Conditional Skewness in Asset Pricing: 25 Years of Out-of-Sample Evidence*

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Abstract

Much attention is paid to portfolio variance, but skewness is also important for both portfolio design and asset pricing. We revisit the empirical research on systematic skewness that we initiated 25 years ago. In an out-of-sample test, we find that the risk premium associated with skewness is similar to the one reported in our original paper.

Introduction

The genesis of modern finance is often attributed to Markowitz (1952). We all know (and every textbook has a picture) of the mean-variance frontier. Markowitz makes an important qualification, however (p. 91). He realizes that if investor utility is a function of the mean, variance, and skewness, his famous portfolio optimization is only valid if $\partial U/\partial M_3=0$, where M_3 is the third moment, or skewness in his terminology. Most investors care about downside risks. Further, asset returns are routinely non-normal, yet for decades, financial training has focused on the mean-variance frontier.

Twenty-five years ago, in Harvey and Siddique (2000), we addressed what we considered a deficiency in modern finance. Too much attention was paid to mean-variance analysis and associated measures such as Sharpe ratios. Indeed, Sharpe ratios of different investment styles shows considerable variation. Why don't all investors just choose the high Sharpe ratio styles? The highest Sharpe ratio styles often have the highest negative skew—which is why the Sharpe ratio is high—and investors need to be rewarded for taking that downside risk.

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* We appreciate the comments of Juhani Linnainmaa. Kay Jaitly provided editorial assistance. The views expressed in this paper are those of the authors only and do not represent the views of the Comptroller of the Currency. For Akhtar Siddique, the work has been done on his own time and using his own resources.

The economic foundation for asset pricing with skewness is strong. Indeed, adding a skew term is a simple expansion of the Sharpe (1964) capital asset pricing model (CAPM). Rubinstein (1973) and Kraus and Litzenberger (1976) saw the potential. In the basic CAPM, risk is defined as an asset's contribution to the variance of a well-diversified portfolio (covariance). In the CAPM with skewness, the definition is augmented. Risk also includes the asset's contribution to the skewness of a well-diversified portfolio (coskewness).

In the early 1990s, factor research exploded (see Harvey, Liu, and Zhu, 2016). Empirical factors such as the value and size factors of Fama and French (1992) were added to the CAPM making the three-factor model the *de facto* asset pricing model. We saw an opportunity to conduct a horse-race between popular empirical factor models and the skewness CAPM, which is based on economic first principles.

We also saw the opportunity to redo the standard mean-variance frontier. Our paper (Harvey and Siddique, 2000) presented a three-dimensional mean-variance-skew frontier. Slicing the frontier at a particular level of skewness delivers the classic mean-variance frontier. Slicing at a particular level of variance, however, shows that portfolios with more negative skew have higher expected returns.

Our empirical work provided evidence which suggested that skew is important. We rejected the null hypothesis that the skew premium was zero. Our evidence suggested the premium was in the range of 200–300 basis points per annum. Our work also pointed to the sensitivity of the results to research design choices.

Testing a model with three moments is more difficult than testing a model with two. Consider the issue of nonstationarity. Even the original tests of the CAPM by Fama and MacBeth (1973) allowed betas to be estimated over a five-year window. We realized that it was essential to allow for time variation in our measures of coskewness, or skew beta. The challenge is that even moments, such as variance and kurtosis, are highly persistent. Odd moments, such as expected return and skew, are not persistent and are subject to large estimation error. Another way to view this challenge is that whereas expected returns and skew can be positive or negative, variances are never negative.

We were aware when we wrote our paper of the many research choices that needed to be made (see Harvey, 2017) in order to conduct a discussion of research choices and how they impact out-of-sample performance. For example, how many observations should be used in calculating the coskew measure? Indeed, how much information is in a historical measure of coskew? Suppose a company falls into a period of bad luck and suffers a substantial drop in its share price. A statistical estimate of the skewness could be quite negative based on past performance, but assets are priced based on the expected (co)skew. Just because the *ex post* skew is negative does not mean the *ex ante* skew is negative.

