Skewness Managed Portfolios

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Abstract

Due to positive skewness in the distribution of monthly stock returns, a few stocks play a disproportionally outsized role in the performance of factors. Because skewed stocks can end up in either the long or short leg of the portfolio, their impact depends on how skewness is related to the characteristic used to create the anomaly. Anomalies that long skewed stocks benefit, while those short lose. In a sample of anomalies underlying recent factor models, a skewness managed strategy that seeks skewness in the long leg while avoiding it in the short leg improves the average return by five to ten percentage points per year. Factor models fail to price skewness managed versions of their own factors, resulting in alphas that are up to as large as the original anomaly premium.

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1 Introduction

The distribution of monthly stock returns exhibits a positive skewness which results in disproportionately few stocks playing a key role in the equity premium. I build portfolios that use firms' expected skewness to target these potential high performers in the long leg and avoid them in the short leg of anomaly strategies. This skewness management strategy greatly improves the performance of anomaly strategies based on characteristics underlying some of the most up to date factor models. Factor models fail to price the skewness managed versions of portfolios based on their own underlying characteristics. In essence, managing skewness turns factors back into anomalies relative to their own factor models.

I motivate the analysis by demonstrating the impact of positive outliers on 15 anomaly strategies. I isolate the impact by reconstructing these anomalies from a monthly return distribution where the right tail has been winsorized. Limiting the best performing observations in the sample either hurts or helps the performance of an anomaly based on whether these positive outliers tend to end up on the long or short leg. Small, value stocks tend to be positive outliers, thus capping the sample *reduces* the performance of anomalies based on size and book-to-market (b/m). Low profitability stocks with poor past performance also tend to be positive outliers, thus capping the sample *improves* the performance of anomalies based on ROE, operating profitability (OP), and momentum. These results show how firm characteristics available at portfolio formation can potentially predict a stock's potential for high positive performance.

I develop a skewness management strategy that takes advantage of this relation between firm characteristics and future skewness. To start, I construct an off-the-shelf measure of ex-post realized skewness as in Amaya et al (2015) and project it onto firm characteristics as in Boyer, Mitton, and Vorkink (2010) to obtain an (ex-ante) expected skewness measure. I then use this expected skewness measure to enhance the skewness profile of any given anomaly strategy through a sequential sort that seeks skewness in the long leg and avoids it in the short leg. As an example, consider the value strategy of buying the highest book-to-market decile and selling the lowest book-to-market decile. I sort each book-to-market decile into three expected skewness portfolios and then form my skewness managed value strategy by buying the highest expected skewness portfolio of the highest book-to-market decile and selling the lowest expected skewness portfolio in the lowest book-to-market decile.

I apply my skewness management strategy to the 15 anomaly portfolios underlying the construction of the factors in several recent factor models.[1] Overall, I find that my skewness management strategy improves the average returns of anomalies by up to ten percentage points per year and Sharpe ratios by up to 0.46. The strategy also enhances portfolio skewness and produces positive and significant alphas against the original anomalies and all factor models in Footnote 1. The improvements in performance are concentrated in the leg of the anomaly strategy most impacted by high performing observations.

Interestingly, the factor models I explore are not even able to price the skewness managed versions of test portfolios based on their own underlying characteristics. Figure 1 contains the the comparison of alphas between standard and skewness managed version of the 15 anomaly long-short portfolios. Skewness managed versions of models' own test assets generate alphas that are between 3.7 and 11.5 percentage points larger than those from the standard anomalies, with all but one of the resulting alphas being significant.

Managing skewness alters portfolios' exposure to factors, though not in way that suggests an increased overall exposure. For all of the 15 considered anomaly long-short portfolios, skewness manged versions tend to load higher on size related factors (SMB, ME), and the market (MKT) but lower on profitability (ROE, RMW, EG), investment (IA, CMA) and value (HML) related factors. The composite behavioral factors tend to load both higher (PEAD) or lower (MGMT, FIN). The fact that the factor loadings tend in either direction suggests that the improvements in performance are not coming from changes in exposure to the model factors.

[1] Fama and French (1993), Fama and French (2015), Hou, Xue, and Zhang (2015), Hou et al (2021), Stambaugh and Yuan (2017), and Daniel, Hirshliefer and Sun (2020)

One concern is that expected skewness is simply a return predictor that contains information from the characteristics it uses as inputs or another unmeasured risk, and indeed, a long short strategy based on expected skewness deciles does show an annual return of approximately 8.83%. I address this concern with two points. First, I test the performance of the skewness management strategy without the known return predictors. I find that the skewness management strategy still generates benefits when these return predictors are removed. Second, as a robustness I run spanning regressions between the skewness managed strategy and a long-short strategy based on the expected skewness measure. I find that variation in my skewness management strategy is not fully explained by the expected skewness portfolio.

Finally, while using realized skewness is natural given my objective, I also replicate my results using firms idiosyncratic skewness, which is the original measure used by Boyer, Mitton, and Vorkink (2010). I find that idiosyncratic skewness produces very similar performance improvements for anomaly portfolios. In certain cases, idiosyncratic skewness may even act as a better proxy for the effect I aim to capture with this strategy. Managing skewness with a measure based on idiosyncratic skewness improves average returns up to eleven percentage points per year and Sharpe ratios up to 0.43.

This paper is inspired by Bessembinder (2018) who demonstrates the impact of positive outliers on the equity premium and portfolios of public equities more generally. This paper differs by showing how disproportionally few stocks can play an outsized role in anomaly strategies. I map how the effect plays out in several common anomalies and in long-short strategies more broadly. I produce a skewness management strategy that combines an outlier measure with several features of anomaly construction to improve the overall performance and downside risk profile of common anomalies. Finally, I show that the most up-to-date factor models fail to price skewness managed versions of portfolios based on their own underlying characteristics.

The inability of factor models to price skewness managed versions of their own underlying factors is an important result that contributes to a growing literature showing the limitations of factor models. Baba Yara, Boyer and Davis (2022) highlight how no single model is able to fully price the cross section of stock returns despite the weak theoretical assumptions needed for one the exist. This same limitation extends to models' ability to price alternate test assets generated from their underlying characteristics. Baba Yara, Boons and Tamoni (2021) illustrate how, in a subset of characteristics, factor models are unable to price test assets based on older sorts of the same characteristic. This effect is most pronounced in models with more factors, that is, models with more factors price newer sorts of test assets well, but struggle with portfolios that have longer holding periods. Chernov, Lochstoer, and Lundeby (2022) use multi-horizon returns as an endogenous test asset and find that recent factor models fail to price returns of their own factors at longer horizons. This paper compliments the literature by looking at endogenously generated test assets to assess the performance of factor models. I find that several prominent models are unable to price versions of their underlying test assets that have been altered to enhance the skewness feature of the return data.

The role of skewness in stock returns is a topic that has been discussed since Markowitz (1952) first derived the mean-variance frontier by assuming investors should not have preferences over the third moment. Since that time other work has expanded the CAPM framework to include stocks' contributions to skewness as an additional risk factor (Rubinstein 1973, Kraus and Litzenberger 1976). Stocks with higher coskewness (those more exposed to systematic skewness) command a return premium (Harvey and Siddique 2000). Recent work shows this effect to persist in the modern data (Harvey and Siddique 2022). Also, coskewness is a potential explanation for the alpha generated by low risk anomalies (Schneider, Wagner, Zechner 2020).

Skewness in individual stocks also plays a role in the cross-section when investors have a skewness preference (Mitton and Vorkink 2007, Brunnermeier et al., 2007, Barberis and Huang 2008). This conclusion is supported by the empirical evidence, which shows that stocks with higher idiosyncratic skewness command a negative return premium. This negative premium has been shown when skewness is measured over different time horizons using different methods (Boyer, Mitton, and Vorkink 2010, Ameya et al 2015, Bali et al 2011, Conrad et al. 2014). More recent work applies these insights to explain anomaly premiums, in which skewness preferences lead to overpricing of the short leg of strategies (Kumar, Motahari, and Taffler 2019) or idiosyncratic skewness being a proxy for growth options (Bali et al 2019). These final two papers focus on the equilibrium effect in which investors with skewness preferences bid up prices resulting in lower subsequent returns. My findings differ by focusing on the importance in realized outliers and their disproportionate role in the performance of a given portfolio.

This paper is also related to a growing literature looking at managing volatility in portfolios. Barrosa and Santa-Clara (2015) and Daniel and Moskowitz (2016) show that a strategy that uses portfolio volatility to scale exposure to momentum can help combat momentum crashes. My findings demonstrate that these momentum crashes are also related to positive outliers. Daniel and Moskowitz highlight how momentum crashes are related to the fact that stocks rebounding after a market downturn tend to end up in the short leg of momentum. I find that these rebounding stocks tend to be those outliers that drive the effect I discuss in this paper, thus limiting positive skewness helps to alleviate some of the downside risk of the momentum strategy.

Moreira and Muir (2017) use past volatility to improve the performance of several other common factor strategies, including momentum, and are able to generate alpha over the original factors. Recent work by Barrosa and Detzel (2021) shows that implementing these scaling strategies can incur extra trading costs that mitigate the benefits and propose a set of solutions that decrease the potential costs. Cederberg et al (2020) highlight that alpha may not be the best indicator of whether volatility management improves outcomes, instead the authors focus on how these strategies often fail to create a meaningful increase in Sharpe ratios.

The paper proceeds as follows. Section 2 motivates the question by showing the impact of outliers through winsorization. Section 3 outlines the model used to predicted individual stock skewness. Section 4 outlines the construction of the skewness management strategy and reports the results. Section 5 provides robustness checks. Section 6 concludes.

2 Motivation

In this section I show the role of the extreme returns in anomaly premiums by calculating the performance of common anomalies in a winsorized sample of stock returns.

2.1 Data

I draw my sample from the Center for Research in Security Prices (CRSP) universe of common stocks, focusing on the period from July 1963 to December 2021 (where available). The 15 anomaly strategies are constructed using data from Compustat, CRSP, and the Open Source Asset Pricing database from Chen and Zimmerman (2021).[2] Further details are provided in Appendix A. In the next section I look at percentiles to determine which observations are part of the "tail" of the distribution. To calculate these percentiles I use the historical distribution each month, which includes all observations from January 1926 up to each month t. All the insights are robust to looking at percentiles in the full distribution.

2.2 The Role of Skewness

How skewed is the return distribution? Panel A of Figure 2 shows a histogram of monthly returns from July 1963 to December 2021. The long right tail, though nearly impossible to see at this scale, extends to an impressive 2400% monthly return. It accounts for a part of the right-skewed asymmetry that amounts to a skewness of 7.64 and a kurtosis of 414. These observations do not come evenly in each month, rather these extreme observations are clustered in time. Panel B of Figure 2 plots the percent of stocks above a certain return cutoff (26.6 percent, approximately the top 5% of observations). Overall, These outliers appear to be at least partially related to the rebounds that occur following downturns in the market. The most recent peaks occur in January 2001, April 2009, and April 2020 aligning with the tech bubble, the great financial crisis, and the covid crisis, respectively.

[2] https://www.openassetpricing.com/

The prior literature finds that this positive skewness in the distribution of stock returns is a driver of performance, that is, disproportionately few high performing observations are key for the overall performance of a portfolio of stocks. In the case of anomalies, the long-short structure means that these important observations could either work for (long) or against (short) a potential investor. Therefore, the importance of these observations on the final performance of a characteristic sorted long-short strategy is a function of how outliers are related to the underlying characteristic.

Strategies in which the long side of the portfolio tend to have shares with a more skewed return distributions will benefit as a result. Strategies in which the short side of the portfolio tend to have shares with a more skewed return distributions will suffer as a result. It is also possible that a given characteristic underlying a strategy is unrelated to the skewness in the individual stock's distributions and thus unrelated to the ultimate realization of observations on the tail of the distribution. Therefore, I propose a simple test to explore the impact of these outliers on all considered anomalies. In this test, I recreate the anomaly portfolios from a sample of stocks in which returns are capped (ex-post). This capped sample should reflect an investment opportunity set with a limited positive tail and thus show what strategies look like absent these outliers.

The sample cap is selected from the distribution of monthly stock returns for each month based on historical data. Each month, the 90th, 95th, and 99th percentiles of the monthly return distribution are calculated using all prior return data. These percentiles are equal to approximately 15.5, 23.9, and 51.5 percent (186.5, 286.4, and 618.4 percent annualized).

