Risk-scaled anomalies*

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Abstract

Existing studies imply that risk-managed portfolios lead to improved performance. Using a comprehensive set of 125 anomaly portfolios, I analyze the effectiveness of risk management. Risk-managed portfolio returns are 43% lower in pre-sample and 61% lower in post-sample consistent with the puzzle in the cross-sectional literature. Managed portfolios do not outperform their corresponding original counterparts in direct comparisons of Sharpe ratios. Portfolios whose profile exhibits the crash risk (a very long left tail) benefit most from risk management and produce higher Sharpe ratios. In the spanning regressions, risk-scaled portfolios tend to exhibit positive and significant alphas inside of the momentum group, whereas other categories show mixed evidence. My findings suggest that the benefit of risk management is isolated to strategies that have negative skewness and high kurtosis, eliminating the crash risk.

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JEL Code: G10, G11

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1 Introduction

Prior studies explore trading strategies called risk-managed portfolios, which exploit patterns in returns, by dynamically varying portfolios in a manner that utilizes leverage inversely with risk. This methodology produces significant abnormal returns and large increases in investor utility.[1] The justification underlying the performance of risk-managed portfolios is the absence of a strong risk-return tradeoff for factor returns, which means that during times of high volatility, positions can be scaled back without a commensurate reduction in returns. Following periods of low-realized volatility, managing risk in the aforementioned paradigm is equivalent to increasing leverage in factor portfolios. Volatility is predictable while the respective time-series risk-return trade-off remains elusive, a stylized fact that this counterintuitive approach exploits.[2] The success of these strategies raises questions about the most fundamental relation in finance, the relation between risk and return.

Existing studies, such as those by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), imply that risk-managed portfolios routinely lead to improved performance. Therein, the authors demonstrate that risk-managed momentum strategies virtually eliminate momentum crashes and nearly double the Sharpe ratio of the original momentum strategy. Furthermore, Moreira and Muir (2017) show that risk-managed portfolios produce larger alphas, higher Sharpe ratios, and larger utility gains for investors relative to

[1]See, for example, Fleming et al. (2001, 2003), Marquering and Verbeek (2004), Kirby and Ostdiek (2012), Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), Moreira and Muir (2017, 2019), Barroso et al. (2017), Cederburg et al. (2020), Eisdorfer and Misirli (2020), and Barroso and Detzel (2021).

[2]Prior studies provide evidence that the risk-return trade-off for the market factor is unstable. If this is the case, past data for a given factor are less likely to be informative about the future potential for risk management. See, for example, French, Schwert and Stambaugh (1987), Harvey (2001), Glosten, Jagannathan and Runkle (1993), and Brandt and Kang (2004), Ludvigson and Ng (2007), and Lettau and Ludvigson (2010).

the original portfolio. However, the effectiveness of risk management across factors is not straightforward, as suggested by Cederburg et al. (2020), who show that utility gains from risk management may not be achievable out of sample. Additional criticism about the benefits of risk management are provided by Barroso and Detzel (2021), who report transaction costs may entirely erode the gains from volatility management.

In this article, I analyze the value of risk-managed portfolios, and in particular, whether managed portfolios produce large alphas, and therefore increase the Sharpe ratios. For a broader assessment of the benefits of risk management, I consider well-known puzzles in cross-sectional literature, a strand of literature that investigates whether anomaly portfolios were attenuated or disappeared entirely, prior to 1960 or after 1990. With respect to *post-sample decay*, McLean and Pontiff (2016) find that anomaly portfolio returns are 26% lower out-of-sample, and 58% lower post-publication, given the average return of 97 trading strategies. With regard to *pre-sample decay*, Linnainmaa and Roberts (2018) report that of the 36 strategies that they study, 20 strategies generate insignificant alphas in the prediscovery period going back to 1926. One of the questions that this paper investigates is whether risk-managed portfolios are stable without being affected by both pre- and post-sample decay. If risk-managed versions of popular trading strategies exhibit impressive performance relative to the original portfolio, then managed portfolios are more likely to produce large alphas regardless of the pre-sample and post-sample degradation. In contrast, if they are affected by the puzzles (i.e., pre- and post-sample decay) akin to the original portfolios, then the potential of risk management is questionable.

To answer this question, I test a comprehensive set of 125 anomaly portfolios that are based on pricing factors in different settings: pre-sample, in-sample, and post-sample. I contribute to the literature in three primary ways. First and foremost, I find that after scaling risk, managed portfolio returns are 43% lower pre-sample and 61% lower post-sample, which is consistent with the puzzle in the cross-sectional literature. Second, I confirm that Cederburg et al.'s (2020) finding of risk-managed portfolios do not systematically outperform their corresponding unscaled portfolios. I assess the value of risk management by directly comparing the Sharpe ratios earned by scaled strategies with the original Sharpe ratios earned by the corresponding unmanaged strategies. Managed portfolios do not outperform their corresponding original portfolios in terms of the Sharpe ratio, which means that they are unlikely to obtain gains from volatility management. Consistent with Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), only portfolios related to the momentum strategy increase Sharpe ratios after scaling risk. Third, in the spanning regressions, risk-managed portfolios tend to exhibit positive but insignificant alphas in most cases. This implies that risk-managed portfolios do not expand the mean-variance frontier relative to the original factor. Overall, my findings suggest that the benefit of risk management is isolated to momentum strategies and does not necessarily lead to improved performances.

Following Barroso and Santa-Clara (2015), my baseline formulation of risk-managed portfolios is defined as follows. I use the realized volatility $\hat{\sigma}_{i,t}=\sqrt{RV_{i,t}}$ to scale the monthly factor returns. I simply scale the long-short anomaly portfolio return by its realized volatility in the previous six months in order to achieve a given σ_{target}:

$$r_{i,t}^{\sigma} = \frac{\sigma_{target}}{\hat{\sigma}_{i,t}} \times r_{i,t}, \tag{1}$$

where $r_{i,t}$ is the anomaly i's value weighted original long-short portfolio return in month t; $r_{i,t}^{\sigma}$ is the corresponding risk-scaled portfolios return, and σ_{target} is a constant and represents the target level of volatility. Scaling risk corresponds to imposing a weight on the long and shorts legs that is different from one and varies over time. As in Barroso and Santa-Clara (2015), I pick a target corresponding to an annualized volatility of 12% (σ_{target}). I call $r_{i,t}^{\sigma}$ risk-managed, volatility-managed, or just scaled portfolios. These portfolios simply assign a weight in a return that is proportional to the inverse of its realized volatility in the previous six months. In other words, risk-managed portfolios reduce risk-taking when volatility was recently high and vice versa.

The benefit of risk management is isolated to strategies that have negative skewness and high kurtosis. After risk management, momentum-based strategies have a higher average return, with a gain of 31 bps per month and substantially less standard deviation (less 18.60 percentage points per year). The Sharpe ratio improves from 0.65 to 0.96 after managing risks. Outside of the momentum group, the evidence is not straightforward. The average monthly return of trading frictions strategies drops from 0.50 bps to 0.48. Ironically, risk management increases the standard deviation of investment-based strategies from 2.12 to 3.07. The improvement in the higher-order moments after scaling risks is remarkable. Risk management plays a role in reducing a negative skewness, which results in less risk in large negative realizations and less tail risk (Kelly and Jiang; 2014; Bollerslev, Todorov and Xu; 2015). Managing the risk of momentum-related portfolios achieves a less pronounced left skewness from -3.54 to -1.23. In contrast, the evidence for other categories is mixed. At the same time, a high value of kurtosis is much reduced across all categories after risk management. For example, the kurtosis of the momentum group drops from 44.64 to 15.21. This essentially eliminates the crash risk of the portfolio strategies. Furthermore, negative extreme returns can be avoided. The minimum one-month return becomes much lower: -88.70% for original momentum and -47.64% for risk-managed momentum. Overall, the benefits of risk management are concentrated among momentum-based strategies whose profiles exhibit crash risk (i.e., a very long left tail).

Prior work (e.g, Barroso and Santa-Clara; 2015; Daniel and Moskowitz; 2016; Moreira and Muir; 2017; Cederburg et al.; 2020; Eisdorfer and Misirli; 2020; Barroso and Detzel; 2021) assesses the value of risk management by directly comparing the Sharpe ratios earned by scaled strategies similar to those in equation 1 with the Sharpe ratios earned by the corresponding unscaled strategies. Following this approach, the results suggest that risk management improves performance for most of the momentum strategies, whereas other managed portfolios do not benefit. Outside of the momentum group, 74 cases out of the 111 managed portfolios over the full sample earn a higher Sharpe ratio than the original strategy does, whereas the original portfolio outperforms in the remaining 37 cases. 26 of the 111 differences are significantly positive as the risk-managed versions achieve Sharpe ratio gains by outperforming the original portfolios. About half of the 111 managed portfolios have lower

Sharpe ratios than their unmanaged counterparts both in post-sample and post-1993 periods, while most cases are statistically insignificant. Overall, scaling risk yields no performance improvements in some cases and even significantly reduces Sharpe ratios.

Inside of the momentum group, the managed momentum strategies exhibit statistically significant outperformance relative to the original portfolios. Over the full sample, all managed momentum strategies achieve significant Sharpe ratio improvements. The subsample results generally resemble the full sample results: most of the managed momentum strategies have positive and significant alphas. Overall, the benefits of risk management are isolated to momentum strategies, making it difficult to draw broad conclusions. These findings are consistent with the impressive performance of risk-managed momentum portfolios demonstrated by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). I complement this result by showing that the improved performance of risk-managed momentum can be applied to several alternative definitions of the momentum strategy itself.

Finally, I revisit Moreira and Muir's (2017) spanning regression tests to offer a broader assessment of the merits of risk management. I run a time-series regression of the risk-managed portfolios on the original factor portfolios,

$$r_{i,t}^{\sigma} = \alpha + \beta r_{i,t} + \epsilon_t, \tag{2}$$

where $r_{i,t}^{\sigma}$ ($r_{i,t}$) is the monthly return for the risk-managed (original) factor. A positive intercept implies that risk management produces higher alphas and thereby increases Sharpe ratios relative to the original factor portfolios.

With respect to momentum strategies, the evidence provides strong empirical support for the benefits of scaled momentum strategies. Almost all of the estimates earn positive alphas in univariate spanning regressions across different kinds of subsamples. Furthermore, the bulk of positive estimates are statistically significant at the 5% level in most cases. However, apart from the momentum category, the evidence is not straightforward. Across 111 managed portfolios in the full sample period, 91 cases earn positive alphas in univariate spanning tests while 42 estimates are statistically significant at the 5% level. In the post sample period, 64 out of the 111 risk-scaled portfolios earn positive alphas in spanning tests, with 16 significantly positive estimates compared to 4 significantly negative ones. The general conclusions are robust when the three Fama and French (1993) factors are included in the spanning regressions as additional controls. My broad-based findings suggest a more tempered interpretation of the potential economic gains from risk management relative to prior studies.

Perhaps the study most closely related to this paper is that of Cederburg et al. (2020), who examine a comprehensive set of 103 equity strategies. Their study shows that volatility-management generates statistically significant Sharpe ratio improvements for only eight out of 103 strategies. Consistent with their findings, my evidence confirms that the trading strategies related to momentum strategies largely benefit from scaling risk. A key difference between my study and theirs is that I assess the potential of risk management with respect to important phenomena in the cross-sectional literature: pre- and post-sample decay. My evidence indicates that portfolio returns decline in pre- and post-sample periods even after managing the risks. Furthermore, after scaling portfolios' volatility, Sharpe ratios remain basically unchanged in most cases, and thereby I find no evidence to suggest there are benefits from risk management. This is supported by evidence in the spanning regressions that there are no positive, statistically significant intercepts in most cases. From a practical investment perspective, my results speak to the potential limitations of volatility-managed portfolios. My findings suggest that pre- and post-sample degradation are severe in risk-managed settings in addition to the original unmanaged portfolios. Furthermore, the benefits from risk management are concentrated among strategies whose profiles represent crash risk (i.e., a very long left tail).

The remainder of the paper is organized as follows. Section 2 describes the data and formulation of risk-managed portfolios. Section 3 compares risk-managed and original portfolios regarding alphas and the Sharpe ratio in various settings. Section 4 contains spanning regression tests. The Appendix presents additional detail on pricing factors, and the Internet Appendix reports supplementary results.

2 Data and methodology

2.1 Asset Pricing Factors

Appendix A lists asset pricing factors and anomalies used in this study, totalling 125 portfolios. All stocks listed on NYSE, NASDAQ, and AMEX markets with a share code of 10 or 11 are considered and the individual stock returns are obtained from CRSP. Following

Fama and French (1993), I assume that accounting data are available six months after the end of the fiscal year. My 125 previously-identified anomaly portfolios are subset of 205 factors documented in Chen and Zimmermann (2020).[3] These set of portfolios rely on the extensive empirical asset pricing literature and overlap McLean and Pontiff (2016), Harvey, Liu and Zhu (2016), Green, Hand and Zhang (2017), and Hou, Xue and Zhang (2020). Each anomaly portfolio is based on a firm-specific variable (characteristic), for example, the size and book-to-market ratio. Then, all the stocks traded on U.S. market are sorted into five quintile portfolios based on the corresponding firm-specific characteristic. Return associated with anomaly is long-short portfolios that buy the highest quintile and sell the lowest quintile portfolio. As noted by Fama and French (2008), the issue from microcaps (stocks with market cap below the 20^{th} NYSE percentile) can be influential when using equal-weighted hedge portfolio returns. Thus, I employ the value-weighted zero cost portfolios and this allows me to circumvent the issues from microcaps.

2.2 Portfolio Formation

Following Barroso and Santa-Clara (2015), my baseline formulation of volatility-managed portfolios is defined as follows. First, I compute the realized variance RV_t from daily returns in the previous six months (126 trading days).[4] Let $\{r_{i,t}\}_{t=1}^{T}$ be the monthly returns of anomaly i and $\{r_{i,d}\}_{d=1}^{D}$, $\{d_t\}_{t=1}^{T}$ be the daily returns and the time series of the dates of the last trading sessions of each month. Then the realized variance of factor i in month t is the

[3] I am grateful to the authors for making the data available.

[4] Using one-month $\left(\sum_{j=0}^{20} r_{i,d_{t-1}-j}^2\right)$ or three-month $\left(\frac{\sum_{j=0}^{62} r_{i,d_{t-1}-j}^2}{3}\right)$ realized variances, produces similar results.

summation of the squared daily returns

$$\hat{\sigma}^2_{i,t} = RV_{i,t} = \frac{\sum_{j=0}^{125} r^2_{i,d_{t-1}-j}}{6}. \tag{3}$$

Next, I use the realized volatility $\hat{\sigma}_{i,t} = \sqrt{RV_{i,t}}$ to scale the monthly factor returns.[5] I simply scale the long-short portfolio return by its realized volatility in the previous six months in order to achieve a given σ_{target}:

$$r^{\sigma}_{i,t} = \frac{\sigma_{target}}{\hat{\sigma}_{i,t}} \times r_{i,t}, \tag{4}$$

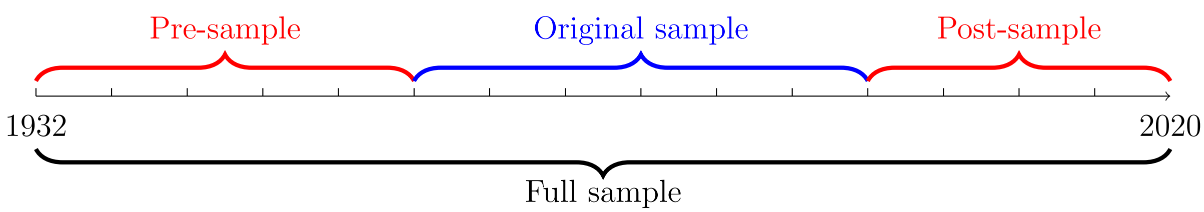
where $r_{i,t}$ represents the original (unscaled) excess return for a long-short portfolio for a given anomaly i in month t; $r^{\sigma}_{i,t}$ is the corresponding risk-managed portfolio return after risk scaling, and σ_{target} is a constant and represents the target level of volatility. Scaling portfolios corresponds to imposing a weight on the long and shorts legs that is different from one and varies over time. As in Barroso and Santa-Clara (2015), I pick a target corresponding to an annualized volatility of $\sigma_{target} = 12\%$.[6] I call $r^{\sigma}_{i,t}$ risk-managed, volatility-managed, or just scaled portfolios. These portfolios simply assign a weight in a return that is proportional to the inverse of its realized volatility in the previous six months. In other words, each portfolio is scaled by that portfolio's past realized volatility.

[5]An alternative way to implement volatility scaling is proposed in Moreira and Muir (2017). They propose scaling by the inverse of realized variance. I use realized volatility as in Barroso and Santa-Clara (2015), as it is less prone to spikes.

[6]The choice of volatility target is arbitrary but influences directly the maximum, minimum, mean, and the standard deviation of returns. However, this choice does not affect scale-invariant measures of portfolio performance, such as the Sharpe ratio, skewness, and excess kurtosis.

2.3 Original versus risk-managed portfolio

I independently investigate 125 risk-managed and unmanaged portfolios that are constructed based on well-known anomalies using a long sample of 90 years of monthly returns from January 1932 to December 2020 (see Appendix A for a description of the anomalies). I segment periods based on both the start-of-sample and end-of-sample date.



Pre-sample denotes the sample frame spanning from 1932 prior to the in-sample period (e.g., 1932 to 1963).[7] *In-sample* denotes the sample frame used in the original discovery of an anomaly (e.g., 1964 to 1992). *Post-sample* denotes the sample frame occurring after the in-sample period (e.g., 1993 to 2020). Though the start and end dates for each period vary by anomaly, each portfolio I study spans these three eras.

Panel A of Table 1 describes the summary statistics of the risk-managed and original versions of 125 anomaly factors in different subsamples. For the 125 risk-scaled portfolios, the average monthly in-sample return is 0.804%. The average monthly post-sample return is 0.340%, whereas the average pre-sample return is 0.449%. In all cases, risk-managed portfolio has a higher average return with less standard deviation relative to the original portfolio. In all samples, volatility management improves the anomaly portfolio's Sharpe ratio. The

[7] To perform the pre-sample analysis, I exclude a couple of well-known anomalies. For example, Banz (1981) discovers a size effect by using the sample period from 1926 to 1975, which published in 1981. In this case, in-sample period for size is from 1926 to 1975. Given CRSP data starts from 1926, I exclude size anomaly.

Sharpe ratio improves from 0.49 to 0.57 in the full sample and from 0.74 to 0.80 in the in sample. The last column in Panel A reports the p-values, which represent the differences in means between original and risk-managed portfolio. With the except post-sample case, the p-values are around zero, implying that risk-managed portfolios exhibit greater mean returns, which is statistically significant.

Panel B of Table 1 provides the number of the alphas that surpass the hurdle of $|t| \geq 1.96$ and $|t| \geq 3$ in the univariate anomaly regression. Taking a suggestion from Harvey et al. (2016) into account, I report a test statistic cutoff of 3.00 in addition to the conventional 1.96 for a two-sided test at the 5% level. The pre-sample results provide, 53 (61) out of the 125 original (risk-managed) portfolios earn average returns that are positive and statistically significant at the 5% level consistent with Linnainmaa and Roberts (2018). More importantly, this evidence implies that the performance difference between managed portfolios and original counterparts is negligible regardless of scaling risk. As would be anticipated, the results across in-sample periods confirm the stylized fact that anomalies are strong until they were discovered (i.e., original sample) both in original and managed factors. At the same time, the evidence in the post period is in parallel with McLean and Pontiff's (2016) finding that once the anomalies are discovered and then disappeared after publication. Put differently, less than half of the anomaly portfolios that earn statistically significant alphas in the in-sample period are weaker both economically and statistically. At the same time, there is no dramatic difference in the number of the significant alphas between original and risk-managed factors, which potentially implies volatility scaling is not effective for both pre- and post-sample decay.

Panel C of Table 1 projects the long-short portfolio returns onto the Fama and French (1993) three factors (market, size, and value). A statistically significant alpha infers that the left-hand side factor improves the asset pricing model (Barillas and Shanken; 2017). The patterns of evidence are indistinguishable from those found in Panel B. With regard to pre-sample and post-sample period, some factors who generate insignificant alphas in Panel B, now yield significant alphas after controlling for FF3 factors. For example, out of 125 portfolios, the numbers of significant anomalies that clear the cutoff of $|t| \geq 1.96$ are 60 (65) in original (risk-managed) portfolios. This is in contrast to the evidence in Panel B that 33 (47) original (risk-managed) strategies pass the threshold during the post-sample. This difference is unsurprising as in Jensen, Kelly and Pedersen (2021), who point out, "Some factors are insignificant in terms of raw return or CAPM alpha, but their alpha becomes significant after controlling for other factors." Overall, my evidence show, risk-managed portfolios work poorly in the pre-sample and post-sample consistent with the puzzles in the cross-sectional literature. In other words, there is the out-of-sample performance degradation even after scaling risk.

3 Main Results

3.1 Pre-sample and Post-sample decay

In this section I formally study the returns of original and managed portfolios relative to their pre- and post-sample periods. My baseline regression model is described in equation 5.

$$r_{i,t}^{\sigma}\ (r_{it}) = \alpha_i + \beta\ \textit{Pre Sample Dummy}_{i,t} + \varepsilon_{it}, \tag{5}$$

$$r_{i,t}^{\sigma}\ (r_{it}) = \alpha_i + \gamma\ \textit{Post Sample Dummy}_{i,t} + \varepsilon_{it}. \tag{6}$$

In equation 5, $r_{i,t}$ represents the original (unscaled) long short portfolio return for a given anomaly i in month t; $r_{i,t}^{\sigma}$ is the corresponding risk-scaled portfolio return after risk management. The pre-sample dummy is equal to one if month t falls in the time period before the start of the original sample, and zero otherwise, whereas the post-sample dummy is equal to one if month t is included in the time period after the end of the original sample and zero otherwise. The parameter α_i captures portfolio fixed effects, which by inclusion controls for time-invariant portfolio characteristics. With respect to time fixed effects, I absorb any time-varying shocks at the portfolio level. However, I exclude time fixed effects because risk-managed portfolio, by construction, has time-varying positions depending on realized volatility in the previous six months.