Another choice is how to treat missing values (i.e., what minimum number of values should we use to calculate the coskew?). These choices are the same faced by those who tested the original CAPM. In our case, the estimation is much more sensitive to these choices because of the third moment—that is, any noise is amplified by the power of three not two.

More fundamentally, how do we even measure skew? The literature offers many choices. Consider the four measures detailed by Kim and White (2004),

$$\begin{aligned} SK1 &= (\frac{r_t - \mu}{\sigma})^3 \\ SK2 &= \frac{Q_3 + Q_1 - 2Q_1}{Q_3 - Q_1} \\ SK3 &= \frac{\mu - Q_2}{E|y - \mu|} \\ SK4 &= \frac{\mu - Q_2}{\sigma} \end{aligned}$$

where Q_1, Q_2, and Q_3 represent quartiles. SK_2 was originally proposed by Bowley (1920). SK_3 is a generalization of SK_2 proposed by Hinkley (1975).

We proposed a direct measure of skew beta, β_{SKD},

$$\hat{\beta}_{\mathrm{SKD}_i} = \frac{E[\epsilon_{i,t+1}\epsilon^2_{M,t+1}]}{\sqrt{E[\epsilon^2_{i,t+1}]}E[\epsilon^2_{M,t+1}]}$$

where ϵ_i represents residuals from a market model regression and ϵ_M represents the demeaned market excess return.

We also noted another choice for skew beta estimation: an extension of the market model regression in which the model is augmented with the squared market return, and the resulting coefficient on the square is an alternative metric.

Once the inputs are estimated, how should we test the model? Should we use Fama and MacBeth (1973) tests or the hedge portfolio technique? The latter would involve being long negative coskew stocks (which we called S^-) and being short positive coskew stocks (S^+), a technique pioneered by Fama and French (1992).

Our research strategy was to 1) try different methods and 2) report all results in order to be fully transparent, allowing the reader to choose the method they thought was most appropriate.

One further complication arose. During the time of our research, CRSP had partially included NASDAQ stocks. Should we include these stocks or exclude? We chose to include this limited list of stocks.

Twenty-five years later a rich research agenda linked to skewness exists. When we were writing our paper, we could not have imagined it would gather 3,000 citations. Many of these papers (too many to cite) offered alternative research choices. Overall, the finding in these papers suggested that a risk premium is associated with skewness. Further, the effect has not gone away with time.

Replications

Replication plays an increasingly important role in financial economics Harvey (2020). Replication should not be confused with reproduction (reproducing the same result on the same historical data). Replication tests whether an effect still exists when applied to a different data set, such as a different country or recent out-of-sample data. A number of researchers have replicated our work on skewness.

McLean and Pontiff (2016) studied the out-of-sample and post-publication predictability of 97 variables. Their important study shows that portfolio returns are 26% lower out of sample and 58% lower post publication. Their results are consistent with some degree of overfitting in the original studies. Their method used quintile-based sorts and the Fama and MacBeth (1973) method.

McLean and Pontiff (2016) provided both a reproduction over the original sample and out-of-sample evidence. Their "reproduction" is not a reproduction in the usual sense because the data had changed (expansion of the CRSP database to include all NASDAQ stocks). Nevertheless, they were able to reproduce the premium in sample. McLean and Pontiff (2016) did not report statistics on the individual measures, but in private correspondence one of the authors wrote: "my recollection was that the out-of-sample performance was also very good."

Chen and Zimmerman (2021) conducted a large-scale reproduction project. Again, this is not a reproduction in the usual sense given the change in data. They found a significant effect in sample with a *t*-statistic of 2.2 and a risk premium of 3.2% per annum. The risk premium reported in the original paper was 3.6% per annum.

