1.44%	3.64%	5.09%	7.12%	19.50%	
CVOL	956,240	0.081	0.080	0.006	0.033	0.058	0.099	0.585	
AVERANK	1,415,425	51.70	18.75	0.60	38.29	53.00	65.80	100.00	

Table 1.2: Anomaly returns

The table reports average daily excess (benchmark-adjusted) returns in short and long legs, as well as long-short spreads for anomalies. The benchmark-adjusted returns are the estimates of α_i in regression $R_{i,t} = \alpha_i + \beta_{M,i} MKTRF_t + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's excess return on day t. The sample period is from August 1965 to October 2015. Panel A reports returns for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports returns for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	return	t value	return	t value	return	t value	return	t value	return	t value	return	t value
Net stock issuance	5.18	(4.82)	0.40	(0.30)	4.78	(8.80)	3.35	(5.51)	-2.04	(-2.97)	5.38	(10.25)
Composite equity issuance	5.16	(5.94)	1.48	(1.16)	3.69	(5.56)	3.57	(6.99)	-1.08	(-1.84)	4.66	(8.04)
Accruals	3.34	(2.53)	0.88	(0.57)	2.46	(4.33)	1.16	(1.48)	-1.74	(-2.01)	2.89	(4.90)
Net operating assets	4.04	(3.65)	-0.39	(-0.28)	4.43	(7.23)	2.18	(3.48)	-2.83	(-3.75)	5.00	(8.59)
Asset growth	3.95	(2.99)	-0.46	(-0.30	4.41	(6.95)	1.85	(2.31)	-3.13	(-3.59)	4.98	(7.38)
Investment to assets	4.49	(3.60)	-0.39	(-0.27)	4.88	(8.89)	2.41	(3.25)	-2.99	(-3.71)	5.40	(9.44)
Failure Probabilty	5.06	(4.82)	2.60	(1.87)	2.46	(3.45)	2.60	(4.76)	-0.36	(-0.45)	2.96	(4.48)
O-score	3.56	(3.21)	0.94	(0.62)	2.62	(3.70)	1.28	(2.73)	-1.34	(-1.37)	2.62	(3.49)
Momentum (f11h1)	8.57	(6.22)	-0.95	(-0.59)	9.52	(8.76)	6.07	(6.83)	-3.34	(-3.50)	9.41	(8.55)
Gross Profitability	4.60	(3.85)	1.84	(1.61)	2.76	(4.74)	2.57	(4.08)	-0.01	(-0.02)	2.59	(4.25)
Return on assets	6.12	(4.76)	-1.62	(-0.91)	7.74	(8.33)	3.34	(5.29)	-4.56	(-3.89)	7.91	(7.97)
MGMT	5.14	(5.00)	-0.70	(-0.47)	5.85	(7.82)	3.46	(5.50)	-3.34	(-4.31)	6.80	(9.89)
PERF	5.79	(5.27)	-1.12	(-0.80	6.90	(8.98)	3.62	(6.77)	-3.23	(-3.93)	6.84	(8.80)
PEAD	8.71	(6.21)	2.58	(1.78)	6.13	(14.32)	5.97	(7.92)	-0.17	(-0.24)	6.14	(14.41)
FIN	5.87	(6.10)	2.96	(2.26)	2.90	(4.77)	4.26	(7.38)	0.50	(0.78)	3.76	(6.79)

Table 1.2: Continued

Panel B: Momentum based anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	return	t value	return	t value	return	t value	return	t value	return	t value	return	t value
F3H1	6.83	(5.12)	0.49	(0.31)	6.35	(6.68)	4.52	(5.26)	-2.00	(-2.33)	6.53	(7.31)
F3H3	6.55	(4.93)	0.57	(0.37)	5.98	(7.25)	4.18	(5.07)	-1.84	(-2.22)	6.02	(7.63)
F3H6	6.50	(4.90)	0.85	(0.57)	5.65	(8.47)	4.09	(5.30)	-1.50	(-1.84)	5.59	(8.53)
F6H1	8.14	(6.08)	-0.31	(-0.19)	8.45	(7.74)	5.76	(6.56)	-2.76	(-2.98)	8.52	(8.11)
F6H3	7.77	(5.76)	-0.17	(-0.11)	7.94	(8.30)	5.32	(6.39)	-2.56	(-2.83)	7.88	(8.39)
F6H6	7.56	(5.63)	0.12	(0.08)	7.44	(9.23)	5.07	(6.35)	-2.22	(-2.56)	7.29	(8.79)
F9H1	8.40	(6.15)	-0.47	(-0.29)	8.87	(8.11)	5.94	(6.83)	-2.89	(-3.02)	8.84	(8.20)
F9H3	8.15	(5.95)	-0.56	(-0.36)	8.72	(8.95)	5.64	(6.59)	-2.93	(-3.17)	8.56	(8.53)
F9H6	7.40	(5.43)	0.08	(0.05)	7.32	(8.62)	4.85	(5.91)	-2.23	(-2.49)	7.08	(7.74)
F11H1	8.57	(6.22)	-0.95	(-0.59)	9.52	(8.76)	6.07	(6.83)	-3.34	(-3.50)	9.41	(8.55)
F11H3	7.87	(5.69)	-0.53	(-0.33)	8.40	(8.66)	5.31	(6.17)	-2.86	(-3.07)	8.17	(8.00)
F11H6	7.11	(5.16)	0.38	(0.25)	6.72	(7.76)	4.52	(5.48)	-1.91	(-2.10)	6.43	(6.77)

Table 1.3: Investor sentiment and anomalies

The table reports the estimates of β_S in regression $R_{i,t} = \alpha_i + \beta_S Sentiment_{m-1}(+\beta_{M,i} MKTRF_t) + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's daily excess return on day t in month m, and $MKTRF_t$ is market excess return on day t. The Sample period is from August 1965 to October 2015. Sentiment is measured as rankings (from 1 to 10) of Baker and Wurgler sentiment index across time. Panel A reports results for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports results for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
Net stock issuance	-0.47	(-1.23)	-1.15	(-2.38)	0.68	(3.41)	-0.25	(-1.25)	-0.87	(-3.84)	0.61	(3.58)
Composite equity issuance	-0.10	(-0.33)	-0.98	(-2.06)	0.88	(3.22)	0.10	(0.61)	-0.66	(-3.44)	0.75	(3.78)
Accruals	-1.10	(-2.36)	-1.51	(-2.70)	0.41	(1.85)	-0.85	(-3.28)	-1.21	(-4.21)	0.36	(1.83)
Net operating assets	-0.44	(-1.13)	-1.44	(-2.83)	1.00	(4.83)	-0.22	(-1.14)	-1.15	(-4.73)	0.93	(5.37)
Asset growth	-1.03	(-2.30)	-1.64	(-2.84)	0.60	(2.32)	-0.79	(-3.09)	-1.33	(-4.45)	0.54	(2.31)
Investment to assets	-0.99	(-2.26)	-1.56	(-2.93)	0.57	(2.77)	-0.74	(-3.03)	-1.25	(-4.94)	0.51	(2.88)
Failure Probabilty	-0.33	(-0.83)	-1.08	(-1.97)	0.75	(2.54)	0.10	(0.49)	-0.57	(-1.84)	0.67	(2.44)
O-score	-0.39	(-0.99)	-1.47	(-2.90)	1.07	(4.74)	-0.13	(-0.83)	-1.20	(-4.07)	1.07	(4.73)
Momentum (f11h1)	-1.04	(-2.18)	-1.42	(-2.44)	0.39	(1.05)	-0.66	(-2.54)	-1.06	(-3.08)	0.40	(1.01)
Gross Profitability	-0.41	(-0.99)	-0.61	(-1.51)	0.20	(0.94)	-0.18	(-0.85)	-0.39	(-1.84)	0.22	(1.05)
Return on assets	-0.38	(-0.77)	-1.95	(-2.94)	1.57	(4.58)	-0.09	(-0.4)	-1.64	(-4.11)	1.56	(4.61)
MGMT	-0.42	(-1.17)	-1.47	(-2.73)	1.05	(3.61)	-0.23	(-1.05)	-1.17	(-4.55)	0.94	(4.03)
PERF	-0.37	(-1.00)	-1.19	(-2.37)	0.82	(3.04)	-0.14	(-0.89)	-0.96	(-3.48)	0.83	(3.01)
PEAD	-0.61	(-1.17)	-0.84	(-1.50)	0.23	(1.38)	-0.40	(-1.49)	-0.63	(-2.32)	0.23	(1.43)
FIN	-0.38	(-1.10)	-0.95	(-1.98)	0.57	(2.45)	-0.19	(-0.98)	-0.67	(-3.12)	0.47	(2.60)

Table 1.3: Continued

Panel B: Momentum based anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
F3H1	-0.89	(-2.05)	-1.37	(-2.40)	0.47	(1.32)	-0.54	(-2.05)	-0.99	(-3.07)	0.45	(1.31)
F3H3	-0.83	(-1.90)	-1.42	(-2.57)	0.59	(1.92)	-0.47	(-1.88)	-1.05	(-3.46)	0.59	(1.97)
F3H6	-0.88	(-1.98)	-1.44	(-2.68)	0.56	(2.33)	-0.51	(-2.18)	-1.08	(-3.71)	0.56	(2.27)
F6H1	-0.72	(-1.61)	-1.60	(-2.69)	0.87	(2.14)	-0.36	(-1.31)	-1.22	(-3.54)	0.86	(2.17)
F6H3	-0.83	(-1.85)	-1.54	(-2.67)	0.71	(2.15)	-0.46	(-1.78)	-1.17	(-3.54)	0.71	(1.99)
F6H6	-0.94	(-2.06)	-1.45	(-2.62)	0.50	(1.73)	-0.56	(-2.44)	-1.09	(-3.52)	0.52	(1.72)
F9H1	-0.88	(-1.88)	-1.60	(-2.72)	0.73	(1.90)	-0.50	(-1.85)	-1.23	(-3.57)	0.74	(1.83)
F9H3	-0.95	(-2.01)	-1.49	(-2.61)	0.54	(1.62)	-0.57	(-2.27)	-1.13	(-3.45)	0.57	(1.56)
F9H6	-1.09	(-2.29)	-1.34	(-2.43)	0.25	(0.83)	-0.70	(-2.80)	-0.98	(-3.15)	0.29	(0.91)
F11H1	-1.04	(-2.18)	-1.42	(-2.44)	0.39	(1.05)	-0.66	(-2.54)	-1.06	(-3.08)	0.40	(1.01)
F11H3	-1.08	(-2.24)	-1.36	(-2.40)	0.28	(0.81)	-0.69	(-2.65)	-1.00	(-3.05)	0.31	(0.86)
F11H6	-1.15	(-2.39)	-1.25	(-2.28)	0.10	(0.33)	-0.76	(-3.00)	-0.90	(-2.85)	0.15	(0.46)

Table 1.4: Number of firms double sorted on anomalies and valuation uncertainty

The table reports average number of firms. The sample period is from January 1983 to October 2015. At the end of month $t-1$, stocks are assigned to 10 times 10 portfolios according to an anomaly and an uncertainty proxy. The number of firms on the resulting 100 portfolios are then counted in each month. The time-series averages of monthly firm numbers are recorded, with long (short) leg of an anomaly on the left (right), and low (high) uncertainty in the top(bottom). The last column reports the difference of average firm numbers between short and long legs of an anomaly within each decile of AVERANK. The uncertainty proxy AVERANK is the average of ranking scores (from 1 to 100) of uncertainty proxies, one-year-ahead analyst forecast dispersion, long-term growth analyst forecast dispersion, firm size, firm age, analyst coverage, stock volatility and cash flow volatility. Panel A reports results based on anomaly of composite stock issuance. Panel B reports results based on anomaly of PEAD (four-day cumulative abnormal return (t-2, t+1) around the latest quarterly earnings announcement date).

Panel A: AVERANK against composite stock issuance											
	Long	2	3	4	5	6	7	8	9	Short	Short-Long
Low	51.46	70.13	53.02	42.29	26.91	14.36	12.29	13.01	14.86	11.41	-40
2	38.10	47.00	47.08	42.10	33.52	23.31	18.66	20.29	22.65	17.49	-21
3	34.95	38.99	40.37	40.38	35.23	27.02	23.14	23.79	25.25	21.26	-14
4	32.41	32.31	34.74	36.61	35.13	30.16	27.40	28.35	27.96	25.07	-7
5	30.10	27.60	29.72	31.72	33.07	33.18	30.58	32.16	32.42	29.57	-1
6	26.63	24.73	27.20	29.34	33.11	34.58	34.09	33.15	33.93	33.82	7
7	27.44	22.18	25.09	27.53	29.46	35.07	36.42	35.85	34.73	36.48	9
8	27.22	19.61	21.87	23.68	29.71	36.47	38.58	37.71	35.72	39.59	12
9	24.65	16.78	18.36	21.38	27.85	37.02	43.02	40.59	37.81	42.71	18
High	16.72	10.92	12.86	15.15	26.13	39.28	46.10	45.32	44.99	52.41	36

Panel B: AVERANK against PEAD											
	Long	2	3	4	5	6	7	8	9	Short	Short-Long
Low	6.39	23.12	35.82	43.46	47.60	47.28	44.22	36.49	24.99	9.47	3
2	13.82	30.12	36.78	38.71	39.66	40.01	38.79	35.96	29.82	15.62	2
3	20.12	33.60	36.21	35.77	35.24	35.73	35.68	34.71	31.52	20.93	1
4	26.01	34.29	34.61	33.48	34.15	32.92	32.89	33.41	32.09	25.37	-1
5	31.30	33.98	32.81	32.41	30.96	30.92	31.11	32.08	32.68	30.83	0
6	35.63	32.93	31.55	31.11	29.43	29.71	30.54	31.00	32.86	34.86	-1
7	39.05	33.38	30.39	29.17	28.92	28.73	28.76	30.15	33.01	37.81	-1
8	42.75	32.91	28.93	27.64	26.89	27.54	28.24	29.78	33.36	41.42	-1
9	47.37	32.37	27.79	25.24	25.06	24.74	25.97	29.18	34.58	46.87	-1
High	56.48	32.73	24.43	22.40	21.60	21.64	23.11	26.66	34.40	55.61	-1

Table 1.5: Market-wide attention and anomalies

The table reports the estimates of β_S in regression $R_{i,t} = \alpha_i + \beta_A Attention_{t-1}(+\beta_{M,i}MKTRF_t) + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's daily excess return on day t in month m, and $MKTRF_t$ is market excess return on day t. The Sample period is from January 1996 to October 2015. Attention is measured as the equal-weighted total number of news covered by Thomson Reuters News Data. We use rankings (from 1 to 10) of attention across time as dependent variable. Panel A reports results for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports results for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
Net stock issuance	0.54	(0.83)	0.77	(0.94)	-0.23	(-0.69)	0.50	(1.85)	0.71	(2.06)	-0.21	(-0.70)
Composite equity issuance	0.43	(0.79)	1.00	(1.20)	-0.56	(-1.41)	0.40	(1.77)	0.94	(2.93)	-0.54	(-1.61)
Accruals	0.37	(0.46)	0.80	(0.90)	-0.43	(-1.48)	0.32	(0.91)	0.74	(1.83)	-0.42	(-1.49)
Net operating assets	0.36	(0.55)	1.07	(1.27)	-0.71	(-2.09)	0.32	(1.02)	1.02	(2.93)	-0.69	(-2.44)
Asset growth	0.25	(0.32)	1.02	(1.14)	-0.77	(-2.17)	0.20	(0.52)	0.96	(2.27)	-0.76	(-2.16)
Investment to assets	0.39	(0.52)	0.93	(0.97)	-0.54	(-1.54)	0.35	(1.03)	0.87	(2.07)	-0.53	(-1.67)
Failure Probabilty	0.11	(0.18)	1.50	(1.85)	-1.38	(-3.44)	0.07	(0.28)	1.44	(3.26)	-1.37	(-3.45)
O-score	0.55	(0.73)	0.19	(0.20)	0.36	(1.01)	0.49	(1.79)	0.13	(0.26)	0.36	(0.94)
Momentum (f11h1)	-0.58	(-0.66)	1.36	(1.33)	-1.94	(-2.67)	-0.64	(-1.38)	1.30	(2.28)	-1.94	(-2.58)
Gross Profitability	0.59	(0.84)	0.56	(0.85)	0.02	(0.07)	0.54	(1.77)	0.52	(1.45)	0.02	(0.06)
Return on assets	0.09	(0.13)	1.00	(1.01)	-0.91	(-1.92)	0.04	(0.15)	0.94	(1.67)	-0.90	(-1.98)
MGMT	0.39	(0.68)	1.03	(1.14)	-0.64	(-1.45)	0.35	(1.36)	0.97	(2.58)	-0.62	(-1.79)
PERF	0.02	(0.02)	1.00	(1.21)	-0.98	(-2.16)	-0.03	(-0.13)	0.94	(1.95)	-0.98	(-2.10)
PEAD	0.22	(0.26)	1.38	(1.57)	-1.16	(-4.45)	0.16	(0.45)	1.32	(3.51)	-1.16	(-4.50)
FIN	0.62	(1.04)	0.86	(1.08)	-0.23	(-0.62)	0.58	(2.22)	0.80	(2.45)	-0.22	(-0.65)

Table 1.5: Continued

Panel B: Momentum based anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
F3H1	-0.30	(-0.36)	1.40	(1.39)	-1.70	(-2.94)	-0.35	(-0.80)	1.33	(2.78)	-1.69	(-2.94)
F3H3	-0.23	(-0.27)	1.27	(1.33)	-1.50	(-2.91)	-0.29	(-0.67)	1.21	(2.59)	-1.50	(-2.79)
F3H6	-0.09	(-0.10)	1.20	(1.30)	-1.29	(-3.18)	-0.14	(-0.37)	1.14	(2.54)	-1.29	(-3.05)
F6H1	-0.71	(-0.83)	1.55	(1.50)	-2.26	(-3.05)	-0.77	(-1.58)	1.49	(2.72)	-2.26	(-3.09)
F6H3	-0.44	(-0.50)	1.42	(1.46)	-1.86	(-3.06)	-0.50	(-1.13)	1.36	(2.66)	-1.86	(-3.02)
F6H6	-0.23	(-0.26)	1.21	(1.27)	-1.44	(-2.84)	-0.29	(-0.71)	1.15	(2.33)	-1.44	(-2.76)
F9H1	-0.75	(-0.86)	1.55	(1.51)	-2.30	(-3.16)	-0.81	(-1.72)	1.48	(2.64)	-2.29	(-3.11)
F9H3	-0.41	(-0.46)	1.33	(1.34)	-1.74	(-2.75)	-0.47	(-1.07)	1.27	(2.38)	-1.74	(-2.66)
F9H6	-0.08	(-0.09)	0.98	(1.03)	-1.06	(-1.99)	-0.14	(-0.33)	0.92	(1.82)	-1.06	(-1.87)
F11H1	-0.58	(-0.66)	1.36	(1.33)	-1.94	(-2.67)	-0.64	(-1.38)	1.30	(2.28)	-1.94	(-2.58)
F11H3	-0.26	(-0.29)	1.12	(1.14)	-1.38	(-2.19)	-0.32	(-0.73)	1.06	(1.98)	-1.39	(-2.09)
F11H6	0.13	(0.15)	0.74	(0.79)	-0.61	(-1.15)	0.07	(0.18)	0.68	(1.35)	-0.61	(-1.08)

Table 1.6: Market-wide attention and anomalies (controlling for time trend)

The table reports the estimates of β_S in regression $R_{i,t} = \alpha_i + \beta_A Attention_{t-1}(+\beta_{M,i} MKTRF_t) + \beta_T Month_m + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's daily excess return on day t in month m, and $MKTRF_t$ is market excess return on day t. The Sample period is from January 1996 to October 2015. Attention is measured as the equal-weighted total number of news covered by Thomson Reuters News Data. We use rankings (from 1 to 10) of attention across time as dependent variable. Month is the index of month based on time order.

Panel A reports results for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports results for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
Net stock issuance	0.60	(0.91)	0.66	(0.79)	-0.06	(-0.18)	0.59	(2.20)	0.65	(1.83)	-0.06	(-0.19)
Composite equity issuance	0.52	(0.90)	0.94	(1.11)	-0.42	(-1.00)	0.51	(2.21)	0.93	(2.80)	-0.42	(-1.26)
Accruals	0.34	(0.42)	0.64	(0.72)	-0.30	(-0.97)	0.33	(0.91)	0.62	(1.56)	-0.29	(-1.00)
Net operating assets	0.39	(0.59)	0.83	(0.97)	-0.44	(-1.24)	0.38	(1.22)	0.82	(2.31)	-0.44	(-1.47)
Asset growth	0.20	(0.27)	0.78	(0.85)	-0.57	(-1.51)	0.19	(0.52)	0.76	(1.77)	-0.57	(-1.57)
Investment to assets	0.37	(0.49)	0.75	(0.76)	-0.38	(-0.97)	0.36	(1.09)	0.74	(1.71)	-0.38	(-1.11)
Failure Probabilty	0.11	(0.17)	1.45	(1.72)	-1.34	(-3.28)	0.10	(0.38)	1.43	(3.20)	-1.34	(-3.38)
O-score	0.62	(0.79)	-0.05	(-0.05)	0.67	(1.79)	0.61	(2.12)	-0.06	(-0.12)	0.67	(1.80)
Momentum (f11h1)	-0.40	(-0.46)	1.19	(1.19)	-1.59	(-2.29)	-0.41	(-0.90)	1.17	(2.12)	-1.59	(-2.28)
Gross Profitability	0.62	(0.90)	0.47	(0.70)	0.15	(0.47)	0.61	(1.98)	0.46	(1.33)	0.15	(0.48)
Return on assets	0.19	(0.25)	0.77	(0.77)	-0.57	(-1.26)	0.18	(0.65)	0.75	(1.40)	-0.57	(-1.31)
MGMT	0.48	(0.80)	0.82	(0.90)	-0.34	(-0.74)	0.47	(1.79)	0.80	(2.12)	-0.33	(-0.93)
PERF	0.12	(0.17)	0.80	(0.96)	-0.68	(-1.47)	0.11	(0.41)	0.79	(1.64)	-0.68	(-1.47)
PEAD	0.29	(0.35)	1.40	(1.57)	-1.11	(-4.19)	0.28	(0.76)	1.39	(3.73)	-1.11	(-4.27)
FIN	0.69	(1.14)	0.81	(0.98)	-0.12	(-0.30)	0.68	(2.61)	0.79	(2.33)	-0.11	(-0.34)

Table 1.6: Continued

Panel B: Momentum based anomalies												
	Excess Returns						Benchmark-Adjusted Returns					
	Long		Short		Spread		Long		Short		Spread	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
F3H1	-0.20	(-0.24)	1.35	(1.34)	-1.55	(-2.58)	-0.21	(-0.5)	1.34	(2.58)	-1.55	(-2.66)
F3H3	-0.13	(-0.16)	1.17	(1.23)	-1.31	(-2.55)	-0.15	(-0.36)	1.16	(2.38)	-1.31	(-2.56)
F3H6	0.05	(0.06)	1.07	(1.18)	-1.02	(-2.56)	0.04	(0.09)	1.05	(2.36)	-1.02	(-2.56)
F6H1	-0.52	(-0.63)	1.38	(1.37)	-1.91	(-2.88)	-0.54	(-1.18)	1.37	(2.46)	-1.91	(-2.81)
F6H3	-0.24	(-0.27)	1.23	(1.28)	-1.47	(-2.49)	-0.25	(-0.59)	1.22	(2.39)	-1.47	(-2.50)
F6H6	-0.04	(-0.05)	1.03	(1.11)	-1.07	(-2.17)	-0.06	(-0.14)	1.02	(2.13)	-1.07	(-2.17)
F9H1	-0.52	(-0.61)	1.38	(1.37)	-1.90	(-2.83)	-0.53	(-1.18)	1.36	(2.48)	-1.90	(-2.78)
F9H3	-0.21	(-0.24)	1.15	(1.19)	-1.36	(-2.22)	-0.23	(-0.52)	1.14	(2.19)	-1.36	(-2.22)
F9H6	0.08	(0.09)	0.85	(0.92)	-0.77	(-1.46)	0.07	(0.16)	0.84	(1.71)	-0.77	(-1.46)
F11H1	-0.40	(-0.46)	1.19	(1.19)	-1.59	(-2.29)	-0.41	(-0.90)	1.17	(2.12)	-1.59	(-2.28)
F11H3	-0.10	(-0.11)	0.98	(1.02)	-1.07	(-1.72)	-0.11	(-0.25)	0.96	(1.85)	-1.07	(-1.72)
F11H6	0.28	(0.31)	0.64	(0.69)	-0.36	(-0.69)	0.27	(0.65)	0.63	(1.28)	-0.36	(-0.70)