I use percentiles calculated from an extending sample of common stock returns from January 1926 through December 2021. That is, each return month is assigned percentiles based on the distribution of returns from January 1926 through the prior month. These percentiles are used to winsorize the returns of samples ranked by anomaly characteristic. Therefore, the sample is winsorized after individual stocks are sorted into portfolios, but prior to the calculation of the strategy return.

Table 1 displays the outcomes from a selection of anomaly strategies winsorized as described.

The impact of winsorizing depends on which portfolio (long or short) tends to be most related to outlier return observations.For example, anomalies based on size and book-to-market tend to be negatively impacted by limiting the upside on the long side of the portfolio, indicating that small and growth stocks tend to be more skewed than large, value stocks. On the other side, anomalies based on profitability and momentum tend to be positively affected by capping the best performing monthly return observations. This finding is consistent with stocks that have low profitability and poor past performance having a more skewed distribution. For a neutral example, low investment stocks do not appear to come from a distribution that is more skewed than high investment stocks.

I draw thee conclusions from this analysis to motivate my skewness enhanced strategy. First, it appears that certain anomaly strategies are harmed by skewness while others are helped depending on which leg of the anomaly tends to contain the more skewed stocks. Thus, strategies would generally benefit from being calculated in a high or low skewed sample depending on which leg is most effected by skewness. Second, I infer from these results that while the overall effect tends to come from one leg or the other, an investor will generally prefer drawing a short portfolio from the less skewed distribution and the long portfolio from the more skewed distribution. Finally, I observe that potential high performers are related to firm characteristics available at portfolio formation. These insights motivate my skewness management strategy outlined in the following sections.

3 Predicting Skewness

I use a model of realized skewness to proxy for stocks that are more likely to exhibit extreme returns in the coming month, I call this measure expected skewness. The model uses available firm characteristics to predict realized skewness in daily returns each month. A firm i's realized skewness is calculated from the daily returns in month t as

$$rs_{i,t} = \frac{1}{N(t)} \frac{\sum_{d=1}^{N(t)} r_{i,d}^3}{rv_t^3}, \tag{1}$$

$$rv_{i,t} = \left(\frac{1}{N(t)} \sum_{d=1}^{N(t)} r_{i,d}^2 \right)^{1/2}, \tag{2}$$

in which d is from the set of trading days in month t, r is daily return of stock i on day d, N(t) is the total number of trading days in month t.[3]

Unsurprisingly, this contemporaneous measure of skewness captures a large majority of tail events. 97%, of monthly return observations in the positive tail of the distribution lie above median realized skewness.[4] Conversely, approximately 97 percent of those stocks that lie in the left tail fall below median rs.

Figure 3 plots the 10th, 30th, 50th, 70th, and 90th percentiles of realized skewness. I limit noise by plotting a 3-year rolling average. Realized skewness, though noisy month to month, is relatively stable over time. The most significant movement in the measure is that the highest and lowest percentiles disperse starting in 1970 and converge starting in the 1980's up until 2000.

The second part of the expected skewness measure is using firm characteristics to model realized skewness. Setting up an ex-ante measure of realized skewness presents a challenge. With measures of volatility, it is common to use a lagged value to proxy for future outcomes. With skewness, there is very little persistence. Thus, any ex-ante measure of future realized skewness requires a more complex method. I use the model of idiosyncratic skewness presented in Boyer, Mitton, and Vorkink (2012) as an example. To model expected skewness for stock i in month $t+1$, I first estimate separate, cross-sectional regressions for realized skewness at the end of month t.

$$rs_{i,t} = \beta_t + \lambda_t' X_{i,t-1} + \epsilon_{i,t} \tag{3}$$

in which X is a vector of firm characteristics available at the end of month $t-1$, and skewness is measured in month t. Following Boyer, Mitton, and Vorkink (2010) I run the model separately

[3] $N(t)$ is the number of trading days minus an adjustment for degrees of freedom of one for volatility and two for skewness.

[4] The positive tail is defined as those observations above the historic 90th percentile.

each month, which allows the relation between firm variables and skewness to vary over time. I use the coefficients from equation (3) to generate a measure of expected skewness for month $t+1$ based on characteristics available at the end of month t.

$$E[rs_{i,t+1}] = \beta_t + \lambda_t' X_{i,t}. \tag{4}$$

I choose the firm specific variables, X, based on the prior literature. The variables include skewness (RS) and volatility (RV) measured as described in equations (1) and (2), momentum measured as the return over the last year less the most recent month, prior month return, turnover, and indicators for size, Fama and French 48 industry, and membership on the Nasdaq. Table 2 reports the summary statistics. Panel A reports descriptive statistics and Panel B reports correlations between continuous variables.

As with the prior literature I focus on a parsimonious specification that maximizes the available observations. The final version of the model includes the above variables less turnover, which is only available for Nasdaq stocks after 1988. Prior works have also found book-to-market to be a valuable predictor (Chen, Hong, and Stein (2001)). Again, I omit this variable in favor of minimizing the number of observations lost to missing data so that the recalculated anomaly strategies have as similar a sample as possible to the original.

Table 3 reports the results from the cross-sectional regression models, with each row representing a different combination of the firms' characteristics. The reported coefficients are the average of the all the coefficients from each monthly, cross-sectional model. To represent the importance of each characteristic I report the percentage of months in which the estimated coefficents are significant at the 10% level that have the same sign as the average coefficient ($\%sig$). Based on this measure, realized volatility and prior month return appear to be the most consistent in predicting realized skewness in the upcoming month. As with prior findings, the impact of a standard deviation increase in volatility is around twice as large as that for a standard deviation increase in skewness when predicting future skewness. A standard deviation increase in prior return leads to an increase in predicted skewness that is not quite twice as large as volatility. I use model 7 through the remainder of the paper. I note that the R-squared of 4.8% is commensurate with other projections of firm skewness for shorter horizons.

4 Skewness Managed Portfolios

I use the expected skewness measure outlined in Section 3 to enhance the performance of anomaly portfolios. I select 15 anomalies that are used in the construction of several modern factor models. The primary skewness management strategy uses a second, sequential sort to split anomaly portfolios into high and low expected skewness stocks. The strategy buys the long leg of the anomaly in a high expected skewness sample and buys the short leg in the low expected skewness sample. This matches the intuition that an investor wants to seek positive outliers in a long strategy and avoid them in a short strategy.

4.1 Sequential Sorts on Expected Skewness

I construct each anomaly based on the description provided in Appendix A. I then separately estimate stock level expected skewness using the full sample of common stocks in CRSP. The full sample I consider is the intersection of stocks ranked by their anomaly characteristic and those with an available expected skewness measure. There is a small loss of observations from this process when compared to the original anomaly sample, though with only a limited difference in overall performance.

In each month, the 10 characteristic portfolios are then split into terciles (30th, 70th) based on expected skewness which results in 30 portfolios double sorted on the strategy characteristic and expected skewness. Each portfolio's return is calculated as the value-weighted return based on the lagged market cap. As an illustration, The average returns of each of the 30 portfolios can be found in Table 4 for a selection of anomalies. Part A looks at anomaly strategies in which skewness is concentrated in the long leg, while part B looks at anomalies in which skewness is concentrated in the short leg.

Table 4 shows how calculating anomalies in different expected skewness samples leads to very different average returns that follow the predictions from the motivation in Section 2. In Panel A, b/m and size based anomalies perform better in the high expected skewness sample as shown in the final row in each table. The column on the far right of each table represents the difference between each anomaly portfolios between the high and low sample. The difference column shows that the improvement comes primarily from the long leg, that is, the leg most impacted by skewness. Investment presents an interesting case, in that the effect is weaker that others in the winorizing exercise from Section 2, but returns change with the sort on expected skewness. Panel B shows that anomalies based on momentum and profitability perform best in the low expected skewness sample. Again, the difference columns demonstrates that the largest impact on returns comes from the short leg of the strategy, as predicted. Momentum tends to be the weakest of the strategies that are more skewed in the short leg.

The findings confirm that sorting on expected skewness has the greatest impact on the most skewed anomaly portfolio. It also shows that strategies constructed in the ideal skewness sample generally outperform their originals. The primary skewness management strategy is calculated by taking the long leg of an anomaly from the high expected skewness sample, and the short leg from the low expected skewness sample. This arrangement takes advantage of the insight that you would prefer to draw a long portfolio from a more skewed sample and the short portfolio from a less skewed sample. Table 5 reports the performance of the skewness management strategy. Panel A presents the full sample version of the anomaly, calculated using observations with non-missing expected skewness. Panel B presents the results from the skewness management strategy, and Panel C is the difference between the two.

Managing skewness improves the performance of all considered anomaly strategies. This includes improving anomaly average returns, Sharpe ratios, and the downside risk profile in the forms of skewness. Increases in average return are large, ranging from 5% to 10% annually. Sharpe ratios generally improve, with the exception of Announcement Returns. Returns skewness only decreases in three cases, all of which have large increases in returns and Sharpe ratios.

Table 6 reports alphas when the skewness managed version of an anomaly is compared to the original anomaly. All strategies produce significant, positive alphas and produce betas that are around 1. The strategy alphas are between five to eleven percent when compared to the original anomaly in the full sample. Overall, I find evidence that skewness management results in broad performance improvements against the standard anomaly while retaining a large exposure.

Table 7 shows how much larger the alphas from the skewness managed strategy are when compared against the standard long-short anomaly strategy. Alpha increases for all anomalies and models, often very significantly. This effect is most striking for anomalies that are related to the factors in which alphas go from small and insignificant to large and significant.

Tables 8, 9, and 10 illustrate how skewness management changes exposure to different factors. Table 8 shows changes in beta for univariate factor regressions between standard and skewness managed versions of the anomaly L-S portfolio. Managing Skewness increases exposure to size related factors (SMB and ME) and lowers exposure to profitability related factors (ROE and RMW). This is also the case in the multivariate specifications in table 9 and 10. The change in exposure mirrors the relation between these two characteristics and extreme returns illustrated in Section 2. Additionally, skewness management increases exposure to the market factor, though the relation appears strongest in the univariate setting.

4.2 Validating Expected Skewness

In this section I aim to verify that my measure of expected skewness captures the intended effect. I address this in two layers. First, sorting on expected skewness should should have the greatest impact on the portfolio most affected by skewness. I look at the impact of sorting on the differences in portfolios' average returns and the differences for skewness in portfolio returns. Second, sorting on expected skewness should lead to differences in firms' realized skewness. That is, portfolios with high expected skewness should contain stocks that have higher realized skewness on average.

Table 4 shows that an additional sort on expected skewness creates a return spread between the high and low expected skewness samples. As predicted, this return spread is largest in the portfolio that is most impacted by skewness. The difference between the high and low sample is reported in the H-L column in each table. Panel A shows that portfolios based on B/M, size, and investment have the largest return spread in the long portfolio. Panel B shows that portfolios based on momentum and profitability have the largest return spread in the short portfolio.

As an additional test, I look at how sorting on expected skewness impacts the average realized skewness in each of the 30 portfolios generated in my strategy. Table 13 reports the time series average of stocks' realized skewness in each of the 30 portfolios. As with portfolio returns and return skewness, the average realized skewness is consistently higher in the high expected skewness sample, and the difference seems to be largest in the leg of the strategy most affected by skewness. Panel A shows that portfolios based on B/M, size, and investment have the largest difference in realized skewness in the long portfolio. Panel B shows that portfolios based on momentum and profitability have the largest difference in realized skewness in the short portfolio.

5 Robustness

5.1 Expected Skewness Predicts Returns

The task of anticipating positive skewness predicts returns. Firms with higher expected skewness tend to outperform those that have lower expected skewness. The average premium for a long-short strategy based on decile portfolios of expected skewness is 8.32%, with a positive and significant Carhart 4-factor alpha. This finding is consistent with the empirical fact that realized skewness is positively associated with monthly returns when measured in the same month, that is, stocks with higher monthly returns have more positively skewed daily returns. Nevertheless, there exists the possibility that the model of expected skewness I use introduces an unmeasured risk that accounts for the return improvement or that I am simply incorporating additional information from the return predictors used in my expected skewness model. I provide two points to address this potential explanation.

