Asymmetric correlation as an explanation for the effect of asset skewness on equity returns

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Abstract

Assets with asymmetric correlation tend to cause portfolios to have negative skewness. We develop measures of asymmetric correlation based on portfolio skewness. We find that asymmetric correlation is better measured with the skewness of smaller portfolios. The skewness of individual-stock returns has the most significant and consistent explanatory power for stock returns, indicating that asymmetric correlation is generated at the asset level of individual firms.

Keywords: Asymmetric Correlation, Skewness, Fama-French Factors, Suppressor Variables

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Abstract

Assets with asymmetric correlation tend to cause portfolios to have negative skewness. We develop measures of asymmetric correlation based on portfolio skewness. We find that asymmetric correlation is better measured with the skewness of smaller portfolios. The skewness of individual-stock returns has the most significant and consistent explanatory power for stock returns, indicating that asymmetric correlation is generated at the asset level of individual firms.

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I. Introduction

Fama and French (1992, 1993) show that size and book-to-market-equity can explain stock returns. (See also Keim (1983) and Graham and Dodd (1934).) However, since size and book-to-market alone have little economic basis to act as risk factors, researchers have tried to explain size and book-to-market with other risk factors. Chan and Chen (1991) find evidence that size is a proxy for financial distress. Kapadia (2011) argues that distress risk is the source of both Fama-French factors. Jagadeesh and Titman (1993) find momentum helps explain asset returns.

Many authors have used higher-order co-moments to explain asset returns: Kraus and Litzenberger (1976), Friend and Westerfield (1980), Sears and Wei (1985), Lim (1989), Bonsal and Viswanathan (1993), Harvey and Siddique (1999, 2000), Perez-Quiros and Timmermann (2000), Kan and Wang (2001), Dittmar (2002), Hung, Shackleton, and Xu (2004), Chung, Johnson, and Schill (2006), Mitton and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), and Conrad, Dittmar, and Ghysels (2013).

In this paper, we test the relationship between asymmetric correlation and stock returns, as well as the relationship with size and book-to-market. We are thus building on the huge and growing literature on asset pricing. See, e.g., Novy-Marx (2013), Avramov et. al (2013), Israel and Moskowitz (2013), Obreja (2013), and references therein. See also Cochrane (2011).

Albuquerque (2012) points out that assets usually have positive skewness, but portfolios usually have negative skewness. He notes that this can be caused by asymmetric correlation (Ang and Chen (2002)). Since people generally like positive skewness and dislike negative skewness (Scott and Horvath (1980)), an asset with asymmetric correlation has an undesirable property. In equilibrium all assets must be held, so assets with asymmetric correlation should have higher expected returns to induce investors to hold them. To measure this property, we examine if a stock has a significant influence on the skewness of a portfolio. Our first method aims to capture a stock's significant influence on portfolio skewness. We calculate the skewness of a randomly generated portfolio and add a stock to the portfolio. If a stock flips the sign of the portfolio from positive to negative, it can serve as a strong indication of asymmetric correlation. As our second method, we calculate the skewness of various-sized portfolios and assign the skewness as the measure of asymmetric correlation for component stocks. Our portfolio size varies from four to sixty-four stocks. These approaches are similar to the concept of co-skewness. While co-skewness is typically measured as the contribution of a stock to the whole market portfolio, we measure the influence of a stock after forming portfolios of various sizes. We find that even tiny (e.g., two assets) portfolios are strongly affected by asymmetric correlation, and often have negative skewness.

Both measures either yield inconsistent or insignificant effects in asset pricing regressions for the cases of larger portfolios. On the other hand, the results indicate that the asymmetric correlation of a stock is better measured at a smaller level. In fact, we find that the skewness of the stock (not co-skewness) is the best measure of asymmetric correlation among our methods. The conventional wisdom is that the skewness of the stock should not explain returns because the skewness terms should be swamped by the co-skewness terms in a portfolio. However, as we shall see in the next section, skewness can be important as a measure of asymmetric correlation. Think of the stock as a portfolio of assets. If the skewness is negative, as it is for about 15 percent of stocks, that means one or more of the assets of the firm cause negative skewness. Those assets will also affect portfolios containing those assets. We should get the same effect, only weaker, if the stock's skewness is positive. Note that we do not require investors to behave sub-optimally: For us, skewness is just a special case of a variable we design to measure asymmetric correlation.