Table 1.7: Attention, sentiment, and anomalies (excess return controlling for time trend)

The table reports the estimates of β_A and β_S in regression $R_{i,t} = \alpha_i + \beta_A Attention_{t-1} + \beta_S Sentiment_{m-1} + \beta_T Month_m + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's excess return on day t in month m. The Sample period is from January 1996 to October 2015. Attention is measured as the equal-weighted total number of news covered by Thomson Reuters News Data. We use rank (from 1 to 10) of attention across time as dependent variable. Sentiment is measured as rank (from 1 to 10) of Baker and Wurgler sentiment index across time. Month is the index of month based on time order. Panel A reports results for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports results for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Long				Short				Spread			
	Attent		Sent		Attent		Sent		Attent		Sent	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
Net stock issuance	0.62	(0.92)	-0.26	(-0.42)	0.80	(0.94)	-1.50	(-1.65)	-0.18	(-0.52)	1.24	(2.79)
Composite equity issuance	0.51	(0.87)	0.08	(0.15)	1.06	(1.24)	-1.29	(-1.47)	-0.55	(-1.32)	1.37	(2.35)
Accruals	0.48	(0.58)	-1.47	(-1.65)	0.81	(0.88)	-1.82	(-1.75)	-0.32	(-1.07)	0.35	(0.85)
Net operating assets	0.49	(0.73)	-1.14	(-1.63)	0.98	(1.14)	-1.54	(-1.69)	-0.49	(-1.38)	0.41	(1.07)
Asset growth	0.35	(0.44)	-1.48	(-1.73)	1.00	(1.09)	-2.38	(-2.17)	-0.65	(-1.76)	0.90	(1.61)
Investment to assets	0.47	(0.61)	-1.08	(-1.36)	0.93	(0.94)	-1.82	(-1.84)	-0.46	(-1.19)	0.74	(1.69)
Failure Probabilty	0.11	(0.18)	-0.15	(-0.25)	1.53	(1.81)	-0.86	(-0.96)	-1.41	(-3.42)	0.72	(1.36)
O-score	0.71	(0.90)	-1.03	(-1.26)	0.20	(0.22)	-2.50	(-2.39)	0.51	(1.38)	1.47	(3.23)
Momentum (f11h1)	-0.31	(-0.35)	-1.26	(-1.37)	1.36	(1.35)	-2.25	(-1.87)	-1.67	(-2.35)	1.00	(1.10)
Gross Profitability	0.70	(0.99)	-0.94	(-1.25)	0.62	(0.90)	-1.52	(-1.98)	0.09	(0.28)	0.57	(1.55)
Return on assets	0.26	(0.33)	-0.74	(-0.98)	1.12	(1.12)	-3.69	(-3.00)	-0.86	(-1.92)	2.94	(4.16)
MGMT	0.51	(0.82)	-0.35	(-0.59)	0.98	(1.06)	-1.74	(-1.73)	-0.48	(-1.06)	1.39	(2.25)
PERF	0.18	(0.25)	-0.73	(-1.09)	1.01	(1.19)	-2.14	(-2.29)	-0.83	(-1.79)	1.41	(2.58)
PEAD	0.44	(0.53)	-1.62	(-1.77)	1.56	(1.74)	-1.76	(-1.77)	-1.12	(-4.21)	0.14	(0.49)
FIN	0.71	(1.13)	-0.23	(-0.40)	0.95	(1.16)	-1.64	(-1.83)	-0.25	(-0.63)	1.41	(2.61)

Table 1.7: Continued

Panel B: Momentum based anomalies												
	Long				Short				Spread			
	Attent		Sent		Attent		Sent		Attent		Sent	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
F3H1	-0.10	(-0.12)	-1.38	(-1.53)	1.51	(1.48)	-2.05	(-1.64)	-1.61	(-2.70)	0.67	(0.79)
F3H3	-0.06	(-0.07)	-1.12	(-1.22)	1.33	(1.37)	-2.02	(-1.72)	-1.39	(-2.64)	0.90	(1.27)
F3H6	0.13	(0.15)	-1.13	(-1.22)	1.22	(1.32)	-2.04	(-1.84)	-1.10	(-2.70)	0.91	(1.63)
F6H1	-0.46	(-0.54)	-0.94	(-1.06)	1.57	(1.54)	-2.45	(-1.95)	-2.04	(-2.88)	1.51	(1.65)
F6H3	-0.17	(-0.2)	-0.96	(-1.05)	1.41	(1.44)	-2.28	(-1.90)	-1.58	(-2.63)	1.32	(1.63)
F6H6	0.03	(0.03)	-1.04	(-1.12)	1.19	(1.27)	-2.14	(-1.90)	-1.16	(-2.33)	1.10	(1.63)
F9H1	-0.45	(-0.51)	-1.02	(-1.14)	1.57	(1.54)	-2.47	(-2.02)	-2.02	(-2.88)	1.45	(1.58)
F9H3	-0.14	(-0.15)	-1.06	(-1.13)	1.33	(1.36)	-2.24	(-1.93)	-1.46	(-2.33)	1.19	(1.44)
F9H6	0.17	(0.18)	-1.18	(-1.24)	1.01	(1.07)	-2.02	(-1.83)	-0.84	(-1.58)	0.84	(1.19)
F11H1	-0.31	(-0.35)	-1.26	(-1.37)	1.36	(1.35)	-2.25	(-1.87)	-1.67	(-2.35)	1.00	(1.10)
F11H3	-0.01	(-0.01)	-1.16	(-1.22)	1.14	(1.17)	-2.06	(-1.80)	-1.15	(-1.82)	0.91	(1.11)
F11H6	0.37	(0.41)	-1.22	(-1.25)	0.79	(0.84)	-1.92	(-1.76)	-0.42	(-0.78)	0.70	(0.96)

Table 1.8: Attention, sentiment, and anomalies (excess return controlling for time trend and macroeconomic variables)

The table reports the estimates of β_A and β_S in regression $R_{i,t} = \alpha_i + \beta_A Attention_{t-1} + \beta_S Sentiment_{m-1} + \beta_T Month_m + \beta_{M6} X_{m-1} + \epsilon_{i,t}$, where $R_{i,t}$ is a strategy's excess return on day t in month m. The Sample period is from January 1996 to October 2015. Attention is measured as the equal-weighted total number of news covered by Thomson Reuters News Data. We use rank (from 1 to 10) of attention across time as dependent variable. Sentiment is measured as rank (from 1 to 10) of Baker and Wurgler sentiment index across time. Month is the index of month based on time order. The variables X, including growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions, are macroeconomic conditions considered in Baker and Wurgler (2006). Panel A reports results for commonly used anomalies. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. In each month, firms are sorted equally into 10 deciles based on each of the above mentioned characteristics, and the two extreme deciles are assigned as long and short leg portfolios. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. Panel B reports results for momentum strategies based on different ranking and holding periods. Given a month m, we calculate cumulative return of $m-f$ to $m-1$ to form 10 decile portfolios. We skip one month, and report daily returns with holding period of h months for $F(f)H(h)$. All portfolio returns are equal weighted, reported in basis points. All t-statistics are based on the heteroskedasticity-consistent standard errors of Newey and West (1987).

Panel A: Commonly used anomalies												
	Long				Short				Spread			
	Attent		Sent		Attent		Sent		Attent		Sent	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
Net stock issuance	0.61	(0.92)	0.27	(0.33)	0.92	(1.08)	-1.66	(-1.41)	-0.31	(-0.83)	1.92	(3.50)
Composite equity issuance	0.52	(0.91)	0.59	(0.89)	1.14	(1.34)	-1.41	(-1.22)	-0.62	(-1.43)	2.00	(2.72)
Accruals	0.59	(0.71)	-1.40	(-1.23)	0.86	(0.93)	-2.19	(-1.58)	-0.27	(-0.85)	0.79	(1.52)
Net operating assets	0.56	(0.83)	-1.26	(-1.44)	0.93	(1.10)	-1.47	(-1.20)	-0.37	(-1.06)	0.22	(0.41)
Asset growth	0.48	(0.60)	-1.51	(-1.40)	1.03	(1.10)	-2.83	(-1.96)	-0.55	(-1.41)	1.31	(1.90)
Investment to assets	0.56	(0.73)	-0.93	(-0.95)	0.89	(0.90)	-1.65	(-1.26)	-0.33	(-0.83)	0.72	(1.29)
Failure Probabilty	0.23	(0.35)	0.18	(0.23)	1.59	(1.87)	-1.11	(-0.99)	-1.36	(-3.21)	1.29	(2.00)
O-score	0.81	(1.00)	-1.23	(-1.15)	0.41	(0.45)	-2.89	(-2.07)	0.40	(1.10)	1.67	(2.96)
Momentum (f11h1)	-0.03	(-0.03)	-1.52	(-1.30)	1.40	(1.34)	-2.29	(-1.52)	-1.42	(-1.99)	0.77	(0.68)
Gross Profitability	0.71	(0.99)	-0.69	(-0.71)	0.75	(1.11)	-1.99	(-2.03)	-0.05	(-0.15)	1.30	(2.97)
Return on assets	0.34	(0.44)	-0.53	(-0.54)	1.35	(1.35)	-4.64	(-2.90)	-1.01	(-2.33)	4.11	(4.51)
MGMT	0.49	(0.80)	-0.01	(-0.01)	1.00	(1.08)	-1.80	(-1.35)	-0.50	(-1.08)	1.79	(2.21)
PERF	0.26	(0.37)	-0.59	(-0.67)	1.17	(1.33)	-2.73	(-2.23)	-0.90	(-1.92)	2.14	(3.13)
PEAD	0.48	(0.57)	-1.77	(-1.51)	1.63	(1.81)	-1.98	(-1.56)	-1.15	(-4.19)	0.22	(0.58)
FIN	0.65	(1.05)	0.28	(0.39)	1.05	(1.25)	-1.90	(-1.63)	-0.40	(-0.96)	2.18	(3.09)

Table 1.8: Continued

Panel B: Momentum based anomalies												
	Long				Short				Spread			
	Attent		Sent		Attent		Sent		Attent		Sent	
	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value	coef	t value
F3H1	0.19	(0.22)	-1.65	(-1.49)	1.58	(1.51)	-2.31	(-1.46)	-1.39	(-2.19)	0.65	(0.64)
F3H3	0.18	(0.21)	-1.25	(-1.08)	1.41	(1.42)	-2.21	(-1.51)	-1.23	(-2.29)	0.96	(1.16)
F3H6	0.37	(0.42)	-1.23	(-1.07)	1.29	(1.34)	-2.18	(-1.57)	-0.92	(-2.26)	0.94	(1.45)
F6H1	-0.11	(-0.13)	-1.06	(-0.96)	1.54	(1.46)	-2.69	(-1.72)	-1.65	(-2.32)	1.63	(1.53)
F6H3	0.13	(0.15)	-1.03	(-0.90)	1.40	(1.38)	-2.43	(-1.62)	-1.27	(-2.10)	1.40	(1.48)
F6H6	0.32	(0.37)	-1.18	(-1.01)	1.22	(1.25)	-2.23	(-1.57)	-0.90	(-1.81)	1.05	(1.31)
F9H1	-0.14	(-0.17)	-1.22	(-1.09)	1.53	(1.46)	-2.55	(-1.67)	-1.68	(-2.39)	1.33	(1.21)
F9H3	0.17	(0.19)	-1.21	(-1.02)	1.35	(1.34)	-2.23	(-1.53)	-1.18	(-1.88)	1.02	(1.03)
F9H6	0.46	(0.51)	-1.43	(-1.19)	1.07	(1.10)	-1.93	(-1.38)	-0.62	(-1.15)	0.51	(0.58)
F11H1	-0.03	(-0.03)	-1.52	(-1.30)	1.40	(1.34)	-2.29	(-1.52)	-1.42	(-1.99)	0.77	(0.68)
F11H3	0.28	(0.32)	-1.43	(-1.17)	1.20	(1.21)	-1.96	(-1.36)	-0.92	(-1.45)	0.53	(0.53)
F11H6	0.65	(0.72)	-1.51	(-1.22)	0.89	(0.93)	-1.82	(-1.31)	-0.24	(-0.45)	0.31	(0.34)

Figure 1.1: Market-wide attention and investor sentiment

This figure plots the monthly investor attention proxy with Baker and Wurgler (2006) investor sentiment index, both of which are standardized to have mean of 0 and standard deviation of 1. Investor attention is constructed using average number of news coverage across firms. We first count the number of news articles of each firm each day and then calculate the average number of news coverage across firms, namely

$$Attention_t = \frac{\sum_{k=1}^{K} \# \text{ of news}_k}{K},$$

where K stands for total number of firms covered by media news. Monthly investor attention hence can be calculated as average of daily investor attention. News data is from Thomson Reuters News Analytics service for the period 1996 to 2014. The red line stands for investor attention and blue line stands for Baker and Wurgler (2006) sentiment index. The shaded periods correspond to NBER-dated recessions.

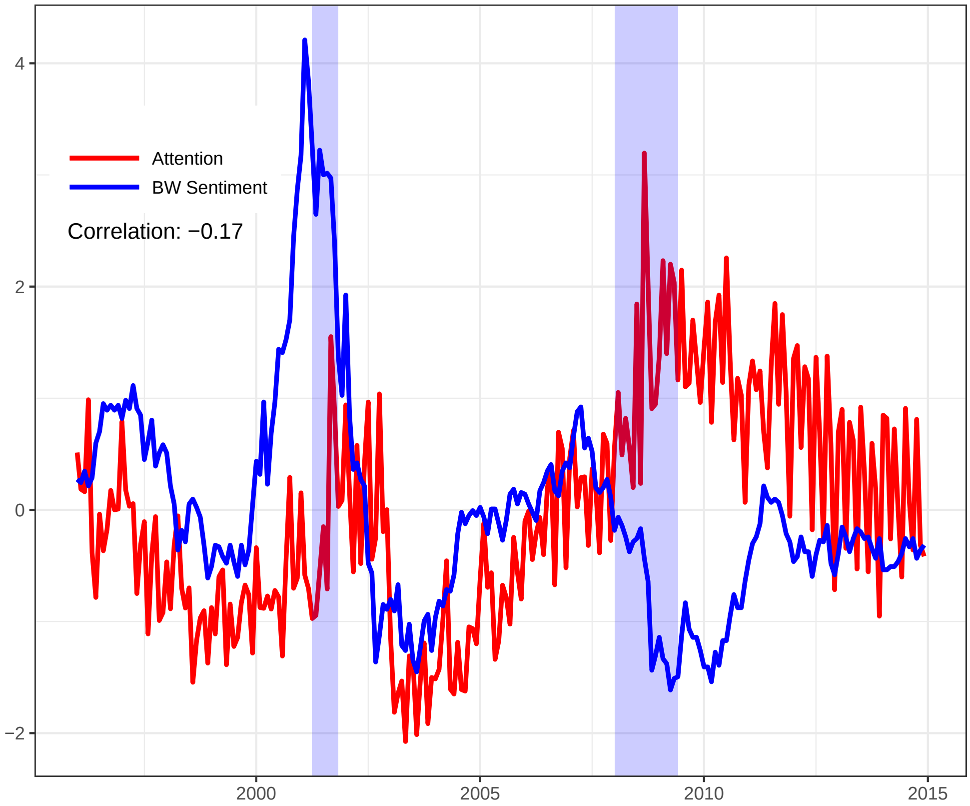
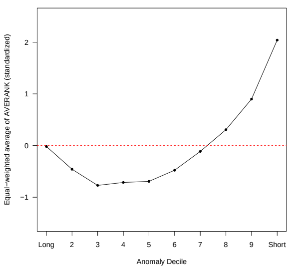
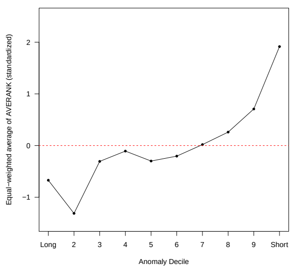


Figure 1.2: AVERANK and MGMT cluster anomalies

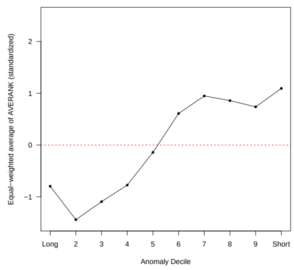
The graphs report equal weighted AVERANK in each decile of MGMT cluster anomalies. The sample period is from January 1983 to October 2015. MGMT is constructed based on average ranking scores of six anomalies, net stock issuance, composite equity issuance, accruals, net operating assets, aggregate growth and investment to assets. AVERANK is constructed based on average ranking scores of seven uncertainty proxies, firm size, age, analyst coverage, short-term and long-term analyst forecast dispersion, stock volatility and cash flow volatility. Given a month m, equal weighted average of AVERANK in $m-1$ is calculated for in each decile of a given anomaly. Such results are standardized to have zero mean and one standard deviation across all months and all deciles for each anomaly. The average of standardized equal weighted AVERANK across all month are reported in the graphs.



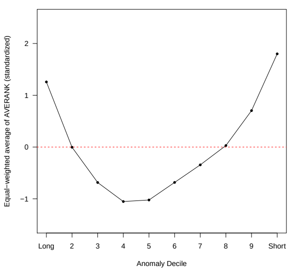
(a) MGMT



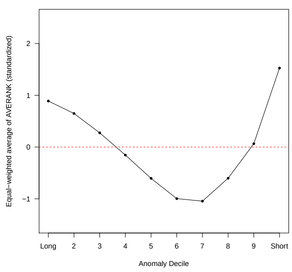
(b) Net stock issuance



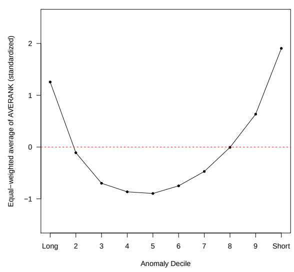
(c) Composite equity issuance



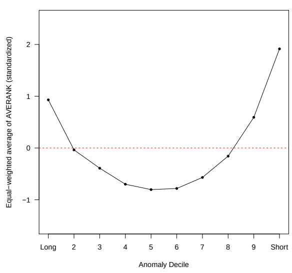
(d) Accruals



(e) Net operating assets



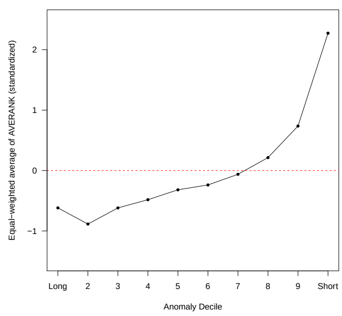
(f) Asset growth



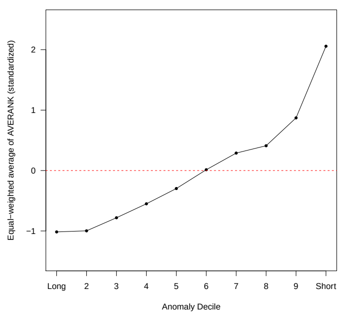
(g) Investment to assets

Figure 1.3: AVERANK and PERF cluster anomalies

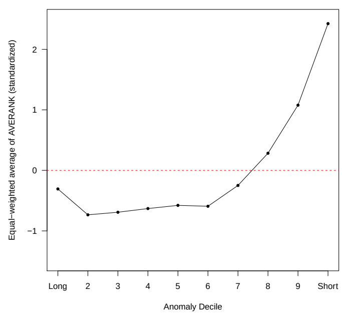
The graphs report equal weighted AVERANK in each decile of MGMT cluster anomalies. The sample period is from January 1983 to October 2015. PERF is constructed based on average ranking scores of five anomalies, distress, o-score, momentum, gross profitability and return on assets. AVERANK is constructed based on average ranking scores of seven uncertainty proxies, firm size, age, analyst coverage, short-term and long-term analyst forecast dispersion, stock volatility and cash flow volatility. Given a month m, equal weighted average of AVERANK in $m-1$ is calculated for in each decile of a given anomaly. Such results are standardized to have zero mean and one standard deviation across all months and all deciles for each anomaly. The average of standardized equal weighted AVERANK across all month are reported in the graphs.



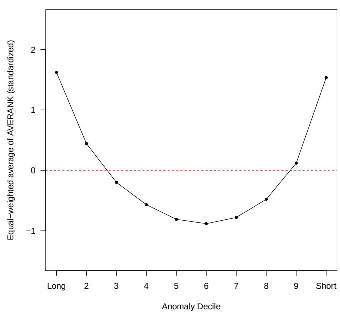
(a) PERF



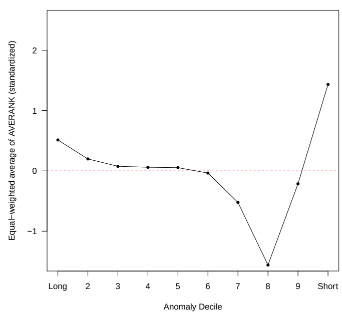
(b) Failure Probability



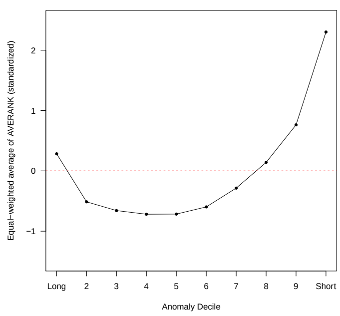
(c) O-score



(d) Momentum



(e) Gross profitability

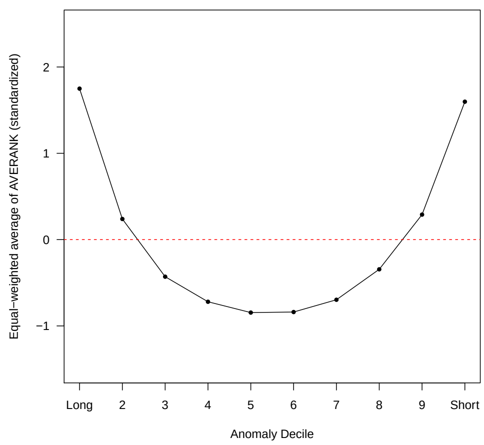


(f) Return on assets

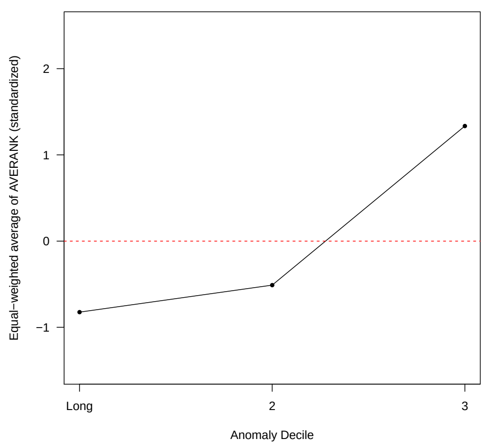
Figure 1.4: AVERANK of PEAD and FIN

The graphs report equal weighted AVERANK in each decile of PEAD and FIN. The sample period is from January 1983 to October 2015. The portfolios of PEAD are formed based on the four-day cumulative abnormal return $(t-2, t+1)$ around the latest quarterly earnings announcement date. The portfolios of FIN are constructed based on the combination of net stock issuance and composite stock issuance. A firm is assigned to long (short) leg of FIN if both the two anomalies belong to high (low) rank group. AVERANK is constructed based on average ranking scores of seven uncertainty proxies, firm size, age, analyst coverage, short-term and long-term analyst forecast dispersion, stock volatility and cash flow volatility. Given a month m, equal weighted average of AVERANK in $m-1$ is calculated for in each decile of a given anomaly. Such results are standardized to have zero mean and one standard deviation across all months and all deciles for each anomaly. The average of standardized equal weighted AVERANK across all month are reported in the graphs.

