Idiosyncratic Skewness of Commodity Futures Returns

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Abstract

We examine the ability of idiosyncratic skewness to explain the cross section of commodity futures returns at both the characteristic and factor levels. We find that idiosyncratic skewness negatively and significantly predicts cross-sectional commodity futures returns, and largely accounts for the skewness effect documented in previous studies. Furthermore, we find that a long/short trading strategy based on the idiosyncratic skewness generates significant abnormal returns, which cannot be explained by the traditional risk factors in commodity futures markets and persists up to 12 months. Moreover, idiosyncratic skewness appears to be a priced risk factor in commodity futures markets. Finally, we find that a novel asymmetry measure, IE, is better at capturing the effect of idiosyncratic skewness than the traditional measure.

JEL classification: G11; G12; G13

Keywords: Idiosyncratic skewness; Cross section; Commodity futures returns; IE

1 Introduction

The relation between the idiosyncratic skewness and expected return has received much attention. As an early work, Bakshi, Kapadia, and Madan (2003) decompose the total skewness into a systematic component and an idiosyncratic component. Substantial theoretical as well as empirical work has been done to further study the effect of the idiosyncratic skewness on the expected return. Mitton and Vorkink (2007), Barberis and Huang (2008), and Han, Hirshleifer, and Walden (2019) theoretically demonstrate that idiosyncratic skewness negatively impacts the cross-section of expected stock returns. Boyer, Mitton, and Vorkink (2010), Annaert, De Ceister. Amd Verstegem (2013), and Baghdadabad and Mallik (2018), among others, have provided substantial evidence to support this negative relation.

In the commodity literature, Fernandez-Perez, Frijns, Fuertes, and Miffre (2018) document a negative relation between the total skewness and the expected commodity futures return. However, they do not answer the question whether this negative relation is due to the idiosyncratic component or the systematic one. Furthermore, the aforementioned theoretical papers are built based on the idiosyncratic skewness instead of the total skewness. Thus, in this paper, we extend the literature by examining whether the idiosyncratic skewness influences the expected return in commodity futures markets, and whether the negative relation between the total skewness and expected return is driven by the idiosyncratic skewness.

In addition to the traditional measure of idiosyncratic skewness, we also apply a new measure proposed by Jiang, Wu, Zhou, and Zhu (2020) — IE, which is defined as the difference between the upside and downside return probabilities. As confirmed by Jiang et al. (2020), IE is considered as a proxy for skewness or asymmetry, and it can detect asymmetry with greater power than the skewness. Thus, IE can provide additional information beyond what can be inferred from the skewness alone.

Specifically, our paper tries to answer the following questions. (1) Can idiosyncratic skewness (IE) explain the cross section of commodity futures returns? (2) Is the skewness effect mainly driven by the idiosyncratic skewness (IE) in the commodity futures markets? (3) Is idiosyncratic skewness a priced risk factor in the commodity futures markets?

First, we use both Fama-MacBeth regressions and portfolio sorts to investigate the effect of the idiosyncratic skewness on the cross section of commodity futures returns. We compare the results of IE with those of the traditional measures and find that IE is better at capturing the negative relation between the idiosyncratic skewness and expected returns. Based on the Fama-MacBeth regression results, we find that a one percentage point increase in the idiosyncratic skewness will reduce the expected returns of commodities by 2.63 basis points (bps). It is consistent with the theories of Mitton and Vorkink (2007), Barberis and Huang (2008), and Han et al. (2019). Our finding is robust to adding additional control variables for gambling preference, liquidity, and financial crisis, using alternative methods to roll over the commodity futures contracts.

For the portfolio sorting analysis, we form a monthly rebalanced long-short portfolio which takes the long position in commodity futures with the highest idiosyncratic skewness and takes the short position in those with the lowest idiosyncratic skewness. The return spread for this long-short portfolio is -0.56% per month, or -6.72% annually. It is economically and statistically significant, and the result is robust after considering the common risk factors in the commodity futures markets. The sequential double-sorting results further confirm that the idiosyncratic skewness effect could not be explained by other control variables. Both the Fama-MacBeth regression and portfolio sorting results show that stocks with higher idiosyncratic skewness tend to have lower expected return. Furthermore, the significant negative relation between the idiosyncratic skewness and the commodity futures return persists up to 12 months, which suggests that the idiosyncratic skewness could be a priced risk factor in the commodity futures markets.

Additionally, we investigate whether the skewness effect documented by Fernandez-Perez et al. (2018), is mainly driven by the idiosyncratic skewness. We find that the effect of idiosyncratic skewness is more important. By including both the idiosyncratic skewness and total skewness in the same regression, we find that the idiosyncratic skewness is still significant, whereas the total skewness becomes insignificant. The sequential double-sorting results by the total skewness and idiosyncratic skewness also support the finding that the idiosyncratic skewness is the main driver of the skewness effect.

Finally, we show that idiosyncratic skewness is a priced risk factor in the commodity futures markets. Using the Fama and MacBeth (1973) approach, that is, first running the daily time-series regressions for each commodity month-by-month to obtain the commodity betas, and then running the cross-sectional regression using the idiosyncratic skewness betas, we find that the price of the idiosyncratic skewness factor is -0.63%. This finding is robust to adding liquidity, inflation, and investor sentiment as control variables.

We contribute to the existing literature by documenting the importance of idiosyncratic skewness in commodity futures markets. First, the idiosyncratic skewness is important in explaining the cross section of the commodity futures returns. Limited work has been done to study the effect of idiosyncratic skewness in the commodity futures markets. We fill the gap by showing that idiosyncratic skewness negatively affects the cross section of the commodity futures returns, and the tradable strategy based on the idiosyncratic skewness in the commodity futures markets can generate significant profits. Furthermore, we show that the idiosyncratic skewness is a priced risk factor in the commodity futures markets.

We also contribute to the existing literature by showing that the skewness effect is mainly driven by the idiosyncratic skewness in the commodity futures market. Fernandez-Perez et al.

(2018) document the existence of a total skewness effect, while we show that the total skewness effect is subsumed by the idiosyncratic skewness whereas the negative effect of the idiosyncratic skewness is still significant.

The rest of this paper is organized as follows: In Section 2, we introduce the data source and definitions of variables. In Section 3, we discuss the effect of idiosyncratic skewness at the characteristic level and test whether the effect of idiosyncratic skewness mainly drives the effect of skewness. In Section 4, we construct a tradable strategy based on idiosyncratic skewness in commodity futures markets and analyze its performance. In Section 5, we examine the performance of idiosyncratic skewness factor and their ability to explain the cross section of commodity futures returns. In Section 6, we provide the conclusion.

2 Data

2.1 Commodity futures returns

Our main data are daily settlement prices from Bloomberg on front-end futures contracts for 27 commodities from distinct sectors. These sectors include: energy (Brent crude oil, WTI crude oil, heating oil, natural gas); grains (corn, oats, soybean, soybean meal, soybean oil, wheat, rough rice); livestock (feeder cattle, hogs, live cattle); metals (aluminum, copper, gold, palladium, platinum, silver); and softs (cocoa, coffee, cotton, orange juice, sugar, milk, lumber).

To construct continuous time series of prices, we assume that for each commodity futures, we always hold the first nearby contract (front month contract) up to the expiration, and then roll our position over to the second nearby contract and hold that contract up to maturity. The procedure is repeated to the next set of nearest and second-nearest contracts. As a robustness test, we also consider an alternative method to roll over the contracts: we roll over to the next nearest contract at the end of the month prior to maturity.

Returns are computed as follows: $R_{i,t} = \left(p_{i,t} - p_{i,t-1}\right) / p_{i,t-1}$, where $p_{i,t}$, $i = 1, \ldots, 27$ is the price of commodity i at time t. For daily returns, $p_{i,t-1}$ is the price of commodity i in the prior trading day. For monthly returns, $p_{i,t-1}$ is the price of commodity i in the prior month.