Others have found that skewness can help explain returns (see Boyer, Mitton, and Vorkink (2010) and references therein). One problem with skewness is that it is not stable over time (Harvey and Siddique (1999)). We use a quantile-based estimator of skewness and a fairly long interval (five years) for estimating skewness. With this simple adjustment, we are able to find significant explanatory power for skewness on asset returns.

The explanatory power of skewness depends on the size factor. The skewness variable becomes particularly significant when the size variable is included in our asset-pricing test. The skewness variable, on the other hand, cannot replace size. This type of variable, which enhances another variable's explanatory power but has less explanatory power by itself, is called a 'suppressor' variable in statistics (e.g., Howell (2001)).

In the next section we discuss the data and present our results. Section III gives our conclusions.

II. Data and Results

Following Ang and Chen (2002), we base most of our analyses on weekly returns. Ang and Chen (2002) focus on weekly frequency, as this frequency represents the best trade-off to avoid the market-microstructure biases at daily frequencies, yet provide a large number of observations. We use daily stock-return data from the Center for Research in Security Prices (CRSP). The daily return is aggregated to a weekly return by calculating the total buy-and-hold return from the end of every Friday to the end of the following Friday. Friday is chosen to match the returns with weekly asset-pricing factors posted on Ken French's Data Library. We obtain accounting data from COMPUSTAT. Our asset-pricing tests are on weekly returns from Jan 1st, 1969 to December 31st, 2009.

Beta, size, and book-to-market for each firm are calculated according to the method in Fama and French (1992). The accounting data for the fiscal year-end in calendar year t-1 are matched with the returns for July of year t to June of t+1. The firm's market-equity value, calculated at the end of December of year t-1, is used to compute the book-to-market ratio for t-1, and the market-equity value for June of year t is used to measure size. Beta is estimated from 10 size-sorted portfolios, using all time-series returns in our sample. Details of these measures are in Fama and French (1992). With these numbers, we are able to replicate the results of Fama and French (1992) – insignificant beta, negatively significant size, and positively significant book-to-market.

We use a quantile-based estimator for skewness (See. e.g., Kim and White (2004)):

$$\frac{g(1-\alpha)+g(\alpha)-2g(\frac{1}{2})}{g(1-\alpha)-g(\alpha)}, \quad (1)$$

where α is the quantile (0.1 in almost all our tests) and *g* is the inverse of the cumulative probability. This estimator for skewness should work better than the conventional measure because it is not as sensitive to outliers (Kim and White (2004)) and also, perhaps, because it is based on the tails of the distribution, which presumably matter a great deal to investors.

To acquire a general idea about portfolio skewness, we form portfolios from the CRSP database and measure the skewness. Every calendar year, we sort stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. This process gives us *nxn* categories. Sorting by size and then book-to-market is a common practice in asset-pricing studies to prevent size and book-to-market from interacting with some other asset-pricing factor (see, e.g., Jegadeesh and Titman (1993)). We randomly select one stock from each of the *nxn* categories and form an equal-weighted portfolio. The random selection is repeated 1,000 times. The skewness (not co-skewness) of weekly returns of this *nxn* -stock portfolio is calculated. To account for the time-varying portion of skewness (Harvey and Siddique (1999)), we estimate skewness every five years.

Table 1 reports the signs of portfolio skewness. A negative skewness indicates that some of the stocks in the portfolio have asymmetric correlation. An interesting pattern is that the number of negative-skewness portfolios is increasing by portfolio size; portfolios with a larger number of stocks tend to have negative skewness. This result is consistent with Albuquerque (2012), who contrasts the positive skewness of individual stocks with the negative skewness of the market portfolio.

We conjecture at this point that the asymmetric correlation of a stock can be measured by its ability to influence the sign of portfolio skewness. If a portfolio's skewness flips from positive to negative by adding a stock to the portfolio, it is an indication that the stock has a strong asymmetric-correlation property. Harvey and Siddique (1999, 2000) use coskewness of a stock with the market return to measure this property. However, investors may not hold the exact market portfolio in finance datasets, and the coskewness measure may not capture the actual contribution of a stock as a result. Our test portfolios need not be realistic portfolios; however, any investor wishing to avoid negative skewness will have to hold such a small portfolio, as shown in Table 1.