Table 2 presents regression estimates of how portfolio return changes pre-sample and post-sample. Panel A reports the results for my main specification, which estimates equation 5 on my full sample of 125 risk-managed portfolios spanning from January 1932 to

December 2020. Panel B describes the results for the original portfolio. In Column (1) of Panel A, the pre-sample coefficient is -0.357%, and statistically significant. Thus, my best estimate of the pre-sample decay is 35.7 bps. In Column (2), the post-sample coefficient is -0.507, and it is also statistically significant. Theses results show that, on average, risk-managed anomaly portfolio returns are 50.7 bps lower during out-of-sample periods compared to the sample period in the original study. Table 1 shows that the scaled portfolio has an in-sample mean return of 80.4 bps per month. Hence, pre-sample and post-sample returns decline relative to the original-sample mean by 43% (35.7/80.4) and 61% (50.7/80.4), respectively.

The evidence in column (1) and (2) of Panel B shows how original portfolio return changes before scaling risk. The pre-sample and post-sample coefficients are -0.309 and -0.394, respectively. Averaging the in-sample returns for the 125 original portfolios results in 0.676 (Table 1). Pre- and post-sample degradation in returns for the original counterparts, as compared to the in-sample mean return, are 45% and 58%, respectively. This is consistent with evidence in McLean and Pontiff (2016) and Linnainmaa and Roberts (2018). My findings suggest that pre- and post-sample decay are similar both in risk-managed and original portfolios.

The regression in the third and fourth column includes the portfolio fixed effects along with interaction term between the in-sample mean return of each portfolio and the pre- and post-sample dummy variables. The interactions test whether managed portfolio returns with higher in-sample means decline more in pre- or post-sample periods.

In column (3), the coefficient on the pre-sample dummy is -0.078, whereas the coefficient on the interaction between post-sample dummy and the in-sample means is -0.417. Given the average in-sample monthly return for the 125 risk-scaled portfolios is 0.804 in Table 1, so the overall pre-sample effect is -0.078 + $(-0.417 \times 0.804) = -0.413$, similar to the post-sample coefficient in column (1). In column (4), the coefficient on the post-sample dummy is -0.164, whereas the coefficient on the interaction between post-sample dummy and the in-sample means is -0.495. Given the average in-sample monthly return for the 125 risk-scaled portfolios is 0.804 in Table 1, so the overall post-sample effect is -0.164 + $(-0.495 \times 0.804) = -0.562$, similar to the post-sample coefficient in column (2). Overall, after scaling risk, managed portfolio is unlikely to exhibit better performance compared to the original portfolio.

In column (5), I investigate the possibility that my findings reflect a time effect. I construct a time variable that starts from 0.01 in January 1932 and increases by 1/100 each month, and ends 10.68 in December 2020. Column (5) of Panel A estimates a regression of risk-managed portfolio returns on the time variable with portfolio fixed effects. Managed portfolios have a negative slope coefficient, -0.019, on the time variable and statistically significant at the 10% level. This implies that portfolio returns decline over time. For the original portfolio in Panel B, the time variable produces a negative but insignificant slope coefficient.

In column (6), I estimate the effect of an indicator variable that is equal to one if the year is after 1993 and zero otherwise. Following Schwert (2003), I use the 1993 cutoff is the point with which delineate how anomalies are actively traded by arbitrageurs such as the quantitative equity hedge funds with the growth in the hedge fund industry. Furthermore, seminal works on cross-sectional anomalies emerge (e.g., Jegadeesh; 1990; Fama and French; 1993; Jegadeesh and Titman; 1993), which accelerates anomalies-based tradings such as size, value and momentum. In accordance with a kink in 1993, the post-1993 coefficient is -0.236, and it is statistically significant. As for the original portfolios, the post-1993 coefficient is negative significant though the magnitude is smaller than managed counterparts.

In column (7), I relate post-sample decay to a time trend and the post-1993 dummy variable. In Panel A, the time trend variable is still negative and significant. The post-1993 indicator variable becomes positive, but remains insignificant, while the post-sample coefficient is significant (-0.285). Thus, the inclusions of a time trend and a kink in 1993 have no significant impact on post-sample return degradation irrespective of scaling portfolio risks.

In columns (8) and (9) of Table 2, I test whether both pre- and post-sample decays are robust, after controlling for persistence. Two prior studies, Moskowitz, Ooi and Pedersen (2012) and Asness, Moskowitz and Pedersen (2013), find broad momentum across asset classes. I include the original and managed portfolio's prior-month's return in column (8) and (9). The lagged return coefficients are positive and significant both in managed and original portfolio cases, which is consistent with evidence of Moskowitz, Ooi and Pedersen (2012). After controlling for persistence, the pre- and post-sample coefficient remains significant, suggesting a pre- and post-sample decline of 34 and 48 bps, respectively.

3.1.1 Six Categories

In this section, I group 125 portfolios into six categories and examine variations in post-sample return decay. Similarly to Freyberger, Neuhierl and Weber (2020) and Hou, Xue and Zhang (2020), I arrange the anomalies into six categories based on economic concepts: momentum, value versus growth, investment, profitability, intangibles, and trading frictions. In Table 3, monthly original (risk-managed) portfolio returns are regressed on an indicator variable representing one of the six categories, a post-sample dummy, and the interaction between the category dummy and the post-sample:

$$
\begin{aligned}
r^{\sigma}_{i,t}\ (r_{it}) = &\alpha_i + \beta_1 \textit{Post Sample Dummy}_i + \beta_2 \textit{Portfolio Category Dummy}_i \\
&+ \beta_3 \textit{Post Sample Dummy}_i \times \textit{Portfolio Category Dummy}_i + \varepsilon_{it}.
\end{aligned} \tag{7}
$$

The coefficient on the *Portfolio Category Dummy*, β_2, estimates whether the in-sample average returns of a category are different from those of the other categories. The evidence show that, for the risk-managed portfolio, momentum-based portfolios have the highest in-sample returns. The coefficient is 0.646, and it is statistically significant. Compared to the other categories of portfolios, the magnitude is economically large. This implies that scaling risk statistically significantly improves the in-sample performance of momentum portfolios relative to other categories. On the other hand, intangibles portfolio returns have the lowest average in-sample returns among six categories. With respect to the original portfolio, momentum-based portfolios again have the highest average in-sample returns, while investment portfolios have the lowest average returns, both of which is significant.

The coefficient on the interaction term, β_3, tests whether post-sample declines vary across categories. With regard to the risk-scaled portfolio, the decline for the momentum portfolio returns is largest although it is not significantly different from the decay for the other categories. Profitability portfolio returns have the smallest declines post-sample. As for the original portfolio, the largest decline in return is for the momentum portfolio but it is insignificant. Still, the smallest decline among six categories comes from profitability portfolio returns.

3.2 Momentum crashes and high-order moments

A momentum strategy relies on past returns, buying past winners and selling past losers. When the stock market performs well during a formation period, for instance, over the previous 12 months, winners consist of high-beta stocks, and losers, of low-beta stocks. In contrast, following market declines, momentum portfolios typically involve the buying of low-beta stocks (past winners), and the selling of high-beta stocks (past losers). Therefore, the winner-minus-losers strategy has a negative beta following bear markets (Grundy and Martin; 2001). When the markets rebound quickly, momentum portfolios crash because they have conditionally large negative betas. The two worst periods for the momentum strategy were in 1932 and in 2009. These two bottoms are followed by the financial crisis and the great depression. The crashes happened as the market rebounded with large losses.

Panel A of Figure 1 shows the returns of an original momentum portfolio, and Panel

B of Figure 1 corresponds to the returns of a risk-managed portfolio during the two crash periods. In July 1932, the original Mom12m (i.e., buying past winners and selling past losers from t-12 to t-2 month returns) strategy delivers a -88.70% in just one month. A reduction in crash risk is the most important benefit of risk management. After managing risks, the pattern in Panel B is flat, which means risk management eliminates the crash risk. Panel C of Figure 1 depicts the monthly realized volatility of momentum. This reaches peak after the crash period. Since the managed portfolio is scaled by its past realized volatility, risk management dictates the assignment of lower weights on original strategies, following high levels of realized volatility. As a result, Panel D of Figure 1 provides evidence of how risk-managed portfolio return avoids crash risk after managing risks. The weights range between 0.09 and 0.76 for 12 month momentum, and 0.07 and 1.20 for six month momentum, respectively, reaching the most significant lows after the crash period.

Figure 3 shows the density function of original momentum portfolio and their managed versions. A reduction in crash risk is the most important benefit of risk management. In particular, the negative extreme returns can be avoided. After scaling risk, a very long left tail is much reduced consistent with Figure 1.

Table 4 provides a summary of economic performance from 1932 to 2020. After risk management, momentum-based strategies have higher average returns, with a gain of 31 bps per month, with a substantially less standard deviation (18.60 percentage points lower per year). The Sharpe ratio improves from 0.65 for original momentum to 0.96 for its managed version. Outside of the momentum group, the evidence is not straightforward.

The average monthly return of trading frictions strategies drop from 0.50 to 0.48. Ironically, risk management increases the standard deviation of investment-based strategies from 2.12 to 3.07.

The last two columns in Panel A of Table 4 systematically evaluate whether risk management improves the average return and the Sharpe ratios. The p-values measure whether the differences in means between original and risk-managed portfolio are significant. Managing risks has an positive and significant impact on momentum, investment, profitability, and intangibles category whereas value&growth and trading frictions category do not benefit with p-value 0.29 and 0.62, respectively. As for the Sharpe ratio, I assess statistical significance of the differences using Jobson and Korkie (1981). Only momentum-based strategies achieve a significant improvement in Sharpe ratio with positive and significant z-statistics, 4.74.

Panel B of Table 4 shows that the improvement in the higher-order moments after scaling risks is remarkable. Risk management plays a role in reducing a negative skewness, which results in less risk in large negative realizations and less tail risk.[8] It turns out that managing the risk of momentum-related portfolios reduces the left skewness from -3.54 to -1.23. The evidence for other categories is mixed. On the other hand, a high value of kurtosis is much reduced across all categories after risk management. For example, the kurtosis of momentum group drops from 44.64 to 15.21. This essentially eliminates the crash risk of the portfolio strategies. Indeed, the minimum one-month return for original portfolio ranges from -88.70% to -19.38%; for risk-managed portfolio spans from -51.20%

[8] Kelly and Jiang (2014) and Bollerslev, Todorov and Xu (2015) point out that a negative skewness can be regarded as a source of tail risk.

to -24.35%. In particular, the minimum one-month return becomes much lower, -88.70% for original momentum; -47.64% for risk-managed momentum. Overall, the benefits from risk management are concentrated among momentum-based strategies that have a negative skewness and a high value of kurtosis.

3.2.1 The time-varying risk

One plausible interpretation of the aforementioned phenomena is that excess kurtosis may come from time varying risk.[9] To shed light on the dynamics of the risk, I use the AR(1) that regresses the realized variance of each month on its own lagged value and a constant. Consistent with equation 3, realized variances are summations of squared daily returns in the previous month. Table 5 shows the results of AR(1) regressions of the realized variances of Fama and French (1993) three factors (MKT, SMB, and HML) and momentum portfolios:

$$RV_{i,t} = \alpha_i + \rho RV_{i,t-1} + \epsilon_t \tag{8}$$

Panel A presents the results, for which I have data available from 1933:03 to 2020:12. Panel B supplements the results for eleven momentum portfolios, for which data are available only from 1971:08 onward.

The column (3) of Table 5 shows, the risk of six momentum-based strategies tends to be persistent. In Panel A, the AR(1) coefficients of the realized variance of six momentum strategies range from 0.59 to 0.66, all of each momentum strategy is more than for the MKT

[9]See, Engle (1982) and Bollerslev (1987) for details.

(0.50) and SMB (0.40) with the except for the AR(1) coefficient on HML. For 1971:08 onward, in Panel B, momentum strategies generally be more persistent compared with MKT and SMB with the AR(1) coefficient spanning from 0.41 to 0.81. The risk of `RevenueSurprise` is the most persistent, whereas `Momrev` is the least.

With regard to the average realized volatility (i.e., $\overline{\sigma}$), in the column (5) of Panel A, momentum strategies are more volatile than SMB and HML. The realized volatility of momentum-based strategies ranges across 8.85 to 22.20, more than the 7.22 (7.44) of the size (value) factor. Three momentum strategies (`Mom12m, Mom6m, and MomVol`) tend to be more volatile when compared with MKT, whereas other three do not. In Panel B, the average realized volatility of four momentum strategies (`Mom12m, Mom6m, MomRev, and MomVol`) is higher than the 14.72 of the market portfolio.

In the column (6) of Panel A, the standard deviation of monthly realized volatility (i.e., σ_σ) is higher for four momentum strategies (`High52, Mom12m, Mom6m, and MomVol`) than the market (8.76). In Panel B, momentum portfolios (`High52, Mom12m, Mom6m, MomRev, and MomVol`) have a higher standard deviation of monthly realized volatilises than the market (8.94).

Motivated by Welch and Goyal (2008), I investigate the out-of-sample predictability of risk. I predict the future realized variance utilizing a sequence of expanding windows. For the first window, I use the first 240 months (τ_0) as a training sample, $t = 1, \ldots, \tau_0$ for running an initial AR(1). Then, for the sample ending in month $\tau = \tau_0, \ldots, T-1$, I run the predictive regression

$$RV_{i,t+1} = \alpha_i + \rho RV_{i,t} + \eta_{t+1}, \qquad t = 1,\ \ldots,\ \tau. \tag{9}$$

As the sample size τ increases from τ_0 to $T-1$, I generate a sequence of $T_{OOS} = T - \tau_0$ out-of-sample risk forecasts with information available up to time τ:

$$\widehat{RV_{i,\tau+1}} = E[RV_{i,\tau+1}|RV_\tau] = \hat{\alpha}_\tau + \hat{\rho}_\tau RV_{i,\tau}, \qquad \tau = \tau_0,\ \ldots,\ T-1. \tag{10}$$

I also denote by $\overline{RV}_{i,\tau} = \frac{1}{\tau}\sum_{t=1}^{\tau} RV_{i,t}$ the historical mean of realized variances up to time τ. For each month, within the framework of an expanding window, I yield OOS forecasts and further compare these ($\widehat{RV_{i,\tau+1}}$) with the historical mean of the realized variances ($\overline{RV}_{i,t}$). I estimate the OOS R-square as

$$R^2_{i,OOS}{}^{10} = 1 - \frac{MSE_P}{MSE_N}, \tag{11}$$

where $MSE_P = \frac{1}{T_{OOS}}\sum_{t=\tau_0}^{T-1}(RV_{i,t+1} - \widehat{RV_{i,t+1}})^2$ (i.e., the MSE of the OOS predictions based on the model), $MSE_N = \frac{1}{T_{OOS}}\sum_{t=\tau_0}^{T-1}(RV_{i,t+1} - \overline{RV}_{i,t})^2$ (i.e., the MSE based on the sample mean).

$\hat{\alpha}_t$, $\hat{\rho}_t$, and $\overline{RV}_{i,t}$ are estimated based on the information available up to time t and τ_0 corresponds to the initial training sample (i.e., the first 240 months). The positive (negative)

[10] Barroso and Santa-Clara (2015) find that the OOS R-square for the market (momentum) is, 38.81% (57.82%) respectively, from 1927:03 to 2011:12. Furthermore, spanning from 1963:07 to 2011:12, they find that the OOS R-square for the market (momentum) is, 25.46% (55.26%) respectively. Based on these evidence, they argue that more than half of the risk of momentum is predictable.

$R^2_{i,OOS}$ comes from when the model predicts risks with higher (lower) accuracy than the historical mean.

The column (8) of Table 5 reports the OOS R-squares of each autoregression. In Panel A, the R^2_{OOS} of six momentum-based strategies ranges over 25.72% to 47.15%, all of which is more than the market (17.42%). With the except `IndRetBig` (R^2_{OOS} =25.67%), about two-fifths of the risk of momentum is predictable. In Panel B, the OOS predictability varies depending on each momentum strategy. The two highest levels of the OOS predictability come from `RevenueSurprise` and `NumEarnIncrease`, each of which has an OOS R-square of 67.27% and 55.49%, respectively. On the other hand, the OOS predictability of `MomRev` risk is close to zero while `IndRetBig` has negative OOS predictability, which implies the risk is unlikely to be predictable.

3.3 Sharpe ratio

Most prior studies assess the value of risk management by directly comparing the Sharpe ratios earned by scaled strategies similar to those in equation 1 with the Sharpe ratios earned by the corresponding unscaled strategies. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) compare Sharpe ratios and cumulative returns for scaled and unscaled versions of the momentum factor. Barroso, Detzel and Maio (2017) and Eisdorfer and Misirli (2020) present similar evidence for the betting-against-beta and financial distress strategies, respectively. I use direct performance comparisons in this section and contribute to the literature by investigating a much broader set of risk-managed portfolios in important subsamples. I separates the results for the 14 momentum portfolios and 111 non-momentum strategy types relating to other categories such as value&growth, investment, profitability, intangibles, and trading frictions.[11] I assign 14 momentum strategies similarly to Hou, Xue and Zhang (2020) and Freyberger, Neuhierl and Weber (2020). To test the null hypothesis of equal Sharpe ratios for portfolios i and j, I compute the test statistic proposed by Jobson and Korkie (1981).

Table 6 provides a summary of the Sharpe ratio differences between the risk-managed and original strategies. In particular, each column reports the number of Sharpe ratio differences that are positive or negative and the number of these differences at the 5% significant level in the square brackets. I assess statistical significance of the Sharpe ratio differences using the Jobson and Korkie (1981) z-statistics, $z(SR(r^{\sigma}))$, from the null that $SR(r^{\sigma}) - SR(r) = 0$.[12] Positive (negative) differences represent outperformance (underperformance) for the risk-scaled versions. The results suggest that risk management improves performance for most of the momentum strategies whereas other managed portfolios do not benefit. Over the full sample, 74 cases out of the non-momentum 111 managed portfolios earns a higher Sharpe ratio than the original strategy does, whereas the original portfolio outperforms in the

[11] 14 momentum strategies are as follows: the Chan, Jegadeesh and Lakonishok (1996) earnings announcement return; the Foster, Olsen and Shevlin (1984) earnings surprise; the Hou (2007) earnings surprise and industry return of big firms; the Zhang (2006) firm age momentum; the George and Hwang (2004) 52 week high; the Moskowitz and Grinblatt (1999) industry momentum; the Jegadeesh and Titman (1993) momentum (12 month and 6 month); the Avramov et al. (2007) junk stock momentum; the Chan and Kot (2006) momentum and LT reversal; Lee and Swaminathan (2000) momentum in high volume stocks; the Loh and Warachka (2012) earnings streak length; the Jegadeesh and Livnat (2006) revenue surprise.

[12] Let $\hat{\mu_i}$ and $\hat{\sigma_i}$ ($\hat{\mu_j}$ and $\hat{\sigma_j}$) be the mean and standard deviation of excess returns for original portfolio i (risk-managed portfolio j) over a period of length T. $\hat{\sigma}_{i,j}$ is the covariance between excess returns for the two portfolios. The test statistic is asymptotically distributed as a standard normal: $\hat{z}_{JK} = \frac{\hat{\sigma_j}\hat{\mu_i} - \hat{\sigma_i}\hat{\mu_j}}{\sqrt{\hat{\theta}}}$, where $\hat{\theta} = \frac{1}{T}\left(2\hat{\sigma}_i^2\hat{\sigma}_j^2 - 2\hat{\sigma}_i\hat{\sigma}_j\hat{\sigma}_{i,j} + \frac{1}{2}\hat{\mu}_i^2\hat{\sigma}_j^2 + \frac{1}{2}\hat{\mu}_j^2\hat{\sigma}_i^2 - \frac{\hat{\mu_i}\hat{\mu_j}}{\hat{\sigma_i}\hat{\sigma_j}}\hat{\sigma}_{i,j}^2\right)$.

remaining 37 cases. 26 of the 111 differences are significantly positive as the risk-managed versions achieve Sharpe ratio gains by outperforming the original portfolios. About half of 111 managed portfolios have lower Sharpe ratios than their unmanaged counterparts both in post sample and post 1993 periods while most cases are statistically insignificant. Overall, risk-managed portfolios do not systematically produce higher Sharpe ratios than their original unmanaged counterparts do.

Inside of the momentum group, the managed momentum strategies exhibit statistically significant outperformance relative to the original portfolios. Over the full sample, all managed momentum strategies achieve significant Sharpe ratio improvements. The subsample results generally resemble the full sample results: most of managed momentum strategies has positive Sharpe ratio differences and most cases are statistically significant except for a very few of them. Overall, Table 6 shows that the benefits of risk management is isolated to momentum strategies, making it difficult to draw broad conclusions. Outside of the momentum group, scaling risk yields no performance improvements in some cases and even significantly reduces Sharpe ratios.

Furthermore, I use the monthly market-based sentiment series constructed by Baker and Wurgler (2006). The sentiment index spans over 53 years, from July 1965 to December 2018. Based on the sentiment index, I split the sample in two halves. I classify each month as a high-sentiment month (a low-sentiment month) if the value of the sentiment index in the prior month is above (below) the median value for the period following Stambaugh, Yu and Yuan (2012).

The asymmetric improvement in the Sharpe ratio for the momentum category in Table 6 leads me to further study the dynamics of the momentum strategies individually. Figure 4 shows a considerable economic performance of momentum portfolios after scaling risk. Yellow regions of the heatmap in Panel A and B (Panel C) correspond to regions with the higher Sharpe ratio (z-statistics).

The takeaway from Panel A of Figure 4 is that, with the except in-sample and high sentiment periods, the original Sharpe ratio is relatively smaller in most cases. On the other hand, in Panel B, managed momentum portfolios produce higher Sharpe ratios after scaling volatility. Taking the historical long run Sharpe ratio of investing in the stock market has been close to 0.4 (Mehra and Prescott; 1985) into account, this improvement is remarkable. For example, the full-sample Sharpe ratio of the Jegadeesh and Titman (1993, Mom12) momentum strategy improves from 0.30 for the raw momentum to 0.71 for its managed version with z-statistics of 6.91. Panel C reports z-statistic from the null that $SR(r^{\sigma}) - SR(r) = 0$ using the Jobson and Korkie (1981) approach. The overall pattern shows that risk management statistically significantly improves Sharpe ratio relative to the base case. The evidence are consistent with prior studies on the benefits of risk management for the momentum (Barroso and Santa-Clara; 2015; Daniel and Moskowitz; 2016). I complement this result by showing that the performance of managed momentum strategies is also robust to several alternative definitions of the momentum strategies whose profile represent the crash risk (i.e., a very long left tail).