2.2 Idiosyncratic skewness

We employ the new measure of idiosyncratic skewness proposed by Jiang et al. (2020). Specifically, to assess the upside (downside) asymmetry, we compute the excess tail probability (ETP) following Jiang et al. (2020)'s IE_{φ} :

$$IE = \int_{0.5}^{+\infty} f(x)dx - \int_{-\infty}^{-0.5} f(x)dx = \int_{0.5}^{\infty} \left[f(x) - f(-x) \right] dx , \tag{1}$$

where the probabilities are evaluated at a half standard deviation away from the mean (zero), and x is the idiosyncratic return of commodity i, that is, the residual $\varepsilon_{i,d,t}$, in the following regression after standardized to have a unit variance, $R_{i,d,t} = \alpha_{i,t} + \beta_{i,t} R_{m,d,t} + \gamma_{i,t} R_{m,d,t}^2 + \varepsilon_{i,d,t}$, where $R_{i,d,t}$ is the daily return of commodity i on day d, and $R_{m,d,t}$ is the daily market return (i.e. the daily return of S&P GSCI) on day d. Each month, we run the regression using 6 months of daily returns (from month $t-5$ to t) to estimate the residuals. The first term of Equation (1) measures the cumulative chance of large gains, while its second term measures the cumulative chance of large losses. If IE is positive, the probability of large gains is higher than the probability of large losses, and thus the return is positively skewed.

We also employ the traditional measure of idiosyncratic skewness, denoted as ISKEW, which is defined as the skewness of the daily residuals in the same daily regression above. Specifically, at each month t, we estimate the ISKEW using the Pearson's three-moment coefficient of skewness,

$$ISKEW_{i,t} = \frac{1/D \sum_{d=1}^{D} \left(\varepsilon_{i,d,t} - \mu_{\varepsilon,i,t} \right)^3}{\sigma_{\varepsilon,i,t}^3} , \tag{2}$$

where $\varepsilon_{i,d,t}$ is the same daily residual of commodity i on day d defined earlier, $\mu_{\varepsilon,i,t}$ and $\sigma_{\varepsilon,i,t}$ are its mean and standard deviation ($\sigma_{\varepsilon,i,t} = \sqrt{\frac{1}{D-1} \sum_{d=1}^{D} (\varepsilon_{i,d,t} - \mu_{\varepsilon,i,t})^2}$), respectively.

Table 1 reports IE, the traditional idiosyncratic skewness measure (ISKEW) and the total skewness (SKEW) of all the 27 commodity returns. IE and ISKEW usually have the same signs, but the magnitude of IE is much smaller than that of ISKEW. On the other hand, ISKEW is much closer to the total skewness (SKEW) in magnitude. For different sectors of commodity futures, the idiosyncratic skewness (IE and ISKEW) and total skewness (SKEW) can be very different. For example, the idiosyncratic and total skewness of grain and soft commodities are usually positive, while those of livestock are usually negative, and either positive and negative signs are found for energy and metals.

[Insert Table 1 here]

2.3 Control variables

To control for the characteristics of commodity futures, we include volatility, trading volume, open interest, and past cumulative returns in the short term, median term and long term (that is, the last month return, 12-month momentum from $t-2$ to $t-12$, and past 60-month cumulative return from $t-2$ to $t-60$) (Han et al., 2016). These are the important characteristics of a commodity futures which may influence its returns.

To control for the systematic risks, we include four traditional risk factors, the market returns of the commodity futures market (MARKET factor), a term structure portfolio (TS factor), a momentum portfolio (MOM factor) following Bakshi et al. (2019), and a hedging pressure factor (HP factor) following Basu and Miffre (2013). While the MARKET factor captures the overall commodity market risk based on S&P GSCI index, the TS, MOM, and HP factors are the proxies for the risks associated with the backwardation/contango cycle of commodity futures markets.

All the variable definitions are described in the Appendix A. Data of commodity futures are obtained from Bloomberg, and positions are obtained from the U.S. Commodity Futures Trading Commission (CFTC).

3 The effect of idiosyncratic skewness at the characteristics level

In this section, we examine the ability of idiosyncratic skewness to explain the cross section of commodity returns at the characteristic level. In Subsection 3.1, we focus on the effect of idiosyncratic skewness using IE. In Subsection 3.2, we compare the results of IE with the traditional measure of idiosyncratic skewness (ISKEW). In Subsection 3.3, we compare the effect of idiosyncratic skewness with that of the total skewness. In Subsection 3.4, we check the robustness of our findings.

We investigate the effect of idiosyncratic skewness using the following Fama-MacBeth regression:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} skewness_{i,t} + \Lambda control_{i,t} + \varepsilon_{i,t+1} \quad (3)$$

where $R_{i,t+1}$ is the monthly return of commodity i at time $t+1$, $skewness_{i,t}$ is the idiosyncratic skewness measured either by IE or by ISKEW for commodity i estimated at time t. $control_{i,t}$ is a set of control variables, including volatility, volume, open interest, prior month return, momentum, and prior 60-month return. Since prior month return, momentum, and prior 60-month return represent the historical performance of commodity futures at short term, median term, and long term respectively, we attempt to add them into Eq. (3) separately or together.

3.1 The effect of idiosyncratic skewness using IE

The idiosyncratic skewness negatively affects the cross section of commodity futures returns. Table 2 reports the results. In column (1), the coefficient of IE is -0.0263 with a t-statistics of -2.4221, which is significant at 5% level. It indicates that an increase in the idiosyncratic skewness will reduce the expected returns of commodities. Even after controlling for other characteristics of commodities, the significantly negative effect still exists. The commodity characteristics include volatility, volume, open interest, and historical returns in short term, medium term, and long term. From column (2) to (5), the coefficients of IE are -0.0378 ($t = -2.8629$), -0.0230 ($t = -1.7600$), -0.0281 ($t = -2.2427$), and -0.0290 ($t = -1.9450$), respectively. These imply that the idiosyncratic skewness as measured by IE captures additional information beyond the common characteristics of commodities.

The negative effect of idiosyncratic skewness could be explained in several ways. The theory of Mitton and Vorkink (2007) explains the effect by preference for skewness, or preference for lottery-like assets. Investors who prefer a positively skewed asset, or a lottery-like asset, will overprice the asset and lead to lower expected returns. The theory of Barberis and Huang (2008) explains the effect under cumulative prospect theory. They assume that investors will overweight the probability of extreme events, such as extremely positive outcomes. Thus, they are willing to pay more for an asset with a small probability of an extremely positive outcome. Therefore, positively skewed assets will then become overpriced and will have lower expected returns. The theory of Han et al. (2018) explains the effect through social transmission bias. The self-enhancing transmission bias of information senders will lead to an attraction of skewness for information receivers, since assets with higher returns are most likely to be discussed. Thus, this kind of assets will be overpriced and have lower expected returns.

[Insert Table 2 here]

3.2 The effect of idiosyncratic skewness using ISKEW

Considering the traditional measure of idiosyncratic skewness, the effect is still negative but becomes marginal significant or insignificant. Table 3 reports the results. The coefficient of ISKEW is -0.0167 ($t = -1.4765$) without control variables. When adding the control variables including volatility, volume, open interest, prior month return, the coefficient of ISKEW is still insignificant (-0.0220 with a *t*-statistics of -1.6173). Only when we change the short term historical performance to the median or long term, the coefficient of ISKEW becomes marginally significant -0.0248 ($t = -1.9485$) and -0.0224 ($t = -1.7403$). After taking all these control variables into consideration, the coefficient of ISKEW remains insignificant (-0.0214 with a *t*-statistics of -1.5964). It implies that IE is better at capturing the effect of idiosyncratic skewness.

These results are in line with Jiang et al. (2020) who conclude that the IE effect is similar to the effect of idiosyncratic skewness and, moreover, it also captures higher order asymmetry that goes beyond skewness. Jiang et al. (2020) suggest that the greater the asymmetry, the greater the skewness. Furthermore, when finding a specific return that has zero skewness yet is asymmetric (e.g., that is positively asymmetric), Jiang et al. (2020) demonstrate that IE is also positive and can imply lower expected returns. Thus, IE is a better measure than the traditional idiosyncratic skewness in capturing the skewness effect.

[Insert Table 3 here]

3.3 The effect of idiosyncratic skewness vs total skewness

Since the total skewness has been shown to have a significant impact on the commodity future returns (Fernandez-Perez et al. 2018), we conduct further analysis in this subsection to test whether the effect of the skewness is mainly driven by the effect of the idiosyncratic skewness. To this end, we include both the idiosyncratic skewness and total skewness in the same regression.