Panel A: PEAD



Panel B: FIN



Appendix: Anomalies Construction

In this appendix, we detail the construction of anomalies used in the paper. The anomaly measures are computed at the end of each month. Stock returns, prices and number of outstanding shares are from the Center for Research in Securities Prices (CRSP), And accounting information is from the Compustat Annual and Quarterly Fundamental Files. The sample includes all common stocks (share codes 10 and 11) with prices larger than $5 from 1983 through 2016. The values computed at the end of month $t-1$ for each anomaly are constructed as follows:

Net Stock Issuance: The stock issuing market has long been viewed as producing an anomaly arising from sentiment-driven mispricing: smart managers issue shares when sentiment driven traders push prices to overvalued levels. Ritter (1991) and Loughran and Ritter (1995) show that, in post-issue years, equity issuers underperform matching nonissuers with similar characteristics. Motivated by this evidence, Fama and French (2008) show that net stock issuance and subsequent returns are negatively correlated. Following Fama and French (2008), we measure net issuance as the annual log change in split-adjusted shares outstanding. Split-adjusted shares equal shares outstanding (Compustat annual item CSHO) times the adjustment factor (Compustat annual item ADJEX_C). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Composite Equity Issuance: Daniel and Titman (2006) find that issuers underperform nonissuers using a measure they denote as composite equity issuance, defined as the growth in the firm's total market value of equity minus (i.e., not attributable to) the stock's rate of return. We compute this measure by subtracting the 12-month cumulative stock return from the 12-month growth in equity market capitalization. We lag the quantity four months, to make its timing more coincident with the above measure of net stock issuance.

Accruals: Sloan (1996) shows that firms with high accruals earn abnormally lower average returns than firms with low accruals, and he suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Following Sloan (1996), we measure total accruals as the annual change in noncash working capital minus depreciation and amortization expense (Compustat annual item DP), divided by average total assets (item AT) for the previous two fiscal years. Noncash working capital is computed as the change in current assets (item ACT) minus the change in cash and short-term investment (item CHE), minus the change in current liabilities (item DLC), plus the change in debt included in current liabilities (item LCT), plus the change in income taxes payable (item TXP). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Net Operating Assets: Hirshleifer et al. (2004) find that net operating assets, defined as the difference on the balance sheet between all operating assets and all operating liabilities, scaled by total assets, is a strong negative predictor of long-run stock returns. The authors suggest that investors with limited attention tend to focus on accounting profitability, neglecting information about cash profitability, in which case net operating assets (equivalently measured as the cumulative difference between operating income and free cash flow) captures such a bias. Following Equations (4), (5), and (6) of that study, we measure net operation assets as operating assets minus operating liabilities, divided by lagged total assets (Compustat annual item AT). Operating assets equal total assets (item AT) minus cash and short-term investment (item CHE). Operating liabilities equal total assets minus debt included in current liabilities (item DLC), minus long-term debt (item DLTT), minus common equity (item CEQ), minus minority interests (item MIB), minus preferred stocks (item PSTK). (The last two items are zero if missing.) The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Asset Growth: Cooper et al. (2008) find that companies that grow their total assets more earn lower subsequent returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions.Asset growth is measured as the growth rate of total assets in the previous fiscal year. Following that study, we measure asset growth as the most recent year-over-year annual growth rate of total assets (Compustat annual item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Investment to Assets: Titman et al. (2004) and Xing (2007) show that higher past investment predicts abnormally lower future returns. Titman et al. (2004) attribute this anomaly to investors' initial underreaction to overinvestment caused by managers' empire-building behavior. Here, investment to assets is measured as the annual change in gross property, plant, and equipment, plus the annual change in inventories, scaled by lagged book value of assets. Following the above studies, we compute investment-to-assets as the changes in gross property, plant, and equipment (Compustat annual item PPEGT) plus changes in inventory (item INVT), divided by lagged total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

MGMT: Stambaugh and Yuan (2016) find that the six anomalies described above can be controlled by firm management directly. They use the average score ranking of these six anomalies to capture for the commonality in mispricing. Stocks are ranked from 0 to 100 based on each anomaly. Mispricing measure MGMT, ranging between 0 and 100, is the arithmetic average of the six ranking scores. The stocks with the highest values of MGMT are the most "overpriced", and those with the lowest values are the most "underpriced". When constructing MGMT at the end of month $t-1$, a stock is required to have non-missing values at the end of that month for at least three anomalies. Also, in order for an anomaly to be included in MGMT at the end of month $t-1$, there should be at least 30 stocks to have non-missing values for that anomaly.

Failure Probability: Financial distress is often invoked to explain otherwise anomalous patterns in the cross-section of stock returns. However, Campbell et al. (2008) find that firms with high failure probability have lower rather than higher subsequent returns. The authors suggest that their finding is a challenge to standard models of rational asset pricing. Failure probability is estimated with a dynamic logit model that uses several equity market variables, such as stock price, book-to-market, stock volatility, size relative to the S&P 500, and cumulative excess return relative to the S&P 500. Specifically, using the above study's equations (2) and (3) along with its Table IV (12-month column), we compute the distress anomaly measure–failure probability–as

$$\pi = -20.26NIMTAAVG + 1.42TLMTA - 7.13EXRETAVG + 1.41SIGMA$$
$$- 0.045RSIZE - 2.13CASHMTA + 0.075MB - 0.058PRICE - 9.16,$$

where

$$NIMTAAVG_{t,t-11} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t,t-1}+\cdots+\phi^9 NIMTA_{t-9,t-11})$$

$$EXRETAVG_{t,t-11} = \frac{1-\phi}{1-\phi^{12}}(EXRET_t + \cdots + \phi^{11}EXRET_{t-11}$$

and $\phi = 2^{-1/3}$. $NIMTA$is net income (Compustat quarterly item NIQ) divided by firm scale, where the latter is computed as the sum of total liabilities (item LTQ) and market equity capitalization (data from CRSP). $EXRET_s$ is the stock's monthly log return in month s minus the log return on the S&P500 index. Missing values for $NIMTA$ and $EXRET$ are replaced by those quantities' cross-sectional means. $TLMTA$ equals total liabilities divided by firm scale. $SIGMA$ is the stock's daily standard deviation for the most recent three months, expressed on an annualized basis. At least five non-zero daily returns are required. $RSIZE$ is the log of the ratio of the stock's market capitalization to that of the S&P500 index. $CASHMTA$ equals cash and short-term investment (item CHEQ) divided by firm scale. MB is the market-to-book ratio. Following Campbell et al. (2008), we increase book equity by 10% of the difference between market equity and book equity. If the resulting value of book equity is negative, then book equity is set to \$1. $PRICE$ is the log of the share price, truncated above at \$15. All explanatory variables except $PRICE$ are winsorized above and below at the 5% level in the cross section. CRSP based variables, $EXRETAVG$, $SIGMA$,

$RSIZE$ and $PRICE$ are for month $t-1$. NIQ is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, whereas the items requiring information from the balance sheet (LTQ, $CHEQ$ and MB) are for the prior quarter.

O-score: This distress measure, from Ohlson (1980), predicts returns in a manner similar to the measure above. It is the probability of bankruptcy estimated in a static model using accounting variables. Following Ohlson (1980), we construct it as:

$$
\begin{aligned}
O &= -0.407SIZE + 6.03TLTA - 1.43WCTA + 0.076CLCA - 1.72OENEG \\
&= -2.37NITA - 1.83FUTL + 0.285INTWO - 0.521CHIN - 1.32,
\end{aligned}
$$

where $SIZE$ is the log of total assets (Compustat annual item AT), $TLTA$ is the book value of debt (item DLC plus item DLTT) divided by total assets, $WCTA$ is working capital (item ACT minus item LCT) divided by total assets, $CLCA$ is current liabilities (item LCT) divided by current assets (item ACT), $ONEEG$ is 1 if total liabilities (item LT) exceed total assets and is zero otherwise, $NITA$ is net income (item NI) divided by total assets, $FUTL$ is funds provided by operations (item PI) divided by total liabilities, $INTWO$ is equal to 1 if net income (item NI) is negative for the last 2 years and zero otherwise, $CHIN$ is $(NI_j - NI_{j-1})/(|NI_j| + |NI_{j-1}|)$, in which NI_j is the income (item NI) for year j, which is the most recent reporting year that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Momentum: The momentum effect, discovered by Jegadeesh and Titman (1993), is one of the most robust anomalies in asset pricing. It refers to the phenomenon whereby high (low) past recent recent returns forecast high (low) future returns. The momentum ranking at the end of month $t-1$ uses the cumulative returns from month $t-12$ to month $t-2$. This is the choice of ranking variable used by Carhart (1997) to construct the widely used momentum factor.

Gross Profitability Premium: Novy-Marx (2013) shows that sorting on the ratio of gross profit to assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones. He argues that gross profit is the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability. Following that study, we measure gross profitability as total revenue (Compustat annual item REVT) minus the cost of goods sold (item COGS), divided by current total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

Return on Assets: Fama and French (2006) find that more profitable firms have higher expected returns than less profitable firms. Chen et al. (2011) show that firms with higher past return on assets earn abnormally higher subsequent returns. Return on assets is measured as the ratio of quarterly earnings to last quarter's assets. Wang and Yu (2013) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty, suggesting that mispricing is a culprit. Following Chen et al. (2011), we compute return on assets as income before extraordinary items (Compustat quarterly item IBQ) divided by the previous quarter's total assets (item ATQ). Income is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, and assets are for the prior quarter.

PERF: Stambaugh and Yuan (2016) find that the five anomalies described above are more related to the firm performance. They use the average score ranking of these five anomalies to capture for the commonality in mispricing. Stocks are ranked from 0 to 100 based on each anomaly. Mispricing measure PERF, ranging between 0 and 100, is the arithmetic average of the six ranking scores. The stocks with the highest values of PERF are the most "overpriced", and those with the lowest values are the most "underpriced". When constructing PERF at the end of month $t-1$, a stock is required to have non-missing values at the end of that month for at least three anomalies. Also, in order for an anomaly to be included in PERF at the end of month $t-1$, there should be at least 30 stocks to have non-missing values for that anomaly.

FIN: Daniel et al. (2017) sort firms into one of the three financing groups (low "L", middle "M", or high "H") based on the net stock issuance (NSI) and composite equity issuance (CEI) as in the first cluster of Stambaugh and Yuan (2016) anomalies. Firms are first sorted into three CEI groups (low, middle, or high) using 20% and 80% breakpoints for NYSE firms. Firms are also classified into repurchasing firms (with negative NSI) and issuing firms (with positive NSI). Repurchasing firms are sorted into two groups based on NYSE median breakpoints, and issueing firms are sorted into three groups using NYSE 30% and 70% breakpoints. Firms in the bottom groups of repurchasing firms are assigned to the low NSI group, firms in the top groups of issuing firms are assigned to the high NSI group, and all the other firms are assigned to the middle group. FIN is an index based on NSI and CEI rankings. A firm is assigned to low FIN group if it belongs to low NSI and CEI group if available. A firm is assigned to high FIN group if it belongs to high NSI and CECI group if available.

All the rest firms are assigned to middle FIN group.

Post earnings announcement drift(PEAD): Following Chan et al. (1996), earnings surprise is calculated as the four-day cumulative abnormal returns (t-2, t+1) around the latest quarterly earnings announcement date (Compustat quarterly item RDQ):

$$CAR_i = \sum_{d=-2}^{d=1} R_{i,d} - R_{m,d},$$

where $R_{i,d}$ is stock i's return on day d and $R_{m,d}$ is the market return on day d relative to the earnings announcement date. PEAD with the latest quarterly earnings announcement date (Compustat quarterly item RDQ) prior to month $t-1$ is used. Observations with more than 6 months from the fiscal quarter end are excluded to avoid stale earnings. Earnings announcement date is required to be after the corresponding fiscal quarter end to exclude recording errors.

Momentum strategies (F3/6/9/11_H1/3/6): A strategy for the selection of the stocks based on the returns over the last $f(3/6/9/11)$ months and were held for $h(1/3/6)$ months (we will refer to this as a F-month/H-month strategy) is established in below: During the initial age of each month t, a rank of the securities was made according to the ascending order based on their returns during last f months. According to these rankings, there are ten decile portfolios being formulated, in which the stocks are equally weighted. The top decile portfolio is called the "losers" decile and the bottom decile is called the "winners" decile. During each month t, the strategy would purchase the winner portfolio while sell the loser portfolio. The position would be held for h months. Additionally, the position initiated in month $t-h$ is closed out by the strategy. Therefore, due to such trading strategy, the weights were revised on $\frac{1}{h}$ of the securities in the entire portfolio in any given h month and carry over the rest from the previous month. The profits of the above strategies were calculated for both a series of buy and hold portfolios and a series of portfolios that were rebalanced daily to maintain equal weights.

Chapter 2

Factor Style

Xinrui Duan and Ran Zhang

ABSTRACT

We use systematic methods to solve factor timing problem and to improve the performance of factor investing. Past factor returns predict the cross section of factor returns, and this predictability is at its strongest at the one-month horizon (Arnott et al. 2019). We find that factor momentum is pervasive in international stock markets. We show that factor momentum can be captured by trading almost any set of factors. We further find that stock factor momentum, stock factor IVOL, and cross-assets factor momentum can generate alphas. These alphas cannot be explained by current asset pricing models.

JEL classification: G11, G14, G15

2.1 Introduction

Investors are bombarded by a variety of investment strategies from a growing and increasingly complex financial industry, each claiming to improve returns and reduce risks. Amid the clamour, academic research has sifted through the vast landscape and found many factor investment strategies that, when applied effectively, have delivered positive long-term returns with low correlation to each other and traditional markets. However, Individual factors can experience periods of disappointing performance. McLean and Pontiff (2016) found that most factors' abnormal returns disappear or decrease after publications. Financial literature has found performance of factors diversification is better than the performance of individual factor (Asness et al., 2013).

However, a more rational approach to 'timing' these factors is rarely studied before. Deciding whether to tactically monitor and adjust exposures to different factors and, if so, how to go about it, is often raised as a major difficulty (Asness, 2016; Dimson et al., 2017). In this paper, we propose systematic methods to factors' timing and to improve the performance of factor investing.

Past factor returns predict the cross section of factor returns, and this predictability is at its strongest at the one-month horizon (Arnott et al. 2019). We first confirm this result by considering a strategy that rotates 50 factors based on their prior one-month returns and long three best factors and short three worst factors. The strategy earns an average return of 1.89% per month with a t-value of 4.13. Such factor momentum is at its strongest with one-month formation and holding periods.

We also construct random sets of factors that differ in size. The profitability of a strategy that trades factor momentum using a random set of, say, ten factors is nearly the same as that of the full set. In fact, a strategy that captures momentum in factor returns by rotating between just two randomly selected factors is typically statistically significant as well. Factor momentum is also robust to implementation restrictions. The effect remains significant even when we introduce a delay between the formation and holding periods.

We test whether factor momentum is robust in international 23 developed markets and regional markets based on MSCI 2017 market classification. We use Carhart (1997) four factors and AQR (2014; 2017) six factors to test international evidence of factor momentum. We find factor momentum alphas in all five regional markets (Global, Global ex USA, Asia, Europe, and North America) and 16 developed markets except Austria, Belgium, Ireland, Italy, Netherlands, Norway, and Sweden.

We test whether factor momentum is robust in cross-assets (stocks, equity indices, fixed income, commodity futures, and currencies). We use Asness et al. (2013) cross-assets three-factor model to explain alphas of cross-assets factor momentum. We find cross-assets factor momentum alphas which cannot be explained by Asness et al. (2013) cross-assets three-factor model.

We further find that factor IVOL earns more risk-adjusted profits than those associated with individual factors. Factors with high idiosyncratic volatility relative to the Fama and French (1993) three-factor model have abysmally low average returns. We take long and short positions in the bottom and top factors based on previous 12-month daily idiosyncratic volatility (against Fama and French three-factor model). A zero-cost portfolio, long the factor with lowest IVOL and short the factor with highest

IVOL, earns an average return of 1.46% per month with a t-value of 5.99. This result is consistent with finding of Ang et al. (2006; 2009). Ang et al. (2006; 2009) found that stocks with high sensitivities to innovations in aggregate volatility have low average returns.

Our paper is built upon the recent work by Arnott el al. (2019) in analysing factor momentum. Their work focuses on the factor momentum in the US equity market. Our findings provide further evidence of momentum in international market, and across different asset market. In addition, We also provide factor IVOL as another factor style which generates abnormal alpha. Our paper is also related to Gupta and Kelly (2019) in analysing factor momentum in international market. Our findings differs in considering factor momentum in multiple countries, instead of simply consider the whole global market.

2.2 Data

2.2.1 CRSP and Compustat

We use monthly and daily returns data on stocks listed on NYSE, AMEX, and Nasdaq from the Center for Research in Securities Prices (CRSP). We include ordinary common shares (share codes 10 and 11) and use CRSP delisting returns. If a stock's delisting return is missing and the delisting is performance-related, we impute a return of 30% for NYSE and AMEX stocks (Shumway, 1997) and 55% for Nasdaq stocks (Shumway and Warther, 1999).

We obtain accounting data from annual Compustat files to compute some of the return predictors we detail in Section 2.2. We follow the standard convention and lag accounting information by six months (Fama and French, 1993). For example, if a firm's fiscal year ends in December in year t, we assume that this information is available to investors at the end of June in year t + 1.

We compute returns on our factors from July 1963 through December 2017. Some of the predictors that we use to form the factors—such as idiosyncratic volatility and market beta—however, use some pre-1963 return data.

2.2.2 Universe of factors

Table 2.1 reports average returns and Fama and French (2015; 2018) five- and six-factor model alphas for the 50 factors that we examine throughout this study. These factors are among those examined in Hou et al. (2015), Fama and French (2015; 2018), McLean and Pontiff (2016), Novy-Marx and Velikov (2016), Stambaugh and Yuan (2016), and Daniel, Hirshleifer, and Sun (2018). In Table 2.1 we divide the factors into four groups, basic factors, low turnover factors, medium turnover factors, high turnover factors.

We construct each factor as an HML-like factor by sorting stocks into six portfolios by size and return predictor. We use NYSE breakpoints—median for size and the 30th and 70th percentiles for the return predictor—and use independent sorts in the two dimensions. The exceptions to this rule are factors that use discrete signals. The high and low portfolios of the debt issuance factor, for example, include firms that did not issue (high portfolio) or issued (low portfolio) debt during the prior fiscal year. We compute value-weighted returns on the six portfolios. A factor's return is the average return on the two high portfolios minus that on the two low

portfolios. In assigning stocks to the high and low portfolios, we sign the return predictors so that the high portfolios contain those stocks that the original study identifies as earning higher average returns. We rebalance factors monthly. The Table 2.1 reports average returns, alphas, t-values, Sharpe ratio, and max drawdown for the standard factors.
(Insert Table 2.1 about here)

2.3 Factor momentum

We follow Arnott et al. (2019) in defining the factor momentum strategy. For each month t, we rank factors by their average returns over a prior 1 month period (t-L+1, t), and long best performers and short worst performers. The strategy invests an equal amount in each factor in the strategy's long and short sides. We then hold this strategy over the following H months (t+1, t+H). Each strategy is therefore described by an L/H pair. We let the factor momentum strategy take long and short positions in n=1,2,3 factors. Our full set has 50 factors, but we later consider subsets of basic factors and other factors.

For simplicity, table 2.2 only shows factor momentum strategy with L=1, H=1. It earns statistically significant average returns and abnormal returns over the sample period. We find that three combinations of factors momentum generate alphas which cannot be explained by popular factor models.

(Insert Table 2 about here)

2.4 International factor momentum

In this section, we test whether factor momentum alphas exist in international developed markets and regional markets. We test 23 developed markets based on 2017 MSCI market classification, There are 5 developed markets in Asia Pacific, 16 developed markets in Europe, and 2 developed markets in North America. We use Fama and French (1993) and Carhart (1997) four factors (market, size, value, and momentum) and AQR six factors, respectively. AQR 6 factors add Frazzini and Pedersen (2012) BAB (Betting against Beta) and Asness et al. (2017) QMJ (Quality minus Junk) factors to Fama-French-Carhart 4 factors and use HML devil factor (Asness and Frazzini, 2013) instead of HML factor (Fama and French, 1993).

Table 3 shows international factor momentum alphas by using Fama and French (1993) and Carhart (1997) four factors. We find that all regional samples' stock factor momentum can generate alphas which cannot be explained by popular factor models. We find that Fama and French (2018) six-factor monthly abnormal returns of the stock factor momentum portfolio through the different geographical samples such as Global, Global ex USA, Europe, North America, and Pacific, which equal to 0.94%, 1.07%, 1.08%, 0.64%, and 1.15%, respectively.

The individual developed markets' stock factor momentum results are mixed. We find significant stock factor momentum Fama and French (2018) six-factor model alphas in 12 developed markets: AUS, CAN, CHE, DNK, ESP, FIN, GBR, HKG, ISR, PRT, SGP, USA. With regard to the portfolio, the highest six-factor alphas are found for ISR, followed by HKG, CAN, and FIN. The magnitude of abnormal returns ranges from 1.47% to 1.62%.

(Insert Table 3 about here)

Table 4 shows international factor momentum alphas by using AQR six factors. We find that all regional samples' stock factor momentum can generate alphas which cannot be explained by popular factor models. We find that Fama and French (2018) six-factor monthly abnormal returns of the stock factor momentum portfolio through the different geographical samples such as Global, Global ex USA, Europe, North America, and Pacific, which equal to 0.94%, 0.73%, 0.98%, 0.96%, and 1.16%, respectively.

The individual developed markets' stock factor momentum results are mixed. We find significant stock factor momentum Fama and French (2018) six-factor model alphas in 11 developed markets: AUT, CAN, CHE, FIN, GBR, HKG, ISR, JPN, NOR, SGP, USA. With regard to the portfolio, the highest six-factor alphas are found for HKG, followed by ISR, AUT, and FIN. The magnitude of abnormal returns ranges from 1.54% to 2.47%.

To sum up, we find that Pacific's stock factor momentum generates the largest alphas, compared with other four regional samples' alphas. HKG, ISR, and FIN have largest stock factor momentum alphas, compared with other 20 developed markets.

(Insert Table 4 about here)

2.5 Cross-assets factor momentum

We construct different assets' style (value and momentum) factors based on Asness, Moskowitz, and Pedersen (2013). The 8 asset classes include 4 individual equity markets (stock selection) and 4 broad asset classes (asset allocation). The 4 stock selection markets are: U.S. equities (US), U.K. equities (UK), Continental Europe equities (EU), Japanese equities (JP). The 4 asset allocation classes are: global equity indices (EQ), currencies

(FX), fixed income (FI), and commodities (CM). The 3 global averages are: "EVERYWHERE" i.e., all global asset classes, "ALL EQUITIES (SS)" (based on the four stock selection markets), and "ALL OTHER (AA)" (based on the four asset allocation categories).

We calculate the factor momentum between AA (based on four asset allocation categories) and stocks (SS, US, UK, EU, JP). We find that cross-assets factor momentum generates alphas which cannot be explained by Asness, Moskowitz, and Pedersen (2013) cross-assets three-factor model.

For example, we use factor momentum method to combine AA value with SS value and SS momentum, respectively. They generate 0.55% and 0.73% abnormal returns per month. we use factor momentum method to combine AA momentum with SS value and SS momentum, respectively. They generate 0.76% and 0.32% abnormal returns per month.

(Insert Table 5 about here)

2.6 Factor idiosyncratic volatility strategy

We test factor idiosyncratic volatility (IVOL) style. Ang et al. (2006; 2009) found that stocks with high sensitivities to innovations in aggregate volatility have low average returns. Stocks with high idiosyncratic volatility relative to the Fama and French (1993) three-factor model have abysmally low average returns.

Similarly, we find factor IVOL effect in our sample. We consider factors including operating profitability, investment, short-term reversal, momentum and long-term reversal. Strategies are based on either equal-weighted (ew) or value-weighted (vw) returns. Portfolios are constructed based on the extreme 30%, 20% (quintile) or 10% (decile) stocks. We take long and short positions in the bottom and top n (=1) factors based on previous 12-month daily idiosyncratic volatility (against Fama and French (1993) three-factor factor model). We report returns with 12 months holding periods.

We find that factor IVOL can generate alphas which cannot be explained popular factor models. For example, US quintile value-weighted portfolio has monthly 0.6% alphas with a t-value of 4.31 and US quintile equal-weighted portfolio has monthly 0.7% alphas with a t-value of 5.03.