We construct a sign-flip measure. The portfolio formation process is identical to the process outlined in Table 1. Then we add each stock in our sample to the *nxn* stock portfolio to form a $nxn+1$ stock portfolio (equal-weighted) and calculate the skewness of weekly returns of the $nxn+1$ stock portfolio using five years of data. The nxn stock portfolio is required to have a positive skewness. If the $nxn+1$ stock portfolio has a negative skewness, we count it as a case of sign flipping. We repeat this portfolio-formation process for *N* iterations, for all stocks in the CRSP database, and see how many times out of *N* the added stock can flip the sign of an nxn stock portfolio. Thus the sign-flipping measure for stock *i* is defined as:

Number of times that stock i flipped the portfolio-skewness sign to negative / N

We use 100 iterations for this empirical test. More iterations increase computing time exponentially, as the procedure is to check the contribution of every stock in the CRSP database to the skewness of randomly generated portfolios. Portfolios do not always have positive skewness, as shown in Table 1. If we run 100 iterations, only a portion of the iterations would have positive a portfolio-skewness, so *N* is typically smaller than 100. Or, we may repeat the formation process until a positive skewness portfolio is formed. In this restricted case, *N* is 100. The latter process used is what we call "positive only" in Table 2.

Since the sign-flipping measure uses five years of time-series data to calculate the skewness of a portfolio, stocks with relatively short time-series return data such as one or two years would have little influence on the portfolio skewness. Thus, we restrict our sample stocks to have a minimum of five years of return data. However, the results are qualitatively similar when we include all the stocks in the CRSP database.

We present our results in Table 2. We report the t-statistics of the coefficients in our tables, as our focus is to identify a variable significantly correlated with asset returns. Regression 1 shows that the sign-flip variable is insignificant when $n = 2$. This could be due to multicollinearity (see Table 4). Regressions 7 and 8 (size variable (Log *SIZE*) omitted) show that for $n = 4$ and $n = 6$ sign flip is insignificant. The problem for a large n is that it is hard to measure the individual contribution from each stock. Note that Regression 1 has the highest adjusted R^2.

As our second measure, we form portfolios of various sizes and measure the skewness of the portfolios. A stock's contribution can be estimated by the skewness of the portfolios that include the stock ("Portfolio Skewness Measure"). We use 1,000 iterations for this test as the computing time is a fraction of that for the sign-flip measure. We also report the result of a much larger portfolio ($n = 8$), which has 64 stocks.

We present our results in Table 3. The regressions show that, except for $n = 4$, the portfolio-skewness variable is negative and increases in absolute value as n decreases. The regressions have similar R-squares. The correlation coefficients reported in Table 4 indicate that multicollinearity is not causing the insignificance. Regression 4, which is the case of $n = 2$, shows a t-statistic close to a significant level (-1.30). Regression 5 is the case of $n = 1$. Here we pick one stock and then add one more to form a two-stock portfolio. The t-statistic is -2.72, which is significant at the 5% level. A stock's contribution to portfolio skewness may be more prominent in smaller portfolios. It seems natural to check $n = 0$, i.e., no sorting, just one stock.

Regression 6 shows that for $n = 0$ the portfolio-skewness variable is significant at 1%. Because firms hold a diversified set of assets, even a stock can be thought of as a portfolio. The case $n = 0$ is just the skewness of the stock. In other words, we try the individual stock's skewness as our explanatory variable. Skewness can make sense as an explanatory variable because it can act as a measure of asymmetric correlation.

Additional results for individual-stock skewness are given in Table 5. Skewness is highly significant in all model specifications. The correlation coefficients (Table 6) are not huge. In particular, there is not much correlation with size. It is interesting that there is very little correlation with co-skewness. The co-skewness of a stock is calculated using five years of value-weighted market returns, which is basically the methodology used in Harvey and Siddique (2000).

The results for monthly returns are in Table 7. We find that skewness is significant, but only when size is included in the regression. Table 8 gives the correlation coefficients for the monthly-returns cases. Note that skewness is strongly correlated with size. Ordinarily, when two explanatory variables are highly correlated and one is omitted from the regression, the significance of the other increases. Here, we have just the opposite. This behavior is characteristic of what is called a suppressor variable, in this case, skewness.