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} IE_{i,t} + \lambda_{2,t} SKEW_{i,t} + \Lambda control_{i,t} + \varepsilon_{i,t+1}, \quad (4)$$

where $SKEW_{i,t}$ represents the total skewness for commodity i at time t.

Columns (1) and (2) of Table 4 report the regression results either without or with the controls. Although SKEW is significant in column (1), it becomes insignificant after adding the control variables. IE is insignificant in both cases. Since IE and the total skewness are highly correlated (see Table A.2 of the Appendix A), the insignificance is likely due to multicollinearity.

To alleviate the problem of multicollinearity, we replace the total skewness with its component that is orthogonal to IE, i.e., the residuals of the regression of the total skewness on idiosyncratic skewness. In columns (3) and (4), we replace the total skewness with the residuals from the time-series regressions. The coefficient of IE is $-0.0211\,(t = -1.8398)$ or $-0.0375\ (t = -2.4971)$ without or with the control variables, whereas the coefficient of the total skewness is $-0.0184\,(t = -1.3682)$ or $-0.0154\,(t = -1.0520)$. It shows that the idiosyncratic skewness (IE) is still significant, while the total skewness becomes insignificant. Similar results are obtained in columns (5) and (6) when we replace the total skewness with the residuals from the cross-sectional regressions. These results indicate that the effect of the skewness in the commodity futures markets is mainly driven by the idiosyncratic skewness (IE).

[Insert Table 4 here]

3.4 Robustness

In this subsection, we check the robustness of the idiosyncratic skewness effect. Since the preference for idiosyncratic skewness reflects a gambling motivation (Barberis and Huang, 2008; Mitton and Vorkink, 2007), we also test the robustness by adding proxies for the gambling preference as additional control variables, such as MAX (Bali, Cakici, and Whitelaw, 2011), MIN (Bali et al., 2011), and COKURT (Dittmar, 2002). As mentioned in Marshall, Nguyen, and Visaltanachoti (2012) and Szymanowska, De Roon,Nijman, and Van Den Goorbergh (2014), liquidity also plays an important role in commodity asset pricing. Therefore, we add liquidity as the additional control variable, which is defined as the dollar trading volume associated with the absolute return (Amihud, Mendelson, and Lauterbach, 1997). The definitions of the additional control variables are provided in the Appendix A.

The negative effect of the idiosyncratic skewness is also robust after adding MAX as a control variable. Column (1) of Table 5 shows the result after controlling for MAX. The coefficient of IE is -0.0342 and statistically significant at the 5% level ($t = -2.2180$), while MAX is not significant. It implies that the idiosyncratic skewness is not just a proxy for lottery preference. Similarly, the negative effect is still significant after controlling for MIN. Column (2) of Table 5 shows that the coefficient of IE is -0.0336 with a t-statistic of -2.2798. The idiosyncratic skewness contains extra information beyond MIN. In addition, after controlling for the higher order risk, as measured by cokurtosis, the negative effect of the idiosyncratic skewness still exists as shown in column (3) of Table 5. The coefficients of IE is negative and significant (-0.0328 with a t-statistic of -2.1740). It indicates that the effect is not challenged by cokurtosis. Furthermore, the negative effect of idiosyncratic skewness remains even after controlling for liquidity. Column (4) of Table 5 shows the results; the coefficient of IE is -0.0228 with a t-statistic of -1.8443.

[Insert Table 5 here]

We also consider the impact of the financial crisis since the financial crisis may greatly influence asset prices. To increase the power of the test, we use a dummy variable representing the financial crisis in the second step of the Fama-MacBeth regression instead of subdividing the samples. Table 6 reports the results. The negative effect of IE is robust after controlling for the financial crisis; the coefficient of IE is still negative and statistically significant with or without control variables. Without controlling for the characteristics of the commodities, the coefficient of IE is -0.0261 with a t-statistic of -2.3964. Even after adding the control variables, the coefficient is -0.0308 with a t-statistic of -2.0275. Both of them are significant at 5% level. Furthermore, the financial crisis does not have any significant impact on the effect of IE as the dummy always has the insignificant coefficients.

[Insert Table 6 here]

In addition to the method we have used, there are several alternative ways to roll over the commodity contracts (e.g. Szymanowska, et al., 2014; Gorton, Hayashi, and Rouwenhorst, 2012). Thus, we check the robustness by using an alternative method to roll over the commodity contracts. That is, we roll over to the next nearest contract 1 months before maturity. We re-estimate the regressions in Eq. (3) with or without the control variables.

The negative effect of IE is robust when the alternative method is used to roll over commodity contracts. Columns (1) of Table 7 report the result when rolling over to the next nearest contract at the end of the month prior to maturity. The coefficient of IE is -0.0328 ($t = -2.7589$) without the control variables. After adding the control variables, the effect of the idiosyncratic skewness remains negative and significant.

[Insert Table 7 here]

4 The idiosyncratic skewness trading strategy

Given the close relation between the idiosyncratic skewness and expected return in the commodity futures markets, we construct long-short portfolios by sorting commodity futures according to their idiosyncratic skewness.

First, we rank the commodity futures ($N = 27$) by their idiosyncratic skewness at the end of each month t. Then we group them into three portfolios: Portfolio Q1, which contains the 30% of commodities with the lowest idiosyncratic skewness, up to portfolio Q3, which contains the 30% of commodities with the highest idiosyncratic skewness. Then we conduct the monthly rebalanced long-short portfolio which takes long positions in the commodity futures with the most positive idiosyncratic skewness (Q3) and takes short positions in the commodity futures with the most negative idiosyncratic skewness (Q1). All portfolios are fully collateralized. To further assess whether the profitability of the long-short portfolio based on idiosyncratic skewness is merely the compensation for exposure to traditional commodity risk factors, we estimate the alpha of the long-short portfolio relative to a four-factor commodity pricing model.

$$r_{p,t} = \alpha_p + \theta_{p,EW} \cdot MARKET + \theta_{p,\mathrm{TS}} \cdot TS + \theta_{p,\mathrm{MOM}} \cdot MOM + \theta_{p,\mathrm{HP}} \cdot HP + \upsilon_{p,t}\,, \quad (5)$$

where $r_{p,t}$ denotes the return of the long-short portfolio at month t.

Second, we use the sequential double-sorting method to confirm that the idiosyncratic skewness effect is robust to the control variables. Specifically, at each month we first sort the commodity futures into two groups by one of the control variables. Within each group of the control variable, we then sort the commodity futures into two portfolios by the idiosyncratic skewness (i.e. the 2×2 double-sorting method).

Third, we use the portfolio sorting approach to test whether the idiosyncratic skewness mainly drives the skewness effect in the commodity futures markets. In line with the method in Section 3, we use the residuals of the regressions of total skewness on idiosyncratic skewness to represent the total skewness. We sort the commodity futures into three portfolios by the total skewness represented by the residuals. Furthermore, we do a double-sorting by the total skewness and idiosyncratic skewness to further verify the robustness of the idiosyncratic skewness effect (i.e. the 2×2 double-sorting method).

Finally, we investigate the long-term predictive power of the idiosyncratic skewness. We hold the same portfolio formation, that is, ranking the commodities in cross section according to their idiosyncratic skewness each month, but instead of calculating the returns in month *t+1*, we take a further look at the monthly returns and alphas of the portfolios from month *t+2* to *t+12*.

4.1 Single-sorting

Table 8 reports the performance of the IE-sorted tercile portfolios and the long-short portfolio. Since idiosyncratic skewness is the signal used to group the commodities into portfolios, it is not surprising to find that the ranking idiosyncratic skewness is the lowest in Q1 and the highest in Q3. The IE of Q1 is -0.0191 and that of Q3 is 0.0250. Meanwhile, the mean return monotonically decreases from Q1 (negatively skewed) to Q3 (positively skewed). The mean return of Q1 is 0.97% (*t*-statistics = 2.9208) and that of Q3 is 0.41%

(t-statistics =1.7798).