(Insert Table 6 about here)

2.7 Robustness test

2.7.1 Performance differences per decade

Table 7 shows the average returns of factor momentum per decade over our sample period. We test factor momentum of cross-assets, stock, and assets per decade. In Panel A, we calculate the average returns of different factors combinations' momentum. In Panel B, we calculate the average returns of corresponding individual factors. We find the factor momentum is much stable than the individual factor. For example, to compare momentum of all assets' value and momentum (Everywhere val mom) with all assets' value (Everywhere val) and all assets' momentum (Everywhere mom), respectively. The factor momentum has larger alphas than individual factors. Many individual factors are insignificant in many decade periods. All assets' factor momentum (Everywhere val mom) is strongly significant in 1970s, 1980s, 1990s, and 2000s. However, all assets' value (everywhere val) strategy is strongly significant only in 1980s, and 2000s and all assets' momentum (Everywhere mom) strategy is strongly significant only in 1980s and 1990s. Hence, we find factor momentum is much stable and robust than individual factors

(Insert Table 7 about here)

2.7.2 Business cycle effects

We continue our analysis with investigating the performance of factor momentum strategies over the business cycle. Chordia and Shivakumar (2002) report that stock momentum performs poorly during contractions as defined by the NBER. Because of this characteristic, momentum returns are often associated with a priced risk factor. We argue that the poor performance of stock momentum during economic contractions can be attributed to the stylized fact that the largest market reversals tend to take place during recessionary periods. For example, over our sample period from July 1963 to December 2017, the average return on the market factor is -22.9% per annum in the early phase of economic recessions as defined by the NBER business cycle indicator, while its average return is 10.9% in the late phase. As we have seen in our previous analysis, we expect total return momentum to tilt towards the low-beta segment of the market after early recessions, which causes large underperformance when the market recovers during the late recessionary phases. Because factor momentum exhibits significantly smaller exposures to the Fama and French factors, we expect the strategy to be less affected by business cycle effects. To investigate this issue, we evaluate the returns of stock and factor momentum strategies with one-month holding periods during NBER expansion or contraction phases.

The results in Panel A of Table 8 indicate that factor momentum is strongly significant in the expansion periods. Although it is normally insignificant in recession periods, its magnitude is still positive.

Panel B of Table 8 which shows the results during the early and late stages of expansions and recessions confirms that the losses of stock momentum (SS mom) during recessions are indeed concentrated in the second half of recessions, when the market tends to revert. When we consider the performance of stock factor momentum (SS val mom), we see that the performance of stock factor momentum is quite stable over the business cycle. During recessions it still averages returns above 0.91% per month, and even during the second half of recessions it manages to avoid a negative return. By design stock factor momentum has less dynamic exposures to the factor returns and hence it is not susceptible to losses when factor returns revert. When we calculate market betas of both momentum strategies during late recessions, we find a beta of -0.74 for stock momentum and a beta of -0.24 for factor momentum.

(Insert Table 8 about here)

These results are consistent with our notion that stock momentum strategies tend to tilt towards the low-beta segment of the market during early recessionary periods and that this effect is less pronounced for factor momentum. Overall, our results indicate that stock factor momentum produces consistent alpha in all economic environments, which makes it more difficult to attribute this anomaly to a priced risk factor.

2.7.3 Calendar month effect

Finally, we investigate the performances of stock momentum and factor momentum per calendar month. Several authors document strong seasonal patterns in stock momentum returns. For example, Grinblatt and Moskowitz (2004) and Jegadeesh and Titman (1993, 2001) find a January effect for the stock momentum strategy. In particular, average returns in January are found to be negative. The cited reason is the tax-loss selling effect. Fund managers tend to sell small-cap loser stocks in December, resulting in downward price pressure in that month, which is followed by a correction in January. Because a stock momentum strategy is typically short in small-cap loser stocks, this effect causes a large positive return for the strategy in December followed by a large negative return in January. We refer to Ferris et al. (2001), Griffiths and White (1993) and Roll (1983), for a detailed documentation of this effect.

Because factor momentum is less concentrated in small-cap stocks compared to stock momentum, we expect the January effect to have a smaller impact on the strategy's performance. To investigate this issue in more detail, we examine the average monthly returns during each calendar month for the stock momentum versus the factor momentum strategies.

The results in Table 9 confirm the weak performance of international stock momentum in Januaries, with an average return of 0.04% with a t-value of 0.08. stock factor momentum, on the other hand, earns an average return of 1.43% with a t-value of 2.75 in Januaries, as shown in Table 9.

(Insert Table 9 about here)

Our results illustrate another notable seasonality in momentum returns. We observe that most of the profits of stock momentum and stock value are generated in a handful of months during the years. For example, the t-statistics of the stock momentum (SS mom) strategy's returns exceed plus two only in four out of 12 months and the t-statistics of the stock value (SS val) strategy's returns exceed plus two only in three out of 12 months. By contrast, stock factor momentum (SS val mom) returns have t-statistics larger than plus two in eight out of 12 months. We thus conclude that stock factor momentum is also more robust than stock momentum and stock value during the calendar year.

The all assets factor momentum is also more robust than all assets' momentum and all assets' value, respectively. For instance, the t-statistics of the all assets' momentum (everywhere mom) strategy's returns exceed plus two only in five out of 12 months and the t-statistics of the all assets' value (everywhere val) strategy's returns exceed plus two only in two out of 12 months. By contrast, all assets' factor momentum (everywhere val mom) returns have t-statistics larger than plus two in seven out of 12 months.

2.8 Conclusions

Arnott et al. (2019) show that prior one-year factor returns predict the cross section of factor returns. Our results show that such factor momentum is also pervasive in international market and across asset classes. We also show factor IVOL as another factor style which generate alphas.

Bibliography

ASNESS, C. S., R. B. PORTER, AND R. L. STEVENS (2000): "Predicting stock returns using industry-relative firm characteristics," *AQR Capital Management working paper*.

AVRAMOV, D., S. CHENG, A. SCHREIBER, AND K. SHEMER (2017): "Scaling up market anomalies," *Journal of Investing*, 26, 89–105.

AVRAMOV, D., T. CHORDIA, G. JOSTOVA, AND A. PHILIPOV (2007): "Momentum and credit rating," *The Journal of Finance*, 62, 2503–2520.

BARBERIS, N. AND A. SHLEIFER (2003): "Style investing," *Journal of financial Economics*, 68, 161–199.

BARILLAS, F. AND J. SHANKEN (2017): "Which alpha?" *The Review of Financial Studies*, 30, 1316–1338.

BARROSO, P. AND P. SANTA-CLARA (2015): "Momentum has its moments," *Journal of Financial Economics*, 116, 111–120.

BARRY, C. B. AND S. J. BROWN (1984): "Differential information and the small firm effect," *Journal of financial economics*, 13, 283–294.

BHANDARI, L. C. (1988): "Debt/equity ratio and expected common stock returns: Empirical evidence," *The journal of finance*, 43, 507–528.

BLUME, M. E. AND F. HUSIC (1973): "Price, beta, and exchange listing," *The Journal of Finance*, 28, 283–299.

CAMPBELL, J. Y., J. HILSCHER, AND J. SZILAGYI (2008): "In search of distress risk," *The Journal of Finance*, 63, 2899–2939.

CARHART, M. M. (1997): "On persistence in mutual fund performance," *The Journal of finance*, 52, 57–82.

CHEN, N.-F., R. ROLL, AND S. A. ROSS (1986): "Economic forces and the stock market," *Journal of business*, 383–403.

COHEN, R. B. AND C. POLK (1996): "An investigation of the impact of industry factors in asset-pricing tests," *Working Paper*.

CONRAD, J. AND G. KAUL (1998): "An anatomy of trading strategies," *The Review of Financial Studies*, 11, 489–519.

DA, Z., Q. LIU, AND E. SCHAUMBURG (2013): "A closer look at the short-term return reversal," *Management science*, 60, 658–674.

DANIEL, K. AND T. J. MOSKOWITZ (2016): "Momentum crashes," *Journal of Financial Economics*, 122, 221–247.

DIMSON, E., P. MARSH, AND M. STAUNTON (2017): "Factor-based investing: The long-term evidence," *Journal of Portfolio Management*, 43, 15.

FAMA, E. F. AND K. R. FRENCH (1993): "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 33, 3–56.

——— (2015): "A five-factor asset pricing model," *Journal of financial economics*, 116, 1–22.

——— (2016): "Dissecting anomalies with a five-factor model," *The Review of Financial Studies*, 29, 69–103.

——— (2018): "Choosing factors," *Journal of Financial Economics*, 128, 234–252.

GERVAIS, S., R. KANIEL, AND D. H. MINGELGRIN (2001): "The high-volume return premium," *The Journal of Finance*, 56, 877–919.

GRUNDY, B. D. AND J. S. M. MARTIN (2001): "Understanding the nature of the risks and the source of the rewards to momentum investing," *The Review of Financial Studies*, 14, 29–78.

GUPTA, T. AND B. T. KELLY (2019): "Factor momentum everywhere," *Journal of Portfolio Management*, 45, 13–36.

HOBERG, G. AND G. M. PHILLIPS (2018): "Text-based industry momentum," *Journal of Financial and Quantitative Analysis*, 53, 2355–2388.

HOU, K., C. XUE, AND L. ZHANG (2015): "Digesting anomalies: An investment approach," *The Review of Financial Studies*, 28, 650–705.

HUBERMAN, G. AND S. KANDEL (1987): "Mean-variance spanning," *The Journal of Finance*, 42, 873–888.

JEGADEESH, N. (1990): "Evidence of predictable behavior of security returns," *The Journal of finance*, 45, 881–898.

JEGADEESH, N., J. NOH, K. PUKTHUANTHONG, R. ROLL, AND J. WANG (2019): "Empirical tests of asset pricing models with individual assets: Resolving the errors-in-variables bias in risk premium estimation," *Journal of Financial Economics*.

JEGADEESH, N. AND S. TITMAN (1993): "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 48, 65–91.

——— (2001): "Profitability of momentum strategies: An evaluation of alternative explanations," *The Journal of finance*, 56, 699–720.

KELOHARJU, M., J. T. LINNAINMAA, AND P. NYBERG (2016): "Return seasonalities," *The Journal of Finance*, 71, 1557–1590.

KOTHARI, S. P. AND J. SHANKEN (1992): "Stock return variation and expected dividends: A time-series and cross-sectional analysis," *Journal of Financial Economics*, 31, 177–210.

LEE, C. M. AND B. SWAMINATHAN (2000): "Price momentum and trading volume," *the Journal of Finance*, 55, 2017–2069.

LEWELLEN, J. (2002): "Momentum and autocorrelation in stock returns," *The Review of Financial Studies*, 15, 533–564.

MCLEAN, R. D. AND J. PONTIFF (2016): "Does academic research destroy stock return predictability?" *The Journal of Finance*, 71, 5–32.

MOREIRA, A. AND T. MUIR (2017): "Volatility-Managed Portfolios," *The Journal of Finance*, 72, 1611–1644.

MOSKOWITZ, T. J. AND M. GRINBLATT (1999): "Do industries explain momentum?" *The Journal of finance*, 54, 1249–1290.

Nagel, S. (2012): "Evaporating liquidity," *The Review of Financial Studies*, 25, 2005–2039.

Novy-Marx, R. (2012): "Is momentum really momentum?" *Journal of Financial Economics*, 103, 429–453.

——— (2013): "The other side of value: The gross profitability premium," *Journal of Financial Economics*, 108, 1–28.

Novy-Marx, R. and M. Velikov (2015): "A taxonomy of anomalies and their trading costs," *The Review of Financial Studies*, 29, 104–147.

Ohlson, J. A. (1980): "Financial ratios and the probabilistic prediction of bankruptcy," *Journal of accounting research*, 109–131.

Shumway, T. (1997): "The delisting bias in CRSP data," *The Journal of Finance*, 52, 327–340.

Shumway, T. and V. A. Warther (1999): "The delisting bias in CRSP's Nasdaq data and its implications for the size effect," *The Journal of Finance*, 54, 2361–2379.

Stambaugh, R. F. and Y. Yuan (2016): "Mispricing factors," *The Review of Financial Studies*, 30, 1270–1315.

Table 2.1: Average returns and five- and six-factor model alphas of standard factors

This table shows average returns, and five- and six-factor model alphas associated with 50 factors. Factors are divided into four groups, basic factors, low turnover factors, medium turnover factors, high turnover factors. We construct each factor as an HML-like factor by sorting stocks into six portfolios by size and return predictor. We use NYSE breakpoints—median for size and the 30th and 70th percentiles for the return predictor—and use independent sorts in the two dimensions. The exceptions to this rule are factors that use discrete signals. The high and low portfolios of the debt issuance factor, for example, include firms that did not issue (high portfolio) or issued (low portfolio) debt during the prior fiscal year. We compute value-weighted returns on the six portfolios. A factor's return is the average return on the two high portfolios minus that on the two low portfolios. In assigning stocks to the high and low portfolios, we sign the return predictors so that the high portfolios contain those stocks that the original study identifies as earning higher average returns. We rebalance factors monthly. The Table 1 reports average returns, alphas, t-values, Sharpe ratio, and max drawdown for the standard factors. The factor return data begin in July 1963 and end in December 2017.

No.	Factor	average returns		FF5 alpha		FF6 alpha		Sharpe ratio	Max drawdown
		r	t(r)	r	t(r)	r	t(r)		
		Basic factors							
1	Excess market	0.53%	3.1	-	-	-	-	0.42	55.68%
2	SMB	0.25%	2.12	-	-	-	-	0.29	56.95%
3	HML	0.35%	3.15	-	-	-	-	0.43	41.60%
4	RMW	0.25%	2.85	-	-	-	-	0.39	41.70%
5	CMA	0.29%	3.68	-	-	-	-	0.5	17.53%
6	Mom	0.66%	4.01	0.73%	3.63	-	-	0.55	57.42%
7	Earnings to price	0.35%	3.06	0.05%	0.7	0.04%	0.58	0.42	38.43%
8	Cash flow to price	0.29%	2.51	0.00%	-0.04	-0.03%	-0.37	0.34	41.92%
9	Dividents to price	0.10%	0.77	-0.02%	-0.21	0.06%	0.6	0.1	52.01%

10	Short-term reversals	0.48%	3.98	0.37%	2.7	0.50%	3.84	0.54	33.09%
11	Long-term Reversals	0.26%	2.64	0.03%	0.31	0.02%	0.2	0.35	38.87%
12	Accruals	0.32%	3.54	0.43%	4.56	0.37%	3.58	0.49	26.23%
13	Market beta	0.12%	0.55	-0.01%	-0.08	0.11%	0.79	0.07	78.97%
14	Net share issues	0.33%	3.1	0.14%	1.4	0.08%	0.85	0.42	26.65%
15	Variance	0.22%	0.88	0.22%	1.71	0.09%	0.64	0.12	75.35%
16	Residual variance	0.29%	1.24	0.30%	2.74	0.16%	1.34	0.17	68.10%
17	Quality minus junk	0.36%	3.92	0.37%	7.36	0.33%	6.64	0.53	29.39%
18	Betting against beta	0.80%	6.43	0.42%	2.98	0.31%	2.16	0.87	52.82%
				Low turnover factors					
19	Size	0.33%	1.67	-0.03%	-0.36	-0.04%	-0.46	0.23	83.82%
20	Gross Profitability	0.41%	2.96	0.29%	2.36	0.26%	2.18	0.41	48.05%
21	Value	0.48%	2.7	-0.17%	-1.71	-0.16%	-1.53	0.38	54.89%
22	ValProf	0.83%	5.2	0.31%	2.29	0.37%	2.67	0.73	44.64%
23	Accruals	0.27%	2.11	0.35%	2.92	0.31%	2.38	0.3	35.41%
24	Net Issuance (A)	0.77%	6.43	0.48%	4.05	0.44%	3.83	0.91	21.76%
25	Asset Growth	0.37%	2.54	-0.11%	-0.96	-0.12%	-0.99	0.36	34.98%
26	Investment	0.57%	4.49	0.36%	3.13	0.31%	2.58	0.63	38.91%
27	Piotroski's F-score	0.20%	1.03	0.14%	0.81	0.05%	0.33	0.15	67.41%
28	Asset Turnover	0.45%	2.9	0.03%	0.21	0.04%	0.26	0.4	42.64%
29	Gross Margins	-0.01%	-0.11	0.33%	2.77	0.37%	2.99	-0.01	68.17%
30	Ohlson's O-score	0.20%	1.18	0.32%	2.37	0.18%	1.31	0.17	66.28%
				Medium Turnover factors					
31	Net Issuance (M)	0.63%	4.77	0.32%	2.93	0.34%	2.65	0.68	33.27%

32	Return-on-bookequity	0.57%	2.96	0.38%	2.65	0.19%	1.43	0.42	60.13%
33	Failure Probability	0.68%	2.52	0.81%	3.09	0.27%	1.39	0.35	70.58%
34	ValMomProf	1.43%	7.41	1.22%	5.27	0.65%	4.37	1.04	41.44%
35	ValMom	0.93%	4.82	0.58%	2.87	-0.05%	-0.5	0.68	55.60%
36	Idiosyncratic Volatility	0.63%	2.13	0.54%	3.56	0.36%	2.24	0.3	76.83%
37	Momentum	1.32%	4.77	1.34%	3.81	0.29%	2.38	0.68	81.04%
38	PEAD (SUE)	0.58%	4.51	0.60%	4.39	0.35%	2.91	0.63	27.81%
39	PEAD (CAR3)	0.73%	6.49	0.80%	6.96	0.66%	5.6	0.91	27.33%
40	Long Run Reversals	0.48%	2.39	0.06%	0.37	0.12%	0.74	0.34	58.86%
41	Return-on-market equity	0.89%	4.63	0.51%	3.26	0.30%	1.99	0.65	64.19%
42	Return-on-assets	0.46%	2.6	0.39%	3.02	0.21%	1.77	0.37	50.14%
43	Beta Arbitrage	0.50%	2.69	-0.03%	-0.19	-0.02%	-0.11	0.38	56.35%
	High Turnover factors								
44	Industry Momentum	0.93%	3.97	1.06%	4.09	0.84%	3.47	0.56	73.44%
45	Industry Relative Reversals	0.99%	5.72	0.88%	4.51	1.11%	6.32	0.81	55.30%
46	High-Frequency Combo	1.60%	11.18	1.55%	10.37	1.52%	10.02	1.58	29.53%
47	Short-term reversals	0.37%	1.71	0.20%	0.87	0.46%	2.39	0.24	68.65%
48	Seasonality	0.84%	5.19	0.92%	4.84	0.84%	4.3	0.73	51.61%
49	Industry Relative Reversals (Low Volatility)	1.25%	9.36	1.12%	8.2	1.20%	8.06	1.32	37.31%
50	High-Frequency Combo (with Seasonality)	1.58%	10.36	1.61%	10.24	1.53%	9.57	1.46	36.61%

Table 2.2: Factor momentum strategies

Panel A reports annualized average returns, standard deviations, and t-values of factor momentum strategies. This table reports the average monthly returns and benchmark adjusted returns of anomaly momentum in US market. For given N anomalies, we take long and short positions in the top and bottom n anomalies based on previous month return. The row with 'basic' reports the result based on 18 anomalies provided by French's and AQR website, including market excess return, size (SMB), value (HML), profitability (RMW), investment (CMA), momentum, E/P, CF/P, D/P, short-term reversal, long-term reversal, accruals, market beta, net share issues, daily variance, daily residual variance, quality minus junk (QMJ), and betting against beta (BAB). The row with 'others' reports the result based on 32 anomalies provided by Novy-Marx's website. The last row of 'all' is a combination of these two sets of anomalies. We report the returns with significance (***¡0.01¡**¡0.05¡*¡0.1), and the corresponding t statistics. The factor return data begin in July 1963 and end in December 2017.

Panel A	**Average returns**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
n=1						
basic	0.9***	[5.33]	-0.57***	[-2.94]	1.47***	[4.61]
others	1.37***	[4.95]	-0.27	[-1.23]	1.52***	[3.56]
all	1.36***	[4.54]	-0.58**	[-2.47]	1.83***	[3.52]
n=2						
basic	0.9***	[6.00]	-0.47***	[-2.7]	1.37***	[4.82]
others	1.47***	[5.79]	-0.19	[-1.04]	1.54***	[3.98]
all	1.4***	[5.15]	-0.56***	[-2.65]	1.80***	[3.70]
n=3						
basic	0.85***	[6.59]	-0.45***	[-2.79]	1.29***	[5.08]
others	1.44***	[6.37]	-0.18	[-1.05]	1.49***	[4.35]
all	1.37***	[5.72]	-0.62***	[-3.15]	1.86***	[4.17]

Panel B	**CAPM alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
n=1						
basic	0.86***	[5.07]	-0.78***	[-4.26]	1.64***	[5.18]
others	1.58***	[5.92]	-0.24	[-1.11]	1.71***	[4.02]
all	1.49***	[5.02]	-0.68***	[-2.96]	2.09***	[4.08]
n=2						
basic	0.85***	[5.65]	-0.69***	[-4.28]	1.54***	[5.47]
others	1.7***	[7.03]	-0.16	[-0.85]	1.72***	[4.48]

all	1.53***	[5.7]	-0.67***	[-3.18]	2.05***	[4.28]
n=3						
basic	0.81***	[6.26]	-0.66***	[-4.48]	1.46***	[5.84]
others	1.65***	[7.69]	-0.14	[-0.83]	1.66***	[4.88]
all	1.49***	[6.30]	-0.74***	[-3.77]	2.11***	[4.82]

Panel C	**Fama and French (1993) three-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
n=1						
basic	0.84***	[4.91]	-0.74***	[-4]	1.58***	[4.93]
others	1.52***	[5.57]	-0.31	[-1.39]	1.73***	[3.99]
all	1.50***	[4.94]	-0.64***	[-2.73]	2.06***	[3.94]
n=2						
basic	0.84***	[5.58]	-0.71***	[-4.44]	1.55***	[5.42]
others	1.69***	[6.85]	-0.24	[-1.27]	1.82***	[4.66]
all	1.59***	[5.82]	-0.64***	[-3.00]	2.1***	[4.31]
n=3						
basic	0.76***	[5.92]	-0.69***	[-4.85]	1.45***	[5.72]
others	1.62***	[7.46]	-0.2	[-1.15]	1.71***	[4.93]
all	1.53***	[6.37]	-0.71***	[-3.58]	2.14***	[4.81]

Panel D	**Fama and French (2015) five-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
n=1						
basic	0.93***	[5.27]	-0.68***	[-3.61]	1.61***	[4.89]
others	1.03***	[3.81]	-0.54**	[-2.4]	1.48***	[3.34]
all	1.26***	[4.03]	-0.67***	[-2.76]	1.81***	[3.36]
n=2						
basic	0.91***	[5.91]	-0.64***	[-3.93]	1.55***	[5.3]
others	1.24***	[5.09]	-0.51***	[-2.71]	1.64***	[4.14]
all	1.35***	[4.84]	-0.7***	[-3.19]	1.89***	[3.75]
n=3						
basic	0.8***	[6.1]	-0.59***	[-4.1]	1.4***	[5.38]
others	1.21***	[5.64]	-0.48***	[-2.85]	1.59***	[4.49]
all	1.31***	[5.3]	-0.74***	[-3.62]	2.05***	[4.13]

Panel E	**Fama and French (2018) six-factor alphas**

	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
n=1						
basic	0.91***	[5.07]	-0.7***	[-3.65]	1.61***	[4.81]
others	0.71***	[2.84]	-0.66***	[-2.91]	1.27***	[2.87]
all	1.08***	[3.49]	-0.75***	[-3.04]	1.83***	[3.14]
n=2						
basic	0.90***	[5.78]	-0.65***	[-3.91]	1.55***	[5.23]
others	0.95***	[4.23]	-0.60***	[-3.2]	1.55***	[3.67]
all	1.18***	[4.28]	-0.76***	[-3.44]	1.94***	[3.50]
n=3						
basic	0.79***	[5.93]	-0.60***	[-4.06]	1.39***	[5.27]
others	0.94***	[4.80]	-0.60***	[-3.58]	1.54***	[4.06]
all	1.14***	[4.71]	-0.79***	[-3.82]	1.93***	[3.85]

Table 2.3: International four factors momentum strategies

This table reports the average monthly returns and benchmark adjusted returns of factor momentum in Fama-French and Carhart four factors from international 23 developed markets or 5 regional markets. We consider Fama-French and Carhart four factors (including MKT_RF, SMB, HML, and UMD) of different individual markets and regional markets. For given four time series returns, we take long and short positions in the top and bottom (n=1) strategies based on previous month return. We report the returns with significance (***¡0.01¡**¡0.05¡*¡0.1), and the corresponding t statistics. The factor return data begin in July 1995 and end in December 2017.