First, I drop all continuous return predictors from my expected skewness measure to see how the skewness management strategy performs. Table 14 contains results comparing the standard versions of each anomaly to versions in while realized volatility, momentum and prior month return has been removed. The model performs well without these return predictors, resulting in large increases in both returns and strategy Sharpe ratios.

Second, I calculate alphas for each skewness management strategy while controlling for the return predictability of expected skewness. As a control, I employ a long-short portfolio based on decile sorts of expected skewness. The portfolio is long high expected skewness stocks and short low expected skewness stocks. This portfolio is included alongside the original anomaly and the Carhart 4-factor model in a spanning test against the skewness managed portfolios. Table 15 reports the results. Panel A shows that all skewness managed anomalies generate alpha above what is predicted by a simple sort on expected skewness. Panels B and C show that including the original factor generally leaves anomalies with positive alphas, though not all are statistically different from zero. This final, strictest test illustrates which anomalies benefit from skewness management absent the spread associated with expected skewness.

5.2 Replacing Realized Skewness with Idiosyncratic Skewness

For the main results I choose realized skewness in daily returns as my proxy for return skewness, here I recreate the skewness management strategy using idiosyncratic skewness as an alternate. Overall, using idiosyncratic skewness proves equally as effective, and in certain cases more effective at improving performance.

I define idiosyncratic skewness as

$$is_{i,t} = \frac{1}{N(t)} \frac{\sum_{d=1}^{N(t)} \epsilon_{i,d}^3}{iv_t^3}, \tag{5}$$

$$iv_{i,t} = \left(\frac{1}{N(t)} \sum_{d=1}^{N(t)} \epsilon_{i,d}^2 \right)^{1/2}. \tag{6}$$

In which d comes from the set of trading days in month t, ϵ is the residual taken from regressing the daily return of stock i on the market factor, $N(t)$ is the total number of trading days in month t.[5]

I use an identical method for modeling expected skewness. I first estimate the cross-sectional regressions for idiosyncratic skewness at the end of month t.

$$is_{i,t} = \beta_t + \lambda_t' X_{i,t-1} + \epsilon_{i,t} \tag{7}$$

in which X is a vector of firm characteristics available at the end of month $t-1$, and skewness is measured in month t. Following Boyer, Mitton, and Vorkink (2010) I run the model separately each month. I use the coefficients to generate a measure of expected skewness for month $t+1$ based on characteristics available at the end of month t as in the following equation:

$$E[is_{i,t+1}] = \beta_t + \lambda_t' X_{i,t} \tag{8}$$

Table 11 summarizes the regression results. As with realized skewness, I find that volatility and prior month return are both consistent predictors of expected skewness. I find that idiosyncratic skewness is harder to explain, as shown by the lower adjusted R-squared.

Idiosyncratic skewness provides a very similar performance outcome to using realized skewness. The results from Table 12 indicate that a skewness management strategy based on idiosyncratic skewness increases performance of all considered anomalies. Panels A and B report the outcomes from the original and skewness managed strategies, respectively. Panel C reports the difference be-

[5] $N(t)$ is the number of trading days minus an adjustment for degrees of freedom of one for volatility and two for skewness.

tween the two strategies. Skewness Management based on idiosyncratic skewness produces overall improvements of a similar magnitude to the results using realized skewness, with some anomalies having a slightly better improvement in their performance (value, investment, and momentum), and others with smaller improvements (size and profitability). This also applies to downside risk. Managed portfolios using size, investment, and ROE have more muted gains or mild declines in skewness while value and momentum have larger improvements.

6 Conclusions

This paper explores the role of skewness in monthly stock returns on anomaly strategies. I find these strategies are disproportionately affected by positive outliers, and that the direction of this effect is determined by which leg of the strategy, long or short, tends to be more impacted by positive outliers. This impact can be exploited to improve portfolio performance by targeting stocks with higher predicted skewness on the long leg and avoiding the same stocks on the short leg. This skewness management strategy improves the overall performance as measured by the Sharpe ratio, and large and significant alphas against a set of modern factor models. Most importantly, I find that factor models fail to price skewness managed strategies based on their own characteristics. This finding illustrates the limits of the most modern factor models in explaining the cross section of returns once the skewness feature of the data has been incorporated.

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Table 1: **Winsorized Performance**

This table shows the performance of anomalies calculated in samples in which the right tail of monthly returns has been winsorized at the 90th, 95th and 99th percentiles. Winsorization takes place after portofolio construction, but before performance calculations are made. The three panels show the average return premium, the Sharpe ratio, and the return skewness of each strategy. In each panel, the statistics from every sample is provided along with the difference between the original and the 90th percentile samples.

Sample	B/M	Size	ag	mom	ROE	OP	Accrual	AnnRet	CoEqIs	FailProb	GP	InPPEIn	NOA	ROAQ
Return														
Original	5.18	3.19	4.32	13.65	7.95	2.08	3.91	10.73	6.03	4.27	4.96	4.88	6.81	3.48
win99	4.21	-1.12	3.89	15.70	9.80	3.66	3.93	10.89	3.93	7.26	5.42	4.60	6.86	5.04
win95	1.89	-11.30	3.39	19.99	14.90	8.82	4.11	11.01	4.11	15.28	6.31	3.89	7.76	9.10
win90	-0.44	-19.43	3.42	22.50	19.43	13.87	4.18	10.75	4.18	22.67	6.68	3.83	9.00	13.09
Difference	-5.62	-22.61	-0.90	8.84	11.48	11.79	0.27	0.02	-1.84	18.40	1.72	-1.05	2.19	9.61
Sharpe														
Original	0.32	0.19	0.38	0.55	0.44	0.14	0.34	0.94	0.34	0.19	0.43	0.45	0.58	0.19
win99	0.26	-0.07	0.35	0.67	0.57	0.25	0.34	0.97	0.34	0.35	0.47	0.43	0.58	0.29
win95	0.12	-0.83	0.32	0.98	0.94	0.64	0.38	1.04	0.38	0.80	0.56	0.37	0.68	0.58
win90	-0.03	-1.57	0.34	1.22	1.31	1.08	0.41	1.12	0.41	1.26	0.61	0.38	0.84	0.89
Difference	-0.35	-1.76	-0.05	0.66	0.87	0.94	0.07	0.17	0.07	1.07	0.18	-0.07	0.26	0.69
Skewness														
Original	0.10	0.75	0.30	-1.41	0.14	0.15	0.17	-0.14	0.17	-0.24	-0.09	0.02	-0.17	0.47
win99	-0.05	0.24	0.29	-0.96	0.47	0.38	0.16	-0.13	0.16	0.18	-0.08	0.02	-0.18	0.64
win95	-0.22	-0.16	0.38	-0.35	0.91	0.70	0.12	-0.12	0.12	0.67	-0.07	0.05	-0.06	0.04
win90	-0.39	-0.29	0.48	-0.05	1.17	0.85	0.09	0.03	0.09	0.88	-0.10	0.11	0.01	0.03
Difference	-0.49	-1.04	0.18	1.35	1.03	0.70	-0.08	0.17	-0.08	1.12	-0.02	0.08	0.18	-0.44

Table 2: **Prediction Variable Summary Statistics**

The following table summarizes the main continuous variables used in creating expected skewness. In which rv is realized volatility and rs is realized skewness. Momentum is defined as the prior year return omitting the most recent month, and prior is the last month return. The sample includes all common stocks trading on the AMEX, Nasdaq, and NYSE from July 1963 - December 2021.

Panel A: Summary Stats							
	mean	**std**	**min**	**25%**	**50%**	**75%**	**max**
rv	0.03	0.03	0.00	0.01	0.02	0.04	4.16
rs	0.26	1.29	-4.91	-0.48	0.27	1.03	4.91
momentum	1.14	0.75	0.00	0.82	1.06	1.31	437.68
prior	0.01	0.17	-0.99	-0.06	0.00	0.07	24.00
Panel B: Correlation table							
	rv	**rs**	**momentum**				
rs	0.14						
momentum	-0.09	-0.01					
prior	0.16	0.55	0.00				

Table 3: **Predictive Regressions**

This table reports the time series average from the first regression in the predictive model. %sig is the percent of coefficients that are statistically significant at the 5% level (and of the same sign as the average coefficient). Sample is the collection of common stocks trading on the AMEX, NYSE, and Nasdaq. Momentum (mom) is the prior year return omitting the most recent month, prior is the return in the last month, dummy variables are included for NASDAQ stocks, stocks in the small (sm) and medium (med) terciles, and ff48 industries (ind). The adjusted R-squared and Nobs are the cross-sectional average.

Model		**rv_t-1**	**rs_t-1**	**mom**	**turnover**	**nasdaq**	**sm**	**med**	**prior**	**ind**	**adjrsq**	**nobs**
1	**Avg**	1.87	-0.01							No	0.009	6008
	%Sig	(0.51)	(0.39)									
2	**Avg**	1.94	-0.02	0.02	1.58	-0.05	0.06	0.05		No	0.021	4822
	%Sig	(0.53)	(0.44)	(0.35)	(0.17)	(0.28)	(0.43)	(0.41)				
3	**Avg**									yes	0.025	5492
	%Sig											
4	**Avg**	1.83	-0.03	0.01	1.08	-0.06	0.06	0.04		yes	0.044	4773
	%Sig	(0.52)	(0.48)	(0.30)	(0.15)	(0.26)	(0.41)	(0.40)				
5	**Avg**								-0.37	no	0.004	5652
	%Sig								(0.59)			
6	**Avg**	2.09	0.01	0.01	2.90	-0.06	0.04	0.04	-0.58	yes	0.47	4771
	%Sig	(0.55)	(0.26)	(0.28)	(0.18)	(0.26)	(0.39)	(0.38)	(0.80)			
7	**Avg**	2.02	0.02	0.01		-0.02	0.03	0.04	-0.61	yes	0.044	5032
	%Sig	(0.57)	(0.33)	(0.30)		(0.30)	(0.39)	(0.38)	(0.82)			

Table 4: **Average Returns by Portfolio**

This panel shows the average return of all 30 portfolios for each of the 6 anomaly strategies we consider. Portfolios are first sorted on the anomaly characteristic and then merged with stock level expected skewness. The second sort is done sequentially within the characteristic portfolio. The final result is 30 portfolios, based on Sequential sorts. Returns are calculated using value weighting by prior month market cap. Differences are calculated in the last column and row, while the bottom right corner provides the diagonal, long/high minus short/low.

Panel A: Skewness in Long Leg

B/M

port	high	med	low	H-L
Long	24.56	14.87	12.80	11.76
9	19.42	16.32	10.28	9.14
8	17.76	14.89	9.79	7.96
7	15.68	13.91	9.75	5.92
6	14.96	13.50	10.84	4.12
5	15.45	12.44	10.67	4.77
4	13.70	12.82	8.77	4.93
3	14.51	11.33	9.59	4.93
2	14.21	12.52	9.88	4.33
Short	12.32	9.59	9.60	2.72
L-S	12.25	5.29	3.20	14.96

Size

port	high	med	low	H-L
Long	22.85	14.65	5.86	16.98
2	20.83	14.99	6.42	14.42
3	20.70	14.66	8.07	12.63
4	19.70	13.46	8.00	11.71
5	19.77	13.74	9.56	10.20
6	17.98	12.11	8.74	9.23
7	17.70	12.70	8.87	8.83
8	16.86	12.74	9.23	7.64
9	15.50	12.04	8.80	6.70
Short	12.51	10.96	9.00	3.51
L-S	10.34	3.69	-3.13	13.85

Inv

port	high	med	low	H-L
Long	20.61	14.33	8.33	12.28
2	18.58	13.20	11.93	6.65
3	17.32	13.43	10.09	7.23
4	15.99	12.24	8.83	7.16
5	13.65	11.94	9.94	3.71
6	14.59	12.49	8.40	6.19
7	14.00	12.43	10.07	3.93
8	14.62	11.90	8.95	5.67
9	16.05	12.16	8.74	7.31
Short	11.57	9.07	7.04	4.54
L-S	9.04	5.26	1.29	13.57

Panel B: Skewness in Short Leg

MOM

port	high	med	low	H-L
Long	20.25	18.56	15.03	5.22
9	15.42	14.48	12.54	2.88
8	16.16	14.17	9.04	7.12
7	15.07	11.39	9.82	5.26
6	13.58	11.36	8.43	5.16
5	14.05	11.71	7.50	6.55
4	13.99	11.27	8.69	5.30
3	15.30	11.33	6.86	8.43
2	12.64	9.32	7.29	5.35
Short	10.72	2.76	1.32	9.40
L-S	9.54	15.80	13.71	18.94

ROE

port	high	med	low	H-L
Long	17.97	15.57	13.31	4.66
9	14.50	13.02	12.28	2.22
8	13.95	13.13	11.52	2.43
7	10.99	13.67	10.64	0.35
6	13.21	12.25	10.44	2.76
5	12.39	14.72	9.64	2.75
4	12.20	10.02	8.67	3.53
3	15.12	11.09	6.39	8.74
2	15.46	12.56	5.68	9.77
Short	16.32	8.16	0.08	16.24
L-S	1.65	7.41	13.23	17.89

OP

port	high	med	low	H-L
Long	15.35	10.64	11.17	4.18
9	15.89	13.19	10.24	5.65
8	15.89	11.87	10.90	4.99
7	13.78	12.14	9.09	4.69
6	13.77	12.03	8.45	5.32
5	14.17	13.46	9.70	4.47
4	14.66	12.77	9.74	4.92
3	15.67	10.60	8.35	7.31
2	15.47	10.14	5.68	9.79
Short	16.42	10.85	4.16	12.26
L-S	-1.07	-0.21	7.00	11.19

Table 5: **Skewness Management Strategy Performance**

This table compares the original to the skewness managed versions of each anomaly. Panel A lists performance in the full sample in which both the characteristic and expected skewness are non-missing. Panel B lists the performance of the skewness managed version of each anomaly in which the long leg comes from the high expected skewness sample and the short leg comes from the low expected skewness sample. Panel C reports the difference. The Sharpe ratio t-statistics from Jobson and Korkie (1981) are listed in parenthesis.