The trading strategy based on idiosyncratic skewness does generate a significant profit. The spread of Q3–Q1 is -0.56% with a t statistic of -1.6655. The significant negative spread indicates that the idiosyncratic skewness and expected returns are negative correlated in the commodity futures markets, consistent with the results discussed in Section 3. The profitability of the long-short portfolio based on the idiosyncratic skewness cannot be fully explained by the traditional risk factors in the commodity futures markets. Table 8 also reports the alpha of the tercile portfolios and the spread portfolio from the four-factor commodity pricing model. The alpha of Q1 is 0.80% with a t-statistics of 2.3580, that of Q3 is 0.15% with a t-statistics of 0.8030, and that of the spread portfolio is -0.65% with a t-statistic of -1.7920.

[Insert Table 8 here]

4.2 Double-sorting

Table 9 reports the results for the sequential double-sorting with the control variables. When controlling for the volatility of commodity futures returns, we find that the returns of the long-short portfolio within each of the volatility portfolios are all negative. The spread of Q2-Q1 is -0.20% and -0.86% in volatility Low and volatility High respectively. When averaged across the volatility portfolios, the spread return is -0.53% with a t-statistics of -2.4054, which is statistically significant at 5% level. After adjusting for the common commodity risk factors, the alpha is still significant and negative (-0.59% with a t-statistics of -2.9802, and significant at 1% level).

Similar results are found after controlling for volume, open interest, momentum, prior month return, prior 60-month return, MAX, MIN, COKURT, and liquidity, respectively. These results indicate that the IE effect could not be explained by other control variables, consistent with the results reported in Section 3.

[Insert Table 9 here]

4.3 Idiosyncratic skewness versus total skewness

Using portfolio sorts, Table 10 confirms that the idiosyncratic skewness mainly drives the skewness effect in the commodity futures markets. In Panel A where we sort the commodities by the residuals of the time-series regression of the total skewness on IE, the mean return of the portfolio with the lowest total skewness is 0.68% (t-statistics = 2.9879), and that of the portfolio with the highest total skewness is 0.39% (t-statistics = 1.8323). But the mean return of the spread portfolio (*High-Low*) is insignificant (-0.28% with a t-statistics of -1.1744). Similar results are obtained when we sort the commodities by the residuals of the cross-sectional regression of the total skewness on IE. These results imply that idiosyncratic skewness is the main component of skewness effect in the commodity futures markets, consistent with the findings in Section 3.

Furthermore, Panel B compares the effect of the idiosyncratic skewness and the total skewness using the double-sorting method. When we first sort the commodities by the residual from the time-series regressions, we find that the spread return between the positively skewed portfolio (Q2) and negatively skewed (Q1) within each skewness portfolio is always negative. On average, the spread return is -0.60% with a t-statistics of -2.7841 which is statistically significant at 1% level. After adjusting for the common commodity risk factors, the alpha is still significant and negative (-0.63% with a t-statistics of -3.2003, and significant at 1% level). Similar results are found using the residuals from the cross-sectional regressions.

[Insert Table 10 here]

4.4 Longer-term analysis

Table 11 shows that the significant profits persist for several month into the future. During the second month after the portfolio formation, the mean return of Q1 (negatively skewed) is 1.20% and that of Q3 (most positively skewed) is 0.27%. The return spread of the long-short portfolio Q3-Q1 is -0.93% with a t-statistics of -2.7684. The significant negative spread persists until the 11*th* month after the portfolio formation month with a spread of -0.72% and a t-statistics of -1.8897. Although it becomes insignificant in the 12*th* month, the negative spread still exists (-0.63% with a t-statistics of -1.6443). Similar patterns are found for the alpha of the spread portfolios, which is still significant up to the 12*th* month. Furthermore, the magnitude of the spread remains largely stable over the 12 months. These results suggest that the IE effect is rather stable and is likely not driven by mispricing. Note that limit to arbitrage is normally not an issue in the futures market and any mispricing should be quickly arbitraged away. Therefore, it is plausible that the idiosyncratic skewness is a priced risk factor in the commodity futures markets. We will continue to explore this issue in the next section.

[Insert Table 11 here]

5 The idiosyncratic skewness factor

In this section, we investigate whether idiosyncratic skewness is a priced risk factor. First, we estimate the time-series regressions month-by-month (daily data in one month) for each commodity to obtain the commodity monthly betas for the idiosyncratic skewness and other risk factors:

$$r_{i,t,d} = \alpha_{i,t} + \beta_{i,t}^{F} F_{t,d} + \upsilon_{i,t,d}, \tag{6}$$

where $r_{i,t,d}$ is the daily commodity return at date d for commodity i in month t, $d = 1, \ldots, D$, where D denotes the number of trading days in month t. $F_{t,d}$ represents the daily returns on the idiosyncratic skewness (IE) or other traditional risk factors (MARKET, TS, MOM, HP) in month t.

Then we estimate the cross-sectional regression month by month

$$r_{i,t+1} = \lambda_0 + \lambda_{IE,t}\hat{\beta}_{i,t}^{IE} + \Lambda_{F,t}\hat{\beta}_{i,t}^{F} + e_{i,t+1}, \tag{7}$$

where $\hat{\beta}_{i,t}^{IE}$ represents the factor loading of the idiosyncratic skewness (IE) factor for commodity i at month t, and $\hat{\beta}_{i,t}^{F}$ represents the factor loading of all other risk factors (MARKET, TS, MOM, HP) for commodity i at month t. We report the average $\lambda_{IE,t}$ and $\Lambda_{F,t}$ of the pass-two cross-sectional regression in Eq. (7).

5.1 Cross-sectional asset pricing tests

Table 12 presents the results of the two-pass cross-sectional regressions, which show that the idiosyncratic skewness factor can explain the cross section of the commodity futures returns. When regressing the commodity returns on the IE beta alone, the price of the skewness factor

($\lambda_{IE,t}$) is -0.0063 with a t-statistic of -2.9479 (significant at the 1% level). It indicates that investors require compensation for the exposure to the commodity futures with a lower level of idiosyncratic skewness (i.e. a more negative idiosyncratic skewness). After controlling for the traditional risk factors separately or jointly, the price of IE is still negative and significant. It is also worth noting that all the traditional risk factors but the hedging pressure (HP) do not have significant risk premiums.

[Insert Table 12 here]

5.2 Robustness

To examine the robustness of the performance of the idiosyncratic skewness risk factor, we include additional risk factors in the commodity futures markets into the Fama-MacBeth two-pass regressions. First, following Marshall et al. (2012), Szymanowska et al. (2014), and Amihud et al. (1997), we include a liquidity beta based on the Amihud's measure. Second, considering the influence of the macro economy, we also include an inflation beta estimated by regressing the monthly commodity futures returns in the prior 60 months on changes in the one-month US CPI. Third, to test whether investor sentiment would alter the prices of the idiosyncratic skewness factor (Bi and Zhu, 2020), we employ a sentiment beta as the slope coefficient in the regression of the prior 12 months commodity futures returns on the sentiment index (Baker and Wurgler, 2006).

The performance of the idiosyncratic skewness risk factor is robust after controlling for the alternative risk factors and the results are reported in Table 13. In column (1), after considering the liquidity risk factor, the price of IE is still significant at the 1% level (-0.0151 with a t-statistic of -3.0679). After controlling for the inflation risk factor, the price of IE is -0.0096 with a t statistic of -2.8841 (significant at the 1% level). After considering investors sentiment, the price of IE is -0.0132 (significant at the 5% level). Even after we add all the risk factors together, the price of IE is still negative and significant (-0.0155 with a t-statistics of -3.3578). The information contents in idiosyncratic skewness is not a proxy for alternative economic and financial risk factors.

[Insert Table 13 here]

6 Conclusion

In this paper, we investigate the ability of idiosyncratic skewness to explain the cross section of the commodity futures returns at both the characteristic and factor levels. We first test the effect of the idiosyncratic skewness on the cross section of the commodity futures returns at the characteristic level using both Fama-MacBeth regressions and portfolio sorts. We find that the idiosyncratic skewness explains the cross section of commodity futures returns and significantly predict the commodity futures returns negatively. Furthermore, a new asymmetric measure, IE, is better at capturing the effect of the idiosyncratic skewness than the traditional measure. In addition, we find that the skewness effect documented in the literature is mainly driven by the idiosyncratic skewness in the commodity futures markets. Moreover, we show that the idiosyncratic skewness effect is very persistent and stable, which leads us to investigate whether idiosyncratic skewness is a priced risk factor.