4 Spanning regressions

Whereas the results in Section 3 provide evidence that risk-managed portfolios do not systematically outperform original factor portfolios aside from momentum strategies, Moreira and Muir's (2017) spanning regression tests suggest whether risk-managed portfolios are potentially more valuable when used in combination with their original counterparts rather than as stand-alone investments. They find that, with the exception of the size factor, each of their risk-managed portfolios generates a positive intercept, and most of the estimates are statistically significant.[13] I revisit Moreira and Muir's (2017) spanning regression by applying portfolio by portfolio analysis consistent with Section 3.

I run a time-series regression of the risk-managed portfolio on the original factor portfolios,

$$r_{i,t}^{\sigma} = \alpha + \beta r_{i,t} + \epsilon_t, \tag{12}$$

where $r_{i,t}^{\sigma}$ ($r_{i,t}$) is the monthly return for the risk-managed (original) factor. A positive intercept implies that risk management produces higher alphas and thereby increased Sharpe ratios relative to the original factor portfolios.[14] When this test is applied to a wide range of anomaly factors that are based on firm-specific characteristic, a positive alpha in equation 12 does indicate that the optimal ex post combination of risk-managed and original factor portfolios (with positive weight on the scaled factor) expands the mean-variance frontier

[13] Moreira and Muir (2017) focus on 10 well-known pricing factors: market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), return on equity (ROE), investment (IA), and betting-against-beta factors (BAB), as well as the currency carry trade (FX).

[14] A statistically significant alpha suggests that the right-hand side (original portfolio) is not mean-variance efficient, which means the Sharpe ratio can be improved by including the left hand side (managed portfolio).

relative to the original factor (e.g., Gibbons et al.; 1989). Table 7 summarizes results from running spanning regressions of monthly risk-managed portfolio returns on original portfolio returns with detailed results available in the Internet Appendix.[15]

The results in Panel A of Table 7 provide mixed evidence for the potential of risk management. With respect to the 14 momentum strategies, the evidence in Column (3) and (4) provides a strong empirical support for the benefits of scaled momentum strategies. All estimates earn positive alphas in univariate spanning regressions across different kinds of subsamples. Furthermore, the bulk of the positive estimates are statistically significant at the 5% level in most cases. On the other hand, apart from the momentum category, the evidence in Column (1) and (2) of Panel A is not straightforward. Across 111 managed portfolios in the full sample period, 91 cases earn positive alphas in univariate spanning tests while 42 estimates are statistically significant at the 5% level. In the post sample period, 64 out of the 111 risk-scaled portfolios earn positive alphas in spanning tests, with 16 significantly positive estimates compared with 4 significantly negative ones.

Panel B of Table 7 shows that the general conclusions are robust when the three Fama and French (1993) factors are included in the spanning regressions as additional controls. With regard to momentum strategies, Column (3) and (4) in Panel B show that the spanning regression alphas generally are positive and statistically significant in accord with Panel A. In the combined sample of 111 trading strategies during out-of-sample period, the risk-managed versions outperform in 72 cases, whereas the original versions outperform in 39 cases. I

[15]To save the space, I omit detailed results on performance comparisons for the 125 individual anomaly portfolios in Table IA.3 in the Internet Appendix.

find that managed momentum portfolios yield statistically significant positive alphas in the spanning regressions giving support to the potential benefits of scaling risk in parallel with the conclusions from Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). My broad-based findings from Table 7 suggest a more tempered interpretation of the potential economic gains from risk management relative to prior studies.

5 Concluding Remarks

Recent literature suggests that risk-managed portfolios produce significant abnormal returns and large increases in investor utility by dynamically varying portfolios leverage inversely with risk. Nonetheless, there is no consensus whether managed portfolios indeed outperform their original counterparts. I analyze the value of risk-managed portfolios, and in particular, whether managed portfolios produce large alphas, and therefore increase the Sharpe ratios. One of the questions that this paper investigates is whether risk-managed portfolios are stable without being affected by both pre- and post-sample decay. My evidence show that risk-managed portfolio returns are 43% lower in pre-sample and 61% lower in post-sample consistent with the puzzle in the cross-sectional literature. Furthermore, after scaling portfolios' volatility, Sharpe ratios remain basically unchanged in most cases, and thereby I find no evidence to suggest there are benefits from risk management. Third, in the spanning regressions, risk-managed portfolios tend to exhibit positive but insignificant alphas in most cases. This implies that risk-managed portfolios do not expand the mean-variance frontier relative to the original factor.

Portfolios whose profile exhibits the crash risk (a very long left tail) benefit most from risk management and produce higher Sharpe ratios. The Sharpe ratio improves from 0.65 for original momentum to 0.96 for its managed version. Outside of the momentum group, the evidence is not straightforward. Risk management plays a role in reducing a negative skewness, which results in less risk in large negative realizations and less tail risk (Kelly and Jiang; 2014; Bollerslev, Todorov and Xu; 2015). Managing the risk of momentum-related portfolios achieves a less pronounced left skewness from -3.54 to -1.23. At the same time, a high value of kurtosis is much reduced across all categories after risk management. The kurtosis of the momentum group drops from 44.64 to 15.21. This essentially eliminates the crash risk of the portfolio strategies. These findings are consistent with the impressive performance of risk-managed momentum portfolios demonstrated by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). I complement this result by showing that the improved performance of risk-managed momentum can be applied to several alternative definitions of the momentum strategy itself. More importantly, my findings suggest that the benefit of risk management is isolated to strategies that have negative skewness and high kurtosis, eliminating the crash risk.

Appendices

A Cross-sectional predictors

No.	Acronym	Original Paper	Original Sample	Datasets Start-End	Description	Journal
1	Accruals	Sloan (1996)	1962-1991	1952-2020	Accruals	AR
2	AccrualssBM	Bartov and Kim (2004)	1980-1998	1964-2020	Book-to-market and accruals	RQFA
3	AdExp	Chan, Lakonishok and Sougiannis (2001)	1975-1996	1964-2020	Advertising Expsense	JF
4	AM	Fama and French (1992)	1963-1990	1951-2020	Total assets to market	JF
5	AnnoucementReturn	Chan, Jegadeesh and Lakonishok (1996)	1977-1992	1971-2020	Earnings annoucement return	JF
6	AssetGrowth	Cooper, Gulen and Schill (2008)	1968-2003	1952-2020	Asset growth	JF
7	BetaTailRisk	Kelly and Jiang (2014)	1963-2010	1932-2020	Tail risk beta	RFS
8	BidAskSpread	Amihud and Mendelson (1986)	1961-1980	1926-2020	Systematic volatility	JFE
9	BM	Rosenberg, Reid and Lanstein (1985)	1973-1984	1961-2020	Book to market using most recent ME	JF
10	BMdec	Fama and French (1992)	1963-1990	1952-2020	Book to market using December ME	JPM
11	BookLeverage	Fama and French (1992)	1963-1990	1951-2020	Book leverage (annual)	JF
12	BrandInvest	Belo, Lin and Vitorino (2014)	1975-2010	1965-2020	Brand capital investment	RED
13	CashProd	Chandrashekar and Rao (2009)	1963-2003	1951-2020	Cash Productivity	WP
14	CF	Lakonishok, Shleifer and Vishny (1994)	1968-1990	1951-2020	Cash flow to market	JF
15	cfp	Desai, Rajgopal and Venkatachalam (2004)	1973-1997	1964-2020	Operating Cash flows to price	AR
16	ChAssetTurnover	Soliman (2008)	1984-2002	1953-2020	Change in Asset Turnover	AR
17	ChForecastAccrual	Barth and Hutton (2004)	1981-1996	1976-2020	Change in Forecast and Accrual	RAS
18	ChInv	Thomas and Zhang (2002)	1970-1997	1952-2020	Inventory Growth	RAS
19	ChInvIA	Abarbanell and Bushee (1998)	1974-1988	1952-2020	Change in capital inv (ind adj)	AR
20	ChNCOA	Soliman (2008)	1984-2002	1952-2020	Change in Noncurrent Operating Assets	AR
21	ChNWC	Soliman (2008)	1984-2002	1952-2020	Change in Net Working Capital	AR
22	ChTax	Thomas and Zhang (2011)	1977-2006	1962-2020	Change in Taxes	JAR
23	CompEqulss	Daniel and Titman (2006)	1968-2003	1931-2020	Composite equity issuance	JF
24	CompositeDebtIssuance	Lyandres, Sun and Zhang (2008)	1970-2005	1956-2020	Composite debt issuance	RFS
25	ConvDebt	Valta (2016)	1985-2012	1951-2020	Convertible debt indicator	JFQA
26	Coskewness	Harvey and Siddique (2000)	1964-1993	1927-2020	Coskewness	JF
27	DelCOA	Richardson et al. (2005)	1962-2001	1952-2020	Change in current operating assets	JAE
28	DelCOL	Richardson et al. (2005)	1962-2001	1952-2020	Change in current operating liabilities	JAE
29	DelFINL	Richardson et al. (2005)	1962-2001	1952-2020	Change in financial liabilities	JAE
30	DelLTI	Richardson et al. (2005)	1962-2001	1953-2020	Change in long-term investment	JAE
31	DelNetFin	Richardson et al. (2005)	1962-2001	1952-2020	Change in net financial assets	JAE
32	Divlnit	Michaely, Thaler and Womack (1995)	1964-1988	1926-2020	Dividend Initiation	JF
33	DivOmit	Michaely, Thaler and Womack (1995)	1964-1988	1927-2020	Dividend Omission	JF
34	DolVOl	Brennan, Chordia and Subrahmanyam (1998)	1966-1995	1926-2020	Past trading volume	JFE

(*Continued*)

No.	Acronym	Original Paper	Original Sample	Datasets Start-End	Description	Journal
35	EarningsConsistency	Alwathainani (2009)	1971-2002	1953-2020	Earnings Consistency	BAR
36	EarningsSurprise	Foster, Olsen and Shevlin (1984)	1974-1981	1963-2020	Earnings Surprise	AR
37	EarnSupBig	Hou (2007)	1972-2001	1963-2020	Earnings surprise of big firms	RFS
38	EntMult	Loughran and Wellman (2011)	1963-2009	1951-2020	Enterprise Multiple	JFQA
39	EP	Basu (1977)	1957-1971	1951-2020	Earnings-to-Price Ratio	JF
40	FEPS	Cen, Wei and Zhang (2006)	1983-2002	1976-2020	Analyst earnings per share	WP
41	FirmAgeMom	Zhang (2006)	1983-2003	1926-2020	Firm Age - Momentum	JF
42	Frontier	Nguyen and Swanson (2009)	1980-2003	1963-2020	Efficient frontier index	JFQA
43	GP	Novy-Marx (2013)	1963-2010	1951-2020	Gross Profits / total assets	JFE
44	GrAdExp	Lou (2014)	1974-2010	1965-2020	Growth in advertising expenses	RFS
45	grcapx	Anderson and Garcia-Feijoo (2006)	1976-1999	1953-2020	Change in capex (two years)	JF
46	grcapx3y	Anderson and Garcia-Feijoo (2006)	1976-1999	1954-2020	Change in capex (three years)	JF
47	GrLTNOA	Fairfield, Whisenant and Yohn (2003)	1964-1993	1952-2020	Growth in long term operating assets	AR
48	GrSaleToGrInv	Abarbanell and Bushee (1998)	1974-1988	1952-2020	Sales growth over inventory growth	AR
49	GrSaleToGrOverhead	Abarbanell and Bushee (1998)	1974-1988	1952-2020	Sales growth over overhead growth	AR
50	Herf	Hou and Robinson (2006)	1963-2001	1951-2020	Industry Concentration (sales)	JF
51	HerfAsset	Hou and Robinson (2006)	1963-2001	1951-2020	Industry Concentration (assets)	JF
52	HerfBE	Hou and Robinson (2006)	1963-2001	1951-2020	Industry Concentration (equity)	JF
53	High52	George and Hwang (2004)	1963-2001	1926-2020	52 week high	JF
54	IdioRisk	Ang et al. (2006)	1963-2000	1926-2020	Idiosyncratic risk	JF
55	IdioVol3F	Ang et al. (2006)	1963-2000	1926-2020	Idiosyncratic risk (3 factor)	JF
56	IdioVolAHT	Ali, Hwang and Trombley (2003)	1976-1997	1927-2020	Idiosyncratic risk (AHT)	JFE
57	Illiquidity	Amihud (2002)	1964-1997	1927-2020	Amihud's illiquidity	JFM
58	IndMom	Moskowitz and Grinblatt (1999)	1963-1995	1926-2020	Industry Momentum	JFE
59	IndRetBig	Hou (2007)	1972-2001	1926-2020	Industry return of big firms	RFS
60	IntanCFP	Daniel and Titman (2006)	1968-2003	1956-2020	Intangible return using CFtoP	JF
61	IntanEP	Daniel and Titman (2006)	1968-2003	1956-2020	Intangible return using EP	JF
62	IntanSP	Daniel and Titman (2006)	1968-2003	1956-2020	Intangible return using Sale2P	JF
63	Investment	Titman, Wei and Xie (2004)	1973-1996	1953-2020	Investment to revenue	JFQA
64	InvestPPEInv	Lyandres, Sun and Zhang (2008)	1970-2005	1952-2020	Change in ppe and inv/assets	RFS
65	InvGrowth	Belo and Lin (2012)	1965-2009	1952-2020	Inventory Growth	RFS
66	MaxRet	Bali, Cakici and Whitelaw (2011)	1962-2005	1926-2020	Maximum return over month	JF
67	MeanRankRevGrowth	Lakonishok, Shleifer and Vishny (1994)	1968-1990	1957-2020	Revenue Growth Rank	JF
68	Mom12m	Jegadeesh and Titman (1993)	1964-1989	1927-2020	Momentum (12 month)	JF
69	Mom12mOffSeason	Heston and Sadka (2008)	1965-2002	1926-2020	Momentum without the seasonal part	JFE
70	Mom6m	Jegadeesh and Titman (1993)	1964-1989	1926-2020	Momentum (6 month)	JF
71	Mom6mJunk	Avramov et al. (2007)	1985-2003	1978-2017	Junk Stock Momentum	JF
72	MomOffSeason	Heston and Sadka (2008)	1965-2002	1927-2020	Off season long-term reversal	JFE
73	MomOffSeason06YrPlus	Heston and Sadka (2008)	1965-2002	1931-2020	Off season reversal years 6 to 10	JFE
74	MomOffSeason11YrPlus	Heston and Sadka (2008)	1965-2002	1936-2020	Off season reversal years 11 to 15	JFE
75	MomOffSeason16YrPlus	Heston and Sadka (2008)	1965-2002	1943-2020	Off season reversal years 16 to 20	JFE
76	MomRev	Chan and Kot (2006)	1965-2001	1929-2020	Momentum and LT Reversal	JIM
77	Momseason	Heston and Sadka (2008)	1965-2002	1928-2020	Return seasonality years 2 to 5	JFE

(*Continued*)

No.	Acronym	Original Paper	Original Sample	Datasets Start-End	Description	Journal
78	Momseason06YrPlus	Heston and Sadka (2008)	1965-2002	1932-2020	Return seasonality years 6 to 10	JFE
79	Momseason11YrPlus	Heston and Sadka (2008)	1965-2002	1937-2020	Return seasonality years 11 to 15	JFE
80	Momseason16YrPlus	Heston and Sadka (2008)	1965-2002	1942-2020	Return seasonality years 16 to 20	JFE
81	MomseasonShort	Heston and Sadka (2008)	1965-2002	1927-2020	Return seasonality last year	JFE
82	MomVol	Lee and Swaminathan (2000)	1965-1995	1928-2020	Momentum in high volume stocks	JF
83	NetPayoutYield	Boudoukh et al. (2007)	1984-2003	1953-2020	Net Payout Yield	JF
84	NumEarnIncrease	Loh and Warachka (2012)	1987-2009	1964-2020	Earnings streak length	MS
85	OperProf	Fama and French (2006)	1977-2003	1963-2020	Operating Profits / Book Equity	JFE
86	OPLeverage	Novy-Marx (2011)	1963-2008	1951-2020	Operating Leverage	RF
87	OrderBacklog	Rajgopal, Shevlin and Venkatachalam (2003)	1981-1999	1971-2020	Order backlog	RAS
88	OrgCap	Eisfeldt and Papanikolaou (2013)	1970-2008	1951-2020	Organizational capital	JF
89	OScore	Dichev (1998)	1981-1995	1972-2020	O Score	JF
90	PayoutYield	Boudoukh et al. (2007)	1984-2003	1953-2020	Payout Yield	JF
91	PctAcc	Hafzalla et al. (2011)	1989-2008	1964-2020	Percent Operating Accruals	AR
92	PriceDelayRsq	Hou and Moskowitz (2005)	1964-2001	1927-2020	Price delay r square	RFS
93	PriceDelaySlope	Hou and Moskowitz (2005)	1964-2001	1927-2020	Price delay coeff	RFS
94	PriceDelayTstat	Hou and Moskowitz (2005)	1964-2001	1927-2020	Price delay SE adjusted	RFS
95	PS	Piotroski (2000)	1976-1996	1972-2020	Piotroski F-score	AR
96	RD	Chan, Lakonishok and Sougiannis (2001)	1975-1995	1951-2020	R&D over market cap	JF
97	RDAbility	Cohen, Diether and Malloy (2013)	1980-2009	1957-2020	R&D ability	RFS
98	ReturnSkew	Bali, Engle and Murray (2016)	1963-2012	1926-2020	Return skewness	Book
99	ReturnSkew3F	Bali, Engle and Murray (2016)	1963-2012	1926-2020	Idiosyncratic skewness (3F model)	Book
100	RevenueSurprise	Jegadeesh and Livnat (2006)	1987-2003	1963-2020	Revenue Surprise	JAE
101	RIO_MB	Nagel (2005)	1980-2003	1963-2020	Inst Own and Market to Book	JFE
102	RIO_Turnover	Nagel (2005)	1980-2003	1926-2020	Inst Own and Turnover	JFE
103	RIO_Volatility	Nagel (2005)	1980-2003	1926-2020	Inst Own and Idio Vol	JFE
104	roaq	Balakrishnan, Bartov and Faurel (2010)	1976-2005	1966-2020	Return on assets (qtrly)	JAE
105	RoE	Haugen and Baker (1996)	1979-1993	1961-2020	net income / book equity	JFE
106	sfe	Elgers, Lo and Pfeiffer Jr (2001)	1982-1998	1976-2020	Earnings Forecast to price	AR
107	ShareIss1Y	Pontiff and Woodgate (2008)	1970-2003	1927-2020	Share issuance (1 year)	JF
108	ShareIss5Y	Daniel and Titman (2006)	1968-2003	1931-2020	Share issuance (5 year)	JF
109	ShareRepurchase	Ikenberry, Lakonishok and Vermaelen (1995)	1980-1990	1972-2020	Share repurchases	JFE
110	ShareVol	Datar, Naik and Radcliffe (1998)	1962-1991	1926-2020	Share Volume	JFM
111	SP	Barbee Jr, Mukherji and Raines (1996)	1979-1991	1951-2020	Sales-to-price	FAJ
112	Spinoff	Cusatis, Miles and Woolridge (1993)	1965-1988	1926-2020	Spinoffs	JFE
113	std_turn	Chordia, Roll and Subrahmanyam (2001)	1966-1995	1928-2020	Share turnover volatility	JFE
114	STreversal	Jegadeesh (1990)	1934-1987	1926-2020	Short term reversal	JF
115	SurpriseRD	Eberhart, Maxwell and Siddique (2004)	1974-2001	1952-2020	Unexpected R&D increase	JF
116	tang	Hahn and Lee (2009)	1973-2001	1951-2020	Tangibility	JF
117	Tax	Lev and Nissim (2004)	1973-2000	1951-2020	Taxable income to income	AR
118	TotalAccruals	Richardson et al. (2005)	1962-2001	1952-2020	Total accruals	JAE
119	VarCF	Haugen and Baker (1996)	1979-1993	1953-2020	Cash-flow to price variance	JFE
120	VolMkt	Haugen and Baker (1996)	1979-1993	1927-2020	Volume to market equity	JFE

(*Continued*)

No.	Acronym	Original Paper	Original Sample	Datasets Start-End	Description	Journal
121	VolSD	Chordia, Roll and Subrahmanyam (2001)	1966-1995	1928-2020	Volume Variance	JFE
122	VolumeTrend	Haugen and Baker (1996)	1979-1993	1928-2020	Volume Trend	JFE
123	zerotrade	Liu (2006)	1960-2003	1927-2020	Days with zero trades	JFE
124	zerotradeAlt1	Liu (2006)	1960-2003	1927-2020	Days with zero trades	JFE
125	zerotradeAlt12	Liu (2006)	1960-2003	1927-2020	Days with zero trades	JFE

- A. 14 momentum anomalies: AnnouncementReturn, EarningsSurprise, EarnSupBig, FirmAgeMom, High52, IndMom, IndRetBig, Mom12m, Mom6m, Mom6mJunk, MomRev, MomVol, NumEarnIncrease, RevenueSurprise.

- B. 20 value versus growth anomalies: AccrualsBM, AM, BM, BMdec, BookLeverage, CF, cfp, DivInit, DivOmit, EntMult, EP, IntanCFP, IntanEP, IntanSP, MeanRankRevGrowth, NetPayoutYield, PayoutYield, RIO_MB, sfe, SP.

- C. 23 investment anomalies: Accruals, AssetGrowth, ChInv, ChInvIA, ChNCOA, CompEquIss, CompositeDebtIssuance, DelCOA, DelCOL, DelFINL, DelLTI, DelNetFin, grcapx, grcapx3y, GrLTNOA, Investment, InvestPPEInv, InvGrowth, PctAcc, ShareIss1Y, ShareIss5Y, ShareRepurchase, TotalAccruals.