Jensen, Kelly, and Pedersen (2022) also provided a replication of the coskew variable. They reported an alpha of 1.4% for the U.S. market and 3.4% for developed markets excluding the U.S. They found no effect for emerging markets. They also presented a test for statistical significance in which the p-value needs to be less than 0.025. The estimation on the U.S. data provides a p-value of 0.05 and on the developed excluding U.S. data of 0.02.

Finally, Anghel et al. (2022) provided both a replication and an extension that explores alternative measures of coskew. They found that the estimates are fairly different from Harvey and Siddique (2000), even though many of the qualitative results remain the same. They noted a large discrepancy between the Harvey and Siddique sample size of 9,268 and their sample size of 14,988. The discrepancy is largely a result of CRSP's adding all NASDAQ stocks to its database in the interim.

Focusing on the long–short portfolio returns, Anghel et al. (2022) reported a replication of the risk premium at 2.6%, which is somewhat lower than the original 3.6%. In the recent out-of-sample period, the premium is 1.6%.

Anghel et al. (2022) also showed the performance of alternative measures of coskew proposed by Langlois (2020). The goal of the Langlois measure, which uses information on firm characteristics, is to reduce the noise in the estimate of coskew. Anghel et al. (2022) also provided a modified measure that only uses information from past stock returns. They noted: "We confirm the intuition in Harvey and Siddique (2000) that coskewness is priced in the cross-section of stocks." They showed that the alternative measures of coskew appear to dominate the original measure from our 2000 paper.

Sensitivity to Research Choices

We have also reproduced and replicated our paper. Of particular interest is the sensitivity of results to different research choices.

In Table 1, we reproduce the long–short results of Harvey and Siddique (2000) and focus on three choices: 1) value or equal-weighted portfolios, 2) estimation window for coskew, and 3) maximum number of missing values allowed. Each of the results in Table 1 uses 30/70 break points, which is also a research choice, but is consistent with Fama and French (1992). Our 2000 paper reported a premium of 3.6%, which replicates well with a 3.8% premium. Remember, the reproduction is using 50% more securities, given the additional NASDAC stocks that were added to CRSP. The table shows considerable variation—from 2.1% to 3.9%—in the premium.

In Table 2, we explore the choice of break points over the original sample by looking at 20/80, quintiles implemented by McLean and Pontiff (2016), as well as 10/90 (deciles). Interestingly, the highest premium occurs in the 10/90 portfolios. In this set-up, the long portfolio has the top decile of negative coskewed stocks. In the equal-weighted implementation, the premium is 6.3% and in the value-weighted results is 4.7%. Our original choice, 30/70, is among the worst performers.

Hou, Xue, and Zhang (2020) showed that many factor premia are sensitive to the inclusion of small stocks. As such, Table 3 shows the sensitivity of results to dropping the smallest 1st, 2nd, and 4th percent of all stocks based on market capitalization. Not surprisingly, this exercise has little impact on the value-weighted formulation, although we observe some variation in the equal- weighted analysis. The effect is surprising in the context of Hou, Xue, and Zhang in that dropping the smaller stocks increases the premium associated with skewness. A reasonable interpretation is that the estimate of coskew for smaller stocks is much noisier than for large stocks. This interpretation is also consistent with the usefulness of alternative measures of coskew that are less sensitive to noise (Langlois, 2020, and Anghel et al., 2022).

Our out-of-sample analysis focuses on the 1994–2019 period. We present results for the full out-of-sample period as well as for two subperiods, 1994–2007 and 2008–2019. Consistent with other replications, the mean premium is smaller in the out-of-sample period, 2.0%, using the measure initially reported in our 2000 paper (i.e., the equal-weighted portfolio with a limit of 12 missing observations). The first subperiod has a 1.4% premium and the second a 2.6% premium.

Consistent with the earlier reproduction, some of the highest premiums reported in Table 4 are from different breakpoints, particularly the 10/90. In the full out-of-sample period, the equal-weighted premium is 3.9% and the value-weighted is 4.7%. While we observe some variation across the subperiods, the premium is always positive. For example, for the value-weighted construction, the 10/90 breakpoint delivers 5.7% in the first subperiod and 3.6% in the second subperiod.