We show that the idiosyncratic skewness is a priced risk factor in the commodity futures markets. It has a significant and negative risk premium. The result is robust when adding other traditional risk factors (MARKET, TS, MOM, HP), and risk factors such as liquidity, inflation, and investor sentiment.

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Table 1 Descriptive Statistics of Skewness

This table summarizes the skewness of the listed commodities. We include 27 commodities from distinct sectors: energy (Brent crude oil, WTI crude oil, heating oil, natural gas), grains (corn, oats, soybean, soybean meal, soybean oil, wheat, rough rice), livestock (feeder cattle, hogs, live cattle), metals (aluminum, copper, gold, palladium, platinum, silver), and softs (cocoa, coffee, cotton, orange juice, sugar, milk, lumber). IE is computed using Eq. (1), ISKEW and SKEW are computed using the Pearson's three moment coefficient of idiosyncratic skewness and total skewness. The sample period is from Jan 1987 to May 2018.

		IE	ISKEW	SKEW
Energy	Brent Crude Oil	0.0053	0.1002	-0.0174
	WTI Crude Oil	0.0058	0.1542	-0.0017
	Heating Oil	0.0076	0.0839	0.0264
	Natural Gas	0.0086	0.1072	0.1518
Grains	Corn	0.0035	0.0784	0.0837
	Oats	0.0060	0.0778	0.0857
	Soybean	-0.0045	-0.0435	-0.0533
	Soybean Meal	0.0128	0.1454	0.1530
	Soybean Oil	0.0169	0.2543	0.2314
	Wheat	0.0094	0.1099	0.1254
	Rough Rice	0.0080	0.1013	0.1277
Livestock	Feeder Cattle	-0.0017	-0.0234	-0.0399
	Hogs	-0.0082	-0.0625	-0.0584
	Live Cattle	-0.0032	-0.0039	-0.0239
Metals	Aluminum	0.0080	0.0477	0.0219
	Copper	0.0037	0.0236	0.0237
	Gold	-0.0040	-0.0018	-0.1212
	Palladium	-0.0053	-0.0613	-0.0919
	Platinum	-0.0044	-0.0570	-0.0960
	Silver	-0.0087	-0.1445	-0.2419
Softs	Cocoa	0.0059	0.0639	0.0245
	Coffee	0.0044	0.1252	0.0972
	Cotton	0.0054	0.0458	0.0132
	Orange Juice	0.0070	0.4000	0.4078
	Sugar	0.0037	0.1284	0.1053
	Milk	-0.0021	0.0603	0.0233
	Lumber	0.0130	0.1150	0.1118

Table 2 Characteristic level: the effect of idiosyncratic skewness on cross-section of commodity returns

This table reports the time-series average of the slope coefficients and their *t*-values from the Fama-MacBeth cross-sectional regressions of the commodity futures returns on the idiosyncratic skewness and control variables using Eq. (3). The control variables include a set of characteristics of commodity futures. The Appendix A provides a detailed description of all variables. The Newey-West *t*-statistics are reported in parentheses. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)	(5)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
IE_t	-0.0263**	-0.0378***	-0.0230*	-0.0281**	-0.0290*
	(-2.4221)	(-2.8629)	(-1.7600)	(-2.2427)	(-1.9450)
$\mathrm{volatility}_t$		-0.0095	-0.0018	-0.0004	0.0000
		(-0.573)	(-0.1073)	(-0.0228)	(-0.0017)
volume_t		-0.0064	-0.0042	-0.0014	-0.0108
		(-0.3264)	(-0.1981)	(-0.0661)	(-0.4956)
$\mathrm{open\_interest}_t$		-0.0060	-0.0182	-0.0020	-0.0004
		(-0.2990)	(-0.8738)	(-0.1003)	(-0.0199)
$\mathrm{prior\_month\_r}_t$		0.0118			0.0239
		(0.3898)			(0.8228)
$\mathrm{momentum}_t$			0.0253		0.0346**
			(1.5453)		(2.1763)
$\mathrm{prior60\_month\_r}_t$				-0.0058	-0.0269
				(-0.2640)	(-0.9749)
$\mathrm{Intercept}_t$	0.0000	-0.0005	-0.0002	-0.0043	-0.0035
	(0.031)	(-0.0762)	(-0.0385)	(-0.7351)	(-0.4616)
adjusted R^2	0.02%	10.01%	10.10%	8.79%	17.51%

Table 3 Using the traditional measure of idiosyncratic skewness

This table reports the time-series average of the slope coefficients and their t-values from the Fama-MacBeth cross-sectional regressions of the commodity futures returns on the traditional measure of the idiosyncratic skewness (ISKEW) and control variables. The control variables include a set of characteristics of commodity futures. The Appendix A provides a detailed description of all variables. The Newey-West t-statistics are reported in parentheses. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)	(5)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
ISKEW_t	-0.0167	-0.0220	-0.0248*	-0.0224*	-0.0214
	(-1.4765)	(-1.6173)	(-1.9485)	(-1.7403)	(-1.5964)
volatility_t		-0.0098	-0.015	-0.0032	-0.0069
		(-0.601)	(-0.8898)	(-0.2041)	(-0.3809)
volume_t		-0.0086	-0.0154	-0.0069	-0.0194
		(-0.395)	(-0.7584)	(-0.3311)	(-0.9114)
open_interest_t		-0.017	-0.0042	-0.0053	0.0039
		(-0.7931)	(-0.2013)	(-0.2535)	(0.1825)
prior_month_r_t		0.0312*			0.0505***
		(1.9303)			(3.3049)
momentum_t			-0.0019		0.0226
			(-0.0498)		(0.6059)
prior60_month_r_t				-0.002	-0.0201
				(-0.0882)	(-0.7795)
Intercept_t	0.0008	-0.001	-0.0036	-0.0037	-0.004
	(0.8934)	(-0.1918)	(-0.4575)	(-0.6371)	(-0.4615)
adjusted R^2	1.13%	11.01%	11.04%	10.08%	17.86%

Table 4 Characteristic level: idiosyncratic skewness versus total skewness

This table reports the time-series average of the slope coefficients and their *t*-values from the Fama-MacBeth cross-sectional regressions of the commodity futures returns on both the total and idiosyncratic skewness. We replace the total skewness with the residuals of the regressions of the total skewness on idiosyncratic skewness to eliminate the multicollinearity problem. The control variables include a set of characteristics of commodity futures. The Appendix A provides a detailed description of all variables. The Newey-West *t*-statistics are reported in parentheses. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
	R_{t+1} (original SKEW)	R_{t+1} (original SKEW)	R_{t+1} (residuals of SKEW: time series regression)	R_{t+1} (residuals of SKEW: time series regression)	R_{t+1} (residuals of SKEW: cross-sectional regression)	R_{t+1} (residuals of SKEW: cross-sectional regression)
IE_t	-0.0044	-0.0244	-0.0211*	-0.0375**	-0.0255**	-0.0348**
	(-0.2975)	(-1.3554)	(-1.8398)	(-2.4971)	(-2.3512)	(-2.4039)
SKEW_t	-0.0315**	-0.0202	-0.0184	-0.0154	-0.0238*	-0.0168
	(-2.1656)	(-1.2289)	(-1.3682)	(-1.0520)	(-1.9581)	(-1.2475)
$\mathrm{volatility}_t$		-0.0052		-0.0037		-0.0052
		(-0.2842)		(-0.2059)		(-0.2842)
volume_t		-0.0176		-0.0151		-0.0176
		(-0.7897)		(-0.6514)		(-0.7897)
$\mathrm{open\_interest}_t$		0.0052		-0.0005		0.0052
		(0.2385)		(-0.0209)		(0.2385)
$\mathrm{momentum}_t$		0.027		0.021		0.027
		(0.6365)		(0.4903)		(0.6365)
$\mathrm{prior\_month\_r}_t$		0.0474***		0.0477***		0.0474***
		(2.9279)		(2.9291)		(2.9279)
prior60_month_r		-0.0368		-0.0348		-0.0368
		(-1.3384)		(-1.3229)		(-1.3384)
$\mathrm{Intercept}_t$	0.0014	-0.0018	0.0012	-0.0019	0.0014	-0.0017
	(1.3675)	(-0.1904)	(1.1944)	(-0.2049)	(1.4185)	(-0.18)
adjusted R^2	1.31%	18.29%	1.57%	18.73%	1.31%	18.29%