- D. 11 profitability anomalies: ChAssetTurnover, ChNWC, FEPS, GP, OperProf, OScore, PS, roaq, RoE, Tax, VarCF.

- E. 32 intangibles anomalies: AdExp, BrandInvest, CashProd, ChForecastAccrual, ChTax, ConvDebt, EarningsConsistency, Frontier, GrAdExp, GrSaleToGrInv, GrSaleToGrOverhead, Herf, HerfAsset, HerfBE, Mom12mOffSeason, MomOffSeason, MomOffSeason06YrPlus, MomOffSeason11YrPlus, MomOffSeason16YrPlus, MomSeason, MomSeason06YrPlus, MomSeason11YrPlus, MomSeason16YrPlus, MomSeasonShort, OPLeverage, OrderBacklog, OrgCap, RD, RDability, Spinoff, SurpriseRD, tang.

- F. 24 trading frictions anomalies: BetaTailRisk, BidAskSpread, Coskewness, DolVol, IdioRisk, IdioVol3F, IdioVolAHT, Illiquidity, MaxRet, PriceDelayRsq, PriceDelaySlope, PriceDelayTstat, ReturnSkew, ReturnSkew3F, RIO_Turnover, ShareVol, std_turn, STreversal, VolMkt, VolSD, VolumeTrend, zerotrade, zerotradeAlt1, zerotradeAlt12.

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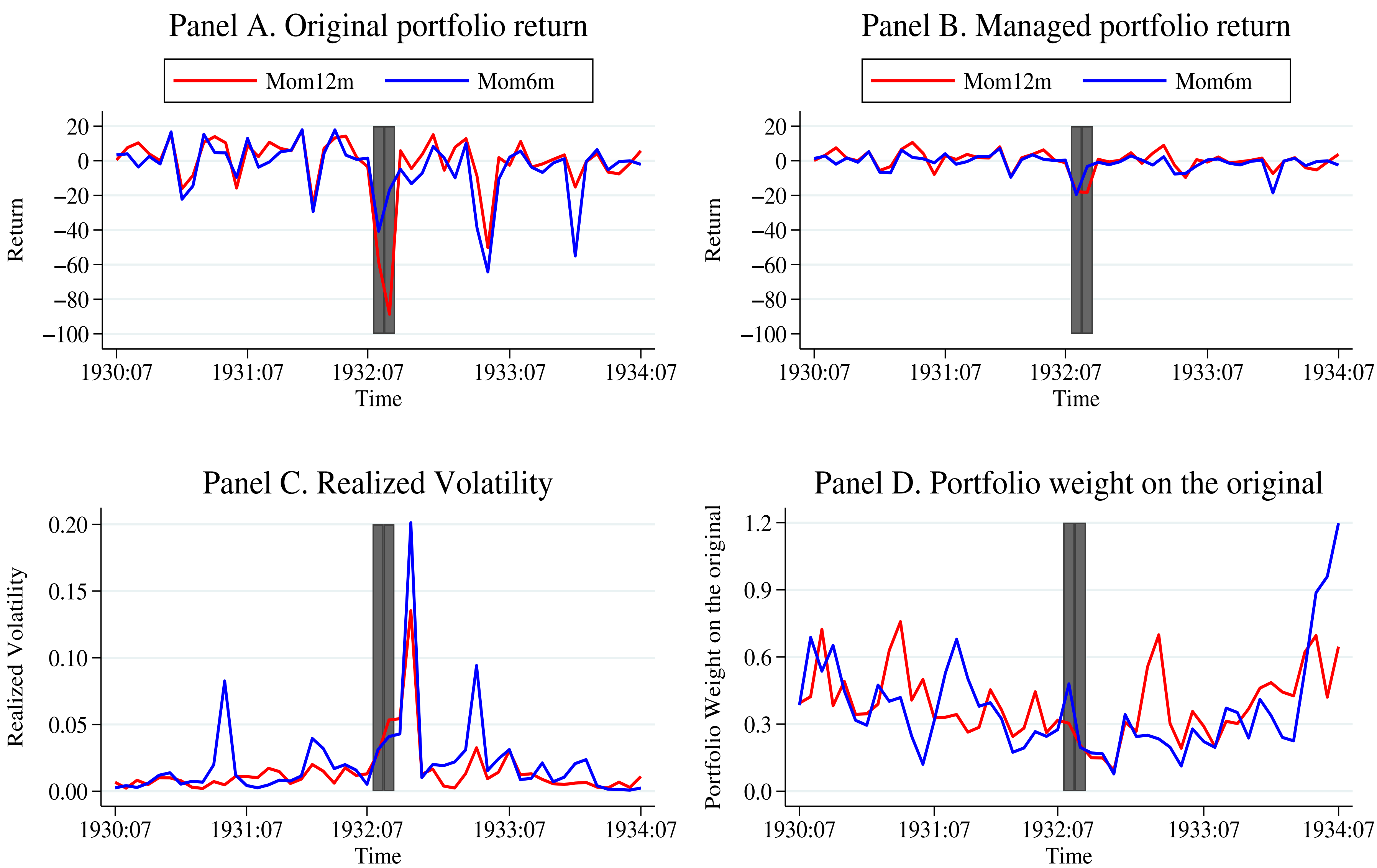

Figure 1: **Momentum crash in 1932**

Red line (blue line) represents 12 month (6month) momentum strategy, respectively. Panel A shows the original momentum portfolio return and Panel B corresponds the risk-managed portfolio return. Panel C depicts the realized volatility of momentum obtained from daily returns in each month. Panel D shows the weights on the original momentum strategy.

Interpretation : Risk management eliminates the crash risk in 1932.

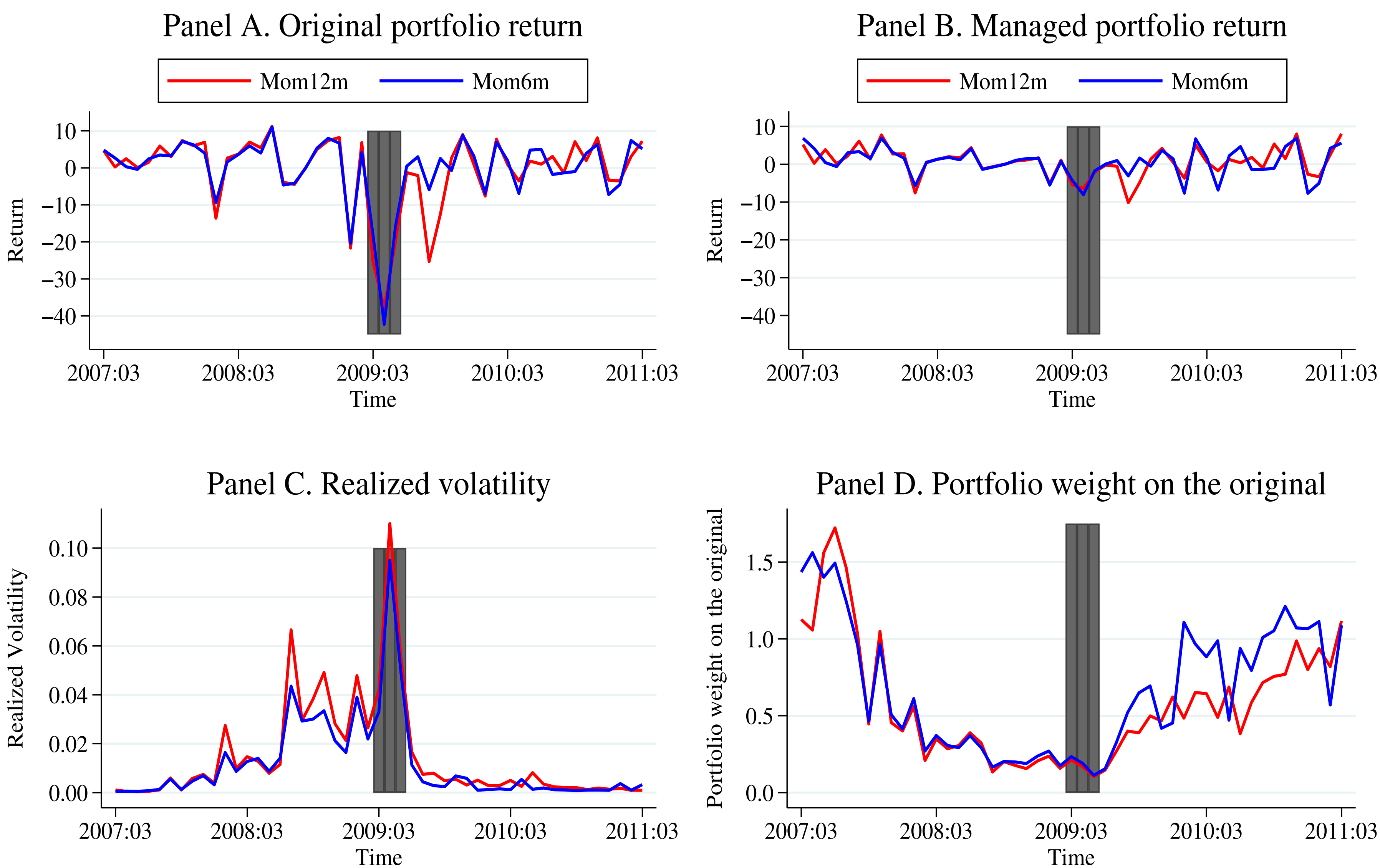

Figure 2: **Momentum crash in 2009**

Red line (blue line) represents 12 month (6month) momentum strategy, respectively. Panel A shows the original momentum portfolio return and Panel B corresponds the risk-managed portfolio return. Panel C depicts the realized volatility of momentum obtained from daily returns in each month. Panel D shows the weights on the original momentum strategy.

Interpretation : Risk management eliminates the crash risk in 2009.

Table 1: **Original and risk-managed portfolios**

The table compares the performance of risk-managed and original versions of 125 anomaly factors. For a given portfolio, the risk-managed portfolio return in month t is $r^{\sigma}_{i,t} = (\sigma_{target}/\hat{\sigma}_{i,t})r_{i,t}$, where $r_{i,t}$ is the monthly return for the original factor, σ_{target} is a constant corresponding to the target level of volatility, and $\hat{\sigma}_{i,t}$ is realized volatility in the previous one month in order to achieve a given σ_{target}. Panel A presents the mean return, standard deviation, and the Sharpe ratio for each original (risk-managed) factor. The p-values represent the differences in means between original and risk-managed portfolio. The means and standard deviations are reported in percentage per month. Panel B (Panel C) reports the number of significant excess returns (FF3 alphas) for both 125 original and risk-managed factors.

Panel A: Summary statistics

	Original Portfolio				Risk-managed Portfolio				t-test
Period	N	Mean	Stdev	Sharpe	N	Mean	Stdev	Sharpe	p-value
Full sample	109,432	0.478	4.180	0.49	108,207	0.564	3.593	0.57	0.00
Pre sample	33,157	0.362	4.699	0.38	31,939	0.449	3.623	0.47	0.00
In sample	44,832	0.676	3.657	0.74	44,832	0.804	3.711	0.80	0.01
Post sample	31,443	0.316	4.286	0.32	31,436	0.340	3.362	0.37	0.08

Panel B: Univariate regressions (Portfolio N = 125)

	Excess returns							
	Original Portfolio				Risk-managed Portfolio			
Period	$\|t\| \geq 1.96$	Percent	$\|t\| \geq 3$	Percent	$\|t\| \geq 1.96$	Percent	$\|t\| \geq 3$	Percent
Full sample	104	83%	74	59%	111	89%	91	73%
Pre sample	53	42%	28	22%	61	49%	38	30%
In sample	114	91%	73	58%	113	90%	82	66%
Post sample	33	26%	13	10%	47	38%	18	14%

Panel C: Additional controls for Fama and French (1993) factors (Portfolio N = 125)

	Three-factor model alphas							
	Original Portfolio				Risk-managed Portfolio			
Period	$\|t\| \geq 1.96$	Percent	$\|t\| \geq 3$	Percent	$\|t\| \geq 1.96$	Percent	$\|t\| \geq 3$	Percent
Full sample	103	82%	88	70%	105	84%	94	75%
Pre sample	74	59%	47	38%	77	62%	54	43%
In sample	102	82%	90	72%	105	84%	90	72%
Post sample	60	48%	32	26%	65	52%	40	32%

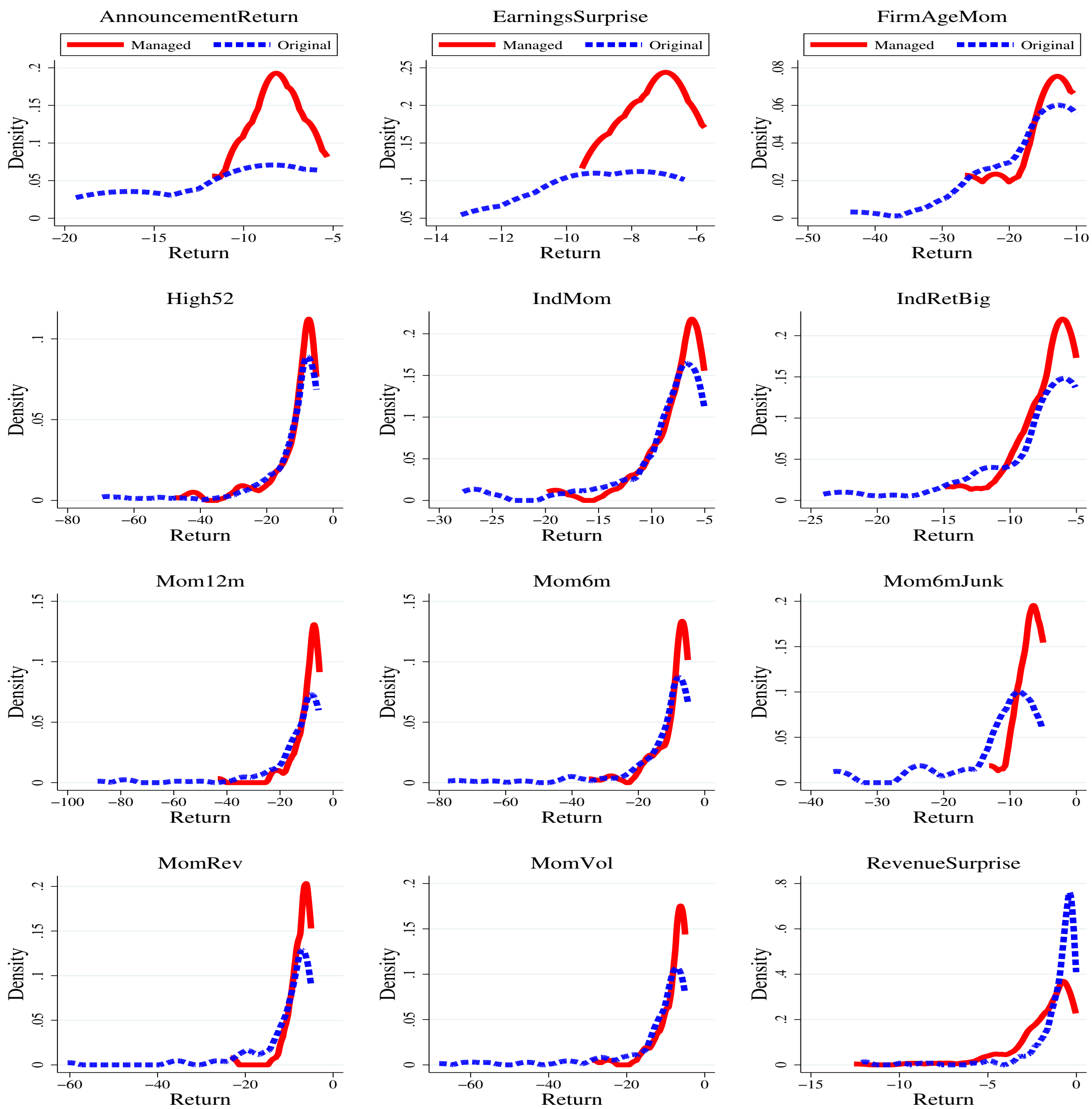

Figure 3: **The density of original and risk-managed momentum portfolio returns**

This figure plots empirical densities for momentum portfolio returns. The dashed blue line (the solid red line) is the return distribution for the original momentum (risk-managed momentum) strategies, respectively. Interpretation: After scaling risk, a very long left tail is much reduced.

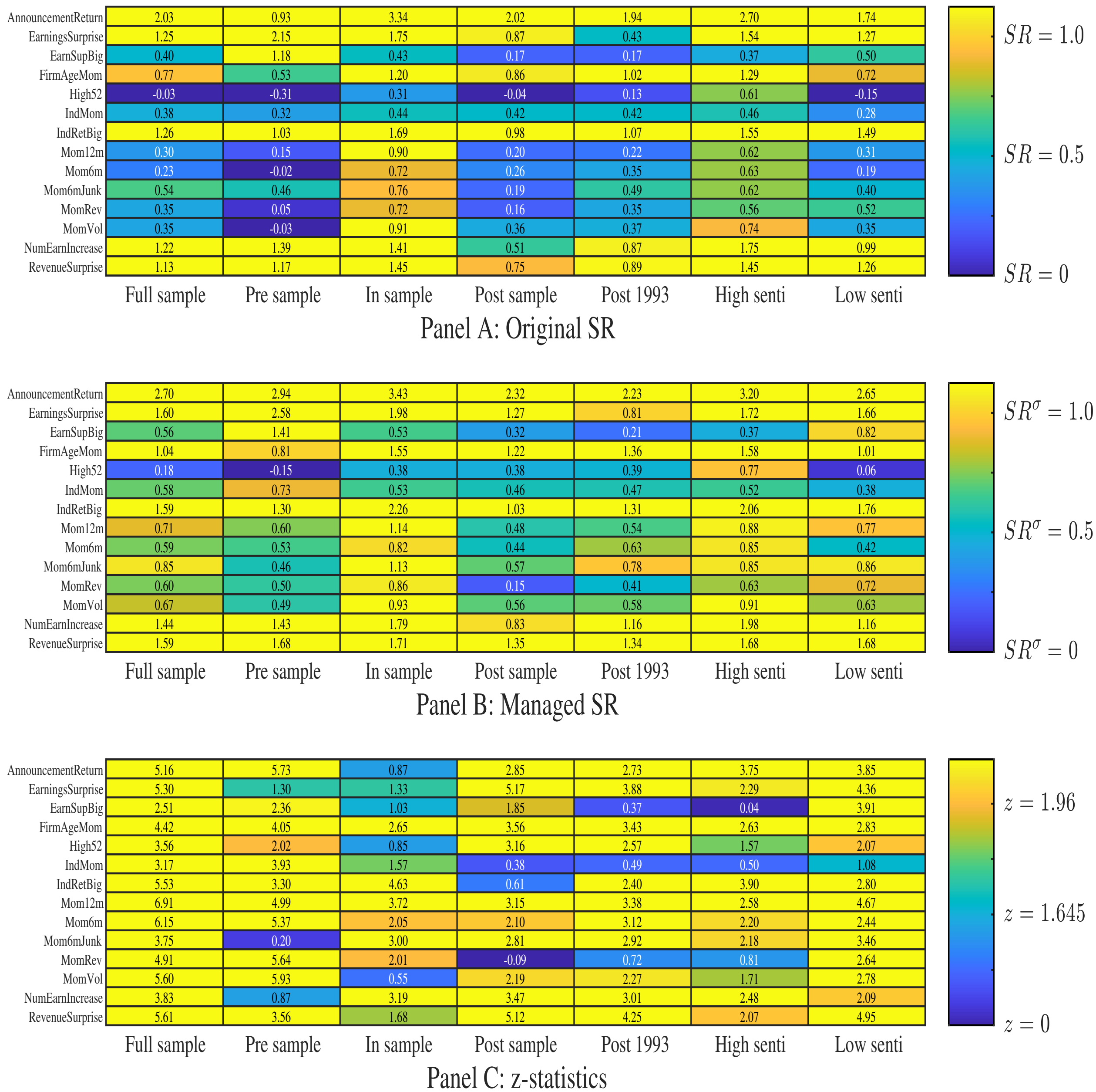

Figure 4: **Plain- versus Risk-managed 14 momentum portfolios (Sharpe ratio)**

Yellow regions of the heatmap in Panel A and B (Panel C) correspond to regions with the higher Sharpe ratio (z-statistics). I assess statistical significance of the Sharpe ratio differences using the Jobson and Korkie (1981). z-statistic is from the null that $SR(r^{\sigma}) - SR(r) = 0$.

Interpretation : Momentum-based portfolios benefit from risk management in terms of the Sharpe ratio.