Panel A	**Average returns**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	1.40***	[6.09]	0.32	[1.26]	1.08***	[2.88]
AUT	0.49*	[1.81]	0.22	[0.67]	0.27	[0.58]
BEL	0.47*	[1.80]	0.26	[0.97]	0.22	[0.51]
CAN	1.17***	[5.22]	0.04	[0.16]	1.13***	[3.01]
CHE	0.87***	[3.73]	-0.18	[-0.82]	1.06***	[3.11]
DEU	0.77***	[2.66]	-0.01	[-0.04]	0.78*	[1.67]
DNK	1.02***	[4.12]	0.08	[0.30]	0.94**	[2.42]
ESP	0.97***	[3.52]	-0.02	[-0.06]	0.98**	[2.27]
FIN	1.34***	[3.64]	-0.31	[-0.81]	1.65***	[2.62]
FRA	0.67***	[2.88]	0.14	[0.49]	0.54	[1.25]
GBR	1.16***	[5.41]	-0.34	[-1.35]	1.50***	[3.96]
HKG	1.15***	[3.7]	-0.29	[-0.81]	1.44***	[2.66]
IRL	0.61	[1.38]	-0.08	[-0.17]	0.7	[0.89]
ISR	1.28***	[4.01]	-0.09	[-0.26]	1.36***	[2.65]
ITA	0.24	[0.85]	0.02	[0.06]	0.22	[0.47]
JPN	0.24	[1.03]	-0.42	[-1.6]	0.65*	[1.65]
NLD	0.26	[1.04]	0.04	[0.17]	0.21	[0.53]
NOR	0.71**	[2.45]	0.28	[0.83]	0.43	[0.87]
NZL	0.9***	[3.38]	0.16	[0.56]	0.74*	[1.68]
PRT	0.81**	[2.51]	-0.02	[-0.06]	0.83*	[1.66]
SGP	1.15***	[3.95]	-0.47	[-1.37]	1.62***	[3.18]
SWE	0.65**	[1.98]	0.11	[0.31]	0.55	[0.98]
USA	0.60***	[4.58]	0.06	[0.39]	0.54**	[2.38]
Global	0.70***	[4.50]	-0.22	[-1.09]	0.92***	[3.11]
Global.Ex.USA	0.90***	[5.17]	-0.12	[-0.58]	1.02***	[3.28]
Europe	0.91***	[4.45]	-0.19	[-0.81]	1.10***	[3.10]
North.America	0.69***	[4.20]	0.18	[0.83]	0.52*	[1.72]
Pacific	0.52**	[2.45]	-0.41*	[-1.68]	0.93**	[2.52]

Panel B	CAPM alphas					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	1.32***	[5.77]	0.1	[0.40]	1.23***	[3.31]
AUT	0.41	[1.52]	0	[0.01]	0.41	[0.86]
BEL	0.37	[1.42]	0.16	[0.61]	0.21	[0.48]
CAN	1.32***	[5.09]	-0.27	[-0.96]	1.59***	[3.66]
CHE	0.84***	[3.59]	-0.35*	[-1.69]	1.19***	[3.57]
DEU	0.74**	[2.55]	-0.19	[-0.77]	0.93**	[2]
DNK	0.97***	[3.92]	-0.03	[-0.14]	1.00**	[2.57]
ESP	0.86***	[3.17]	-0.26	[-0.98]	1.12***	[2.6]
FIN	1.17***	[3.27]	-0.46	[-1.24]	1.63**	[2.59]
FRA	0.68***	[2.89]	-0.04	[-0.17]	0.72*	[1.72]
GBR	1.19***	[5.37]	-0.52**	[-2.09]	1.7***	[4.36]
HKG	0.97***	[3.21]	-0.56	[-1.62]	1.53***	[2.80]
IRL	0.66	[1.47]	-0.18	[-0.37]	0.84	[1.07]
ISR	1.21***	[3.81]	-0.21	[-0.61]	1.41***	[2.74]
ITA	0.15	[0.54]	-0.17	[-0.60]	0.33	[0.69]
JPN	0.24	[1.01]	-0.45**	[-1.99]	0.69*	[1.70]
NLD	0.23	[0.93]	-0.12	[-0.49]	0.35	[0.88]
NOR	0.73**	[2.49]	0.11	[0.34]	0.62	[1.26]
NZL	0.82***	[3.1]	-0.05	[-0.19]	0.88**	[1.99]
PRT	0.78**	[2.4]	-0.2	[-0.62]	0.99**	[1.98]
SGP	0.99***	[3.48]	-0.72**	[-2.22]	1.71***	[3.34]
SWE	0.56*	[1.72]	-0.07	[-0.22]	0.63	[1.13]
USA	0.54***	[4.14]	-0.18	[-1.34]	0.72***	[3.18]
Global	0.70***	[3.97]	-0.36*	[-1.70]	1.06***	[3.21]
Global.Ex.USA	0.86***	[4.61]	-0.35*	[-1.76]	1.21***	[3.60]
Europe	0.89***	[4.22]	-0.41*	[-1.86]	1.29***	[3.54]
North.America	0.80***	[4.19]	0.01	[0.06]	0.78**	[2.31]
Pacific	0.49**	[2.23]	-0.55**	[-2.28]	1.04***	[2.73]

Panel C	Fama and French (1993) three-factor alphas					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	1.3***	[5.57]	0.3	[1.30]	1.00***	[2.67]
AUT	0.37	[1.37]	0.03	[0.08]	0.34	[0.72]
BEL	0.34	[1.31]	0.15	[0.56]	0.19	[0.44]
CAN	1.28***	[4.94]	-0.34	[-1.23]	1.62***	[3.71]
CHE	0.77***	[3.29]	-0.3	[-1.44]	1.07***	[3.22]
DEU	0.61**	[2.14]	-0.22	[-0.92]	0.83*	[1.82]
DNK	0.96***	[3.87]	-0.13	[-0.52]	1.09***	[2.79]

ESP	0.83***	[3.02]	-0.33	[-1.25]	1.16***	[2.66]
FIN	1.14***	[3.16]	-0.53	[-1.41]	1.67***	[2.62]
FRA	0.57**	[2.47]	-0.1	[-0.38]	0.67	[1.58]
GBR	1.15***	[5.17]	-0.55**	[-2.23]	1.7***	[4.33]
HKG	0.84***	[2.74]	-0.64*	[-1.84]	1.48***	[2.65]
IRL	0.65	[1.44]	-0.24	[-0.49]	0.89	[1.12]
ISR	1.20***	[3.7]	-0.04	[-0.11]	1.24**	[2.35]
ITA	0.07	[0.25]	-0.2	[-0.7]	0.28	[0.58]
JPN	0.21	[0.91]	-0.46**	[-2.04]	0.67*	[1.67]
NLD	0.18	[0.71]	-0.15	[-0.59]	0.33	[0.81]
NOR	0.69**	[2.34]	0	[0.01]	0.69	[1.40]
NZL	0.84***	[3.10]	-0.04	[-0.13]	0.88*	[1.96]
PRT	0.71**	[2.17]	-0.22	[-0.67]	0.93*	[1.87]
SGP	0.79***	[2.82]	-0.49	[-1.49]	1.27**	[2.50]
SWE	0.51	[1.55]	-0.16	[-0.49]	0.67	[1.19]
USA	0.52***	[3.95]	-0.18	[-1.35]	0.70***	[3.07]
Global	0.65***	[3.65]	-0.39*	[-1.86]	1.04***	[3.13]
Global.Ex.USA	0.77***	[4.09]	-0.34*	[-1.68]	1.11***	[3.25]
Europe	0.81***	[3.89]	-0.43**	[-1.97]	1.24***	[3.40]
North.America	0.78***	[4.08]	-0.02	[-0.07]	0.80**	[2.34]
Pacific	0.51**	[2.30]	-0.49**	[-2.00]	1.01**	[2.59]

Panel D	**Fama and French (2015) five-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	1.08***	[4.43]	0.09	[0.38]	0.99**	[2.50]
AUT	0.24	[0.81]	-0.01	[-0.03]	0.25	[0.48]
BEL	0.07	[0.26]	0.23	[0.79]	-0.15	[-0.33]
CAN	1.03***	[3.87]	-0.41	[-1.42]	1.44***	[3.17]
CHE	0.55**	[2.19]	-0.38*	[-1.69]	0.94***	[2.6]
DEU	0	[0.01]	-0.15	[-0.59]	0.16	[0.32]
DNK	0.83***	[3.09]	-0.23	[-0.87]	1.06**	[2.48]
ESP	0.59**	[2.02]	-0.35	[-1.24]	0.95**	[2.02]
FIN	0.96**	[2.45]	-0.71*	[-1.75]	1.67**	[2.41]
FRA	0.28	[1.14]	-0.17	[-0.62]	0.45	[0.99]
GBR	0.83***	[3.50]	-0.66**	[-2.54]	1.49***	[3.54]
HKG	0.68**	[2.10]	-0.48	[-1.30]	1.16**	[1.97]
IRL	0.61	[1.27]	-0.26	[-0.48]	0.87	[1.02]
ISR	1.36***	[3.95]	-0.22	[-0.60]	1.57***	[2.83]
ITA	-0.02	[-0.08]	-0.32	[-1.01]	0.29	[0.57]
JPN	0.13	[0.56]	-0.49**	[-2.18]	0.62	[1.53]
NLD	-0.08	[-0.29]	-0.19	[-0.70]	0.11	[0.25]
NOR	0.19	[0.61]	-0.19	[-0.55]	0.38	[0.72]

NZL	0.68**	[2.37]	-0.18	[-0.62]	0.86*	[1.82]
PRT	0.54	[1.52]	-0.29	[-0.83]	0.83	[1.54]
SGP	0.57*	[1.95]	-0.35	[-1.01]	0.92*	[1.71]
SWE	-0.06	[-0.17]	-0.26	[-0.72]	0.2	[0.33]
USA	0.66***	[4.79]	-0.42***	[-2.82]	1.08***	[4.51]
Global	0.46**	[2.45]	-0.59***	[-2.64]	1.04***	[2.94]
Global.Ex.USA	0.59***	[2.93]	-0.51**	[-2.36]	1.10***	[2.98]
Europe	0.42*	[1.92]	-0.61***	[-2.64]	1.03***	[2.62]
North.America	0.59***	[3.01]	-0.07	[-0.29]	0.65*	[1.85]
Pacific	0.34	[1.45]	-0.57**	[-2.20]	0.91**	[2.22]

Panel E	**Fama and French (2018) six-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.99***	[3.88]	-0.1	[-0.40]	1.08***	[2.65]
AUT	0.26	[0.88]	-0.23	[-0.69]	0.48	[0.95]
BEL	0.14	[0.51]	0.11	[0.37]	0.04	[0.07]
CAN	0.88***	[3.31]	-0.59**	[-2.04]	1.47***	[3.17]
CHE	0.33	[1.30]	-0.45**	[-2.01]	0.77**	[2.1]
DEU	-0.05	[-0.16]	-0.27	[-1.03]	0.22	[0.45]
DNK	0.8***	[2.94]	-0.4	[-1.50]	1.20***	[2.78]
ESP	0.53*	[1.78]	-0.43	[-1.47]	0.96**	[2.01]
FIN	0.8**	[1.98]	-0.68	[-1.64]	1.47**	[2.08]
FRA	0.1	[0.39]	-0.37	[-1.34]	0.47	[1]
GBR	0.64***	[2.72]	-0.82***	[-3.16]	1.46***	[3.38]
HKG	0.57*	[1.73]	-0.96***	[-2.6]	1.53**	[2.52]
IRL	0.55	[1.11]	-0.56	[-1.05]	1.11	[1.27]
ISR	1.24***	[3.52]	-0.39	[-1.07]	1.62***	[2.85]
ITA	-0.24	[-0.77]	-0.53*	[-1.67]	0.29	[0.55]
JPN	0.07	[0.33]	-0.48**	[-2.18]	0.55	[1.38]
NLD	-0.32	[-1.19]	-0.32	[-1.16]	0	[0.00]
NOR	0.18	[0.58]	-0.25	[-0.69]	0.43	[0.79]
NZL	0.65**	[2.21]	0	[-0.01]	0.66	[1.35]
PRT	0.46	[1.3]	-0.55	[-1.60]	1.02*	[1.87]
SGP	0.45	[1.49]	-0.84**	[-2.50]	1.3**	[2.36]
SWE	-0.08	[-0.24]	-0.43	[-1.21]	0.35	[0.57]
USA	0.45***	[3.45]	-0.61***	[-4.24]	1.07***	[4.39]
Global	0.26	[1.40]	-0.69***	[-3.22]	0.94***	[2.61]
Global.Ex.USA	0.42**	[2.12]	-0.64***	[-3.07]	1.07***	[2.85]
Europe	0.28	[1.31]	-0.8***	[-3.49]	1.08***	[2.68]
North.America	0.4**	[2.12]	-0.24	[-1.07]	0.64*	[1.79]
Pacific	0.27	[1.12]	-0.88***	[-3.62]	1.15***	[2.77]

Table 2.4: International six factors momentum strategies

This table reports the average monthly returns and benchmark adjusted returns of factor momentum in AQR six factors from international 23 developed markets or 5 regional markets. We consider AQR four factors (including MKT_RF, SMB, HML devil, and UMD, BAB, and QMJ) of different individual markets and regional markets. For given four time series returns, we take long and short positions in the top and bottom (n=1) strategies based on previous month return. We report the returns with significance (***¡0.01¡**¡0.05¡*¡0.1), and the corresponding t statistics. The factor return data begin in July 1995 and end in December 2017.

Panel A	**Average returns**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.92***	[3.78]	0.23	[0.84]	0.69*	[1.74]
AUT	0.75**	[2.36]	-0.09	[-0.25]	0.84*	[1.69]
BEL	0.76***	[2.63]	0.1	[0.34]	0.66	[1.47]
CAN	1.44***	[5.66]	-0.06	[-0.23]	1.5***	[3.72]
CHE	0.96***	[4.00]	-0.08	[-0.3]	1.04***	[2.66]
DEU	0.96***	[3.10]	0.21	[0.70]	0.75	[1.55]
DNK	0.47	[1.58]	0.14	[0.49]	0.33	[0.72]
ESP	0.56*	[1.75]	-0.17	[-0.51]	0.72	[1.43]
FIN	1.17***	[3.14]	-0.59	[-1.53]	1.77***	[2.83]
FRA	1.01***	[3.8]	0.26	[0.86]	0.75*	[1.66]
GBR	0.72***	[3.33]	-0.28	[-1.2]	0.99***	[2.92]
HKG	2.35***	[5.60]	-0.27	[-0.73]	2.62***	[3.89]
IRL	0.69	[1.27]	-0.03	[-0.05]	0.71	[0.79]
ISR	1.32***	[4.02]	-0.22	[-0.6]	1.54***	[2.73]
ITA	0.58*	[1.95]	0.03	[0.09]	0.55	[1.11]
JPN	0.72***	[3.20]	0.05	[0.19]	0.68*	[1.72]
NLD	0.65**	[2.09]	0.52*	[1.73]	0.13	[0.26]
NOR	1.43***	[4.51]	0.09	[0.27]	1.34***	[2.60]
NZL	0.78***	[2.69]	0.35	[1.07]	0.43	[0.95]
PRT	0.89*	[1.88]	0.44	[0.94]	0.45	[0.65]
SGP	1.45***	[4.47]	-0.29	[-0.9]	1.74***	[3.27]
SWE	0.84***	[2.62]	0.09	[0.25]	0.75	[1.37]
USA	0.82***	[7.40]	-0.15	[-1.06]	0.97***	[4.87]
Global	0.77***	[4.86]	-0.11	[-0.6]	0.89***	[3.16]
Global.Ex.USA	0.71***	[4.19]	-0.06	[-0.3]	0.77**	[2.51]
Europe	0.81***	[4.02]	-0.09	[-0.39]	0.90**	[2.57]
North.America	0.89***	[5.11]	0.04	[0.23]	0.85***	[2.84]
Pacific	0.78***	[3.88]	-0.18	[-0.79]	0.96***	[2.81]

Panel B	CAPM alphas					
	Long		Short		L-S	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.79***	[3.39]	0.05	[0.21]	0.74*	[1.86]
AUT	0.69**	[2.18]	-0.3	[-0.86]	0.99**	[2.01]
BEL	0.71**	[2.46]	-0.05	[-0.18]	0.77*	[1.70]
CAN	1.46***	[5.50]	-0.33	[-1.34]	1.79***	[4.33]
CHE	1.00***	[4.14]	-0.22	[-0.92]	1.22***	[3.22]
DEU	0.94***	[3.01]	0.03	[0.1]	0.91*	[1.90]
DNK	0.47	[1.57]	-0.02	[-0.06]	0.49	[1.07]
ESP	0.47	[1.48]	-0.38	[-1.25]	0.85*	[1.69]
FIN	1.13***	[3.01]	-0.77**	[-2.02]	1.89***	[3.03]
FRA	1.02***	[3.80]	0.04	[0.14]	0.98**	[2.25]
GBR	0.69***	[3.19]	-0.47**	[-2.19]	1.16***	[3.48]
HKG	2.33***	[5.51]	-0.48	[-1.37]	2.81***	[4.2]
IRL	0.69	[1.25]	-0.24	[-0.44]	0.93	[1.03]
ISR	1.30***	[3.9]	-0.47	[-1.27]	1.77***	[3.12]
ITA	0.49	[1.64]	-0.23	[-0.78]	0.72	[1.44]
JPN	0.71***	[3.21]	0.03	[0.11]	0.68*	[1.74]
NLD	0.7**	[2.24]	0.34	[1.17]	0.36	[0.77]
NOR	1.38***	[4.33]	-0.04	[-0.12]	1.41***	[2.73]
NZL	0.73**	[2.5]	0.16	[0.52]	0.57	[1.27]
PRT	0.89*	[1.88]	0.27	[0.61]	0.62	[0.91]
SGP	1.32***	[4.17]	-0.53*	[-1.75]	1.85***	[3.47]
SWE	0.73**	[2.32]	-0.08	[-0.22]	0.81	[1.47]
USA	0.84***	[7.51]	-0.37***	[-3.00]	1.21***	[6.45]
Global	0.75***	[4.58]	-0.28	[-1.61]	1.03***	[3.67]
Global.Ex.USA	0.71***	[4.18]	-0.21	[-1.16]	0.93***	[3.07]
Europe	0.75***	[3.75]	-0.31	[-1.49]	1.07***	[3.11]
North.America	0.98***	[5.42]	-0.15	[-0.78]	1.13***	[3.77]
Pacific	0.73***	[3.64]	-0.32	[-1.48]	1.05***	[3.08]

Panel C	Fama and French (1993) three-factor alphas					
	Long		Short		L-S	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.73***	[3.06]	0.18	[0.67]	0.55	[1.37]
AUT	0.67**	[2.07]	-0.31	[-0.89]	0.98*	[1.96]
BEL	0.65**	[2.23]	-0.08	[-0.27]	0.73	[1.61]
CAN	1.40***	[5.3]	-0.38	[-1.57]	1.78***	[4.28]
CHE	0.9***	[3.76]	-0.2	[-0.81]	1.10***	[2.89]
DEU	0.73**	[2.48]	-0.1	[-0.34]	0.83*	[1.74]
DNK	0.41	[1.36]	-0.18	[-0.65]	0.59	[1.28]

ESP	0.42	[1.31]	-0.49	[-1.62]	0.91*	[1.79]
FIN	1.07***	[2.82]	-0.82**	[-2.15]	1.89***	[2.98]
FRA	0.87***	[3.34]	-0.13	[-0.47]	1.00**	[2.28]
GBR	0.52**	[2.53]	-0.57***	[-2.69]	1.08***	[3.24]
HKG	2.25***	[5.27]	-0.45	[-1.26]	2.71***	[3.96]
IRL	0.74	[1.34]	-0.38	[-0.69]	1.13	[1.24]
ISR	1.29***	[3.77]	-0.4	[-1.07]	1.69***	[2.92]
ITA	0.41	[1.38]	-0.28	[-0.97]	0.69	[1.39]
JPN	0.66***	[3.00]	-0.04	[-0.18]	0.71*	[1.79]
NLD	0.67**	[2.11]	0.24	[0.83]	0.43	[0.90]
NOR	1.23***	[3.92]	-0.17	[-0.54]	1.4***	[2.68]
NZL	0.73**	[2.43]	0.2	[0.62]	0.53	[1.15]
PRT	0.82*	[1.71]	0.12	[0.26]	0.71	[1.02]
SGP	1.06***	[3.44]	-0.44	[-1.43]	1.50***	[2.83]
SWE	0.65**	[2.06]	-0.18	[-0.52]	0.83	[1.50]
USA	0.71***	[6.45]	-0.45***	[-3.65]	1.16***	[6.10]
Global	0.64***	[3.96]	-0.35**	[-2.00]	0.99***	[3.47]
Global.Ex.USA	0.57***	[3.36]	-0.25	[-1.34]	0.82***	[2.67]
Europe	0.63***	[3.24]	-0.41**	[-1.98]	1.04***	[3.01]
North.America	0.91***	[5.13]	-0.22	[-1.17]	1.13***	[3.74]
Pacific	0.74***	[3.61]	-0.27	[-1.23]	1.02***	[2.91]

Panel D	**Fama and French (2015) five-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.5**	[1.98]	-0.12	[-0.43]	0.62	[1.43]
AUT	0.99***	[2.88]	-0.51	[-1.35]	1.49***	[2.80]
BEL	0.33	[1.08]	-0.24	[-0.78]	0.57	[1.17]
CAN	1.09***	[4.06]	-0.36	[-1.45]	1.45***	[3.41]
CHE	0.76***	[2.95]	-0.39	[-1.47]	1.15***	[2.80]
DEU	0.38	[1.21]	-0.03	[-0.11]	0.42	[0.81]
DNK	0.11	[0.34]	-0.28	[-0.97]	0.39	[0.79]
ESP	0.14	[0.41]	-0.53	[-1.64]	0.68	[1.23]
FIN	0.98**	[2.41]	-1.04**	[-2.54]	2.02***	[2.98]
FRA	0.6**	[2.16]	-0.14	[-0.49]	0.74	[1.57]
GBR	0.37*	[1.68]	-0.67***	[-2.95]	1.04***	[2.86]
HKG	1.92***	[4.25]	-0.38	[-0.98]	2.3***	[3.17]
IRL	0.67	[1.12]	-0.65	[-1.08]	1.32	[1.34]
ISR	1.37***	[3.86]	-0.55	[-1.42]	1.92***	[3.21]
ITA	0.45	[1.42]	-0.36	[-1.17]	0.82	[1.51]
JPN	0.6***	[2.69]	-0.08	[-0.33]	0.68*	[1.70]
NLD	0.58*	[1.71]	-0.03	[-0.09]	0.61	[1.19]
NOR	0.93***	[2.78]	-0.3	[-0.88]	1.23**	[2.18]

NZL	0.46	[1.46]	0.06	[0.17]	0.41	[0.84]
PRT	0.66	[1.25]	0.39	[0.79]	0.27	[0.35]
SGP	0.75**	[2.34]	-0.27	[-0.84]	1.03*	[1.85]
SWE	0.11	[0.33]	-0.21	[-0.56]	0.32	[0.54]
USA	0.62***	[5.21]	-0.55***	[-4.04]	1.16***	[5.60]
Global	0.41**	[2.46]	-0.53***	[-2.84]	0.93***	[3.08]
Global.Ex.USA	0.37**	[2.04]	-0.41**	[-2.06]	0.77**	[2.33]
Europe	0.42**	[2.02]	-0.57**	[-2.58]	1.00***	[2.65]
North.America	0.69***	[3.85]	-0.27	[-1.38]	0.96***	[3.07]
Pacific	0.6***	[2.76]	-0.38*	[-1.66]	0.98***	[2.65]

Panel E	**Fama and French (2018) six-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
AUS	0.61**	[2.4]	-0.07	[-0.24]	0.68	[1.55]
AUT	0.98***	[2.82]	-0.57	[-1.49]	1.55***	[2.86]
BEL	0.45	[1.43]	-0.32	[-1.03]	0.77	[1.55]
CAN	1.09***	[3.99]	-0.34	[-1.34]	1.43***	[3.31]
CHE	0.66**	[2.53]	-0.46*	[-1.71]	1.12***	[2.68]
DEU	0.38	[1.19]	-0.08	[-0.26]	0.46	[0.88]
DNK	-0.03	[-0.11]	-0.22	[-0.75]	0.19	[0.37]
ESP	0.17	[0.49]	-0.54	[-1.62]	0.71	[1.27]
FIN	0.7*	[1.74]	-0.83**	[-2.02]	1.54**	[2.28]
FRA	0.62**	[2.19]	-0.14	[-0.48]	0.77	[1.59]
GBR	0.45**	[2.00]	-0.57**	[-2.49]	1.01***	[2.75]
HKG	2***	[4.31]	-0.47	[-1.19]	2.47***	[3.32]
IRL	0.64	[1.06]	-0.44	[-0.73]	1.08	[1.09]
ISR	1.38***	[3.72]	-0.76*	[-1.88]	2.14***	[3.43]
ITA	0.4	[1.24]	-0.39	[-1.24]	0.8	[1.45]
JPN	0.60***	[2.65]	-0.07	[-0.29]	0.67*	[1.66]
NLD	0.62*	[1.79]	0	[0.01]	0.62	[1.18]
NOR	0.95***	[2.77]	-0.38	[-1.11]	1.33**	[2.32]
NZL	0.43	[1.34]	0.3	[0.87]	0.14	[0.28]
PRT	0.68	[1.28]	0.39	[0.77]	0.3	[0.39]
SGP	0.9***	[2.74]	-0.28	[-0.83]	1.18**	[2.08]
SWE	0.22	[0.66]	-0.23	[-0.6]	0.45	[0.75]
USA	0.64***	[5.30]	-0.56***	[-4.05]	1.2***	[5.66]
Global	0.38**	[2.25]	-0.55***	[-2.99]	0.94***	[3.03]
Global.Ex.USA	0.35*	[1.88]	-0.38*	[-1.92]	0.73**	[2.16]
Europe	0.40*	[1.89]	-0.58**	[-2.58]	0.98**	[2.58]
North.America	0.67***	[3.63]	-0.3	[-1.51]	0.96***	[3.02]
Pacific	0.66***	[2.96]	-0.5**	[-2.13]	1.16***	[3.07]

Table 2.5: Cross-assets factor momentum

This table constructs different assets' style (value and momentum) factors based on Asness, Moskowitz, and Pedersen (2013). The 8 asset classes include 4 individual equity markets (stock selection) and 4 broad asset classes (asset allocation). The 4 stock selection markets are: U.S. equities (US), U.K. equities (UK), Continental Europe equities (EU), Japanese equities (JP). The 4 asset allocation classes are: global equity indices (EQ), currencies (FX), fixed income (FI), and commodities (CM). The 3 global averages are: "EVERYWHERE" i.e., all global asset classes, "ALL EQUITIES (SS)" (based on the four stock selection markets), and "ALL OTHER (AA)" (based on the four asset allocation categories).