	Size	b/m	Inv	MOM	ROE	OP	EG	AnnRet	Accruals	ComEqIs	FailProb	GP	InPPEInv	NOA	roaq
							Panel A: Standard Anomaly								
Mean	3.63	5.03	4.44	13.69	7.48	2.15	11.80	10.71	4.18	6.04	4.18	4.76	4.88	6.84	3.47
Sharpe	0.21	0.30	0.40	0.55	0.42	0.14	0.84	0.93	0.36	0.42	0.19	0.41	0.45	0.58	0.19
Skew	0.81	0.10	0.29	-1.41	0.09	0.17	0.12	-0.09	0.13	-0.34	-0.25	-0.07	0.02	-0.17	0.49
							Panel B: Skewness Managed								
Mean	13.85	14.96	13.57	18.94	17.80	11.19	18.45	16.58	13.31	13.18	13.92	15.27	9.55	13.52	12.25
Sharpe	0.60	0.65	0.58	0.66	0.81	0.60	0.89	0.82	0.61	0.52	0.57	0.83	0.47	0.69	0.61
Skew	1.85	1.04	3.10	-0.61	0.36	-0.01	0.27	0.58	1.18	2.20	-0.43	0.65	0.22	-0.12	0.29
							Panel C: Difference								
Mean	10.22	9.93	9.13	5.24	10.32	9.04	6.65	5.87	9.13	7.14	9.75	10.51	4.67	6.68	8.78
Sharpe	0.39	0.34	0.18	0.10	0.39	0.46	0.05	-0.11	0.26	0.09	0.38	0.42	0.02	0.11	0.41
	(5.46)	(3.40)	(1.24)	(1.38)	(3.26)	(4.24)	(0.40)	-(0.75)	(1.81)	(0.78)	(4.30)	(3.14)	(0.14)	(0.74)	(3.28)
Skew	1.03	0.93	2.81	0.79	0.27	-0.18	0.15	0.67	1.05	2.55	-0.19	0.73	0.20	0.06	-0.19

Table 6: **Skewness Managed vs Standard Anomaly Spanning Test**

This table reports alphas and betas from spanning tests of a skewness managed vs a standard long-short anomaly portfolio. The Specification is such that $R_{skew} = \alpha + \beta R_{Standard} + \epsilon$. Heteroskedasticity robust t-stats are in parenthesis.

	Alpha	Beta	Adjrsq
Size	9.64	1.16	0.74
	(6.51)	(16.92)	
B/M	9.94	1.00	0.51
	(4.70)	(17.14)	
AG	10.05	0.79	0.14
	(3.50)	(10.77)	
MOM	5.48	0.98	0.71
	(2.60)	(28.56)	
ROE	11.59	0.82	0.44
	(4.72)	(12.96)	
OP	9.49	0.79	0.43
	(5.13)	(15.91)	
EG	9.63	0.75	0.26
	(3.86)	(11.08)	
AnnRet	6.65	0.89	0.24
	(2.45)	(8.24)	
Accrual	10.04	0.78	0.18
	(3.81)	(6.02)	
CoEqIs	6.99	1.03	0.33
	(2.61)	(13.39)	
FailProb	9.12	0.90	0.66
	(4.38)	(19.58)	
GP	11.67	0.76	0.23
	(5.56)	(12.40)	
InPPEIn	5.78	0.77	0.17
	(2.35)	(8.15)	
NOA	8.94	0.67	0.16
	(3.54)	(7.36)	
roaq	9.61	0.77	0.36
	(4.21)	(12.76)	

Table 7: **Alphas of H-L Portfolios**

This table Contains Alphas from factor regression on both standard and skewness managed version of decile portfolios based on 15 anomalies. Heteroskedasticity robust t-stats are in parenthesis.

	α on Standard H-L Portfolio							α on Skewness Managed H-L Portfolio						
Signal	ff3	ff5	ffc4	q4	q5	SY4	DHS3	ff3	ff5	ffc4	q4	q5	SY4	DHS3
b/m	-1.9	-0.6	-1.6	-0.4	0.3	-0.7	4.0	7.3	8.7	7.9	9.6	7.9	7.3	13.8
	-(1.8)	-(0.6)	-(1.5)	-(0.2)	(0.1)	-(0.4)	(1.5)	(3.3)	(3.7)	(3.1)	(3.6)	(2.9)	(2.4)	(3.4)
size	-0.3	0.6	-0.3	1.7	2.7	-0.7	7.0	9.4	11.4	8.9	12.9	12.0	9.1	16.8
	-(0.4)	(0.7)	-(0.3)	(1.6)	(2.5)	-(0.5)	(2.5)	(4.7)	(5.6)	(4.3)	(5.4)	(5.1)	(3.6)	(4.4)
ag	3.3	0.4	2.4	0.7	-0.1	-2.2	2.7	11.3	10.3	10.1	11.9	9.9	7.1	13.6
	(2.6)	(0.3)	(1.8)	(0.6)	-(0.1)	-(1.7)	(1.6)	(3.7)	(3.0)	(3.3)	(3.2)	(3.0)	(2.1)	(3.1)
mom	19.0	16.2	3.5	6.3	-0.7	1.1	-0.1	23.2	21.3	7.3	10.3	4.7	7.4	4.6
	(6.3)	(4.6)	(2.4)	(1.7)	-(0.2)	(0.4)	(0.0)	(6.3)	(4.9)	(3.0)	(2.2)	(0.9)	(1.9)	(0.9)
roe	11.3	5.4	7.8	-0.2	-1.0	4.2	0.6	20.4	16.3	15.7	9.8	9.2	13.8	10.2
	(5.4)	(3.3)	(3.9)	-(0.2)	-(0.7)	(2.1)	(0.2)	(6.7)	(5.0)	(5.2)	(3.1)	(3.0)	(4.2)	(3.0)
op	5.4	-0.8	4.8	-0.5	-1.8	-0.2	-0.3	12.5	7.4	11.2	6.1	4.5	7.1	6.3
	(3.3)	-(0.7)	(3.0)	-(0.3)	-(1.0)	-(0.1)	-(0.1)	(5.3)	(3.2)	(4.4)	(2.3)	(1.6)	(2.6)	(2.2)
eg	15.0	12.1	12.9	9.7	-1.8	7.1	7.8	20.6	19.7	18.3	16.1	6.2	15.0	14.8
	(9.2)	(7.4)	(8.1)	(6.0)	-(1.4)	(4.6)	(4.2)	(7.4)	(6.8)	(6.4)	(5.4)	(2.1)	(4.6)	(4.4)
Accrual	5.8	6.5	5.6	7.7	4.2	5.4	4.3	12.9	14.2	12.3	15.3	13.0	12.0	11.5
	(3.8)	(4.2)	(3.2)	(4.3)	(2.1)	(2.7)	(2.0)	(4.3)	(4.7)	(3.8)	(4.4)	(3.6)	(3.5)	(2.8)
NOA	5.4	5.5	4.9	3.8	2.3	1.8	2.2	11.8	13.9	11.2	12.4	9.9	9.5	10.2
	(4.0)	(4.0)	(3.5)	(2.3)	(1.3)	(1.1)	(1.1)	(4.5)	(4.8)	(4.2)	(4.0)	(3.2)	(3.0)	(3.0)
InPPEIn	4.0	3.3	3.5	2.4	2.2	0.4	3.2	6.9	6.4	6.0	6.0	4.1	3.1	5.6
	(3.0)	(2.6)	(2.5)	(1.8)	(1.5)	(0.3)	(1.9)	(2.7)	(2.3)	(2.2)	(2.0)	(1.3)	(1.0)	(1.5)
ComEqis	8.4	8.7	5.0	7.4	4.2	5.8	2.9	11.9	12.4	10.2	13.1	8.8	11.0	8.9
	(5.0)	(4.9)	(2.8)	(3.7)	(2.1)	(3.0)	(1.2)	(4.1)	(4.1)	(2.4)	(3.3)	(2.3)	(2.5)	(1.6)
AnnRet	13.2	12.8	10.7	11.2	9.6	9.6	2.0	16.7	18.0	13.0	15.9	14.1	13.2	6.9
	(8.4)	(7.9)	(7.0)	(6.6)	(5.8)	(5.8)	(1.6)	(5.9)	(5.8)	(4.6)	(5.0)	(4.4)	(3.8)	(2.5)
Failprob	10.8	5.2	6.2	2.9	-1.1	-1.5	-2.3	19.3	14.5	14.1	12.5	8.0	8.7	8.4
	(4.7)	(2.3)	(2.6)	(1.2)	-(0.4)	-(0.6)	-(0.7)	(6.5)	(4.6)	(4.9)	(4.1)	(2.4)	(2.8)	(2.4)
GP	6.1	2.9	5.5	2.2	0.3	0.2	0.5	15.0	13.5	14.7	12.1	10.9	11.7	10.5
	(4.1)	(2.1)	(3.6)	(1.4)	(0.2)	(0.1)	(0.3)	(6.2)	(5.2)	(5.7)	(4.4)	(3.9)	(3.9)	(3.4)
roaq	6.7	1.3	3.8	-2.2	-4.4	-1.1	-2.5	14.4	10.3	10.8	5.6	5.1	7.0	5.3
	(3.4)	(0.8)	(2.0)	-(1.5)	-(2.9)	-(0.6)	-(1.1)	(5.1)	(3.7)	(3.8)	(2.0)	(1.8)	(2.3)	(1.7)

Table 8: **Changes in Univariate Betas due to Skewness Management**

This table contains differences in β between univariate regressions of factors on skewness managed and standard anomaly portfolios. Heteroskedasticity robust t-stats are in parenthesis.