Table 5 Robustness at characteristic level: additional control variables

This table presents the results of the robustness tests of the idiosyncratic skewness effect after controlling for MAX (Bali et al., 2011), MIN (Bali et al., 2011), COKURT (Dittmar, 2002), and liquidity (Amihud et al., 1997), respectively. It reports the time-series average of the slope coefficients and their *t*-values from the Fama-MacBeth cross-sectional regressions of the commodity futures returns on idiosyncratic skewness and control variables. The Newey-West *t*-statistics are reported in parentheses. Details on the construction of the variables are listed in the Appendix A. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
IE_t	-0.0342**	-0.0336**	-0.0328**	-0.0288*
	(-2.2180)	(-2.2798)	(-2.1740)	(-1.8443)
MAX_t	0.0242			
	(0.6412)			
MIN_t		0.0258		
		(0.7087)		
COKURT_t			-0.0063	
			(-0.3494)	
liquidity_t				0.0140
				(0.7166)
volatility_t	-0.0154	-0.0071	-0.0033	-0.0233
	(-0.665)	(-0.3102)	(-0.1494)	(-0.9531)
volume_t	-0.003	-0.0128	-0.0046	-0.0074
	(-0.133)	(-0.5702)	(-0.2242)	(-0.3488)
open_interest_t	0.0495*	0.034	0.0287	0.0249
	(1.6724)	(1.3195)	(0.5873)	(0.8002)
momentum_t	0.0393**	0.0368**	0.0449**	0.0412**
	(2.167)	(2.2011)	(2.509)	(2.491)
prior_month_r_t	-0.0189	-0.0255	-0.0099	-0.0215
	(-0.6855)	(-0.9324)	(-0.3719)	(-0.7406)
prior60_month_r_t	-0.0156	-0.0332	0.0004	0.0283
	(-0.4294)	(-0.886)	(0.0189)	(1.6426)
Intercept_t	0.0005	-0.0074	0.0021	-0.0036
	(0.067)	(-0.9612)	(0.1978)	(-0.4545)
adjusted R^2	20.09%	19.83%	21.99%	17.81%

Table 6 Robustness at characteristic level: financial crisis

This table consider the impact of the financial crisis. We include a dummy for the financial crisis at the second stage of the Fama-MacBeth cross-sectional regression. The regressions are modified as follows,

First stage: $R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} IE_{i,t} + \Lambda control_{i,t} + \varepsilon_{i,t+1}$

Second stage: $\lambda_{k,t} = \gamma_{0,k} + \gamma_{1,k} dummy_t + \epsilon_{k,t},\ k = 0,1,\cdots,$

where $\lambda_{k,t}$ are the coefficients of the idiosyncratic skewness and control variables in the first stage, k represents the *k*th variable, and *i* represents the *i*th commodity. We report the average value of $\gamma_{0,k}$ and $\gamma_{1,k}$ from the second stage, where $\gamma_{1,k}$ indicates the effect of the financial crisis on the coefficients. The Newey-West *t*-statistics are reported in the parentheses, respectively. Details on the construction of the variables are listed in the Appendix A. The sample period is Jan 1987 to May 2018.

	R_{t+1}		R_{t+1}	
	$\gamma_{0,k}$	$\gamma_{1,k}$	$\gamma_{0,k}$	$\gamma_{1,k}$
IE_t	-0.0261**	-0.0057	-0.0308**	0.0345
	(-2.3964)	(-0.0750)	(-2.0275)	(0.4600)
$volatility_t$			0.0011	-0.0229
			(0.0600)	(-0.4485)
$volume_t$			-0.0080	-0.0500
			(-0.355)	(-0.7384)
open_interest$_t$			-0.0022	0.0283
			(-0.1005)	(0.3243)
$momentum_t$			0.0283	-0.0864
			(0.9305)	(-1.241)
prior_month_r$_t$			0.0305*	0.0817
			(1.8428)	(1.5814)
prior60_month_r$_t$			-0.0329	0.1196
			(-1.1630)	(0.9787)
$Intercept_t$	0.0000	0.0006	-0.0043	0.0157
	(-0.0369)	(0.4703)	(-0.5415)	(0.8584)
adjusted R^2	-0.26%		-0.18%	

Table 7 Robustness at characteristic level: a different rolling-over method

This table reports the results of the Fama-MacBeth cross-sectional regressions of the commodity futures returns on idiosyncratic skewness and control variables. We roll over to the next nearest contract 1 month before maturity. The control variables include a set of characteristics of commodity futures. The Appendix A provides a detailed description of all variables. The Newey-West *t*-statistics are reported in parentheses. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)	(5)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
IE_t	-0.0328***	-0.043***	-0.027*	-0.0316**	-0.0357**
	(-2.7589)	(-2.902)	(-1.7949)	(-2.2753)	(-2.1445)
$\mathrm{volatility}_t$		-0.0032	-0.0016	0.0048	0.0034
		(-0.1936)	(-0.0985)	(0.3105)	(0.184)
volume_t		-0.0044	-0.0025	0.0029	-0.0106
		(-0.2205)	(-0.1165)	(0.1361)	(-0.4802)
$\mathrm{open\_interest}_t$		-0.0118	-0.0239	-0.0082	-0.0043
		(-0.5846)	(-1.1683)	(-0.4104)	(-0.2038)
$\mathrm{momentum}_t$		0.0107			0.0223
		(0.3573)			(0.7665)
$\mathrm{prior\_month\_r}_t$			0.0205		0.0286*
			(1.2249)		(1.7721)
$\mathrm{prior60\_month\_r}_t$				-0.0078	-0.028
				(-0.3484)	(-1.0628)
$\mathrm{Intercept}_t$	0.0004	0.0012	-0.0007	-0.0059	-0.0024
	(0.4293)	(0.1616)	(-0.1132)	(-1.0795)	(-0.3116)
adjusted R^2	0.40%	10.76%	10.69%	9.07%	18.21%

Table 8 Summary statistics for idiosyncratic-skewness-sorted portfolios

This table summarizes the performance of the idiosyncratic skewness trading strategy. The commodities are sorted into terciles according to their idiosyncratic skewness (IE), and equal-weighted portfolios are constructed for each tercile. Portfolio Q1 contains the 30% most negatively skewed commodities, while Q3 contains the 30% most positively skewed commodities. The portfolios are rebalanced every month. The spread portfolio (Q3-Q1) longs Q3 and shorts Q1. We report the summary statistics of the monthly commodity returns for each portfolio, and the alpha from regressing the returns of the spread portfolio on the traditional commodity risk factors MARKET, TS, MOM and HP using Eq. (5). Details on the construction of the factors are listed in the Appendix A. The sample period is Jan 1987 to May 2018.

	Q1	Q2	Q3	Q3-Q1
Mean return	0.0097***	0.0059***	0.0041*	-0.0056*
	(2.9208)	(2.9796)	(1.7798)	(-1.6655)
Adjusted return (α)	0.0080**	0.0028*	0.0015	-0.0065*
	(2.3580)	(1.9180)	(0.8030)	(-1.7920)
StDev	0.0646	0.0383	0.0446	0.0657
Ranking skewness	-0.0191	0.0038	0.0250	0.0441
Sharp ratio	0.1506	0.1537	0.0918	-0.0859
Min	-0.1775	-0.1203	-0.2478	-0.9591
Max	0.9840	0.2406	0.1425	0.1687

Table 9 Double-sorted portfolio returns

This table presents sequential double-sorted portfolio returns sorted by one of the control variables and idiosyncratic skewness (IE). At each month, we first sort the commodities into two groups by each control variable (*portfolio Low* and *portfolio High* denote the lowest and highest portfolios for the control variable, respectively). Within each group of the control variable, we then sort the commodities into two portfolios by the idiosyncratic skewness. The spread portfolio (Q2-Q1) longs Q2 and shorts Q1. *Avg* reports the average across the two control variable groups. For each portfolio, we report the average return and alpha from regressing the returns on the traditional commodity risk factors MARKET, TS, MOM and HP using Eq. (5). The *t*-statistics are presented in parentheses. The sample period is Jan 1987 to May 2018.