Suppressor variables are explained clearly and concisely in Howell's lecture notes (Howell (2001)), and are summarized here. There are three kinds: (1) classical suppressor: The suppressor variable is not correlated with the left-hand-side variable but is correlated with another of the right-hand-side variables. Inclusion of the suppressor variable improves the regression. Skewness, in the monthly-returns case, is an example of a classical suppressor: When we omit size from the regression, skewness becomes unimportant (Regressions 2 and 4). Howell (2001) discusses two other types of suppressor variables: (2) net suppressor: The suppressor variable is positively correlated with the left-hand-side variable and with one of the right-hand-side variables. The suppressor variable has a negative sign in the regression. (3) cooperative suppressor: The suppressor variable is positively correlated with the left-hand-side variable, but negatively correlated with one of the right-hand-side variables. The suppressor variable greatly improves the regression. A suppressor variable is important, and should not be left out of a regression: It is the garlic of regression – not much good by itself, but helps the final product. The suppressor works by suppressing some of the error variance in one of the right-hand-side variables. One should check for suppressor variables whenever two right-hand-side variables are strongly correlated.

In Table 9, we present some robustness checks. Line 1 gives the results using daily returns. Compared to weekly and monthly, size has a bigger coefficient, but the other variables have similar coefficients. Since much of the size effect has occurred in January, we tried omitting January returns (line 2). The size coefficient is much smaller and statistically insignificant but otherwise the results are similar to those for the full sample. We also tried regressing returns on skewness for each calendar month. The only striking result is that skewness has a significantly positive sign for January with weekly returns (and insignificantly positive with monthly returns). Results are available upon request. Lines 3 and 4 give the results for different values of α (the quantile in the skewness estimator). Line 3 uses $\alpha = .05$ in Equation (1) to calculate skewness. Line 4 uses $\alpha = .25$. Results are similar to what we obtained using $\alpha = .1$.

We also investigate leverage as another possible suppressor variables in asset pricing. We thought we might be able to explain the leverage puzzle (wrong sign in return regressions) by showing leverage variable is a suppressor variable. Briefly, we find, for our data, leverage and size are negatively correlated. Both size and leverage are significantly correlated with stock returns if they are used alone. The coefficient for leverage decreases when size is included. Thus, leverage does not behave like a suppressor variable. Changing the method of measuring leverage has overall little effect. Results are available upon request.

III. Conclusions

Asymmetric correlation causes portfolios to have negative skewness, even if every asset in the portfolio has positive skewness. Some other effect might cause a sign change in skewness as assets are added to a portfolio, but the central limit theorem greatly restricts such possibilities. We attempt to capture the asymmetric correlation of a stock by examining the skewness of the portfolios that contain the stock. Among the various methods we use, a stock's skewness works best as a measure of asymmetric correlation. Asymmetric correlation is not well captured with larger portfolios, indicating that asymmetric correlation is generated at the asset level of individual firms. Skewness is highly significant in a weekly-returns regression, but acts as a suppressor variable in a monthly-returns regression. It may be better to use weekly returns instead of monthly to avoid complications caused by the correlation between size and skewness in monthly returns. Since it is not entirely clear why size is such an important explanatory variable in a return regression, one might think that size would be the suppressor variable that interacts with other risk factors, but this is not what we find.

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Table 1

Skewness Signs by Portfolio Size

Every calendar year, we sort stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. This process gives us *nxn* categories. Each year, the skewness of weekly returns of this *nxn* -stock portfolio is calculated using the previous five years of data. We repeat this process 1,000 times for all stocks in the CRSP database with replacement, creating 1,000 portfolios for each calendar year. We report the number of skewness signs of all the yearly skewness observations and the ratios are in the parentheses.

n	Number of Negative-skewness Portfolios	Number of Positive-skewness Portfolios
8	36,210 (80.5%)	8,790 (19.5%)
6	31,710 (70.5%)	13,290 (29.5%)
4	23,440 (52.1%)	21,560 (47.9%)
2	10,460 (23.3%)	34,540 (76.7%)

Table 2

Cross-Sectional Regression of Weekly Stock Returns on Fama-French Factors and the Sign-Flip Variable

We run Fama-MacBeth cross sectional regressions for the following form:

$$r_{i,t}^{e} = \alpha + \delta_1 \cdot beta + \delta_2 \cdot \log SIZE + \delta_3 \cdot \log BTM + \delta_4 SignFlip + \varepsilon_{i,t}$$

where $r_{i,t}^{e}$ is the return on stock *i* in week *t* excess of the risk-free rate, beta is estimated stock beta, *SIZE* is the market value at the end of the previous year, *BTM* is the book-to-market ratio calculated from publicly available accounting and market-price data at the beginning of the year, and *SignFlip* is our sign-flip variable. The variables *beta*, *SIZE*, and *BTM* for each firm are calculated according to the method in Fama and French (1992). We take natural logs of pricing factors following Fama and French (1992).