Panel A	**Asness, Moskowitz, and Pedersen (2013) cross-assets three-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
VAL.SS_VAL.AA	0.26***	[3.10]	-0.29***	[-3.46]	0.55***	[3.32]
VAL.SS_MOM.AA	0.31***	[2.79]	-0.45***	[-3.96]	0.76***	[3.93]
MOM.SS_VAL.AA	0.44***	[3.57]	-0.29**	[-2.38]	0.73***	[3.35]
MOM.SS_MOM.AA	0.17**	[1.99]	-0.15	[-1.65]	0.32**	[2.03]

Panel B	**Asness, Moskowitz, and Pedersen (2013) cross-assets three-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
VAL.AA_VAL.US	0.17	[1.26]	-0.37***	[-2.92]	0.54**	[2.31]
VAL.AA_MOM.US	0.31*	[1.81]	-0.21	[-1.37]	0.52**	[1.98]
VAL.AA_VAL.UK	0.25**	[2.13]	-0.37***	[-3.17]	0.62***	[3.05]
VAL.AA_MOM.UK	0.8***	[4.97]	-0.39***	[-2.60]	1.19***	[4.53]
VAL.AA_VAL.EU	0.2**	[2.28]	-0.31***	[-3.60]	0.52***	[3.37]
VAL.AA_MOM.EU	0.47***	[3.45]	-0.28**	[-2.12]	0.74***	[3.22]
VAL.AA_VAL.JP	0.53***	[4.01]	-0.12	[-0.91]	0.66***	[3.01]
VAL.AA_MOM.JP	0.26	[1.44]	-0.35**	[-2.06]	0.61**	[2.30]

Panel C	**Asness, Moskowitz, and Pedersen (2013) cross-assets three-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
MOM.AA_VAL.US	0.23	[1.41]	-0.54***	[-3.61]	0.76***	[3.05]
MOM.AA_MOM.US	0.05	[0.38]	-0.08	[-0.6]	0.13	[0.55]
MOM.AA_VAL.UK	0.26*	[1.96]	-0.51***	[-3.45]	0.77***	[3.27]
MOM.AA_MOM.UK	0.48***	[3.62]	-0.19	[-1.51]	0.66***	[2.99]
MOM.AA_VAL.EU	0.28**	[2.46]	-0.51***	[-4.68]	0.79***	[4.18]
MOM.AA_MOM.EU	0.19*	[1.69]	-0.11	[-1.09]	0.30**	[1.99]
MOM.AA_VAL.JP	0.47***	[3.18]	-0.18	[-1.14]	0.64***	[2.80]
MOM.AA_MOM.JP	-0.13	[-0.81]	-0.07	[-0.48]	-0.06	[-0.24]

Table 2.6: Factor idiosyncratic volatility alphas

This table reports the average monthly returns and benchmark adjusted returns of anomaly idiosyncratic volatility strategy in US market. We consider anomalies including operating profitability, investment, short-term reversal, momentum and long-term reversal. Strategies are based on either equal-weighted(ew) or value-weighted(vw) returns. Strategies are constructed based on the extreme 30%, 20%(quintile) or 10%(decile) stocks. We take long and short positions in the bottom and top n(=1) anomalies based on previous 12-month daily idiosyncratic volatility (against FF3 factor model). This table reports returns with 12 months holding periods. The returns with significance (***<0.01<**<0.05<*¡0.1), and the corresponding t statistics.

Panel A	**Average returns**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
US_30%_vw	0.13**	[2.06]	-0.34***	[-2.75]	0.47***	[3.46]
US_30%_ew	0.19***	[2.8]	-0.66***	[-5.26]	0.85***	[6.32]
US_quintile_vw	0.3***	[4.07]	-0.41***	[-2.73]	0.71***	[4.45]
US_quintile_ew	0.29***	[3.64]	-0.52***	[-3.45]	0.81***	[5.17]
US_decile_vw	0.35***	[2.95]	0.02	[0.08]	0.34	[1.16]
US_decile_ew	0.16	[1.21]	-1.32***	[-5.38]	1.48***	[5.99]

Panel B	**CAPM alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
US_30%_vw	0.15**	[2.44]	-0.24**	[-2.04]	0.39***	[2.95]
US_30%_ew	0.23***	[3.47]	-0.54***	[-4.55]	0.77***	[5.84]
US_quintile_vw	0.34***	[4.56]	-0.29**	[-2]	0.63***	[3.96]
US_quintile_ew	0.33***	[4.21]	-0.4***	[-2.77]	0.74***	[4.73]
US_decile_vw	0.41***	[3.4]	0.21	[0.77]	0.21	[0.71]
US_decile_ew	0.2	[1.56]	-1.19***	[-4.92]	1.38***	[5.64]

Panel C	**Fama and French (1993) three-factor alphas**					
	Long		**Short**		**L-S**	
	return	**t-stat**	**return**	**t-stat**	**return**	**t-stat**
US_30%_vw	0.14**	[2.4]	-0.17	[-1.42]	0.31**	[2.35]
US_30%_ew	0.14**	[2.41]	-0.48***	[-4.02]	0.62***	[4.87]
US_quintile_vw	0.23***	[3.34]	-0.2	[-1.37]	0.43***	[2.81]
US_quintile_ew	0.23***	[3.04]	-0.32**	[-2.19]	0.55***	[3.63]
US_decile_vw	0.35***	[3.17]	0.25	[0.93]	0.11	[0.41]
US_decile_ew	0.17	[1.4]	-1.17***	[-4.83]	1.33***	[5.48]

Panel D	Fama and French (2015) five-factor alphas					
	Long		Short		L-S	
	return	t-stat	return	t-stat	return	t-stat
US_30%_vw	-0.06	[-1.29]	-0.25**	[-2.06]	0.19	[1.45]
US_30%_ew	-0.06	[-1.32]	-0.59***	[-4.82]	0.52***	[4.02]
US_quintile_vw	-0.01	[-0.11]	-0.32**	[-2.19]	0.32**	[2.03]
US_quintile_ew	-0.01	[-0.1]	-0.45***	[-3.02]	0.44***	[2.88]
US_decile_vw	0.02	[0.22]	0.04	[0.14]	0	[0.01]
US_decile_ew	-0.12	[-1.07]	-1.45***	[-5.91]	1.31***	[5.27]

Panel E	Fama and French (2018) six-factor alphas					
	Long		Short		L-S	
	return	t-stat	return	t-stat	return	t-stat
US_30%_vw	-0.07	[-1.44]	-0.47***	[-4.14]	0.4***	[3.2]
US_30%_ew	-0.07	[-1.42]	-0.8***	[-7.15]	0.73***	[6.01]
US_quintile_vw	0	[-0.01]	-0.6***	[-4.6]	0.6***	[4.31]
US_quintile_ew	-0.02	[-0.33]	-0.73***	[-5.47]	0.7***	[5.03]
US_decile_vw	0.01	[0.14]	-0.19	[-0.76]	0.22	[0.8]
US_decile_ew	-0.15	[-1.29]	-1.65***	[-7.24]	1.48***	[6.26]

Table 2.7: Factor momentum performances per decade

Panel A	**1970s**	**1980s**	**1990s**	**2000s**	**2010s**
Everywhere val mom	1.15%	0.76%	0.65%	0.75%	0.18%
	2.17	4.85	4.52	3.72	1.17
SS val mom	1.03%	0.89%	1.04%	1.45%	0.34%
	3.19	4.39	4.38	3.29	1.39
AA val mom	1.68%	0.35%	0.51%	0.30%	-0.02%
	2.02	1.82	3.64	2.59	-0.19
SS val AA val	1.55%	0.49%	0.46%	1.01%	-0.02%
	2.35	2.54	3.12	3.25	-0.15
SS mom AA mom	0.96%	0.59%	0.84%	0.50%	0.25%
	1.78	2.85	3.6	1.36	1.14
SS val AA mom	1.50%	0.79%	0.43%	1.16%	0.03%
	2.84	3.96	2.77	3.77	0.2
SS mom AA val	0.96%	0.80%	1.08%	0.49%	0.39%
	1.33	4.09	4.99	1.39	1.67
Panel B	**1970s**	**1980s**	**1990s**	**2000s**	**2010s**
Everywhere val	0.71%	0.46%	0.16%	0.43%	0.00%
	1.31	3.08	1.33	2.15	0.01
Everywhere mom	0.90%	0.52%	0.52%	0.25%	0.21%
	1.83	3.04	3.33	1	1.33
SS val	0.66%	0.47%	-0.13%	0.98%	-0.13%
	1.69	1.96	-0.54	2.27	-0.65
SS mom	0.64%	0.61%	0.81%	0.21%	0.49%
	3.38	2.96	3.37	0.42	1.79
AA val	0.73%	0.45%	0.36%	0.06%	0.09%
	0.87	2.5	3.16	0.52	0.83
AA mom	1.08%	0.45%	0.32%	0.28%	0.03%
	1.33	2.24	2.19	2.19	0.22

Table 2.8: Factor momentum over the NBER business cycle

Panel A	Expansion	Recession	Early expansion	Late expansion	Early recession	Late recession
Everywhere val mom	0.73%	0.49%	0.75%	0.71%	0.41%	0.57%
	7.26	0.87	5.1	5.15	0.52	0.7
SS val mom	0.98%	0.91%	0.95%	1.01%	0.93%	0.88%
	7.19	1.72	6.11	4.51	0.96	0.7
AA val mom	0.61%	0.04%	0.80%	0.42%	0.03%	0.05%
	4.53	0.05	3.43	3.1	0.03	0.05
SS val AA val	0.65%	0.95%	0.72%	0.58%	1.19%	0.72%
	4.5	1.69	3.74	2.69	1.47	0.9
SS mom AA mom	0.73%	0.00%	0.85%	0.60%	0.01%	-0.01%
	4.8	0	4.12	2.72	0.02	-0.02
SS val AA mom	0.80%	0.67%	0.71%	0.89%	0.82%	0.53%
	6.2	1.33	4.14	4.61	1.31	0.65
SS mom AA val	0.75%	0.75%	0.62%	0.87%	1.01%	0.49%
	5.03	0.96	3.1	3.97	1.05	0.4
Panel B	**Expansion**	**Recession**	**Early expansion**	**Late expansion**	**Early recession**	**Late recession**
Everywhere val	0.29%	0.76%	0.33%	0.25%	1.32%	0.21%
	2.78	1.51	2.31	1.64	2.12	0.26
Everywhere mom	0.56%	-0.09%	0.51%	0.60%	-0.31%	0.14%
	5.2	-0.2	3.2	4.2	-0.5	0.2
SS val	0.31%	0.84%	0.51%	0.12%	1.25%	0.43%
	2.15	1.72	3.46	0.46	2.31	0.53
SS mom	0.65%	-0.17%	0.65%	0.65%	0.46%	-0.80%
	4.71	-0.3	3.9	2.96	0.79	-0.84
AA val	0.27%	0.71%	0.21%	0.34%	1.37%	0.06%
	1.95	1	0.92	1.99	1.58	0.05
AA mom	0.49%	-0.03%	0.41%	0.57%	-0.84%	0.78%
	3.53	-0.04	1.82	3.47	-0.93	0.66

Table 2.9: Factor momentum per calendar month

Panel A	January	February	March	April	May	June	July	August	September	October	November	December
Everywhere val mom	0.39%	1.12%	0.53%	1.17%	1.00%	0.58%	1.10%	-0.12%	0.96%	0.05%	0.79%	0.82%
	0.85	2.67	1.23	2.59	2.76	1.75	3.28	-0.31	2.37	0.1	2.48	2.9
SS val mom	1.43%	1.27%	0.21%	1.17%	0.52%	1.12%	1.21%	0.42%	1.31%	0.49%	1.09%	1.42%
	2.75	2.21	0.39	2.15	1.25	2.53	3.39	1.27	2.85	0.89	2.1	3.95
AA val mom	-0.09%	1.07%	0.32%	1.11%	1.05%	0.38%	0.53%	0.38%	0.61%	0.03%	0.44%	0.57%
	-0.15	2.02	0.54	1.62	2.03	1.02	1.12	0.48	1.19	0.05	1.2	2.29
SS val AA val	1.61%	0.48%	1.46%	1.37%	0.82%	0.15%	0.54%	0.74%	0.29%	0.56%	0.51%	-0.23%
	3.82	1.2	2.59	1.82	1.78	0.4	1.15	1.1	0.66	1.15	1.05	-0.6
SS mom AA mom	0.09%	0.87%	-0.40%	0.17%	0.72%	1.01%	1.23%	1.07%	1.47%	-0.63%	1.03%	0.94%
	0.2	1.47	-0.69	0.37	1.5	2.18	2.86	1.87	2.76	-1.03	2.88	2.63
SS val AA mom	1.51%	0.99%	0.27%	1.60%	1.29%	0.01%	1.00%	0.46%	0.09%	0.26%	0.92%	1.01%
	2.89	2.06	0.71	3.01	2.46	0.02	2.46	1.44	0.2	0.51	1.95	4.01
SS mom AA val	0.62%	1.28%	1.01%	0.43%	0.43%	1.24%	1.09%	0.13%	1.25%	-0.06%	1.06%	0.48%
	1.83	2.03	1.38	0.61	1.09	3.32	2.54	0.15	2.45	-0.08	2.9	0.96
Panel B	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
Everywhere val	1.07%	0.22%	1.45%	0.76%	0.23%	0.19%	0.33%	0.13%	-0.02%	0.01%	0.13%	-0.26%
	3.52	0.5	3.89	1.76	0.85	0.66	0.95	0.25	-0.06	0.02	0.41	-0.82
Everywhere mom	-0.21%	0.82%	-0.19%	-0.16%	0.49%	0.76%	0.21%	0.94%	1.13%	0.09%	0.74%	1.03%
	-0.49	2.11	-0.5	-0.35	1.27	2.38	0.58	1.89	3.04	0.18	2.05	3.98
SS val	1.81%	0.03%	1.18%	1.20%	0.19%	-0.37%	0.24%	0.23%	-0.15%	0.19%	-0.18%	0.22%
	3.41	0.04	2.35	2.44	0.45	-1.01	0.66	0.66	-0.38	0.39	-0.27	0.51
SS mom	0.04%	1.02%	0.36%	-0.87%	0.01%	1.55%	0.94%	0.21%	1.52%	0.07%	0.40%	1.30%
	0.08	1.79	0.65	-1.33	0.01	3.58	2.56	0.61	3.5	0.15	0.73	3.14
AA val	0.55%	0.35%	1.63%	0.46%	0.26%	0.57%	0.39%	0.07%	0.06%	-0.12%	0.34%	-0.59%
	2.1	0.7	2.96	0.69	0.73	1.52	0.78	0.08	0.1	-0.18	1.09	-1.44
AA mom	-0.38%	0.69%	-0.57%	0.32%	0.82%	0.23%	-0.28%	1.44%	0.85%	0.11%	0.97%	0.85%
	-0.65	1.58	-1.36	0.55	1.64	0.62	-0.49	1.89	1.79	0.14	2.65	2.98

Chapter 3

Investing in Anomalies: An Optimal Portfolio Approach

Xinrui Duan, Jun Tu, Ran Zhang, and Guofu Zhou

ABSTRACT

We take an optimal portfolio approach on investing in multiple anomalies. We find that a variety of estimated optimal rules outperform substantially investing in any single anomaly. In addition, although statistical bias issue and market arbitrage activities may significantly destroy a given anomaly's standalone economic value, we show that these anomalies are still valuable collectively in the optimal portfolio even after they are out-of-sample or published.

JEL classification: G11, G14.

Keywords: Anomaly Investing, Anomaly Choice, Mean-Variance Analysis, Parameter Uncertainty, Sharpe ratio, CER.

3.1 Introduction

Currently, there exist plenty of investment strategies in the growing financial market. How these strategies should be used to increase returns and reduce risks remains a key question to investors. Furthermore, in the last 30 years, academia has found numerous anomalies which can predict stock returns and generate long-term returns. However, investors have little knowledge and limited skills to invest in anomalies optimally.

Investors may lack systematic methods to invest in anomalies. Traditionally, investors use the naïve 1/N rule to invest in anomalies. This rule, attributed to the Talmud by Duchin and Levy (2009), has been known for about 1,500 years, and corresponds to the equal weight portfolio in practice. Asness et al. (2013) proposed a 50/50 strategy to equally invest in value anomalies and momentum anomalies. They found that the 1/N rule generates larger Sharpe ratios than that of independent investing, either through the value anomaly or momentum anomaly, within and across different asset classes. The other conventional investing rule is based on one's past performance. Arnott et al. (2018), following Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999), defined an anomaly-momentum strategy. Here, investors buy good anomalies and sell bad anomalies, based on the anomalies' past cross-sectional performance. They found that anomaly momentum investing can generate larger average returns than any individual anomaly investing.

Investors are concerned and uncertain about issues of statistical bias relating to anomalies. To which, academic research explores new anomalies by testing different samples' periods. Many anomalies become unexploitable when tested out-of-sample. Hou, Xue, and Zhang (2018) found that more than half of anomalies available become insignificant when out-of-sample. McLean and Pontiff (2016) found anomaly returns to be 26% lower, out-of-sample, due to statistical bias. To address this, Fama (1991, p.1585) remarked: "With many clever researchers on both sides of the efficiency fence, rummaging for forecasting variables, we are sure to find instances of 'reliable' return predictability that are in fact spurious."

Investors also worry about market arbitrage activities, which can impact anomalies' main profits once those anomalies are published. McLean and Pontiff (2016) found anomaly returns to be 58% lower post-publication due to market arbitrage. When one anomaly is published, sophisticated investors can learn about and trade that published anomaly; hence it is expected that returns associated with that published anomaly should disappear, or at least, decay.

In this paper, we explore new methods to invest in anomalies. We find that a variety of estimated optimal rules outperform the I/N rule and the momentum rule. In addition, although statistical bias issues and market arbitrage activities may destroy a given anomaly's economic value, we show that these out-of-sample or published anomalies are still valuable collectively, in the optimal portfolio. We use four optimization rules, namely the Markowitz rule, the Kan and Zhou (2012) rule, the combined Markowitz rule, as well as the combined Kan and Zhou rule, to invest in anomalies in optimal fashion.

Taken from Markowitz's (1952) seminal paper, the mean-variance (MV) framework is the major model used in practice today in asset allocation and active portfolio management, despite numerous other models developed by academics. Although the Markowitz rule has serious estimation error issues, Tu and Zhou (2011) proposed an optimal combination of the naïve 1/N rule with highly sophisticated strategies – the Markowitz rule and the Kan and Zhou (2007) rule – as a way to improve stock investing performance. The combined rules not only have a significant impact of improving these sophisticated strategies, but also outperform the 1/N rule in most scenarios.

We conduct our analysis using anomalies examined in McLean and Pontiff (2016), using long-short portfolio strategies that simultaneously buy and sell extreme quintiles based on each anomaly. We compare each anomaly's returns over three distinct periods: (i) in-sample: the original study's sample period, (ii) out-of-sample: the period after the original sample but prior to publication, and (iii) post-publication: the post-publication period. These settings are consistent with the study by McLean and Pontiff (2016). We select anomalies based on t-values or returns of anomalies in-sample, post-publication, and out-of-sample. We design eight subsamples of anomalies, including anomalies with in-sample t$\geq$1.65 & post-publication t$\leq$1.65, anomalies with in-sample t$\geq$1.96 & post-publication t$\leq$1.96, anomalies with in-sample t$\geq$1.96 & post-publication return decrease $\geq$30%, anomalies with in-sample t$\geq$1.96 & post-publication return decrease $\geq$50%, anomalies with in-sample t$\geq$1.65 & out-of-sample t$\leq$1.65, anomalies with in-sample t$\geq$1.96 & out-of-sample t$\leq$1.96, anomalies with in-sample t$\geq$1.96 & out-of-sample return decrease $\geq$30%, and anomalies with in-sample t$\geq$1.96 & out-of-sample return decrease $\geq$50%. We use these eight subsamples of anomalies, since we want to observe changes in anomalies' investing performance, post-publication and out-of-sample.

We find our four optimization rules to be substantially better than the naïve 1/N rule and momentum rule in almost all scenarios within our study, even when the sample size (T) is as small as 120. For example, when T = 120, γ = 1, in the first sample of anomalies with in-sample t$\geq$1.65 and post-publication t$\leq$1.65, the Sharpe ratios of the Markowitz rule, the Kan and Zhou (2012) rule, the combined Markowitz rule, and the combined Kan and Zhou rule are 0.6734, 0.6688, 0.6796, and 0.6782, respectively. However, the Sharpe ratios of the 1/N rule and momentum rule are 0.3792 and 0.2048 respectively. The Sharpe ratios of the four optimization rules are 1 to 2 times larger than that of the other two rules. It is surprising that the Markowitz rule also works well in anomaly portfolio optimization, showing similar Sharpe ratios with the 3 other optimization rules. Nevertheless, in the first sample, we observe that certain-equivalent returns (CERs) of the Markowitz rule, the Kan and Zhou (2012) rule, the combined Markowitz rule, and the combined Kan and Zhou rule are 163.76, 251.79, -447.43, and 161.81 respectively. However, the CERs of the 1/N rule and momentum rule are 5.78 and 17.95 respectively. The CERs of the optimization rules, except the Markowitz rule, are dramatically larger than that of the other two rules. Due to large estimation errors, the CERs of the Markowitz rule are usually negative. The combined Markowitz rule and the combined Kan and Zhou rule are shown to be the two best optimization rules to invest in anomaly portfolios. The findings are consistent with Tu and Zhou's (2011) findings – combination rules are better than the sophisticated rules.

Although academic research may decrease anomaly returns, post-publication and out-of-sample, based on the evidence of McLean and Pontiff (2016), investors have more interest in anomaly portfolios' Sharpe ratios and CERs. McLean and Pontiff (2016) studied anomalies' first moment value-relevant information – returns; however, they did not consider anomalies' second moment value-relevant information – namely the variance-covariance matrix. From optimal anomaly portfolio analyses, we find that out-of-sample or published anomalies still contribute to the portfolio, which weakens the evidence in McLean and Pontiff (2016). Despite this, investors should still invest in those anomalies when they are published or out-of-sample, since optimization rules can comprehensively analyze the anomaly portfolio's returns and variance, which can maximize the anomaly portfolio's Sharpe ratios and CERs.

In our tests, we compare the Sharpe ratios and certain-equivalent returns of different rules, post-publication and out-of-sample. We explore whether optimization rules generate larger Sharpe ratios and certain-equivalent returns than the 1/N rule and the momentum rule under these conditions, and the Sharpe ratios and certain-equivalent returns of different rules after removing anomalies from our portfolio, once those anomalies are published. We define two scenarios: in scenario one, we remove anomalies from our portfolio once those anomalies are published. In scenario two, we remove anomalies in the 5 years following those anomalies' publication, and add them back into our anomaly portfolio after 5 years.