Table 2: **Regression of Anomaly Portfolio Returns on Decay Indicators**

This table tests for changes in original (managed) portfolio returns relative to the anomaly's sample-start and end dates. The dependent variable is the monthly return for the original (risk-managed) portfolio. *Pre-Sample (PS)* is equal to one if the month is before the sample period used in the original paper and zero otherwise. *Post-Sample (OOS)* is equal to one if the month is after the sample period used in the original sample period and zero otherwise. $Mean$ ($Mean^{\sigma}$) is the mean return of the original (risk-managed) portfolio during the original sample period. *1-Month Return* is the portfolio's return from the last month. $Time$ starts from 1/100 in January 1930 and increase by 1/100 each month, and ends in December 2020. *Post-1993* is equal to one if the year is after 1993 and zero otherwise. For a given portfolio, the risk-managed portfolio return in month t is $r^{\sigma}_{i,t} = (\sigma_{target}/\hat{\sigma}_{i,t})r_{i,t}$, where $r_{i,t}$ is the monthly return for the original factor, σ_{target} is a constant corresponding to the target level of volatility, and $\hat{\sigma}_{i,t}$ is realized volatility in the previous six months in order to achieve a given σ_{target}. Standard errors are clustered at the portfolio level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

	Panel A: Risk-managed Portfolio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-Sample (PS)	-0.357***		-0.078					-0.340***	
	(0.041)		(0.083)					(0.039)	
Post-Sample (OOS)		-0.507***		-0.164**			-0.285***		-0.481***
		(0.037)		(0.056)			(0.069)		(0.035)
PS × Mean			-0.417**						
			(0.128)						
OOS × Mean				-0.495***					
				(0.090)					
Time					-0.019*		-0.077**		
					(0.008)		(0.023)		
Post-1993						-0.236***	0.023		
						(0.032)	(0.053)		
1-Month Return								0.054***	0.068***
								(0.008)	(0.008)
Observations	76,771	76,268	76,771	76,268	108,207	108,207	76,268	76,771	76,268
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolios (N)	125	125	125	125	125	125	125	125	125
	Panel B: Original Portfolio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-Sample (PS)	-0.309***		0.018					-0.283***	
	(0.049)		(0.132)					(0.043)	
Post-Sample (OOS)		-0.394***		-0.018			-0.369***		-0.367***
		(0.034)		(0.035)			(0.071)		(0.033)

(Continued)

Table 2: Regression of Anomaly Portfolio Returns on Decay Indicators

	Panel B: Original Portfolio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PS × Mean			-0.487*						
			(0.222)						
OOS × Mean				-0.542***					
				(0.054)					
Time					-0.008		-0.084**		
					(0.011)		(0.025)		
Post-1993						-0.078*	0.310***		
						(0.033)	(0.053)		
1-Month Return								0.065***	0.069***
								(0.010)	(0.010)
Observations	77,989	76,275	77,989	76,275	109,432	109,432	76,275	77,864	76,275
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolios (N)	125	125	125	125	125	125	125	125	125

Table 3: **Original and risk-managed portfolios across six categories**

This table tests for changes in original (managed) portfolio returns relative to the anomaly's sample-start and end dates. To conduct this analysis, I split my portfolios into six groups: (i) momentum, (ii) value versus growth, (iii) investment, (iv) profitability, (v) intangibles, and (vi) trading frictions. I regress monthly original (risk-managed) portfolio returns on dummy variables that signify each portfolio group. Each column reports how each portfolio type differs from the other five types. *Post-Sample (OOS)* is equal to one if the year is after the sample period used in the original sample period and zero otherwise. For a given portfolio, the risk-managed portfolio return in month t is $r^{\sigma}_{i,t} = (\sigma_{target}/\hat{\sigma}_{i,t})r_{i,t}$, where $r_{i,t}$ is the monthly return for the original factor, σ_{target} is a constant corresponding to the target level of volatility, and $\hat{\sigma}_{i,t}$ is realized volatility in the previous six months in order to achieve a given σ_{target}. Standard errors are clustered at the portfolio level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

	Panel A: Risk-managed Portfolio					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-sample (OOS)	-0.482***	-0.504***	-0.474***	-0.512***	-0.522***	-0.510***
	(0.036)	(0.042)	(0.042)	(0.038)	(0.043)	(0.040)
Momentum	0.646**					
	(0.229)					
OOS × Momentum	-0.183					
	(0.170)					
Value vs Growth		-0.066				
		(0.090)				
OOS × Value vs Growth		0.025				
		(0.070)				
Investment			0.094			
			(0.092)			
OOS × Investment			-0.145			
			(0.079)			
Profitability				-0.064		
				(0.177)		
OOS × Profitability				0.140		
				(0.150)		
Intangibles					-0.205*	
					(0.086)	
OOS × Intangibles					0.082	
					(0.080)	
Trading Frictions						-0.148
						(0.107)
OOS × Trading Frictions						0.043
						(0.095)
Constant	0.753***	0.834***	0.805***	0.828***	0.877***	0.853***
	(0.039)	(0.052)	(0.053)	(0.047)	(0.056)	(0.052)
Observations	76,268	76,268	76,268	76,268	76,268	76,268
Portfolios	125	125	125	125	125	125
	Panel B: Original Portfolio					
	(1)	(2)	(3)	(4)	(5)	(6)

(*Continued*)

Table 3: Original and risk-managed portfolios across six categories

	Panel B: Original Portfolio					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-sample (OOS)	-0.369***	-0.398***	-0.402***	-0.398***	-0.396***	-0.367***
	(0.036)	(0.039)	(0.040)	(0.036)	(0.039)	(0.037)
Momentum	0.499**					
	(0.176)					
OOS × Momentum	-0.188					
	(0.125)					
Value vs Growth		0.011				
		(0.090)				
OOS × Value vs Growth		0.057				
		(0.070)				
Investment			-0.183*			
			(0.082)			
OOS × Investment			0.072			
			(0.071)			
Profitability				-0.059		
				(0.189)		
OOS × Profitability				0.131		
				(0.144)		
Intangibles					-0.115	
					(0.094)	
OOS × Intangibles					0.028	
					(0.084)	
Trading Frictions						0.008
						(0.130)
OOS × Trading Frictions						-0.104
						(0.090)
Constant	0.633***	0.684***	0.721***	0.691***	0.717***	0.684***
	(0.044)	(0.052)	(0.053)	(0.047)	(0.055)	(0.048)
Observations	76,275	76,275	76,275	76,275	76,275	76,275
Portfolios	125	125	125	125	125	125

Table 4: **The economic gains from managing risks**

The table compares the performance of risk-managed and original versions of 125 anomaly factors. For a given portfolio, the risk-managed portfolio return in month t is $r^{\sigma}_{i,t} = (\sigma_{target}/\hat{\sigma}_{i,t})r_{i,t}$, where $r_{i,t}$ is the monthly return for the original factor, σ_{target} is a constant corresponding to the target level of volatility, and $\hat{\sigma}_{i,t}$ is realized volatility in the previous six months in order to achieve a given σ_{target}. Panel A reports the number of observations, mean return, Sharpe ratio, p-values, and Jobson and Korkie (1981)'s z-statistics for each category. The p-values represent the differences in means between original and risk-managed portfolio. Panel B presents the standard deviation, the minimum one-month return, skewness, and kurtosis. The means and standard deviations are reported in percentage per month.

Panel A: Average return and Sharpe ratio

	Original Portfolio			Risk-managed Portfolio			t-test	SR test
Category	N	Mean	Sharpe	N	Mean	Sharpe	p-value	z-stat
Momentum	12,331	0.68	0.65	12,174	0.99	0.96	0.00	4.74
Value&Growth	15,952	0.48	0.43	15,713	0.50	0.47	0.29	0.53
Investment	19,158	0.38	0.67	18,985	0.60	0.69	0.00	0.44
Profitability	7,877	0.38	0.40	7,804	0.45	0.49	0.02	1.55
Intangibles	27,451	0.45	0.46	27,210	0.50	0.52	0.00	1.03
Trading frictions	25,598	0.50	0.37	25,278	0.48	0.44	0.62	0.97
Combination	109,432	0.48	0.49	108,207	0.56	0.57	0.00	1.30

Panel B: High-order moments

	Original Portfolio				Risk-managed Portfolio			
Category	Stdev	Min	Skewness	Kurtosis	Stdev	Min	Skewness	Kurtosis
Momentum	5.58	-88.70	-3.54	44.64	4.03	-47.64	-1.23	15.21
Value&Growth	3.94	-54.94	0.02	15.21	3.68	-31.22	0.17	6.75
Investment	2.12	-19.38	2.04	32.26	3.07	-24.35	0.50	7.58
Profitability	4.03	-42.77	-0.43	18.66	3.63	-36.85	-0.47	7.46
Intangibles	3.64	-87.63	0.37	47.38	3.36	-51.20	0.73	15.90
Trading frictions	5.14	-45.88	1.79	34.90	3.90	-31.46	0.51	9.13
Combination	4.18	-88.70	-0.05	44.76	3.59	-51.20	0.16	11.00

Table 5: **AR(1) of one-month realized variances**

This table shows the results of AR(1) regressions of the realized variances of Fama and French (1993) three factors (MKT, SMB, and HML) and momentum portfolios: $RV_{i,t} = \alpha_i + \rho RV_{i,t-1} + \epsilon_t$. The AR(1) regresses the realized variance of each month on its own lagged value and a constant. The realized variances are the summation of squared daily returns in each month. Column (5) and (6) represent, the average realized volatility ($\overline{\sigma}$) and its standard deviation (σ_σ), respectively. For column (8), I yield OOS forecasts ($\widehat{RV_{i,\tau+1}}$) and further compare these with the historical mean of the realized variances ($\overline{RV}_{i,t}$). The OOS R-square is estimated as $R^2_{i,OOS} = 1 - \frac{MSE_P}{MSE_N}$, where $MSE_P = \frac{1}{T_{OOS}} \sum_{t=\tau_0}^{T-1} (RV_{i,t+1} - \widehat{RV_{i,t+1}})^2$ (i.e., the MSE of the OOS predictions based on the model), $MSE_N = \frac{1}{T_{OOS}} \sum_{t=\tau_0}^{T-1} (RV_{i,t+1} - \overline{RV}_{i,t})^2$ (i.e., the MSE based on the sample mean). The sample period of Panel A (Panel B) is from 1933:03 to 2020:12 (1971:08 to 2020:12), respectively.

Panel A: 1933:03 to 2020:12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomalies	α	t_α	ρ	t_ρ	$\overline{\sigma}$	σ_σ	R^2	R^2_{OOS}
MKT	0.0011	8.15	0.50	18.90	13.70	8.76	25.35	17.42
SMB	0.0004	9.41	0.40	14.23	7.22	4.36	16.14	9.41
HML	0.0002	5.45	0.73	35.08	7.44	5.41	53.92	57.01
High52	0.0007	6.56	0.59	23.95	11.19	8.94	35.29	37.35
IndMom	0.0004	6.36	0.63	26.62	8.85	6.14	40.24	37.67
IndRetBig	0.0005	7.21	0.59	23.79	9.53	6.56	34.99	25.72
Mom12m	0.0016	7.11	0.64	26.79	18.60	12.86	40.56	41.32
Mom6m	0.0015	6.82	0.62	25.54	17.54	12.56	38.28	42.58
MomVol	0.0020	7.22	0.66	28.35	22.20	14.54	43.31	47.15
Panel B: 1971:08 to 2020:12								
MKT	0.0010	5.94	0.56	15.72	14.72	8.94	31.14	40.98
SMB	0.0004	8.16	0.33	8.18	8.12	4.01	10.91	25.60
HML	0.0001	3.98	0.76	27.17	7.52	5.41	57.49	57.21
AnnouncementReturn	0.0003	5.44	0.57	22.95	7.68	5.18	49.15	33.52
EarningsSurprise	0.0003	6.14	0.61	18.20	8.53	5.02	37.76	35.01
EarnSupBig	0.0003	6.40	0.55	15.44	7.44	4.56	30.40	15.51
High52	0.0007	4.33	0.64	19.48	12.15	9.71	41.01	35.73
IndMom	0.0004	4.20	0.65	20.06	9.41	6.94	42.42	29.16
IndRetBig	0.0005	4.89	0.58	16.67	9.91	7.30	33.73	-2.12
Mom12m	0.0017	4.88	0.66	20.60	21.11	14.44	43.73	39.91
Mom6m	0.0016	4.68	0.65	19.96	19.49	13.62	42.19	36.60
MomRev	0.0022	7.71	0.41	10.64	18.90	10.78	17.16	0.87
MomVol	0.0023	5.20	0.69	22.36	25.99	15.80	47.79	45.89
NumEarnIncrease	0.0001	4.66	0.74	25.64	4.72	2.86	54.62	55.49
RevenueSurprise	0.0001	4.40	0.81	32.16	6.64	3.76	65.45	67.27

Table 6: **Sharpe ratios**

This table shows the Sharpe ratio in different sample periods. $SR(r)$ and $SR(r^{\sigma})$ are Sharpe ratios for the original and managed portfolios, respectively. I assess statistical significance of the Sharpe ratio differences using the Jobson and Korkie (1981). [Signif.] corresponds the number of statistically significant z-statistic from the null that $SR(r^{\sigma}) - SR(r) = 0$. I use the monthly sentiment index constructed by Baker and Wurgler (2006) and the index spans from July 1965 to December 2018. A high-sentiment month is one which the value of the BW sentiment index is above the median value and the low sentiment months are those with below-median values.

Sharpe ratio difference (Null: $SR(r^{\sigma}) - SR(r) = 0$)

	111 portfolios excluding Mom		Momentum (14)		Value & Growth (20)		Investment (23)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]
Full sample	74 [26]	37 [4]	14 [14]	0 [0]	13 [6]	7 [3]	12 [4]	11 [0]
Pre sample	62 [19]	49 [5]	13 [11]	1 [0]	10 [2]	10 [0]	11 [2]	12 [0]
In sample	80 [18]	31 [4]	14 [7]	0 [0]	11 [0]	9 [0]	17 [6]	6 [0]
Post sample	59 [15]	52 [8]	13 [10]	1 [0]	10 [3]	10 [2]	9 [2]	14 [3]
Pre 1993	75 [25]	36 [3]	14 [12]	0 [0]	9 [1]	11 [1]	13 [4]	10 [0]
Post 1993	61 [11]	50 [6]	14 [11]	0 [0]	11 [4]	9 [1]	9 [1]	14 [3]
High sentimet	70 [21]	41 [3]	14 [9]	0 [0]	11 [4]	9 [0]	13 [2]	10 [0]
Low sentiment	80 [18]	31 [1]	14 [13]	0 [0]	11 [1]	9 [0]	18 [5]	5 [0]

	Profitability (11)		Intangibles (32)		Trading frictions (24)	
	(1)	(2)	(3)	(4)	(5)	(6)
Period	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]	ΔSR> 0 [Signif.]	ΔSR< 0 [Signif.]
Full sample	10 [2]	1 [0]	20 [7]	12 [0]	18 [7]	6 [1]
Pre sample	6 [2]	5 [1]	20 [9]	12 [2]	14 [9]	10 [2]
In sample	11 [5]	0 [0]	20 [2]	12 [2]	20 [2]	4 [2]
Post sample	7 [3]	4 [0]	17 [4]	15 [2]	15 [4]	9 [1]
Pre 1993	9 [4]	2 [0]	24 [11]	8 [1]	19 [11]	5 [1]
Post 1993	8 [2]	3 [0]	18 [1]	14 [1]	14 [1]	10 [1]
High sentimet	10 [6]	1 [0]	22 [6]	10 [2]	14 [6]	10 [1]
Low sentiment	11 [1]	0 [0]	20 [7]	12 [1]	19 [7]	5 [0]

Table 7: **Spanning regression**

This table summarizes results from spanning regressions for 125 anomaly strategies. The spanning regressions are given by $r^{\sigma}_{i,t} = \alpha + \beta r_{i,t} + \epsilon_t$, where $r^{\sigma}_{i,t}$ ($r_{i,t}$) is the monthly return for the risk-managed (original) factor. The results in Panel A correspond to univariate spanning regressions, and those in Panel B are for regressions that add the Fama and French (1993) three factors as controls. For each set of regressions, the table reports the number of alphas that are positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level. I use the monthly sentiment index constructed by Baker and Wurgler (2006) and the index spans from July 1965 to December 2018. A high-sentiment month is one which the value of the BW sentiment index is above the median value and the low sentiment months are those with below-median values.

Panel A: Univariate regressions

	111 portfolios excluding Mom		Momentum (14)		Value & Growth (20)		Investment (23)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]
Full sample	91 [42]	20 [0]	14 [14]	0 [0]	14 [7]	6 [0]	19 [7]	4 [0]
Pre sample	66 [17]	45 [1]	14 [9]	0 [0]	10 [3]	10 [0]	11 [1]	12 [0]
In sample	94 [30]	17 [1]	14 [9]	0 [0]	16 [0]	4 [0]	21 [9]	2 [0]
Post sample	64 [16]	47 [4]	14 [11]	0 [0]	10 [3]	10 [1]	10 [2]	13 [2]
Pre 1993	92 [27]	19 [0]	14 [13]	0 [0]	15 [1]	5 [0]	18 [5]	5 [0]
Post 1993	72 [19]	39 [2]	14 [11]	0 [0]	12 [4]	8[1]	10 [1]	13 [0]
High sentiment	81 [33]	30 [1]	14 [9]	0 [0]	12 [7]	8 [0]	15 [6]	8 [0]
Low sentiment	87 [20]	24 [0]	14 [11]	0 [0]	14 [2]	6 [0]	19 [7]	4 [0]

	Profitability (11)		Intangibles (32)		Trading frictions (24)	
Period	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]
Full sample	11 [5]	0 [0]	26 [11]	6 [0]	20 [12]	4 [0]
Pre sample	5 [1]	6 [0]	21 [7]	11 [1]	18 [5]	6 [0]
In sample	11 [7]	0 [0]	25 [5]	7 [1]	20 [9]	4 [0]
Post sample	10 [2]	1 [0]	18 [5]	14 [0]	15 [4]	9 [1]
Pre 1993	10 [3]	1 [0]	27 [10]	5 [0]	21 [8]	3 [0]
Post 1993	9 [4]	2 [0]	23 [4]	9[0]	17 [6]	7 [1]
High sentiment	11 [6]	0 [0]	25 [7]	7 [1]	17 [7]	7 [0]
Low sentiment	10 [2]	1 [0]	22 [5]	10 [0]	21 [3]	3 [0]

Panel B: Additional controls for Fama and French (1993) factors

	111 portfolios excluding Mom	Momentum (14)	Value & Growth (20)	Investment (23)

(*Continued*)

Table 7: Spanning regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]
Full sample	93 [49]	18 [0]	14 [14]	0 [0]	16 [8]	4 [0]	17 [6]	6 [0]
Pre sample	70 [16]	41 [1]	14 [10]	0 [0]	8 [3]	12 [0]	14 [0]	9 [0]
In sample	86 [29]	25 [0]	14 [9]	0 [0]	13 [1]	7 [0]	18 [7]	5 [0]
Post sample	72 [19]	39 [4]	14 [10]	0 [0]	11 [5]	9 [1]	10 [1]	13 [3]
Pre 1993	91 [36]	20 [0]	14 [12]	0 [0]	14 [1]	6 [0]	18 [5]	5 [0]
Post 1993	72 [13]	39 [3]	14 [11]	0 [0]	13 [3]	7 [0]	10 [1]	13 [2]
High sentiment	82 [39]	29 [3]	14 [10]	0 [0]	14 [8]	6 [0]	15 [5]	8 [1]
Low sentiment	91 [26]	20 [1]	14 [11]	0 [0]	16 [5]	4 [0]	20 [5]	3 [1]

	Profitability (11)		Intangibles (32)		Trading frictions (24)	
Period	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]
Full sample	11 [7]	0 [0]	27 [12]	5 [0]	21 [16]	3 [0]
Pre sample	6 [0]	5 [0]	22 [8]	10 [1]	19 [5]	5 [0]
In sample	11 [6]	0 [0]	23 [4]	9 [0]	20 [11]	4 [0]
Post sample	10 [2]	1 [0]	20 [5]	12 [0]	20 [6]	4 [0]
Pre 1993	11 [4]	0 [0]	25 [11]	7 [0]	22 [15]	2 [0]
Post 1993	9 [1]	2 [0]	20 [3]	12[0]	19 [5]	5 [1]
High sentiment	10 [9]	1 [0]	23 [7]	9 [1]	19 [10]	5 [1]
Low sentiment	10 [1]	1 [0]	23 [7]	9 [0]	21 [7]	3 [0]

Internet Appendix

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Table IA.1: **Original portfolios**

This table reports averages and accompanying t-statistics for the excess monthly returns on the long-short return spreads in six different sample periods: pre-sample, in-sample, post-sample, pre-2003, 1993-2003, and post-2003 period. Alpha is the intercept on a regression of monthly excess return. Pre-sample denotes the sample frame spanning from 1932 prior to the in-sample period. In-sample denotes the sample frame used in the original discovery of an anomaly. Post-sample denotes the sample frame occurring after the in-sample period. Pre-1993, 1993-2003, and post-2003 denotes the sample frame, 1932-1992, 1993-2003 and 2004-2020, respectively. Alphas are reported in basis points per month. Values in the parentheses are t-statistics based on standard errors following Newey and West (1987). Appendix A describes 125 anomalies. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

	Value-weighted (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
Accruals	0.41**	(3.05)	0.56***	(4.51)	0.27***	(3.45)	0.55***	(5.56)	0.52***	(3.74)	0.05	(0.62)
AccrualsBM	1.19*	(2.55)	1.44***	(4.36)	1.13**	(3.17)	1.17***	(3.72)	2.03***	(4.72)	0.87*	(2.21)
AdExp	0.27	(0.39)	0.65**	(2.69)	0.37	(1.47)	0.53	(1.73)	0.73*	(2.02)	0.17	(0.59)
AM	0.15	(0.68)	0.63**	(3.19)	0.35	(1.09)	0.53***	(3.45)	1.02	(1.48)	-0.21	(-0.68)
AnnouncementReturn	0.81*	(2.01)	1.20***	(12.13)	1.09***	(10.48)	1.10***	(8.74)	1.50***	(9.77)	0.83***	(6.50)
AssetGrowth	0.24	(1.61)	1.50***	(6.85)	0.28	(1.10)	0.78***	(5.57)	2.40***	(4.53)	0.28	(1.10)
BetaTailRisk	0.35	(1.13)	0.46**	(2.93)	-0.09	(-0.26)	0.43*	(2.36)	0.51	(1.51)	0.01	(0.03)
BidAskSpread	1.57*	(2.33)	0.71	(1.56)	-0.04	(-0.11)	0.89*	(2.39)	0.90	(1.03)	-0.39	(-0.83)
BM	-0.08	(-0.26)	1.60***	(3.70)	0.98***	(3.68)	0.89***	(3.83)	1.75**	(3.04)	0.37	(1.01)
BMdec	0.39	(1.66)	0.98***	(4.98)	0.50*	(2.54)	0.80***	(5.15)	1.12**	(2.85)	0.09	(0.49)
BookLeverage	-0.29*	(-2.08)	0.28**	(2.98)	0.15	(0.57)	0.09	(1.07)	0.06	(0.09)	0.28	(1.11)
BrandInvest	0.12	(0.21)	0.56	(1.87)	-0.01	(-0.03)	0.46	(1.55)	0.75	(1.01)	0.00	(0.01)
CashProd	0.10	(0.48)	0.56**	(3.02)	-0.18	(-0.73)	0.38**	(2.72)	0.75	(1.51)	-0.18	(-0.73)
CF	0.15	(0.69)	0.83***	(3.87)	0.15	(0.52)	0.48**	(2.84)	0.11	(0.22)	0.29	(0.85)
cfp	0.40	(1.37)	0.36	(1.93)	0.18	(0.46)	0.26	(1.65)	0.18	(0.26)	0.42	(1.31)
ChAssetTurnover	0.18**	(2.70)	0.29***	(3.93)	-0.00	(-0.06)	0.21***	(3.83)	0.22*	(2.13)	0.00	(0.04)
ChForecastAccrual	0.43*	(2.11)	0.36***	(3.83)	0.12	(1.61)	0.41***	(4.35)	0.15	(1.37)	0.12	(1.40)
ChInv	0.55***	(3.94)	0.77***	(5.83)	0.43**	(2.68)	0.66***	(6.31)	1.11***	(4.01)	0.13	(1.15)
ChInvIA	0.26**	(3.32)	0.50***	(5.63)	0.34**	(3.10)	0.34***	(5.66)	0.79***	(4.02)	0.10	(0.72)
ChNCOA	0.26***	(3.94)	0.35***	(4.12)	0.04	(0.57)	0.26***	(4.58)	0.39***	(3.58)	0.03	(0.43)
ChNWC	0.25***	(4.07)	0.16**	(2.76)	-0.04	(-0.60)	0.26***	(5.01)	0.07	(0.93)	-0.05	(-0.78)
ChTax	1.38***	(6.03)	1.09***	(8.83)	0.31	(1.92)	1.44***	(10.36)	0.71***	(3.65)	0.32*	(2.33)
CompEquIss	0.33	(1.23)	0.27*	(2.21)	0.44**	(3.00)	0.32	(1.93)	0.14	(0.72)	0.44**	(3.00)
CompositeDebtIssuance	0.05	(0.46)	0.31***	(4.66)	0.22*	(2.36)	0.23**	(3.20)	0.29***	(3.37)	0.21*	(2.49)