	MKT	SMB	HML	UMD	RMW	CMA	ME	IA	ROE	EG	MGMT	PERF	PEAD	FIN
b/m	0.10	0.31	-0.12	-0.03	-0.34	-0.02	0.31	-0.02	-0.28	-0.14	-0.15	0.04	0.30	-0.20
	(1.0)	(2.4)	-(0.8)	-(0.2)	-(1.4)	-(0.1)	(2.3)	-(0.1)	-(1.5)	-(0.6)	-(1.2)	(0.2)	(0.8)	-(1.4)
size	0.17	0.26	-0.26	0.06	-0.49	-0.22	0.24	-0.26	-0.28	-0.21	-0.30	0.03	0.38	-0.34
	(2.0)	(2.1)	-(1.3)	(0.3)	-(1.6)	-(1.1)	(1.8)	-(0.9)	-(1.6)	-(1.1)	-(1.7)	(0.2)	(0.8)	-(1.6)
ag	0.23	0.66	-0.36	0.03	-0.80	-0.39	0.65	-0.58	-0.57	-0.59	-0.46	0.01	0.55	-0.56
	(3.1)	(2.6)	-(1.7)	(0.2)	-(1.8)	-(2.6)	(2.2)	-(2.1)	-(2.4)	-(2.8)	-(2.5)	(0.1)	(1.0)	-(2.0)
mom	0.15	0.24	-0.11	0.02	-0.45	-0.05	0.24	-0.06	-0.24	-0.39	-0.23	-0.08	0.24	-0.25
	(1.1)	(1.0)	-(0.5)	(0.3)	-(1.1)	-(0.2)	(0.9)	-(0.2)	-(0.8)	-(1.3)	-(1.0)	-(0.5)	(0.6)	-(1.0)
roe	0.14	0.30	-0.13	0.09	-0.43	-0.25	0.27	-0.21	-0.22	-0.30	-0.21	-0.01	0.34	-0.26
	(1.5)	(2.4)	-(0.7)	(0.8)	-(2.3)	-(0.9)	(2.2)	-(0.9)	-(1.7)	-(1.8)	-(1.2)	-(0.1)	(1.1)	-(2.1)
op	0.17	0.30	0.02	0.03	-0.34	-0.08	0.31	-0.06	-0.17	-0.25	-0.17	-0.09	0.19	-0.16
	(2.5)	(3.0)	(0.1)	(0.3)	-(2.1)	-(0.4)	(3.1)	-(0.3)	-(1.1)	-(1.6)	-(1.3)	-(0.9)	(0.8)	-(1.7)
eg	0.18	0.24	-0.13	-0.01	-0.47	-0.24	0.21	-0.15	-0.26	-0.42	-0.29	-0.14	0.17	-0.30
	(2.4)	(1.9)	-(1.0)	-(0.1)	-(2.6)	-(1.3)	(1.7)	-(0.8)	-(1.9)	-(3.2)	-(2.4)	-(1.5)	(0.8)	-(2.7)
Accrual	0.19	0.45	0.01	-0.02	-0.51	0.04	0.44	0.01	-0.33	-0.48	-0.19	-0.07	0.37	-0.27
	(2.2)	(2.8)	(0.0)	-(0.2)	-(2.1)	(0.2)	(2.4)	(0.1)	-(1.8)	-(2.5)	-(1.2)	-(0.6)	(1.2)	-(1.7)
NOA	0.22	0.43	-0.47	0.04	-0.67	-0.49	0.41	-0.62	-0.33	-0.42	-0.55	0.01	0.41	-0.52
	(3.3)	(2.8)	-(3.4)	(0.4)	-(2.8)	-(3.1)	(2.5)	-(3.5)	-(2.2)	-(2.7)	-(4.6)	(0.1)	(1.6)	-(3.5)
InPPEInv	0.19	0.32	-0.04	0.00	-0.19	-0.16	0.31	-0.14	-0.21	-0.20	-0.22	0.02	0.25	-0.20
	(2.8)	(2.3)	-(0.3)	(0.0)	-(0.9)	-(1.1)	(2.1)	-(0.8)	-(1.2)	-(1.2)	-(1.9)	(0.2)	(0.9)	-(1.4)
ComEqis	0.26	0.41	0.24	-0.25	-0.31	0.12	0.41	0.18	-0.57	-0.47	-0.07	-0.26	-0.13	-0.12
	(2.3)	(2.5)	(1.4)	-(0.9)	-(1.3)	(0.6)	(2.3)	(0.8)	-(1.8)	-(2.1)	-(0.5)	-(1.1)	-(0.3)	-(0.9)
AnnRet	0.22	0.33	-0.05	0.06	-0.48	-0.17	0.29	-0.14	-0.33	-0.38	-0.22	-0.02	0.20	-0.26
	(2.9)	(1.9)	-(0.4)	(0.6)	-(1.9)	-(0.9)	(1.6)	-(0.7)	-(2.0)	-(2.3)	-(1.5)	-(0.2)	(1.1)	-(1.8)
FailProb	0.06	0.20	-0.14	0.06	-0.25	-0.16	0.17	-0.19	-0.17	-0.16	-0.23	0.04	0.17	-0.21
	(0.6)	(1.3)	-(0.7)	(0.4)	-(0.9)	-(0.6)	(1.0)	-(0.6)	-(0.9)	-(0.7)	-(1.3)	(0.3)	(0.6)	-(1.6)
GP	0.12	0.19	0.08	-0.06	-0.31	-0.06	0.17	0.01	-0.22	-0.28	-0.10	-0.09	0.11	-0.14
	(1.9)	(2.1)	(0.7)	-(0.7)	-(1.8)	-(0.4)	(1.7)	(0.1)	-(1.6)	-(1.9)	-(1.0)	-(0.8)	(0.6)	-(1.4)
roaq	0.17	0.25	-0.14	0.04	-0.40	-0.20	0.22	-0.16	-0.16	-0.38	-0.27	-0.02	0.19	-0.26
	(2.1)	(2.2)	-(0.9)	(0.4)	-(2.2)	-(0.8)	(2.0)	-(0.7)	-(1.4)	-(2.4)	-(1.7)	-(0.2)	(0.8)	-(2.5)

Table 9: **Changes in Multivariate Betas due to Skewness Management**

This table contains differences in β from multi-factor regressions on skewness managed and standard anomaly portfolios. Multi-factor specifications are arranged by model. Heteroskedasticity robust t-stats are in parenthesis.

	FF3			DHS3			FFC4				SY4			
	MKT	SMB	HML	MKT	PEAD	FIN	MKT	SMB	HML	UMD	MKT	SMB	MGMT	PERF
b/m	0.03	0.30	-0.10	0.04	0.29	-0.17	0.02	0.30	-0.11	-0.03	0.08	0.24	-0.01	0.07
	(0.4)	(2.6)	-(0.9)	(0.3)	(0.8)	-(0.9)	(0.4)	(2.5)	-(1.1)	-(0.2)	(1.1)	(1.9)	-(0.1)	(0.6)
size	0.09	0.22	-0.22	0.08	0.37	-0.28	0.10	0.22	-0.20	0.05	0.12	0.17	-0.15	0.07
	(1.7)	(1.7)	-(1.9)	(0.6)	(1.0)	-(1.1)	(1.9)	(1.7)	-(1.8)	(0.7)	(1.6)	(1.1)	-(1.1)	(0.8)
ag	0.07	0.63	-0.32	-0.01	0.50	-0.56	0.07	0.63	-0.31	0.03	0.04	0.49	-0.28	0.05
	(0.7)	(2.3)	-(1.6)	-(0.1)	(1.0)	-(1.7)	(0.8)	(2.3)	-(1.8)	(0.2)	(0.4)	(1.8)	-(1.5)	(0.4)
mom	0.10	0.20	-0.07	0.08	0.24	-0.20	0.11	0.20	-0.06	0.04	0.06	0.12	-0.15	-0.06
	(0.7)	(0.9)	-(0.3)	(0.5)	(0.7)	-(0.9)	(1.5)	(1.9)	-(0.5)	(0.5)	(0.5)	(0.6)	-(0.6)	-(0.4)
roe	0.09	0.26	-0.10	0.07	0.34	-0.21	0.11	0.27	-0.05	0.12	0.10	0.25	-0.07	0.04
	(1.0)	(2.1)	-(0.6)	(0.7)	(1.3)	-(1.6)	(1.4)	(2.1)	-(0.3)	(1.2)	(1.1)	(1.8)	-(0.5)	(0.4)
op	0.14	0.24	0.07	0.17	0.23	-0.06	0.15	0.24	0.10	0.08	0.15	0.28	0.04	-0.03
	(1.9)	(2.3)	(0.6)	(2.2)	(1.2)	-(0.6)	(2.2)	(2.3)	(0.8)	(0.8)	(2.2)	(2.4)	(0.3)	-(0.3)
eg	0.13	0.18	-0.09	0.09	0.17	-0.24	0.13	0.18	-0.08	0.02	0.10	0.12	-0.17	-0.10
	(1.7)	(1.4)	-(0.7)	(1.0)	(0.8)	-(2.0)	(1.8)	(1.5)	-(0.6)	(0.2)	(1.2)	(1.0)	-(1.2)	-(1.0)
Accrual	0.12	0.40	0.05	0.09	0.37	-0.21	0.12	0.40	0.07	0.03	0.12	0.34	0.00	-0.02
	(1.2)	(2.4)	(0.3)	(0.8)	(1.4)	-(1.2)	(1.2)	(2.4)	(0.4)	(0.3)	(1.0)	(2.0)	(0.0)	-(0.2)
NOA	0.08	0.39	-0.43	0.04	0.38	-0.49	0.09	0.39	-0.43	0.01	0.09	0.27	-0.40	0.04
	(1.0)	(2.2)	-(3.0)	(0.4)	(1.7)	-(2.8)	(1.0)	(2.2)	-(3.1)	(0.1)	(1.0)	(1.6)	-(2.8)	(0.5)
InPPEIn	0.15	0.26	0.01	0.14	0.28	-0.11	0.15	0.26	0.03	0.04	0.13	0.22	-0.05	0.06
	(1.9)	(1.7)	(0.1)	(1.4)	(1.0)	-(0.6)	(2.2)	(1.7)	(0.3)	(0.4)	(1.6)	(1.5)	-(0.4)	(0.6)
CoEqis	0.24	0.32	0.32	0.20	-0.08	-0.01	0.21	0.32	0.26	-0.16	0.19	0.30	0.17	-0.20
	(2.1)	(2.0)	(1.9)	(1.5)	-(0.2)	(0.0)	(2.1)	(2.1)	(1.8)	-(0.6)	(1.7)	(1.8)	(1.0)	-(0.9)
AnnRet	0.17	0.26	0.01	0.12	0.21	-0.19	0.20	0.27	0.05	0.12	0.19	0.22	-0.01	0.06
	(2.1)	(1.5)	(0.0)	(1.4)	(1.3)	-(1.5)	(2.6)	(1.7)	(0.4)	(1.3)	(2.1)	(1.3)	(0.0)	(0.6)
FailProb	0.01	0.20	-0.14	-0.01	0.16	-0.21	0.02	0.20	-0.12	0.06	0.01	0.17	-0.18	0.05
	(0.1)	(1.3)	-(0.9)	(0.0)	(0.6)	-(1.5)	(0.2)	(1.4)	-(0.8)	(0.6)	(0.1)	(1.2)	-(1.3)	(0.5)
GP	0.11	0.15	0.11	0.06	0.11	-0.10	0.11	0.15	0.11	-0.02	0.09	0.08	-0.01	-0.06
	(1.6)	(1.6)	(1.1)	(0.8)	(0.6)	-(1.0)	(1.6)	(1.6)	(1.0)	-(0.2)	(1.2)	(0.7)	-(0.1)	-(0.6)
roaq	0.12	0.20	-0.10	0.09	0.19	-0.21	0.14	0.20	-0.07	0.07	0.12	0.18	-0.13	0.04
	(1.6)	(1.8)	-(0.8)	(1.1)	(0.9)	-(1.8)	(1.9)	(1.8)	-(0.6)	(0.7)	(1.6)	(1.5)	-(1.0)	(0.4)

Table 10: **Changes in Multivariate Betas due to Skewness Management (Cont'd)**

This table Contains differences in β from multi-factor regressions on skewness managed and standard anomaly portfolios. Multi-factor specifications are arranged by model. Heteroskedasticity robust t-stats are in parenthesis.