Table 5 provides some benchmarking for the out-of-sample analysis. The original construction of the coskew factor has a 2% return over this period. As we previously mentioned, the subperiod performance was consistent with 1.4% in the first half and 2.6% in the second half. The Fama and French (1992) value factor, HML, has a 1.6% premium in our out-of-sample period with inconsistent performance in the two subperiods (4.7% and −2.0%). The premium on the size factor, SMB, is modest at 0.9%, with consistent performance in both subperiods. The largest premium is for momentum, which has a 4.8% premium in the full out-of-sample period, but displays very inconsistent performance. In the first period, momentum has a 9.7% return and in the second period a −0.8% return.

Conclusions

The economic foundation that skewness plays an important role in asset pricing is solid. Investors need to be rewarded for purchasing assets that add downside risk to their portfolio. Twenty-five years ago, we proposed an empirical asset pricing model that added coskewness as a risk measure. Our results presented in Harvey and Siddique (2000) suggested that the risk premium was greater than 3% on an annualized basis.

A number of papers have successfully reproduced our results on the original sample. In the out-of-sample period, the premium is estimated to be smaller, but is consistent across subperiod and is always positive. In contrast, some other popular empirical asset pricing factors, such as HML and momentum, flip signs. SMB has consistent performance, but with an estimated risk premium less than 1%.

We have also documented that research choices have a considerable influence on the measurement of the skewness risk premium. For example, in our original paper, we chose a long–short portfolio with the top and bottom 30% of stocks based on our measured coskewness. The estimated risk premium both in sample and out of sample is much larger for measures that use the top and bottom quintiles or deciles. Our original paper happened to choose the measure that delivered the lowest premium. Nevertheless, the premium successfully replicated.

There is also a fundamental decision of how to measure skewness and coskewness. As we point out, it is very challenging to measure higher moments such as skewness. Harvey et al. (2010) proposed a Bayesian approach to portfolio design that explicitly takes the uncertainty in the skew measures into account. Langlois (2020) offered a novel approach that reduces the noise in the coskew measure by using nonprice information. Anghel et al. (2022) modified the Langlois approach. All of these research initiatives are promising.

Unfortunately, after 25 years and many successful replications, too many students of finance are only exposed to the mean-variance frontier. Our courses also feature empirical factor models. The importance of skewness has been validated over the past decades. We are hopeful that textbooks and curricula of the future will deepen the discussion of risk.

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Table 1: **Reproducing Realized Skewness Premium and Robustness** We compute the coskewness risk premium, following Harvey and Siddique (2000) for all stocks listed on NYSE/Amex and Nasdaq over the period July 1963 to December 1993. Standardized direct coskewness, $\hat{\beta}_{\mathrm{SKD}_i}$, for each of the stocks is computed using a fixed window such as the previous 60 months of returns. The stocks were then ranked based on their coskewness. Three portfolios are formed, such as the lowest 30 percent with the most negative coskewness, called S^-, middle such as the middle 40 percent, called S^0, and top such 30 percent with the most positive coskewness, called S^+. The post-ranking month, such as the 61st month for a 60 month rolling estimation window, spread between S^- and S^+ is then used to proxy for the return on coskewness. In the table below, this spread is computed over varying Window (36, 48, 60 and 72). Limit Missing indicates how many months (out of the Window) are allowed to be missing before a stock is not used in the $\hat{\beta}_{\mathrm{SKD}_i}$ calculation. The boldfaced line represents the choices made in Harvey and Siddique (2000). The results illustrate the considerable variation —from 2.1% to 3.9% — in the risk premium.