We construct our sign-flip measure as follows. Every calendar year, we sort stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. This process gives us *nxn* categories. We randomly select one stock from each of the *nxn* categories and form an equal-weighted portfolio. The skewness of weekly stock returns of this nxn -stock portfolio is calculated using the previous five years of data. Then we add each stock in our sample to the nxn stock portfolio to form a $nxn+1$ stock portfolio (equal-weighted) and calculate the skewness of weekly returns of the $nxn+1$ stock portfolio using the same time-series data. The nxn stock portfolio is required to have a positive skewness. If the $nxn+1$ stock portfolio has a negative skewness, we count it as a case of sign flipping. We repeat this portfolio-formation process for *N* iterations, for all stocks in the CRSP database, and see how many times out of *N* the added stock can flip the sign of a nxn stock portfolio. Thus the sign-flipping measure for stock *i* is defined as *Number of times that stock i flipped the portfolio-skewness sign to negative / N.* N = 100 for "Pos. only" cases. For other cases, N is the number of times positive portfolios are formed out of 100 iterations. To separate the variable-estimation period from the testing period, we apply the estimated sign-flip variable to the asset-pricing test in the next year.

Reported t-statistics are corrected by the Newey-West method and are given in the table. Coefficients significant at 1% and 5% levels are marked with a and b, respectively.

Regression	*beta*	Log *SIZE*	Log *BTM*	*SignFlip*	n	Pos. only	Obs.	Adj. R^2
1	-0.12	-4.93[a]	4.51[a]	0.52	2	no	2279	2.22%
2	-0.16	-5.49[a]	4.49[a]	0.96	2	yes	2279	1.97%
3	-0.20	-5.64[a]	4.35[a]	3.56[a]	4	no	2279	2.09%
4	-0.22	-6.09[a]	4.38[a]	2.81[b]	4	yes	2279	2.05%
5	-0.20	-5.63[a]	4.41[a]	4.06[a]	6	no	2279	2.10%
6	-0.22	-6.05[a]	4.43[a]	3.02[a]	6	yes	2279	2.05%
7	0.03		8.06[a]	-0.18	4	no	2279	1.49%
8	0.00		8.16[a]	0.89	6	no	2279	1.48%

Table 3

Cross-Sectional Regression of Weekly Stock Returns on Fama-French Factors and the Portfolio-Skewness Variable

We run Fama-MacBeth cross sectional regressions for the following form:

$$r_{i,t}^{e} = \alpha + \delta_1 \cdot beta + \delta_2 \cdot \log SIZE + \delta_3 \cdot \log BTM + \delta_4 \cdot PortSkew + \varepsilon_{i,t}$$

where $r_{i,t}^{e}$ is the return on stock *i* in week *t* in excess of the risk-free rate, beta is estimated stock beta, *SIZE* is the market value at the end of the previous year, *BTM* is the book-to-market ratio calculated from publicly available accounting and market-price data at the beginning of the year, and *PortSkew* is our measure of asymmetric correlation. The variables *beta*, *SIZE*, and *BTM* for each firm are calculated according to the method in Fama and French (1992). We take natural logs of pricing factors, following Fama and French (1992).

We construct our measure as follows. Every calendar year, we sort stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. This process gives us *nxn* categories. We randomly select one stock from each of the *nxn* categories and form an equal-weighted portfolio. The skewness of weekly returns of this nxn -stock portfolio is calculated using the previous five years of data. We repeat this process 1,000 times for all stocks in the CRSP database with replacement, creating 1,000 portfolios. A stock's asymmetric correlation is measured as the average skewness of the portfolios that include the stock. To separate the variable-estimation period from the testing period, we apply the estimated variable to the asset-pricing test in the next year.

Reported t-statistics are corrected by the Newey-West method and are given in the table. Coefficients significant at 1% and 5% levels are marked with a and b, respectively.