(*Continued*)

Table IA.1: Original portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
ConvDebt	0.10	(1.10)	0.38***	(3.98)	0.31	(1.89)	0.13	(1.72)	0.65***	(4.04)	0.24	(1.83)
Coskewness	-0.20	(-1.14)	0.27	(1.91)	0.20	(1.64)	0.01	(0.06)	0.17	(0.82)	0.27	(1.84)
DelCOA	0.21	(1.74)	0.54***	(5.40)	0.17	(1.25)	0.39***	(4.16)	1.01***	(6.23)	-0.02	(-0.17)
DelCOL	-0.19	(-1.29)	0.35***	(4.11)	0.12	(0.88)	0.15	(1.90)	0.82***	(4.60)	-0.04	(-0.34)
DelFINL	0.10	(0.93)	0.73***	(11.71)	0.27**	(3.09)	0.54***	(8.27)	0.88***	(8.01)	0.22*	(2.53)
DelLTI	0.21*	(2.37)	0.17*	(2.40)	0.13	(1.74)	0.15**	(2.98)	0.40*	(2.01)	0.04	(0.61)
DelNetFin	0.05	(0.46)	0.55***	(8.84)	0.04	(0.33)	0.40***	(6.68)	0.44**	(2.64)	0.12	(1.03)
DivInit	0.25	(1.05)	0.58***	(5.23)	0.20	(1.26)	0.39**	(2.88)	0.34	(0.95)	0.07	(0.44)
DivOmit	0.70*	(2.31)	0.51**	(3.18)	0.68*	(2.26)	0.61***	(3.57)	0.21	(0.43)	0.99*	(2.25)
DolVol	1.06*	(2.57)	0.75**	(2.79)	0.45*	(2.25)	0.89***	(3.37)	1.30***	(3.45)	0.07	(0.41)
EarningsConsistency	0.38*	(2.22)	0.21*	(2.40)	0.23	(1.44)	0.30**	(3.23)	0.06	(0.33)	0.30	(1.80)
EarningsSurprise	1.37***	(8.37)	1.16***	(5.31)	0.45***	(4.69)	1.15***	(11.99)	0.55***	(3.64)	0.06	(0.37)
EarnSupBig	0.56**	(2.98)	0.37*	(2.11)	0.15	(0.73)	0.45***	(3.88)	0.34	(0.81)	0.10	(0.50)
EntMult	0.49**	(2.87)	0.85***	(4.97)	-0.09	(-0.32)	0.60***	(3.99)	1.31**	(2.90)	0.30	(1.32)
EP	0.47	(1.95)	0.39*	(2.26)	0.23	(1.78)	0.39**	(3.09)	0.37	(1.47)	-0.04	(-0.21)
FEPS	-0.09	(-0.22)	1.46**	(2.74)	0.28	(0.84)	0.81**	(2.70)	1.19	(1.27)	0.41	(1.23)
FirmAgeMom	0.79***	(3.71)	2.20***	(5.26)	1.23***	(3.61)	0.88***	(4.67)	2.99***	(4.31)	1.23***	(3.61)
Frontier	0.64*	(2.05)	2.09***	(6.14)	0.81*	(2.24)	1.10***	(4.35)	2.57***	(4.49)	0.81*	(2.24)
GP	0.45	(1.75)	0.30*	(2.23)	0.56	(1.79)	0.34*	(2.40)	0.53	(1.75)	0.30	(1.38)
GrAdExp	-0.37	(-0.35)	0.44***	(3.66)	0.02	(0.10)	0.18	(0.54)	0.70**	(3.02)	0.02	(0.12)
grcapx	0.30***	(4.08)	0.50***	(4.70)	0.20	(1.45)	0.33***	(4.80)	0.87***	(4.31)	0.02	(0.17)
grcapx3y	0.37***	(4.57)	0.59***	(4.47)	0.12	(0.87)	0.42***	(4.96)	0.85***	(3.90)	-0.05	(-0.38)
GrLTNOA	0.04	(0.23)	0.37**	(3.31)	0.08	(0.79)	0.27**	(2.87)	0.23	(1.21)	-0.00	(-0.01)
GrSaleToGrInv	0.35***	(4.06)	0.31***	(3.48)	0.17*	(2.07)	0.35***	(5.77)	0.45**	(3.15)	-0.08	(-0.83)
GrSaleToGrOverhead	0.16	(1.96)	-0.06	(-0.38)	-0.10	(-1.06)	0.07	(0.89)	-0.23	(-1.43)	-0.04	(-0.33)
Herf	-0.15	(-1.21)	0.21*	(2.04)	0.03	(0.16)	-0.04	(-0.63)	0.88**	(2.90)	-0.06	(-0.39)
HerfAsset	-0.26	(-1.68)	0.18	(1.49)	-0.08	(-0.52)	-0.09	(-1.15)	0.83*	(2.33)	-0.17	(-1.02)
HerfBE	-0.18	(-1.42)	0.22	(1.80)	-0.04	(-0.24)	-0.04	(-0.61)	0.88*	(2.40)	-0.11	(-0.71)
High52	-0.77	(-1.60)	0.51*	(2.12)	-0.06	(-0.15)	-0.18	(-0.66)	0.57	(0.90)	-0.01	(-0.02)
IdioRisk	0.03	(0.08)	0.99**	(3.03)	0.16	(0.34)	0.44	(1.85)	1.19	(1.33)	0.09	(0.23)
IdioVol3F	-0.04	(-0.10)	0.96**	(2.87)	0.11	(0.23)	0.40	(1.64)	1.11	(1.18)	0.07	(0.17)
IdioVolAHT	-0.19	(-0.69)	0.89*	(2.17)	0.03	(0.05)	0.12	(0.48)	0.46	(0.42)	-0.00	(-0.00)

(*Continued*)

Table IA.1: Original portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
Illiquidity	0.46*	(2.17)	0.57***	(3.32)	0.04	(0.22)	0.52***	(3.59)	0.53	(1.70)	-0.15	(-1.30)
IndMom	0.29	(1.82)	0.27*	(2.00)	0.52*	(2.03)	0.29**	(2.69)	1.13*	(2.26)	0.05	(0.29)
IndRetBig	0.98***	(5.31)	2.22***	(8.07)	1.06***	(4.47)	1.32***	(9.28)	2.80***	(4.27)	0.85***	(3.64)
IntanCFP	0.13	(0.86)	0.40*	(2.22)	0.20	(0.82)	0.31*	(2.24)	0.41	(1.02)	0.20	(0.82)
IntanEP	0.32	(1.83)	0.34*	(2.33)	0.09	(0.43)	0.31*	(2.38)	0.41	(1.56)	0.09	(0.43)
IntanSP	0.41*	(2.01)	0.53*	(2.30)	0.07	(0.21)	0.38*	(2.02)	0.90	(1.94)	0.07	(0.21)
Investment	0.16	(1.21)	0.25*	(2.13)	0.11	(0.53)	0.19*	(2.06)	0.22	(0.62)	0.10	(0.53)
InvestPPEInv	0.37***	(3.70)	0.80***	(7.39)	0.18	(1.39)	0.55***	(6.56)	1.18***	(5.90)	0.13	(1.11)
InvGrowth	0.42**	(2.86)	0.87***	(6.51)	0.01	(0.03)	0.74***	(6.61)	1.40***	(4.14)	-0.06	(-0.38)
MaxRet	0.28	(0.60)	0.89**	(2.64)	0.07	(0.13)	0.64*	(2.28)	0.98	(0.99)	-0.09	(-0.19)
MeanRankRevGrowth	0.16	(1.39)	0.55***	(3.76)	-0.00	(-0.05)	0.38***	(3.54)	-0.10	(-0.65)	0.10	(0.71)
Mom12m	0.40	(0.79)	1.37***	(5.11)	0.49	(1.12)	0.78**	(2.64)	0.92	(1.15)	0.33	(0.60)
Mom12mOffSeason	0.48	(1.13)	1.23***	(4.54)	0.61	(1.06)	0.79**	(2.87)	1.23*	(2.30)	0.71	(1.20)
Mom6m	-0.05	(-0.11)	1.04***	(4.00)	0.63	(1.69)	0.36	(1.35)	1.36*	(2.02)	0.46	(1.00)
Mom6mJunk	0.58	(1.04)	1.58***	(3.62)	0.29	(0.71)	0.85**	(2.72)	1.96**	(2.79)	0.29	(0.71)
MomOffSeason	1.14**	(3.26)	1.31***	(4.84)	0.10	(0.25)	1.19***	(4.87)	1.51***	(3.83)	0.00	(0.01)
MomOffSeason06YrPlus	0.64**	(2.80)	0.59***	(4.31)	0.87***	(4.08)	0.63***	(4.33)	0.65**	(2.77)	0.79***	(3.65)
MomOffSeason11YrPlus	0.39	(1.90)	0.24*	(2.03)	0.13	(0.68)	0.31*	(2.55)	0.25	(1.05)	0.13	(0.66)
MomOffSeason16YrPlus	0.17	(1.14)	0.35*	(2.52)	0.32	(1.89)	0.35**	(3.02)	0.03	(0.12)	0.32	(1.80)
MomRev	0.09	(0.28)	1.19***	(4.53)	0.24	(0.64)	0.51*	(2.35)	2.03**	(2.96)	-0.09	(-0.26)
MomSeason	0.89***	(3.97)	0.82***	(5.59)	0.47	(1.96)	0.75***	(5.26)	1.37***	(4.88)	0.48	(1.91)
MomSeason06YrPlus	0.83***	(4.20)	0.74***	(6.02)	0.21	(1.01)	0.75***	(5.91)	0.93***	(4.31)	0.22	(1.02)
MomSeason11YrPlus	0.41**	(3.24)	0.75***	(7.23)	0.29	(1.66)	0.59***	(6.66)	0.51*	(2.37)	0.39*	(2.20)
MomSeason16YrPlus	0.38**	(3.16)	0.59***	(4.89)	0.48**	(2.86)	0.46***	(4.84)	0.64**	(3.07)	0.53**	(3.04)
MomSeasonShort	0.88**	(2.77)	1.36***	(8.47)	-0.13	(-0.53)	1.12***	(5.77)	1.07***	(3.53)	-0.09	(-0.37)
MomVol	-0.08	(-0.17)	1.59***	(4.79)	1.12*	(1.97)	0.73*	(2.45)	1.77*	(2.14)	0.65	(1.01)
NetPayoutYield	0.40*	(2.28)	0.87*	(2.32)	0.80*	(2.38)	0.54***	(3.39)	0.77	(1.24)	0.80*	(2.38)
NumEarnIncrease	0.48***	(5.42)	0.52***	(6.26)	0.18	(1.76)	0.52***	(7.20)	0.59***	(4.80)	0.19*	(2.02)
OperProf	-0.14	(-0.71)	0.72**	(2.65)	0.34*	(2.00)	0.36**	(2.72)	0.63	(1.01)	0.34*	(2.00)
OPLeverage	0.23	(1.41)	0.35*	(2.12)	0.73*	(2.27)	0.40**	(2.94)	0.15	(0.34)	0.53*	(2.05)
OrderBacklog	-0.30	(-1.00)	0.51**	(3.01)	-0.18	(-1.11)	0.20	(1.11)	0.20	(0.90)	-0.22	(-1.19)
OrgCap	0.53***	(3.49)	0.37**	(2.77)	0.17	(1.15)	0.41***	(3.70)	0.32	(1.01)	0.36*	(2.48)

(*Continued*)

Table IA.1: Original portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		In-Sample		Post-Sample		Pre-1993		1993-2003		Post-2003	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
OScore	0.15	(0.42)	1.01**	(2.80)	0.74*	(2.13)	0.59*	(2.06)	0.99	(1.59)	0.69*	(2.01)
PayoutYield	0.18	(0.98)	0.43*	(2.45)	-0.00	(-0.00)	0.28	(1.80)	0.29	(1.15)	-0.00	(-0.00)
PctAcc	0.50**	(2.99)	0.46**	(3.29)	0.09	(0.83)	0.45**	(2.94)	0.67***	(3.77)	0.13	(1.28)
PriceDelayRsq	0.72*	(2.31)	0.48**	(2.84)	0.31	(1.27)	0.61***	(3.32)	0.82*	(2.00)	0.03	(0.18)
PriceDelaySlope	0.29	(1.53)	0.17*	(2.09)	0.19	(1.25)	0.24*	(2.18)	0.30*	(2.43)	0.09	(0.53)
PriceDelayTstat	-0.13	(-1.18)	0.15	(1.63)	0.02	(0.14)	-0.01	(-0.17)	0.29	(1.24)	-0.03	(-0.28)
PS	-0.60	(-0.73)	0.92**	(3.08)	0.92	(1.89)	0.70*	(2.16)	1.02	(1.55)	0.76	(1.38)
RD	0.61**	(2.99)	1.01***	(4.77)	1.08*	(2.42)	0.67***	(4.65)	2.66**	(3.12)	0.34	(1.01)
RDAbility	-0.26	(-1.01)	0.27	(1.49)	-0.12	(-0.60)	-0.02	(-0.10)	0.30	(0.80)	-0.11	(-0.73)
ReturnSkew	0.61***	(5.99)	0.41***	(4.58)	0.10	(0.51)	0.57***	(8.80)	0.35	(1.14)	0.08	(0.64)
ReturnSkew3F	0.57***	(5.86)	0.29***	(4.15)	-0.02	(-0.19)	0.49***	(8.18)	0.17	(0.73)	0.02	(0.23)
RevenueSurprise	0.67***	(6.76)	0.75***	(6.30)	0.37**	(2.83)	0.73***	(8.07)	0.63***	(4.49)	0.37**	(2.83)
RIO_MB	0.95	(1.96)	0.90***	(3.42)	0.16	(0.80)	0.84**	(2.75)	1.14*	(2.56)	0.16	(0.80)
RIO_Turnover	0.33	(1.65)	0.65*	(2.30)	0.30	(1.15)	0.33	(1.95)	1.04*	(2.00)	0.30	(1.15)
RIO_Volatility	0.40	(1.69)	1.01***	(3.88)	0.57	(1.79)	0.55**	(2.83)	0.90	(1.87)	0.57	(1.79)
roaq	0.32	(0.59)	1.69***	(5.30)	0.59	(1.64)	1.36***	(5.00)	1.37	(1.83)	0.68*	(2.03)
RoE	-0.00	(-0.02)	0.32*	(2.38)	0.33	(1.66)	0.16	(1.30)	0.45	(1.05)	0.21	(1.38)
sfe	0.58	(1.34)	0.81*	(2.31)	0.18	(0.31)	0.80**	(2.75)	0.04	(0.04)	0.42	(0.99)
ShareIss1Y	0.25**	(2.80)	0.62***	(4.76)	0.44*	(2.31)	0.31***	(4.69)	1.06**	(3.15)	0.44*	(2.31)
ShareIss5Y	0.36**	(2.63)	0.52***	(4.42)	0.25*	(2.03)	0.43***	(4.45)	0.46	(1.96)	0.25*	(2.03)
ShareRepurchase	0.22**	(3.33)	0.32***	(3.52)	0.10	(0.90)	0.22**	(3.17)	0.13	(0.73)	0.13	(0.88)
ShareVol	0.19	(0.58)	0.91***	(4.01)	0.27	(1.41)	0.56**	(2.89)	0.07	(0.20)	0.33	(1.58)
SP	0.61**	(3.21)	0.71*	(2.22)	0.75**	(2.61)	0.69***	(4.22)	1.05	(1.86)	0.46	(1.47)
Spinoff	0.37	(1.19)	0.40*	(2.13)	0.16	(0.90)	0.37*	(1.99)	0.05	(0.11)	0.24	(1.35)
std_turn	0.37	(1.76)	0.80***	(3.47)	0.20	(0.42)	0.52**	(3.25)	0.86	(1.63)	0.00	(0.01)
STreversal	15.51***	(4.83)	2.94***	(12.10)	1.64***	(4.88)	3.38***	(11.56)	2.51**	(3.35)	0.58	(1.83)
SurpriseRD	-0.18	(-1.39)	0.29**	(2.61)	0.09	(0.78)	-0.04	(-0.47)	0.55	(1.94)	0.08	(0.83)
tang	0.11	(0.69)	0.71**	(3.20)	0.14	(0.55)	0.27*	(2.49)	1.12*	(2.05)	0.10	(0.41)
Tax	0.19	(1.59)	0.45**	(3.21)	0.41***	(3.88)	0.28**	(3.20)	0.63*	(2.27)	0.36***	(3.35)
TotalAccruals	0.52**	(3.30)	0.28*	(2.36)	0.22	(0.99)	0.25**	(3.00)	0.97*	(2.45)	-0.02	(-0.12)
VarCF	-0.65*	(-2.47)	-0.56	(-1.73)	-0.21	(-0.58)	-0.57**	(-2.74)	-0.82	(-1.39)	0.04	(0.10)
VolMkt	0.10	(0.44)	0.45	(1.58)	0.38	(1.28)	0.17	(0.91)	0.75	(1.13)	0.19	(0.93)

(*Continued*)

Table IA.1: Original portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
VolSD	0.36	(1.85)	0.38**	(3.22)	0.05	(0.23)	0.39**	(3.14)	0.06	(0.23)	0.04	(0.14)
VolumeTrend	0.55**	(3.03)	0.54*	(2.53)	0.66***	(5.07)	0.52***	(3.53)	1.32***	(5.32)	0.32**	(2.77)
zerotrade	0.77*	(2.36)	0.49**	(2.94)	0.21	(0.58)	0.68***	(3.73)	0.16	(0.48)	0.21	(0.58)
zerotradeAlt1	0.50	(1.61)	0.64***	(3.93)	0.33	(0.90)	0.61***	(3.49)	0.43	(1.39)	0.33	(0.90)
zerotradeAlt12	0.71*	(2.57)	0.40**	(3.05)	0.01	(0.04)	0.57***	(3.80)	0.23	(0.84)	0.01	(0.04)

Table IA.2: **Risk-managed portfolios**

This table reports averages and accompanying t-statistics for the excess monthly returns on the long-short return spreads in six different sample periods: pre-sample, in-sample, post-sample, pre-2003, 1993-2003, and post-2003 period. Alpha is the intercept on a regression of monthly excess return. Pre-sample denotes the sample frame spanning from 1932 prior to the in-sample period. In-sample denotes the sample frame used in the original discovery of an anomaly. Post-sample denotes the sample frame occurring after the in-sample period. Pre-1993, 1993-2003, and post-2003 denotes the sample frame, 1932-1992, 1993-2003 and 2004-2020, respectively. Alphas are reported in basis points per month. Values in the parentheses are t-statistics based on standard errors following Newey and West (1987). Appendix A describes 125 anomalies. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