Window	Limit Missing	Break Points	Cap Month	Mean	StdDev
Equally weighted – Change in Limit on Missing					
60	0	30, 70	12	2.47	5.47
60	**12**	**30, 70**	**12**	**3.78**	**4.76**
60	24	30, 70	12	3.72	4.74
Value weighted – Change in Limit on Missing					
60	0	30, 70	12	2.18	7.65
60	12	30, 70	12	2.45	7.55
60	24	30, 70	12	2.48	7.56
Equally weighted – Change in Window					
36	24	30, 70	12	3.74	4.79
48	24	30, 70	12	3.44	4.80
60	24	30, 70	12	3.72	4.74
72	24	30, 70	12	3.58	4.77
Value weighted – Change in Window					
36	24	30, 70	12	3.88	7.61
48	24	30, 70	12	2.19	7.42
60	24	30, 70	12	2.48	7.56
72	24	30, 70	12	2.12	7.77

Table 2: **Reproducing Realized Skewness Premium: Changing Break Points**

We compute the coskewness risk premium, following Harvey and Siddique (2000) for all stocks listed on NYSE/Amex and Nasdaq over the period July 1963 to December 1993. Standardized direct coskewness, $\hat{\beta}_{\mathrm{SKD}_i}$, for each of the stocks is computed using a fixed window such as the previous 60 months of returns. The stocks were then ranked based on their coskewness. Three portfolios are formed, such as the lowest 30 percent with the most negative coskewness, called S^-, middle such as the middle 40 percent, called S^0, and top such 30 percent with the most positive coskewness, called S^+. The 61st month (i.e. post-ranking) spread between S^- and S^+ is then used to proxy for the return on coskewness. In the table below, this spread is computed over a fixed window of 60 months. Break Points show what percentiles are used for S− and S+. The results show the significant impact from Break Points, with the largest premium occurring with a 10/90 break point, i.e. deciles.

Window	Limit Missing	Break Points	Cap Month	Mean	StdDev
Equally weighted – Change in Break Points					
60	**12**	**30, 70**	**12**	**3.78**	**4.76**
60	24	30,70	12	3.72	4.74
36	24	20,80	12	4.40	5.85
60	12	20,80	12	5.14	5.86
60	24	20,80	12	5.06	5.85
60	24	10,90	12	6.32	7.62
Value weighted – Change in Break Points					
60	24	30,70	12	2.48	7.56
36	24	20,80	12	4.67	8.63
60	12	20,80	12	3.43	9.23
60	24	20,80	12	3.37	9.23
60	24	10,90	12	4.66	10.45

Table 3: **Reproducing Realized Skewness Premium: Dropping Small Firms**

We compute the coskewness risk premium, following Harvey and Siddique (2000) for all stocks listed on NYSE/Amex and Nasdaq over the period July 1963 to December 1993. Standardized direct coskewness, $\hat{\beta}_{\mathrm{SKD}_i}$, for each of the stocks is computed using a fixed window such as the previous 60 months of returns. The stocks were then ranked based on their coskewness. Three portfolios are formed, such as the lowest 30 percent with the most negative coskewness, called S^-, middle such as the middle 40 percent, called S^0, and top such 30 percent with the most positive coskewness, called S^+. The 61st month (i.e. post-ranking) spread between S^- and S^+ is then used to proxy for the return on coskewness. In the table below, this spread is computed over a fixed window of 60 months. We present the impact of dropping the smallest 1, 2 and 4 percentile of firms by capitalization. There is not a large impact.

Window	Limit Missing	Break Points	Percentile Dropped	Cap Month	Mean	StdDev
Equally weighted – Dropping the Lowest Percentiles by Cap						
60	24	30,70	1	12	3.87	4.80
60	24	30,70	2	12	3.92	4.77
60	24	30,70	4	12	4.04	4.76
Value weighted – Dropping the Lowest Percentiles by Cap						
60	24	30,70	1	12	2.48	7.56
60	24	30,70	2	12	2.48	7.56
60	24	30,70	4	12	2.48	7.56