	Q4				Q5					FF5				
	MKT	ME	IA	ROE	MKT	ME	IA	ROE	EG	MKT	SMB	HML	RMW	CMA
b/m	0.04	0.26	0.06	-0.17	0.07	0.29	0.02	-0.26	0.28	0.05	0.26	-0.19	-0.16	0.24
	(0.5)	(2.2)	(0.4)	-(1.2)	(1.0)	(2.4)	(0.1)	-(1.6)	(1.4)	(0.7)	(2.8)	-(1.4)	-(1.1)	(1.3)
size	0.09	0.14	-0.15	-0.19	0.12	0.17	-0.18	-0.27	0.24	0.09	0.14	-0.25	-0.36	0.11
	(1.4)	(1.0)	-(1.0)	-(1.9)	(2.0)	(1.2)	-(1.2)	-(2.2)	(1.6)	(1.8)	(1.7)	-(1.9)	-(2.2)	(0.7)
ag	0.02	0.51	-0.46	-0.36	0.04	0.53	-0.48	-0.41	0.15	0.05	0.51	-0.30	-0.50	0.00
	(0.2)	(1.7)	-(1.8)	-(2.2)	(0.4)	(1.7)	-(1.8)	-(2.0)	(0.7)	(0.5)	(2.8)	-(1.3)	-(1.5)	(0.0)
mom	0.13	0.16	0.09	-0.13	0.11	0.14	0.11	-0.07	-0.17	0.10	0.12	-0.12	-0.33	0.16
	(1.0)	(0.6)	(0.2)	-(0.5)	(0.8)	(0.5)	(0.3)	-(0.2)	-(0.5)	(0.7)	(0.6)	-(0.5)	-(1.0)	(0.4)
roe	0.08	0.20	-0.12	-0.11	0.08	0.20	-0.11	-0.10	-0.02	0.05	0.18	0.01	-0.31	-0.18
	(1.3)	(2.0)	-(0.6)	-(0.8)	(1.2)	(2.0)	-(0.6)	-(0.7)	-(0.1)	(0.7)	(1.5)	(0.0)	-(1.6)	-(0.8)
op	0.14	0.25	0.11	-0.01	0.15	0.26	0.10	-0.03	0.05	0.12	0.19	0.11	-0.22	-0.07
	(2.1)	(2.4)	(0.7)	-(0.1)	(2.1)	(2.4)	(0.6)	-(0.2)	(0.3)	(1.9)	(1.8)	(0.8)	-(1.4)	-(0.4)
eg	0.13	0.11	-0.01	-0.17	0.11	0.09	0.01	-0.11	-0.18	0.10	0.09	0.00	-0.39	-0.15
	(1.7)	(0.8)	-(0.1)	-(1.2)	(1.6)	(0.7)	(0.1)	-(0.7)	-(1.1)	(1.3)	(0.7)	(0.0)	-(2.2)	-(0.6)
Accrual	0.13	0.36	0.20	-0.14	0.12	0.35	0.21	-0.09	-0.14	0.12	0.33	-0.01	-0.29	0.19
	(1.2)	(1.9)	(0.9)	-(0.8)	(1.1)	(1.7)	(1.0)	-(0.4)	-(0.7)	(1.3)	(2.7)	(0.0)	-(1.3)	(0.7)
NOA	0.06	0.30	-0.51	-0.18	0.07	0.31	-0.53	-0.23	0.13	0.06	0.28	-0.40	-0.46	-0.02
	(0.7)	(1.7)	-(2.7)	-(1.4)	(0.9)	(1.8)	-(2.7)	-(1.5)	(0.7)	(0.8)	(2.0)	-(2.1)	-(2.3)	-(0.1)
InPPEIn	0.15	0.23	0.04	-0.06	0.17	0.25	0.01	-0.13	0.21	0.14	0.25	0.03	-0.02	-0.04
	(1.9)	(1.5)	(0.2)	-(0.4)	(2.2)	(1.6)	(0.0)	-(0.8)	(1.1)	(1.9)	(2.0)	(0.2)	-(0.1)	-(0.2)
CoEqis	0.23	0.24	0.44	-0.40	0.25	0.25	0.42	-0.44	0.13	0.25	0.30	0.30	-0.10	0.08
	(1.9)	(1.5)	(1.6)	-(1.3)	(1.9)	(1.5)	(1.7)	-(1.3)	(0.5)	(2.0)	(1.8)	(1.3)	-(0.4)	(0.3)
AnnRet	0.17	0.17	0.03	-0.20	0.17	0.18	0.03	-0.20	0.02	0.15	0.18	0.07	-0.34	-0.09
	(1.8)	(0.9)	(0.2)	-(1.3)	(1.9)	(0.9)	(0.2)	-(1.1)	(0.1)	(1.8)	(1.2)	(0.4)	-(1.6)	-(0.3)
FailProb	0.00	0.12	-0.17	-0.11	0.01	0.13	-0.17	-0.13	0.05	0.00	0.16	-0.11	-0.15	-0.04
	(0.0)	(0.7)	-(0.7)	-(0.6)	(0.1)	(0.8)	-(0.8)	-(0.6)	(0.2)	(0.0)	(1.0)	-(0.6)	-(0.6)	-(0.1)
GP	0.10	0.09	0.12	-0.14	0.09	0.08	0.13	-0.12	-0.09	0.08	0.09	0.21	-0.26	-0.20
	(1.5)	(0.9)	(0.7)	-(1.1)	(1.3)	(0.8)	(0.8)	-(0.8)	-(0.5)	(1.2)	(0.8)	(1.6)	-(1.6)	-(1.0)
roaq	0.13	0.15	-0.02	-0.05	0.11	0.13	0.00	0.02	-0.22	0.10	0.13	-0.07	-0.28	-0.02
	(2.1)	(1.5)	-(0.1)	-(0.4)	(1.7)	(1.2)	(0.0)	(0.1)	-(1.2)	(1.5)	(1.1)	-(0.5)	-(1.6)	-(0.1)

Table 11: **Predictive Regressions on Idiosyncratic Skewness**

This table reports the time series average from the first regression in the predictive model: (insert regression equation). %sig is the percent of coefficients that are statistically significant at the 5% level (and of the same sign as the average coefficient). Sample is the collection of common stocks trading on the AMEX, NYSE, and Nasdaq. Momentum is the prior year return omitting the most recent month, prior is the return in the last month, dummy variables are included for NASDAQ stocks, stocks in the small and medium terciles, and ff48 industries. The adjusted R-squared and nobs are the cross-sectional average.

Model		**iv_t-1**	**is_t-1**	**mom**	**turnover**	**nasdaq**	**sm**	**med**	**prior**	**ind**	**adjrsq**	**nobs**
1	**Avg**	2.72	0.02							No	0.009	5976
	%Sig	(0.69)	(0.28)									
2	**Avg**	2.30	0.01	-0.01	2.48	-0.03	0.10	0.08		No	0.016	4805
	%Sig	(0.71)	(0.25)	(0.24)	(0.20)	(0.27)	(0.61)	(0.61)				
3	**Avg**									yes	0.012	5480
	%Sig											
4	**Avg**	1.98	0.01	-0.02	1.76	-0.05	0.09	0.07		yes	0.024	4756
	%Sig	(0.68)	(0.20)	(0.26)	(0.14)	(0.28)	(0.56)	(0.54)				
5	**Avg**								-0.20	no	0.002	5637
	%Sig								(0.39)			
6	**Avg**	2.28	0.02	-0.02	2.69	-0.05	0.08	0.06	-0.32	yes	0.026	4754
	%Sig	(0.71)	(0.42)	(0.24)	(0.18)	(0.30)	(0.52)	(0.51)	(0.75)			
7	**Avg**	2.21	0.03	-0.02		-0.01	0.07	0.07	-0.35	yes	0.026	5010
	%Sig	(0.71)	(0.46)	(0.25)		(0.32)	(0.53)	(0.50)	(0.79)			

Table 12: **Skewness Management Using Idiosyncratic Skewness**

This table compares the original to the skewness managed versions of each anomaly (using idiosyncratic skewness). Panel A lists the performance in the full sample in which both the characteristic and expected skewness are non-missing. Panel B lists the performance of the skewness managed version of each anomaly in which the long leg comes from the high expected skewness sample and the short leg comes from the low expected skewness sample. Panel C reports the difference. The Sharpe ratio t-statistics from Jobson and Korkie (1981) are listed in parenthesis.

	Size	B/M	Inv	MOM	ROE	OP	EG	AnnRet	Accrual	CoEqIs	FailProb	GP	InPPEIn	NOA	roaq
Panel A: Standard Anomaly															
mean	3.56	5.03	4.44	13.67	7.49	2.15	11.80	10.71	4.18	6.04	4.18	4.76	4.88	6.84	3.48
sharpe	0.21	0.30	0.40	0.55	0.42	0.14	0.84	0.93	0.36	0.42	0.19	0.41	0.45	0.58	0.20
skew	0.81	0.10	0.29	-1.41	0.09	0.17	0.12	-0.09	0.13	-0.34	-0.25	-0.07	0.02	-0.17	0.49
Panel B: Skewness Managed															
mean	9.27	16.30	15.84	19.27	14.25	10.73	19.54	17.76	10.07	15.01	12.42	14.95	9.99	11.26	11.87
sharpe	0.37	0.63	0.64	0.70	0.69	0.57	0.99	0.82	0.41	0.55	0.52	0.72	0.44	0.54	0.60
skew	1.56	1.41	1.67	-0.31	-0.03	0.16	0.42	0.85	1.23	2.27	-0.02	1.98	0.42	0.25	0.28
Panel C: Difference															
mean	5.71	11.27	11.40	5.60	6.76	8.58	7.74	7.04	5.89	8.98	8.24	10.19	5.11	4.43	8.39
sharpe	0.16	0.32	0.25	0.15	0.27	0.43	0.16	-0.11	0.05	0.12	0.33	0.31	-0.01	-0.04	0.41
skew	0.75	1.31	1.38	1.09	-0.12	-0.01	0.31	0.94	1.10	2.61	0.22	2.05	0.40	0.43	-0.21

Table 13: **Average Realized Skewness by Portfolio**

Portfolios are first sorted on the anomaly characteristic and then merged with stock level expected skewness. The second sort is done sequentially within characteristic portfolio. The final result is 30 portfolios, based on sequential sorts. Returns are calculated using value weighting by prior month market cap. Differences are calculated in the last column and row, while the bottom right corner provides the diagonal, long/high minus short/low.

Panel A: Skewness in Long Leg

B/M

port	high	med	low	H-L
Long	0.43	0.34	0.25	0.18
9	0.38	0.31	0.23	0.16
8	0.36	0.29	0.23	0.13
7	0.35	0.28	0.21	0.14
6	0.33	0.28	0.21	0.12
5	0.33	0.27	0.20	0.13
4	0.32	0.26	0.19	0.13
3	0.32	0.25	0.20	0.12
2	0.32	0.25	0.19	0.13
Short	0.32	0.25	0.19	0.14
L-S	0.10	0.09	0.06	0.24

Size

port	high	med	low	H-L
Long	0.42	0.32	0.22	0.21
2	0.36	0.30	0.23	0.13
3	0.34	0.28	0.23	0.11
4	0.32	0.27	0.22	0.10
5	0.30	0.26	0.22	0.09
6	0.29	0.25	0.22	0.07
7	0.28	0.24	0.21	0.08
8	0.27	0.23	0.19	0.08
9	0.24	0.21	0.19	0.05
Short	0.22	0.21	0.20	0.03
L-S	0.20	0.12	0.02	0.23

Inv

port	high	med	low	H-L
Long	0.43	0.34	0.23	0.20
2	0.37	0.30	0.22	0.15
3	0.36	0.29	0.21	0.15
4	0.34	0.27	0.21	0.13
5	0.33	0.27	0.21	0.12
6	0.31	0.26	0.21	0.11
7	0.33	0.27	0.20	0.12
8	0.33	0.26	0.20	0.13
9	0.33	0.26	0.20	0.12
Short	0.33	0.27	0.20	0.14
L-S	0.10	0.08	0.03	0.23

Panel B: Skewness in Short Leg

MOM

port	high	med	low	H-L
Short	0.42	0.31	0.20	0.22
2	0.34	0.28	0.20	0.14
3	0.33	0.26	0.19	0.15
4	0.33	0.27	0.19	0.14
5	0.34	0.27	0.19	0.14
6	0.33	0.27	0.20	0.13
7	0.34	0.27	0.21	0.13
8	0.33	0.28	0.21	0.12
9	0.35	0.28	0.23	0.12
Long	0.36	0.30	0.25	0.11
S-L	0.06	0.00	-0.04	0.17

ROE

port	high	med	low	H-L
Short	0.41	0.31	0.23	0.17
2	0.34	0.28	0.21	0.13
3	0.33	0.27	0.22	0.10
4	0.31	0.27	0.22	0.10
5	0.30	0.26	0.22	0.08
6	0.30	0.25	0.22	0.07
7	0.29	0.26	0.23	0.06
8	0.28	0.25	0.21	0.07
9	0.27	0.24	0.22	0.05
Long	0.32	0.27	0.23	0.09
S-L	0.08	0.04	0.00	0.17

OP

port	high	med	low	H-L
Short	0.41	0.32	0.22	0.20
2	0.35	0.29	0.22	0.14
3	0.35	0.28	0.21	0.14
4	0.33	0.27	0.21	0.12
5	0.32	0.26	0.20	0.11
6	0.32	0.26	0.21	0.12
7	0.31	0.26	0.20	0.11
8	0.31	0.25	0.20	0.11
9	0.30	0.25	0.20	0.10
Long	0.32	0.26	0.22	0.10
S-L	0.09	0.06	0.00	0.19

Table 14: **Skewness Managed Performance without Continuous Return Predictors**

This table compares the original to the skewness managed versions of each anomaly where expected skewness has been calculated without certain return predictors. Panel A lists performance in the full sample in which both the characteristic and expected skewness are non-missing. Panel B lists the performance of the skewness managed version of each anomaly where expected skewness in calculated without realized volatility. Panel C lists the performance of the skewness managed version of each anomaly where expected skewness in calculated without realized volatility, momentum, and prior return.