	Value-weighted (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
Accruals	0.49**	(2.80)	0.82***	(4.80)	0.38**	(3.31)	0.79***	(5.74)	0.63***	(3.98)	0.11	(0.75)
AccrualsBM	0.98**	(2.92)	1.05***	(4.43)	0.46*	(2.21)	0.91***	(4.08)	1.17***	(4.35)	0.38	(1.54)
AdExp	-0.03	(-0.09)	0.70*	(2.13)	0.13	(0.56)	0.45	(1.71)	0.58	(1.89)	-0.04	(-0.14)
AM	0.28	(0.70)	1.01**	(3.10)	0.47	(1.64)	0.84**	(3.26)	1.18*	(2.17)	-0.13	(-0.47)
AnnouncementReturn	1.91***	(6.24)	2.49***	(11.77)	1.86***	(11.26)	2.36***	(13.11)	2.07***	(10.90)	1.72***	(7.15)
AssetGrowth	0.24	(1.18)	1.46***	(7.38)	0.20	(0.64)	0.88***	(5.41)	1.90***	(4.73)	0.20	(0.64)
BetaTailRisk	0.23	(1.18)	0.42*	(2.50)	-0.26	(-0.88)	0.43**	(2.78)	0.17	(0.72)	-0.18	(-0.81)
BidAskSpread	0.61	(1.83)	0.67	(1.58)	-0.22	(-0.89)	0.36	(1.53)	0.61	(1.18)	-0.41	(-1.49)
BM	0.32	(0.93)	1.76**	(3.34)	0.83***	(3.66)	1.13***	(4.28)	1.67***	(3.57)	0.07	(0.24)
BMdec	0.53	(1.38)	1.44***	(4.90)	0.60*	(2.56)	1.16***	(4.92)	1.45**	(3.34)	0.08	(0.32)
BookLeverage	-0.53*	(-2.27)	0.49**	(2.79)	0.04	(0.18)	0.17	(1.18)	-0.01	(-0.03)	0.13	(0.48)
BrandInvest	0.11	(0.41)	0.50*	(1.98)	-0.12	(-0.34)	0.51*	(1.99)	0.48	(0.90)	-0.07	(-0.31)
CashProd	0.16	(0.38)	0.79***	(3.32)	-0.25	(-0.72)	0.52*	(2.32)	1.17*	(2.26)	-0.25	(-0.72)
CF	0.27	(0.96)	0.85***	(3.85)	0.35	(1.71)	0.55**	(3.06)	0.19	(0.64)	0.57*	(2.27)
cfp	0.42	(1.68)	0.54*	(1.97)	0.36	(0.98)	0.38	(1.71)	0.29	(0.47)	0.67	(1.94)
ChAssetTurnover	0.33**	(3.09)	0.56***	(4.21)	0.00	(0.00)	0.42***	(4.42)	0.36*	(2.23)	0.01	(0.06)
ChForecastAccrual	0.83	(1.54)	0.82***	(3.94)	0.32*	(2.30)	0.89***	(4.03)	0.36	(1.89)	0.35	(1.93)
ChInv	0.73***	(3.68)	1.06***	(6.20)	0.40*	(2.22)	0.89***	(6.42)	1.19***	(4.44)	0.15	(0.80)
ChInvIA	0.44**	(3.14)	1.27***	(5.64)	0.43*	(2.58)	0.71***	(5.57)	1.20***	(4.22)	0.03	(0.13)
ChNCOA	0.47***	(4.40)	0.64***	(3.93)	0.05	(0.28)	0.51***	(4.99)	0.61***	(3.39)	0.03	(0.16)
ChNWC	0.47***	(4.07)	0.40**	(3.31)	-0.15	(-1.06)	0.53***	(5.16)	0.13	(1.26)	-0.18	(-1.18)
ChTax	1.45***	(6.30)	1.43***	(8.71)	0.69**	(2.89)	1.78***	(10.54)	0.74***	(3.87)	0.66**	(3.27)
CompEquIss	0.09	(0.51)	0.56**	(3.09)	0.73***	(4.28)	0.35*	(2.36)	0.22	(1.06)	0.73***	(4.28)
CompositeDebtIssuance	0.18	(0.91)	0.86***	(5.41)	0.57*	(2.56)	0.70***	(4.20)	0.68***	(3.66)	0.55**	(2.69)

(*Continued*)

Table IA.2: Risk-managed portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		In-Sample		Post-Sample		Pre-1993		1993-2003		Post-2003	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
ConvDebt	0.43**	(2.92)	0.90***	(4.04)	0.81*	(2.19)	0.52***	(3.75)	1.09***	(3.99)	0.75*	(2.29)
Coskewness	-0.14	(-0.68)	0.40	(1.52)	0.26	(1.30)	0.09	(0.53)	0.13	(0.36)	0.46	(1.86)
DelCOA	0.39	(1.82)	0.88***	(5.44)	0.15	(0.73)	0.74***	(4.58)	1.22***	(5.56)	-0.09	(-0.44)
DelCOL	-0.25	(-1.04)	0.52***	(4.13)	0.07	(0.33)	0.30*	(2.28)	0.93***	(4.61)	-0.15	(-0.77)
DelFINL	0.29	(1.41)	1.56***	(12.42)	0.63**	(3.31)	1.23***	(9.18)	1.66***	(8.38)	0.57**	(2.84)
DelLTI	0.52**	(2.73)	0.41*	(2.57)	0.17	(0.93)	0.38**	(2.83)	0.78*	(2.13)	0.02	(0.08)
DelNetFin	0.15	(0.71)	1.13***	(9.28)	0.23	(1.00)	0.92***	(7.35)	0.69*	(2.53)	0.39	(1.65)
DivInit	0.16	(1.04)	0.75***	(5.11)	0.32*	(2.35)	0.43***	(4.12)	0.29	(1.11)	0.31	(1.70)
DivOmit	0.25	(1.61)	0.37*	(2.54)	0.40	(1.91)	0.31**	(2.96)	0.22	(0.75)	0.55	(1.66)
DolVol	0.68**	(2.78)	0.88**	(2.96)	0.32	(1.93)	0.71***	(3.64)	1.26***	(3.54)	0.01	(0.07)
EarningsConsistency	0.42*	(2.15)	0.29*	(2.55)	0.43*	(2.01)	0.39***	(3.38)	0.00	(0.03)	0.50*	(2.29)
EarningsSurprise	2.14***	(7.86)	1.80***	(5.53)	0.93***	(6.81)	1.91***	(11.90)	0.84***	(4.03)	0.43*	(2.19)
EarnSupBig	1.39**	(3.13)	0.76*	(2.48)	0.35	(1.32)	1.10***	(4.04)	0.31	(0.57)	0.31	(1.12)
EntMult	0.59**	(2.70)	0.72***	(4.98)	-0.01	(-0.04)	0.63***	(4.07)	0.90**	(3.36)	0.27	(1.48)
EP	0.79	(1.92)	0.61*	(2.27)	0.21	(1.27)	0.59**	(3.05)	0.38	(1.37)	-0.27	(-1.19)
FEPS	-0.39	(-0.69)	1.54***	(3.95)	0.39	(1.44)	1.09*	(2.57)	0.83	(1.55)	0.49	(1.78)
FirmAgeMom	0.85***	(5.71)	1.35***	(6.68)	0.92***	(5.06)	0.92***	(6.78)	1.45***	(5.79)	0.92***	(5.06)
Frontier	0.60*	(2.32)	1.21***	(6.34)	0.50*	(2.24)	0.84***	(4.51)	1.29***	(4.53)	0.50*	(2.24)
GP	0.85*	(2.20)	0.46*	(2.32)	0.82*	(2.18)	0.66**	(2.90)	0.60	(1.69)	0.35	(1.31)
GrAdExp	0.13	(0.38)	0.40***	(3.75)	0.16	(0.84)	0.36*	(2.43)	0.50**	(3.22)	0.13	(0.82)
grcapx	0.54***	(4.05)	0.86***	(4.32)	0.10	(0.62)	0.61***	(4.52)	1.10***	(4.86)	-0.07	(-0.42)
grcapx3y	0.63***	(4.34)	0.96***	(4.09)	0.03	(0.16)	0.71***	(4.54)	1.17***	(4.44)	-0.19	(-1.02)
GrLTNOA	0.07	(0.30)	0.56***	(3.80)	0.07	(0.52)	0.42**	(3.28)	0.27	(1.57)	-0.04	(-0.21)
GrSaleToGrInv	0.55***	(3.90)	0.68***	(3.78)	0.32*	(2.33)	0.64***	(5.77)	0.74***	(3.39)	-0.09	(-0.52)
GrSaleToGrOverhead	0.27	(1.84)	0.02	(0.10)	-0.06	(-0.45)	0.17	(1.42)	-0.14	(-0.80)	-0.07	(-0.36)
Herf	-0.28	(-1.24)	0.26	(1.76)	-0.03	(-0.16)	-0.02	(-0.18)	0.83**	(3.26)	-0.11	(-0.50)
HerfAsset	-0.31	(-1.32)	0.17	(0.97)	-0.14	(-0.73)	-0.10	(-0.67)	0.79*	(2.30)	-0.21	(-1.05)
HerfBE	-0.30	(-1.46)	0.25	(1.41)	-0.06	(-0.35)	-0.07	(-0.48)	0.97*	(2.42)	-0.14	(-0.76)
High52	-0.29	(-0.83)	0.70*	(2.28)	0.45	(1.47)	0.21	(0.83)	0.42	(0.92)	0.58	(1.84)
IdioRisk	0.38	(1.69)	1.09***	(3.78)	0.22	(0.86)	0.72***	(3.61)	0.79	(1.59)	0.31	(1.13)
IdioVol3F	0.35	(1.57)	1.08***	(3.72)	0.23	(0.90)	0.71***	(3.54)	0.76	(1.47)	0.33	(1.20)
IdioVolAHT	0.05	(0.21)	0.94*	(2.12)	-0.01	(-0.04)	0.33	(1.46)	0.11	(0.21)	0.09	(0.28)

(*Continued*)

Table IA.2: Risk-managed portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
Illiquidity	0.63**	(2.69)	0.78**	(3.24)	0.03	(0.18)	0.71***	(3.97)	0.54*	(2.02)	-0.12	(-0.87)
IndMom	0.79***	(3.72)	0.56*	(2.43)	0.47*	(2.09)	0.69***	(4.32)	0.83	(1.87)	0.20	(0.91)
IndRetBig	1.48***	(7.32)	3.59***	(11.29)	1.04***	(4.83)	2.21***	(11.67)	3.45***	(5.67)	0.87***	(4.02)
IntanCFP	0.13	(0.59)	0.46*	(2.23)	-0.04	(-0.20)	0.37*	(1.99)	0.40	(1.16)	-0.04	(-0.20)
IntanEP	0.41	(1.46)	0.42*	(2.15)	0.05	(0.29)	0.40*	(2.00)	0.49	(1.95)	0.05	(0.29)
IntanSP	0.58	(1.90)	0.45	(1.77)	-0.33	(-1.16)	0.40	(1.66)	0.72	(1.94)	-0.33	(-1.16)
Investment	0.24	(1.13)	0.60*	(2.34)	0.22	(0.88)	0.41*	(2.23)	0.56	(1.58)	0.12	(0.42)
InvestPPEInv	0.77***	(4.00)	1.55***	(7.04)	0.36	(1.48)	1.23***	(6.43)	1.87***	(6.01)	0.27	(1.17)
InvGrowth	0.54*	(2.59)	0.85***	(6.82)	0.04	(0.16)	0.86***	(6.71)	1.06***	(4.46)	-0.06	(-0.37)
MaxRet	0.42	(1.90)	0.81***	(3.47)	0.29	(1.08)	0.72***	(4.05)	0.63	(1.33)	0.10	(0.39)
MeanRankRevGrowth	0.21	(1.15)	0.84***	(3.74)	0.10	(0.63)	0.60***	(3.67)	0.06	(0.32)	0.17	(0.70)
Mom12m	0.88***	(3.52)	1.35***	(6.05)	0.52**	(2.91)	1.05***	(6.26)	0.60	(1.79)	0.55**	(2.74)
Mom12mOffSeason	0.79***	(3.70)	1.10***	(5.43)	0.63***	(3.36)	0.95***	(5.73)	0.90**	(3.19)	0.70***	(3.72)
Mom6m	0.70**	(2.89)	1.05***	(4.37)	0.48**	(2.83)	0.77***	(4.59)	0.70*	(2.48)	0.57**	(2.96)
Mom6mJunk	0.45	(0.91)	1.13***	(4.91)	0.45*	(1.99)	0.92**	(3.22)	1.05**	(3.31)	0.45*	(1.99)
MomOffSeason	0.82**	(3.23)	1.18***	(4.66)	-0.11	(-0.45)	1.02***	(4.98)	1.10***	(3.66)	-0.23	(-0.93)
MomOffSeason06YrPlus	0.65**	(3.24)	0.72***	(4.45)	0.84***	(4.16)	0.73***	(5.09)	0.54**	(2.68)	0.78***	(3.77)
MomOffSeason11YrPlus	0.50*	(2.06)	0.28*	(2.05)	0.19	(1.07)	0.41**	(2.73)	0.16	(1.08)	0.19	(1.03)
MomOffSeason16YrPlus	0.14	(0.68)	0.40*	(2.49)	0.39*	(2.03)	0.39**	(2.60)	0.02	(0.08)	0.37	(1.88)
MomRev	0.52*	(2.54)	0.87***	(5.10)	0.12	(0.62)	0.66***	(4.66)	1.13***	(3.53)	-0.05	(-0.29)
MomSeason	1.14***	(6.39)	0.88***	(5.47)	0.49*	(2.35)	0.98***	(7.27)	1.05***	(4.52)	0.51*	(2.37)
MomSeason06YrPlus	0.94***	(5.19)	0.79***	(5.44)	0.14	(0.67)	0.87***	(6.73)	0.69***	(3.94)	0.16	(0.69)
MomSeason11YrPlus	0.51***	(3.42)	0.86***	(7.11)	0.35	(1.88)	0.73***	(6.85)	0.45*	(2.27)	0.44*	(2.33)
MomSeason16YrPlus	0.60**	(3.27)	0.64***	(4.68)	0.49**	(2.63)	0.63***	(4.95)	0.50**	(3.04)	0.54**	(2.81)
MomSeasonShort	1.10***	(4.60)	1.38***	(8.81)	-0.07	(-0.36)	1.31***	(8.29)	0.76***	(3.88)	-0.04	(-0.22)
MomVol	0.56**	(2.79)	1.09***	(4.90)	0.58**	(2.96)	0.84***	(5.34)	0.76**	(2.73)	0.45	(1.90)
NetPayoutYield	0.57**	(2.75)	0.89**	(2.63)	0.75**	(2.86)	0.76***	(3.95)	0.48	(0.98)	0.75**	(2.86)
NumEarnIncrease	1.40***	(5.44)	1.57***	(7.86)	0.84**	(2.92)	1.60***	(7.37)	1.48***	(5.16)	0.88***	(3.79)
OperProf	-0.18	(-0.61)	0.91***	(3.90)	0.44	(1.90)	0.58**	(2.88)	0.49	(1.09)	0.44	(1.90)
OPLeverage	0.48	(1.75)	0.61*	(2.35)	0.38	(1.41)	0.74**	(2.86)	0.10	(0.23)	0.36	(1.34)
OrderBacklog	-0.29	(-1.04)	0.46**	(2.92)	-0.17	(-0.98)	0.20	(1.16)	0.19	(1.17)	-0.22	(-1.05)
OrgCap	0.95***	(3.75)	0.60***	(3.36)	0.29	(1.04)	0.77***	(4.28)	0.29	(1.11)	0.53*	(2.22)

(*Continued*)

Table IA.2: Risk-managed portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
OScore	0.18	(0.63)	0.82**	(3.06)	0.54*	(2.49)	0.50*	(2.38)	0.70	(1.84)	0.55*	(2.30)
PayoutYield	0.14	(0.70)	0.44**	(2.68)	-0.08	(-0.39)	0.27	(1.59)	0.23	(1.13)	-0.08	(-0.39)
PctAcc	0.37**	(2.90)	0.64***	(3.54)	0.14	(0.72)	0.39**	(2.90)	0.78***	(3.74)	0.23	(1.32)
PriceDelayRsq	0.44	(1.85)	0.51**	(3.03)	0.14	(0.85)	0.50**	(3.19)	0.55	(1.88)	-0.01	(-0.03)
PriceDelaySlope	0.11	(0.79)	0.22*	(2.29)	0.12	(0.79)	0.16	(1.82)	0.39*	(2.48)	-0.01	(-0.08)
PriceDelayTstat	-0.31	(-1.89)	0.26	(1.68)	0.06	(0.30)	-0.05	(-0.41)	0.32	(1.18)	0.04	(0.19)
PS	-0.14	(-0.32)	0.88**	(3.27)	0.42	(1.86)	0.79**	(2.92)	0.62	(1.95)	0.30	(1.10)
RD	0.60**	(3.15)	1.17***	(4.76)	0.62*	(2.19)	0.72***	(4.85)	1.82***	(3.65)	0.25	(0.85)
RDAbility	-0.23	(-1.32)	0.11	(0.97)	-0.08	(-0.40)	-0.04	(-0.29)	0.02	(0.12)	-0.08	(-0.60)
ReturnSkew	1.06***	(6.78)	0.72***	(4.86)	0.46	(1.10)	1.03***	(9.17)	0.33	(0.75)	0.37	(1.47)
ReturnSkew3F	0.99***	(6.19)	0.56***	(4.12)	0.07	(0.22)	0.92***	(8.27)	0.18	(0.49)	0.06	(0.25)
RevenueSurprise	1.35***	(7.62)	1.49***	(5.79)	1.15***	(5.13)	1.59***	(8.35)	0.93***	(5.01)	1.15***	(5.13)
RIO_MB	0.67	(1.74)	0.62**	(3.13)	0.09	(0.42)	0.61*	(2.49)	0.74*	(2.42)	0.09	(0.42)
RIO_Turnover	0.32*	(2.03)	0.28	(1.48)	0.24	(0.84)	0.28*	(2.07)	0.44	(1.62)	0.24	(0.84)
RIO_Volatility	0.29*	(2.09)	0.69***	(4.16)	0.52*	(2.22)	0.44***	(3.61)	0.37	(1.63)	0.52*	(2.22)
roaq	-0.01	(-0.03)	1.78***	(6.94)	0.67**	(2.61)	1.52***	(5.62)	1.04*	(2.38)	0.74**	(3.04)
RoE	-0.29	(-1.21)	0.65**	(2.74)	0.45*	(2.02)	0.17	(0.97)	0.45	(1.14)	0.40	(1.62)
sfe	0.55	(1.19)	0.84*	(2.38)	0.04	(0.13)	0.81*	(2.59)	-0.05	(-0.08)	0.31	(1.26)
ShareIss1Y	0.50**	(2.72)	1.15***	(5.30)	0.82*	(2.55)	0.73***	(4.94)	1.26**	(2.89)	0.82*	(2.55)
ShareIss5Y	0.45*	(2.19)	0.97***	(5.09)	0.34	(1.48)	0.69***	(4.42)	0.81**	(2.66)	0.34	(1.48)
ShareRepurchase	0.74***	(3.66)	1.15***	(3.60)	0.32	(1.33)	0.78***	(3.36)	0.16	(0.49)	0.58	(1.78)
ShareVol	0.18	(0.83)	0.78***	(3.91)	0.30	(1.86)	0.50***	(3.45)	0.11	(0.48)	0.37	(1.75)
SP	1.08***	(3.50)	0.90	(1.92)	0.90***	(3.34)	1.06***	(4.20)	1.10*	(2.37)	0.68*	(2.05)
Spinoff	0.03	(0.16)	0.46	(1.85)	0.29	(1.43)	0.22	(1.45)	0.35	(0.95)	0.25	(0.94)
std_turn	0.30	(1.86)	0.83***	(4.14)	0.43	(1.51)	0.48***	(3.71)	1.10*	(2.29)	0.26	(0.86)
STreversal	2.50**	(3.37)	2.28***	(15.24)	0.99***	(4.89)	2.33***	(16.20)	1.51***	(4.59)	0.11	(0.52)
SurpriseRD	-0.18	(-1.13)	0.57**	(2.91)	0.13	(0.52)	0.04	(0.37)	0.95*	(2.18)	0.13	(0.58)
tang	0.22	(0.90)	0.83***	(3.63)	0.05	(0.21)	0.45**	(2.59)	1.00*	(2.24)	-0.01	(-0.03)
Tax	0.28	(1.36)	0.77***	(3.83)	0.68***	(3.80)	0.47**	(3.05)	0.97**	(2.93)	0.66***	(3.39)
TotalAccruals	0.79**	(3.22)	0.39*	(2.40)	-0.03	(-0.08)	0.39**	(2.67)	0.90*	(2.59)	-0.21	(-0.63)
VarCF	-0.95*	(-2.56)	-0.53	(-1.23)	0.05	(0.14)	-0.73*	(-2.56)	-0.83	(-1.48)	0.43	(1.18)
VolMkt	0.18	(1.00)	0.61*	(2.03)	0.34	(1.70)	0.27	(1.72)	0.36	(1.02)	0.38	(1.62)

(*Continued*)

Table IA.2: Risk-managed portfolios

	Value-weighted portfolios (Excess returns)											
	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
VolSD	0.21	(1.22)	0.49**	(3.25)	0.16	(0.57)	0.36**	(2.90)	0.12	(0.51)	0.18	(0.46)
VolumeTrend	0.58**	(2.93)	0.65*	(2.11)	0.85***	(5.46)	0.56***	(3.31)	1.57***	(5.35)	0.51**	(3.27)
zerotrade	0.23	(1.71)	0.41***	(3.57)	0.35	(1.30)	0.37***	(3.88)	0.18	(0.82)	0.35	(1.30)
zerotradeAlt1	0.13	(0.91)	0.56***	(4.34)	0.52	(1.87)	0.40***	(3.67)	0.39	(1.76)	0.52	(1.87)
zerotradeAlt12	0.52**	(2.75)	0.39***	(3.33)	0.23	(0.72)	0.47***	(4.28)	0.26	(0.99)	0.23	(0.72)

Table IA.3: **Spanning regressions**

This figure shows alphas from univariate spanning regressions of risk-managed factor returns on the corresponding original factor returns. The spanning regressions are given by $r^{\sigma}_{i,t} = \alpha + \beta r_{i,t} + \epsilon_t$, where $r^{\sigma}_{i,t}$ $(r_{i,t})$ is the monthly return for the risk-managed (original) factor. The estimates of α are reported in percentage per month. Pre-sample denotes the sample frame spanning from 1932 prior to the in-sample period. In-sample denotes the sample frame used in the original discovery of an anomaly. Post-sample denotes the sample frame occurring after the in-sample period. Pre-1993, 1993-2003, and post-2003 denotes the sample frame, 1932-1992, 1993-2003 and 2004-2020, respectively. Alphas are reported in basis points per year. Values in the parentheses are t-statistics based on standard errors following Newey and West (1987). Appendix A describes 125 anomalies. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