In scenario one, we find that the four optimization rules' Sharpe ratios and CERs decrease when anomalies are removed post-publication and out-of-sample, in most cases. However, the 1/N rule and momentum rule's Sharpe ratios and CERs do not decrease when anomalies are removed post-publication and out-of-sample, in most cases. In some instances especially, the 1/N rule and momentum rule's Sharpe ratios increase when anomalies are removed post-publication and out-of-sample. It illustrates the misconception of anomaly investors, that removing anomalies post-publication and out-of-sample can increase the Sharpe ratios of their anomaly portfolios, following the 1/N rule. This finding is partially consistent with the imperfect conclusions of McLean and Pontiff (2016). We use the estimation window T = 240, with risk aversion $\gamma = 1$. In the sample of anomalies with in-sample t$\geq$1.96 & post-publication t$\leq$1.96, we find the average Sharpe ratio of the four optimization rules to decrease dramatically, from 0.82 to 0.60, with 1% significance level. However, the Sharpe ratio of the I/N rule decreases from 0.39 to 0.34, while the Sharpe ratio of the momentum rule decreases slightly from 0.1996 to 0.1977. Both results are not significant. The changes in CERs of the six rules are consistent with their corresponding changes in Sharpe ratios, with the exception of the 1/N rule, which increases from 5.99 to 6.37.

In scenario two, we find that the Sharpe ratios and CERs of the four optimization rules decrease when anomalies are removed in the 5 years following those anomalies' publication, and added back into our anomaly portfolio thereafter. However, the 1/N rule and momentum rule's Sharpe ratios and CERs only decrease slightly in most cases, under the same conditions. In some cases especially, the 1/N rule and momentum rule's Sharpe ratios increase when removed anomalies are added back into our anomaly portfolio after 5 years. We use the estimation window T = 240, and risk aversion $\gamma = 1$. In the sample of anomalies with in-sample t$\geq$1.96 & post-publication t$\leq$1.96, we find the average Sharpe ratio of the four optimization rules to decrease dramatically, from 0.82 to 0.76, with 5% significance level. However, the Sharpe ratio of the I/N rule decreases, from 0.39 to 0.35, while the Sharpe ratio of the momentum rule decreases slightly, from 0.1996 to 0.1871. Both results are not significant. The changes to CERs in these six rules are consistent with the changes to their Sharpe ratios, except the 1/N rule, which increases from 5.99 to 6.18.

Both scenarios' results support our hypothesis: investors should still invest in those anomalies when they are published or out-of-sample.

The remainder of the paper is organized as follows: Section 2 provides methodologies for several rules; Section 3 reports the summary statistics for selected anomalies; Section 4 evaluates and compares the performance of different rules post-publication and out-of-sample; and Section 5 gives a conclusion.

3.2 Methodologies

In this section, we illustrate four different optimization rules, namely, the Markowitz rule (Markowitz, 1952), the combined Markowitz rule (Tu and Zhou 2011), the KZ rule (Kan and Zhou, 2007), and the combined KZ rule (Tu and Zhou, 2011). We furtherly introduce the naïve 1/N rule, attributed to the Talmud by Duchin and Levy (2009), and the momentum rule, first proposed to stock investing by Jagadeesh and Titman (1993) and recently extended to anomaly investing by Arnott et al. (2018).

3.2.1 Markowitz rule and combined Markowitz rule

The simplest case is the standard maximum likelihood (ML) rule or the (estimated) Markowitz rule. The combined Markowitz rule combines the 1/N rule with the standard Markowitz rule. Let $\hat{\mu}$ and $\hat{\Sigma}$ be the sample mean and covariance matrix of R_{T+1}, then the ML rule is given by $\hat{w}^{ML} = \hat{\Sigma}^{-1}\hat{\mu}/\gamma$. Instead of using $\hat{w}^{ML}$, we use a scaled variable:

$$\bar{w} = \frac{1}{\gamma}\tilde{\Sigma}^{-1}\hat{\mu} \tag{3.1}$$

where $\tilde{\Sigma} = (T/(T-N-2))\hat{\Sigma}$. The scaled $\bar{w}$ is unbiased and performs slightly better than $\hat{w}^{ML}$. The combination rule is

$$\hat{w}_c = (1-\delta)w_e + \delta\bar{w} \tag{3.2}$$

Then the expected loss associated with $\hat{w}_c$ is (all proofs are in the appendices)

$$L(w^*, \hat{w}_c) = \frac{\gamma}{2}[(1-\delta)^2\pi_1 + \delta^2\pi_2], \tag{3.3}$$

where $\pi_1 = (w_e - w^*)'\Sigma(w_e - w^*), \pi_2 = E[(\bar{w} - w^*)'\Sigma(\bar{w} - w^*)]$. Note that π_1 measures the impact from the bias of the 1/N rule, and π_2 measures the impact from the variance of $\bar{w}$. Thus, the combination coefficient δ determines the tradeoff between bias and variance. The optimal choice is easily shown as

$$\delta^* = \frac{\pi_1}{\pi_1 + \pi_2}. \tag{3.4}$$

Summarizing the result, we have

PROPOSITION 1 *If $\pi_1 > 0$, then there exists an optimal $\delta^*, 0 < \delta^* < 1$, such that*

$$L(w^*, \hat{w}_c) < min[L(w^*, w_e), L(w^*, \bar{w})],$$

i,e., the optimal combination rule $\hat{w}_c$ strictly dominates both the 1/N rule and $\bar{w}$.

The condition $\pi_1 > 0$ is trivially satisfied in practice because the 1/N rule will not be equal to the truly optimal rule, with a probability of one. Proposition 1 says that the optimal combination rule $\hat{w}_c$ indeed provides vast improvements over both the 1/N rule and $\bar{w}$. [1] Suppose $\pi_1 = \pi_2$, then $\delta^* = 1/2$, and the loss of $\hat{w}_c$ will be only one-half of the loss of either the 1/N rule or $\bar{w}$. This works exactly like a diversification over two independent and identically distributed risky assets.

To estimate δ^*, we only need to estimate π_1 and π_2, which can be done as follows:

$$\hat{\pi}_1 = w_e'\hat{\Sigma}w_e - \frac{2}{\gamma}w_e'\hat{\mu} + \frac{1}{\gamma^2}\tilde{\theta}^2, \tag{3.5}$$

$$\hat{\pi}_2 = \frac{1}{\gamma^2}(c_1 - 1)\tilde{\theta}^2 + \frac{c_1}{\gamma^2}\frac{N}{T}, \tag{3.6}$$

where $\tilde{\theta}^2$ is an estimator of $\theta^2 = \mu'\Sigma^{-1}\mu$ given by Kan and Zhou (2007),

[1]

and $c_1 = (T-2)(T-N-2)/(T-N-1)(T-N-4)$. The condition of $T > N+4$ is needed here to ensure the existence of the second moment of $\hat{\Sigma}^{-1}$. Summarizing, we have

PROPOSITION 2 *Assume $T > N+4$. On the combination of the 1/N rule with $\bar{w}$, $\hat{w}_c = (1-\delta)w_e + \delta\bar{w}$, the estimated optimal one is*

$$\hat{w}^{CML} = (1-\hat{\delta})w_e + \hat{\delta}\bar{w}$$

, where $\hat{\delta} = \hat{\pi}_1/(\hat{\pi}_1 + \hat{\pi}_2)$ with $\hat{\pi}_1$ and $\hat{\pi}_2$ given by (5) and (6).

Proposition 2 provides a simple way to optimally combine the 1/N rule with the unbiased ML rule $\bar{w}$. This combination rule is easy to carry out in practice, since it is only a given function of the data. However, due to the errors in estimating δ^*, there is no guarantee that the estimated optimal combination rule, $\hat{w}^{CML}$, will always be better than either the 1/N rule or $\bar{w}$. Nevertheless, in our later simulations, the magnitude of the errors in estimating δ^*, though varying over different scenarios, are generally small. Hence, $\hat{w}^{CML}$ does improve upon $\bar{w}$, and can either outperform the 1/N rule or achieve comparable performances in most scenarios. Therefore, this combination does provide improvements overall. In addition, as T goes to infinity, $\hat{w}^{CML}$ converges to the true optimal portfolio rule.

3.2.2 Kan and Zhou (2007) rule and combined Kan and Zhou (2007) rule

In the Kan and Zhou (2007) rule, $\hat{w}^{KZ}$ is motivated to minimize the impact of estimation errors via a three-fund portfolio. The associated three-fund optimal portfolio weights are then given by

$$\hat{w}^{III} = \frac{c_3}{\gamma}\left[\left(\frac{\hat{\psi}_a^2}{\hat{\psi}_a^2 + \frac{N}{T}}\right)\hat{\Sigma}^{-1}\hat{\mu} + \left(\frac{\frac{N}{T}}{\hat{\psi}_a^2 + \frac{N}{T}}\right)\hat{\mu}_g\hat{\Sigma}^{-1}1_N\right] \tag{3.7}$$

where

$$c_3 = \frac{(T-N-1)(T-N-4)}{T(T-2)}, \tag{3.8}$$

$$\hat{\mu}_g = \frac{\hat{\mu}'\hat{\Sigma}^{-1}1_N}{1_N'\hat{\Sigma}^{-1}1_N}, \tag{3.9}$$

$$\hat{\psi}_a^2 = \frac{(T-N-1)\hat{\psi}^2 - (N-1)}{T} + \frac{2(\hat{\psi}^2)^{\frac{N-1}{2}}(1+\hat{\psi}^2)^{-\frac{T-2}{2}}}{TB_{\hat{\psi}^2/(1+\hat{\psi}^2)}((N-1)/2,(T-N+1)/2)} \tag{3.10}$$

Consider now the combination of the 1/N rule with the Kan and Zhou (2007) rule, we have

PROPOSITION 3 *Assume $T > N+4$. In the combination of the 1/N rule with the Kan and Zhou (2007) rule, $\tilde{w}_c = (1-\delta_k)w_e + \delta_k\hat{w}^{KZ}$, the estimated optimal one is*

$$\hat{w}^{CKZ} = (1-\hat{\delta}_k)w_e + \hat{\delta}_k\hat{w}^{KZ}, \tag{3.11}$$

where $\hat{\delta}_k = (\hat{\pi}_1 - \hat{\pi}_{13})/(\hat{\pi}_1 - 2\hat{\pi}_{13} + \hat{\pi}_3)$ with $\hat{\pi}_1$ given by (9), and $\hat{\pi}_{13}$ and $\hat{\pi}_3$ given by

$$\hat{\pi}_{13} = \frac{1}{\gamma^2}\tilde{\theta}^2 - \frac{1}{\gamma}w_e'\hat{\mu} + \frac{1}{\gamma c_1}\left([\hat{\eta}w_e'\hat{\mu} + (1-\hat{\eta})\hat{\mu}_g w_e'1_N] - \frac{1}{\gamma}[\hat{\eta}\hat{\mu}'\tilde{\Sigma}^{-1}\hat{\mu} + (1-\hat{\eta})\hat{\mu}_g\hat{\mu}'\tilde{\Sigma}^{-1}1_N]\right), \tag{3.12}$$

$$\hat{\pi}_3 = \frac{1}{\gamma^2}\tilde{\theta}^2 - \frac{1}{\gamma^2 c_1}\left(\tilde{\theta}^2 - \frac{N}{T}\hat{\eta}\right). \tag{3.13}$$

Proposition 3 provides the estimated optimal combination rule that combines the 1/N rule with $\hat{w}^{KZ}$. By design, it should be better than the 1/N rule if the errors in estimating the true optimal δ_k are small and if the 1/N rule is not exactly identical to the true optimal portfolio rule.

3.2.3 1/N rule

In contrast to the above sophisticated strategies, the naïve 1/N diversification rule, which invests equally across N anomalies of interest, relies on neither any theory nor any data.

3.2.4 Momentum rule

Arnott et al. (2018), following Jegadeesh and Titman (1993), and Moskowitz and Grinblatt (1999), defined the anomaly momentum strategy. Each month, anomalies are ranked by their lagged one-month returns, and then taken as long and short positions via the single best and the single worst performing anomaly.

3.3 Summary statistics

We conduct our analysis using anomalies examined in McLean and Pontiff (2016). We use long-short portfolio strategies that simultaneously buy and sell extreme quintiles that are based on each anomaly. We compare each anomaly's returns over three distinct periods: (i) in-sample: the original study's sample period, (ii) out-of-sample: the period after the original sample but prior to publication, and (iii) post-publication: the post-publication period. These settings are consistent with those in McLean and Pontiff's (2016) study.

Table 3.1 reports the summary statistics for selected anomalies' returns, Sharpe ratios, and certain-equivalent returns (CERs) with both risk aversion coefficients. We select anomalies based on those examined in McLean and Pontiff (2016) and make different anomaly subsamples based on different scenarios. Table 3.1 reports mean values, minimum values, median values, maximum values, and standard deviations for selected anomalies' returns, Sharpe ratios, and certain-equivalent returns (CERs) and reports the number of anomalies in each subsample. The sample period lasts till June 2018.

Panel A selects anomalies based on t-values or returns of anomalies in-sample and post-publication. Panel A summarizes four subsamples of anomalies, including anomalies with in-sample t>1.65 & post-publication t<1.65, anomalies with in-sample t>1.96 & post-publication t<1.96, anomalies with in-sample t>1.96 & post-publication return decrease>30%, and anomalies with in-sample t>1.96 & post-publication return decrease>50%. There are 31 anomalies with t-values over 1.96 in-sample, but having their returns decrease over 30% post-publication. The average returns and Sharpe ratios of these 31 anomalies are 0.59 and 0.19, respectively. The average CERs of these 31 anomalies are 6.40 ($\gamma = 1$) and 4.92 ($\gamma = 3$).

Panel B selects anomalies based on t-values or returns of anomalies in-sample and post-publication. Panel B summarizes four subsamples of anomalies, including anomalies with in-sample t>1.65 & out-of-sample t<1.65, anomalies with in-sample t>1.96 & out-of-sample t<1.96, anomalies with in-sample t>1.96 & out-of-sample return decrease>30%, and anomalies with in-sample t>1.96 & out-of-sample return decrease >50%. There are 23 anomalies with t-values over 1.96 in-sample, but having their returns decrease over 30% out-of-sample. The average returns and Sharpe ratios of these 23 anomalies are 0.55 and 0.20, respectively. The average CERs of these 23 anomalies are 6.01 ($\gamma = 1$) and 4.74 ($\gamma = 3$).

3.4 Performance evaluation

In this section, we evaluate and compare the performance of different rules, post-publication and out-of-sample.

3.4.1 Sharpe ratios and certain-equivalent returns for different rules

In this subsection, we explore whether optimization rules generate larger Sharpe ratios and certain-equivalent returns than the naïve 1/N rule and momentum rule.

Given a sample size of M, we use a rolling estimation approach with two estimation windows of length T = 120 and 240 months, respectively. In each month t, starting from t - T + 1, we use the data in the most recent T months, up to month t, to compute the various portfolio rules, and apply them to determine the investments for the next month. For instance, let $w_{z,t}$ be the estimated optimal portfolio rule in month t for a given rule 'z' and let r_{t+1} be the excess return on the anomalies realized in month $t+1$. The realized excess return on the portfolio would be $r_{z,t+1} = w'_{z,t} r_{t+1}$. We then compute the average value of the $M - T$ realized returns, $\hat{\mu}_z$, and the standard deviation, $\hat{\sigma}_z$. The certainty-equivalent return (CER) is thus given by

$$CER_z = \hat{\mu}_z - \frac{\gamma}{2}\hat{\sigma}_z^2, \tag{3.14}$$

which can be interpreted as the risk-free rate of return that an investor is willing to accept instead of adopting the given anomaly rule z. Clearly, the higher the CER, the better the rule. As before, we set the risk aversion coefficient γ to 3. Note that all CERs have a common term of the average realized risk-free rate, which is canceled out in their difference. Hence, as in the case for the expected utilities, we report the CERs by ignoring the risk- free rate term.

With the real data, the truly optimal rule is unknown. We approximate it by using the ML estimator based on the entire sample. This will be referred to as the in-sample ML rule. Although this rule is not implementable in practice, it is the rule that one would have obtained based on the ML estimator, had one known all the data in advance. Its performance may serve as a useful benchmark to measure how estimation errors affect the out-of-sample results.

Table 3.2 reports the Sharpe ratio for different rules, including the 1/N rule, the Markowitz (ML) strategy, the Kan and Zhou (KZ) rule, both of Tu and Zhou's (2011) combined rules (CML, CKZ), and the momentum rule. All rules are based on two estimation windows of length T = 120 and 240 months, respectively. Correspondingly, the risk aversion coefficients γ are 1 and 3, respectively.

We find that the four optimization rules have similar Sharpe ratios in each anomaly subsample. These four optimization rules generate larger Sharpe ratios than the naïve 1/N rule and momentum rule in all subsamples. The momentum rule has the lowest Sharpe ratio, compared to the optimization rules and naïve 1/N rule.

Table 3.3 reports certainty-equivalent returns (CERs) for different rules, including the 1/N rule, the Markowitz (ML) rule, the Kan and Zhou (KZ) rule, both of Tu and Zhou's (2011) combined rules (CML, CKZ), and the momentum rule.

3.4.2 Comparing Sharpe ratios and certain-equivalent returns of different rules post-publication and out-of-sample

In this subsection, we explore whether optimization rules generate larger Sharpe ratios and certain-equivalent returns than the naïve 1/N rule and momentum rule, post-publication and out-of-sample, and how Sharpe ratios and certain-equivalent returns of different rules change after removing anomalies from our anomaly portfolio, once those anomalies are published. We show all rules based on an estimation window of length T = 240 and risk aversion coefficient $\gamma = 1$. We obtain consistent results by using other estimation window lengths and risk aversion coefficients.

Table 3.4 reports three scenarios of anomalies' Sharpe ratios. The first scenario constructs rules based on all available anomalies through June 2018. In the second scenario, we remove anomalies from our anomaly portfolio, once those anomalies are published. In the third scenario, we remove anomalies in the 5 years following those anomalies' publication and add them back into our anomaly portfolio thereafter.

We find that the four optimization rules' Sharpe ratios significantly decrease if anomalies are removed post-publication and out-of-sample in most cases. However, the 1/N rule and momentum rule's Sharpe ratios do not significantly decrease in most cases. In some cases especially, the 1/N rule and momentum rule's Sharpe ratios increase if anomalies are removed post-publication and out-of-sample. It illustrates the misconception of anomaly investors to drop anomalies post-publication and out-of-sample. This partially supports the findings of McLean and Pontiff (2016). They found that the average anomaly's long-short return declines by 26% out-of-sample and the average anomaly's long-short return shrinks 58% post-publication.

Naïve investors using the 1/N method to construct their anomaly portfolio should remove anomalies post-publication and out-of-sample, since their Sharpe ratios increase after removal.

In addition, if investors who use optimization rules remove anomalies in the 5 years following those anomalies' publication, and add them back into their anomaly portfolio thereafter, they would observe this strategy's Sharpe ratios to be significantly lesser than the Sharpe ratios of the four optimization rules in most cases, without the removal of anomalies.

Table 3.5 reports three scenarios of anomalies' certainty-equivalent returns. The first scenario constructs rules based on all available anomalies through June 2018. In the second scenario, we remove anomalies from our anomaly portfolio once those anomalies are published. In the third scenario, we remove anomalies in the 5 years following those anomalies' publication and add them back into our anomaly portfolio thereafter.

Consistent with the Sharpe ratios of Table 3.4, we find that the four optimization rules' CERs decrease if anomalies are removed post-publication and out-of-sample in most cases. However, the 1/N rule's CERs increase if anomalies are removed post-publication and out-of-sample in most cases. It illustrates the misconception of anomaly investors to drop anomalies post-publication and out-of-sample. It also partially supports the findings of McLean and Pontiff (2016). Naïve investors using 1/N methods to construct their anomaly portfolio should remove anomalies post-publication and out-of-sample, since their CERs increase after removal.

In addition, if investors who use optimization rules remove anomalies in the 5 years following those anomalies' publication and add them back into their anomaly portfolio thereafter, they would observe this strategy's CERs to be lesser than the CERs of the four optimization rules in most cases, without the removal of anomalies.

The evidence of Sharpe ratios and CERs supports that investors should always optimally invest in all anomalies, and not drop any anomalies post-publication and out-of-sample.

3.5 Conclusion

The modern portfolio theory pioneered by Markowitz (1952) and its extensions, Kan and Zhou (2007) and Tu and Zhou (2011) laid the cornerstone to portfolio optimization. In this paper, we find these optimization rules are also useful to optimally invest in anomalies. We find four optimization rules are substantially better than the 1/N rule and the momentum rule in different subsamples. The outperformance of optimization rules is robust in different estimation windows and risk aversion coefficients.

The 'post-publication and out-of-sample effects' (McLean and Pontiff, 2016) becomes weak if investors use optimization rules to invest anomaly portfolio. We conclude that investors should still invest those anomalies even if they are published or out-of-sample, since our optimization rules can largely estimate anomaly portfolio's return and variance and maximize anomaly portfolio's Sharpe ratios and CERs.

Bibliography

Arthur, M. B. and D. M. Rousseau (2001): *The boundaryless career: A new employment principle for a new organizational era*, Oxford University Press on Demand.

Baker, M. and J. Wurgler (2006): "Investor sentiment and the cross-section of stock returns," *The journal of Finance*, 61, 1645–1680.

Barber, B. M. and T. Odean (2007): "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors," *The Review of Financial Studies*, 21, 785–818.

Ben-Rephael, A., Z. Da, and R. D. Israelsen (2017): "It depends on where you search: institutional investor attention and underreaction to news," *The Review of Financial Studies*, 30, 3009–3047.

Bidwell, M. and E. Mollick (2015): "Shifts and ladders: Comparing the role of internal and external mobility in managerial careers," *Organization Science*, 26, 1629–1645.

Brayfield, A. H. and W. H. Crockett (1955): "Employee attitudes and employee performance." *Psychological bulletin*, 52, 396.

Cao, J., T. Chordia, and C. Lin (2016): "Alliances and return predictability," *Journal of Financial and Quantitative Analysis*, 51, 1689–1717.

Cappelli, P. (2000): "A market-driven approach to retaining talent." *Harvard business review*, 78, 103–11.

Carhart, M. M. (1997): "On persistence in mutual fund performance," *The Journal of finance*, 52, 57–82.

Chan, L. K., N. Jegadeesh, and J. Lakonishok (1996): "Momentum strategies," *The Journal of Finance*, 51, 1681–1713.

Coff, R. W. (1997): "Human assets and management dilemmas: Coping with hazards on the road to resource-based theory," *Academy of man-*

agement review, 22, 374–402.

Cohen, L. and A. Frazzini (2008): "Economic links and predictable returns," *The Journal of Finance*, 63, 1977–2011.

ENGELBERG, J. and P. Gao (2011): "In search of attention," *The Journal of Finance*, 66, 1461–1499.

Fama, E. F. and K. R. French (1993): "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 33, 3–56.

——— (2015): "A five-factor asset pricing model," *The Journal of finance*, 116, 1–22.

——— (2018): "Choosing factors," *Journal of Financial Economics*, 128, 234–252.

Gardner, T. M. (2005): "Interfirm competition for human resources: Evidence from the software industry," *Academy of Management Journal*, 48, 237–256.

Hall, R. (1993): "A framework linking intangible resources and capabilities to sustainable competitive advantage," *Strategic management journal*, 14, 607–618.

Henderson, W. D. and L. Bierman (2009): "An empirical analysis of lateral lawyer trends from 2000 to 2007: The emerging equilibrium for corporate law firms," *Geo. J. Legal Ethics*, 22, 1395.

Hirshleifer, D., P.-H. Hsu, and D. Li (2013): "Innovative efficiency and stock returns," *Journal of Financial Economics*, 107, 632–654.

——— (2017): "Innovative originality, profitability, and stock returns," *The Review of Financial Studies*, 31, 2553–2605.

Hirshleifer, D. and S. H. Teoh (2003): "Limited attention, information disclosure, and financial reporting," *Journal of accounting and economics*, 36, 337–386.

Hong, H. and J. C. Stein (1999): "A unified theory of underreaction, momentum trading, and overreaction in asset markets," *The Journal of finance*, 54, 2143–2184.

HOU, K. (2007): "Industry information diffusion and the lead-lag effect in stock returns," *The Review of Financial Studies*, 20, 1113–1138.