Table 4: **Realized Skewness Premium: Out of Sample**

We compute the coskewness risk premium, following Harvey and Siddique (2000) for all stocks listed on NYSE/Amex and Nasdaq over the period January 1994 to December 2019. Standardized direct coskewness, $\hat{\beta}_{\mathrm{SKD}_i}$, for each of the stocks is computed using a fixed window of previous 60 months of returns. The stocks were then ranked based on their coskewness. Three portfolios are formed, such as the lowest 30 percent with the most negative coskewness, called S^{-}, middle such as the middle 40 percent, called S^{0}, and top such 30 percent with the most positive coskewness, called S^{+}. The 61st month (i.e. post-ranking) spread between S^{-} and S^{+} is then used to proxy for the return on coskewness. Limit Missing indicates how many months (out of the Window) are allowed to be missing before a stock is not used in the $\hat{\beta}_{\mathrm{SKD}_i}$ calculation, Break Points show what percentiles are used for $S-$ and $S+$.

Weighting	Limit Missing	Break Points	Mean	StdDev
1994 January to 2019 December				
Equal	0	30, 70	3.14	6.12
Equal	**12**	**30, 70**	**1.95**	**6.08**
Equal	24	20, 80	2.90	7.35
Equal	24	10, 90	3.92	9.63
Value	0	30, 70	2.40	8.50
Value	12	30, 70	1.95	7.99
Value	24	20, 80	2.98	8.50
Value	24	10, 90	4.71	12.66
1994 January to 2007 December				
Equal	0	30, 70	2.72	6.22
Equal	**12**	**30, 70**	**1.43**	**6.26**
Equal	24	20, 80	2.15	7.62
Equal	24	10, 90	1.22	9.94
Value	0	30, 70	3.66	9.39
Value	12	30, 70	2.91	8.58
Value	24	20, 80	3.01	12.76
Value	24	10, 90	5.70	13.03
2008 January to 2019 December				
Equal	0	30, 70	3.64	6.02
Equal	**12**	**30, 70**	**2.55**	**5.87**
Equal	24	20, 80	3.78	7.05
Equal	24	10, 90	7.07	9.21
Value	0	30, 70	0.93	7.35
Value	12	30, 70	0.83	7.26
Value	24	20, 80	1.49	9.02
Value	24	10, 90	3.55	12.26

Table 5: **Realized Premia on Fama-French factors and Realized Skewness Premium**

We compute the averages on the risk factors compiled by Fama and French over the period January 1994 January to December 2019. The risk factors are $Mkt - Rf$, HML, SMB, and Momentum. As described on Professor French's website: SMB (Small Minus Big) is the average return on three small portfolios minus the average return on three big portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. Momentum is the average return on the two high prior return (2 to 12 month prior) portfolios minus the average return on the two low prior return portfolios. We compute the coskewness risk premium, following Harvey and Siddique (2000) for all stocks listed on NYSE/Amex and Nasdaq over the period January 1994 to December 2019 . Standardized direct coskewness, $\hat{\beta}_{\mathrm{SKD}_i}$, for each of the stocks is computed using previous 60 months of returns. The stocks were then ranked based on their coskewness. Three portfolios are formed, such as the lowest 30 percent with the most negative coskewness, called S^-, middle such as the middle 40 percent, called S^0, and top such 30 percent with the most positive coskewness, called S^+. The 61st month (i.e. post-ranking) spread between S^- and S^+ is then used to proxy for the return on coskewness.

Factor	Mean	StdDev
January 1994 to December 2019		
MKT-RF	8.20	14.86
HML	1.59	10.47
SMB	0.90	11.21
Momentum	4.83	17.06
Skew	1.95	6.08

January 1994 to December 2007		
MKT-RF	7.08	14.41
HML	4.70	11.20
SMB	0.87	13.36
Momentum	9.70	17.23
Skew	1.43	6.26

January 2008 to December 2019		
MKT-RF	9.52	15.41
HML	-2.04	9.49
SMB	0.94	8.06
Momentum	-0.84	16.76
Skew	2.55	5.87