	Spread return Q2-Q1	Adjusted return (α)		Spread return Q2-Q1	Adjusted return (α)
volatility Low	-0.002 (-0.563)	-0.0025 (-0.8582)	prior60_month_r Low	-0.0056*** (-2.7619)	-0.0054*** (-2.5949)
volatility High	-0.0086*** (-3.0934)	-0.0093*** (-3.2622)	prior60_month_r High	-0.0066 (-1.5724)	-0.0087** (-2.524)
Avg	-0.0053** (-2.4054)	-0.0059*** (-2.9802)	Avg	-0.0061*** (-2.6414)	-0.0071*** (-3.5426)
volume Low	-0.0043* (-1.6779)	-0.005* (-1.9235)	MAX Low	-0.0039 (-1.1491)	-0.0044 (-1.535)
volume High	-0.0053** (-2.191)	-0.0045* (-1.849)	MAX High	-0.0064** (-2.4161)	-0.0073*** (-2.7203)
Avg	-0.0048*** (-2.7375)	-0.0047*** (-2.6609)	Avg	-0.0052** (-2.4139)	-0.0058*** (-3.0683)
open interest Low	-0.0027 (-1.0046)	-0.0039 (-1.4114)	MIN Low	-0.0006 (-0.3129)	-0.0011 (-0.5665)
open interest High	-0.0081*** (-3.0122)	-0.0067** (-2.4242)	MIN High	-0.011** (-2.5451)	-0.0116*** (-3.0828)
Avg	-0.0054*** (-2.6859)	-0.0053** (-2.5506)	Avg	-0.0058** (-2.4566)	-0.0063*** (-3.0446)
momentum Low	-0.0048 (-1.2956)	-0.005 (-1.5954)	COKURT Low	-0.005** (-2.3284)	-0.0044** (-2.0266)
momentum High	-0.0049** (-2.0126)	-0.006** (-2.4423)	COKURT High	-0.0096** (-2.2707)	-0.0115*** (-3.2839)
Avg	-0.0048** (-2.1722)	-0.0055*** (-2.7822)	Avg	-0.0073*** (-3.1287)	-0.0079*** (-3.926)
prior_month_r Low	-0.003 (-0.7663)	-0.0042 (-1.2208)	liquidity Low	-0.0054** (-2.0019)	-0.0059** (-2.1333)
prior_month_r High	-0.0036 (-1.5192)	-0.0038 (-1.5832)	liquidity High	-0.0055** (-2.4732)	-0.0052** (-2.3054)
Avg	-0.0033 (-1.4261)	-0.004* (-1.9327)	Avg	-0.0055*** (-3.0278)	-0.0056*** (-3.0209)

Table 10 Double-sorted portfolio returns: idiosyncratic skewness versus total skewness

This table reports the single-sorted portfolio returns by total skewness represented by residuals, and the sequential double-sorted portfolio returns by total skewness and idiosyncratic skewness. Using the single-sorting method, the commodities are sorted into terciles according to their total skewness (residuals), and equal-weighted portfolios are constructed for each tercile. Portfolio *SKEW Low* contains the 30% most negatively skewed commodities, while *SKEW High* contains the 30% most positively skewed commodities. The portfolios are rebalanced every month. The spread portfolio (*High-Low*) longs the *SKEW High* and shorts the *SKEW Low*. Using the double-sorting method, at each month, we first sort commodities into two portfolios by total skewness (*SKEW Low* and *SKEW High* denote the lowest and highest portfolio for the total skewness, respectively). Within each total skewness portfolio, we then sort commodities into two portfolios by idiosyncratic skewness. The spread portfolio (Q2-Q1) longs Q2 and shorts Q1. *Avg* reports the return spread average of total skewness portfolios. We replace the total skewness with residuals of regressions of total skewness on idiosyncratic skewness to eliminate the multicollinearity problem. We also report the alpha from regressing the returns of the portfolios on the traditional commodity risk factors MARKET, TS, MOM and HP using Eq. (5). The Newey-West *t*-statistics are reported in parentheses. The sample period is Jan 1987 to May 2018.

Panel A: single-sorted portfolio returns by total skewness (residuals)

residuals of time series regression				residuals of cross sectional regression			
SKEW Low	SKEW 2	SKEW High	High-Low	SKEW Low	SKEW 2	SKEW High	High-Low
0.0068***	0.0084***	0.0039*	-0.0028	0.0067***	0.0091***	0.0032	-0.0036
(2.9879)	(2.7467)	(1.8323)	(-1.1744)	(3.0352)	(2.9898)	(1.4089)	(-1.4995)

Panel B: double-sorted portfolio returns by idiosyncratic skewness and total skewness

	Q2-Q1 spread return	Adjusted Return (α)		Q2-Q1 spread return	Adjusted Return (α)
SKEW Low	-0.0057	-0.0063*	SKEW Low	-0.0042	-0.0056*
(res of time series reg)	(-1.5301)	(-1.904)	(res of cross sectional reg)	(-1.1279)	(-1.7733)
SKEW High	-0.0062***	-0.0064***	SKEW High	-0.0059***	-0.0058**
(res of time series reg)	(-2.8664)	(-2.8751)	(res of cross sectional reg)	(-2.6167)	(-2.5757)
Avg	-0.006***	-0.0063***	Avg	-0.005**	-0.0057***
	(-2.7841)	(-3.2003)		(-2.3467)	(-2.9581)

Table 11 Longer-term portfolio returns

This table presents the longer-term returns of the tercile portfolios formed monthly by sorting on the idiosyncratic skewness (IE). Portfolio Q1 contains the 30% most negatively skewed commodities, while Q3 contains the 30% most positively skewed commodities. The table reports the average of the monthly returns and the risk-adjusted return (alpha from regressing the returns on the traditional commodity risk factors MARKET, TS, MOM and HP using Eq. (5)) for each tercile from 2 to 12 months ahead after portfolio formation. Q3-Q1 is the long-short spread portfolio. t-statistics are presented in parentheses. The sample period is Jan 1987 to May 2018.

	Return				Adjusted Return (α)			
	Q1	Q2	Q3	Q3-Q1	Q1	Q2	Q3	Q3-Q1
t+2	0.0120***	0.0054***	0.0027	-0.0093***	0.0094***	0.0031**	-0.0001	-0.0095***
	(3.5239)	(2.7594)	(1.2692)	(-2.7684)	(2.7767)	(2.0668)	(-0.0445)	(-2.6257)
t+3	0.0096***	0.0066***	0.0032	-0.0064*	0.0074**	0.0044***	-0.0001	-0.0075**
	(2.8077)	(3.3316)	(1.4634)	(-1.8705)	(2.1567)	(2.9387)	(-0.0521)	(-2.0412)
t+4	0.0101***	0.0055***	0.0032	-0.0068**	0.0082**	0.0032**	0.0005	-0.0077**
	(2.9784)	(2.7789)	(1.4912)	(-2.0389)	(2.427)	(2.084)	(0.3059)	(-2.1154)
t+5	0.0088***	0.0082***	0.0015	-0.0072***	0.0065***	0.0064**	-0.0013	-0.0078***
	(4.1179)	(2.6766)	(0.6963)	(-3.2111)	(3.619)	(2.1468)	(-0.7429)	(-3.2975)
t+6	0.0075***	0.0089***	0.0018	-0.0057**	0.0054***	0.0070**	-0.0009	-0.0063***
	(3.5874)	(2.8845)	(0.835)	(-2.4947)	(2.9238)	(2.3942)	(-0.5317)	(-2.6197)
t+7	0.0070***	0.0090***	0.0023	-0.0047**	0.0047**	0.0069**	-0.0001	-0.0049**
	(3.2489)	(2.8942)	(1.0023)	(-2.0409)	(2.5898)	(2.3063)	(-0.0839)	(-2.081)
t+8	0.0082***	0.0078**	0.0026	-0.0056**	0.0061***	0.0056*	0.0004	-0.0057**
	(3.8592)	(2.5313)	(1.1589)	(-2.4633)	(3.4417)	(1.9133)	(0.2375)	(-2.462)
t+9	0.0106***	0.0062***	0.0015	-0.0091**	0.0087**	0.0043***	-0.0011	-0.0097***
	(3.0697)	(3.1718)	(0.6431)	(-2.5681)	(2.5463)	(2.8439)	(-0.5914)	(-2.6046)
t+10	0.0103***	0.0064***	0.0021	-0.0082**	0.0083**	0.0047***	-0.0006	-0.0090**
	(2.7371)	(3.1789)	(0.9389)	(-2.1638)	(2.2147)	(2.9985)	(-0.3551)	(-2.2576)
t+11	0.0101***	0.0058***	0.0030	-0.0072*	0.0086**	0.0037**	0.0008	-0.0078*
	(2.6977)	(2.7641)	(1.3825)	(-1.8897)	(2.273)	(2.4023)	(0.4863)	(-1.9507)
t+12	0.0098**	0.0058***	0.0034	-0.0063	0.0084**	0.0035**	0.0012	-0.0072*
	(2.5766)	(2.7119)	(1.5735)	(-1.6443)	(2.2083)	(2.2498)	(0.7345)	(-1.7815)