HOU, K. AND T. J. MOSKOWITZ (2005): "Market frictions, price delay, and the cross-section of expected returns," *The Review of Financial Studies*, 18, 981–1020.

HOU, K., W. XIONG, AND L. PENG (2009): "A tale of two anomalies: The implications of investor attention for price and earnings momentum," .

HUANG, X. (2015): "Thinking outside the borders: Investors' underreaction to foreign operations information," *The Review of Financial Studies*, 28, 3109–3152.

HUBERMAN, G. AND T. REGEV (2001): "Contagious speculation and a cure for cancer: A nonevent that made stock prices soar," *The Journal of Finance*, 56, 387–396.

JEGADEESH, N. AND S. TITMAN (1993): "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 48, 65–91.

KAHNEMAN, D. (1973): *Attention and effort*, vol. 1063, Citeseer.

LEE, C., S. T. SUN, R. WANG, AND R. ZHANG (2018): "Technological Links and Predictable Returns," .

MARKMAN, G. D., P. T. GIANIODIS, AND A. K. BUCHHOLTZ (2009): "Factor-market rivalry," *Academy of Management Review*, 34, 423–441.

MERTON, R. C. (1987): "A simple model of capital market equilibrium with incomplete information," *The journal of finance*, 42, 483–510.

MOSKOWITZ, T. J. AND M. GRINBLATT (1999): "Do industries explain momentum?" *The Journal of Finance*, 54, 1249–1290.

Peng, L. and W. Xiong (2006): "Investor attention, overconfidence and category learning," *Journal of Financial Economics*, 80, 563–602.

Phillips, D. J. (2002): "A genealogical approach to organizational life chances: The parent-progeny transfer among Silicon Valley law firms, 1946–1996," *Administrative Science Quarterly*, 47, 474–506.

Ramnath, S. (2002): "Investor and analyst reactions to earnings announcements of related firms: An empirical analysis," *Journal of Accounting Research*, 40, 1351–1376.

Rao, H. and R. Drazin (2002): "Overcoming resource constraints on product innovation by recruiting talent from rivals: A study of the mutual fund industry, 1986–1994," *Academy of management Journal*, 45, 491–507.

Schneider, B., P. J. Hanges, D. B. Smith, and A. N. Salvaggio (2003): "Which comes first: employee attitudes or organizational financial and market performance?" *Journal of applied psychology*, 88, 836.

Seasholes, M. S. and G. Wu (2007): "Predictable behavior, profits, and attention," *Journal of Empirical Finance*, 14, 590–610.

Singh, J. and A. Agrawal (2011): "Recruiting for ideas: How firms exploit the prior inventions of new hires," *Management Science*, 57, 129–150.

Weitz, J. and R. C. Nuckols (1955): "Job satisfaction and job survival." *Journal of Applied Psychology*, 39, 294.

Wurgler, J. and E. Zhuravskaya (2002): "Does arbitrage flatten demand curves for stocks?" *The Journal of Business*, 75, 583–608.

Yu, T. and A. A. Cannella Jr (2007): "Rivalry between multinational enterprises: An event history approach," *Academy of Management Journal*, 50, 665–686.

YUAN, Y. (2008): "Attention and trading," *Unpublished Working Paper. University of Pennsylvania.*

ZABLAH, A. R., B. D. CARLSON, D. T. DONAVAN, J. G. MAXHAM III, AND T. J. BROWN (2016): "A cross-lagged test of the association between customer satisfaction and employee job satisfaction in a relational context." *Journal of Applied Psychology*, 101, 743.

ZHANG, X. F. (2006): "Information uncertainty and stock returns," *The Journal of Finance*, 61, 105–137.

Table 3.1: Summary Statistics

This table reports the summary statistics for the anomaly long-short portfolios average return, Sharpe ratio, and certain-equivalent return (CER). Panel A reports summary statistics for anomalies with returns drop after publication. Panel B reports for anomalies with returns drop after sample period end in the original paper. Within each panel, we select anomalies that have significant in-sample returns, and such returns drop after publication or sample period end based on different criterion. Our sample period ends in June 2018.

Panel A: Anomalies with returns drop after publication					
	Mean	Min	Median	Max	Stddev
Anomalies with in-sample t≥1.65 & post-publication t≤1.65 N=21(33%)					
Return	0.44	0.13	0.41	0.94	0.23
Sharpe ratio	0.15	0.07	0.12	0.33	0.08
CER with $\gamma = 1$	4.65	1.36	3.86	10.07	2.50
CER with $\gamma = 3$	3.29	0.36	2.78	7.93	2.33
Anomalies with in-sample t≥1.96 & post-publication t≤1.96 N=22(34%)					
Return	0.50	0.16	0.48	0.94	0.22
Sharpe ratio	0.15	0.09	0.12	0.33	0.07
CER with $\gamma = 1$	5.09	1.76	4.41	10.07	2.31
CER with $\gamma = 3$	3.38	0.36	2.85	7.93	2.20
Anomalies with in-sample t≥1.96 & post-publication return decrease ≥30% N=31(48%)					
Return	0.59	0.16	0.55	1.52	0.28
Sharpe ratio	0.19	0.09	0.19	0.34	0.09
CER with $\gamma = 1$	6.40	1.76	5.84	16.75	3.20
CER with $\gamma = 3$	4.92	0.36	3.93	13.88	3.10
Anomalies with in-sample t≥1.96 & post-publication return decrease ≥50% N=19(30%)					
Return	0.55	0.16	0.51	1.01	0.25
Sharpe ratio	0.21	0.09	0.21	0.34	0.09
CER with $\gamma = 1$	6.06	1.76	5.98	11.43	2.89
CER with $\gamma = 3$	5.01	1.05	5.33	10.06	2.84

Table 3.1: Summary Statistics (Continued)

Panel B: Anomalies with returns drop after sample period end					
	Mean	Min	Median	Max	Stddev
Anomalies with in-sample t≥1.65 & out-of-sample t≤1.65 N=16(25%)					
Return	0.40	0.13	0.40	0.74	0.18
Sharpe ratio	0.12	0.07	0.11	0.32	0.06
CER with $\gamma = 1$	3.93	1.36	3.74	8.58	1.88
CER with $\gamma = 3$	2.30	0.36	1.94	7.93	1.76
Anomalies with in-sample t≥1.96 & out-of-sample t≤1.96 N=16(25%)					
Return	0.43	0.16	0.42	0.74	0.17
Sharpe ratio	0.13	0.09	0.11	0.32	0.06
CER with $\gamma = 1$	4.28	1.76	3.91	8.58	1.72
CER with $\gamma = 3$	2.55	0.36	2.19	7.93	1.72
Anomalies with in-sample t≥1.96 & out-of-sample return decrease ≥30% N=23(36%)					
Return	0.55	0.16	0.51	1.52	0.30
Sharpe ratio	0.20	0.09	0.17	0.34	0.09
CER with $\gamma = 1$	6.01	1.76	5.79	16.75	3.41
CER with $\gamma = 3$	4.74	0.36	3.56	13.88	3.34
Anomalies with in-sample t≥1.96 & out-of-sample return decrease ≥50% N=16(25%)					
Return	0.49	0.16	0.49	0.91	0.20
Sharpe ratio	0.18	0.09	0.14	0.33	0.09
CER with $\gamma = 1$	5.23	1.76	4.63	10.42	2.33
CER with $\gamma = 3$	3.87	0.36	3.19	9.38	2.61

Table 3.2: Sharpe Ratios for Strategies

This table reports Sharpe ratios for different strategies based on 1/N rule, the Markowitz (ML) rule, the Kan and Zhou (KZ) rule, the two Tu and Zhou (2011) combined (CML, CKZ) rules and the momentum (MOM) rule. All strategies are constructed based on all available anomalies through June 2018. All rules are based on two estimation windows of length T=120 and 240 months, respectively. The risk aversion coefficients γ are 1 and 3, respectively. Panel A reports Sharpe ratios of strategies based on anomalies with returns drop after publication. Panel B reports for strategies based on anomalies with returns drop after sample period end in the original paper. Within each panel, we select anomalies that have significant in-sample returns, and such returns drop significantly after publication or sample period end based on different criterion.

Panel A: Anomalies with returns drop after publication

	T=120,$\gamma = 1$	T=120,$\gamma = 3$	T=240,$\gamma = 1$	T=240,$\gamma = 3$
Anomalies with in-sample t≥1.65 & post-publication t≤1.65				
1/N	0.3792	0.3792	0.3288	0.3288
CML	0.6734	0.6737	0.7364	0.7365
CKZ	0.6688	0.6697	0.7387	0.7389
ML	0.6796	0.6796	0.743	0.743
KZ	0.6782	0.6782	0.7448	0.7448
MOM	0.2048	0.2048	0.2145	0.2145
Anomalies with in-sample t≥1.96 & post-publication t≤1.96				
1/N	0.4368	0.4368	0.3863	0.3863
CML	0.7354	0.736	0.8184	0.8187
CKZ	0.7279	0.7291	0.8163	0.8166
ML	0.7401	0.7401	0.8236	0.8236
KZ	0.7373	0.7373	0.8221	0.8221
MOM	0.1934	0.1934	0.1996	0.1996
Anomalies with in-sample t≥1.96 & post-publication return down ≥30%				
1/N	0.6222	0.6222	0.6104	0.6104
CML	0.8619	0.8624	0.888	0.8884
CKZ	0.8587	0.8599	0.8882	0.8886
ML	0.858	0.858	0.8895	0.8895
KZ	0.8656	0.8656	0.8917	0.8917
MOM	0.2103	0.2103	0.1971	0.1971
Anomalies with in-sample t≥1.96 & post-publication return down ≥50%				
1/N	0.5826	0.5826	0.5768	0.5768
CML	0.5861	0.5867	0.6201	0.6203
CKZ	0.592	0.5933	0.6213	0.6215
ML	0.5932	0.5932	0.628	0.628
KZ	0.6044	0.6044	0.6293	0.6293
MOM	0.2098	0.2098	0.2003	0.2003

Table 3.2: Sharpe Ratio for Strategies (Continued)

Panel B: Anomalies with returns drop after sample period end				
	T=120,$\gamma = 1$	T=120,$\gamma = 3$	T=240,$\gamma = 1$	T=240,$\gamma = 3$
Anomalies with in-sample t≥1.65 & out-of-sample t≤1.65				
1/N	0.2704	0.2704	0.2253	0.2253
CML	0.5882	0.5883	0.7213	0.7212
CKZ	0.5822	0.5827	0.729	0.7289
ML	0.6002	0.6002	0.7297	0.7297
KZ	0.5954	0.5954	0.7382	0.7382
MOM	0.2153	0.2153	0.2388	0.2388
Anomalies with in-sample t≥1.96 & out-of-sample t≤1.96				
1/N	0.2824	0.2824	0.2324	0.2324
CML	0.5992	0.5992	0.6978	0.6981
CKZ	0.5965	0.5971	0.7053	0.7057
ML	0.6127	0.6127	0.7034	0.7034
KZ	0.6113	0.6113	0.7113	0.7113
MOM	0.2182	0.2182	0.234	0.234
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥30%				
1/N	0.7094	0.7094	0.7618	0.7618
CML	0.8886	0.8889	0.9989	0.9993
CKZ	0.8892	0.8898	1.0015	1.0019
ML	0.8836	0.8836	0.9982	0.9982
KZ	0.8943	0.8943	1.0037	1.0037
MOM	0.1913	0.1913	0.1733	0.1733
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥50%				
1/N	0.5258	0.5258	0.5805	0.5805
CML	0.6112	0.6115	0.7161	0.7164
CKZ	0.6161	0.6169	0.7155	0.7159
ML	0.619	0.619	0.7246	0.7246
KZ	0.628	0.628	0.7246	0.7246
MOM	0.1775	0.1775	0.1901	0.1901

Table 3.3: Certainty-Equivalent Returns for Strategies

This table reports certain equivalent returns for different strategies based on 1/N rule, the Markowitz (ML) rule, the Kan and Zhou (KZ) rule, the two Tu and Zhou (2011) combined (CML, CKZ) rules and the momentum (MOM) rule. All strategies are constructed based on all available anomalies through June 2018. All rules are based on two estimation windows of length T=120 and 240 months, respectively. The risk aversion coefficients γ are 1 and 3, respectively. Panel A reports certain-equivalent returns of strategies based on anomalies with returns drop after publication. Panel B reports for strategies based on anomalies with returns drop after sample period end in the original paper. Within each panel, we select anomalies that have significant in-sample returns, and such returns drop significantly after publication or sample period end based on different criterion.

Panel A: Anomalies with returns drop after publication

	T=120,$\gamma = 1$	T=120,$\gamma = 3$	T=240,$\gamma = 1$	T=240,$\gamma = 3$
Anomalies with in-sample t≥1.65 & post-publication t≤1.65				
1/N	5.78	5.58	5.55	5.3
CML	163.76	55.05	257.33	86.12
CKZ	251.79	84.27	304.95	101.84
ML	-447.43	-149.14	119.81	39.94
KZ	161.81	53.94	268.73	89.58
MOM	17.95	7.08	20.16	7.41
Anomalies with in-sample t≥1.96 & post-publication t≤1.96				
1/N	6.57	6.37	5.99	5.78
CML	191.72	64.67	320.56	107.3
CKZ	297.37	99.65	371.95	124.26
ML	-612.82	-204.27	138.48	46.16
KZ	184.64	61.55	325.62	108.54
MOM	18.47	3.42	20.12	2.78
Anomalies with in-sample t≥1.96 & post-publication return down ≥30%				
1/N	8.26	8.11	8.03	7.88
CML	83.63	28.99	55.27	19.42
CKZ	395.37	132.42	282.82	94.91
ML	-2893.23	-964.41	-774.35	-258.12
KZ	82.34	27.45	60.39	20.13
MOM	20.62	5.84	19.71	2.52
Anomalies with in-sample t≥1.96 & post-publication return down ≥50%				
1/N	8.19	8.02	8.42	8.24
CML	20.82	7.96	126.25	42.6
CKZ	163.45	55.11	185.16	62.04
ML	-657.21	-219.07	-22.58	-7.53
KZ	44.99	15	139.05	46.35
MOM	15.74	8.72	16.29	7.32

Table 3.3: Certain-Equivalent Returns for Strategies (Continued)

Panel B: Anomalies with returns drop after sample period end				
	T=120,$\gamma = 1$	T=120,$\gamma = 3$	T=240,$\gamma = 1$	T=240,$\gamma = 3$
Anomalies with in-sample t≥1.65 & post-publication t≤1.65				
1/N	5.52	5.15	5.29	4.79
CML	84.42	28.42	306.17	102.1
CKZ	162.58	54.44	318.83	106.22
ML	-274.06	-91.35	279.63	93.21
KZ	86.26	28.75	323.65	107.88
MOM	18.32	8.71	22.3	10.8
Anomalies with in-sample t≥1.96 & out-of-sample t≤1.96				
1/N	6.14	5.72	5.65	5.11
CML	111.46	37.48	268.99	90
CKZ	185.98	62.27	295.12	98.55
ML	-240.47	-80.16	209.06	69.69
KZ	120.9	40.3	284.79	94.93
MOM	18.85	8.93	22.01	10.12
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥30%				
1/N	8.95	8.82	9.49	9.36
CML	161.32	54.5	442.76	148.16
CKZ	402.54	134.61	537.8	179.66
ML	-1339.69	-446.56	127.78	42.59
KZ	164.54	54.85	449.42	149.81
MOM	17.17	4.71	16.11	-0.31
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥50%				
1/N	8.02	7.82	9.11	8.9
CML	16.16	6.12	259.22	86.79
CKZ	156.17	52.57	288.74	96.51
ML	-523.54	-174.51	182.84	60.95
KZ	40.76	13.59	269.28	89.76
MOM	14.37	4.52	17.09	4.45

Table 3.4: Comparison for Sharpe Ratios

This table compares Sharpe ratio of strategies in three scenarios according to the publication year or sample period end of anomalies. The strategies include 1/N rule, the Markowitz (ML) rule, the Kan and Zhou (KZ) rule, the two Tu and Zhou (2011) combined (CML, CKZ) rules and the momentum (MOM) rule. There are three scenarios considered in panel A. The first scenario (full) is to construct rules based on all available anomalies through June 2018. In the second scenario (drop after publication), we remove out anomalies from our anomaly portfolio once those anomalies are published. In the third scenario (drop at [pub+1, pub+5]), we remove anomalies in the 5 years following those anomalies publication and add back anomalies into our anomaly portfolio after 5 years. In panel B, the publication year is changed to sample period end year. We report p-value of the difference between Sharpe Ratio in the last two scenarios from the first scenario in parentheses. All strategies are based on estimation window T=240, and risk aversion coefficient γ=1.

Panel A: Anomalies with returns drop after publication					
	full	Drop after publication		Drop at [pub+1, pub+5]	
	SR	SR	p-value	SR	p-value
Anomalies with in-sample t≥1.65 & post-publication t≤1.65					
1/N	0.3288	0.3722	(0.55)	0.3147	(0.52)
CML	0.7364	0.6457	(0.01)	0.7145	(0.4)
CKZ	0.7387	0.6482	(0)	0.7122	(0.29)
ML	0.743	0.6541	(0.01)	0.7215	(0.41)
KZ	0.7448	0.6555	(0.01)	0.7182	(0.29)
MOM	0.2145	0.2532	(0.32)	0.2047	(0.31)
Anomalies with in-sample t≥1.96 & post-publication t≤1.96					
1/N	0.3863	0.3415	(0.54)	0.3517	(0.22)
CML	0.8184	0.5916	(0)	0.7606	(0.01)
CKZ	0.8163	0.5894	(0)	0.755	(0.01)
ML	0.8236	0.6022	(0)	0.7684	(0.02)
KZ	0.8221	0.5978	(0)	0.7623	(0.01)
MOM	0.1996	0.1977	(0.94)	0.1871	(0.2)
Anomalies with in-sample t≥1.96 & post-publication return down ≥30%					
1/N	0.6104	0.45	(0.02)	0.6223	(0.61)
CML	0.888	0.6328	(0)	0.8279	(0.03)
CKZ	0.8882	0.6315	(0)	0.8191	(0.01)
ML	0.8895	0.6416	(0)	0.8384	(0.08)
KZ	0.8917	0.6379	(0)	0.8296	(0.03)
MOM	0.1971	0.221	(0.5)	0.1751	(0.03)
Anomalies with in-sample t≥1.96 & post-publication return down ≥50%					
1/N	0.5768	0.5765	(1)	0.6553	(0)
CML	0.6201	0.5573	(0)	0.5768	(0.02)
CKZ	0.6213	0.5528	(0)	0.5727	(0.01)
ML	0.628	0.5686	(0)	0.5866	(0.03)
KZ	0.6293	0.5625	(0)	0.5815	(0.01)
MOM	0.2003	0.1953	(0.87)	0.1993	(0.92)

Table 3.4: Comparison for Sharpe Ratios (Continued)

Panel B: Anomalies with returns drop after sample period end					
	full	Drop at out-of-sample period		Drop at [oos+1, oos+5]	
	SR	SR	p-value	SR	p-value
Anomalies with in-sample t≥1.65 & out-of-sample t≤1.65					
1/N	0.2253	0.359	(0.08)	0.2032	(0.2)
CML	0.7213	0.6027	(0.02)	0.6607	(0.12)
CKZ	0.729	0.5945	(0.01)	0.6531	(0.03)
ML	0.7297	0.6146	(0.03)	0.6752	(0.17)
KZ	0.7382	0.6055	(0.01)	0.6664	(0.04)
MOM	0.2388	0.1849	(0.02)	0.2253	(0.25)
Anomalies with in-sample t≥1.96 & out-of-sample t≤1.96					
1/N	0.2324	0.2591	(0.69)	0.2043	(0.11)
CML	0.6978	0.583	(0.01)	0.6156	(0.01)
CKZ	0.7053	0.5848	(0)	0.6155	(0)
ML	0.7034	0.5907	(0.01)	0.6238	(0.01)
KZ	0.7113	0.5924	(0.01)	0.6235	(0)
MOM	0.234	0.1799	(0.02)	0.2196	(0.27)
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥30%					
1/N	0.7618	0.732	(0.73)	0.6959	(0.09)
CML	0.9989	0.7683	(0.03)	0.8466	(0)
CKZ	1.0015	0.7698	(0.03)	0.8414	(0)
ML	0.9982	0.7824	(0.04)	0.8565	(0)
KZ	1.0037	0.7815	(0.03)	0.8518	(0)
MOM	0.1733	0.2145	(0.53)	0.1553	(0.07)
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥50%					
1/N	0.5805	0.5066	(0.4)	0.5462	(0.15)
CML	0.7161	0.6183	(0.02)	0.6927	(0.21)
CKZ	0.7155	0.6123	(0.01)	0.693	(0.23)
ML	0.7246	0.6317	(0.03)	0.7022	(0.24)
KZ	0.7246	0.6247	(0.02)	0.7034	(0.26)
MOM	0.1901	0.2742	(0.18)	0.1648	(0.03)

Table 3.5: Comparison for Certainty-Equivalent Returns

This table compares certain-equivalent returns of strategies in three scenarios according to the publication year or sample period end of anomalies. The strategies include 1/N rule, the Markowitz (ML) rule, the Kan and Zhou (KZ) rule, the two Tu and Zhou (2011) combined (CML, CKZ) rules and the momentum (MOM) rule. There are three scenarios considered in panel A. The first scenario (full) is to construct rules based on all available anomalies through June 2018. In the second scenario (drop after publication), we remove out anomalies from our anomaly portfolio once those anomalies are published. In the third scenario (drop at [pub+1, pub+5]), we remove anomalies in the 5 years following those anomalies publication and add back anomalies into our anomaly portfolio after 5 years. In panel B, the publication year is changed to sample period end year. All strategies are based on estimation window T=240, and risk aversion coefficient γ=1.

Panel A: Anomalies with returns drop after publication			
	full	Drop after publication	Drop at [pub+1, pub+5]
Anomalies with in-sample t≥1.65 & post-publication t≤1.65			
1/N	5.55	6.63	5.73
CML	257.33	141.56	241.2
CKZ	304.95	195.07	280.05
ML	119.81	34.73	130.39
KZ	268.73	157.72	248.27
MOM	20.16	18.19	18.35
Anomalies with in-sample t≥1.96 & post-publication t≤1.96			
1/N	5.99	6.37	6.18
CML	320.56	60.11	242.46
CKZ	371.95	121	293.95
ML	138.48	-71.59	79.9
KZ	325.62	70.79	245.27
MOM	20.12	17.63	17.89
Anomalies with in-sample t≥1.96 & post-publication return down ≥30%			
1/N	8.03	7.99	8.34
CML	55.27	46.06	12.69
CKZ	282.82	144.41	186.68
ML	-774.35	-226.93	-577.31
KZ	60.39	54.4	13.56
MOM	19.71	16.94	16.32
Anomalies with in-sample t≥1.96 & post-publication return down ≥50%			
1/N	8.42	9.13	9.07
CML	126.25	33.1	74.38
CKZ	185.16	88.17	128.88
ML	-22.58	-96.86	-63.01
KZ	139.05	37.59	80.04
MOM	16.29	12.15	15.91

Table 3.5: Comparison for Certainty-Equivalent Returns (Continued)

Panel B: Anomalies with returns drop after sample period end

	full	Drop at out-of-sample period	Drop at [oos+1, oos+5]
Anomalies with in-sample t≥1.65 & out-of-sample t≤1.65			
1/N	5.29	5.73	5.44
CML	306.17	200.06	247.16
CKZ	318.83	203.12	252.5
ML	279.63	186.53	223.6
KZ	323.65	202.18	253.07
MOM	22.3	15.63	20.57
Anomalies with in-sample t≥1.96 & out-of-sample t≤1.96			
1/N	5.65	5.45	5.68
CML	268.99	152.57	173.11
CKZ	295.12	177.86	204.07
ML	209.06	108.95	101.27
KZ	284.79	162.93	182.13
MOM	22.01	15.31	20.23
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥30%			
1/N	9.49	10.39	9.54
CML	442.76	302	160.13
CKZ	537.8	335.46	261.66
ML	127.78	235.12	-136.25
KZ	449.42	320.18	164.84
MOM	16.11	13.78	13.64
Anomalies with in-sample t≥1.96 & out-of-sample return down ≥50%			
1/N	9.11	11.36	10.07
CML	259.22	208.67	231.42
CKZ	288.74	215.48	264.25
ML	182.84	192.57	160.21
KZ	269.28	214.79	246.03
MOM	17.09	14.04	14.09