	Pre-Sample		**In-Sample**		**Post-Sample**		**Pre-1993**		**1993-2003**		**Post-2003**	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
Accruals	-0.04	(-1.42)	0.08	(1.68)	0.01	(0.27)	0.06	(1.57)	0.09*	(1.98)	0.02	(0.51)
AccrualsBM	0.05	(0.53)	0.03	(0.62)	-0.10	(-0.98)	0.04	(0.68)	0.14	(1.66)	-0.10	(-0.85)
AdExp	-0.28*	(-2.18)	-0.14*	(-1.98)	-0.17	(-1.69)	0.03	(0.18)	0.06	(0.52)	-0.20	(-1.76)
AM	0.00	(0.00)	0.04	(0.51)	0.21	(1.76)	-0.01	(-0.18)	0.52**	(2.64)	0.04	(0.25)
AnnouncementReturn	0.30**	(3.31)	0.18***	(3.39)	0.42***	(3.38)	0.26**	(2.61)	0.57***	(5.29)	0.38**	(2.63)
AssetGrowth	-0.04	(-0.80)	0.14*	(2.14)	-0.12	(-1.65)	0.02	(0.50)	0.24**	(2.69)	-0.12	(-1.65)
BetaTailRisk	0.03	(0.31)	-0.03	(-0.46)	-0.19*	(-2.21)	0.12	(1.53)	-0.16	(-1.64)	-0.19*	(-2.54)
BidAskSpread	-0.02	(-0.12)	0.12	(0.85)	-0.20	(-1.82)	-0.09	(-0.89)	0.18	(0.77)	-0.19	(-1.34)
BM	0.20	(1.29)	0.00	(0.02)	0.13	(1.27)	0.04	(0.41)	0.46**	(2.69)	-0.17	(-0.92)
BMdec	-0.02	(-0.36)	0.09	(1.08)	0.09	(1.18)	0.04	(0.65)	0.47**	(3.06)	-0.03	(-0.43)
BookLeverage	-0.06	(-1.60)	0.00	(0.08)	-0.06	(-0.59)	0.02	(0.71)	-0.04	(-0.27)	-0.15	(-1.44)
BrandInvest	-0.07	(-0.92)	0.09	(1.23)	-0.11	(-0.88)	0.11	(1.10)	0.03	(0.24)	-0.08	(-0.95)
CashProd	0.03	(0.48)	0.16	(1.48)	-0.03	(-0.20)	-0.04	(-0.79)	0.53*	(2.52)	-0.03	(-0.20)
CF	0.11*	(2.21)	0.03	(0.41)	0.25**	(3.14)	0.07	(1.41)	0.13	(1.17)	0.40***	(3.60)
cfp	0.10*	(2.02)	0.03	(0.46)	0.22	(1.61)	0.05	(0.67)	0.15	(0.74)	0.28	(1.81)
ChAssetTurnover	0.05*	(2.24)	0.11*	(2.39)	0.01	(0.27)	0.08**	(3.30)	0.07	(1.42)	0.00	(0.10)
ChForecastAccrual	-0.14	(-1.46)	0.03	(0.84)	0.13*	(2.20)	-0.01	(-0.20)	0.15	(1.86)	0.12	(1.66)
ChInv	-0.04	(-1.36)	0.10*	(2.11)	-0.06	(-0.99)	0.04	(1.11)	0.15**	(2.66)	-0.04	(-0.59)
ChInvIA	0.00	(0.08)	0.11	(1.34)	-0.04	(-0.76)	0.05	(1.15)	0.25*	(2.37)	-0.11	(-1.96)
ChNCOA	0.06*	(2.22)	0.02	(0.28)	-0.04	(-0.97)	0.06*	(2.11)	0.04	(0.52)	-0.04	(-0.92)
ChNWC	0.02	(0.74)	0.13*	(2.26)	-0.07	(-1.35)	0.04	(1.87)	0.04	(0.89)	-0.06	(-1.19)
ChTax	0.27**	(2.73)	0.23***	(3.62)	0.27**	(2.81)	0.35**	(3.25)	0.14	(1.88)	0.23**	(2.80)
CompEquIss	-0.06	(-0.62)	0.19**	(3.01)	0.27*	(2.39)	0.12	(1.58)	0.08	(1.15)	0.27*	(2.39)
CompositeDebtIssuance	0.04	(1.69)	0.17***	(3.39)	0.08	(1.17)	0.17***	(3.88)	0.16*	(2.57)	0.07	(1.14)
ConvDebt	0.02	(0.50)	0.11	(1.15)	0.12	(0.93)	0.03	(0.84)	0.21	(1.73)	0.16	(1.45)

(*Continued*)

Table IA.3: Spanning

Anomalies	Pre-Sample α^{Pre}_{Sample}	t	In-Sample α^{In}_{Sample}	t	Post-Sample α^{Post}_{Sample}	t	Pre-1993 α^{Pre}_{1993}	t	1993-2003 α^{1993}_{2003}	t	Post-2003 α^{Post}_{2003}	t
Coskewness	0.08	(0.62)	-0.07	(-0.89)	-0.02	(-0.22)	0.08	(0.87)	-0.11	(-0.90)	0.06	(0.47)
DelCOA	-0.02	(-0.56)	0.05	(0.87)	-0.09	(-1.50)	0.07	(1.46)	0.12*	(2.10)	-0.06	(-0.85)
DelCOL	0.02	(0.28)	0.04	(1.10)	-0.09	(-1.13)	0.04	(1.40)	0.19**	(2.89)	-0.09	(-1.11)
DelFINL	0.02	(0.77)	0.15***	(3.68)	0.05	(0.84)	0.14***	(4.03)	0.14*	(2.13)	0.08	(1.25)
DelLTI	-0.03	(-0.93)	0.05	(1.02)	-0.11*	(-2.07)	-0.03	(-0.88)	0.12	(1.01)	-0.09	(-1.59)
DelNetFin	-0.00	(-0.14)	0.17***	(3.71)	0.16*	(2.44)	0.12**	(3.20)	0.06	(0.70)	0.16*	(2.42)
DivInit	-0.04	(-0.57)	0.00	(0.01)	0.18**	(3.09)	0.09	(1.80)	0.09	(0.86)	0.24***	(3.51)
DivOmit	0.04	(0.53)	-0.06	(-1.28)	-0.05	(-0.55)	0.01	(0.22)	0.10	(1.04)	-0.14	(-1.04)
DolVol	0.15	(1.42)	0.12	(1.39)	-0.01	(-0.14)	0.14	(1.80)	0.21	(1.84)	-0.04	(-0.64)
EarningsConsistency	-0.01	(-0.16)	0.04	(1.10)	0.16*	(2.31)	0.03	(1.11)	-0.04	(-0.61)	0.16*	(2.19)
EarningsSurprise	0.11	(1.87)	0.36	(1.83)	0.36***	(3.78)	0.25**	(2.76)	0.20*	(2.49)	0.37**	(3.34)
EarnSupBig	0.19	(1.72)	0.22	(1.37)	0.17*	(2.05)	0.11	(1.08)	-0.06	(-0.24)	0.18*	(2.09)
EntMult	-0.01	(-0.17)	0.09	(1.38)	0.06	(0.80)	0.01	(0.17)	0.25*	(2.51)	0.06	(0.90)
EP	-0.05	(-0.72)	0.03	(0.57)	-0.04	(-0.64)	0.06	(1.14)	-0.02	(-0.26)	-0.23*	(-2.01)
FEPS	-0.21	(-1.32)	0.67***	(3.58)	0.18*	(2.03)	0.02	(0.23)	0.25	(1.12)	0.18	(1.97)
FirmAgeMom	0.31***	(3.49)	0.48***	(4.59)	0.32**	(2.70)	0.31***	(3.81)	0.46***	(4.26)	0.32**	(2.70)
Frontier	0.14	(1.60)	0.13*	(2.11)	-0.02	(-0.24)	0.07	(1.37)	0.17	(1.66)	-0.02	(-0.24)
GP	0.01	(0.22)	0.05	(0.90)	0.19	(0.97)	0.10	(1.80)	0.03	(0.26)	0.00	(0.02)
GrAdExp	0.15	(1.64)	0.03	(0.99)	0.14*	(2.11)	0.25**	(3.13)	0.05	(1.02)	0.11*	(2.14)
grcapx	0.01	(0.26)	-0.02	(-0.29)	-0.11	(-1.69)	-0.01	(-0.39)	0.23*	(2.33)	-0.10	(-1.82)
grcapx3y	-0.00	(-0.05)	-0.03	(-0.49)	-0.10	(-1.50)	-0.03	(-0.76)	0.25**	(2.65)	-0.13*	(-2.13)
GrLTNOA	-0.02	(-0.51)	0.09**	(2.60)	-0.02	(-0.39)	0.06	(1.93)	0.07	(1.12)	-0.04	(-0.63)
GrSaleToGrInv	0.00	(0.21)	0.07	(1.17)	0.05	(1.11)	0.02	(0.60)	0.14*	(1.98)	0.05	(1.22)
GrSaleToGrOverhead	-0.01	(-0.24)	0.11	(1.91)	0.07	(1.52)	0.06	(1.92)	0.10*	(1.98)	-0.01	(-0.15)
Herf	-0.02	(-0.66)	0.04	(0.46)	-0.07	(-0.88)	0.06*	(1.99)	0.34*	(2.46)	-0.03	(-0.35)
HerfAsset	0.04	(1.11)	-0.02	(-0.18)	-0.04	(-0.60)	0.05	(1.43)	0.27	(1.47)	-0.01	(-0.19)
HerfBE	0.02	(0.88)	0.01	(0.10)	-0.02	(-0.37)	0.02	(0.81)	0.34	(1.61)	-0.02	(-0.26)
High52	0.14	(0.76)	0.19	(1.22)	0.49**	(2.78)	0.28*	(2.07)	0.07	(0.36)	0.59**	(3.06)
IdioRisk	0.36**	(2.97)	0.36**	(3.05)	0.15	(1.09)	0.36***	(3.74)	0.31	(1.24)	0.25	(1.72)
IdioVol3F	0.36**	(3.06)	0.37**	(3.12)	0.18	(1.41)	0.38***	(3.98)	0.30	(1.19)	0.28*	(2.14)
IdioVolAHT	0.17	(1.83)	0.03	(0.28)	-0.03	(-0.19)	0.22**	(2.62)	-0.07	(-0.27)	0.09	(0.91)
Illiquidity	0.16	(1.51)	0.06	(0.92)	-0.00	(-0.07)	0.13	(1.87)	0.11	(1.43)	0.04	(0.74)
IndMom	0.40***	(4.48)	0.11	(1.70)	0.09	(0.89)	0.27***	(4.51)	0.08	(0.36)	0.14	(1.26)

(*Continued*)

Table IA.3: Spanning

Anomalies	Pre-Sample		In-Sample		Post-Sample		Pre-1993		1993-2003		Post-2003	
	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
IndRetBig	0.47***	(5.03)	1.37***	(4.84)	0.11	(1.50)	0.56***	(5.14)	1.31***	(4.27)	0.11	(1.43)
IntanCFP	-0.02	(-0.58)	0.04	(0.55)	-0.18	(-1.80)	-0.02	(-0.40)	0.07	(0.80)	-0.18	(-1.80)
IntanEP	0.02	(0.25)	0.03	(0.46)	-0.02	(-0.21)	0.00	(0.06)	0.14	(1.51)	-0.02	(-0.21)
IntanSP	-0.01	(-0.30)	-0.07	(-0.79)	-0.38*	(-2.39)	-0.04	(-0.59)	0.05	(0.40)	-0.38*	(-2.39)
Investment	0.02	(0.37)	0.08	(1.46)	0.10	(0.88)	0.07	(1.53)	0.36*	(2.53)	-0.02	(-0.12)
InvestPPEInv	-0.06	(-1.41)	0.07	(0.75)	0.06	(0.66)	-0.04	(-0.83)	0.37**	(3.08)	0.04	(0.48)
InvGrowth	-0.06	(-1.52)	0.05	(1.34)	0.03	(0.60)	0.00	(0.18)	0.11	(1.93)	-0.00	(-0.09)
MaxRet	0.25*	(1.98)	0.32**	(2.95)	0.26	(1.60)	0.30**	(2.90)	0.27	(1.09)	0.14	(0.95)
MeanRankRevGrowth	-0.02	(-0.46)	0.00	(0.03)	0.10	(1.75)	0.02	(0.47)	0.17**	(2.96)	0.01	(0.19)
Mom12m	0.45***	(3.88)	0.33***	(4.26)	0.34***	(3.45)	0.43***	(5.39)	0.27	(1.73)	0.43***	(3.53)
Mom12mOffSeason	0.28**	(3.07)	0.35**	(2.87)	0.43***	(3.51)	0.30***	(4.49)	0.43**	(3.04)	0.46***	(3.64)
Mom6m	0.62***	(4.38)	0.16**	(2.86)	0.23*	(2.36)	0.50***	(4.49)	0.21	(1.43)	0.37**	(2.92)
Mom6mJunk	0.05	(0.51)	0.48***	(3.92)	0.32*	(2.59)	0.23**	(3.10)	0.33*	(2.45)	0.32*	(2.59)
MomOffSeason	0.03	(0.32)	0.03	(0.45)	-0.17	(-1.62)	0.06	(0.95)	0.12	(1.53)	-0.23*	(-2.23)
MomOffSeason06YrPlus	0.16*	(2.21)	0.10	(1.96)	0.14	(1.94)	0.16***	(3.50)	0.07	(1.06)	0.13	(1.94)
MomOffSeason11YrPlus	0.08	(1.33)	0.02	(0.54)	0.07	(1.06)	0.06	(1.70)	-0.00	(-0.02)	0.07	(1.00)
MomOffSeason16YrPlus	-0.06	(-1.85)	0.04	(0.83)	0.06	(1.12)	-0.04	(-1.47)	-0.00	(-0.02)	0.05	(0.83)
MomRev	0.33***	(3.45)	0.20*	(2.14)	0.00	(0.06)	0.24**	(3.28)	0.31**	(3.13)	-0.01	(-0.10)
MomSeason	0.47***	(4.28)	0.01	(0.16)	0.11	(1.59)	0.31***	(3.66)	-0.03	(-0.48)	0.13	(1.82)
MomSeason06YrPlus	0.23**	(2.86)	-0.06	(-1.67)	-0.05	(-0.67)	0.14*	(2.46)	-0.06	(-0.96)	-0.05	(-0.61)
MomSeason11YrPlus	0.06	(0.92)	0.04	(1.13)	0.05	(1.11)	0.04	(0.99)	0.04	(0.71)	0.04	(0.81)
MomSeason16YrPlus	0.02	(0.71)	-0.01	(-0.29)	0.01	(0.10)	0.03	(1.06)	-0.02	(-0.34)	0.01	(0.16)
MomSeasonShort	0.36**	(3.18)	0.14*	(2.34)	0.02	(0.32)	0.31***	(3.85)	0.10	(1.64)	0.02	(0.27)
MomVol	0.44***	(4.25)	0.06	(1.10)	0.25*	(2.37)	0.34***	(3.85)	0.29*	(2.42)	0.23	(1.63)
NetPayoutYield	0.10	(1.55)	0.24	(1.85)	0.16	(1.80)	0.12*	(2.28)	-0.03	(-0.21)	0.16	(1.80)
NumEarnIncrease	0.11	(1.67)	0.51***	(4.01)	0.35**	(3.07)	0.17**	(2.67)	0.29**	(2.87)	0.44***	(3.40)
OperProf	0.03	(0.62)	0.39***	(3.83)	0.01	(0.11)	0.05	(1.24)	0.10	(0.59)	0.01	(0.11)
OPLeverage	0.04	(0.97)	0.13	(1.32)	-0.18	(-1.41)	-0.01	(-0.11)	-0.03	(-0.24)	-0.15	(-1.08)
OrderBacklog	-0.01	(-0.22)	-0.02	(-0.97)	-0.01	(-0.13)	0.00	(0.14)	0.06	(1.02)	0.01	(0.18)
OrgCap	0.11	(1.95)	0.16*	(2.36)	0.00	(0.02)	0.15***	(3.75)	0.05	(0.53)	-0.04	(-0.59)
OScore	-0.03	(-0.44)	0.07	(1.12)	0.14	(1.90)	0.02	(0.40)	0.21	(1.50)	0.12	(1.64)
PayoutYield	-0.07	(-1.23)	0.08	(1.73)	-0.08	(-1.12)	-0.04	(-0.90)	0.03	(0.52)	-0.08	(-1.12)
PctAcc	0.04	(0.65)	0.12	(1.90)	-0.00	(-0.02)	0.06	(0.95)	0.11	(1.92)	0.04	(0.64)

(*Continued*)

Table IA.3: Spanning

	Pre-Sample		In-Sample		Post-Sample		Pre-1993		1993-2003		Post-2003	
Anomalies	α^{Pre}_{Sample}	t	α^{In}_{Sample}	t	α^{Post}_{Sample}	t	α^{Pre}_{1993}	t	α^{1993}_{2003}	t	α^{Post}_{2003}	t
PriceDelayRsq	0.05	(0.46)	0.10	(1.47)	-0.05	(-0.75)	0.10	(1.36)	0.05	(0.41)	-0.03	(-0.46)
PriceDelaySlope	-0.10	(-1.45)	0.04	(0.97)	-0.03	(-0.52)	-0.03	(-0.66)	0.02	(0.42)	-0.08	(-1.22)
PriceDelayTstat	-0.10	(-1.52)	0.02	(0.42)	0.03	(0.34)	-0.01	(-0.36)	0.03	(0.27)	0.11	(1.03)
PS	0.08	(1.14)	0.10	(1.81)	0.05	(0.43)	0.16*	(2.47)	0.19	(1.07)	-0.03	(-0.22)
RD	0.07*	(2.12)	0.03	(0.69)	-0.02	(-0.16)	0.08*	(2.25)	0.51**	(2.78)	-0.03	(-0.39)
RDAbility	-0.04	(-0.67)	-0.05	(-1.06)	0.04	(0.70)	-0.01	(-0.21)	-0.11*	(-2.16)	0.01	(0.27)
ReturnSkew	0.25**	(2.79)	0.13	(1.86)	0.27	(1.57)	0.15*	(2.04)	-0.09	(-0.52)	0.23	(1.86)
ReturnSkew3F	0.09	(1.43)	0.06	(0.94)	0.14	(1.39)	0.04	(1.20)	-0.04	(-0.28)	0.01	(0.10)
RevenueSurprise	0.33**	(2.80)	0.43*	(2.12)	0.58***	(4.04)	0.35*	(2.58)	0.30*	(2.21)	0.58***	(4.04)
RIO_MB	-0.06	(-0.53)	-0.00	(-0.07)	-0.08	(-1.29)	-0.05	(-0.74)	0.04	(0.46)	-0.08	(-1.29)
RIO_Turnover	0.05	(1.19)	-0.12	(-1.60)	-0.04	(-0.36)	0.01	(0.36)	-0.07	(-0.79)	-0.04	(-0.36)
RIO_Volatility	0.02	(0.32)	0.10	(1.40)	0.15	(1.84)	0.08	(1.39)	-0.02	(-0.20)	0.15	(1.84)
roaq	-0.14	(-0.97)	0.67***	(5.12)	0.28**	(3.24)	0.61***	(3.81)	0.36*	(2.19)	0.28***	(3.49)
RoE	-0.13	(-1.17)	0.08	(1.43)	0.14	(1.52)	0.02	(0.38)	0.10	(0.68)	0.09	(1.20)
sfe	0.04	(0.40)	0.06	(0.74)	-0.05	(-0.55)	0.02	(0.36)	-0.07	(-0.32)	0.07	(1.08)
ShareIss1Y	0.04	(0.70)	0.34**	(2.66)	0.11	(0.93)	0.11*	(2.19)	0.21	(0.81)	0.11	(0.93)
ShareIss5Y	-0.01	(-0.09)	0.22**	(3.13)	-0.10	(-1.29)	0.06	(0.85)	0.32*	(2.57)	-0.10	(-1.29)
ShareRepurchase	0.00	(0.02)	0.06	(0.97)	0.13	(1.25)	0.05	(1.20)	-0.04	(-0.26)	0.30*	(2.19)
ShareVol	0.13*	(2.04)	0.17*	(2.15)	0.08	(1.39)	0.15**	(2.69)	0.06	(0.96)	0.04	(0.68)
SP	0.19*	(2.30)	-0.12	(-1.22)	0.29**	(2.90)	0.07	(1.04)	0.39*	(2.59)	0.23	(1.71)
Spinoff	-0.09	(-0.72)	-0.02	(-0.33)	0.13	(1.45)	0.01	(0.11)	0.32*	(2.30)	-0.09	(-1.42)
std_turn	0.05	(0.72)	0.18***	(3.64)	0.33*	(2.09)	0.10*	(2.21)	0.34**	(2.76)	0.26	(1.54)
STreversal	0.10	(0.51)	0.37***	(3.83)	0.25*	(2.05)	0.43***	(3.36)	0.71***	(3.70)	-0.23*	(-2.47)
SurpriseRD	-0.01	(-0.19)	0.11	(1.41)	-0.04	(-0.70)	0.07	(1.52)	0.19	(1.37)	-0.04	(-0.78)
tang	0.03	(0.56)	0.20	(1.94)	-0.07	(-1.18)	0.02	(0.42)	0.18	(1.39)	-0.09	(-1.47)
Tax	-0.04	(-0.78)	0.21*	(2.17)	0.04	(0.78)	-0.01	(-0.14)	0.34*	(2.36)	0.06	(1.04)
TotalAccruals	0.02	(0.55)	0.03	(0.47)	-0.29*	(-2.21)	-0.02	(-0.49)	0.13	(1.33)	-0.17	(-1.53)
VarCF	-0.09	(-1.18)	0.21*	(2.19)	0.22	(1.89)	0.02	(0.25)	-0.12	(-0.70)	0.39*	(2.58)
VolMkt	0.08	(1.04)	0.14*	(2.00)	0.12	(1.32)	0.12	(1.85)	0.01	(0.12)	0.18*	(2.11)
VolSD	-0.03	(-0.32)	0.04	(0.72)	0.11	(0.69)	0.05	(0.74)	0.07	(1.08)	0.13	(0.62)
VolumeTrend	0.07	(0.83)	-0.12	(-1.55)	0.20***	(3.73)	0.04	(0.60)	0.27***	(3.50)	0.19**	(2.79)
zerotrade	-0.02	(-0.36)	0.09**	(2.60)	0.21	(1.66)	0.06	(1.40)	0.08	(1.34)	0.21	(1.66)
zerotradeAlt1	-0.06	(-0.96)	0.09*	(2.27)	0.29*	(2.07)	0.08	(1.64)	0.10	(1.93)	0.29*	(2.07)

(*Continued*)

Table IA.3: Spanning

Anomalies	Pre-Sample		In-Sample		Post-Sample		Pre-1993		1993-2003		Post-2003	
	α_{Sample}^{Pre}	t	α_{Sample}^{In}	t	α_{Sample}^{Post}	t	α_{1993}^{Pre}	t	α_{2003}^{1993}	t	α_{2003}^{Post}	t
zerotradeAlt12	0.08	(0.84)	0.05	(1.50)	0.22	(1.54)	0.07	(1.38)	0.06	(1.00)	0.22	(1.54)