Table 12 Cross-sectional pricing ability of the idiosyncratic skewness factor

This table reports the time-series average of the slope coefficients and their *t*-values from the two-pass Fama-MacBeth cross-sectional regressions of the commodity futures returns on the factor loading using Eq. (7). The Newey-West *t*-statistics are reported in parentheses. Details on the construction of the factors are listed in the Appendix A. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
β_t^{IE}	-0.0063***	-0.0094***	-0.0061***	-0.0069**	-0.0045*	-0.0104**
	(-2.9479)	(-3.8217)	(-2.6561)	(-2.4231)	(-1.7985)	(-2.0149)
β_t^{MARKET}		0.0051				-0.0006
		(1.3872)				(-0.0675)
β_t^{TS}			0.0005			0.0219
			(0.1853)			(0.7979)
β_t^{HP}				0.0147**		0.0392*
				(2.4291)		(1.7087)
β_t^{MOM}					-0.0013	0.0162
					(-0.4389)	(0.8595)
Intercept_t	0.006***	0.0053***	0.0066***	0.0056***	0.006***	0.0056***
	(3.4555)	(3.5379)	(3.9895)	(3.4962)	(3.8719)	(3.589)
adjusted R^2	5.94%	13.72%	13.03%	11.97%	12.79%	25.04%

Table 13 Robustness at factor level: additional risk factors

This table presents the robustness of the price of the idiosyncratic skewness factor after controlling for liquidity, inflation, and sentiment. It reports the time-series average of the slope coefficients and their *t*-values from the two-pass Fama-MacBeth cross-sectional regressions of the commodity futures returns on the factor loadings using. Eq. (7). The Newey-West *t*-statistics are reported in parentheses. Details on the construction of the factors are listed in the Appendix A. The sample period is Jan 1987 to May 2018.

	(1)	(2)	(3)	(4)
	R_{t+1}	R_{t+1}	R_{t+1}	R_{t+1}
β_t^{IE}	-0.0151***	-0.0096***	-0.0132**	-0.0155***
	(-3.0679)	(-2.8841)	(-2.3436)	(-3.3578)
β_t^{lr}	0.001			0.0003
	(0.1967)			(0.0599)
$\beta_t^{inflation}$		-0.0004		-0.0005
		(-1.2305)		(-1.4945)
$\beta_t^{sentiment}$			0.0173	0.0094
			(1.0908)	(0.5107)
β_t^{MARKET}	0.0023	0.0049	-0.0004	0.0035
	(0.2294)	(0.4418)	(-0.0423)	(0.2973)
β_t^{TS}	-0.0265	-0.0079	-0.0027	-0.007
	(-1.1392)	(-1.2792)	(-0.3938)	(-0.842)
β_t^{HP}	0.1135	0.0053	0.0237	0.0062
	(1.2235)	(0.2808)	(1.1866)	(0.3021)
β_t^{MOM}	-0.0998	0.0006	-0.0043	-0.0027
	(-1.0104)	(0.0661)	(-0.4609)	(-0.2853)
Intercept_t	0.0048***	0.0042**	0.0046***	0.0044**
	(3.0875)	(2.4009)	(3.2004)	(2.4996)
adjusted R^2	28.33%	26.68%	29.61%	34.92%

Appendix A

Table A.1 Variables Definitions

Variables	Definition
SKEW	The total skewness is defined by the following equation $$SKEW_{i,t} = \frac{1/D\sum_{d=1}^{D}\left(R_{i,d,t} - \mu_{i,t}\right)^3}{\sigma_{i,t}^3}$$ It is obtained at each month-end t using daily return history of commodity i over the preceding $t-5$ to t window.
ISKEW	The idiosyncratic skewness of commodity i in month t is computed using the daily residuals in the equation $R_{i,d} = \alpha_i + \beta_i \cdot R_{m,d} + \gamma_i \cdot R_{m,d}^2 + \varepsilon_{i,d}$ from month $t-5$ to t.
IE	The IE is defined as the difference between the upside and downside return probabilities using Eq. (1).
volatility	The volatility is defined as the standard deviation of daily returns of commodity i in month t.
volume	The trading volume is defined as the number of contracts of commodity i traded in month t.
open interest	The open interest is defined as the total number outstanding of commodity contracts that have not been settled.
momentum	The momentum is defined as the past 6-month average returns from $t-2$ to $t-6$.
prior month r	The prior month r is defined as the last-month return.
prior 60 month r	The prior 60 month r is defined as the past 60-month cumulative return from $t-2$ to $t-60$.
MAX	The MAX (Bali et al., 2011) is the extreme positive returns in month t, which is defined by the following equation $$MAX_{i,t} = max\left(R_{i,d}\right).$$
MIN	The MIN (Bali et al., 2011) is the extreme negative returns in month t, which is defined by the following equation $$MIN_{i,t} = -min\left(R_{i,d}\right).$$
COKURT	The COKURT (Dittmar, 2002) measures the common sensitivity of the variable to the extreme returns, and is defined by the following equation

	$$COKURT_{i,t} = \frac{1/D_t \sum_{d=1}^{D_t} R_{i,d} R_{m,d}^3}{\sqrt{1/D_t \sum_{d=1}^{D_t} R_{i,d}^2} \left(1/D_t \sum_{d=1}^{D_t} R_{m,d}^2\right)^{3/2}}.$$
liquidity	Following Amihud et al. (1997), we define liquidity as the dollar trading volume associated with the absolute return using the following equation $$liquidity_{i,t} = \frac{1}{D} \sum \frac{\$volume_{i,d}}{\lvert r_{i,d} \rvert}.$$
financial crisis	The dummy of financial crisis, which equals 1 between Dec 2007 and June 2009, otherwise equals 0.
MARKET	The factor of market return (S&P GSCI).
TS	The factor of roll yield. The roll yield is measured as the daily difference in logarithmic prices of the front-end and second-nearest contracts. The TS portfolio buys (and simultaneously sells) the 30% tercile with highest (lowest) average roll yield over the previous 12 months.
HP	The factor of the hedgers' and speculators' hedging pressure. The hedging pressure of hedgers (speculators) is measured as the long position of hedgers (speculators) divided by the total positions of hedgers (speculators). The HP portfolio buys (and simultaneously sells) the 30% tercile with highest (lowest) average total hedging pressure over the previous 12 months.
MOM	The factor of momentum. The MOM portfolio buys (and simultaneously sells) the 30% tercile with highest (lowest) average momentum over the previous 12 months.
inflation	It is the changes in one-month US CPI.
sentiment	The sentiment indicator introduced by Baker and Wurgler (2006).

Table A.2 Cross-sectional correlation between the total skewness and idiosyncratic skewness

This table reports the time-series average of the cross-sectional correlation between the total skewness (SKEW) and idiosyncratic skewness (ISKEW and IE).

	SKEW	ISKEW	IE
SKEW	1.0000		
ISKEW	0.8583	1.0000	
IE	0.4008	0.4123	1.0000