Regression	beta	Log SIZE	Log BTM	Portfolio Skewness	n	Obs.	Adj. R^2
1	-0.43	-4.30[a]	3.76[a]	-0.43	8	2099	2.10%
2	-0.44	-4.31[a]	3.75[a]	-0.96	6	2099	2.10%
3	-0.43	-4.29[a]	3.78[a]	0.91	4	2099	2.09%
4	-0.44	-4.26[a]	3.81[a]	-1.30	2	2099	2.11%
5	-0.02	-3.50[a]	4.14[a]	-2.72[b]	1	2099	2.60%
6	-0.28	-4.56[a]	3.56[a]	-4.60[a]	0	2099	2.14%

Table 4

Correlation Coefficients of our Weekly-Returns-Based Portfolio-Skewness Measure with Other Variables

Reported correlation coefficients are from the exercise where we sort our sample stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. Details of the measures are in Fama and French (1992) and in the headings for Tables 2 and 3. *Upside* (*Downside*) *beta* is the stock beta acquired from the subsample of positive (negative) market-return weeks. The market return is the value-weighted average return from the CRSP database. We use the whole time-series data to calculate both betas. *Coskewness* and *Cokurtosis* measure the co-skewness and co-kurtosis of a stock return with the value-weighted market-average return. The *H* statistic is from Ang and Chen (2002). It measures the difference between the actual stock return distribution and the normal distribution. *Distress Risk* of a stock is calculated following Campbell, Hilscher, and Szilagyi (2008).

Correlation Coefficient with	Sign Flip Measure (4 x 4)	Sign Flip Measure (6 x 6)	Portfolio-Skewness Measure (4 x 4)	Portfolio-Skewness Measure (6 x 6)
Beta	4.43%	4.51%	0.12%	1.00%
Upside Beta	-0.21%	-0.26%	-1.21%	-0.74%
Downside Beta	8.10%	7.16%	-2.64%	-0.44%
Log Size	29.28%	28.34%	5.69%	0.24%
Log BTM	7.67%	7.60%	0.22%	-0.16%
Coskewness	1.32%	1.22%	0.42%	0.46%
Cokurtosis	17.43%	16.34%	-0.95%	0.32%
H	6.57%	2.04%	0.70%	3.22%
Distress Risk	-8.54%	-8.86%	0.10%	2.05%

Table 5

Cross-Sectional Regression of Weekly Stock Returns on Fama-French Factors and the Skewness of the Stock

We run Fama-MacBeth cross sectional regressions for the following form:

$$r_{i,t}^{e} = \alpha + \delta_1 \cdot beta + \delta_2 \cdot \log\ SIZE + \delta_3 \cdot \log\ BTM + \delta_4 \cdot Skewness + \varepsilon_{i,t}$$

where $r_{i,t}^{e}$ is the return on stock *i* in week *t* in excess of the risk-free rate, beta is estimated stock beta, *SIZE* is the market value at the end of the previous year, *BTM* is the book-to-market ratio calculated from publicly available accounting and market-price data at the beginning of the year, and *Skewness* is the skewness of the stock. The variables *beta*, *SIZE*, and *BTM* for each firm are calculated according to the method in Fama and French (1992). We take natural logs of pricing factors, following Fama and French (1992).

We construct the skewness of the stock as follows. We take five years of past weekly stock returns and calculate the quantile-based skewness of returns. The skewness measure is applied to the stock returns in the following year of the five-year estimation period.

Reported t-statistics are corrected by the Newey-West method and are given in the table. Coefficients significant at 1% and 5% levels are marked with a and b, respectively.

Regression	*beta*	Log *SIZE*	Log *BTM*	*Skewness*	Obs.	Adj. R^2
1	-0.28	-4.56[a]	3.56[a]	-4.60[a]	2099	2.14%
2				-3.24[a]	2099	0.21%
3		-5.41[a]		-4.11[a]	2099	0.91%
4			5.79[a]	-2.66[b]	2099	0.62%
5	-0.13	-5.39[a]	3.58[a]		2099	2.10%
6		-6.29[a]			2099	0.78%
7			6.44[a]		2099	0.44%

Table 6

Correlation Coefficients of the Weekly-Returns-Based Skewness of the Stock with Other Variables

Reported correlation coefficients are from the exercise where we sort our sample stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. Details of the measures are in Fama and French (1992) and in the headings for Tables 1 and 3.