	Size	B/M	Inv	MOM	ROE	OP	EG	AnnRet	Accrual	CoEqIs	FailProb	GP	InPPEIn	NOA	roaq
Panel A: Standard Anomaly															
mean	3.28	5.04	4.55	13.68	7.71	2.12	11.83	10.88	4.19	6.04	4.18	4.88	4.90	6.83	3.52
sharpe	0.19	0.30	0.41	0.55	0.43	0.14	0.84	0.95	0.36	0.42	0.19	0.42	0.45	0.58	0.20
skew	0.79	0.10	0.30	-1.41	0.15	0.12	0.12	-0.13	0.13	-0.34	-0.25	-0.06	0.03	-0.17	0.48
Panel B: Skewness Managed Less Realized Volatility															
mean	14.43	15.29	12.99	18.75	15.95	11.89	17.91	17.86	11.51	13.92	13.74	13.61	10.29	13.17	12.55
sharpe	0.66	0.66	0.55	0.65	0.71	0.63	0.88	0.92	0.54	0.55	0.55	0.74	0.50	0.70	0.60
skew	1.83	0.81	4.12	-0.82	0.20	0.06	0.36	0.29	1.94	2.81	-0.48	0.03	0.93	-0.08	0.32
Panel C: Skewness Managed Less Realized Volatility, Momentum, Prior Month Return															
mean	12.85	12.68	11.42	16.66	12.23	9.78	16.08	16.60	9.69	12.18	13.90	11.98	10.12	13.43	8.74
sharpe	0.59	0.57	0.52	0.56	0.51	0.50	0.78	0.84	0.44	0.56	0.54	0.65	0.53	0.74	0.41
skew	1.99	0.87	3.75	-0.93	-0.12	0.02	0.11	0.42	1.99	1.35	-0.56	0.17	0.54	0.42	0.16

Table 15: **Spanning Tests with $E[Skew]$ Anomaly**

This table reports alphas from spanning tests of skewness managed anomalies vs several benchmarks. Panel A compares the original anomaly portfolios to a portfolio representing the return predictability of expected skewness. Also included are spanning tests against the E[skew] anomaly + the original factor and E[skew] + original + FFC 4-factor model. heteroskedasticity robust t-stats are in parenthesis.

E[Skew]														
	Size	B/M	AG	MOM	ROE	OP	Accrual	AnnRet	CoEqIs	FailProb	GP	InPPEIn	NOA	roaq
Beta	0.76	0.61	0.76	0.34	0.24	0.23	0.69	0.60	0.86	-0.04	0.48	0.65	0.55	0.25
	(7.11)	(7.66)	(7.11)	(1.86)	(2.36)	(4.25)	(7.54)	(5.02)	(6.94)	-(0.42)	(10.52)	(12.48)	(7.10)	(3.32)
Alpha	8.00	9.54	6.83	15.92	15.77	9.15	7.19	12.23	5.58	14.23	11.04	3.81	8.63	10.41
	(3.12)	(3.49)	(2.85)	(4.52)	(5.20)	(3.74)	(3.06)	(5.16)	(2.15)	(4.15)	(5.11)	(1.69)	(3.70)	(3.79)
adjrsq	0.24	0.21	0.31	0.04	0.04	0.04	0.30	0.28	0.33	0.00	0.20	0.30	0.23	0.04
original + E[Skew]														
Alpha	5.99	5.67	3.25	1.16	7.62	5.54	4.18	2.74	1.29	6.32	7.34	0.22	3.49	5.95
	(5.30)	(3.14)	(1.55)	(0.60)	(3.69)	(3.37)	(2.03)	(1.28)	(0.63)	(3.28)	(3.95)	(0.11)	(1.64)	(2.97)
FFC 4 factor + original + E[Skew]														
Alpha	6.27	5.86	3.36	1.32	6.59	4.00	3.61	1.64	0.29	6.42	7.22	-0.60	3.12	5.26
	(4.72)	(3.03)	(1.56)	(0.69)	(2.82)	(2.12)	(1.61)	(0.76)	(0.13)	(3.05)	(3.54)	-(0.29)	(1.40)	(2.30)

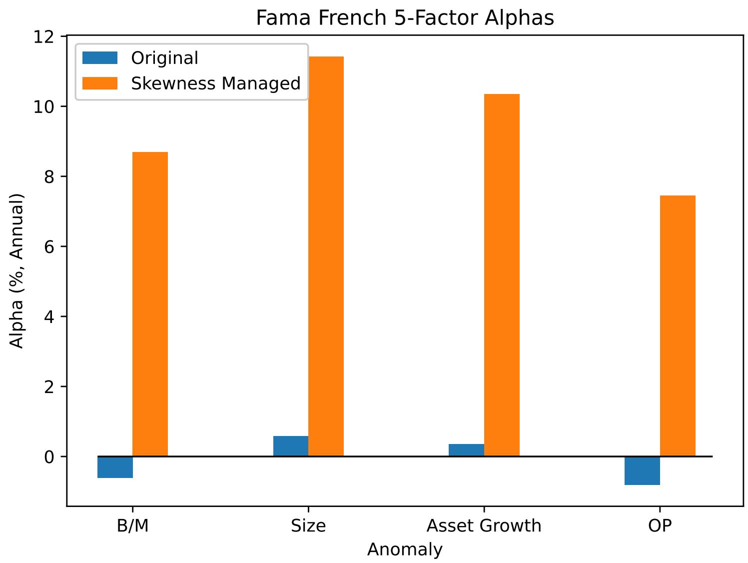
Table 16: **Scaling Strategy Performance**

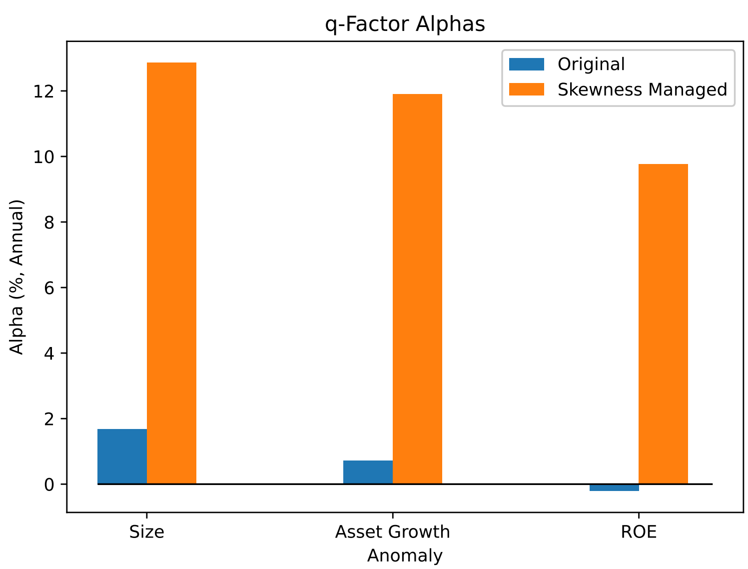
This table details the outcome when managing skewness via the scaling strategy. Exposure to the anomaly scaled the average expected skewness in the long and short portfolio. Strategies in which skewness dominates the long leg increase exposure to the strategy as expected skewness increases, while those in which skewness dominates the long leg decrease exposure. The first row in Panel B tells which scalar is used. Panel A contains the performance of the original factor in which the sample includes all observations in which both the characteristic and expected skewness measure is present. Panel B details the scalar strategy outcome for the correct version of the strategy. Long strategies seek skewness, short focused anomalies avoid skewness. Panel C reports the difference between the original and best scaling strategies.

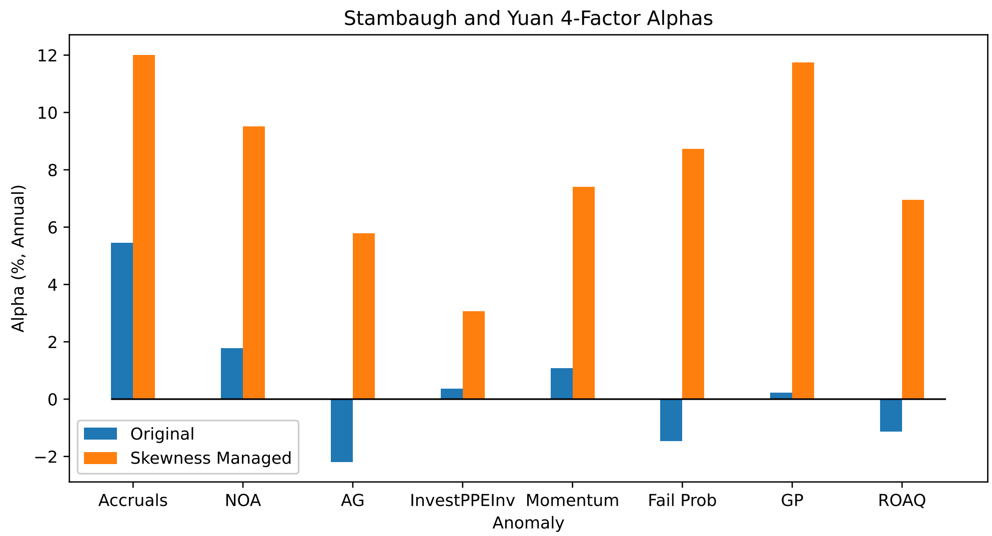
	Size	B/M	MOM	Inv	ROE	OP	IVOL	STR	FailProb	roaq
Panel A: Standard Anomaly										
mean	3.63	5.03	13.67	4.44	7.48	2.15	5.76	4.67	4.18	3.47
sharpe	0.21	0.30	0.55	0.40	0.42	0.14	0.23	0.25	0.19	0.19
skew	0.81	0.10	-1.41	0.29	0.09	0.17	-0.49	0.39	-0.25	0.49
Panel B: Best Skewness Scaling Strategy										
Strategy	Long	Long	Short	Long	Short	Short	Short	Long	Short	Short
mean	13.76	8.62	16.35	5.40	11.31	4.87	13.29	5.02	9.34	5.20
sharpe	0.66	0.48	0.58	0.42	0.58	0.27	0.45	0.24	0.40	0.28
skew	1.69	1.11	-1.08	0.88	0.88	0.38	-0.52	0.63	0.45	-0.12
Panel C: Difference										
Mean	10.14	3.59	2.68	0.95	3.83	2.72	7.53	0.35	5.16	1.73
Sharpe	0.45	0.17	0.02	0.03	0.15	0.13	0.23	0.00	0.21	0.08
Skew	0.88	1.01	0.32	0.59	0.79	0.21	-0.03	0.23	0.69	-0.61

Figure 1: Standard vs Skewness Managed Anomaly Alphas

The figures below plot alphas from running factor regressions against the long-short anomaly portfolio that underlies the factor. The blue bar represents the standard anomaly and the orange bar represents the skewness managed version.






Stambaugh and Yuan 4-Factor Alphas
Alpha (%, Annual)
12
10
8
6
4
2
0
−2
Original
Skewness Managed
Accruals
NOA
AG
InvestPPEInv
Momentum
Fail Prob
GP
ROAQ
Anomaly

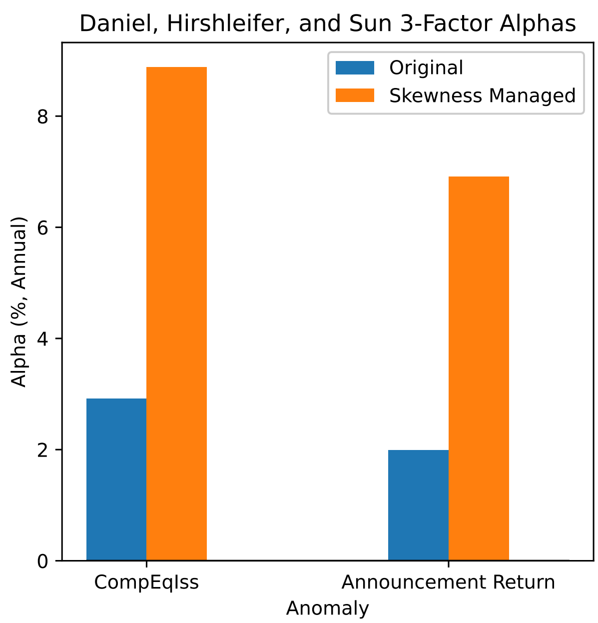
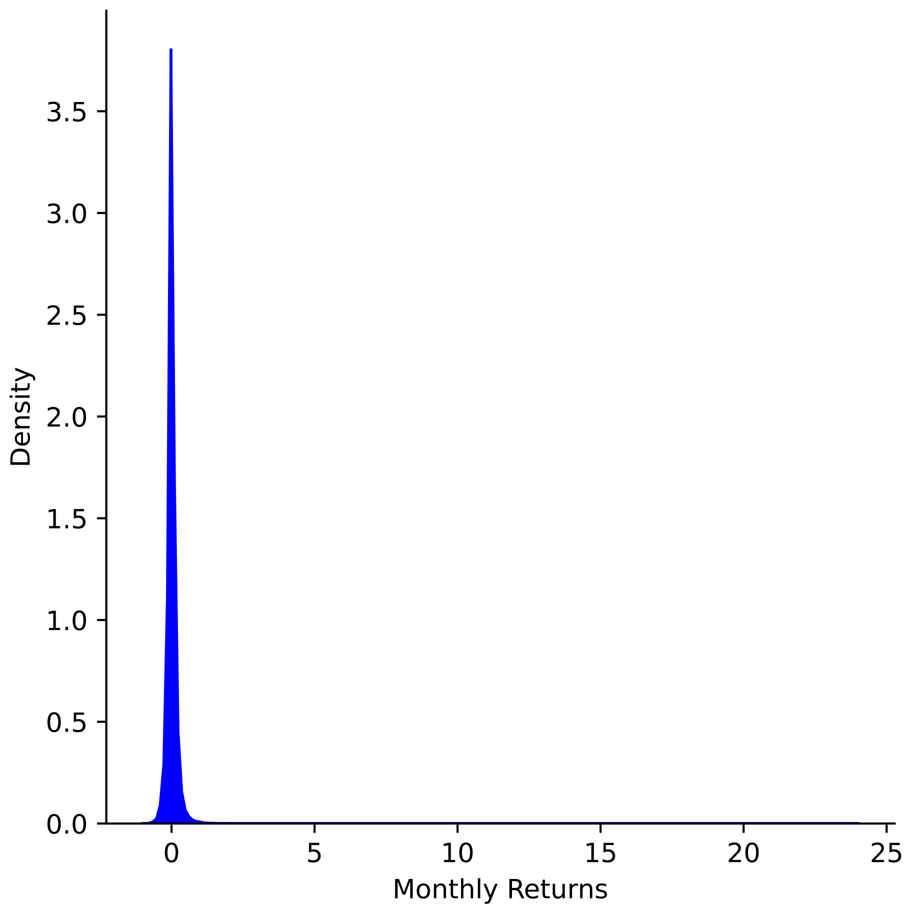

Daniel, Hirshleifer, and Sun 3-Factor Alphas
Alpha (%, Annual)
8
6
4
2
0
Original
Skewness Managed
CompEqIss
Announcement Return
Anomaly

Figure 2: Characterizing Skewness in Monthly Returns

Panel A: Histogram of Monthly Returns

This figure plots a kernel density estimate of monthly return observations for the sample from July 1963- December 2021. Monthly returns are plotted as decimals. The thin tail of the distribution extends out 24 (2400% monthly return).



Panel B: Outlier Percentage by Month

This Figure plots the percentage of stocks in a given month with returns greater than 26.6%, representing those above the 95th percentile during the period from July 1963 - December 2021. Percent is represented as a decimal. The orange line is a reference point representing 5% of stocks each month. The last 3 spikes in the blue line coincide with the periods coming out of the Tech Bubble, the Financial Crisis, and the Covid19 crash, respectively.

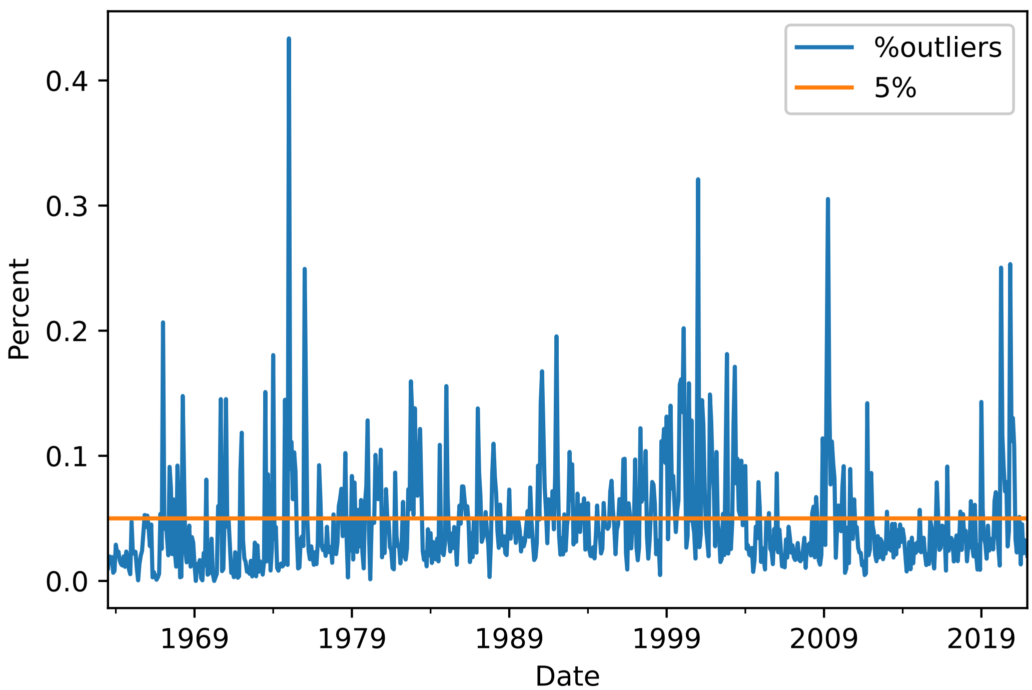
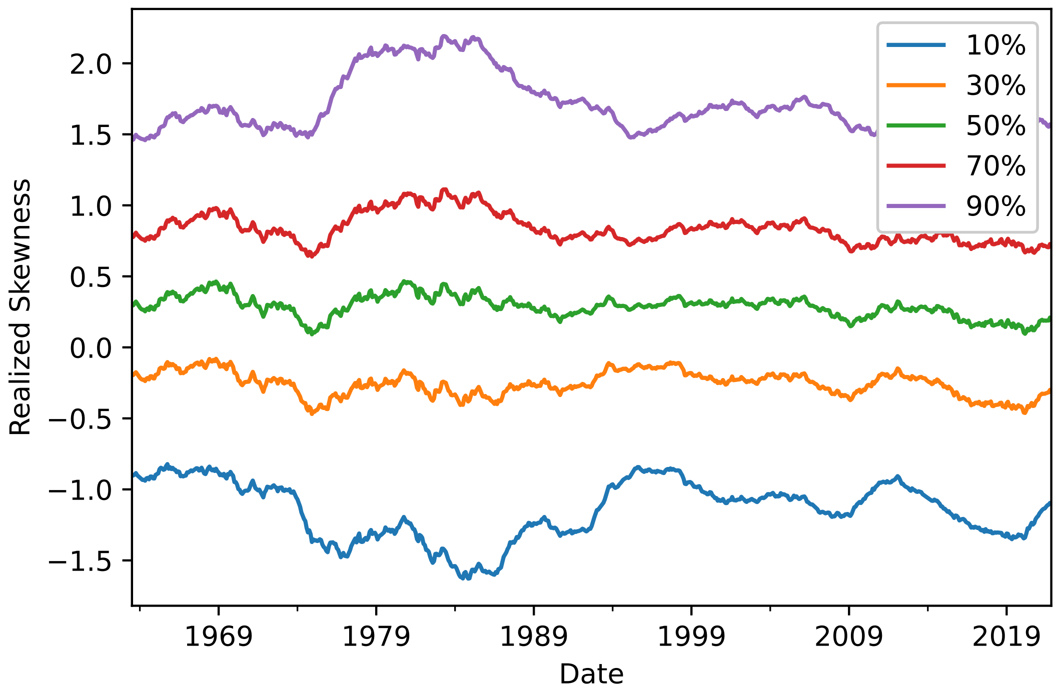


Figure 3: Realized Skewness distribution

This figure graphs the percentiles of realized skewness over time. The plot is of a 36 month moving average of each percentile to smooth out noise. Apart from monthly noise, realized skewness is stable over time.



Internet Appendix

Appendix A: Anomaly Construction

This appendix discusses the details of how the anomalies are constructed. Each signal is constructed as a long-short, self financing strategy based on deciles of firm characteristics. Breakpoints are constructed using NYSE stocks. For a majority of signals I focus on the period from July 1963 to December 2021. Return on Equity uses quarterly files and starts in January 1972. For strategies using annual Compustat files, accounting data for fiscal year-end of year t is matched with stock returns data from July of year t+1 until June of year t+2 to avoid look-ahead bias. ROE uses earnings data from Compustat quarterly files. The data are used in the months immediately after the most recent public quarterly earnings announcement dates (Compustat quarterly item RDQ) where the end of the fiscal quarter that corresponds to its announced earnings is within six months prior of portfolio formation.

The sample includes all common stocks, share code 10 and 11, with available characteristic data and returns. Book equity of firms is calculated by adding the deferred taxes and investment tax credits where available, and preferred stock values were incorporated in the following order of availability: redemption value, liquidation value, or par value of preferred stock. Book-to-market equity is calculated using the December of year t - 1 value for market equity. Tax credits are only added prior to 1993 due to changes in the treatment of deferred taxes. Returns are adjusted for delisting when data are available.

Additional Details:

- Size: Follows Fama and French (1993). size is price times shares outstanding using June Crsp Data.
- Book-to-market (b/m): Follows Fama and French (1993). Book equity from previous fiscal year and market equity from December of prior year. Rebalanced annually.
- Investment (asset growth): Growth in assets from the prior fiscal year, $AssetGrowth = AT/AT_{t-12}$. Rebalanced annually.
- Momentum: Follows Jegadeesh and Titman (1993). Momentum is the cumulative return from the prior year omitting the most recent month. Rebalanced monthly.
- Return on Equity (ROE): Roe is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity where quarterly data book equity data are described above. Rebalanced monthly. Financial Firms omitted.
- Operating Profitability (op): Following Fama and French (2015). Equal to annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1. Rebalanced annually.

- Expected Growth (eg): Following Hou et al (2021). Data Provide by the authors.

The following anomalies use stock characteristics taken from Chen and Zimmermann (2021).

- Accruals: Sloan (1996)
- Announcement Return (AnnouncementReturn): Chan, Jegadeesh and Lakonishok (1996)
- Composite Equity Issuance (CompEquIss): Daniel and Titman (2006)
- Failure Probability (FailureProbability): Campbell, Hilscher and Szilagyi (2008)
- Gross Profits/Total Assets (GP): Novy-Marx (2013)
- change in ppe and inv/assets (InvestPPEInv): Lyandres, Sun and Zhang (2008)
- Net Operating Assets (NOA): Hirshleifer et al. (2004)
- Return on assets, quarterly (roaq): Balakrishnan, Bartov and Faurel (2010)