Correlation Coefficient with	Individual-stock Skewness
Beta	3.46%
Upside Beta	1.82%
Downside Beta	7.39%
Log Size	- 5.52%
Log BTM	-12.31%
Coskewness	0.14%
Cokurtosis	7.66%
H	0.65%
Distress Risk	-7.67%

Table 7

Cross-Sectional Regression of Monthly Stock Returns on Fama-French Factors and the Skewness of the Stock

We run Fama-MacBeth cross sectional regressions for the following form:

$$r_{i,t}^{e} = \alpha + \delta_1 \cdot beta + \delta_2 \cdot \log SIZE + \delta_3 \cdot \log BTM + \delta_4 \cdot Skewness + \varepsilon_{i,t}$$

where $r_{i,t}^{e}$ is the return on stock *i* in month *t* in excess of the risk-free rate, beta is estimated stock beta, *SIZE* is the market value at the end of the previous year, *BTM* is the book-to-market ratio calculated from publicly available accounting and market-price data at the beginning of the year, and *Skewness* is the skewness of the stock. The variables *beta*, *SIZE*, and *BTM* for each firm are calculated according to the method in Fama and French (1992). We take natural logs of pricing factors, following Fama and French (1992).

We construct the skewness of the stock as follows. We take five years of past monthly stock returns and calculate the quantile-based skewness of returns. The skewness measure is applied to the stock returns in the following year of the five-year estimation period.

Reported t-statistics are corrected by the Newey-West method and are given in the table. Coefficients significant at 1% and 5% levels are marked with a and b, respectively.

Regression	*Beta*	Log *SIZE*	Log *BTM*	*Skewness*	Obs.	Adj. R^2
1	-0.70	-3.77[a]	3.23[a]	-2.74[b]	492	3.21%
2				-0.41	492	0.24%
3		-3.77[a]		-2.84[b]	492	1.54%
4			4.90[a]	-0.24	492	0.90%
5	-0.36	-4.46[a]	2.96[b]		492	3.31%
6		-4.48[a]			492	1.53%
7			5.33[a]		492	0.71%

Table 8

Correlation Coefficients of the Monthly-Returns-Based Skewness of the Stock with Other Variables

Reported correlation coefficients are from the exercise where we sort our sample stocks into *n* size ranks and then each size rank is again sorted into *n* book-to-market ranks. Details of the measures are in Fama and French (1992) and in the headings for Tables 1 and 3.

Correlation Coefficient with	Individual-stock Skewness
Beta	16.96%
Upside Beta	-0.18%
Downside Beta	2.34%
Log Size	-23.58%
Log BTM	-4.19%
Coskewness	-0.16%
Cokurtosis	7.41%
H	6.52%
Distress Risk	0.32%

Table 9

Robustness Checks

We run Fama-MacBeth cross sectional regressions for the following form:

$$r_{i,t}^{e} = \alpha + \delta_1 \cdot beta + \delta_2 \cdot \log SIZE + \delta_3 \cdot \log BTM + \delta_4 \cdot Skewness + \varepsilon_{i,t}$$

where $r_{i,t}^{e}$ is the return on stock *i* in week *t* (or day in the regression 1 with daily returns) in excess of the risk-free rate, beta is estimated stock beta, *SIZE* is the market value at the end of the previous year, *BTM* is the book-to-market ratio calculated from publicly available accounting and market-price data at the beginning of the year, and *Skewness* is the skewness of the stock. The variables *beta*, *SIZE*, and *BTM* for each firm are calculated according to the method in Fama and French (1992). We take natural logs of pricing factors, following Fama and French (1992).

We construct the skewness of the stock as follows. We take five years of past weekly stock returns and calculate the quantile-based skewness of returns. The skewness measure is applied to the stock returns in the following year of the five-year estimation period.

We present results of some robustness checks below. Line 1 gives the results using daily returns. Line 2 gives results omitting January returns. Lines 3 and 4 give the results for different values of the quantile (α) in the skewness estimator. Line 3 uses skewness calculated with α = .05, and line 4 uses α = .25.

Reported t-statistics are corrected by the Newey-West method and are given in the table. Coefficients significant at 1% and 5% levels are marked with a and b, respectively.

Regression	*Beta*	Log *SIZE*	Log *BTM*	*Skewness*	Obs.	Adj. R^2
1	-0.06	-11.43[a]	5.84[a]	-2.07[b]	10,347	1.19%
2	-1.30	-1.13	4.03[a]	-3.87[a]	1,922	2.05%
3	-0.33	-4.78[a]	3.61[a]	-3.56[a]	2,099	2.15%
4	-0.34	-4.10[a]	3.74[a]	-4.76[a]	2,099	2.12%